Research Topics

Data-limited research in stock assessment to increase the understanding of fisheries resources and inform and improve management efforts

Edited by
Giuseppe Scarcella, Simone Libralato, Natalie Anne Dowling, Joanna Mills Flemming and Matthias Wolff

Published in
Frontiers in Marine Science

ISSN 1664-8714
ISBN 978-2-83252-009-3
DOI 10.3389/978-2-83252-009-3

About Frontiers

Frontiers is more than just an open access publisher of scholarly articles: it is a pioneering approach to the world of academia, radically improving the way scholarly research is managed. The grand vision of Frontiers is a world where all people have an equal opportunity to seek, share and generate knowledge. Frontiers provides immediate and permanent online open access to all its publications, but this alone is not enough to realize our grand goals.

Frontiers journal series

The Frontiers journal series is a multi-tier and interdisciplinary set of open-access, online journals, promising a paradigm shift from the current review, selection and dissemination processes in academic publishing. All Frontiers journals are driven by researchers for researchers; therefore, they constitute a service to the scholarly community. At the same time, the *Frontiers journal series* operates on a revolutionary invention, the tiered publishing system, initially addressing specific communities of scholars, and gradually climbing up to broader public understanding, thus serving the interests of the lay society, too.

Dedication to quality

Each Frontiers article is a landmark of the highest quality, thanks to genuinely collaborative interactions between authors and review editors, who include some of the world's best academicians. Research must be certified by peers before entering a stream of knowledge that may eventually reach the public - and shape society; therefore, Frontiers only applies the most rigorous and unbiased reviews. Frontiers revolutionizes research publishing by freely delivering the most outstanding research, evaluated with no bias from both the academic and social point of view. By applying the most advanced information technologies, Frontiers is catapulting scholarly publishing into a new generation.

What are Frontiers Research Topics?

Frontiers Research Topics are very popular trademarks of the *Frontiers journals series*: they are collections of at least ten articles, all centered on a particular subject. With their unique mix of varied contributions from Original Research to Review Articles, Frontiers Research Topics unify the most influential researchers, the latest key findings and historical advances in a hot research area.

Find out more on how to host your own Frontiers Research Topic or contribute to one as an author by contacting the Frontiers editorial office: frontiersin.org/about/contact

Data-limited research in stock assessment to increase the understanding of fisheries resources and inform and improve management efforts

Topic editors
Giuseppe Scarcella — National Research Council (CNR), Italy
Simone Libralato — National Institute of Oceanography and Experimental Geophysics (Italy), Italy
Natalie Anne Dowling — Oceans and Atmosphere (CSIRO), Australia
Joanna Mills Flemming — Dalhousie University, Canada
Matthias Wolff — Leibniz Centre for Tropical Marine Research (LG), Germany

Citation
Scarcella, G., Libralato, S., Dowling, N. A., Flemming, J. M., Wolff, M., eds. (2023). *Data-limited research in stock assessment to increase the understanding of fisheries resources and inform and improve management efforts*. Lausanne: Frontiers Media SA. doi: 10.3389/978-2-83252-009-3

Table of contents

frontiers | Frontiers in Marine Science

TYPE Editorial
PUBLISHED 20 April 2023
DOI 10.3389/fmars.2023.1193307

Check for updates

OPEN ACCESS

EDITED AND REVIEWED BY
Stelios Katsanevakis,
University of the Aegean, Greece

*CORRESPONDENCE
Giuseppe Scarcella
giuseppe.scarcella@cnr.it

SPECIALTY SECTION
This article was submitted to Marine Ecosystem Ecology, a section of the journal Frontiers in Marine Science

RECEIVED 24 March 2023
ACCEPTED 07 April 2023
PUBLISHED 20 April 2023

CITATION
Scarcella G, Libralato S, Dowling NA, Flemming JM and Wolff M (2023) Editorial: Data-limited research in stock assessment to increase the understanding of fisheries resources and inform and improve management efforts.
Front. Mar. Sci. 10:1193307.
doi: 10.3389/fmars.2023.1193307

Editorial: Data-limited research in stock assessment to increase the understanding of fisheries resources and inform and improve management efforts

Giuseppe Scarcella[1,2*], Simone Libralato[3], Natalie Anne Dowling[4,5], Joanna Mills Flemming[6] and Matthias Wolff[7]

[1]National Research Council (CNR), Roma, Italy, [2]IRBIM, Istituto per le Risorse Biologiche e le Biotecnologie Marine, Ancona, Italy, [3]National Institute of Oceanography and Experimental Geophysics (Italy), Trieste, Italy, [4]Commonwealth Scientific and Industrial Research Organisation (CSIRO), Canberra, ACT, Australia, [5]CSIRO Oceans and Atmosphere, Horbart, TAS, Australia, [6]Department of Mathematics and Statistics, Dalhousie University, Halifax, NS, Canada, [7]Leibniz Centre for Tropical Marine Research (LG), Bremen, Germany

KEYWORDS

stock assessment, data limited, fishery management, data poor approach, harvest control rule

Editorial on the Research Topic
Data-limited research in stock assessment to increase the understanding of fisheries resources and inform and improve management efforts

Management thinker Peter Drucker is often quoted as saying "You can't manage what you can't measure." Drucker means that you cannot know whether or not you are successful unless success is defined and monitored. Such a quote is fully applicable to fishery science because only when we can estimate the status of stocks can we provide meaningful and successful management advice: that which gets measured gets managed. However, an increasing share of fishers' income is derived from fish from stocks whose status remains unassessed. In such situations, a simple rough model might be more useful than no model at all.

The main reasons for the lack of assessment and associated formal harvest control rules are often associated to:

- lack of (quality) data to reliably inform a fully integrated stock assessment.
- limited capacity and funding.
- associated fishery characteristics, including inconsistent targeting practices, numerous unregulated operators, or profound cultural issues.
- the challenge of selecting from numerous possibilities and the most appropriate assessment and management options given the fishery's context.

However, many methods have been developed to assist in the assessment of the status of so-called data-limited stocks. Although not based on complex integrated models increasingly used in stock assessments, data-limited assessment methods, particularly when paired with precautionary harvest control rules, provide a reliable understanding of the stock status and might be used to achieve fishery sustainability.

A brief search on the Scopus database (www.scopus.com) highlighted approximately 360 documents produced between 1993 and 2023 pertaining to this area of research (TITLE-ABS-KEY [("data-limited" OR "data poor") AND "stock assessment")]. The bibliographic analysis showed an exponential increase with time, especially for "data-limited" approaches (Figure 1). These studies regarded mainly northern hemisphere countries (Figure 2).

The RT included 22 papers from various countries (two from the US, five from Med, and eight from China). The works of the RT are distributed mainly around several topics:

The first application of the data-limited approach to new species (e.g., Angelini et al., 2021; Falsone et al., 2021; Geraci et al., 2021; Shi et al., 2022; Tsikliras et al., 2021; Wang et al., 2021; Wang et al., 2022; Zhang et al., 2021; Zhang et al., 2022; Zhu et al., 2021).

The application of several data-limited approaches for comparison to the same species (e.g., Meissa et al., 2021; Simard et al., 2021; Zheng et al., 2022).

The development of the application of complex approaches adapted for data-limited situations (e.g., Harford et al., 2021;

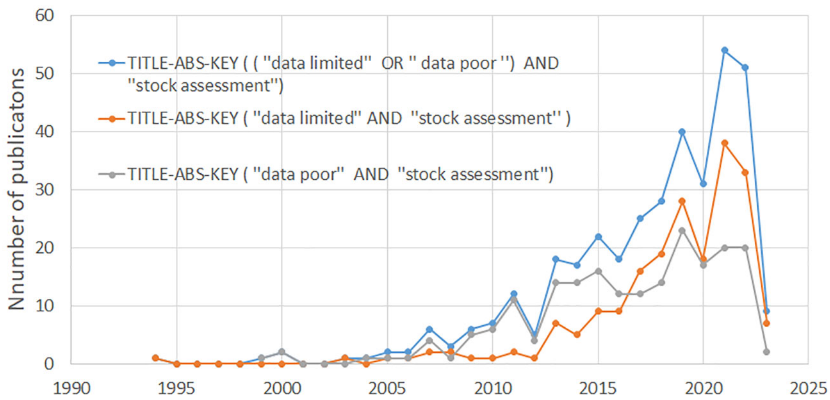


FIGURE 1
Number of publications by year relevant to this research topic. Source: www.scopus.com.

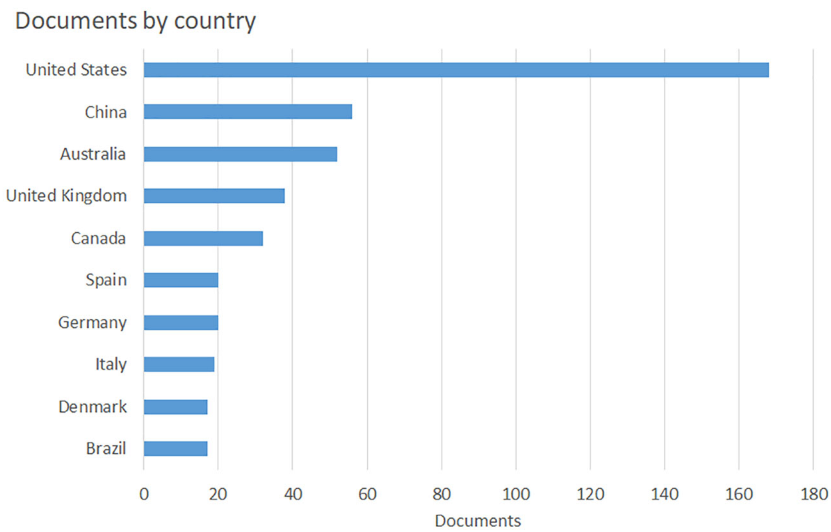


FIGURE 2
Number of publications by country relevant to this research topic (only countries with more than 15 documents are presented). Source: www.scopus.com.

Mannini et al., 2020; Omori et al., 2021; Rudd et al., 2021; Sánchez-Maroño et al., 2021).

The assessment and forecasting approaches for data-limited species (e.g., Armelloni et al., 2021; Pantazi et al., 2020).

how data-limited stocks can undermine a formal management process (e.g., Kell et al., 2022).

The formal management harvest control rules for data-limited fisheries (e.g., Sanchez-Marono et al., 2021; Xia et al., 2021).

From the analysis of the keywords used in the 22 published manuscripts, the heterogeneity in covered topics is evident. However, the most used methodologies within the data-limited paradigm are production models (cited in 16 manuscripts) and length-based approaches (cited in six manuscripts).

Overall, this Research Topic provided a ground for discussing the potential of data-poor methods to be applied in fishery assessments as well as limitations on their use. Moreover, the studies covered a management perspective with a clear objective of resource conservation, sustainable exploitation, economic viability, and a combination of these and other aims. Although many of the data-poor studies in the present RT concentrate on the assessment of the status of biological resources, the overall conclusion is that the proper management of data-limited fisheries has specific research needs to be developed in the following years. These would focus on the application of artificial intelligence in stock assessment methodologies and the implementation of data collection programs dedicated to the understanding of specific parameters (e.g., carrying capacity). Such needs have also to take into account the state of the art depicted in the 22 scientific studies collected under this RT.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Angelini, S., Armelloni, E. N., Costantini, I., De Felice, A., Isajlović, I., Leonori, I., et al. (2021). Understanding the dynamics of ancillary pelagic species in the Adriatic Sea. *Front. Mar. Sci.* 8. 728948. doi: 10.3389/fmars.2021.728948

Armelloni, E. N., Scanu, M., Masnadi, F., Coro, G., Angelini, S., and Scarcella, G. (2021). Data Poor Approach for the assessment of the main target species of rapido trawl fishery in adriatic sea. *Front. Mar. Sci.* 8, 552076. doi: 10.3389/fmars.2021.552076

Falsone, F., Scannella, D., Geraci, M. L., Gancitano, V., Vitale, S., and Fiorentino, F. (2021). How fishery collapses: the case of lepidopus caudatus (Pisces: trichiuridae) in the strait of Sicily (Central Mediterranean). *Front. Mar. Sci.* 7, 584601. doi: 10.3389/fmars.2020.584601

Geraci, M. L., Falsone, F., Gancitano, V., Scannella, D., Fiorentino, F., and Vitale, S. (2021). Assessing cephalopods fisheries in the strait of Sicily by using poor data modeling. *Front. Mar. Sci.* 8, 584657. doi: 10.3389/fmars.2021.584657

Harford, W. J., Amoroso, R., Bell, R. J., Caillaux, M., Cope, J. M., Dougherty, D., et al. (2021). Multi-indicator harvest strategies for data-limited fisheries: a practitioner guide to learning and design. *Front. Mar. Sci.* 8, 757877. doi: 10.3389/fmars.2021.757877

Kell, L. T., Sharma, R., and Winker, H. (2022). Artefact and artifice: Evaluation of the skill of catch-only methods for classifying stock status. *Front. Mar. Sci.* 9, 762203. doi: 10.3389/fmars.2022.762203

Mannini, A., Pinto, C., Konrad, C., Vasilakopoulos, P., and Winker, H. (2020). "The elephant in the room": exploring natural mortality uncertainty in statistical catch at age models. *Front. Mar. Sci.* 7, 585654. doi: 10.3389/fmars.2020.585654

Meissa, B., Dia, M., Baye, B. C., Bouzouma, M., Beibou, E., and Roa-Ureta, R. H. (2021). A comparison of three data-poor stock assessment methods for the pink spiny lobster fishery in Mauritania. *Front. Mar. Sci.* 8, 714250. doi: 10.3389/fmars.2021.714250

Omori, K. L., Tribuzio, C. A., Babcock, E. A., and Hoenig, J. M. (2021). Methods for identifying species complexes using a novel suite of multivariate approaches and multiple data sources: a case study with gulf of Alaska rockfish. *Front. Mar. Sci.* 8, 663375. doi: 10.3389/fmars.2021.663375

Pantazi, V., Mannini, A., Vasilakopoulos, P., Kapiris, K., Megalofonou, P., and Kalogirou, S. (2020). That's all I know: inferring the status of extremely data-limited stocks. *Front. Mar. Sci.* 7, 583148. doi: 10.3389/fmars.2020.583148

Rudd, M. B., Cope, J. M., Wetzel, C. R., and Hastie, J. (2021). Catch and length models in the stock synthesis framework: Expanded application to data-moderate stocks. *Front. Mar. Sci.* 8, 663554. doi: 10.3389/fmars.2021.663554

Sánchez-Maroño, S., Uriarte, A., Ibaibarriaga, L., and Citores, L. (2021). Adapting simple index-based catch rules for data-limited stocks to short-lived fish stocks' characteristics. *Front. Mar. Sci.* 8, 662942. doi: 10.3389/fmars.2021.662942

Shi, Y., Zhang, X., He, Y., Fan, W., and Tang, F. (2022). Stock assessment using length-based Bayesian evaluation method for three small pelagic species in the Northwest pacific ocean. *Front. Mar. Sci.* 9, 775180. doi: 10.3389/fmars.2022.775180

Simard, N. S. M., Militz, T. A., Kinch, J., and Southgate, P. C. (2021). From past to present: construction of a dataset documenting mother-of-Pearl exports from a pacific island nation, Papua new Guinea. *Front. Mar. Sci.* 8, 762610. doi: 10.3389/fmars.2021.762610

Tsikliras, A. C., Touloumis, K., Pardalou, A., Adamidou, A., Keramidas, I., Orfanidis, G. A., et al. (2021). Status and exploitation of 74 un-assessed demersal fish and invertebrate stocks in the Aegean Sea (Greece) using abundance and resilience. *Front. Mar. Sci.* 7, 578601. doi: 10.3389/fmars.2020.578601

Wang, L., Lin, L., Liu, Y., Zhai, L., and Ye, S. (2022). Fishery dynamics, status, and rebuilding based on catch-only data in coastal waters of China. *Front. Mar. Sci.* 8, 757503. doi: 10.3389/fmars.2021.757503

Wang, Y. C., Liang, C., Xian, W., and Wang, Y. B. (2021). Using the LBB method for the assessments of seven fish stocks from the Yangtze estuary and its adjacent waters. *Front. Mar. Sci.* 8, 679299. doi: 10.3389/fmars.2021.679299

Xia, M., Carruthers, T., Kindong, R., Dai, L., Geng, Z., Dai, X., et al. (2021). How can information contribute to management? value of information (VOI) analysis on Indian ocean striped marlin (Kajikia audax). *Front. Mar. Sci.* 8, 646174. doi: 10.3389/fmars.2021.646174

Zhang, K., Li, J., Hou, G., Huang, Z., Shi, D., Chen, Z., et al. (2021). Length-based assessment of fish stocks in a data-poor, jointly exploited (China and Vietnam) fishing ground, northern south China Sea. *Front. Mar Sci.* 8, 718052. doi: 10.3389/fmars.2021.718052

Zhang, Z., Wang, Y., Liu, S., Liang, C., and Xian, W. (2022). Assessing the distribution and sustainable exploitation of lophius litulon in marine areas off Shandong, China. *Front. Mar. Sci.* 9, 759591. doi: 10.3389/fmars.2022.759591

Zheng, L., Wang, Y., Liu, S., Liang, C., and Xian, W. (2022). Using data-limited methods to assess the status of bartail flathead platycephalus indicus stocks in the bohai and yellow seas. *Front. Mar. Sci.* 8, 759465. doi: 10.3389/fmars.2021.759465

Zhu, L., Ge, C., Jiang, Z., Liu, C., Hou, G., and Liang, Z. (2021). Stock assessment of small yellow croaker (Larimichthys polyactis) off the coast of China using per-recruit analysis based on Bayesian inference. *Front. Mar. Sci.* 8, 652293. doi: 10.3389/fmars.2021.652293

frontiers in Marine Science

ORIGINAL RESEARCH
published: 29 October 2020
doi: 10.3389/fmars.2020.583148

That's All I Know: Inferring the Status of Extremely Data-Limited Stocks

Vyronia Pantazi[1], Alessandro Mannini[2], Paraskevas Vasilakopoulos[2], Kostas Kapiris[3], Persefoni Megalofonou[1] and Stefanos Kalogirou[3]**

[1] Department of Biology, National and Kapodistrian University of Athens, Athens, Greece, [2] Joint Research Centre, European Commission, Ispra, Italy, [3] Hellenic Centre for Marine Research, Institute of Marine Biological Resources and Inland Waters, Hydrobiological Station of Rhodes, Rhodes, Greece

There is a growing number of methods to assess data-limited stocks. However, most of these methods require at least some basic data, such as commercial catches and life history information. Meanwhile, there are many commercial stocks with an even higher level of data limitation, for which the inference of stock status and the formulation of advice remain challenging. Here, we present a stepwise approach to achieve the best possible understanding of extremely data-limited stocks and facilitate their management. As a case study we use a stock of the shrimp *Plesionika edwardsii* (Decapoda, Pandalidae) from the eastern Mediterranean Sea, where the only available data was a sub-optimal sample of length frequencies coming from a small-scale trap fishery. We use a suite of different methods to explore and process the data, estimate the growth parameters, estimate the natural and fishing mortalities, and approximate the reference points, in order to provide a preliminary evaluation of stock status. We implement multiple methods for each step of this process, highlighting the strong and weak points of each one of them. Our approach illustrates the better insights that can be gained by applying ensembles of models, rather than a single 'best' model when working with limited data of poor quality. The stepwise approach we propose here is transferable to other extremely data-limited stocks to elucidate their status and inform their management.

Keywords: ensemble modeling, growth, mortality, *Plesionika*, reference points

OPEN ACCESS

Edited by:
Giuseppe Scarcella,
National Research Council (CNR), Italy

Reviewed by:
Athanassios C. Tsikliras,
Aristotle University of Thessaloniki, Greece
Daniel Pauly,
Sea Around Us, Canada

****Correspondence:***
Alessandro Mannini
alessandro.mannini@ec.europa.eu
orcid.org/0000-0002-5910-3413
Stefanos Kalogirou
stefanos.kalogirou@gmail.com
orcid.org/0000-0002-3064-9236

Specialty section:
This article was submitted to Marine Ecosystem Ecology, a section of the journal Frontiers in Marine Science

Received: *14 July 2020*
Accepted: *06 October 2020*
Published: *29 October 2020*

Citation:
Pantazi V, Mannini A, Vasilakopoulos P, Kapiris K, Megalofonou P and Kalogirou S (2020) That's All I Know: Inferring the Status of Extremely Data-Limited Stocks. Front. Mar. Sci. 7:583148. doi: 10.3389/fmars.2020.583148

INTRODUCTION

Depending on the amount of available information, fish stocks can be characterized as data-rich or data-limited. Data-rich stocks contain enough information to carry out analytical stock assessments, while data-limited ones do not. However, there are several levels of data-limitation. The International Council for the Exploration of the Sea (ICES) identifies six different stock categories with regards to data availability (ICES, 2012). Categories 1 and 2 include data-rich stocks with age-structured catch and survey data allowing quantitative assessments. These assessments are considered to describe adequately the true trends of stock size and exploitation levels; as such, trends of category 1 and 2 stocks are used to monitor the effectiveness of fisheries regulations (STECF, 2020). Categories 3–6 include stocks with progressively increasing data limitations. In category 3, survey data are available which can indicate trends of mortality rates, recruitment, and biomass. In category 4, a time-series of catch data is available which allows an approximation of maximum sustainable yield (MSY). In category 5, only landings data are available. Finally, category

6 includes negligible landings stocks and stocks caught as bycatch. This latter category of extremely data-limited stocks is the focus of the current study.

There is an ever-growing number of data-limited assessment methods focusing on stocks falling primarily within data categories 3 to 5. For example, for category 3 stocks, the survey-based assessment method (SURBA) (Beare et al., 2005) or the time-series analysis assessment (TSA) (Fryer et al., 1998; ICES, 2008) can be used to estimate population numbers and fishing mortality rates based on survey data. For category 3/4 stocks, surplus production models can be used to estimate biomass and exploitation level for commercial stocks when their age and size data is absent (Punt, 2003). These models are suitable for stocks with data from commercial catches along with indices of exploitable biomass (from catch-per-unit-effort, or survey data) (Polacheck et al., 1993). For example, Pedersen and Berg (2017) presented a stochastic surplus production model in continuous time (SPiCT) which combines dynamics of biomass and fisheries with remarked error of catches and biomass indices. For category 4/5 stocks, where only time-series of catches or landings are available, methods such as the CMSY have been proposed (Martell and Froese, 2013) to estimate extracted yields in relation to MSY. Froese et al. (2017) updated the CMSY method by using catch and productivity to assess biomass. In addition, this method can approximate exploitation rate, MSY and fishing reference points. Froese et al. (2017) also used a Bayesian state-space estimation model (BSM) (Meyer and Millar, 1999) to verify and evaluate the CMSY model.

The examples of data-limited methods mentioned earlier are not exhaustive, but they are indicative of the fact that most data-limited methods require at least some information from surveys, commercial catches and productivity in order to estimate stock status. However, in the case of extremely data-poor stocks (category 6), it is not possible to apply such methods. In such cases, the starting point is the estimation of life history traits, such as growth and maturity. These life history traits can be used order to infer sustainable harvesting strategies, even if the exact stock status is unknown (Froese, 2004; Froese et al., 2008; Prince and Hordyk, 2019). Growth parameter estimates can also be used to estimate mortality rates, approximate reference points, and infer the stock status; a suite of different methods exists for every step of this way (Gayanilo and Pauly, 1997). Recently, a new method for the analysis of extremely data-limited stocks of fish and invertebrate species was proposed: the Length-based Bayesian Biomass (LBB) method (Froese et al., 2018). LBB requires only length frequency distributions (LFDs) as an input, as it makes a series of assumptions for the estimation of the missing life history information. LBB's key outputs are the current exploited biomass relative to unexploited biomass (B/B0) and the fishing mortality relative to natural mortality (F/M) (Froese et al., 2018).

Typically, in extremely data-poor situations it is difficult to identify a single method that produces the 'best' estimate of a given variable. In that case, an ensemble modeling approach combining the outputs from multiple methods can help produce more robust estimates (Dormann et al., 2018). This process can in turn inform fisheries management more effectively and facilitate measures to promote fisheries sustainability.

In this study, we present a stepwise methodological framework to estimate the stock status of extremely data-limited stocks. We illustrate the use of this framework by estimating the stock status of an extremely data-limited shrimp stock (*Plesionika edwardsii*, Decapoda, Pandalidae), which is a bycatch of a small-scale trap fishery in the eastern Mediterranean Sea. Our proposed framework includes various methods for estimating growth parameters, calculating mortality rates, approximating reference points and eventually characterizing stock status. We synthesize the outputs from different model combinations, illustrating the advantages from using an ensemble modeling approach, and compare our findings with the outputs from a relevant LBB. This way, we elucidate the stock status of the studied shrimp stock and deduce implications for its management, in a way that is reproducible to other extremely data-limited stocks.

MATERIALS AND METHODS

Sampling

Samples were collected in the Dodecanese archipelago (southeastern Aegean Sea) (**Figure 1**) from October 2014 to October 2015 on a monthly basis (except of February 2015 due to adverse weather conditions), under the framework of PLESIONIKA MANAGE project. PLESIONIKA MANAGE studied the biology and exploitation of *Plesionika narval*, a valuable fishery resource in the area (Kalogirou et al., 2017; Maravelias et al., 2018; Vasilakopoulos et al., 2019). *P. edwardsii* was a commercial bycatch of the fishery for *P. narval*, far less valuable than the targeted congeneric species.

Sampling depth ranged from 0 to 280 m and was divided in strata A (0–45 m; depth of thermocline in the summer), B (46–100 m; to the end of the continental shelf), C (>100 m). Circular traps covered with nylon-based net of a mesh size of 12 mm (knot to knot) and with an upper trap opening of 13 cm were used (Kalogirou et al., 2019). Fishing took place during night hours (20:30- 06:00); after 9.5 h all traps were hauled, and the catch was separated in two categories: target (*P. narval*) and by-catch species, the latter including *P. edwardsii*. A random sample of approximately 100 shrimps, mainly *P. narval*, was collected from each stratum. The number, size (carapace length and body weight), sex and maturity stage of *P. edwardsii* shrimps within these samples was also documented (**Figure 2**).

Exploring and Processing Data

Carapace length (CL) was rounded at the nearest millimeter and LFDs were estimated by sex, maturation stage, month and depth strata, using length classes of 1 mm Due to the great variability of the sample size across months, standardized LFDs by month were estimated, by dividing the numbers of individuals within each length class by the total number of monthly samples (**Figure 2**). These standardized LFDs were used to:

(1) identify the main spawning periods;
(2) identify the depth distribution of males and females;

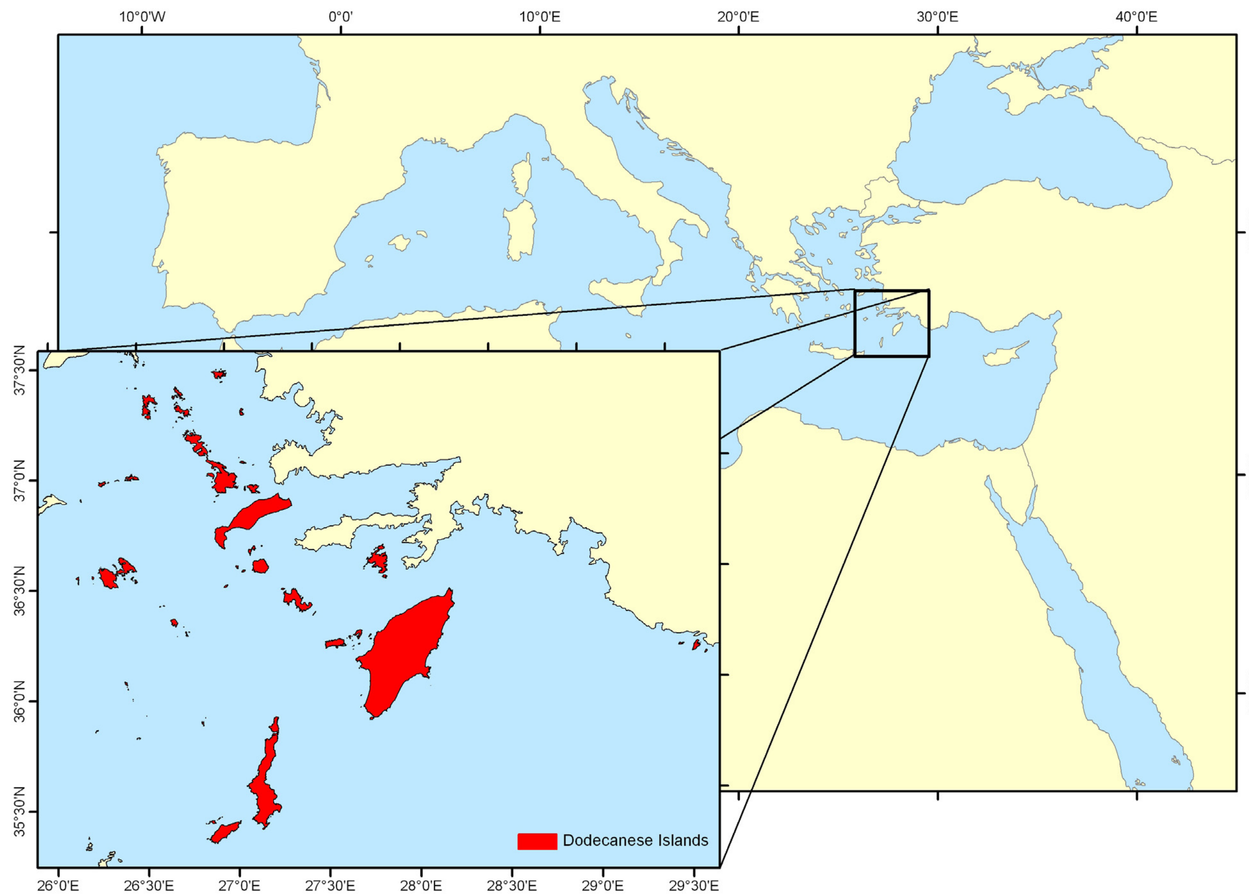


FIGURE 1 | Map of sampling area – Dodecanese Islands, southeastern Aegean Sea, eastern Mediterranean Sea.

(3) estimate the sex ratio within each length class;
(4) create a length frequency object (LFQ) to be used for the estimation of the growth parameters. For this, the sex-combined LFD by month was restructured as a list object containing a catch frequency matrix, a vector of mid-lengths corresponding to rows of the catch matrix and a vector of sample dates corresponding to the columns of the catch matrix.

Estimation of Growth Parameters

This analysis was conducted using R programming language (R Core Team, 2020) and the TropFish R package (Mildenberger et al., 2017; Taylor and Mildenberger, 2017). To estimate growth parameters (**Figure 2**), the ELEFAN (Electronic Length Frequencies Analysis) program (available as tool in the TropFishR package) was used. ELEFAN calculates a moving average (MA) over the LFDs bin, and then compares the observed frequency with this average; values much above the average indicate a "true" mode (Pauly and David, 1981; Pauly, 1985). The LFQ file was prepared for running the ELEFAN by posing a MA to generate the Von Bertalanffy Growth Function (hereafter VBGF) estimations. For this, we set ranges for the infinite length (L_{inf}) and growth coefficient (K) values, and a theoretical time zero (t_0) at which individuals of this species hatch.

Preliminary estimations of L_{inf} were done based on three different approaches:

- the Powell and Wetherall method (Powell, 1979; Wetherall et al., 1987): a linearizing transformation of length classes to estimate L_{inf} by plotting L_{mean} – L' and L'. L_{mean} is the mean length of all individuals greater than L' and L' is the smallest length of fully represented individuals in catches.
- the empirical formula from Froese and Binohlan (2000):$L_{inf}=e^{0.44+0.984 log(Lmax)}$? with L_{inf} being infinite length and L_{max} being maximum observed length.
- the maximum carapace length observed in the samples.

The Powell and Wetherall method is very sensitive to intra-cohort variability in growth and to changes in the occurrence of large individuals in the sample, resulting often in underestimation of the L_{inf} value (Schwamborn, 2018). Exclusion of the largest size classes during the regression procedure or weighing by abundance does not resolve these issues (Schwamborn, 2018). By contrast, the Froese and Binohlan formula tends to overestimate L_{inf} values. Accordingly, two different length ranges for L_{inf} were chosen to run ELEFAN. The

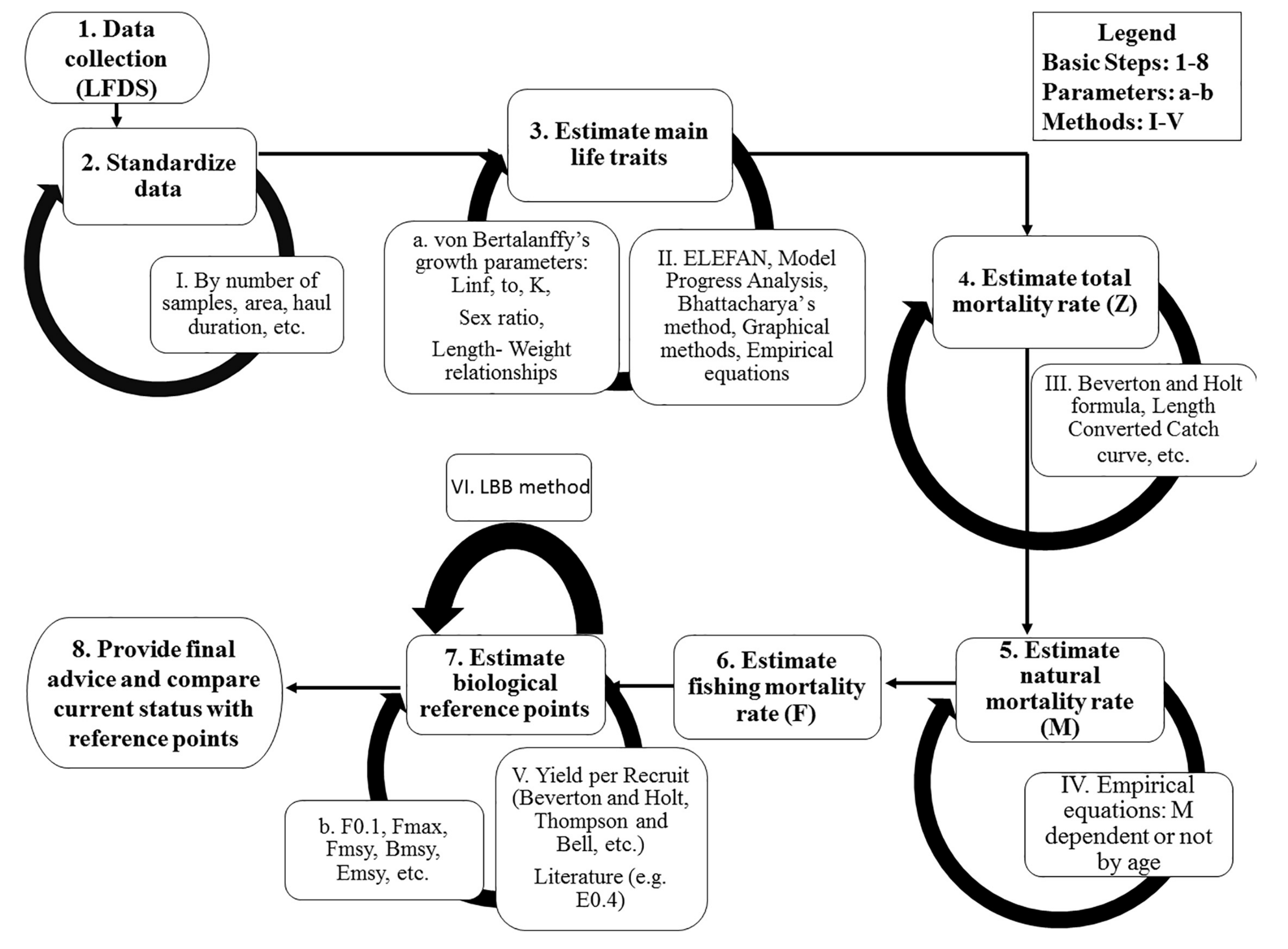


FIGURE 2 | The basic steps (1–8) to assess an extremely data-limited stock, with a selection of associated methods.

first length range had a lower limit of L_{inf} derived from the Powell and Wetherall method and the second one had a lower limit of L_{inf} equal to the maximum length observed in the samples. The L_{inf} value derived by the Froese and Binohlan formula was chosen as the upper limit for the length range of L_{inf} in both cases.

The range of K values was set between 0.4 to 0.9 y^{-1}, based on previous publications on the growth of this species (Santana et al., 1997; Company and Sardà, 2000; García-Rodriguez et al., 2000; Colloca, 2002).

Four different scenarios of the month when length is equal to zero (t_{anchor} in ELEFAN, conceptually similar to t_0 of the VBGF) were explored: (i) February, (ii) May, (iii) August, and (iv) November. The one resulting in the best fit and agreeing with the spawning information was chosen as the optimal t_0 (**Supplementary Figures 6, 7**).

The MA value used in the ELEFAN analysis was set based on two different scenarios. The first scenario used the default setting in FISAT II (Gayanilo and Pauly, 1997), i.e., a width of 5 bins (1 bin = 1 mm) for each cohort. Indeed, the smallest cohort width was up to 5 bins so it was plausible to compare each bin with the average across 5 consecutive bins (i.e., ±2 bins to either side). However, taking into consideration that the MA settings can significantly affect the scoring of the growth curve (Taylor and Mildenberger, 2017) a second scenario was also tested, with a 7-bin cohort width.

The estimation of the best fit was based on searching for the VBGF parameters with the maximum score value (Rn) as a measure of relative fit:

$$Rn = \frac{10^{ESP/ASP}}{10}$$

where the Estimated Sum of Peaks (*ESP*) is the sum of peak values crossed by the growth curves, with the caveat that positively crossed bins are only counted once, while negatively crossed bins are counted every time they are encountered (Pauly, 1985). The Available Sum of Peaks (*ASP*) is the sum of all positive peaks, which represents a maximum possible score (if negative bins are crossed). *Rn* can attain a maximum value of 1.

Fitting scores across the whole range of L_{inf} and K combinations was visualized by a Response Surface Analysis (RSA).

Estimating Total, Natural and Fishing Mortality

The VBGF parameters were used both to compute the length at which 50% of the cumulative catch is captured (L_{50}) and to estimate the total mortality (Z) (**Figure 2**) Z was computed using two methods:

- the Length Converted Catch Curve (LCCC) (Pauly, 1990)
- the relevant B&H formula (Beverton and Holt, 1956)

The Length Converted Catch Curve (Pauly, 1990) is a way to estimate Z plotting the natural logarithm (loge) of the number of fishes in the sample (N) against the relative age corresponding to the midrange of the length class in question [Δt is the time needed to grow from the lower (t_1) to the upper (t_2) limit of a given length class]:

$$log_e\left(\frac{N}{\Delta}\right) = \alpha - Zt$$

where a and Z are the regression parameters.

In the second case (Beverton and Holt, 1956), Z value is calculated as:

$$Z = \frac{K(L_{inf} - L_{mean})}{L_{mean} - L'}$$

where L_{inf} and K are parameters from VBGF, L_{mean} is the mean length in the catches and L' is the smallest length of animals that are fully represented in the catch samples.

A suite of different methods and formulas were used to estimate natural mortality (M) values (**Figure 2** and **Supplementary Table 1**). This great number of methods reflects the fact that M is notoriously difficult to estimate (Kenchington, 2014), and it has a big effect on our perception of stock status (Mannini et al., in review). Four methods (and their variants) provided empirical scalar values (Alverson and Carney, 1975; Pauly, 1980; Hoenig, 1983; Hewitt and Hoenig, 2005; Then et al., 2014). Pauly's (1980) equation was computed using three different bottom temperature values (14, 16, 18°C), based on the seasonal difference in bottom temperature. Seven more methods (and their variants) produced natural mortality vectors by age (Gulland, 1965; Chen and Watanabe, 1989; Caddy, 1991; Abella et al., 1997; Lorenzen, 2000; Gislason et al., 2010; Brodziak et al., 2011; Martiradonna, 2012) (**Supplementary Figure 10**). The estimated VBGF parameters were used to convert the maximum CL observed in the catch into age. For each of the M vectors by age a mean over the range between age 0 and maximum observed age was computed to obtain the corresponding scalar value.

This process resulted in sixteen different M scalar values. These values were subtracted from the two Z values calculated earlier, to provide a set of 32 different values of fishing mortality (F) (**Figure 2**).

Reference Points and Advice

In the final stage of the analysis, reference points for management (Caddy and Mahon, 1995) were computed according to a Yield per Recruit (YpR) model (Beverton and Holt, 1957) (**Figure 2**). In the Mediterranean, two reference points are being used for exploitation levels: $F_{0.1}$ and $E_{0.4}$ (STECF (17-15), 2017; STECF (19-16), 2019). The fishing mortality level $F_{0.1}$ is the F rate at which the slope of the yield per recruit curve as a function of F is 10% of its value at the origin (Gulland and Boerema, 1973). $E_{0.4}$ comes from Patterson (1992) who suggested as reference point in terms of exploitation rate (E), in particular for pelagic stocks, a value of E = F/Z = 0.4.

Thirty two different YpR analyses were run, corresponding to the 32 estimates of F, to extract the respective $F_{0.1}$ values. For all scenarios, L_{50} of the selectivity was set as the length of 50% of the cumulative catch. The status of exploitation was estimated according to two ratios: $\frac{F}{F0.1}$ and $\frac{E}{E0.4}$, for which values over 1 indicate overfishing.

A kobeplot was used to visualize the 32 scenarios results (statuses of exploitation), as well as the mean and the median of them (**Figure 2**). Four areas with different colors based of E status were plotted in a Cartesian system in which x-y intersection is set

TABLE 1 | Monthly (1: January – 12: December) length frequency of *P. edwardsii* in SE Aegean Sea during 2014–2015.

Month		CL																		
		12	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
2014	**10**														1	1		1	1	
	11	9	14	15	28	22	23	41	57	65	88	97	104	69	49	8	2		1	
	12		2	6	7	11	20	38	35	23	53	64	74	68	47	36	11	4	2	
2015	**1**							1					2							
	3	9	10	1	15	19	8	18	18	21	21	13	13	11	3	1				
	4	1	1	3	1	3	1	5	3	10	10	9	10	3	1	1				
	5	2	2	2	2	1	3	8	20	16	24	20	20	18	22	18	10	3	2	1
	6		2	2	5	4	4	3	4	8	18	13	5	5	1	2		1	1	
	7	1	1	6	7	5	4	7	4	7	14	16	7	9	15	15	1	2		
	8			2	2		2						2							
	9				4	9	7	4	4	5	8	6	7	6	3	3	4	2		
	10				1	2	2	7	2	3	6	9	6	10	13	9	4			

CL, carapace length (mm).

TABLE 2 | Standardized monthly (1: January – 12: December) length frequency of mature and immature females of *P. edwardsii* in SE Aegean Sea during 2014–2015.

Month			CL																		
			12	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
2014	**10**	**I**																	1	1	
		M														1	1				
	11	**I**	0.4	0.66	0.66	1	0.93	0.53	2	2.2	3.13	4.6	5.2	6.4	4.46	2.86	0.73	0.13		0.66	
		M										0.66	0.46	0.2	0.13	0.33					0.66
	12	**I**		0.63	0.25	0.31	0.44	1.06	1.69	1.69	0.87	1.62	2.4	3.18	3.06	2.56	1.93	0.68	0.25	0.12	
		M							0.06			0.37	0.06	0.12	0.31	0.62					
2015	**1**	**I**												2							
		M																			
	3	**I**	0.86	1.42		1.28	1.75	0.86	1.85	1.85	2.14	2.28	1.86	1.42	0.14	0.14	0.14				
		M									0.14	0.14		0.43	1.43	0.28					
	4	**I**		0.14		0.14	0.14	0.14	0.57	0.28	0.43	0.14		0.28							
		M	0.14		0.43		0.28				0.71	1.14	1.28	1.14	0.28	0.14	0.14				
	5	**I**	0.22	0.22	0.11	0.11	0.11	0.11		0.11	0.11		0.11		0.22			0.11		0.11	
		M				0.11		0.11	0.33	0.14	0.55	2	1.66	1.89	1.22	2.11	1.89	1	0.33	0.11	0.11
	6	**I**		0.33	0.16	0.33	0.16	0.16				0.66	0.33							0.16	0.33
		M			0.1	0.5	0.5	0.5	0.5	1.66	1	1.83	1.5	0.66	0.83	0.16	0.33		0.16		
	7	**I**	0.11	0.11	0.55	0.55		0.22	0.44	0.22	0.22		0.33	0.11		0.44	0.55		0.11		
		M					0.33	0.22	0.33	0.33	0.33	1.11	0.88	0.33	0.5	1.11	1	0.11	0.11		
	8	**I**			2	2								2							
		M						2													
	9	**I**				0.25	1	1.75	0.5	0.25	1	0.25	0.25	0.75	0.75	0.25	0.75	0.25	0.5		
		M								0.25	0.25	1	0.75	1		0.5		0.75			
	10	**I**				0.11	0.11	0.11	0.77	0.22		0.11	0.11	0.11	0.44	1	0.22	0.22			
		M									0.11	0.33	0.55	0.22	0.11	0.11	0.78	0.22			

CL, carapace length (mm); I, immature females; M, mature females.

at point equal to 1, 1. In the green area fell points having ratios below or equal to 1 for both $\frac{E}{E0.4}$ and $\frac{F}{F0.1}$. In the red area fell points having both ratios over 1 and, in the yellow areas points for which one of the two ratios was over 1.

Applying the LBB Method

LBB (Froese et al., 2018) requires only LFDs and is able to estimate L_{inf}, length at first capture, relative natural mortality (M/K) and relative fishing mortality (F/K). M/K and F/K can be combined to give fishing mortality relative to natural mortality (F/M). LBB also estimates an approximation of current exploited biomass relative to unexploited biomass (B/B_0).

To apply this method, the monthly LFDs we had available were aggregated to a yearly sample. The L_{inf} prior was set equal to our best estimation from ELEFAN. In assigning M/K priors, K was set equal to our best estimation from ELEFAN while M values changed according to the 16 methods presented in chapter "Estimating total, natural and fishing mortality." All other inputs were set to the default values suggested by Froese et al. (2018).

RESULTS

Length Frequency Distributions

In total, 1993 *P. edwardsii* individuals were sampled. Plotting the LFD using the raw data showed strong monthly variability in the number of individuals (unbalanced data), ranging from 4 in October 2014 to 693 in November 2014, and irregular population distributions (**Tables 1**, **2**). The length at which 50% of the cumulative catch is captured (L_{50}) was estimated as 21.70 mm. (**Supplementary Figure 8**).

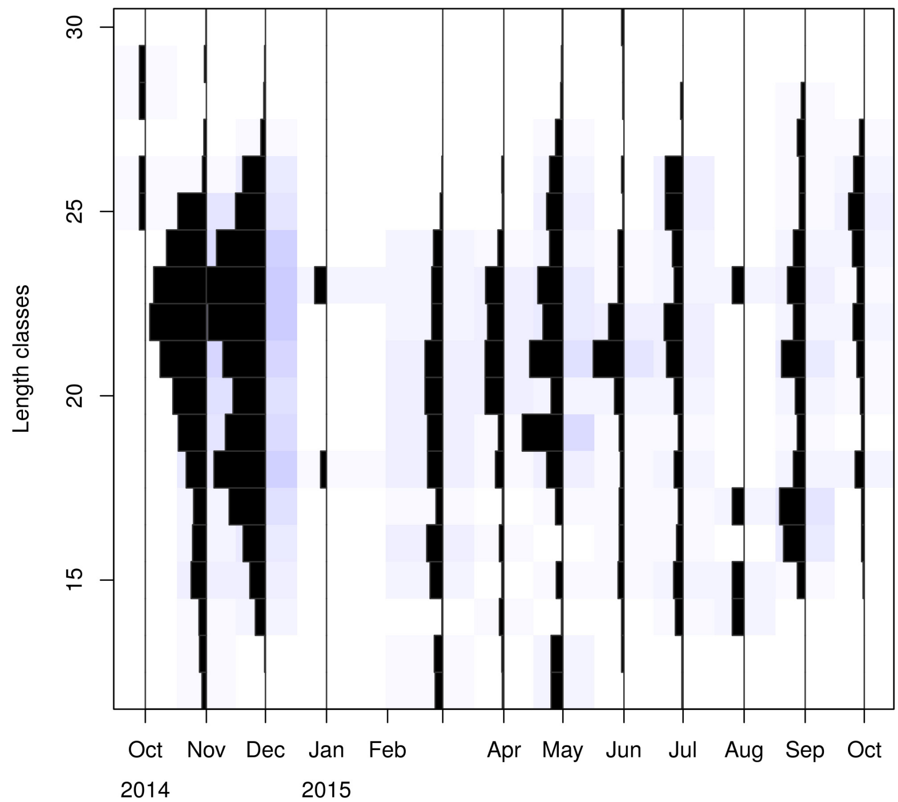


FIGURE 3 | The LFDs analyzed by ELEFAN. Length classes (CL) are in mm.

TABLE 3 | Main settings adopted in running the ELEFAN analysis in terms of L_{inf} and K range, initial t_{anchor} value and Moving Average (MA) and main correspondent outputs.

Methods to estimate L_{inf} range	MA	L_{inf} range	K_{range}	$t_{anchor(in)}$	Rn	L_{inf}	K	t_{anchor}
Powell and Wetherall - Froese and Binohlan	5	26.64–44.13	0.4–0.9	0.42 (May)	0.241	27.24	0.78	0.42
	7	26.64–44.13	0.4–0.9	0.42 (May)	0.290	27.24	0.78	0.42
Maximum observed length - Froese and Binohlan	5	30.00–44.13	0.4–0.9	0.42 (May)	0.219	31.94	0.56	0.31
	7	30.00–44.13	0.4–0.9	0.42 (May)	0.215	35.84	0.40	0.14

L_{inf}, infinite length; K, growth coefficient; t_{anchor}, the month when length is equal to 0; Rn, maximum score value. The red row corresponds to the selected 'best' combination of parameters.

After standardizing the LFDs and examining separately mature and immature individuals, a dominance of mature females emerged between spring and mid-summer indicating a spawning period (**Tables 1**, **2**).

Depth was found to be influential, with more individuals found in the deeper strata (**Supplementary Figure 1**). A dominance of females was evident at all depths with a sex ratio of 0.82 (**Supplementary Figure 2**), complemented by larger females (up to 30 mm) at increased depths (**Supplementary Figures 3**, **4**). Mean size of males (19.83 mm CL) was lower than that of females (21.40 mm CL), with a maximum size of 26 mm.

Growth Parameters

Visualizing the raw and standardized LFQ data (**Tables 1**, **2** and **Figure 3**) showed that recruits to the fishery appear in March at a CL of ~12 mm. After exploring possible months for t_{anchor} (**Supplementary Figure 4**), May was selected (t_{anchor} = 5/12) (**Supplementary Figure 5**). This month provided the best fit, and it was also when the higher fraction of mature females was observed.

L_{inf} estimations varied between the different methods used. L_{inf} was estimated at 26.64 mm by the Powell and Wetherall method (**Supplementary Figure 5**), at 44.13 mm by the Froese and Binohlan formula, while the maximum CL observed in the samples was 30.00 mm (**Table 3**). Although the Powell and Whetherall method estimation with MA = 7 got the highest Rn value (**Table 3**), its resulting VBGF parameter estimates were not retained. That was because the relevant L_{inf} estimation (27.24 mm) was underestimating the population's true L_{inf}, being lower than the larger individuals sampled (30.00 mm) (**Table 3**). By contrast, the L_{inf} estimation by the Froese and Binohlan formula was found to be greater than the larger individuals sampled. Therefore, to select the optimal VBGF parameter estimates we focused on the two runs using the maximum length as a lower limit of the L_{inf} range (**Table 3**). Among these two runs, the one with a MA width of 5 bins had the highest Rn value and a t_{anchor} value closer to the assumed spawning period (**Table 3**). The final VBGF parameter estimates were: L_{inf} = 31.94 mm, K = 0.56 y^{-1}, t_{anchor} = 0.31 y (**Figure 4**). Five age cohorts were estimated by the VBGF model (**Figure 5**).

Total, Natural and Fishing Mortality

Z was estimated as 2.25 y^{-1} by the LCCC method (**Supplementary Figure 9**) and 2.36 y^{-1} by the Beverton and Holt formula. The sixteen different methods used for M, produced values ranging between 0.44 y^{-1} (Alverson_Carney) and 2.01 y^{-1} (Lorenzen) (**Table 4**). The combination of the two values of Z with 16 values of M produced 32 different

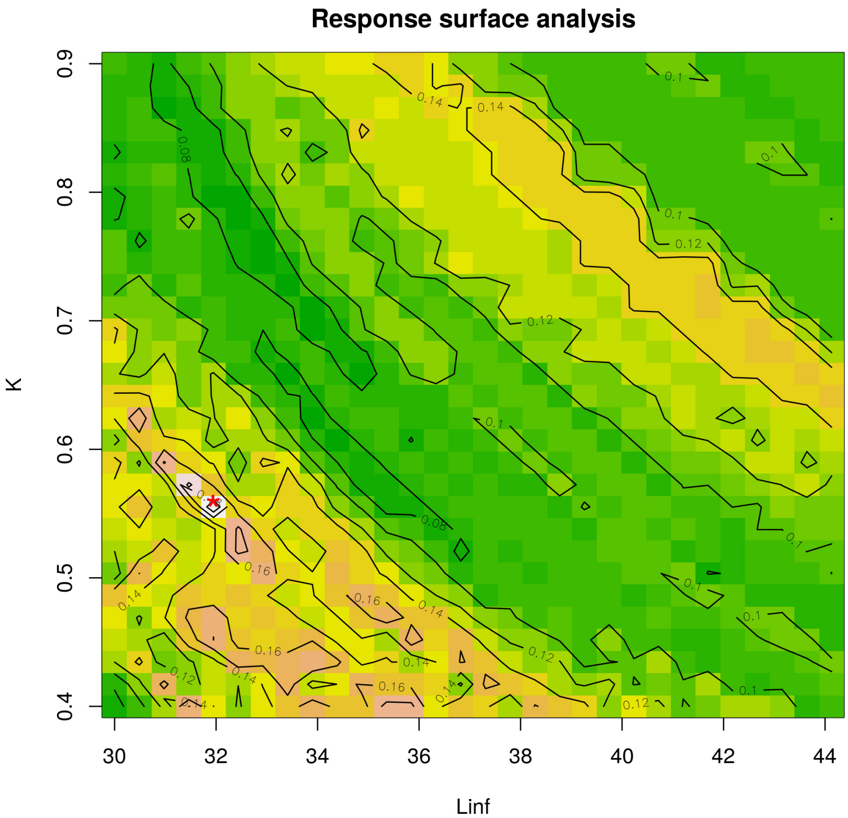


FIGURE 4 | Response surface analysis. The best fit for the combination between Linf (in mm) and K-values is indicated with a red asterisk on the plot. The color scale corresponds to the Rn values from ELEFAN analysis. K ranges between 0.4 and 0.9 and L_{inf} ranges between 30 mm (maximum observed length) and 44.13 mm (estimated by Froese and Binohlan). This analysis corresponds to the optimal combination from **Table 1**.

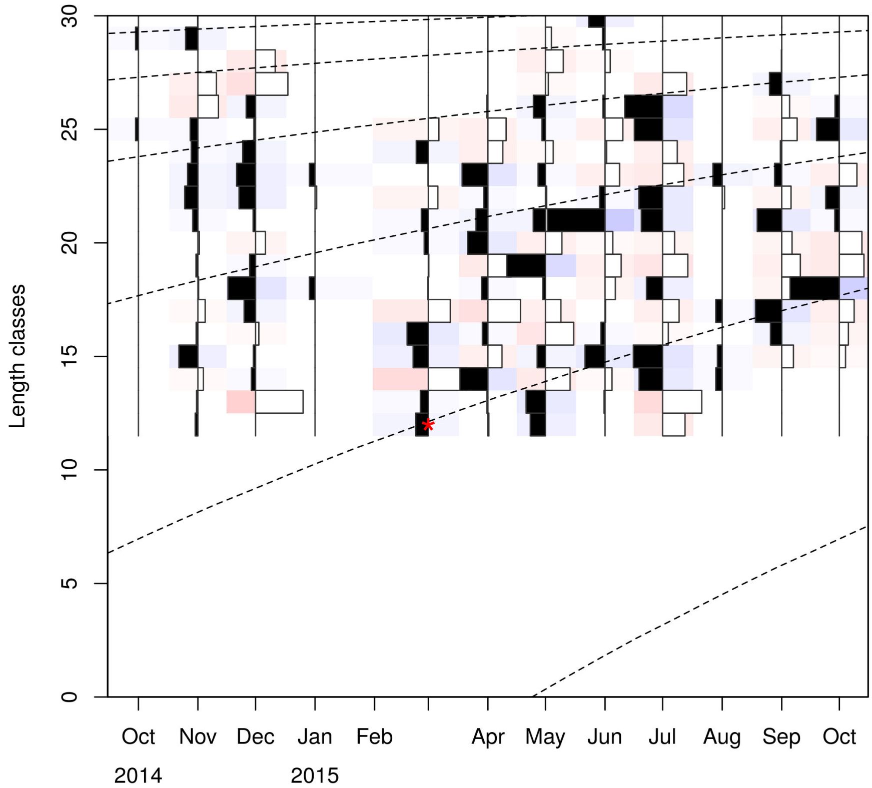


FIGURE 5 | Age cohorts (dashed lines) estimated by the VBGF model. Red asterisk indicates the size at which the youngest individuals are captured. Length classes (CL) are in mm.

TABLE 4 | Values of fishing, natural and total mortality as given by the equation: total mortality rate (Z) = natural mortality rate (M) + fishing mortality rate (F).

		Method for estimation of *Z*			
	Natural mortality	**LCCC**		**Beverton and Holt**	
Method for estimation of *M*	***M***	***Z***	***F***	***Z***	***F***
Pauly_T1	0.87	2.25	1.38	2.36	1.49
Pauly_T2	0.93		1.32		1.43
Pauly_T3	0.98		1.27		1.38
Alverson_Carney	0.44		1.81		1.92
Then_1	0.78		1.47		1.58
Then_2	0.86		1.39		1.50
Hewitt Hoenig	0.59		1.66		1.77
Hoenig	0.57		1.68		1.79
Lorenzen	2.01		0.24		0.35
Then_scaled	0.90		1.35		1.46
Gislason	1.38		0.87		0.98
ChenWatanabe	1.17		1.08		1.19
Brodziak_Tmax	0.69		1.56		1.67
Brodziak_K	0.49		1.76		1.87
Prodbiom	1.96		0.28		0.40
Gulland	1.74		0.51		0.62

LCCC, Length Converted Catch Curve; T1 = 14°C, T2 = 16°C, T3 = 18°C.

values for F ranging between 0.24 y^{-1} (Lorenzen) and 1.92 y^{-1} (Alverson_Carney) (**Table 4**).

Stock Status

In total, only seven out of the 32 estimates of the exploitation state indicated sustainable levels of fishing both in terms of F and in terms of E (**Figure 6**). These included all six cases where the Lorenzen, ProdBiom and Gulland methods were used and one case where the Gislason method was used for the estimation of M. By contrast, 22 estimates of the exploitation state indicated overfishing, both in terms of F and in terms of E (**Figure 5**). These included all cases where the Pauly_T1, Pauly_T2, Pauly_T3, Alverson_Carney, Then_1, Then_2, Hoenig_1, Hoenig_2, Then_scaled, Brodziak_Tmax, and Brodziak_K methods were used for the estimation of M. In three cases, two using ChenWatanabe and one using Gislason for the estimation of M, the stock was found to be overfished in terms of E but non-overfished in terms of F. Both the mean and median stock status was estimated as overfished (**Figure 6**). In particular, for $F/F_{0.1}$ mean values were 1.68 (LCCC method) and 1.81 (Beverton and Holt formula) and median values were 1.43 and 1.56, respectively. For $E/E_{0.4}$ mean values were 1.36 and 1.42 and median values were 1.51 and 1.56 according to the previous sequence. Therefore, our results pointed toward a state of overfishing.

Results From LBB

Table 5 summarizes the main results from the LBB. L_{inf} ranged between 31.92 mm (Lorenzen) and 32.56 mm (Hoenig); M/K ranged from 0.96 (Alverson_Carney) to 3.60 (Lorenzen) and F/M ranged between 0.41 (Prodbiom) to 5.08 (Alverson_Carney). All these values were similar to ones obtained from our original analysis.

The exploitation status of *P. edwarsii* was estimated as non-depleted in three M scenarios (Gulland, Lorenzen and Prodbiom), close to equilibrium in one M scenario (Gislason) and as in moderate or severe depletion in all other scenarios (**Table 5**).

DISCUSSION

This study proposes a stepwise methodological framework to assess stock status of an extremely data-limited exploited stock. Lack of data constitutes a common restrictive factor for fisheries management and the applied methods can be decisive for the outcomes. Our proposed framework is a sequence entailing estimations of basic life traits, mortality rates and biological reference points to infer stock status. The combination of high data uncertainty and multiple method availability (Gayanilo and Pauly, 1997) often lead to tradeoffs in the method(s) to be used. By contrast, the numerous estimates for the same variable offer the opportunity to calculate the average (weighted or not) of values instead of presenting a single-method prediction (Dormann et al., 2018). This is especially relevant when the analyzed data come from small-scale fisheries with low data availability, which are prevalent in the Mediterranean Sea.

The range of outputs estimated by this study underlines the necessity of a multi-method approach. For each of the steps presented in this study, a single method selection would be misleading and would constitute a sub-optimal methodological path selection. Previous studies on the biology of *P. edwardsii* stock (e.g., Colloca, 2002; González et al., 2016) used a single method approach but with much larger and balanced datasets and thus the relevant results were more reliable; however, these studies did not touch upon stock status. In our study, we use a multi-method approach through a stepwise process; the most pronounced example being the estimation of natural mortality rate (M) for which we used 16 different methods. Such a parallel implementation of several methods for M is not usually applied (Kenchington, 2014), and the M value is typically calculated using only one of a handful of M equations (e.g., Pauly, 1980; Hoenig, 1983). The wide range of our results demonstrates the great variability that exists across these 16 approaches used and the complexity of pinpointing the most suitable one. Using various M estimators is often recommended for reducing bias, errors, underestimations and uncertainties of the methods applied (Gunderson et al., 2003; Simpfendorfer et al., 2005). Notably, the range of outputs produced when using our proposed framework was similar to that observed when implementing the novel LBB method (Froese et al., 2018). This highlights how in extremely data-limited situations the choices made with regards to key input parameters (such as M) have a greater impact on the outputs than the analytical method used.

Ensemble modeling use several options and generates more robust outputs. Selection of the most appropriate method may often prove to be more difficult than initially expected because the theoretical and/or empirical background is not precise enough. Applying ensemble modellin is recommended in extremely data-limited situations, because various models can be used for estimating a value and all results can be statistically tested (Kuhn and Johnson, 2013). Using model averaging to infer stock status could be a sufficient solution for decreasing the predicted error. When models are unbiased and with high variance, using an increasing number of different models could minimize the error (Dormann et al., 2018). An alternative to using a simple model mean or median, as used in this study, would be to use a weighted average. Not all estimators may be equally reliable; e.g., some of the M estimators used here may be more suitable for fish than crustaceans. In such cases, a weighted estimation could provide more accurate results (Kenchington, 2014; Dormann et al., 2018).

Extremely data-limited stocks often have a high importance for both fisheries and the marine ecosystem; hence one should strive for analytical examinations to infer stock status. However, the use of a multi-method approach alone does not provide certainty about the real situation in extremely data-limited situations. The analytical framework proposed here, when applied to extremely data-limited stocks, it should be viewed as the first stage of exploration; a starting point to reveal stock status. Next steps should involve a more extensive data collection so that the initial insights could be corroborated or rejected. In the meanwhile, controlling size selectivity and safeguarding stock productivity constitute a sound strategy for the management of extremely data-limited stocks (Prince and Hordyk, 2019),

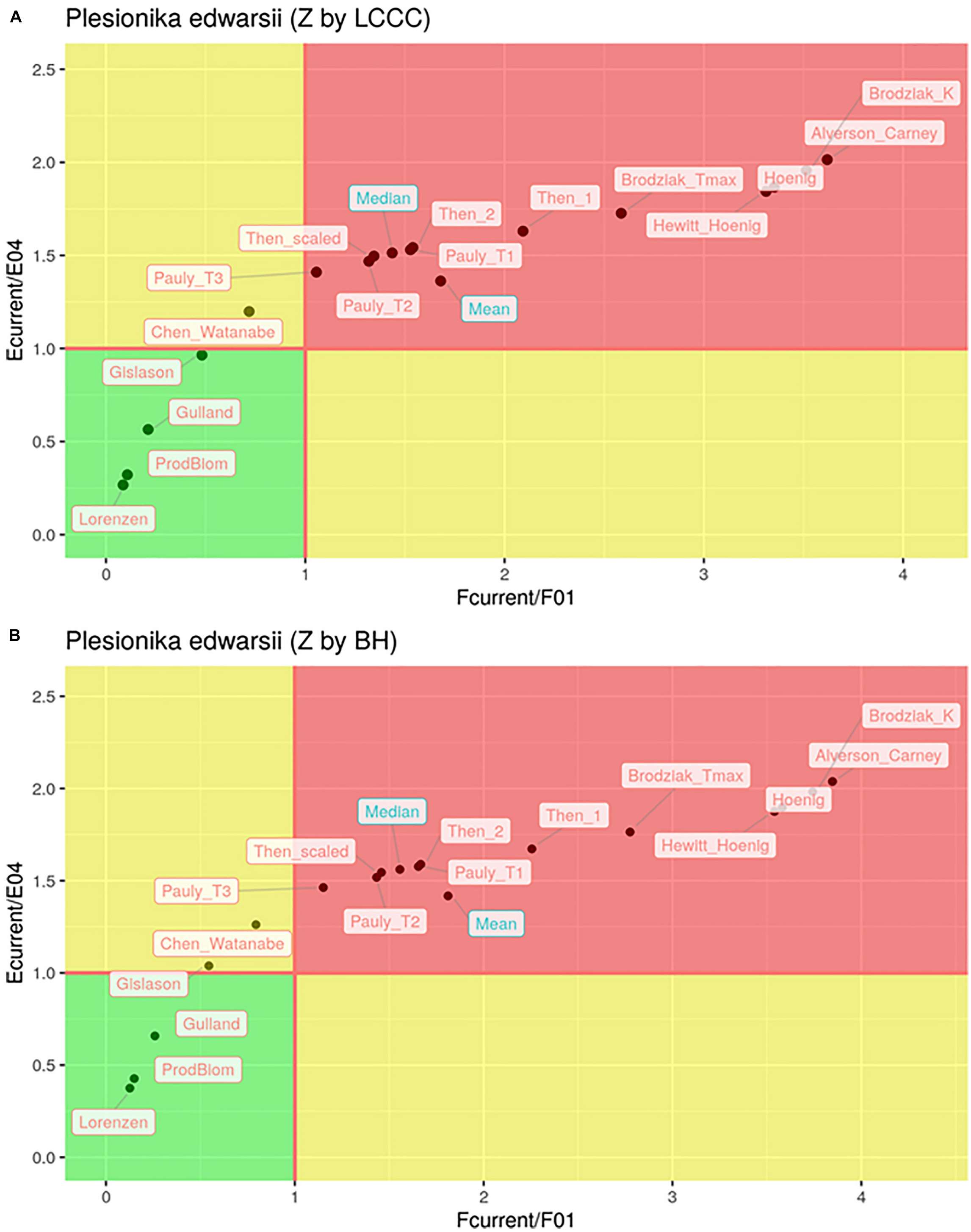


FIGURE 6 | Kobe plot of $\frac{F}{F0.1}$ and $\frac{E}{E0.4}$ for different estimations of natural mortality (M) with total mortality (Z) estimated by LCCC **(A)** or the Beverton and Holt formula **(B)**.

especially in areas such as the Mediterranean Sea which are known to be severely overfished (Vasilakopoulos et al., 2014).

The same principles of better monitoring and precautionary measures also apply to the Dodecanese *P. edwardsii* stock used as a case study here. Our study suggests that the *P. edwardsii* stock is likely overfished, in line with its sympatric *P. narval* stock (Maravelias et al., 2018) and most other assessed crustacean stocks in the Mediterranean Sea

TABLE 5 | Length-based Bayesian Biomass method (LBB) estimates of asymptotic length (L_{inf}), natural mortality relative to somatic growth rate (M/K), fishing mortality relative to natural mortality (F/M) and current biomass relative to unexploited biomass (B/B_0) by M scenario.

Scenario	M/K*	F/M*	F/M**	L_{inf}	L_{inf}.lcl	L_{inf}.ucl	M/K	M/K.lcl	M/K.ucl	F/M	F/M.lcl	F/M.ucl	B/B_0	B/B_0.lcl	B/B_0.ucl
Alverson_Carney	0.79	4.11	4.36	32.54	32.05	33.03	0.96	0.81	1.09	5.08	3.98	6.59	0.11	0.08	0.16
Brodziak_K	0.88	3.59	3.82	32.38	31.99	32.80	1.04	0.91	1.17	4.33	3.52	5.13	0.13	0.10	0.17
Brodziak_T	1.23	2.26	2.42	32.33	31.86	32.84	1.39	1.26	1.54	3.06	2.45	3.84	0.20	0.15	0.27
Chen_Watanabe	2.09	0.92	1.02	32.22	31.67	32.69	2.20	2.09	2.32	1.49	1.10	1.86	0.40	0.26	0.55
Gislason	**2.46**	**0.63**	**0.71**	**32.12**	**31.55**	**32.60**	**2.56**	**2.41**	**2.70**	**1.02**	**0.70**	**1.37**	**0.51**	**0.28**	**0.77**
Gulland	**3.11**	**0.29**	**0.36**	**31.98**	**31.53**	**32.50**	**3.16**	**3.03**	**3.30**	**0.60**	**0.40**	**0.93**	**0.67**	**0.36**	**1.19**
Hewitt_Hoenig	1.05	2.81	3.00	32.47	31.97	32.96	1.21	1.07	1.33	3.68	2.91	4.64	0.16	0.12	0.22
Hoenig	1.02	2.95	3.14	32.56	32.08	33.06	1.17	1.03	1.30	4.03	3.19	4.90	0.15	0.11	0.19
Lorenzen	**3.59**	**0.12**	**0.17**	**31.92**	**31.32**	**32.47**	**3.60**	**3.47**	**3.73**	**0.41**	**0.12**	**0.66**	**0.76**	**0.00**	**1.40**
Pauly1	1.55	1.59	1.71	32.25	31.79	32.71	1.68	1.55	1.83	2.27	1.67	2.80	0.28	0.19	0.36
Pauly2	1.66	1.42	1.54	32.20	31.61	32.70	1.83	1.70	1.97	1.92	1.42	2.28	0.32	0.20	0.40
Pauly3	1.75	1.30	1.41	32.23	31.63	32.79	1.91	1.77	2.06	1.81	1.31	2.24	0.33	0.20	0.44
Prodbiom	**3.50**	**0.14**	**0.20**	**31.92**	**31.52**	**32.37**	**3.50**	**3.41**	**3.64**	**0.41**	**0.23**	**0.75**	**0.76**	**0.29**	**1.60**
Then_scaled	1.61	1.50	1.62	32.22	31.68	32.78	1.75	1.63	1.87	2.05	1.59	2.60	0.30	0.20	0.40
Then1	1.39	1.88	2.03	32.45	31.99	33.01	1.55	1.44	1.68	2.71	2.26	3.28	0.23	0.18	0.30
Then2	1.54	1.62	1.74	32.27	31.72	32.82	1.69	1.57	1.83	2.18	1.63	2.77	0.28	0.18	0.37

For each estimation the lower ('.lcl') and upper limits ('.ucl') are reported. M/K is the M/K prior as a ratio between each M value from* ***Table 2*** *and the best K estimate from ELEFAN (0.56 y^{-1}). F/M* is the ratio between F from the Length Converted Catch Curve (LCCC) method and M values from* ***Table 2****. F/M** is the ratio between F from the Beverton and Holt method and M values from* ***Table 2****. In bold the scenarios for which the stock is considered non-depleted.*

(Vasilakopoulos and Maravelias, 2016). In this context, the managers of the *P. narval* fishery need to strive for better monitoring of the bycatch *P. edwardsii* to obtain a better understanding of its status; e.g., by carrying out targeted sampling in deeper strata where *P. edwardsii* is known to be more abundant than *P. narval*. If the overexploited state of *P. edwardsii* is confirmed, management plans for *P. narval* should take into consideration the state of *P. edwardsii* as well and adjust the fishing activities accordingly.

This study provides a stepwise analytical methodology to be applied to any extremely data-limited stock. The range of methods that we have used in each step is not exhaustive and fisheries scientists are encouraged to use more and/or different methods according to the specific characteristics of the stock at hand. Inferring the stock status of extremely data-limited stocks usually involves unique challenges in every individual case; nevertheless, we are confident that following part or all of the methodological steps proposed here can prove extremely helpful.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

SK, VP, PV, and PM conceived the study. SK and KK contributed to the data collection. AM and VP did the analysis. VP, AM, PV, and SK interpreted the results. VP led the writing of the manuscript with input from all authors. All the authors contributed to the article and approved the submitted version.

FUNDING

This work was supported by the Greek Operational Programme "Fisheries 2007-2013" [grant number 185366, 2014] approved by the European Commission with decision no. E(2007)6402/11-122007, Programme reference No. CCI:2007GR14FPO001.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2020.583148/full#supplementary-material

REFERENCES

Abella, A. J., Caddy, J. F., and Serena, F. (1997). Do natural mortality and availability decline with age? An alternative yield paradigm for juvenile fisheries, illustrated by the hake Merluccius merluccius fishery in the Mediterranean. *Aqua. Liv. Resour.* 10, 257–269. doi: 10.1051/alr:1997029

Alverson, D. L., and Carney, M. J. (1975). A graphic review of the growth and decay of population cohorts. *ICES J. Mar. Sci.* 36, 133–143. doi: 10.1093/icesjms/36.2.133

Beare, D. J., Needle, C. L., Burns, F., and Reid, D. G. (2005). Using survey data independently from commercial data in stock assessment: an example using haddock in ICES Division VIa. *ICES J. Mar. Sci.* 62, 996–1005. doi: 10.1016/j.icesjms.2005.03.003

Beverton, R. J. H., and Holt, S. J. (1956). A review of the methods for estimating mortality rates in fish populations, with special reference to sources of bias in catch sampling. *Rapp. P. V. Réun. Cons. Int. Explor. Mer.* 140, 67–83.

Beverton, R. J. H., and Holt, S. J. (1957). *On the dynamics of exploited fish populations*. Great Britain: Ministry of Agriculture.

Brodziak, J., Ianelli, J., Lorenzen, K., and Methot, R. D. Jr. (2011). *Estimating natural mortality in stock assessment applications*. Department Commerce, NOAA, Tech Memo, NMFS-F/SPO-199, NMFS-F/SPO-199pg. (Washington: NOAA), 38.

Caddy, J. F. (1991). Death rates and time intervals: is there an alternative to the constant natural mortality axiom? *Rev. Fish Biol. Fish.* 1, 109–138. doi: 10.1007/BF00157581

Caddy, J. F., and Mahon, R. (1995). Reference points for fisheries management. *FAO Fisher. Tech. Pap.* 347:83.

Chen, S., and Watanabe, S. (1989). Age Dependence of Natural Mortality Coefficient in Fish Population Dynamics. *Nipp. Suis. Gakka.* 55, 205–208. doi: 10.2331/suisan.55.205

Colloca, F. (2002). Life Cycle of the Deep-Water Pandalid Shrimp Plesionika edwardsii (Decapoda, Caridea) in the Central Mediterranean Sea. *J. Crust. Biol.* 22, 775–783. doi: 10.1651/0278-0372(2002)022[0775:lcotdw]2.0.co;2

Company, J. B., and Sardà, F. (2000). Growth parameters of deep-water decapod crustaceans in the Northwestern Mediterranean Sea: a comparative approach. *Mar. Biol.* 136, 79–90. doi: 10.1007/s002270050011

Dormann, C. F., Calabrese, J. M., Guillera-Arroita, G., Matechou, E., Bahn, V., Bartoň, K., et al. (2018). Model averaging in ecology: a review of Bayesian, information-theoretic, and tactical approaches for predictive inference. *Ecol. Monogr.* 88, 485–504. doi: 10.1002/ecm.1309

Froese, R. (2004). Keep it simple: three indicators to deal with overfishing. *Fish Fisher.* 5, 86–91. doi: 10.1111/j.1467-2979.2004.00144.x

Froese, R., and Binohlan, C. (2000). Empirical relationships to estimate asymptotic length, length at first maturity and length at maximum yield per recruit in fishes, with a simple method to evaluate length frequency data. *J. Fish Biol.* 56, 758–773. doi: 10.1111/j.1095-8649.2000.tb00870.x

Froese, R., Demirel, N., Coro, G., Kleisner, K. M., and Winker, H. (2017). Estimating fisheries reference points from catch and resilience. *Fish Fisher.* 18, 506–526. doi: 10.1111/faf.12190

Froese, R., Stern-Pirlot, A., Winker, H., and Gascuel, D. (2008). Size matters: How single-species management can contribute to ecosystem-based fisheries management. *Fisher. Res.* 92, 231–241. doi: 10.1016/j.fishres.2008.01.005

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2018). A new approach for estimating stock status from length frequency data. *ICES J. Mar. Sci.* 75, 2004–2015. doi: 10.1093/icesjms/fsy078

Fryer, R. F., Needle, C. L., and Reeves, S. A. eds. (1998). "Kalman filter assessments of cod, haddock and whiting in VIa," in *Working Document WD1 to the ICES Working Group on the Assessment of Northern Shelf Demersal Stocks*, (Copenhagen: *ICES*).

García-Rodriguez, M., Esteban, A., and Perez Gil, J. L. (2000). Considerations on the biology of *Plesionika edwardsi* (Brandt, 1851) (Decapoda, Caridea, Pandalidae) from experimental trap catches in the Spanish western Mediterranean Sea. *Scient. Mar.* 64, 369–379. doi: 10.3989/scimar.2000.64n4369

Gayanilo, F. C., and Pauly, D. eds. (1997). "FAO-ICLARM Stock Assessment Tools: Reference Manual," in *FAO Computerized Information Series (Fisheries) 8*, (Rome: Food and Agriculture Organization of the United Nations).

Gislason, H., Daan, N., Rice, J. C., and Pope, J. G. (2010). Size, growth, temperature and the natural mortality of marine fish. *Fish Fisher.* 11, 149–158. doi: 10.1111/j.1467-2979.2009.00350.x

González, J. A., Pajuelo, J. G., Triay-Portella, R., Ruiz-Díaz, R., Delgado, J., Góis, A. R., et al. (2016). Latitudinal patterns in the life-history traits of three isolated Atlantic populations of the deep-water shrimp Plesionika edwardsii (Decapoda, Pandalidae). *Deep Sea Res. Part I Oceanogr. Res. Pap.* 117, 28–38. doi: 10.1016/j.dsr.2016.09.004

Gulland, J. A. (1965). "Estimation of mortality rates," in *Annex to Arctic Fisheries Working Group Report.(ICES Council Meeting papers)*, (Cambridge: ICES Gadoid Fish.Comm).

Gulland, J. A., and Boerema, L. K. (1973). Scientific advice on catch levels. *Fisher. Bull.* 71, 325–335.

Gunderson, D. R., Zimmermann, M., Nichol, D. G., and Pearson, K. (2003). Indirect estimates of natural mortality rate for arrowtooth flounder (Atheresthes stomias) and dark-blotched rockfish (Sebastes crameri). *Fisher. Bull.* 101, 175–182.

Hewitt, D. A., and Hoenig, J. M. (2005). Comparison of two approaches for estimating natural mortality based on longevity. *Fisher. Bull.* 103, 433–437.

Hoenig, J. M. (1983). Empirical Use of Longevity Data to Estimate Mortality Rates. *Fisher. Bull.* 82, 898–903.

ICES (2008). *Report of the Working Group on the Assessment of Northern Shelf Demersal Stock (WGNSDS), 15-21 May 2008*, ICES CM 2008/ACOM 08, Copenhagen, 757.

ICES (2012). *ICES Implementation of Advice for Data-limited Stocks in 2012 in its 2012 Advice*. ICES CM 2012/ACOM, Copenhagen, 68, 42.

Kalogirou, S., Anastasopoulou, A., Kapiris, K., Maravelias, C. D., Margaritis, M., Smith, C., et al. (2017). Spatial and temporal distribution of narwal shrimp Plesionika narval (Decapoda, Pandalidae) in the Aegean Sea (eastern Mediterranean Sea). *Reg. Stud. Mar. Sci.* 16(Suppl. C), 240–248. doi: 10.1016/j.rsma.2017.09.014

Kalogirou, S., Pihl, L., Maravelias, C. D., Herrmann, B., Smith, C. J., Papadopoulou, N., et al. (2019). Shrimp trap selectivity in a Mediterranean small-scale-fishery. *Fisher. Res.* 211, 131–140. doi: 10.1016/j.fishres.2018.11.006

Kenchington, T. J. (2014). Natural mortality estimators for information-limited fisheries. *Fish Fisher.* 15, 533–562. doi: 10.1111/faf.12027

Kuhn, M., and Johnson, K. (2013). *Applied predictive modeling*. Berlin: Springer.

Lorenzen, K. (2000). Allometry of natural mortality as a basis for assessing optimal release size in fish-stocking programmes. *Can. J. Fisher. Aqua. Sci.* 57, 2374–2381. doi: 10.1139/f00-215

Mannini, A., Pinto, C., Konrad, C., Vasilakopoulos, P., and Winker, H. (in review). The elephant in the room': Exploring natural mortality uncertainty in statistical catch at age models. *Front. Mar. Sci.*

Maravelias, C. D., Vasilakopoulos, P., Kalogirou, S., Handling, and Raúl, P. (eds) (2018). Participatory management in a high value small-scale fishery in the Mediterranean Sea. *ICES J. Mar. Sci.* 75, 2097–2106. doi: 10.1093/icesjms/fsy119

Martell, S., and Froese, R. (2013). A simple method for estimating MSY from catch and resilience. *Fish Fisher.* 14, 504–514. doi: 10.1111/j.1467-2979.2012.00485.x

Martiradonna, A. (2012). *Modelli di dinamica delle popolazioni ittiche: stima dei fattori di incremento e decremento dello stock*. Italy: Università di Bari.

Meyer, R., and Millar, R. B. (1999). BUGS in Bayesian stock assessments. *Can. J. Fisher. Aqua. Sci.* 56, 1078–1087. doi: 10.1139/f99-043

Mildenberger, T. K., Taylor, M. H., and Wolff, M. (2017). TropFishR: an R package for fisheries analysis with length-frequency data. *Methods Ecol. Evol.* 8, 1520–1527. doi: 10.1111/2041-210X.12791

Patterson, K. (1992). Fisheries for small pelagic species: an empirical approach to management targets. *Rev. Fish Biol. Fisher.* 2, 321–338. doi: 10.1007/BF00043521

Pauly, D. (1980). On the interrelationships between natural mortality, growth parameters, and mean environmental temperature in 175 fish stocks. *ICES J. Mar. Sci.* 39, 175–192. doi: 10.1093/icesjms/39.2.175

Pauly, D. (1985). On Improving Operation and Use of the ELEFAN Programs. Part 1, Avoiding Drift of K Towards Low Values. *Fishbyte* 11, 13–14.

Pauly, D. (1990). Length-Converted Catch Curves and the Seasonal Growth of Fishes. *Fishbyte* 8, 24–29.

Pauly, D., and David, N. (1981). ELEFAN I, a BASIC program for the objective extraction of growth parameters from length-frequency data. *Berich der Deutschen WissenschafHichen Kommission fiir Meeresforschung* 28, 205–211.

Pedersen, M. W., and Berg, C. W. (2017). A stochastic surplus production model in continuous time. *Fish Fisher.* 18, 226–243. doi: 10.1111/faf.12174

Polacheck, T., Hilborn, R., and Punt, A. E. (1993). Fitting Surplus Production Models: Comparing Methods and Measuring Uncertainty. *Can. J. Fisher. Aqua. Sci.* 50, 2597–2607. doi: 10.1139/f93-284

Powell, D. G. (1979). Estimation of mortality and growth parameters from the length frequency of a catch [model]. *Rapp. Proc. Verb. Reun.* 175, 167–169.

Prince, J., and Hordyk, A. (2019). What to do when you have almost nothing: A simple quantitative prescription for managing extremely data-poor fisheries. *Fish and Fisheries* 20, 224–238. doi: 10.1111/faf.12335

Punt, A. E. (2003). Extending production models to include process error in the population dynamics. *Can. J. Fisher. Aqua. Sci.* 60, 1217–1228. doi: 10.1139/f03-105

R Core Team. (2020). *R: A language and environment for statistical computing*. URL https://www.R-project.org/, (Vienna: R Foundation for Statistical Computing).

Santana, J. I., Gonzales, J. A. A., Lozano, I. J., and Tuset, V. M. (1997). Life history of Plesionika edwardsii (Crustacea, Decapoda, Pandalidae) around the Canary Islands, Eastern Central Atlantic. *Afr. J. Mar. Sci.* 18, 39–48. doi: 10.2989/025776197784161045

Schwamborn, R. (2018). How reliable are the Powell–Wetherall plot method and the maximum-length approach? Implications for length-based studies of growth and mortality. *Rev. Fish Biol. Fisher.* 28, 587–605. doi: 10.1007/s11160-018-9519-0

Simpfendorfer, C. A., Bonfil, R., Latour, R. J., Musick, J. A., and Bonfil, R. (2005). "Mortality estimation," in *Management Techniques for Elasmobranch Fisheries*, eds Edn, Vol. 474, (FAO Fisheries Technical Paper), 127–142.

STECF (17-15) (2017). *Scientific, Technical and Economic Committee for Fisheries (STECF) - Mediterranean Stock Assessments 2017 part I (STECF-17-15)*. (Luxembourg: Publications Office of the European Union), ISBN 978-92-79-67487-7.

STECF (19-16) (2019). *Scientific, Technical and Economic Committee for Fisheries (STECF) - Stock Assessments: demersal stocks in the western Mediterranean Sea (STECF-19-10)*. (Luxembourg: Publications Office of the European Union), ISBN 978-92-76-11288-4.

STECF (2020). *Scientific, Technical and Economic Committee for Fisheries (STECF) - Monitoring the Performance of the Common Fisheries Policy (STECF-Adhoc-20-01)*. (Luxembourg: Publications Office of the European Union), ISBN 978-92-76-18115-6. doi: 10.2760/230469

Taylor, M. H., and Mildenberger, T. K. (2017). Extending electronic length frequency analysis in R. *Fisher. Manag. Ecol.* 24, 330–338. doi: 10.1111/fme.12232

Then, A. Y., Hoenig, J. M., Hall, N. G., Hewitt, D. A., and Jardim, H. E. E. (2014). Evaluating the predictive performance of empirical estimators of natural mortality rate using information on over 200 fish species. *ICES J. Mar. Sci.* 72, 82–92. doi: 10.1093/icesjms/fsu136

Vasilakopoulos, P., and Maravelias, C. D. (2016). A tale of two seas: A meta-analysis of crustacean stocks in the NE Atlantic and the Mediterranean Sea. *Fish Fisher.* 17, 617–636. doi: 10.1111/faf.12133

Vasilakopoulos, P., Maravelias, C. D., Anastasopoulou, A., Kapiris, K., Smith, C. J., and Kalogirou, S. (2019). Premium small scale: the trap fishery for Plesionika narval (Decapoda, Pandalidae) in the eastern Mediterranean Sea. *Hydrobiologia* 826, 279–290. doi: 10.1007/s10750-018-3739-0

Vasilakopoulos, P., Maravelias, C. D., and Tserpes, G. (2014). The alarming decline of Mediterranean fish stocks. *Curr. Biol.* 24, 1643–1648. doi: 10.1016/j.cub.2014.05.070

Wetherall, J. A., Polovina, J. J., and Ralston, S. (1987). Estimating growth and mortality in steady-state fish stocks from length-frequency data. *ICLARM Conf. Proc.* 13, 53–74.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 15 December 2020
doi: 10.3389/fmars.2020.585654

"The Elephant in the Room": Exploring Natural Mortality Uncertainty in Statistical Catch at Age Models

Alessandro Mannini†, Cecilia Pinto, Christoph Konrad†, Paraskevas Vasilakopoulos and Henning Winker*

Joint Research Centre (JRC), European Commission, Ispra, Italy

The natural mortality rate (M) of a fish stock is typically highly influential on the outcome of age-structured stock assessment models, but at the same time extremely difficult to estimate. In data-limited stock assessments, M usually relies on a range of empirically or theoretically derived M estimates, which can vary vastly. This article aims at evaluating the impact of this variability in M using seven Mediterranean stocks as case studies of statistical catch-at-age assessments for information-limited fisheries. The two main bodies carrying out stock assessments in the Mediterranean and Black Seas are European Union's Scientific Technical Economic Committee for Fisheries (STECF) and Food and Agriculture Organization's General Fisheries Commission for the Mediterranean (GFCM). Current advice in terms of fishing mortality levels is based on a single "best" M assumption which is agreed by stock assessment expert working groups, but uncertainty about M is not taken into consideration. Our results demonstrate that not accounting for the uncertainty surrounding M during the assessment process can lead to strong underestimation or overestimation of fishing mortality, potentially biasing the management process. We recommend carrying out relevant sensitivity analyses to improve stock assessment and fisheries management in data-limited areas such as the Mediterranean basin.

Keywords: data limited stocks, Mediterranean Sea, reference points, stock status advice, stock assessment, natural mortality

OPEN ACCESS

Edited by:
Giuseppe Scarcella,
National Research Council (CNR), Italy

Reviewed by:
Dimitrios K. Moutopoulos,
University of Patras, Greece
Erika M. D. Porporato,
International Marine Centre Foundation, Italy

***Correspondence:**
Alessandro Mannini
alessandro.mannini@ec.europa.eu

†ORCID:
Alessandro Mannini
orcid.org/0000-0002-5910-3413
Christoph Konrad
orcid.org/0000-0002-9975-4704

Specialty section:
This article was submitted to Marine Ecosystem Ecology, a section of the journal Frontiers in Marine Science

Received: *21 July 2020*
Accepted: *23 November 2020*
Published: *15 December 2020*

Citation:
Mannini A, Pinto C, Konrad C, Vasilakopoulos P and Winker H (2020) "The Elephant in the Room": Exploring Natural Mortality Uncertainty in Statistical Catch at Age Models. Front. Mar. Sci. 7:585654. doi: 10.3389/fmars.2020.585654

INTRODUCTION

The natural mortality rate (M) is a key parameter for modeling age-structured fish population dynamics. M can be defined as the proportion of fish dying from all causes except fishing (e.g., senescence, predation, cannibalism, disease, and pollution) (Froese and Pauly, 2019). Although M is often treated as constant; it is usually age- or size-dependent and may exhibit a high interannual- as well as spatial variability between subpopulations (Kenchington, 2013). Meanwhile, fishing mortality (F), the main concern for fisheries managers, is commonly estimated by deducting M from an estimate of total mortality (Z) (Quinn and Deriso, 1999; Haddon, 2011). As a result, both the perceived stock status and the associated fisheries advice rely greatly on the chosen value of M.

In contrast to several other stock assessment parameters that describe somatic growth, maturation and longevity, M is rarely directly estimable from the available data of exploited stocks, as M is essentially confounded with fishing mortality F and recruitment (Beverton and Holt, 1957;

Clark, 1991, 1999; Punt et al., 2014a). Direct estimates of M could be conceptually obtained from age-length keys of resident species from inside- (closed population) and outside a protected area (Götz et al., 2008), from long data series that include size- or age- samples from early phases of light exploitation (Ricker, 1975; Csirke and Caddy, 1983), or from carefully designed mark-recapture experiments (Quinn and Deriso, 1999); however, such information is extremely scarce. Under certain data-rich circumstances, it is possible to estimate M within a statistical assessment model by integrating multiple data series including a time series of annually collected age-length keys over several years and preferably data from a large-scale tagging experiment (Lee et al., 2011; Cadigan, 2015). However, even then it is challenging to separate the effect of M from the confounding effects of recruitment variability and the size- and/or age-dependent population selectivity (Punt et al., 2014b), the latter expressing the combined effects of gear retention and differential availability, e.g., due to spatial structuring (Vasilakopoulos et al., 2020). Additionally, intrinsic parameters such as recapture reporting rates can affect the interpretation of data coming from tagging experiments (Konrad et al., 2016). Given that most datasets provide little or no information on M, assuming fixed values of M is common practice in stock assessments (Mangel et al., 2013).

In data-limited situations, analysts mostly rely on a wide range of empirical M estimators to approximate M (Kenchington, 2013 and references therein). These estimators may be derived from life history traits (e.g., Chen and Watanabe, 1989; Jensen, 1996) or from meta-analysis of datasets of unfished or lightly fished stocks (e.g., Pauly, 1980; Hoenig, 1983; Gislason et al., 2010) and consider various combinations of age, growth parameters, maturity and environmental variables to produce either a fixed value (Pauly, 1980; Hoenig, 1983; Jensen, 1996; Hewitt and Hoenig, 2005) or an age-based vector of M (e.g., Chen and Watanabe, 1989; Lorenzen, 2000). These estimators have been shown to be sensitive to the state of the population and its exploitation level, as well as the taxonomic group to which the species belongs (Kenchington, 2013). Consequently, different estimation methods for M applied to a given stock may produce estimates with high level of variation.

Accounting for uncertainty in M is fundamental not only to estimate the range of variability in the output but also to evaluate the outputs' robustness against model assumptions (Scott et al., 2016), as already highlighted with regards to deterministic Virtual Population Analysis (VPA) (Pope, 1972) and Extended Survival Analysis (XSA) models (Cheilari and Raetz, 2009). In age-structured models, the link between the population estimates and M occurs on two levels: in the basic population dynamics equations:

$$N_{a,y} = N_{a-1,y-1}e^{-\left(M_a+F_{a-1,y-1}\right)} \tag{1}$$

and in the Baranov catch equation;

$$C_{a,y} = N_{a,y}\frac{F_{y,a}}{M_a + F_{y,a}}\left(1 - e^{-\left(M_a+F_{a,y}\right)}\right) \tag{2}$$

where $N_{a,y}$ is the number at age a in year y, $C_{a,y}$is the catch in numbers and $F_{a,y}$ is the fishing mortality that is formulated here as an implicit function of the fishery selectivity pattern at age that may vary from year to year. It is obvious that when M is misspecified, F will be wrong. This can have major implications if the fisheries are managed through reference points that rely on F (e.g., F_{msy}, $F_{0.1}$). Beverton and Holt (1956) showed that as M increases, F_{msy} increases and vice versa. Therefore, if M is fixed in the model, this makes *a priori* presumptions about key reference points (Mangel et al., 2013).

This article aims at evaluating the impact of using alternative M estimates in seven data-limited Mediterranean stock assessments that were conducted with a statistical catch at age model implemented using the "Assessment for All framework" (a4a Jardim et al., 2014). The two main bodies carrying out stock assessments in the Mediterranean and Black Seas are European Union's Scientific Technical Economic Committee for Fisheries (STECF) and Food and Agriculture Organization's General Fisheries Commission for the Mediterranean (GFCM). Fishing activities are managed mainly by controlling effort (usually in terms of fishing days) to achieve sustainable $F \leq F_{0.1}$ values (STECF, 2019a), with advice being based on the outputs of a single stock assessment model. Generally a single "best" M assumption is agreed by the relevant stock assessment expert working groups prior to being used in the assessment. However, uncertainty in M is currently not taken into consideration, which makes the issue of misspecifying M particularly acute.

MATERIALS AND METHODS

Stock Assessment in the Mediterranean Sea and Case Studies

In the Mediterranean context, the main geographical fishery Management Unit corresponds to the FAO Geographical Sub-Area (GSA) (**Figure 1**; for more details please visit the following website)[1].

Seven demersal stocks, for which the STECF provided official advice in 2019 (STECF, 2019a,c) were considered as case studies here: blue and red shrimp [ARA – *Aristeus antennatus* (Risso 1816)] in GSAs 9, 10, and 11, Giant red shrimp [ARS – *Aristaeomorpha foliacea* (Risso 1827)] in GSAs 9, 10, and 11, Deep-water rose shrimp [DPS – *Parapenaues longirostris* (Lucas 1846)] in GSAs 9, 10, and 11, Norway lobster [NEP – *Nephrops norvegicus* (Linnaeus 1758)] in GSA 9, Red mullet (MUT – *Mullus barbatus* Linnaeus 1758) in GSA 9 and European hake [HKE – *Merluccius merluccius* (Linnaeus 1758)] in GSAs 9, 10, and 11, all exploited in the Italian waters of the Western Mediterranean Sea, and, common sole [SOL – *Solea solea* (Linnaeus 1758)] in GSA 17 exploited by the fleets of the Northern Adriatic Sea.

All seven stocks were assessed using a statistical catch-at-age model implemented in a4a, which utilizes the automatic differentiation within the Automatic Differentiation Model Builder (ADMB) (Jardim et al., 2014). The model is implemented in R [R 3.6.3, R Core Team (2020)] making use of the Fishery Library in R (FLR) platform (Kell et al., 2007)[2].

[1] http://www.fao.org/gfcm/data/maps/gsas

[2] https://www.flr-project.org/

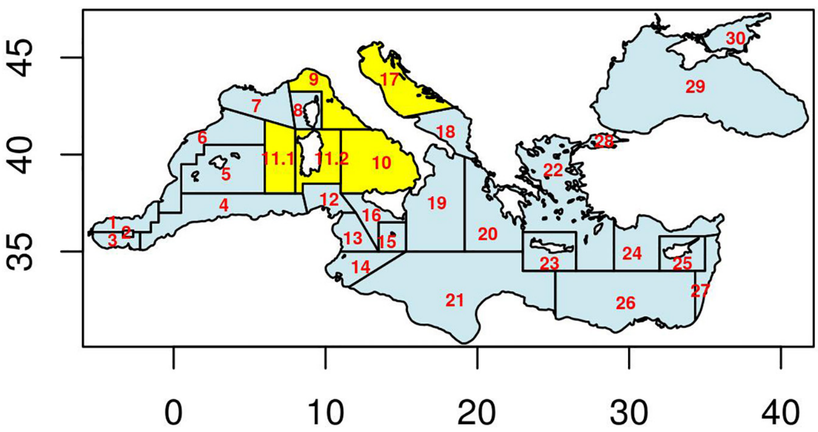


FIGURE 1 | FAO Geographical Subareas (GSAs) in the Mediterranean and Black Sea. Highlighted in yellow are the areas covered in the analysis of the seven stock assessment case studies. Vertical axis is Latitude and horizontal one is Longitude.

The seven stocks chosen as case studies are all characterized by a majority of the total catches coming from demersal otter trawl operations. The available fisheries data sources for the assessments include time series of total annual catches (including discard estimates), corresponding length composition data that are raised to total numbers at length for each fishery. Abundance information in the form of density estimates by length class is obtained from the international bottom trawl survey of the Mediterranean (MEDITS). Catch and densities at length are converted into numbers at age using length slicing techniques when age-length keys were not available. The main biological parameters used as inputs in the stock assessment models are listed in **Table 1**. According to Brodziak et al. (2011) an estimation of the length at first maturation is needed to compute a natural mortality at age (M_a) vector (see **Table 2**). For all the stocks a mean value of the female length at first maturation reported by Follesa and Carbonara (2019) all the stocks was chosen.

The stock assessment model settings and the input data, such as catch at age, fishery independent index of abundance by age, weight at age, baseline M, and proportion of mature individuals by age are fully described in the 2019 STECF reports (STECF, 2019a,c). The only input parameter that we modified compared to the official STECF assessments was M.

Estimating Natural Mortality Rates

A range of common methods to estimate M for the purpose of stock assessment were explored during two recent benchmark meetings on European hake (*Merluccius merluccius*), which were organized by the GFCM: one for hake in the Adriatic Sea[3] and one for hake in all other Mediterranean areas[4]. Here, we used the same 12 methods and approaches explored in these GFCM benchmarks. Five non-age-dependent methods for the calculation of M estimate empirical scalar values: Alverson and Carney (1975), Pauly (1980), Hoenig (1983), Hewitt and Hoenig (2005), and Then et al. (2014). Age-dependent M vectors were estimated using seven different methods: Gulland (1965), Chen and Watanabe (1989), ProdBiom [Caddy (1991), Abella et al. (1997)], Lorenzen (2000), Gislason et al. (2010), Brodziak et al. (2011). Some assumptions were made considering the species' habitat; since the bottom sea temperature in the Mediterranean rarely goes down below 12°C and considering that all the species analyzed are demersal, when computing the Pauly equation three different scenarios of bottom temperature were considered: 12-13-14°C. For maximum age (hereafter Tmax) that was used in the Alverson and Carney, Hewitt and Hoenig, and Hoenig and Then equations, the age corresponding to the asymptotic length of the von Bertalanffy growth function ($L\infty$) was used. For the *M* value of the individuals belonging to the older ages (hereafter $M\infty$) that was needed in one of the two Brodziak equations, in the Gulland formula and in the ProdBiom estimation (**Table 2**), we used an average of the methods providing scalar values. The natural mortality vector by age estimated with ProdBiom was computed using the unique solution developed by Martiradonna (2012). Equations and acronyms used are listed in **Table 2**.

Running Stock Assessments

For this analysis, both input data and a4a model configurations were kept as in the official STECF assessments (STECF, 2019a,c). Subsequently, only the M vectors of the official stock assessment were substituted in turn with one of the new *M* values (either as a scalar or as a vector) and the a4a models were refitted. This resulted in 18 new stock trajectories of biomass, catches, recruitment and fishing mortality for each of the seven original assessments.

Reference Points, Advice, and Bar Charts

Reference points for management (Caddy and Mahon, 1995) were computed using a Yield per Recruit model (Beverton and Holt, 1957) available through the FLR package FLBRP (see text footnote 2). The data collection framework

[3]http://www.fao.org/gfcm/meetings/info/en/c/1169692/

[4]http://www.fao.org/gfcm/meetings/info/en/c/1237394/

TABLE 1 | Main biological parameters for the 7 stocks Blue and red shrimp (ARA), Giant red shrimp (ARS), Deep-water rose shrimp (DPS) and European hake (HKE) in the FAO GSAs 9,10 and 11, Red mullet (MUT) and Norway lobster (NEP) in FAO GSA 9 and Common sole (SOL) in FAO GSA 17.

Stock	GSA	Sex	L∞	K	t0	a	b	L50%
ARA	9, 10, 11	F	76.90 CL	0.210	−0.020	0.0028	2.465	24 CL
		M	46.00 CL	0.210	−0.020	0.0042	2.324	
ARS	9, 10, 11	F	73.00 CL	0.435	−0.100	0.0040	2.520	35 CL
		M	50.00 CL	0.400	−0.100	0.0030	2.650	
HKE	9, 11	F	87.18 TL	0.150	−0.270	0.0060	3.066	34 TL
		M	54.78 TL	0.220	−0.300	0.0070	3.027	
	10	F	111.00 TL	0.100	−0.590	0.0040	3.191	
		M	73.00 TL	0.130	−0.820	0.004	3.166	
DPS	9	F	43.50 CL	0.740	−0.130	0.0031	2.49	23 CL
		M	33.10 CL	0.930	−0.050	0.0038	2.42	
	10, 11	F	46.00 CL	0.575	−0.200	0.0031	2.49	
		M	40.00 CL	0.680	−0.250	0.0038	2.42	
MUT	9	F	26.56 TL	0.545	−0.33	0.012	3	12 TL
		M	21.56 TL	0.56	−0.33	0.017	2.84	
NEP	9	F	56 CL	0.21	0	0.00032	3.24848	32 CL
		M	72.1 CL	0.17	0	0.00038	3.18164	
SOL	17	C	40.50 TL	0.310	0.125	0.00735	3.0585	25 TL

L∞, K, and t0, the von Bertalanffy growth function parameters; a and b, the length-weight relationship parameters; L50%, Length at first maturation (L50%); CL, Carapace Length in mm; TL, Total Length in cm; F, female; M, male; C, combined sex.

TABLE 2 | Methods and equations used to estimate M as a constant value or as an age-dependent vector.

Method	Main equation
Pauly_1,2,3	$M = e^{-0.0152+0.6543*log(k)-0.279*log(L\infty)+0.4634*log(T)}$
Alverson_Carney	$M = \frac{3k}{e^{(0.38*T_{max}*k)-1}}$
Then_1	$M = 4.899*T_{max}^{0.916}$
Then_2	$M = 4.118*k^{0.73}*L\infty^{-0.33}$
Hewitt_Hoenig	$M = e^{1.440-0.982*ln(T_{max})}$
Hoenig	$M = e^{1.46-0.101*ln(T_{max})}$
Lorenzen	$M_a = 3*w_a^{-0.288}$ $w = a*L_a^b$
Then_scaled	Then_2 * Lorenzen/mean (Lorenzen)
Gislason	$ln\,(M_a) = 0.55 - 1.61ln\,(L_a) + 1.44ln\,(L_a) + ln\,(k)$
Chen_Watanabe	$M_a = \frac{k}{1-e^{-k*(a-t0)}}$
Brodziak_Tmax	$M_a = M\infty*L_m/L_a$
Brodziak_K	$M_a = k*L_m/L_a$
Gulland	$M = 10^{log(M\infty)-0.5*log(w_a/w\infty)}$ $w = a*L^b, w\infty = a*L\infty^b$
ProdBiom	$t_m = t0 - log\left(1 - \frac{L_m}{L\infty}\right)/K$ $B = \frac{(b*log((1-exp(-k*(T_{max}-t0)))/(1-exp(-k*(0.00274-t0))))-M\infty*(T_{max}-0.00274))}{log(T_{max}/0.00274)-log(T_{max}/t_m)*(Tmax-0.00274)/(T_{max}-t_m)}$ $M_a = M\infty - log\frac{\frac{Tmax}{t_m}*B}{Tmax-t_m}$ $M_a = M_a + a;$
Mean	mean (Lorenzen, Then_scaled, Gislason, Brodziak_Tmax, Brodziak_K, Gulland, and ProdBiom)
Median	median (Lorenzen, Then_scaled, Gislason, Brodziak_Tmax, Brodziak_K, Gulland, and ProdBiom)

L∞, k, and t0: the von Bertalanffy growth function parameters; T_{max}, maximum observed age; M∞, the estimated natural mortality for the older ages; a and b, the length-weight relationship parameters; L_a, Length-at-age; w_a, weight-at-age; L_m, the length of first maturation.

(European Commission [EC], 2000; European Commission [EC], 2017) only began in 2002 in the Mediterranean Sea. As discussed in the introduction, short time series undermine the estimation of reliable stock recruitment relationships needed to estimate typical reference points such as F_{msy} which is commonly used in the ICES area (ICES, 2019). Therefore, in the Mediterranean context the exploitation state is estimated using an F_{msy} proxy, the $F_{0.1}$ value (STECF, 2019a,c; FAO, 2019). The $F_{0.1}$ fishing mortality level is the fishing mortality rate at which the slope of the yield per recruit curve, as a function of fishing mortality, is 10% of its value at the origin (Gulland and Boerema, 1973). Current fishing mortality (hereafter F_{curr}) was defined as the fishing mortality level of the latest year available from the official stock assessment, in agreement with STECF practice (STECF, 2019a,c). The status of exploitation was provided by the ratio between F_{curr} and $F_{0.1}$ for which values over 1 indicate a state of overfishing, while values below or equal to 1 indicate a state of sustainable exploitation. Three levels of exploitation were defined as: Sustainable ($F_{curr}/F_{0.1} <= 1$), Overfishing ($1 < F_{curr}/F_{0.1} <= 2$), Severe overfishing ($F_{curr}/F_{0.1} > 2$).

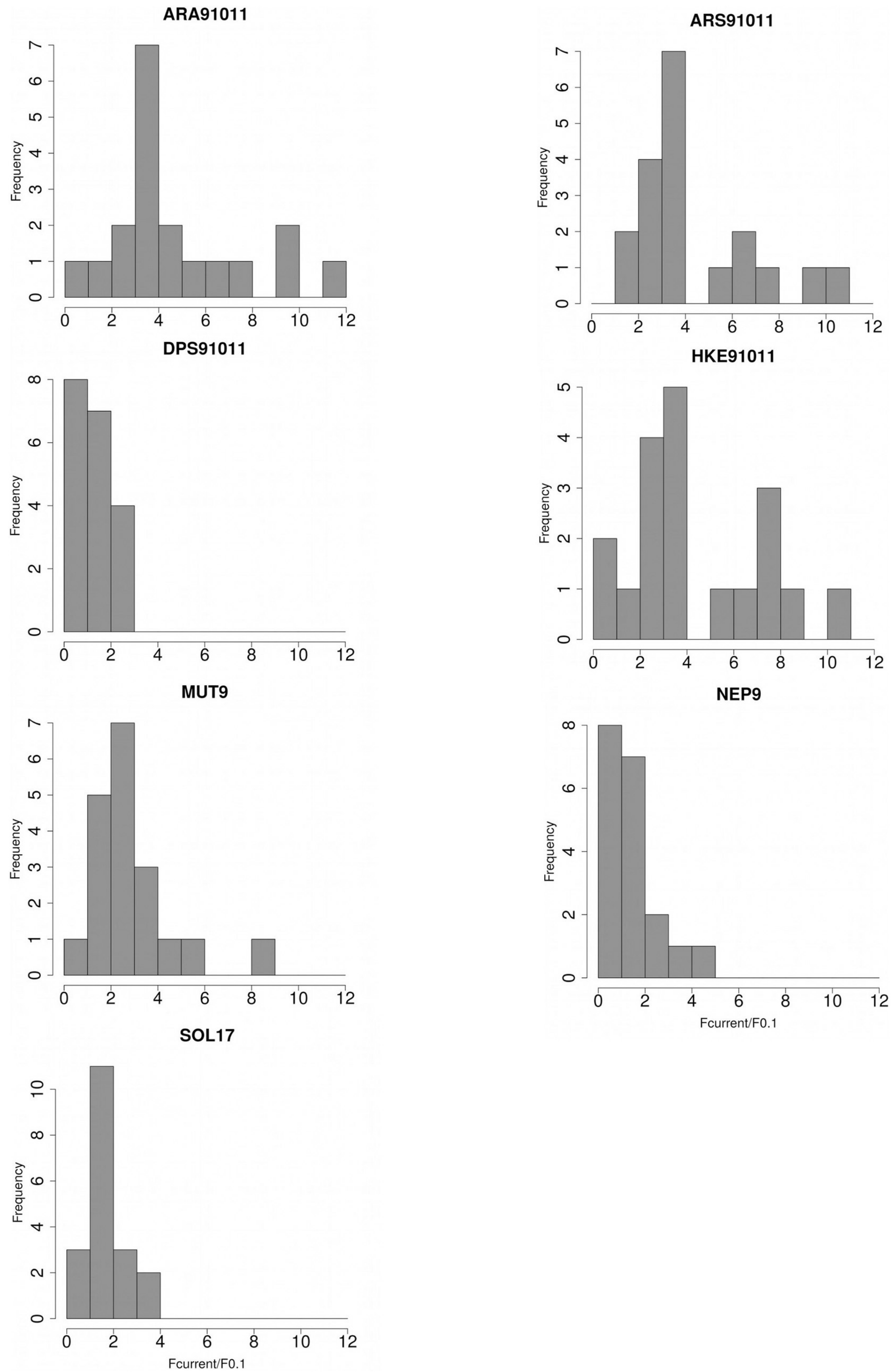


FIGURE 2 | Distributions of the ratios between F_{curr} and $F_{0.1}$ derived from 18 different natural mortality vectors for the seven stocks analyzed: Blue and red shrimp (ARA), Giant red shrimp (ARS), Deep-water rose shrimp (DPS) and European hake (HKE) in GSAs 9,10, and 11, Red mullet (MUT) and Norway lobster (NEP) in GSA 9 and Common sole (SOL) in GSA 17.

TABLE 3 | Current level of fishing mortality (F_{curr}), biological reference level ($F_{0.1}$), and the ratio ($F_{curr}/F_{0.1}$) for the seven stocks.

	ARA			ARS			DPS			HKE			MUT			NEP			SOL		
Method	***Fcurr***	***F0.1***	***Ratio***	***Fcurr***	***F0.1***	***Ratio***	***Fcurr***	***F0.1***	***Ratio***	***Fcurr***	***F0.1***	***Ratio***	***Fcurr***	***F0.1***	***Ratio***	***Fcurr***	***F0.1***	***Ratio***	***Fcurr***	***F0.1***	***Ratio***
Alverson_Carney	1.52	0.15	10.13	1.88	0.19	9.89	1.19	0.44	2.70	1.11	0.11	10.09	1.75	0.40	4.38	0.40	0.10	4.00	0.63	0.19	3.32
Brodziak_K	1.52	0.13	11.69	1.79	0.19	9.42	1.21	0.42	2.88	1.04	0.12	8.67	1.94	0.23	8.43	0.37	0.11	3.36	0.60	0.20	3.00
Brodziak_Tmax	1.51	0.16	9.44	1.71	0.23	7.43	1.16	0.49	2.37	0.98	0.15	6.53	1.80	0.33	5.45	0.33	0.17	1.94	0.53	0.29	1.83
Chen_Watanabe	1.49	0.39	3.82	1.35	0.48	2.81	0.93	0.94	0.99	0.78	0.23	3.39	1.59	0.56	2.84	0.30	0.22	1.36	0.50	0.33	1.52
Gislason	1.46	0.54	2.70	1.32	0.50	2.64	0.87	1.23	0.71	0.62	0.34	1.82	1.50	0.71	2.11	0.28	0.23	1.22	0.47	0.38	1.24
Gulland	1.24	0.72	1.72	1.08	0.85	1.27	0.71	2.55	0.28	0.24	3.69	0.07	1.21	1.75	0.69	0.17	0.45	0.38	0.34	0.78	0.44
Hewitt_Hoenig	1.55	0.23	6.74	1.68	0.30	5.60	1.05	0.66	1.59	1.05	0.14	7.50	1.63	0.51	3.20	0.36	0.15	2.40	0.57	0.25	2.28
Hoenig	1.55	0.22	7.05	1.70	0.28	6.07	1.07	0.64	1.67	1.06	0.14	7.57	1.65	0.49	3.37	0.36	0.14	2.57	0.58	0.24	2.42
Lorenzen	0.52	5.27	0.10	1.16	0.99	1.17	0.68	1.83	0.37	0.12	0.53	0.23	1.51	0.67	2.25	0.04	1.28	0.03	0.39	0.54	0.72
Mean	1.40	0.48	2.92	1.41	0.41	3.44	0.96	0.86	1.12	0.76	0.25	3.04	1.59	0.56	2.84	0.22	0.32	0.69	0.48	0.37	1.30
Median	1.47	0.39	3.77	1.38	0.44	3.14	0.94	0.88	1.07	0.80	0.23	3.48	1.57	0.57	2.75	0.29	0.23	1.26	0.49	0.34	1.44
Pauly_T1	1.49	0.37	4.03	1.45	0.44	3.30	0.94	0.85	1.11	0.59	0.27	2.19	1.43	0.76	1.88	0.24	0.29	0.83	0.45	0.41	1.10
Pauly_T2	1.48	0.39	3.79	1.40	0.50	2.80	0.92	0.90	1.02	0.58	0.27	2.15	1.40	0.81	1.73	0.23	0.29	0.79	0.44	0.43	1.02
Pauly_T3	1.48	0.40	3.70	1.39	0.55	2.53	0.90	0.95	0.95	0.57	0.28	2.04	1.37	0.85	1.61	0.22	0.30	0.73	0.43	0.44	0.98
ProdBiom	1.49	0.44	3.39	1.40	0.45	3.11	0.94	0.86	1.09	0.81	0.23	3.52	1.47	0.70	2.10	0.19	0.40	0.48	0.46	0.40	1.15
Then_1	1.51	0.31	4.87	1.48	0.42	3.52	0.90	0.96	0.94	0.97	0.18	5.39	1.44	0.75	1.92	0.30	0.24	1.25	0.50	0.34	1.47
Then_2	1.50	0.36	4.17	1.46	0.44	3.32	0.90	0.94	0.96	0.60	0.27	2.22	1.37	0.85	1.61	0.25	0.28	0.89	0.45	0.41	1.10
Then_scaled	1.52	0.28	5.43	1.66	0.27	6.15	1.15	0.51	2.25	1.01	0.14	7.21	1.69	0.44	3.84	0.31	0.19	1.63	0.53	0.29	1.83
MEDIAN	***1.49***	***0.38***	***3.92***	***1.43***	***0.44***	***3.31***	***0.94***	***0.87***	***1.08***	***0.79***	***0.23***	***3.43***	***1.54***	***0.62***	***2.50***	***0.29***	***0.24***	***1.23***	***0.49***	***0.36***	***1.37***
MEAN	***1.43***	***0.62***	***4.97***	***1.48***	***0.44***	***4.31***	***0.97***	***0.94***	***1.34***	***0.76***	***0.42***	***4.28***	***1.55***	***0.66***	***2.95***	***0.27***	***0.30***	***1.43***	***0.49***	***0.37***	***1.56***
STDEV	***0.24***	***1.17***	***3.00***	***0.21***	***0.21***	***2.56***	***0.15***	***0.52***	***0.76***	***0.28***	***0.82***	***2.98***	***0.18***	***0.32***	***1.78***	***0.09***	***0.26***	***1.06***	***0.07***	***0.14***	***0.76***
CV	***0.17***	***1.87***	***0.60***	***0.14***	***0.47***	***0.59***	***0.15***	***0.55***	***0.56***	***0.37***	***1.95***	***0.70***	***0.11***	***0.49***	***0.60***	***0.32***	***0.87***	***0.74***	***0.15***	***0.37***	***0.49***
STECF	***1.49***	***0.39***	***3.82***	***1.37***	***0.45***	***3.04***	***0.92***	***0.97***	***0.95***	***0.80***	***0.22***	***3.64***	***1.58***	***0.58***	***2.72***	***0.31***	***0.20***	***1.55***	***0.60***	***0.20***	***3.00***
%MEDIAN	***0.00***	***−2.63***	***2.55***	***4.20***	***−2.27***	***8.16***	***2.13***	***−11.49***	***12.04***	***−1.27***	***4.35***	***−6.12***	***−2.60***	***6.45***	***−8.80***	***−6.90***	***16.67***	***−26.02***	***−22.45***	***44.44***	***−118.98***
%MEAN	***−4.20***	***37.10***	***23.14***	***7.43***	***−2.27***	***29.47***	***5.15***	***−3.19***	***29.10***	***−5.26***	***47.62***	***14.95***	***−1.94***	***12.12***	***7.80***	***−14.81***	***33.33***	***−8.39***	***−22.45***	***45.95***	***−92.31***

Blue and red shrimp (ARA), Giant red shrimp (ARS), Deep-water rose shrimp (DPS), and European hake (HKE) in GSAs 9, 10, and 11, Red mullet (MUT) and Norway lobster (NEP) in GSA 9 and Common sole (SOL) in GSA 17, based on the stock assessment outputs applying the 18 different M vectors. In bold are highlighted: Median, Mean, Standard deviation (STDEV), coefficient of variation (CV), STECF official assessments values (STECF, 2019a,b) and percentage of variation between the median and the mean values compared to the official ones.

The impact of the different M values on the $F_{curr}/F_{0.1}$ ratio was summarized in three main bar charts:

(i) as a distribution of the $F_{curr}/F_{0.1}$ ratios obtained from the range of M values tested for each stock. This was summarized as an histogram of the 18 different values represented as bins with a width of 1 (0–1, 1–2, 2–3, etc.);
(ii) as a histogram by M estimation method showing the ratio between number of stocks for which $F_{curr}/F_{0.1}$ falls in one of the three levels of exploitation over the total number of stocks analyzed.
(iii) as a histogram by stock showing the ratio between the number of cases in which $F_{curr}/F_{0.1}$ falls in one of the three levels of exploitation over the total number of M vectors used.

Finally, the impact on management decisions was compared between the base-case model used in the official advice for each stock by either STECF or GFCM and each of the alternative M scenarios using the relative error (%) of the form:

$$\% = \frac{\left(X_M - X_{ref}\right)}{X_{ref}} \times 100 \quad (3)$$

where X_{ref} is the reference value of F_{curr}/F_{01}. from the official assessment and X_M is the respective value given variation in M for each method.

RESULTS

In **Table 3**, the main outputs in terms of F_{curr} and biological reference points for all the 126 scenarios (18 natural mortality vectors for each of the 7 stocks used) are summarized. The M vector affected more the estimation of the biological reference points rather than the level of F_{curr}. For biological reference points, the coefficient of variation (CV) ranged between a minimum of 0.37 in SOL17 to a maximum of 1.95 in HKE91011, while, for the current level of fishing mortality, the CV ranged between a minimum of 0.11 in MUT9 to a maximum of 0.37 in HKE91011 (**Table 3**).

Even though the model values of the distribution of the ratio by stocks confirms a general pattern of overfishing and severe overfishing (except DPS91011 and NEP9), some of the stocks, such as ARA91011 and HKE91011, officially assessed as in severe overfishing, could be assessed as sustainably fished (**Figure 2**). ARA91011, ARS91011, and HKE91011 showed the widest $F_{curr}/F_{0.1}$ ranges while DPS91011 and SOL17 the narrowest ones (**Figure 2**).

Generally, assessments suggesting severe overfishing scenarios were obtained when applying the Alverson_Carney, Brodziak, Hewitt_Hoenig, and Hoenig methods while more optimistic outcomes were obtained when the Lorenzen and Gulland methods were applied (**Table 4** and **Figure 3**).

The comparison between the official assessments and the median values obtained from the 18 different approaches ranged from the official assessment being quite close to the median (e.g., ARA91011; +2.55%), to stocks where that difference increased

TABLE 4 | Percentage of variation of the current level of fishing mortality (F_{curr}), biological reference level ($F_{0.1}$) and the ratio ($F_{curr}/F_{0.1}$) compared to the official advice estimated for the seven stocks.

	ARA			ARS			DPS			HKE			MUT			NEP			SOL		
Method	**Fcurr**	**F0.1**	**Ratio**	**Fcurr**	**F0.1**	**Ratio**	**Fcurr**	**F0.1**	**Ratio**	**Fcurr**	**F0.1**	**Ratio**	**Fcurr**	**F0.1**	**Ratio**	**Fcurr**	**F0.1**	**Ratio**	**Fcurr**	**F0.1**	**Ratio**
Alverson_Carney	1.97	−160.00	62.29	27.13	−136.84	69.26	22.69	−120.45	64.81	27.93	−100.00	63.92	9.71	−45.00	37.90	22.50	−100.00	61.25	4.76	−5.26	9.64
Brodziak_K	1.97	−200.00	67.32	23.46	−136.84	67.73	23.97	−130.95	67.01	23.08	−83.33	58.02	18.56	−152.17	67.73	16.22	−81.82	53.87	0.00	0.00	0.00
Brodziak_Tmax	1.32	−143.75	59.53	19.88	−95.65	59.08	20.69	−97.96	59.92	18.37	−46.67	44.26	12.22	−75.76	50.09	6.06	−17.65	20.10	−13.21	31.03	−63.93
Chen_Watanabe	0.00	0.00	0.00	−1.48	6.25	−8.19	1.08	−3.19	4.04	−2.56	4.35	−7.37	0.63	−3.57	4.23	−3.33	9.09	−13.97	−20.00	39.39	−97.37
Gislason	−2.05	27.78	−41.48	−3.79	10.00	−15.15	−5.75	21.14	−33.80	−29.03	35.29	−100.00	−5.33	18.31	−28.91	−10.71	13.04	−27.05	−27.66	47.37	−141.94
Gulland	−20.16	45.83	−122.09	−26.85	47.06	−139.37	−29.58	61.96	−239.29	−233.33	94.04	−5100.00	−30.58	66.86	−294.20	−82.35	55.56	−307.89	−76.47	74.36	−581.82
Hewitt_Hoenig	3.87	−69.57	43.32	18.45	−50.00	45.71	12.38	−46.97	40.25	23.81	−57.14	51.47	3.07	−13.73	15.00	13.89	−33.33	35.42	−5.26	20.00	−31.58
Hoenig	3.87	−77.27	45.82	19.41	−60.71	49.92	14.02	−51.56	43.11	24.53	−57.14	51.92	4.24	−18.37	19.29	13.89	−42.86	39.69	−3.45	16.67	−23.97
Lorenzen	−186.54	92.60	−3720.00	−18.10	54.55	−159.83	−35.29	46.99	−156.76	−566.67	58.49	−1482.61	−4.64	13.43	−20.89	−675.00	84.38	−5066.67	−53.85	62.96	−316.67
Mean	−6.43	18.75	−30.82	2.84	−9.76	11.63	4.17	−12.79	15.18	−5.26	12.00	−19.74	0.63	−3.57	4.23	−40.91	37.50	−124.64	−25.00	45.95	−130.77
Median	−1.36	0.00	−1.33	0.72	−2.27	3.18	2.13	−10.23	11.21	0.00	4.35	−4.60	−0.64	−1.75	1.09	−6.90	13.04	−23.02	−22.45	41.18	−108.33
Pauly_T1	0.00	−5.41	5.21	5.52	−2.27	7.88	2.13	−14.12	14.41	−35.59	18.52	−66.21	−10.49	23.68	−44.68	−29.17	31.03	−86.75	−33.33	51.22	−172.73
Pauly_T2	−0.68	0.00	−0.79	2.14	10.00	−8.57	0.00	−7.78	6.86	−37.93	18.52	−69.30	−12.86	28.40	−57.23	−34.78	31.03	−96.20	−36.36	53.49	−194.12
Pauly_T3	−0.68	2.50	−3.24	1.44	18.18	−20.16	−2.22	−2.11	0.00	−40.35	21.43	−78.43	−15.33	31.76	−68.94	−40.91	33.33	−112.33	−39.53	54.55	−206.12
ProdBiom	0.00	11.36	−12.68	2.14	0.00	2.25	2.13	−12.79	12.84	1.23	4.35	−3.41	−7.48	17.14	−29.52	−63.16	50.00	−222.92	−30.43	50.00	−160.87
Then_1	1.32	−25.81	21.56	7.43	−7.14	13.64	−2.22	−1.04	−1.06	17.53	−22.22	32.47	−9.72	22.67	−41.67	−3.33	16.67	−24.00	−20.00	41.18	−104.08
Then_2	0.67	−8.33	8.39	6.16	−2.27	8.43	−2.22	−3.19	1.04	−33.33	18.52	−63.96	−15.33	31.76	−68.94	−24.00	28.57	−74.16	−33.33	51.22	−172.73
Then_scaled	1.97	−39.29	29.65	17.47	−66.67	50.57	20.00	−90.20	57.78	20.79	−57.14	49.51	6.51	−31.82	29.17	0.00	−5.26	4.91	−13.21	31.03	−63.93

Blue and red shrimp (ARA), Giant red shrimp (ARS), Deep-water rose shrimp (DPS), and European hake (HKE) in GSAs 9, 10, and 11, Red mullet (MUT) and Norway lobster (NEP) in GSA 9 and Common sole (SOL) in GSA 17, based on the 18 different M vectors.

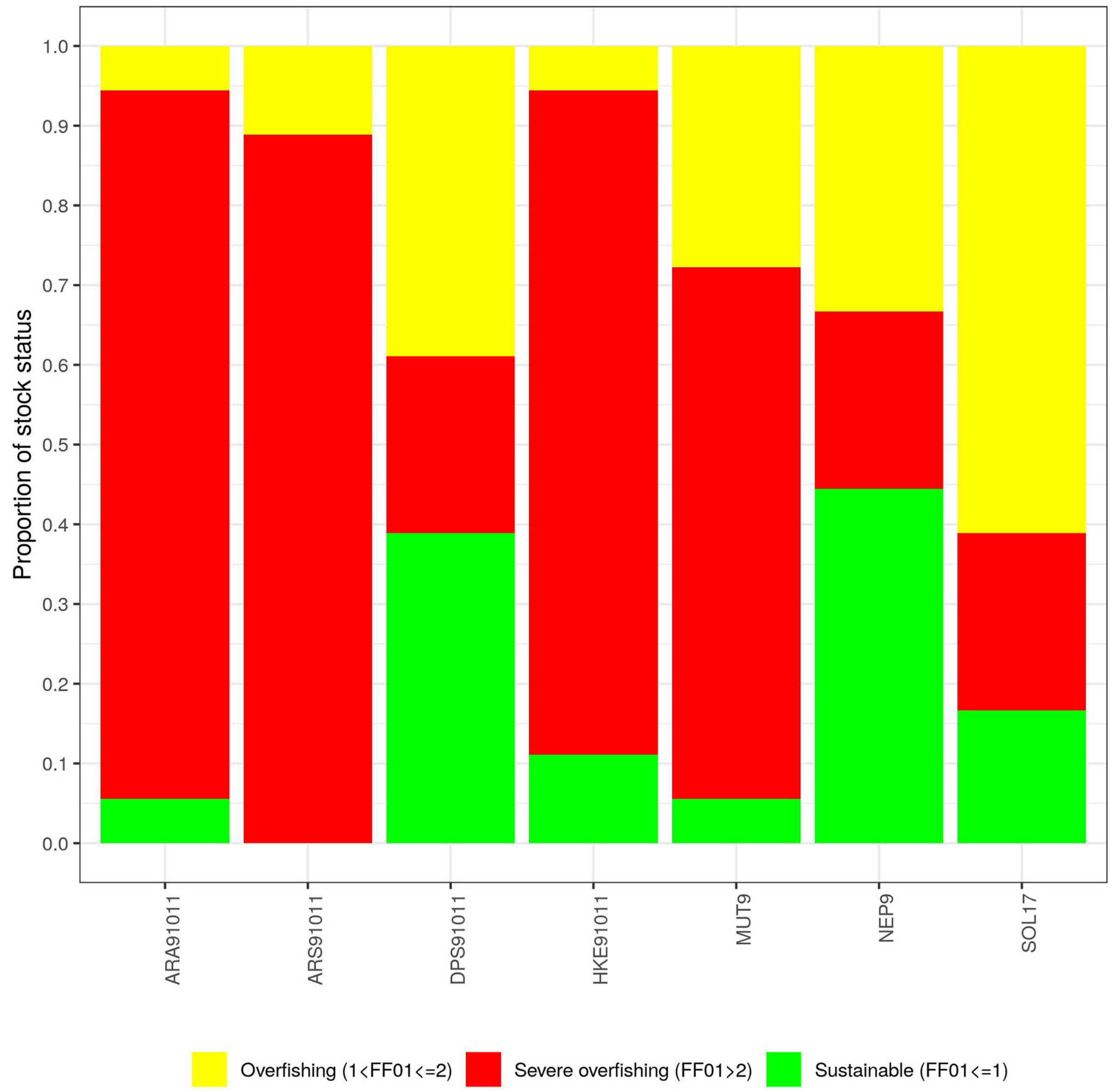


FIGURE 3 | Distribution of the ratios $F_{curr}/F_{0\cdot1}$ by M estimation method. On the *y* axis is reported the proportion of stocks for each level of exploitation over the total number of stocks (7).

(e.g., NEP9; −26.02%), to SOL17 exhibiting the highest difference (−118.98%) (**Table 3**).

Figure 4 shows that irrespective of the M vectors used, in ARS91011 there is always a clear overfishing situation (severe in 90% of the cases). For all other stocks, estimates also included sustainable fishing as a possible outcome. However, HKE91011, ARA91011, and MUT9 mostly exhibited a situation of overfishing, while the patterns in DPS91011, NEP9, and SOL17 describe a more uncertain scenario for which stocks could be either under sustainable or unsustainable fishing pressure. As an example, for SOL17, where the official advice suggested a state of severe overfishing ($F_{curr}/F_{0\cdot1}$ = 3), in 80% of cases a potential scenario of overfishing or sustainable fishing was estimated. The relative error (%) of the ratio $F_{curr}/F_{0\cdot1}$ is shown for each stock by M method with respect to the official assessment (**Figure 5**). Note, that for all the stocks but SOL17, Chen and Watanabe was the method used in computing the M vector at the STECF meeting (STECF, 2019a,c), which therefore explains the lack of divergence from of the official assessment. It is evident that using the Gislason M vector the perception of the stock status improves, while, using the Alverson and Carney or Broziak methods leads to an impression of severe overfishing. Moreover, these effects seem to be unrelated to M being age-dependent or not. For example, the three Pauly values seem to have no effect on red shrimps and Deep water rose shrimp while they gave the worst signal in terms of exploitation for Norway lobster (another crustacean) and the

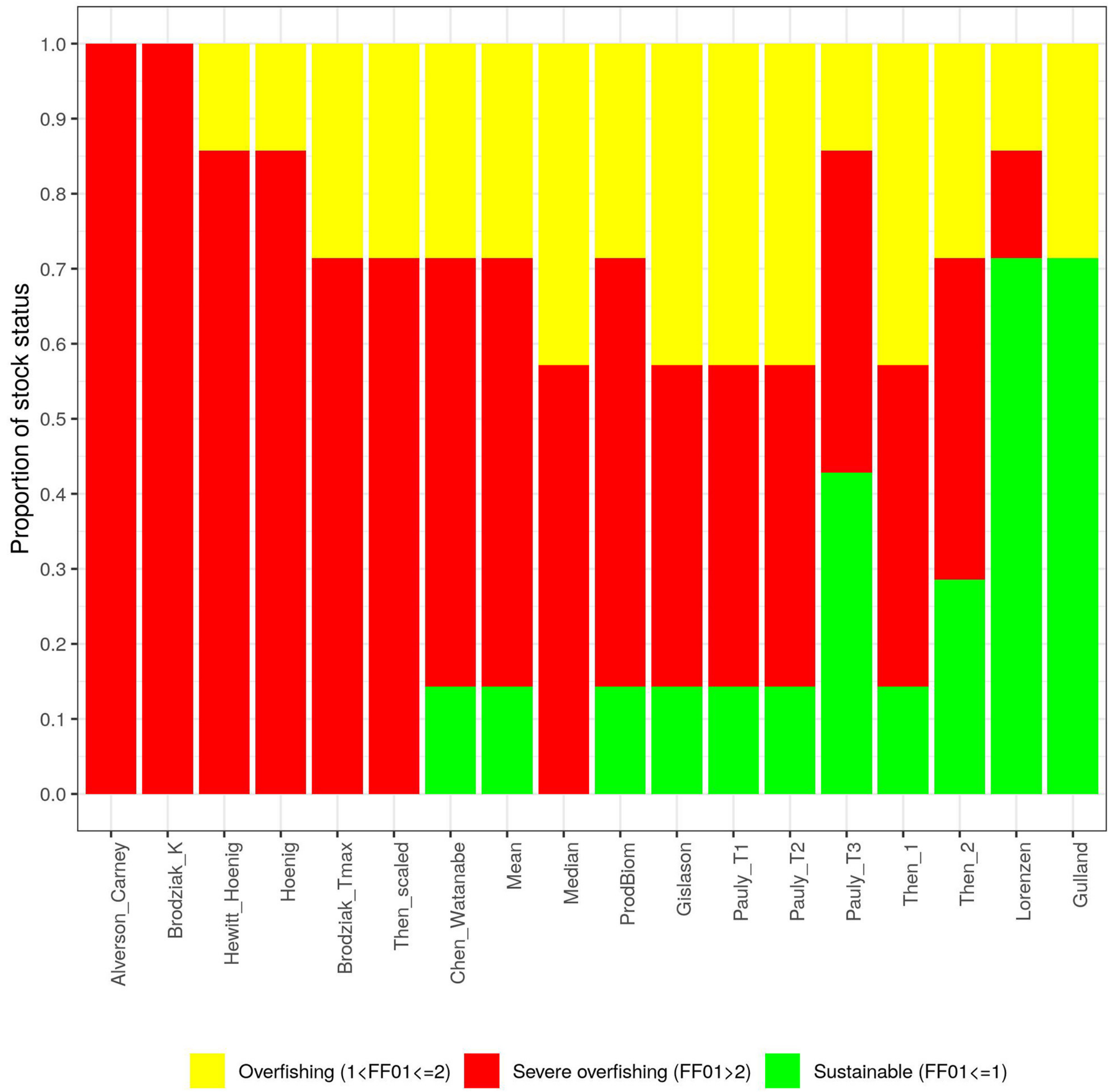


FIGURE 4 | Distribution of the ratios $F_{curr}/F_{0.1}$ by stock. On the *y* axis is reported the proportion of stocks for each level of exploitation over the total number of cases (18).

three teleostean species. At the same time, Then_scaled, even if it is associated with a general pattern of overfishing stock status (except for SOL17) the magnitude of this trend differs a lot by species and phylum.

DISCUSSION

Our results confirm that the choice of the M vector has a major impact on the output of stock assessment models. In six of the seven stocks examined, stock status classification ranged from sustainable to severe overfishing depending on the choice of the M estimation method. Using the "Alverson_Carney" and the "Brodziak_k" estimators, lead to the most severe overfishing classification of all seven stocks. Using the M estimators by Lorenzen and Gulland, in contrast, produced sustainable stock status estimates for 70% of the assessed stocks. However, when considering the median stock status across all stock assessment outputs based on all 18 M scenarios, none of the stocks would be sustainable, and four out of the seven stocks would be in severe overfishing, suggesting that choosing a single M scenario from the extremities of the spectrum is associated with high risk of misclassifying the stock status.

In the Mediterranean Sea, where data-limited situations go hand in hand with a specific behavior of demersal fishery, typically targeting the first two age classes of most demersal

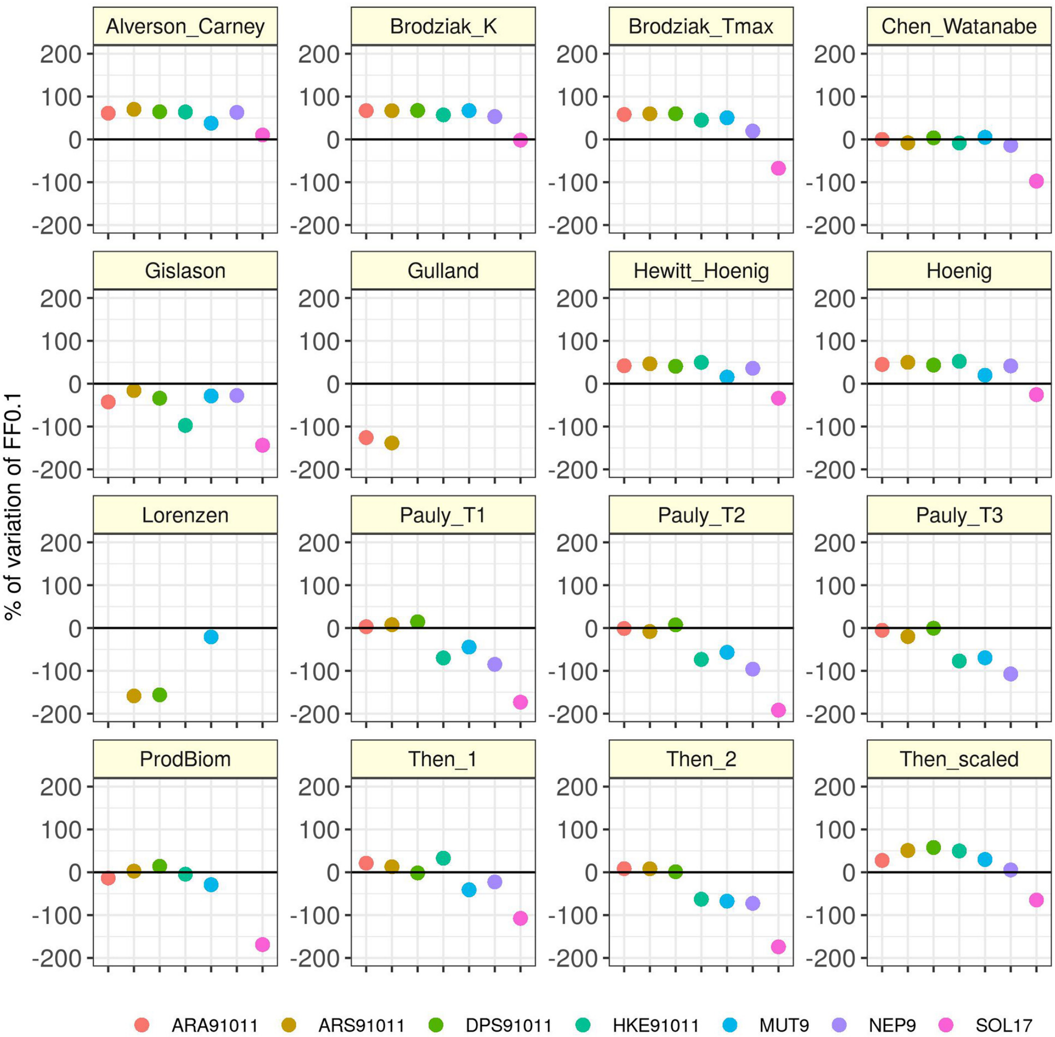


FIGURE 5 | Relative error (%) of $F_{curr}/F_{0.1}$ respect on the baseline [the official STECF assessment advice (black line)]. Percentages more than 200 and less than –200 are not shown (see **Table 4** for values).

stocks (Colloca et al., 2013; Vasilakopoulos et al., 2014), the effects of the M choice are even more crucial. The targeting of juveniles' age classes happens for different reasons: species within the Mediterranean do not grow as large and have a shorter lifespan than corresponding species in colder Atlantic waters. Historically, small fish hold an important slice of the market and as most evaluated stocks that are overfished, they are characterized by a relative lack of older fish (Colloca et al., 2013; Vasilakopoulos et al., 2014). As older ages are less represented, right-end selectivity is rare, introducing additional uncertainty and instability within the assessment process (Magnusson and Hilborn, 2007). Additionally, time series of standardized data in the Mediterranean basin are typically short for statistical catch at age model standards (usually between 13 and 17 years). Such short time series do not allow to obtain correct estimates of the stock-recruitment relationship, which precludes the use of F_{msy} as a reference point, and $F_{0.1}$ is used as a surrogate approximation instead (STECF, 2019a,c). Time series of fisheries catches which are typically dominated by juvenile age classes are unstable as they are more sensitive to environmental variations affecting recruitment (Anderson et al., 2008; Stenseth and Rouyer, 2008). For all these reasons, when assessing Mediterranean stocks it becomes fundamental to explore the effect of parameter uncertainty on model outputs and apply methods which account for the introduction of potential bias within the management process.

The analysis carried out on the seven case studies of Mediterranean stocks clearly showed that the variation of stock assessment models' input parameters, such as the M vector, directly influenced the stock status results. Moreover, the role played by M becomes critical if we think that the perception of the stock status could be driven in one or another direction according to the scope of stakeholders. We recommend that a sensitivity analysis should always be carried out when dealing with stock assessments where uncertainty in the input data is very high. Relevant examples include the Norway lobster in GSA9, the Deep-water rose shrimp in GSA91011 and the Common sole in GSA17, for which our analysis showed that the final perception of the stock status could differ a lot depending on the M estimate used.

Accounting for the uncertainty of M alone may not be enough to improve the estimation's precision of stock exploitation levels. Another important source of bias is related to misreported catches (Van Beveren et al., 2017; Perretti et al., 2020). Pauly et al. (2014) pointed out that actual catches from four Mediterranean countries (Spain, France, Italy, and Turkey) could be from 1.6 to 2.6 times higher than those submitted to the FAO as official values. Non-reported catches were high in all fishing sectors, including industrial, artisanal and recreational fisheries (Pauly et al., 2014). Although catch numbers at age are typically fitted by admitting random observation error, this cannot account for systematic underreporting or system trends in catch reporting. Reducing the level of misreported catches should be therefore a priority for all data collection programs and related sample designs, specifically for areas characterized by data limitation such as the Mediterranean Sea.

Within the Mediterranean basin, fisheries management is based on fishing effort reduction, which can be obtained through area or time closures and by reducing fishing days. In order to evaluate if stocks are responding to fishing effort control measures, objectives of multiannual management plans (MAPs) are evaluated against stock assessment outputs and, more specifically, $F_{curr}/F_{0.1}$. Not accounting for the effect of uncertainty of key input parameters, such as M, in the stock assessment process means not accounting for potential bias in the evaluation of MAPs' objectives and therefore in their implementation. The implementation of MAPs in the Mediterranean and Black Sea is a responsibility of national states, however the development of MAPs can occur at different levels: international, within the European Union, and at national as well as regional level (European Commission [EC], 2013). The scientific bodies responsible for advising on the management of fisheries within the Mediterranean and Black Sea are: the GFCM, the European Commission (EC) and national governments. All these bodies rely on scientific analysis provided by working groups of fisheries science experts, specifically, for the EC, such working groups are coordinated and their output evaluated by the STECF.

Hilborn and Walters (1992), when discussing which could be the best model to be used in assessing stocks recalled an adage that "the truth often lies at the intersection of competing lies". In the context of stock assessment, they explained, this means deliberately comparing a range of alternative models. This statement may well be applied to the results of our analysis: always think that the main input parameters of a stock assessment are not well known, ending up with a range of alternative scenarios for management, which should be scrutinized. To address this, different approaches could be used to improve stock assessment quality and reduce uncertainty in the future. Recent research has been focusing on implementing a more objective model selection approach for experts to reach an agreement on which is the best supported model based on the performance of model diagnostics (Carvalho et al., 2017; Maunder and Piner, 2017; Rudd et al., 2019). Specifically, model ensembles for future stock assessment advice have been proposed as a promising approach to capture structural uncertainty surrounding important biological processes, including M (Scott et al., 2016). Elsewhere, such approaches are already implemented. Maunder et al. (2020), for example, developed a risk-based framework to objectively assign different weights to models in an ensemble, involving the results of several diagnostics tests as well as carefully developed expert criteria to judge the plausibility of each candidate model. The alternative to making benchmarking more risk adverse is by considering a range of alternative stock assessment model scenarios for conditioning of robust harvest control rules within the MSE framework (Punt et al., 2014b, 2016). Such approaches could facilitate expert working groups to reach a transparent and defensible agreement on which could be the best set of candidate models to be used to formulate probabilistic stock advice accounting for uncertainty.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://stecf.jrc.ec.europa.eu/web/stecf/dd/medbs/sambs.

AUTHOR CONTRIBUTIONS

AM and CP conceived the study and colleted the data. AM did the analysis. AM, CP, PV, CK, and HW interpreted the results and wrote the manuscript. All authors contributed to the article and approved the submitted version.

FUNDING

This work was carried out using data provided through European Union's Scientific, Technical and Economic Committee for Fisheries (STECF) and Food and Agriculture Organization's General Fisheries Commission for the Mediterranean (GFCM) and reflects information provided by several member states contracting parties. The contents of this article do not necessarily reflect the point of view of STECF or GFCM and in no way anticipate these Commissions' future policy in this area.

ACKNOWLEDGMENTS

The authors would also like to acknowledge two reviewers for their comments and insights that improved the manuscript.

REFERENCES

Abella, A. J., Caddy, J. F., and Serena, F. (1997). Do natural mortality and availability decline with age? An alternative yield paradigm for juvenile fisheries, illustrated by the hake *Merluccius merluccius* fishery in the Mediterranean. *Aquat. Living Resour.* 10, 257–269. doi: 10.1051/alr:1997029

Alverson, D. L., and Carney, M. J. (1975). A graphic review of the growth and decay of population cohorts. *ICES J. Mar. Sci.* 36, 133–143. doi: 10.1093/icesjms/36.2.133

Anderson, C. N. K., Hsieh, C.-H., Sandin, S. A., Hewitt, R., Hollowed, A., Beddington, J., et al. (2008). Why fishing magnifies fluctuations in fish abundance. *Nature* 452, 835–839. doi: 10.1038/nature06851

Beverton, R. J. H., and Holt, S. J. (1956). A review of the methods for estimating mortality rates in fish populations, with special reference to sources of bias in catch sampling. *Rapp.P.-V. Réun. Cons. Int. Explor. Mer.* 140, 67–83.

Beverton, R. J. H., and Holt, S. J. (1957). *On the Dynamics of Exploited Fish Populations*. Great Britain: Ministry of Agriculture.

Brodziak, J., Ianelli, J., Lorenzen, K., and Methot, R. D. (2011). *Estimating Natural Mortality in Stock Assessment Applications*. Department Commerce, NOAA, Technical Memo, NMFS-F/SPO-199. Washington, DC: NOAA.

Caddy, J. F. (1991). Death rates and time intervals: is there an alternative to the constant natural mortality axiom? *Rev. Fish Biol. Fish.* 1, 109–138. doi: 10.1007/BF00157581

Caddy, J. F., and Mahon, R. (1995). *Reference Points for Fisheries Management. FAO Fisheries Technical Paper*. Rome: FAO, 347–383.

Cadigan, N. G. (2015). A state-space stock assessment model for northern cod, including under-reported catches and variable natural mortality rates. *Can. J. Fish. Aquat. Sci.* 73, 296–308. doi: 10.1139/cjfas-2015-0047

Carvalho, F., Punt, A. E., Chang, Y. J., Maunder, M. N., and Piner, K. R. (2017). Can diagnostic tests help identify model misspecification in integrated stock assessments? *Fish. Res.* 192, 28–40. doi: 10.1016/j.fishres.2016.09.018

Cheilari, A., and Raetz, H.-J. (2009). The effect of natural mortality on the estimation of stock state parameters and derived references for sustainable fisheries management. *Proc. ICES Annu. Sci. Conf.* 2009, 1–12.

Chen, S., and Watanabe, S. (1989). Age dependence of natural mortality coefficient in fish population dynamics. *Nippon Suisan Gakkaishi* 55, 205–208. doi: 10.2331/suisan.55.205

Clark, W. G. (1991). Groundfish exploitation rates based on life history parameters. *Can. J. Fish. Aquat. Sci.* 48, 734–750. doi: 10.1139/f91-088

Clark, W. G. (1999). Effects of an erroneous natural mortality rate on a simple age-structured stock assessment. *Can. J. Fish. Aquat. Sci.* 56, 1721–1731. doi: 10.1139/f99-085

Colloca, F., Cardinale, M., Maynou, F., Giannoulaki, M., Scarcella, G., Jenko, K., et al. (2013). Rebuilding Mediterranean fisheries: a new paradigm for ecological sustainability. *Fish Fish.* 14, 89–109. doi: 10.1111/j.1467-2979.2011.00453.x

Csirke, J., and Caddy, J. F. (1983). Production modeling using mortality estimates. *Can. J. Fish. Aquat. Sci.* 40, 43–51. doi: 10.1139/f83-007

European Commission [EC] (2000). *Council Regulation European Commission [EC] No 1543/2000 of 29 June 2000 Establishing a Community Framework for the Collection and Management of the Data Needed to Conduct the Common Fisheries Policy*. Brussels: European Commission.

European Commission [EC] (2013). *Regulation (EU) No 1380/2013 on the Common Fisheries Policy*. Brussels: European Commission.

European Commission [EC] (2017). *Council Regulation (EC) No 1004/2017 of 17 May 2017 on the Establishment of a Union Framework for the Collection, Management and Use of Data in the Fisheries Sector and Support for Scientific Advice Regarding the Common Fisheries Policy and Repealing Council Regulation (EC) No 199/2008 (Recast)*. Brussels: European Commission.

FAO (2019). *General Fisheries Commission for the Mediterranean. Report of the Twenty-First Session of the Scientific Advisory Committee on Fisheries, Cairo, Egypt, 24–27 June 2019 / Commission générale des pêches pour la Méditerranée. Rapport de la vingt-et-unième session du Comité scientifique consultative des pêches. Le Caire, Égypte, 24-27 juin 2019. FAO Fisheries and Aquaculture Report/FAO Rapport sur les pêches et l'aquaculture No. 1290*. Rome: FAO.

Follesa, M. C., and Carbonara, P. (eds) (2019). *Atlas of the Maturity Stages of Mediterranean Fishery Resources. Studies and Reviews*. General Fisheries Commission for the Mediterranean. No. 99. Rome: FAO.

Froese, R., and Pauly, D. (eds) (2019). *FishBase*. London: World Wide Web electronic publication.

Gislason, H., Daan, N., Rice, J. C., and Pope, J. G. (2010). Size, growth, temperature and the natural mortality of marine fish. *Fish Fish.* 11, 149–158. doi: 10.1111/j.1467-2979.2009.00350.x

Götz, A., Kerwath, S. E., Attwood, C. G., and Sauer, W. H. H. (2008). Effects of fishing on population structure and life history of roman *Chrysoblephus laticeps* (Sparidae). *Mar. Ecol. Prog. Ser.* 362, 245–259. doi: 10.3354/meps07410

Gulland, J. A. (1965). *Estimation of Mortality Rates*. Annex to Arctic Fisheries Working Group Report ICES C. M. Doc 3. Copenhagen: ICES.

Gulland, J. A., and Boerema, L. K. (1973). Scientific advice on catch levels. *Fish. Bull.* 71, 325–335.

Haddon, M. (2011). *Modelling and Quantitative Methods in Fisheries*. London: Chapman and Hall/CRC.

Hewitt, D. A., and Hoenig, J. M. (2005). Comparison of two approaches for estimating natural mortality based on longevity. *Fish. Bull.* 103, 433–437.

Hilborn, R., and Walters, C. J. (1992). *Quantitative Fish Stock Assessment. Choice, Dynamics and Uncertainty*. New York: Chapman and Hall, 570.

Hoenig, J. M. (1983). Empirical use of longevity data to estimate mortality rates. *Fish. Bull.* 82, 898–903.

ICES (2019). *ICES Advice 2019*. Copenhagen: ICES.

Jardim, E., Millar, C. P., Mosqueira, I., Scott, F., Osio, G. C., Ferretti, M., et al. (2014). What is stock assessment is as simple as a linear model? The a4a initiative. *ICES J. Mar. Sci.* 72, 232–236. doi: 10.1093/icesjms/fsu050

Jensen, A. L. (1996). Beverton and Holt life history invariants result from optimal trade-off of reproduction and survival. *Can. J. Fish. Aquat. Sci.* 53, 820–822. doi: 10.1139/f95-233

Kell, L. T., Mosqueira, I., Grosjean, P., Fromentin, J., Garcia, D., Hillary, R., et al. (2007). FLR: an open-source framework for the evaluation and development of management strategies. *ICES J. Mar. Sci.* 64, 640–646. doi: 10.1093/icesjms/fsm012

Kenchington, T. J. (2013). Natural mortality estimators for information-limited fisheries. *Fish Fish.* 15, 533–562. doi: 10.1111/faf.12027

Konrad, C., Brattey, J., and Cadigan, N. G. (2016). Modelling temporal, and spatial variability in tag reporting-rates for Newfoundland cod (*Gadus morhua*). *Environ. Ecol. Stat.* 23, 387–.403. doi: 10.1007/s10651-016-0344-0

Lee, H.-H., Maunder, M. N., Piner, K. R., and Methot, R. D. (2011). Estimating natural mortality within a fisheries stock assessment model: an evaluation using simulation analysis based on twelve stock assessments. *Fish. Res.* 109, 89–94. doi: 10.1016/j.fishres.2011.01.021

Lorenzen, K. (2000). Allometry of natural mortality as a basis for assessing optimal release size in fish-stocking programmes. *Can. J. Fish. Aquat. Sci.* 57, 2374–2381. doi: 10.1139/f00-215

Magnusson, A., and Hilborn, R. (2007). What makes fisheries data informative? *Fish Fish.* 8, 337–358. doi: 10.1111/j.1467-2979.2007.00258.x

Mangel, M., MacCall, A. D., Brodziak, J., Dick, E. J., Forrest, R. E., Pourzand, R., et al. (2013). A perspective on steepness, reference points, and stock assessment. *Can. J. Fish. Aquat. Sci.* 70, 1–11. doi: 10.1139/cjfas-2012-0372

Martiradonna, A. (2012). *Modelli di Dinamica Delle Popolazioni Ittiche: Stima dei Fattori di Incremento e Decremento Dello Stock*. Bari: Tesi di Laurea Magistrale, Dipartimento di Matematica, Università di Bari.

Maunder, M. N., and Piner, K. R. (2017). Dealing with data conflicts in statistical inference of population assessment models that integrate information from multiple diverse data sets. *Fish. Res.* 192, 16–27. doi: 10.1016/j.fishres.2016.04.022

Maunder, M. N., Xu, H., Lennert-Cody, C. E., Valero, J. L., Aires-da-Silva, A., and Minte-Vera, C. (2020). *Implementing Reference Point-Based Fishery Harvest Control Rules Within a Probabilistic Framework that Considers Multiple Hypotheses (No. SAC-11-INF-F), Scientific Advisory Commitee, Inter-American Tropical Tuna Commission*. San Diego, CA: Scientific Advisory Commitee.

Pauly, D. (1980). On the interrelationships between natural mortality, growth parameters, and mean environmental temperature in 175 fish stocks. *ICES J. Mar. Sci.* 39, 175–192. doi: 10.1093/icesjms/39.2.175

Pauly, D., Ulman, A., Piroddi, C., Bultel, E., and Coll, M. (2014). 'Reported' versus 'likely' fisheries catches of four Mediterranean countries. *Sci. Mar.* 78, 11–17. doi: 10.3989/scimar.04020.17a

Perretti, C. T., Deroba, J. J., and Legault, C. M. (2020). Simulation testing methods for estimating misreported catch in a state-space stock assessment model. *ICES J. Mar. Sci.* 77, 911–920. doi: 10.1093/icesjms/fsaa034

Pope, J. G. (1972). An investigation in the accuracy of the virtual population analysis using cohort analysis. *Res. Bull. Int. Comm. NW Atlantic Fish.* 9, 65–74.

Punt, A. E., Butterworth, D. S., de Moor, C. L., De Oliveira, J. A. A., and Haddon, M. (2014a). Management strategy evaluation: best practices. *Fish Fish.* 17, 303–334. doi: 10.1111/faf.12104

Punt, A. E., Butterworth, D. S., de Moor, C. L., De Oliveira, J. A. A., and Haddon, M. (2016). Management strategy evaluation: best practices. *Fish Fish.* 17, 303–334. doi: 10.1002/9781118835531.ch5

Punt, A. E., Ferro, F. H., and Whitten, A. R. (2014b). Model selection for selectivity in fisheries stock assessments. *Fish. Res.* 158, 124–134. doi: 10.1016/j.fishres.2013.06.003

Quinn, T. J. II, and Deriso, R. B. (1999). *Quantitative Fish Dynamics*. Oxford: Oxford University Press.

R Core Team (2020). *R: A Language and Environment for Statistical Computing*. Vienna: R Foundation for Statistical Computing.

Ricker, W. E. (1975). *Computation and Interpretation of Biological Statistics of Fish Populations*. Ottawa: Bulletin of the Fisheries Research Board of Canada.

Rudd, M. B., Thorson, J. T., and Sagarese, S. R. (2019). Ensemble models for data-poor assessment: accounting for uncertainty in life-history information. *ICES J. Mar. Sci.* 76, 870–883. doi: 10.1093/icesjms/fsz012

Scott, F., Jardim, E., Millar, C. P., and Cerviño, S. (2016). An applied framework for incorporating multiple sources of uncertainty in fisheries stock assessments. *PLoS One* 11:e0154922. doi: 10.1371/journal.pone.0154922

STECF (2019a). *Scientific, Technical and Economic Committee for Fisheries (STECF) –Evaluation of Fishing Effort Regime in the Western Mediterranean – part IV (STECF-19-14)*. Luxembourg: Publications Office of the European Union.

STECF (2019b). *Scientific, Technical and Economic Committee for Fisheries (STECF) – Stock Assessments: Demersal stocks in the western Mediterranean Sea (STECF-19-10)*. Luxembourg: Publications Office of the European Union.

STECF (2019c). *Scientific, Technical and Economic Committee for Fisheries (STECF) – 2019. Stock Assessments Part 2: European Fisheries for Demersal Species in the Adriatic Sea (STECF-19-16)*. Luxembourg: Publications Office of the European Union.

Stenseth, N. C., and Rouyer, T. (2008). Ecology: destabilized fish stocks. *Nature* 452, 825–826. doi: 10.1038/452825a

Then, A. Y., Hoenig, J. M., Hall, N. G., Hewitt, D. A., and Jardim, H. E. E. (2014). Evaluating the predictive performance of empirical estimators of natural mortality rate using information on over 200 fish species. *ICES J. Mar. Sci.* 72, 82–92. doi: 10.1093/icesjms/fsu136

Van Beveren, E., Duplise, D., Castonguay, M., Valcroze, T. D., Plourde, S., and Cadigan, N. (2017). How catch underreporting can bias stock assessment of and advice for northwest Atlantic mackerel and a possible resolution using censored catch. *Fish. Res.* 194, 146–154. doi: 10.1016/j.fishres.2017.05.015

Vasilakopoulos, P., Jardim, E., Konrad, C., Rihan, D., Mannini, A., Pinto, C., et al. (2020). Selectivity metrics for fisheries management an advice. *Fish Fish.* 21, 621–638. doi: 10.1111/faf.12451

Vasilakopoulos, P., Maravelias, C., and Tserpes, G. (2014). The alarming decline of mediterranean fish stocks. *Curr. Biol.* 24, 1643–1648. doi: 10.1016/j.cub.2014.05.070

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The handling editor declared a past co-authorship with one of the authors, HW.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 12 January 2021
doi: 10.3389/fmars.2020.578601

Status and Exploitation of 74 Un-Assessed Demersal Fish and Invertebrate Stocks in the Aegean Sea (Greece) Using Abundance and Resilience

Athanassios C. Tsikliras[1], Konstantinos Touloumis[2], Androniki Pardalou[1], Angeliki Adamidou[1,2], Ioannis Keramidas[1,2], Georgios A. Orfanidis[1,2], Donna Dimarchopoulou[1†] and Manos Koutrakis[2]*

[1] Laboratory of Ichthyology, School of Biology, Aristotle University of Thessaloniki, Thessaloniki, Greece, [2] Fisheries Research Institute, ELGO-Demeter, Nea Peramos, Greece

OPEN ACCESS

Edited by:
Giuseppe Scarcella,
National Research Council (CNR), Italy

Reviewed by:
José Lino Vieira De Oliveira Costa,
University of Lisbon, Portugal
Mauro Sinopoli,
University of Naples Federico II, Italy

***Correspondence:**
Athanassios C. Tsikliras
atsik@bio.auth.gr

†Present address:
Donna Dimarchopoulou,
Department of Fisheries, Animal and Veterinary Sciences, College of the Environment and Life Sciences, University of Rhode Island, Kingston, RI, United States

Specialty section:
This article was submitted to Marine Ecosystem Ecology, a section of the journal Frontiers in Marine Science

Received: 30 June 2020
Accepted: 16 December 2020
Published: 12 January 2021

Citation:
Tsikliras AC, Touloumis K, Pardalou A, Adamidou A, Keramidas I, Orfanidis GA, Dimarchopoulou D and Koutrakis M (2021) Status and Exploitation of 74 Un-Assessed Demersal Fish and Invertebrate Stocks in the Aegean Sea (Greece) Using Abundance and Resilience. Front. Mar. Sci. 7:578601. doi: 10.3389/fmars.2020.578601

Stocks with low market value are rarely included in stock assessments because their catch records are generally lacking, thus adding to the already large number of un-assessed fisheries at a global scale. This deficiency is more evident in the Mediterranean Sea where stock assessments are relatively fewer. A new method (AMSY) has been recently developed to assess stocks for which only abundance trends from scientific surveys are available. The AMSY method was used in the Aegean Sea to assess the status of 74 fish and invertebrate stocks (50 actinopterygians, 4 sharks, 5 rays, 12 cephalopods, and 3 crustaceans) for which catch data are lacking; 20 of them have medium or high market value and are being targeted by fishing fleets, while the remaining 54 are either not targeted, but by-caught and often discarded, or are not exploited at all. Overall, 31 of the 54 non-targeted stocks (57%) were healthy in terms of biomass ($B/B_{msy} > 1$), whereas only 6 of the 20 targeted stocks (30%) were healthy. Of the 23 unhealthy non-targeted stocks, 12 were near healthy ($B/B_{msy} > 0.75$), compared to only 1 of the targeted stocks, whereas 10 non-targeted stocks (19%) and 10 targeted ones (50%) were outside safe biological limits ($B < 0.5B_{msy}$). Cephalopods and crustaceans were generally in a better status compared to fishes. The results confirm that fishing does not only affect commercial stocks, but it may also affect by-catch stocks. In general, stocks that are targeted by fishing fleets are in a worse status in terms of biomass compared to those that are only occasionally collected as by-catch or those that inhabit environments that are not accessible to fishing fleets.

Keywords: stock assessment, fisheries management, non-commercial stocks, Mediterranean Sea, un-assessed fisheries

INTRODUCTION

Commercial fish and invertebrate stocks attract the attention of fisheries scientists at a global (Ricard et al., 2012) and regional (Colloca et al., 2013) scale and, as a result, the vast majority of regular assessments have been performed on fish and invertebrate stocks of high commercial interest (Osio et al., 2015). In the eastern Mediterranean Sea, an extensive assessment of the exploitation and status of commercial fish and invertebrate stocks has been recently performed in Greece (Froese et al., 2018b) and Turkey (Demirel et al., 2020). However, in Greece, the number of stocks that have been regularly and officially assessed is still very low compared to the other European countries of the northern Mediterranean coastline (Osio et al., 2018). One of the reasons for the low number of assessments is the lack of complete fisheries data time-series since 2009 due to administrative and financial constraints, while some of the recent official assessments suffer from various biases, one of which is the mixing of catch time-series from multiple fleets (Tsikliras et al., 2020). The number of official assessments is even lower along the southern Mediterranean coastline, one of the data-poorest regions of the northern hemisphere (Chrysafi and Kuparinen, 2016). The lack of adequate number of assessments is an international issue as un-assessed stocks exceed 80% of total catch, globally (Costello et al., 2012).

All recent assessments (Colloca et al., 2013; Vasilakopoulos et al., 2014; Tsikliras et al., 2015; Froese et al., 2018b) clearly show that the Mediterranean stocks are in bad state as a result of ongoing overexploitation. The overall stock status and exploitation pattern is rather uniform across the Mediterranean, with low stock biomass and high fishing pressure being the common characteristics but with the stock specific biomass and exploitation values varying among ecoregions (Froese et al., 2018b). According to a model approach, even most un-assessed demersal fish species are potentially overexploited in most Mediterranean areas (Osio et al., 2015). In any case, overexploitation of the Mediterranean Sea has been reported to occur since the 1950s, when about 40% of stocks were declining in biomass, as later unmasked by their catch history (Froese and Kesner-Reyes, 2002). Recently, it was reported that the stocks of all target species that have been assessed are overexploited, with hake (*Merluccius merluccius*) being the most overexploited stock across the Mediterranean Sea (Cardinale et al., 2017). According to a recent assessment that covers several areas of the world, the Mediterranean Sea is the most heavily exploited area and its stocks are in worse state compared to all other areas that were assessed (Hilborn et al., 2020). Indeed, the exploitation rate in the Mediterranean has been reported as steadily increasing and gear selectivity as deteriorating; both conditions are suspected to lead to shrinking fish stocks (Vasilakopoulos et al., 2014). Technological advancements that improve catchability (effort creep) also increase the overall effectiveness of fishing (Palomares and Pauly, 2019) and the operation of the Greek fishing fleet to international waters throughout the year is also leading to increased pressure at Aegean stocks (Tsikliras, 2014). Nevertheless, all these assessments include only fish and invertebrate stocks with available catch time-series (the correct term is landings as no official data exists for discarded catch in the Mediterranean Sea), while by-catch and discarded catch had been largely ignored mainly for practical reasons, as there was no method to account for their assessment.

Recently, a new method (AMSY) that can assess the exploitation pattern and status of stocks for which no catch data exist using only time-series of abundance (catch-per-unit-of-effort, CPUE) or biomass has been developed (Froese et al., 2020). Other fisheries independent methods also exist but they are time consuming and costly (e.g., underwater television: Morello et al., 2007). Many of these stocks are regularly collected, often in large quantities, during scientific surveys, but their status is rarely assessed as the data-poor stock assessment methods that were available until recently, require at least a time-series of catch (CMSY: Froese et al., 2017) or length frequency distributions (LBB: Froese et al., 2018a, 2019). Some of these species may also be collected by the commercial fishing fleets, especially bottom-trawlers, as by-catch; stocks with no or very low market value are usually discarded (Machias et al., 2001), although in some cases they are mixed with taxonomically related commercial stocks and marketed. The importance of assessing non-commercial stocks is high for ecosystem models (Dimarchopoulou et al., 2019) and for examining the effects of fishing on all components of the ecosystem, thus facilitating and promoting ecosystem-based fisheries management (Dimarchopoulou, 2020). It has been shown that by-catch demersal species that are collected in high numbers may suffer low biomass and truncated size distributions toward smaller lengths similarly to commercial stocks, while some others that are rarely collected maintain population structure and size (Dimarchopoulou et al., 2018).

The aim of the present work was to assess the status of 74 non-commercial demersal fish and invertebrate stocks in the Aegean Sea with the AMSY method using their abundance trends and resilience. As none of these species had been assessed before, the list of stocks for which there is now an assessment in the Aegean Sea is further increased, given that 42 stocks were recently assessed with the CMSY method (Froese et al., 2018b) and will soon be re-assessed using the updated CMSY + method (Tsikliras et al., unpublished data). Moreover, the assessment of stocks that have never been exploited, not even as by-catch (e.g., deep-water fishes and invertebrates), and are only collected during scientific surveys will provide important information on the effects of environmental (e.g., climate change) or ecological (e.g., prey-predator relationships) forcing on stock biomass and trends.

MATERIALS AND METHODS

Study Area

The Aegean Sea is divided by the Cyclades plateau into two sub-basins, the northern and the southern, which display different hydrographic and ecological characteristics due to the input of brackish water from the Black Sea in the northern part and the influence of Levantine Sea waters in the southern part (Ignatiades et al., 2002). Although the Aegean Sea as a whole is generally an oligotrophic sea (Ignatiades et al., 2002), parts of the northern Aegean Sea exhibit higher primary production and nutrient concentration (Siokou-Frangou et al., 2002).

The eutrophic gradient and the more extended continental shelf in its northern part are the main factors differentiating the subareas of the Aegean Sea in terms of productivity, species composition and species diversity (Stergiou and Pollard, 1994), with the northern Aegean Sea being the area with the highest total catches (Sylaios et al., 2010). European anchovy (*Engraulis encrasicolus*) and European pilchard or sardine (*Sardina pilchardus*) dominate the Aegean pelagic catch, while European hake (*Merluccius merluccius*), red mullet (*Mullus barbatus*) and two crustaceans, caramote prawn [*Melicertus (Penaeus) kerathurus*] and deep-water rose shrimp (*Parapenaeus longirostris*) are the main targeted demersal species (Stergiou et al., 2007a,b).

Selection of Stocks

Out of all fish and invertebrate stocks that are being collected during the experimental Mediterranean bottom trawl survey (MEDITS: Bertrand et al., 2002) and for which no official catch time-series exists (i.e., they are considered non-commercial), 74 stocks were included in the analysis. The catch of some of them is being reported at higher taxonomic level, aggregated together with relative species. For example, the catch of thornback ray (*Raja clavata*) is being reported separately, but all other rays are reported as "other rays" (*Raja* spp.). Species with only sporadic occurrence and very low CPUE values were excluded. The CPUE time-series extends from 1994 to 2018 with several missing years after 2009 (see next section); all surveys take place during the summer months (June and July in most cases).

Stocks with an official record of catch (for a list of species see Tsikliras et al., 2013) that form the prime targets of fisheries were excluded from this analysis but their previous assessment (Froese et al., 2018b) was used for comparability purposes (n = 42; **Table 1**). The remaining ones were divided into three categories based on the literature (Machias et al., 2001) and empirical knowledge: (1) alternative or secondary targeted stocks (stocks with no official catch records that are occasionally targeted and have a market value; n = 20), (2) by-catch stocks (stocks with a low market value that are not targeted but may be occasionally marketed; n = 28), and (3) discards (stocks that have never been exploited not even as by-catch and stocks caught in very small quantities as by-catch and are always discarded; n = 26). Spiny dogfish (*Squalus acanthias*) and musky octopus (*Eledone moschata*) were included because their catch records used in the previous assessment (Froese et al., 2018b) may have included their congeneric species, i.e., longnose spurdog (*Squalus blainville*) and curled octopus (*Eledone cirrhosa*), respectively. The first two categories (prime and alternative targets) formed the targeted part of the catch and the other two (by-catch and discards) were the non-targeted part of the catch. Further subdivision of those two commonly used categories was necessary because the effect of fishing might differ between prime and alternative targets and non-targeted (by-catch) or unwanted (discards) catch.

Data Analysis

Three different scientific bottom trawl surveys take place in the Aegean Sea using the same experimental bottom trawling gear but different vessels (one survey in the northern Aegean and two surveys in the southern Aegean, one of which along the southern Greek coastline and Cyclades Islands and the other one in Dodecanese Islands and Crete). Although the surveys are designed under a common framework, they are executed by different survey teams and are not always running simultaneously, conditions that may result in different levels of bias. For those reasons the CPUE data from the three surveys were considered as three different (multiple) and distinct indices.

The Bayesian state-space framework JARA (Just Another Red-List Assessment: Winker and Sherley, 2019) was used to address the issue of missing values and to combine the three abundance indices into a single one. JARA provides the option for fitting relative abundance indices to estimate a mean trend by allowing the simultaneous analysis of one or multiple abundance indices each of which may contain missing years and extend to different time period (Sherley et al., 2020). The model builds on the approach presented in JABBA for averaging relative abundance indices (Just Another Bayesian Biomass Assessment: Winker et al., 2018) and assumes that the mean underlying abundance trend is an unobservable state variable (Winker and Sherley, 2019). JARA was used to combine the three indices into a single one and to fill in the missing years of data from 2002 onward. Overall, 8 out of the 25 (32%) years of data were filled using JARA.

Stock Assessment Method

AMSY (Froese et al., 2020) is a new data-limited method that estimates fisheries reference points regarding stock status (B/B_{msy}: the ratio of observed biomass, B, to the biomass that would provide maximum sustainable yield, B_{msy}: Tsikliras and Froese, 2019) and exploitation level (F/F_{msy}: the level of relative pressure of fishing, measured as fishing mortality F relative to the one associated with the maximum sustainable yield, F_{msy}: Tsikliras and Froese, 2019) from CPUE data, combined with prior estimates of resilience, such as those that are available in FishBase (Froese and Pauly, 2020)[1] for fishes and in SealifeBase (Palomares and Pauly, 2020)[2] for invertebrates. AMSY is meant for wide-ranging or migratory stocks where CPUE is known from surveys or from observers on some of the commercial boats, but where total catch is unknown or unreliable, as well as for by-catch species where CPUE may be available from surveys but the catch is not officially recorded (Froese et al., 2020). In addition to CPUE and resilience, AMSY needs a prior for relative stock size (B) as a fraction of unexploited biomass (k or B_0), i.e., a range of B/k, between 0 and 1 for one of the years in the time-series. For example, if current stock biomass is known to be small compared to the beginning of the fishery, the B/k prior range can be set to 0.15–0.4 for the latest year with CPUE data while, if the stock at the beginning of the CPUE time-series was known to be under-exploited, the stock size was likely close to the unexploited size and the prior range for the first year with CPUE data could be set to a 0.75–1.0. AMSY uses CPUE, resilience prior and biomass prior in a high number of combinations of productivity (the maximum intrinsic rate of population increase r) and unexploited stock size or carrying capacity (k) for their compatibility with these inputs. A detailed description of the theory and equations behind AMSY is given in Froese et al. (2020).

For all the species included in the analysis, a prior was selected for their initial biomass (in 1995) that was set according to their exploitation at the time based on the following

[1] www.fishbase.org

[2] www.sealifebase.org

TABLE 1 | Analysis of 116 stocks in Aegean Sea with indication of existence of catch records, whether targeted (prime or alternative target), by-catch or discarded, biomass relative to the one that can produce the maximum sustainable yield (B/B_{msy}), fishing mortality relative to the one that can produce the maximum sustainable yield (F/F_{msy}), stock status and exploitation based on B/B_{msy} and F/F_{msy} and reference.

No	Class	Species	Catch records	Targeted	B/B_{msy}	F/F_{msy}	Status	Assessment
1	Ray-finned fishes	*Atherina boyeri*	Yes	Prime	0.19	1.09	B/O	Froese et al. (2018b)
2	Ray-finned fishes	*Belone belone*	Yes	Prime	0.22	2.19	B/O	Froese et al. (2018b)
3	Ray-finned fishes	*Boops boops*	Yes	Prime	0.51	1.01	B/O	Froese et al. (2018b)
4	Ray-finned fishes	*Dentex dentex*	Yes	Prime	0.47	1.18	B/O	Froese et al. (2018b)
5	Ray-finned fishes	*Dentex macrophthalmus*	Yes	Prime	0.84	1.08	B/O	Froese et al. (2018b)
6	Ray-finned fishes	*Dicentrarchus labrax*	Yes	Prime	0.28	3.06	B/O	Froese et al. (2018b)
7	Ray-finned fishes	*Diplodus annularis*	Yes	Prime	0.34	1.47	B/O	Froese et al. (2018b)
8	Ray-finned fishes	*Diplodus sargus*	Yes	Prime	0.27	2.51	B/O	Froese et al. (2018b)
9	Ray-finned fishes	*Engraulis encrasicolus*	Yes	Prime	0.69	1.54	B/O	Froese et al. (2018b)
10	Ray-finned fishes	*Epinephelus marginatus*	Yes	Prime	0.33	2.73	B/O	Froese et al. (2018b)
11	Ray-finned fishes	*Lophius budegassa*	Yes	Prime	0.49	1.39	B/O	Froese et al. (2018a)
12	Ray-finned fishes	*Melicertus kerathurus*	Yes	Prime	0.73	1.03	B/O	Froese et al. (2018a)
13	Ray-finned fishes	*Merluccius merluccius*	Yes	Prime	0.520	1.57	B/O	Froese et al. (2018b)
14	Ray-finned fishes	*Micromesistius poutassou*	Yes	Prime	0.28	2.51	B/O	Froese et al. (2018b)
15	Ray-finned fishes	*Mullus barbatus*	Yes	Prime	0.39	1.970	B/O	Froese et al. (2018b)
16	Ray-finned fishes	*Mullus surmuletus*	Yes	Prime	0.45	1.75	B/O	Froese et al. (2018b)
17	Ray-finned fishes	*Pagellus erythrinus*	Yes	Prime	0.62	1.06	B/O	Froese et al. (2018b)
18	Ray-finned fishes	*Pagrus pagrus*	Yes	Prime	0.62	1.30	B/O	Froese et al. (2018a)
19	Ray-finned fishes	*Pomatomus saltatrix*	Yes	Prime	0.37	1.61	B/O	Froese et al. (2018a)
20	Ray-finned fishes	*Sardina pilchardus*	Yes	Prime	0.66	1.07	B/O	Froese et al. (2018a)
21	Ray-finned fishes	*Sardinella aurita*	Yes	Prime	0.75	1.15	B/O	Froese et al. (2018a)
22	Ray-finned fishes	*Sarpa salpa*	Yes	Prime	0.30	2.15	B/O	Froese et al. (2018a)
23	Ray-finned fishes	*Scomber colias*	Yes	Prime	0.26	1.82	B/O	Froese et al. (2018a)
24	Ray-finned fishes	*Scomber scombrus*	Yes	Prime	0.17	1.09	B/O	Froese et al. (2018a)
25	Ray-finned fishes	*Scophthalmus maximus*	Yes	Prime	0.61	1.45	B/O	Froese et al. (2018a)
26	Ray-finned fishes	*Solea solea*	Yes	Prime	0.27	2.32	B/O	Froese et al. (2018a)
27	Ray-finned fishes	*Spicara smaris*	Yes	Prime	0.21	2.18	B/O	Froese et al. (2018a)
28	Ray-finned fishes	*Spondyliosoma cantharus*	Yes	Prime	0.230	2.59	B/O	Froese et al. (2018a)
29	Ray-finned fishes	*Trachurus mediterraneus*	Yes	Prime	0.35	0.92	B/U	Froese et al. (2018a)
30	Ray-finned fishes	*Trachurus trachurus*	Yes	Prime	0.61	0.71	B/U	Froese et al. (2018a)
31	Ray-finned fishes	*Umbrina cirrosa*	Yes	Prime	0.26	2.46	B/O	Froese et al. (2018a)
32	Ray-finned fishes	*Zeus faber*	Yes	Prime	0.480	1.92	B/O	Froese et al. (2018a)
33	Sharks and rays	*Raja clavata*	Yes	Prime	0.57	0.99	B/U	Froese et al. (2018a)
34	Sharks and rays	*Squalus acanthias*	Yes	Prime	0.55	1.38	B/O	Froese et al. (2018a)
35	Cephalopods	*Octopus vulgaris*	Yes	Prime	0.51	1.15	B/O	Froese et al. (2018a)
36	Cephalopods	*Illex coindetii*	Yes	Prime	0.83	1.27	B/O	Froese et al. (2018a)
37	Cephalopods	*Loligo vulgaris*	Yes	Prime	0.63	1.29	B/O	Froese et al. (2018a)
38	Cephalopods	*Eledone moschata*	Yes	Prime	0.75	0.86	B/U	Froese et al. (2018a)
39	Cephalopods	*Sepia officinalis*	Yes	Prime	0.62	0.94	B/U	Froese et al. (2018a)
40	Crustaceans	*Nephrops norvegicus*	Yes	Prime	0.19	4.01	B/O	Froese et al. (2018a)
41	Crustaceans	*Palinurus elephas*	Yes	Prime	0.77	1.23	B/O	Froese et al. (2018a)
42	Crustaceans	*Parapenaeus longirostris*	Yes	Prime	0.35	2.62	B/O	Froese et al. (2018a)
43	Ray-finned fishes	*Arnoglossus laterna*	No	Alternative	0.318	1.723	B/O	Present study
44	Ray-finned fishes	*Lepidorhombus boscii*	No	Alternative	0.421	1.934	B/O	Present study
45	Ray-finned fishes	*Pagellus bogaraveo*	No	Alternative	0.558	1.392	B/O	Present study
46	Ray-finned fishes	*Phycis blennoides*	No	Alternative	1.135	0.917	G/U	Present study
47	Ray-finned fishes	*Scorpaena notata*	No	Alternative	0.480	1.748	B/O	Present study
48	Ray-finned fishes	*Scorpaena porcus*	No	Alternative	1.973	0.191	G/U	Present study
49	Ray-finned fishes	*Scorpaena scrofa*	No	Alternative	1.477	0.633	G/U	Present study
50	Ray-finned fishes	*Trachurus picturatus*	No	Alternative	0.308	1.628	B/O	Present study
51	Ray-finned fishes	*Dentex maroccanus*	No	Alternative	1.743	0.357	G/U	Present study

(Continued)

TABLE 1 | Continued

No	Class	Species	Catch records	Targeted	B/B_{msy}	F/F_{msy}	Status	Assessment
52	Ray-finned fishes	*Trigla lyra*	No	Alternative	0.216	1.288	B/O	Present study
53	Ray-finned fishes	*Lophius piscatorius*	No	Alternative	0.219	1.398	B/O	Present study
54	Ray-finned fishes	*Pagellus acarne*	No	Alternative	1.829	0.241	G/U	Present study
55	Ray-finned fishes	*Trachurus mediterraneus*	No	Alternative	0.185	1.113	B/O	Present study
56	Ray-finned fishes	*Citharus linguatula*	No	Alternative	0.326	1.888	B/O	Present study
57	Ray-finned fishes	*Chelidonichthys lastoviza*	No	By-catch	1.801	0.310	G/U	Present study
58	Ray-finned fishes	*Chelidonichthys lucerna*	No	By-catch	0.838	1.243	B/O	Present study
59	Ray-finned fishes	*Gaidropsarus mediterraneus*	No	By-catch	0.803	1.261	B/O	Present study
60	Ray-finned fishes	*Lepidopus caudatus*	No	By-catch	0.116	2.593	B/O	Present study
61	Ray-finned fishes	*Lepidotrigla cavillone*	No	By-catch	1.141	0.928	G/U	Present study
62	Ray-finned fishes	*Lepidorhombus whiffiagonis*	No	By-catch	1.951	0.188	G/U	Present study
63	Ray-finned fishes	*Symphurus nigrescens*	No	By-catch	0.178	1.70	B/O	Present study
64	Ray-finned fishes	*Uranoscopus scaber*	No	By-catch	0.230	1.823	B/O	Present study
65	Ray-finned fishes	*Serranus cabrilla*	No	By-catch	0.883	1.246	B/O	Present study
66	Ray-finned fishes	*Conger conger*	No	By-catch	1.929	0.293	G/U	Present study
67	Ray-finned fishes	*Helicolenus dactylopterus*	No	By-catch	1.711	0.386	G/U	Present study
68	Ray-finned fishes	*Trachinus draco*	No	By-catch	0.884	1.137	B/O	Present study
69	Ray-finned fishes	*Trisopterus capelanus*	No	By-catch	0.202	1.375	B/O	Present study
70	Ray-finned fishes	*Argentina sphyraena*	No	By-catch	1.287	0.732	G/U	Present study
71	Ray-finned fishes	*Peristedion cataphractum*	No	By-catch	1.894	0.264	G/U	Present study
72	Ray-finned fishes	*Blennius ocellaris*	No	By-catch	0.875	1.305	B/O	Present study
73	Ray-finned fishes	*Gobius niger*	No	By-catch	0.347	1.970	B/O	Present study
74	Ray-finned fishes	*Arnoglossus rueppelii*	No	Discard	1.110	1.017	G/O	Present study
75	Ray-finned fishes	*Arnoglossus thori*	No	Discard	0.437	1.854	B/O	Present study
76	Ray-finned fishes	*Chelidonichthys cuculus*	No	Discard	0.984	1.021	B/O	Present study
77	Ray-finned fishes	*Lepidotrigla dieuzeidei*	No	Discard	1.760	0.232	G/U	Present study
78	Ray-finned fishes	*Argyropelecus hemigymnus*	No	Discard	0.574	1.532	B/O	Present study
79	Ray-finned fishes	*Benthosema glaciale*	No	Discard	1.704	0.473	G/U	Present study
80	Ray-finned fishes	*Lampanyctus crocodilus*	No	Discard	2.097	0.257	G/U	Present study
81	Ray-finned fishes	*Maurolicus muelleri*	No	Discard	0.759	1.602	B/O	Present study
82	Ray-finned fishes	*Capros aper*	No	Discard	1.844	0.283	G/U	Present study
83	Ray-finned fishes	*Cepola macrophthalma*	No	Discard	0.756	1.501	B/O	Present study
84	Ray-finned fishes	*Chlorophthalmus agassizi*	No	Discard	1.739	0.162	G/U	Present study
85	Ray-finned fishes	*Coelorinchus caelorhincus*	No	Discard	1.877	0.384	G/U	Present study
86	Ray-finned fishes	*Deltentosteus quadrimaculatus*	No	Discard	0.885	1.347	B/O	Present study
87	Ray-finned fishes	*Echelus myrus*	No	Discard	1.743	0.216	G/U	Present study
88	Ray-finned fishes	*Etmopterus spinax*	No	Discard	1.935	0.849	G/U	Present study
89	Ray-finned fishes	*Gadiculus argenteus*	No	Discard	1.789	0.331	G/U	Present study
90	Ray-finned fishes	*Hymenocephalus italicus*	No	Discard	1.141	0.955	G/U	Present study
91	Ray-finned fishes	*Macroramphosus scolopax*	No	Discard	1.748	0.174	G/U	Present study
92	Ray-finned fishes	*Serranus hepatus*	No	Discard	0.411	1.880	B/O	Present study
93	Sharks and rays	*Raja asterias*	No	Alternative	0.520	1.927	B/O	Present study
94	Sharks and rays	*Raja miraletus*	No	Alternative	0.716	1.567	B/O	Present study
95	Sharks and rays	*Raja polystigma*	No	Alternative	0.982	1.098	B/O	Present study
96	Sharks and rays	*Scyliorhinus canicula*	No	Alternative	0.482	1.466	B/O	Present study
97	Sharks and rays	*Galeus melastomus*	No	Alternative	1.980	0.334	G/U	Present study
98	Sharks and rays	*Squalus acanthias*	No	Alternative	0.491	3.417	B/O	Present study
99	Sharks and rays	*Torpedo marmorata*	No	By-catch	1.163	1.101	G/O	Present study
100	Sharks and rays	*Dipturus oxyrinchus*	No	By-catch	0.808	1.531	B/O	Present study
101	Sharks and rays	*Squalus blainville*	No	By-catch	1.792	0.942	G/U	Present study
102	Cephalopods	*Sepia elegans*	No	By-catch	1.881	0.25	G/U	Present study
103	Cephalopods	*Sepia orbignyana*	No	By-catch	0.354	1.552	B/O	Present study
104	Cephalopods	*Loligo forbesii*	No	By-catch	1.627	0.255	G/U	Present study

(Continued)

TABLE 1 | Continued

No	Class	Species	Catch records	Targeted	B/B_{msy}	F/F_{msy}	Status	Assessment
105	Cephalopods	*Octopus salutii*	No	By-catch	1.580	0.479	G/U	Present study
106	Cephalopods	*Eledone cirrhosa*	No	By-catch	0.141	0.933	B/U	Present study
107	Cephalopods	*Eledone moschata*	No	By-catch	0.677	1.341	B/O	Present study
108	Cephalopods	*Todaropsis eblanae*	No	By-catch	1.745	0.218	G/U	Present study
109	Cephalopods	*Todarodes sagittatus*	No	By-catch	1.685	0.447	G/U	Present study
110	Cephalopods	*Alloteuthis media*	No	Discard	1.309	0.766	G/U	Present study
111	Cephalopods	*Rossia macrosoma*	No	Discard	1.172	0.914	G/U	Present study
112	Cephalopods	*Scaeurgus unicirrhus*	No	Discard	0.755	1.512	B/O	Present study
113	Cephalopods	*Sepiola spp.*	No	Discard	0.150	2.344	B/O	Present study
114	Crustaceans	*Chlorotocus crassicornis*	No	Discard	1.755	0.145	G/U	Present study
115	Crustaceans	*Plesionika heterocarpus*	No	Discard	1.754	0.178	G/U	Present study
116	Crustaceans	*Plesionika martia*	No	Discard	1.983	0.161	G/U	Present study

G, good status ($B/B_{msy} > 1$; B: bad status ($B/B_{msy} < 1$; O, overexploited ($F/F_{msy} > 1$); U, sustainably exploited ($F/F_{msy} < 1$). Red background: stocks that are being overfished ($F/F_{msy} > 1$) or have low biomass ($B/B_{msy} < 1$); Green area: stocks subject to sustainable fishing pressure ($F/F_{msy} < 1$) and of a healthy stock biomass ($B/B_{msy} > 1$).

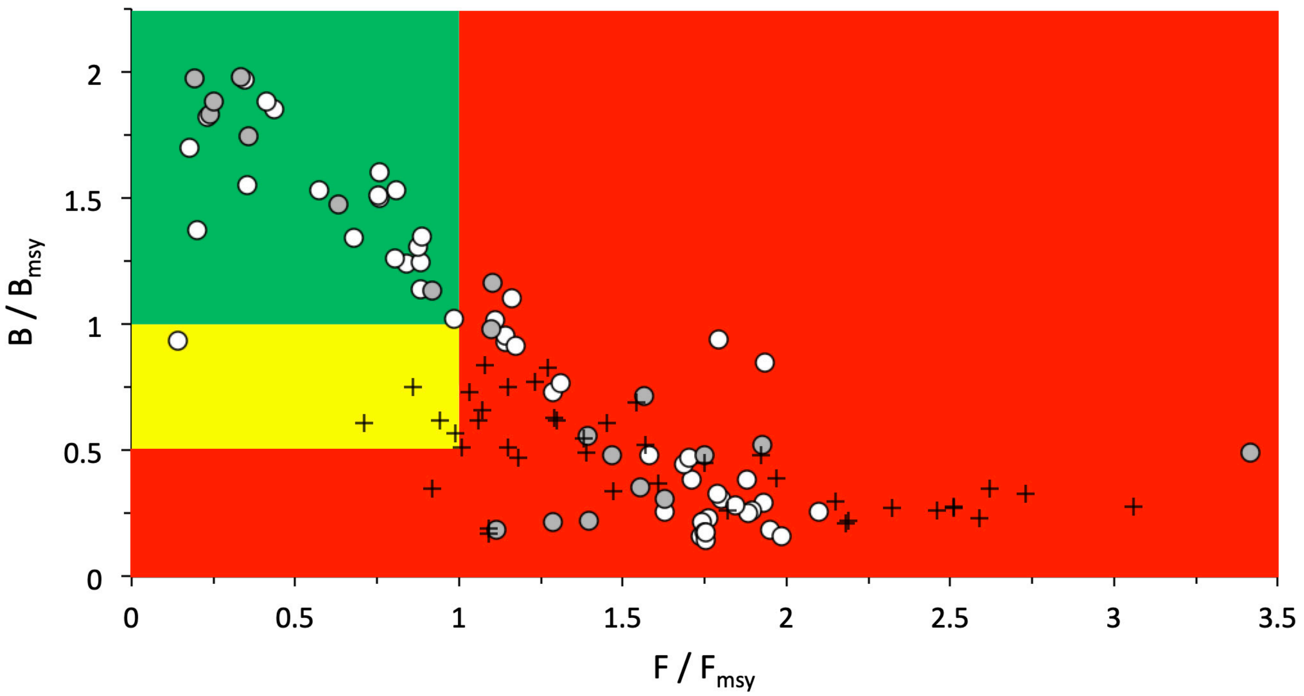


FIGURE 1 | The 74 un-assessed fish and invertebrate stocks of the Aegean Sea presented in a fishing pressure (F/F_{msy}) – stock status (B/B_{msy}) plot. White dots indicate by-catch and discarded stocks (*n* = 54) and gray dots indicate alternatively targeted ones (*n* = 20); black crosses refer to the previous assessment of commercial prime targets (*n* = 42) using the CMSY method (Froese et al., 2018b). Red area, stocks that are being overfished or are outside of safe biological limits; Yellow area, recovering stocks; Green area, stocks subject to sustainable fishing pressure and of a healthy stock biomass.

ranges (Froese et al., 2020) and the following criteria: near unexploited (stocks that have never been exploited not even as by-catch, e.g., deep-water fishes; B/k = 0.75–1.00), more than half (stocks caught in very small quantities as by-catch and have no commercial value, e.g., damselfish *Chromis chromis*; B/k = 0.50–0.85), about half (stocks that are often collected as by-catch and/or stocks with low commercial value and/or commercial stocks that were unexploited or under-exploited in the mid-1990s; B/k = 0.35–0.65), small (commercial stocks with historically maximum catch reached in the mid-1990s and then declined and/or commercial stock with no official catch data that are landed but reported aggregated with other stocks; B/k = 0.15–0.40), very small (commercial stocks with historically maximum catch reached before the mid-1990s and then drastically declined; B/k = 0.01–0.20). The criteria referring to commercial stocks were not applied thus the last two categories were excluded from the analysis.

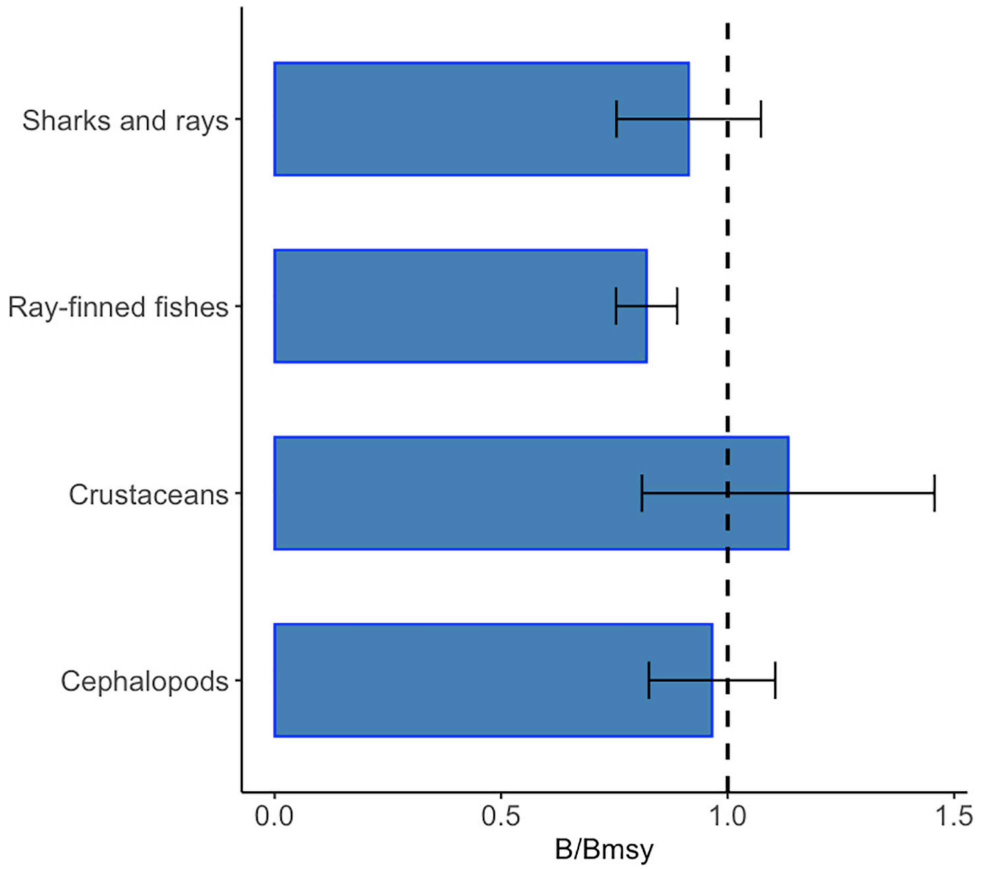


FIGURE 2 | Histogram of the mean B/B_{msy} per taxonomic group for the 74 fish and invertebrate stocks of the Aegean Sea assessed using the AMSY method. The vertical dashed line denotes the limit for healthy stock status ($B > B_{msy}$).

RESULTS

Overall, out of the 100 stocks that fulfilled the criteria of continuous occurrence and CPUE values, 74 stocks, the catch of which is not officially reported by statistical authorities, were included in the present analysis. The remaining 26 stocks were excluded because of sporadic presence (less than 5 years) or negligible biomass. Fifty-nine of those were fish (fifty ray-finned fishes, four sharks and five rays), twelve were cephalopods and three were crustaceans (**Table 1**). Out of the 74 included stocks (**Table 1**), 20 have medium or high commercial values and are being targeted (alternative targets) by fishing fleets, 28 are by-caught and marketed (by-catch) and 26 are discarded (discards).

Based on B/B_{msy} values, the status of non-targeted species (by-catch and discards) was better when compared to targeted (alternative targets) ones that were included in the present study and commercial stocks (prime targets) that had been previously assessed (**Table 1** and **Figure 1**). In the last year with available data, 31 of the 54 non-targeted stocks (57%) were healthy with B/B_{msy} values exceeding 1 whereas only 6 of the 20 targeted stocks (30%) were healthy (**Table 1** and **Figure 1**). Of the unhealthy non-targeted stocks, 12 (22% of the total non-targeted stocks) had B/B_{msy} values exceeding 0.75, compared to only 1 of the targeted stocks (5% of the total targeted stocks). Ten non-targeted stocks (19% of the total non-targeted stocks) and ten targeted ones (50% of the total targeted stocks) were outside of safe biological limits ($B < 0.5\ B_{msy}$). Similarly, 24 of the 54 non-targeted stocks (44%) and 14 out of the 20 targeted ones (70%) were subject to ongoing overfishing ($F > F_{msy}$). Out of fishes, spiny dogfish (*Squalus acanthias*) and silver scabbardfish (*Lepidopus caudatus*) were the most heavily exploited stocks (dogfish: $F/F_{msy} = 3.41$, scabbardfish: $F/F_{msy} = 2.59$), with silver scabbardfish and tonguesole (*Symphurus nigrescens*) exhibiting the lowest biomass (scabbardfish: $B/B_{msy} = 0.12$, tonguesole: $B/B_{msy} = 0.18$).

Cephalopod and crustacean stocks were in a better state compared to ray-finned fishes and sharks and rays (**Figure 2**). Overall, 48% of ray-finned fish stocks were healthy but 54% were subject to ongoing overfishing (**Table 1**). The majority of ray-finned fishes (36 out of 50 stocks, 72%), including several deep-water or mesopelagic stocks, are not targeted by any fisheries. The stocks of six out of nine (67%) sharks and rays, most of which are targeted, were not healthy and subject to ongoing overfishing. Seven out of twelve (58%) cephalopods and all three crustacean stocks were healthy and exploited sustainably. None of the crustaceans and cephalopods are targeted.

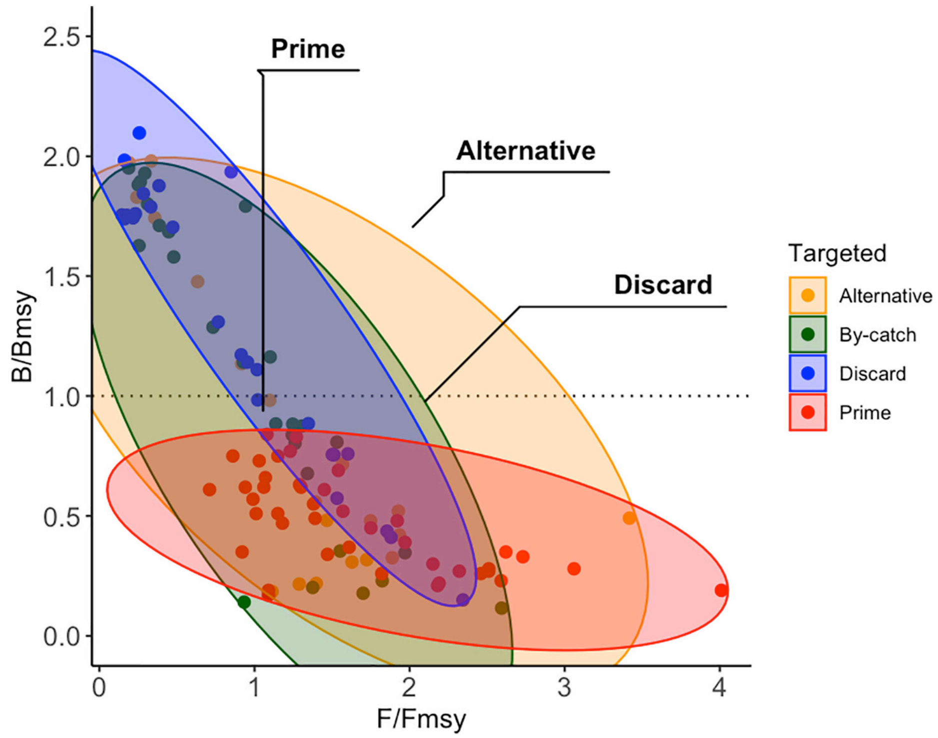


FIGURE 3 | Grouping of 116 fish and invertebrate stocks of the Aegean Sea (42 previously assessed stocks and 74 stocks assessed in the present study) based on their fishing pressure (F/F_{msy}) – stock status (B/B_{msy}) plot. Enclosing ellipses were estimated using the Khachiyan algorithm and expanded to cover all relevant points. Red dots and ellipse indicate prime targets (n = 42), orange dots and ellipse indicate alternative targets (n = 20), green dots and ellipse indicate by-catch species (n = 28) and blue dots and ellipse indicate discarded stocks (n = 26).

The status of the four groups of stocks based on their exploitation (prime targets, alternative targets, by-catch, and discards) is distinct for prime targets (none of them is healthy) that all have biomass below B_{msy} and alternative targets that span over a wider area (30% of them are healthy). The enclosing ellipses clearly indicate that some alternative targets are overlapping with prime targets and some others are ordinated among by-catch and discarded stocks. The ellipses of by-catch and discarded stocks largely coincide, with 50% of the by-catch stocks and 65% of the discard stocks being healthy (**Figure 3**). Finally, it appears that the exploitation is stronger for targeted species across taxonomic groups (**Figure 4**). When the targeted stocks (prime and alternative) and non-targeted stocks (by-catch and discards) were grouped together, the mean B/B_{msy} of non-targeted stocks exceeded 1 across taxonomic groups and was well below 1 for targeted stocks (**Table 2**).

DISCUSSION

Globally, only a small proportion of exploited fisheries stocks are being assessed on a regular basis, with the vast majority of commercial stocks and all non-commercial ones never having been assessed (Costello et al., 2012). The number of stocks assessed in this study triples the number of stock assessments in the Aegean Sea, which now sum to 116 stocks accounting for over 95% of the total catch (Stergiou et al., 2007a,b), with the exception of rarely caught species (Vassilopoulou et al., 2007). According to official and empirical catch records, about 200 stocks are being collected by the Greek fishing fleets either as targeted stocks or as by-catch, some of which are discarded (Machias et al., 2001). Therefore, AMSY (Froese et al., 2020) is a valuable method that allows the assessment of true data-poor fisheries without catch records and offers the possibility of the potential assessment of many demersal stocks that are collected in scientific surveys. AMSY requires only CPUE time-series so it can also be used to assess stocks that are only recorded in fisher's logbooks, even if the number of vessels is low, provided that the gear or method of fishing has not changed during the time-series.

There is a clear gradient of stock status that is directly related to the fishing pressure applied upon stocks, which clearly confirms what is already known for the exploited stocks of European fisheries (Froese et al., 2018b). Based on this gradient, the Aegean Sea stocks can be grouped in three main categories each of which suffers different exploitation, subsequently resulting in different biomass levels. The first category includes highly commercial stocks that are the main targets of, often multiple, fishing fleets and have been exploited for many decades. All stocks in this group are prime targets to the fisheries and the majority of them are suffering the highest fishing pressure that has resulted in the lowest biomass

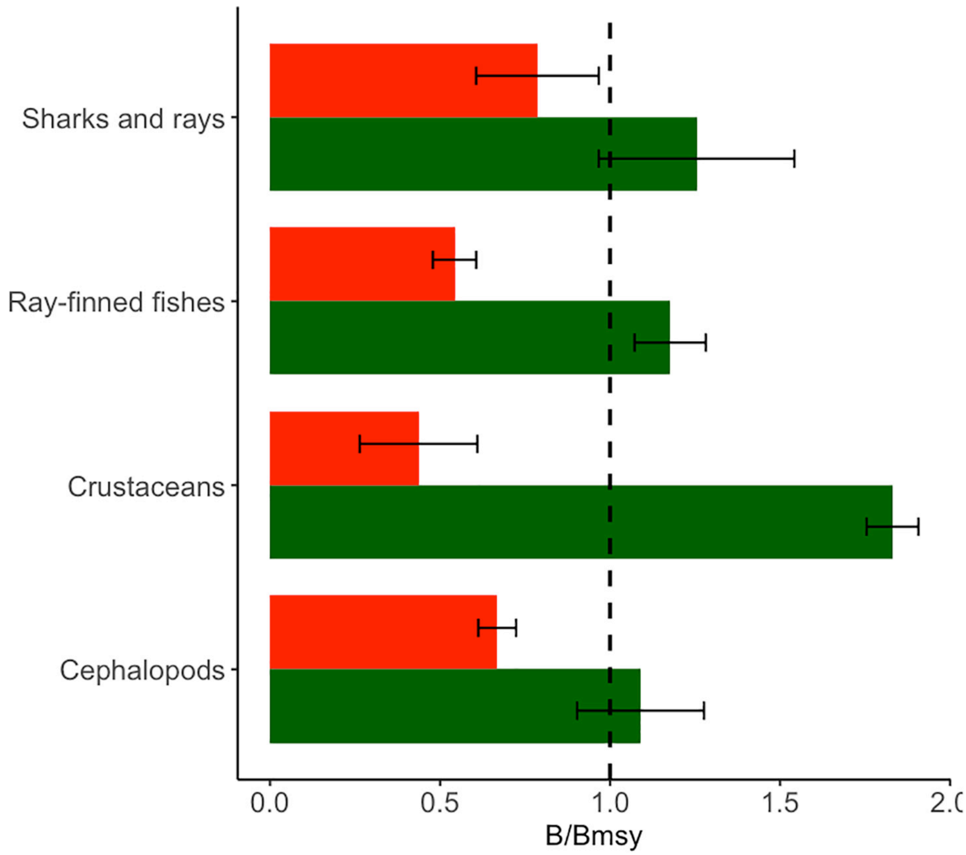


FIGURE 4 | Histogram of the mean B/B_{msy} per taxonomic group for 116 fish and invertebrate stocks of the Aegean Sea (42 previously assessed stocks with the CMSY method and 74 stocks assessed with the AMSY method in the present study). Stocks were grouped as targeted (red bars) that include prime and alternative targets of **Table 1** and non-targeted (green bars) that include by-catch and discard stocks of **Table 1**. The vertical dashed line denotes the limit for healthy status ($B > B_{msy}$).

(**Figure 1**, crosses; data from Froese et al., 2018b). These stocks were included in the most recent assessment of the Aegean and the vast majority of them were overexploited and beyond safe biological limits (Froese et al., 2018b). All recent scientific literature confirms this pattern of overexploitation and bad status of commercial stocks that is evident across the entire Mediterranean Sea (Colloca et al., 2013; Vasilakopoulos et al., 2014; Tsikliras et al., 2015; Stergiou et al., 2016; Cardinale et al., 2017; Hilborn et al., 2020).

TABLE 2 | The mean (±SE) B/B_{msy} of targeted (prime and alternative stocks) and non-targeted (by-catch and discard stocks) fish and invertebrate stocks of the Aegean Sea.

Taxonomic Group	Exploitation	Sample size	Mean B/B_{msy}	SE
Sharks and rays	Targeted	8	0.786	0.180
	Non-targeted	3	1.254	0.287
Ray-finned fishes	Targeted	46	0.542	0.063
	Non-targeted	36	1.176	0.104
Crustaceans	Targeted	3	0.436	0.172
	Non-targeted	3	1.830	0.076
Cephalopods	Targeted	5	0.668	0.055
	Non-targeted	12	1.089	0.186

Red color indicates low biomass ($B/B_{msy} < 1$), while green color indicates healthy stock biomass ($B/B_{msy} > 1$).

The second category refers to stocks with medium commercial value that are targeted by some fisheries, often locally, or are collected as by-catch in large quantities and are marketed (**Table 1**). These stocks, for which no catch records exist, were included in the present work and were assessed for the first time. The majority of these stocks (>60%), which are locally prime targets but in general are alternatively collected, suffer from overexploitation and exhibit declining biomass trends (**Figure 1**, gray dots). However, the stocks of this category span across a wide range of exploitation and status values, indicating that some of them are exploited in some areas but not in others (Machias et al., 2001) or that their exploitation pattern may depend on the availability or catch of prime targets. The status of these stocks can be easily improved with appropriate management (Froese et al., 2018b) as the biomass levels of most of them are still above safe biological limits ($B/B_{msy} > 0.5$). There is no previous assessment of these stocks in the Aegean Sea, but their CPUE data have been included in recent ecological models; declining CPUE trends were apparent especially for those with medium commercial value in heavily exploited areas, such as Thermaikos Gulf, the western part of northern Aegean Sea (e.g., Dimarchopoulou et al., submitted).

Finally, the third category refers to stocks that are only occasionally collected by the fishing fleets or have never been exploited because they live in the mesopelagic zone (there is no gear that exploits mesopelagic waters in the Aegean Sea) or in deep waters (trawling is prohibited beyond 400 m of depth in the Aegean Sea: Petza et al., 2017). The stocks of this category include by-catch species (non-targets that can be occasionally marketed) but also stocks that are always discarded. No catch records exist for these stocks that were included in the present work and were assessed for the first time in the Aegean Sea. Because of their underexploitation, the status of these stocks was much better compared to the previous two categories as the majority of them were healthy (**Figure 1**, white dots). In the absence of intense fishing, any fluctuations in their biomass is attributed to natural population processes that include reproductive success and recruitment (Rothschild et al., 1989) and may be affected by environmental or climatic factors (van Hal et al., 2010) as well as inter-specific relationships (Möllmann et al., 2008). The latter can be indirectly affected by fishing that may potentially remove competitors, predators or prey (Scheffer et al., 2005).

It should be noted here that the status of many stocks that are occasionally collected by either the commercial fleets or scientific surveys, such as large sharks and rays, could never be assessed using the known assessment methodologies that are usually data hungry (Tsikliras and Froese, 2019). Some of these species are listed in the IUCN (International Union for Conservation of Nature) Red List of Threatened Species and are protected in many areas of the world (Dimarchopoulou et al., 2017) including Greek waters (Ministerial Decision 4531/83795/20-7-2016). The inability to assess their status should not be an excuse for continuing their exploitation and masking their catch under broader taxonomic categories, as it commonly happens with large protected sharks.

The results of the present study confirm that fisheries are the main driver of the biomass of exploited marine populations (Pauly et al., 2002) and that large predatory fishes are the prime targets (Myers and Worm, 2003) because of their high commercial value (Tsikliras and Polymeros, 2014). Selective targeting and removal of upper trophic levels by fishing may also affect inter-specific relationships and cause cascading effects across trophic levels (Möllmann et al., 2008). It appears that in the absence of fishing, inter-specific relationships may play a more important role in shaping population biomass and explain the biomass trends of predators and preys (Pinnegar et al., 2000), or at least their role is more apparent.

CONCLUSION

After the present study the number of un-assessed stocks in the Aegean Sea is considerably lower and mainly refers to stocks that cannot be assessed at all. The stocks that are primarily or alternatively targeted by fishing fleets are in a worse status in terms of biomass, compared to those that are only occasionally collected as by-catch or those that inhabit environments that are not exploited by the fishing fleets, such as the midwaters or the very deep waters. The results of the present study are also important for ecosystem models that require data for all ecosystem components in the context of a more integrated ecosystem approach to fisheries management.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

AT conceived the study. KT and DD analyzed the data and prepared the graphs. AP, AA, IK, GO, and MK contributed to data analysis. AT and DD wrote the manuscript with contributions from all authors. All authors contributed to the article and approved the submitted version.

FUNDING

DD, AP, and IK were supported by the European DG-MARE funded project "PROTOMEDEA" (contract number SI2.721917).

ACKNOWLEDGMENTS

The authors would like to thank Rainer Froese and Henning Winker for their valuable suggestions regarding the implementation of the AMSY method.

REFERENCES

Bertrand, J. A., Gil, De Sola, L., Papaconstantinou, C., Relini, G., and Souplet, A. (2002). The general specifications of the MEDITS surveys. *Sci. Mar.* 66(Suppl. 2), 9–17. doi: 10.3989/scimar.2002.66s2

Cardinale, M., Osio, G. C., and Scarcella, G. (2017). Mediterranean Sea: a failure of the European fisheries management system. *Front. Mar. Sci.* 4:72. doi: 10.3389/fmars.2017.00072

Chrysafi, A., and Kuparinen, A. (2016). Assessing abundance of populations with limited data: lessons learned from data-poor fisheries stock assessment. *Environ. Rev.* 24, 25–38. doi: 10.1139/er-2015-0044

Colloca, F., Cardinale, M., Maynou, F., Giannoulaki, M., Scarcella, G., Jenko, K., et al. (2013). Rebuilding mediterranean fisheries: a new paradigm for ecological sustainability. *Fish Fish.* 14, 89–109. doi: 10.1111/j.1467-2979.2011.00453.x

Costello, C., Ovando, D., Hilborn, R., Gaines, S. D., Descenes, O., and Lester, S. E. (2012). Status and solutions for the world's unassessed fisheries. *Science* 338, 517–520. doi: 10.1126/science.1223389

Demirel, N., Zengin, M., and Ulman, A. (2020). First large-scale eastern mediterranean and black sea stock assessment reveals a dramatic decline. *Front. Mar. Sci.* 7:103. doi: 10.3389/fmars.2020.00103

Dimarchopoulou, D. (2020). *Ecosystem Approach to Fisheries Management in the Aegean Sea*. Doctorate Thesis, Aristotle University of Thessaloniki: Greece

Dimarchopoulou, D., Dogrammatzi, A., Karachle, P. K., and Tsikliras, A. C. (2018). Spatial fishing restrictions benefit demersal stocks in the northeastern Mediterranean Sea. *Sci. Rep.* 8:5967.

Dimarchopoulou, D., Stergiou, K. I., and Tsikliras, A. C. (2017). Gap analysis on the biology of Mediterranean marine fishes. *PLoS One* 12:e0175949. doi: 10.1371/journal.pone.0175949

Dimarchopoulou, D., Tsagarakis, K., Keramidas, I, and Tsikliras, A. C. (2019). Ecosystem models and effort simulations of an untrawled gulf in the central Aegean Sea. *Front. Mar. Sci.* 6:648. doi: 10.3389/fmars.2019.00648

Froese, R., Demirel, N., Coro, G., Kleisner, K. M., and Winker, H. (2017). Estimating fisheries reference points from catch and resilience. *Fish Fish.* 18, 506–526. doi: 10.1111/faf.12190

Froese, R., and Kesner-Reyes, K. (2002). *Impact of Fishing on the Abundance of Marine species*. ICES Council Meeting Report CM 12/L. ICES

Froese, R., and Pauly, D. (2020). *FishBase. World Wide Web Electronic Publication*. www.fishbase.org, version (3/2020)

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2018a). A new approach for estimating stock status from length frequency data. *ICES J. Mar. Sci.* 75, 2004–2015. doi: 10.1093/icesjms/fsy078

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2018b). Status and rebuilding of European fisheries. *Mar. Pol.* 93, 159–170. doi: 10.1016/j.marpol.2018.04.018

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2019). On the pile-up effect and priors for Linf and M/K: response to a comment by Hordyk et al., on "A new approach for estimating stock status from length frequency data". *ICES J. Mar. Sci.* 76, 461–465. doi: 10.1093/icesjms/fsy199

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2020). Estimating stock status from relative abundance and resilience. *ICES J. Mar. Sci.* 77, 527–528. doi: 10.1093/icesjms/fsz230

Hilborn, R., Amaroso, R. O., Anderson, C. M., Baum, J. K., Branch, T. A., Costello, C., et al. (2020). Effective fisheries management instrumental in improving fish stock status. *Proc. Natl. Acad. Sci. U S A. PNAS* 117, 2218–2224.

Ignatiades, L., Psarra, S., Zervakis, V., Pagou, K., Souvermezoglou, E., Assimakopoulou, G., et al. (2002). Phytoplankton size-based dynamics in the Aegean Sea (Eastern Mediterranean). *J. Mar. Systems* 36, 11–28. doi: 10.1016/s0924-7963(02)00132-x

Machias, A., Vassilopoulou, V., Vatsos, D., Bekas, P., Kallianiotis, A., Papaconstantinou, C., et al. (2001). Bottom trawl discards in the northeastern Mediterranean Sea. *Fish. Res.* 53, 181–195. doi: 10.1016/s0165-7836(00)00298-8

Möllmann, C., Müller-Karulis, B., Kornilovs, G., and St John, M. A. (2008). Effects of climate and overfishing on zooplankton dynamics and ecosystem structure: regime shifts, trophic cascade, and feedback loops in a simple ecosystem. *ICES J. Mar. Sci.* 65, 302–310. doi: 10.1093/icesjms/fsm197

Morello, E. B., Froglia, C., and Atkinson, R. J. A. (2007). Underwater television as a fishery-independent method for stock assessment of Norway lobster (Nephrops norvegicus) in the central Adriatic Sea (Italy). *ICES J. Mar. Sci.* 64, 1116–1123. doi: 10.1093/icesjms/fsm082

Myers, R., and Worm, B. (2003). Rapid worldwide depletion of predatory fish communities. *Nature* 423, 280–283. doi: 10.1038/nature01610

Osio, G. C., Gibin, M., Mannini, A., Villamor, A., and Orio, A. (2018). *The Mediterranean and Black Sea STECF Stock Assessment Database*. Luxembourg: European Union.

Osio, G. C., Orio, A., and Millar, C. P. (2015). Assessing the vulnerability of Mediterranean demersal stocks and predicting exploitation status of un-assessed stocks. *Fish. Res.* 171, 110–121. doi: 10.1016/j.fishres.2015.02.005

Palomares, M. L. D., and Pauly, D. (2019). On the creeping increase of vessels' fishing power. *Ecol. Soc.* 24:31.

Palomares, M. L. D., and Pauly, P. (2020). *SeaLifeBase. World Wide Web Electronic Publication*. www.sealifebase.org, version (3/2020)

Pauly, D., Christensen, V., Guénette, S., Pitcher, T. J., Sumaila, U. R., Walters, C. J., et al. (2002). Towards sustainability in world fisheries. *Nature* 418, 689–695. doi: 10.1038/nature01017

Petza, D., Maina, I., Koukourouvli, N., Dimarchopoulou, D., Akrivos, D., Kavadas, S., et al. (2017). Where not to fish – reviewing and mapping fisheries restricted areas in the Aegean Sea. *Med. Mar. Sci.* 18, 310–323. doi: 10.12681/mms.2081

Pinnegar, J. K., Polunin, N. V. C., Francour, P., Badalamenti, F., Chemello, R., Harmelin-Vivien, M.-L., et al. (2000). Trophic cascades in benthic marine ecosystems: lessons for fisheries and protected-area management. *Environ. Conserv.* 27, 179–200. doi: 10.1017/s0376892900000205

Ricard, D., Minto, C., Jensen, O. P., and Baum, J. K. (2012). Examining the knowledge base and status of commercially exploited marine species with the RAM legacy stock assessment database. *Fish Fish.* 13, 380–398. doi: 10.1111/j.1467-2979.2011.00435.x

Rothschild, B. J., Osborn, T. R., Dickey, T. D., and Farmer, D. M. (1989). The physical basis for recruitment variability in fish populations. *ICES J. Mar. Sci.* 45, 136–145. doi: 10.1093/icesjms/45.2.136

Scheffer, M., Carpenter, S., and de Young, B. (2005). Cascading effects of overfishing marine systems. *Trends Ecol. Evol.* 20, 579–581. doi: 10.1016/j.tree.2005.08.018

Sherley, R. B., Winker, H., Rigby, C. L., Kyne, P. M., Pollom, R., Pacoureau, N., et al. (2020). Estimating IUCN Red List population reduction: JARA—a decision-support tool applied to pelagic sharks. *Conserv. Lett.* 13:e12688.

Siokou-Frangou, I., Bianchi, M., Christaki, U., Christou, Giannakourou, A., Gotsis, O., et al. (2002). Carbon flow in the planktonic food web along a gradient of oligotrophy in the Aegean Sea (Mediterranean Sea). *J. Mar. Systems* 3, 335–353. doi: 10.1016/s0924-7963(02)00065-9

Stergiou, K. I., Moutopoulos, D. K., Tsikliras, A. C., and Papaconstantinou, C. (2007a). "Hellenic marine fisheries: a general perspective from the national statistical service data," in *State of Hellenic Fisheries*, eds C. Papaconstantinou, A. Zenetos, V. Vassilopoulou, and G. Tserpes, (Athens: Hellenic Centre for Marine Research), 132–140.

Stergiou, K. I., Moutopoulos, D. K., and Tsikliras, A. C. (2007b). "Spatial and temporal variability in Hellenic marine fisheries landings," in *State of Hellenic Fisheries*, eds C. Papaconstantinou, A. Zenetos, V. Vassilopoulou, and G. Tserpes, (Athens: Hellenic Centre for Marine Research), 141–150.

Stergiou, K. I., and Pollard, D. A. (1994). A spatial analysis of the commercial fisheries catches from the Greek Aegean Sea. *Fish. Res.* 20, 109–135. doi: 10.1016/0165-7836(94)90078-7

Stergiou, K. I., Somarakis, S., Triantafyllou, G., Tsiaras, K. P., Giannoulaki, M., Petihakis, G., et al. (2016). Trends in productivity and biomass yields in the Mediterranean Sea large marine ecosystem during climate change. *Environ. Dev.* 17(Suppl. 1), 57–74. doi: 10.1016/j.envdev.2015.09.001

Sylaios, G. K., Koutroumanidis, T., and Tsikliras, A. C. (2010). Ranking and classification of fishing areas using fuzzy models and techniques. *Fish. Manag. Ecol.* 17, 240–253. doi: 10.1111/j.1365-2400.2009.00714.x

Tsikliras, A. C. (2014). Fisheries mismanagement in the Mediterranean: a Greek tragedy. *Fish. Aquacul. J.* 5:1000e113.

Tsikliras, A. C., Dimarchopoulou, D., and Pardalou, A. (2020). Artificial upward trends in Greek marine landings: a case of presentist bias in European fisheries. *Mar. Pol.* 117:103886. doi: 10.1016/j.marpol.2020.103886

Tsikliras, A. C., Dinouli, A., Tsiros, V. Z., and Tsalkou, E. (2015). The Mediterranean and Black Sea fisheries at risk from overexploitation. *PLoS One* 10:e0121188. doi: 10.1371/journal.pone.0121188

Tsikliras, A. C., and Froese, R. (2019). "Maximum Sustainable Yield," in *Encyclopedia of Ecology*, 2nd Edn, ed. B. Fath, (Oxford: Elsevier), 108–115. doi: 10.1016/b978-0-12-409548-9.10601-3

Tsikliras, A. C., and Polymeros, K. (2014). Fish market prices drive overfishing of the 'big ones'. *Peer J* 2, e638. doi: 10.7717/peerj.638

Tsikliras, A. C., Tsiros, V. Z., and Stergiou, K. I. (2013). Assessing the state of Greek marine fisheries resources. *Fish. Manag. Ecol.* 20, 34–41. doi: 10.1111/j.1365-2400.2012.00863.x

van Hal, R., Smits, K., and Rijnsdorp, A. D. (2010). How climate warming impacts the distribution and abundance of two small flatfish species in the North Sea. *J. Sea Res.* 64, 76–84. doi: 10.1016/j.seares.2009.10.008

Vasilakopoulos, P., Maravelias, C. D., and Tserpes, G. (2014). The alarming decline of Mediterranean fish stocks. *Curr. Biol.* 24, 1643–1648. doi: 10.1016/j.cub.2014.05.070

Vassilopoulou, V., Machias, A., and Tsagarakis, K. (2007). "By-catch and discards in multi-species fisheries and their Impact in the Hellenic waters," in *State of Hellenic Fisheries*, eds C. Papaconstantinou, A. Zenetos, V. Vassilopoulou, and G. Tserpes, (Athens: Hellenic Centre for Marine Research), 251–260.

Winker, H., Carvalho, F., and Kapur, M. (2018). JABBA: just Another Bayesian Biomass Assessment. *Fish. Res.* 204, 275–288. doi: 10.1016/j.fishres.2018.03.010

Winker, H., and Sherley, R. M. (2019). JARA: 'Just Another Red-List Assessment'. *bioRxiv* [preprint]. doi: 10.1101/672899

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 20 January 2021
doi: 10.3389/fmars.2020.584601

How Fishery Collapses: The Case of *Lepidopus caudatus* (Pisces: Trichiuridae) in the Strait of Sicily (Central Mediterranean)

Fabio Falsone[1], Danilo Scannella[1]*, Michele Luca Geraci[1,2], Vita Gancitano[1], Sergio Vitale[1] and Fabio Fiorentino[1]

[1] Consiglio Nazionale delle Ricerche, Istituto per le Risorse Biologiche e le Biotecnologie Marine, Mazara del Vallo, Italy,
[2] Laboratorio di Biologia Marina e Pesca di Fano (PU), Dipartimento di Scienze Biologiche, Geologiche ed Ambientali (BiGeA), Universitá di Bologna, Bologna, Italy

OPEN ACCESS

Edited by:
Natalie Anne Dowling,
Oceans and Atmosphere
(CSIRO), Australia

Reviewed by:
Claudio Vasapollo,
Italian National Research Council
(CNR), Italy
Dimitrios K. Moutopoulos,
University of Patras, Greece

***Correspondence:**
Danilo Scannella
danilo.scannella@irbim.cnr.it

Specialty section:
This article was submitted to
Marine Ecosystem Ecology,
a section of the journal
Frontiers in Marine Science

Received: 17 July 2020
Accepted: 11 December 2020
Published: 20 January 2021

Citation:
Falsone F, Scannella D, Geraci ML, Gancitano V, Vitale S and Fiorentino F (2021) How Fishery Collapses: The Case of Lepidopus caudatus (Pisces: Trichiuridae) in the Strait of Sicily (Central Mediterranean). Front. Mar. Sci. 7:584601. doi: 10.3389/fmars.2020.584601

The silver scabbardfish *Lepidopus caudatus* is a mesopelagic species living on the shelf and slope down to 600 m in temperate seas all around the world. In the Mediterranean, the species is caught mainly by longlines with a marked seasonality. In the early 90s in the Strait of Sicily (Central Mediterranean Sea), a new fishery targeting *L. caudatus* was developed. This fishery uses an *ad hoc* pelagic trawl gear called "*spatolara.*" Vessels using spatolara have increased from 1 in 1993 to 10 in 2007 with a growth of catches of up to 1,200 tons in 2011. Development of this fishery was not regulated by any specific management measures and, due to the progressive reduction of catch to 169 tons, only one vessel was active in 2018. The availability of catch and biomass indices from trawl survey since the beginning of trawling exploitation allowed providing the first assessment of the state of *L. caudatus* stock in the Central Mediterranean (GFCM Geographical Sub-Area 16) by using data-limited methods. Catch-Maximum Sustainable Yield (CMSY) and Bayesian State Space Schaefer model (BSM) were fitted to landings and abundance indices (2004–2018). The Abundance-Maximum Sustainable Yield model (AMSY) was also applied to survey data from 1994 (1 year after the start of the spatolara fishery) to 2018 to further corroborate the results. BSM prediction of biomass levels was just above 50% of B_{MSY}, whereas AMSY estimated the current stock levels below 50% of B_{MSY}. The BSM was used for forecasting B/B_{MSY} and catches under different fishing scenarios. Although current exploitation was very close to F_{MSY}, more than a decade would be needed to rebuild the stock to biomass levels producing MSY. A faster rebuilding could be achieved by fishing at least 80% of F_{MSY}, with minimal loss in yield over the next 5–8 years. Following the development of a new fishery since the beginning, the study provides a further example of how unregulated exploitation leads to a heavy overfished state of stock and collapse of fishing activities.

Keywords: stock assessment, surplus production models, data poor approach, CMSY, BSM, AMSY

INTRODUCTION

The Silver scabbardfish, *Lepidopus caudatus*, is a mesopelagic species distributed in warm waters of all oceans and in the Mediterranean Sea. The species occurs both on the continental shelf and slope (Nakamura and Parin, 1993) from 100 m to more than 400 m, on sandy and muddy bottoms (Whitehead et al., 1986). The bathymetric distribution varies according to season, the species being more common on the continental shelf in winter time, and moving to deeper zones in other seasons (Demestre et al., 1993). *L. caudatus* forms schools and migrates vertically from bottom to the water column during night (Figueiredo et al., 2015). Despite its cosmopolitan distribution, knowledge on the biology of this species is poor and limited to growth (Molí et al., 1990; Demestre et al., 1993; D'Onghia et al., 2000) and reproductive cycle (Karlovac and Karlovac, 1976; Orsi Relini et al., 1989; Demestre et al., 1993; D'Onghia et al., 2000).

L. caudatus has a moderate commercial value and is caught mainly as commercial bycatch in several countries worldwide, i.e., Italy, Morocco, New Zealand, Portugal, and Spain, by bottom trawler, pelagic trawler, and longline fisheries (Robertson, 1980; Tuset et al., 2006; Figueiredo et al., 2015, Torre et al., 2019). To the best of our knowledge, only in New Zealand is the species sporadically caught as target by pelagic trawling in August–October off the west coast of the Island (Bentley et al., 2014).

In the Mediterranean Sea, only large specimens of *L. caudatus* have an economic value and are landed as commercial catch in Italy, Spain, Albania, and Tunisia, whereas small individuals are rejected (Demestre et al., 1993; D'Onghia et al., 2000; FAO., 2018). In Italy, the longline fishery catches only large individuals while bottom trawling fishery captures mainly small and immature specimens (D'Onghia et al., 2000). In the Mediterranean region, the capture production of silver scabbardfish reached a peak of almost 5,000 tons in 2011 and then slowly declined (Torre et al., 2011). In 2018, in the same area, the total capture production reached 1,675 tons with the 88% of the total catches belonging to Italy (FAO Fisheries aquaculture software., 2016). In spite of the amount of landings, the stock status of the species was never assessed in the Mediterranean. In this region, there is no targeted fishery for this species with exception of the Strait of Sicily (Central Mediterranean Sea), where the filets of the silver scabbardfish are sold in local markets up to 20 euro per kilo. In this area, until the early 90s, silver scabbardfish was mainly captured using longlines while it was a marginal bycatch from bottom trawlers.

At the beginning of the 1980s, the catch of *L. caudatus* on the entire Sicilian coasts amounted to 544 tons, out of which more than 90% was captured by longline (Cingolani et al., 1986). In the early 1990s, some fishers of Sciacca (south Sicily) developed a new pelagic trawl net locally called "*spatolara*" starting a new fishery for *L. caudatus*. The number of vessels using spatolara has progressively increased from 1 in 1993 to 10 in 2007, with a contextual increase of the catches up to 1,200 tons in 2011 and a shift in proportion of catch origin, with over 70% due to spatolara and the remaining 30% to bottom trawling, longline, and purse seine. The development of the spatolara fishery was not regulated by any specific management measures and, due to the progressive reduction of catch to 169 tons, only one vessel was using spatolara in 2018.

The present study provides the first assessment of the state of *L. caudatus* in the Mediterranean basin and more precisely in the Strait of Sicily (Geographical Sub-Area 16, GSA16 according to the FAO General Fisheries Commission for the Mediterranean), in which the most productive *L. caudatus* fishery of the region takes place (**Supplementary Figure 1**). Owing to the limited amount of data available, the stock status and exploitation rate of *L. caudatus* were evaluated using a data-poor approach by means of a suite of surplus production models (SPMs) based on commercial landing and abundance indices from trawl surveys. This stock assessment should be considered as baseline information for future sustainable fisheries management that could prevent a new collapse of *L. caudatus* fishery. Finally, on the basis of knowledge on biology and fishery *L. caudatus* and similar species, some management options for improving the sustainability of the species exploitation were discussed.

MATERIALS AND METHODS

Data Source

Two different data sources were used for the stock assessment: (i) commercial landings data by gear from 2004 to 2018 collected within the EU data collection framework (DCF), and (ii) stock biomass index from 1994 to 2018 obtained by MEDITS survey (Mediterranean International Trawl Survey, Anonymous., 2017) carried out in GSA 16. MEDITS is carried out annually during late spring/summer in several areas of the Mediterranean Sea using a standardized sampling methodology (Spedicato et al., 2019). MEDITS surveys are conducted during daytime according to a stratified random sampling design with allocation of trawl stations proportional to strata extension (depth strata: 10–50 m, 51–100 m, 101–200 m, 201–500 m, 501–800 m). The same trawl stations were sampled each year in May–July using a GOC 73 trawl net characterized by a vertical opening ranging between 2.4 and 2.9 m and a 20-mm stretched mesh size at cod end (Fiorentini et al., 1999). Although *L. caudatus* was not a target species of the MEDITS surveys, its biomass indices were considered representative of the standing stock at sea due both to the high vertical opening of the GOC 73 trawl net and to the bento-pelagic behavior of the species (Figueiredo et al., 2015).

Stock-Assessment Models

SPMs were chosen for estimating the stock status and exploitation rate of *L. caudatus* as they need less input data compared to age-based models to estimate maximum sustainable yield (MSY) and related reference points for fishery management, i.e., biomass and fishing mortality at MSY (B_{MSY} and F_{MSY}) (Hilborn and Walters, 1992; Punt, 2003). Specifically, the stock status was evaluated by using (i) the Monte Carlo method Catch-Maximum Sustainable Yield (CMSY) based on catch data and (ii) the Bayesian State Space Schaefer model (BSM), using catch and biomass index (Froese et al., 2017, 2018). In addition, considering that the time series of MEDITS trawl survey started in 1994, just 1 year after the beginning of the spatolara fishery, stock status was also assessed by Abundance-Maximum Sustainable

Yield (AMSY), based on biomass index from scientific surveys (Froese et al., 2020).

In comparison with other data-limited stock assessment methods, the requirements of the selected methods appear very parsimonious with our available information. For example, the COMSIR (Catch-Only-Model with Sampling-Importance-Resampling) method (Vasconcellos and Cochrane, 2005) requires catch, priors for r and k, relative bioeconomic equilibrium, and increase in harvest rate over time as inputs to assess the stock status. Then the DCAC (Depletion-Corrected Average Catch) method (MacCall, 2009) needs information on catch, relative depletion, natural mortality (M), and F_{MSY}/M as inputs. On the other hand, the DB-SRA (Depletion-Based Stock Reduction Analysis) method (Dick and MacCall, 2011) wants catch, relative depletion, M, F_{MSY}/M, B_{MSY}/B_{virgin}, and age at maturity as inputs. The SSCOM (State-Space Catch-Only Model) method (Thorson et al., 2013) requires catch, priors for unexploited biomass, initial effort, and parameters of an effort-dynamics model. Additionally, SS-DL (Stock Synthesis Data-Limited) method (Cope, 2013), in the catch data configuration, requires several additional basic biological and selectivity assumptions compared to CMSY.

CMSY and BSM Models

The CMSY model relies on catch time series, an assumed value of intrinsic population growth rate (r; "resilience"), how close the biomass is to carrying capacity (k), and qualitative information on stock status at the beginning and the end of the time series. The model allows the estimation of the biomass that can produce MSY (B_{MSY}) and related fishery reference points such as relative stock size (B/B_{MSY}), exploitation (F/F_{MSY}), intrinsic growth rate of a population (r), and carrying capacity (k) (Froese et al., 2017, 2018).

The BSM, included in the CMSY R-code, needs further relative abundance data (e.g., biomass index) as input (Froese et al., 2017, 2018) to estimate the same parameters of CMSY.

Both models are based on the dynamic formula of the Schaefer SPMs, namely:

$$B_{t+1} = B_t + r\left(1 - \frac{B_t}{k}\right)B_t - C_t \quad (1)$$

where, B_{t+1} is the exploited biomass in year $t + 1$, B_t is the biomass in year t, r is the intrinsic rate of population increase, k is the carrying capacity (i.e., the mean unexploited stock size), and C_t is the catch in year t.

However, when the stock size is severely depleted ($B_t/k < 0.25$), Equation (1) is modified adding the term $4Bt/k$ to account for linear decline of recruitment below half of the biomass that is capable of producing MSY (Myers et al., 1995) as shown in Equation (2):

$$B_{t+1} = B_t + 4\frac{B_t}{k}r\left(1 - \frac{B_t}{k}\right)B_t - C_t \qquad \frac{B_t}{k} < 0.25 \quad (2)$$

Given a time series of catches and qualitative stock status information, probable ranges of parameters r and k are filtered with a Monte Carlo algorithm on the basis of three hypotheses: (i) compatible with the catch time series, (ii) compatible with assumed priors on biomass reductions, and (iii) occur within prior ranges of r and k, corresponding to viable r–k pairs (Froese et al., 2017).

The biological plausible values of r were based on the classification of resilience reported by FishBase and ranging from 0.27 to 0.6 (Froese and Pauly, 2019). The prior ranges for k were derived by Equations (3 and 4) for stocks with low and high prior biomass at the end of the time series, respectively.

$$k_{\text{low}} = \frac{\max(C)}{r_{high}};\ k_{\text{high}} = \frac{4\max(C)}{r_{low}} \quad (3)$$

$$k_{\text{low}} = \frac{2\max(C)}{r_{high}};\ k_{\text{high}} = \frac{12\max(C)}{r_{low}} \quad (4)$$

where k_{low} and k_{high} are the lower and upper bounds of the prior range of k, $max(C)$ is the maximum catch in the time series, and r_{low} and r_{high} are the lower and upper bounds of r range to be explored by the Monte Carlo routine of the CMSY.

Both models can incorporate three uniform priors range for depletion in terms of B/k at the beginning and end of the time series, and optionally also in an intermediate year.

To detect the effect of the B_{start}/k and B_{end}/k on B/B_{MSY} estimations, a sensitivity analysis was performed. For this purpose, the deviations from the "original" value of B/B_{MSY} estimated by reference model were expressed as percentage calculated as follows:

$$\Delta\% = \frac{\frac{B}{B_{MSY}} - \frac{B}{B_{MSY}}s.a.}{\frac{B}{B_{MSY}}}100 \quad (5)$$

where B/B_{MSY} $s.a.$ is the value estimated by sensitive analysis.

CMSY was run considering the landing data from the European Data Collection Framework for time series 2004–2018, while BSM was run using the same landing data and the biomass index coming from MEDITS for time series 2004–2018. For both models, the prior for relative biomass B/k was set to 0.2–0.6 (medium) for the start year (B_{start}/K) and to 0.15–0.4 (small) for the last year (B_{end}/K), while the middle prior was set as default according to the rules provided by Froese et al. (2017). The choice of these priors was supported by knowledge of fishers and by the survey biomass index trend for the times series 1994–2018.

AMSY Model

The AMSY is a new data-limited method that estimates fisheries reference points (F/F_{MSY}, B/B_{MSY}) when no catch data are available, using time series of catch rate from commercial fisheries or scientific surveys combined with prior estimates of resilience (Froese et al., 2020). In addition to these data, AMSY needs a prior for relative stock size (B/k, ranging between 0 and 1) for one of the years in the time series. AMSY uses this information and tests a high number of combinations of resilience (r) and carrying capacity (k) for their compatibility with these inputs. All r–k combinations that are compatible with time series of plausible (never negative, never much too high) predicted that catches are identified by a Monte Carlo approach. A detailed description of the theory and equations behind AMSY is provided by Froese et al. (2020). The AMSY model was performed by using biomass index from MEDITS for the time series 1994–2018. For resilience, the same prior used in CMSY and BSM was set.

Given that only one spatolara vessel targeting *L. caudatus* was active in 1994, the prior for relative biomass B/k in the initial year was set ranging between 0.7 and 1. As for CMSY and BSM, a sensitivity analysis was performed to investigate the effect of the prior (B_{start}/k) on the B/B_{MSY} estimation, and the deviation from the original value was calculated applying (Equation 5).

Forecast

The dynamics of the stock biomass and catch were predicted applying the dynamic Schaefer model in terms of B/B_{MSY} and F_{MSY}. Specifically, as reported by Froese et al. (2018), two different equations were implemented in the model, namely:

$$\frac{B_{t+1}}{B_{MSY}} = \frac{B_t}{B_{MSY}} + 2F_{MSY}\frac{B_t}{B_{MSY}}\left(1-\frac{B_t}{2B_{MSY}}\right) - \frac{B_t}{B_{MSY}}F_t \qquad \frac{B_t}{B_{MSY}} \geq 0.5 \tag{6}$$

$$\frac{B_{t+1}}{B_{MSY}} = \frac{B_t}{B_{MSY}} + 2\frac{B_t}{B_{MSY}}2F_{MSY}\frac{B_t}{B_{MSY}}\left(1-\frac{B_t}{2B_{MSY}}\right) - \frac{B_t}{B_{MSY}}F_t \qquad \frac{B_t}{B_{MSY}} < 0.5 \tag{7}$$

where Equation (6) was used to predict next year's status if current biomass was equal to or higher than half of B_{MSY}, while Equation (7) was applied if biomass was lower than half of B_{MSY}.

Stock trajectories from 2019 to 2030 were predicted considering the stock status estimated by BSM for 2018 and applying the following four scenarios based on Froese et al. (2018):

(i) 0.5 scenario: relative fishing impact of $0.5F_{MSY}$ is considered if the stock size is equal to or larger than half of B_{MSY}. On the other hand, no fishing is considered if the biomass is less than half of B_{MSY}.

(ii) 0.6 scenario: relative fishing impact of $0.6F_{MSY}$ is considered if the stock size was equal to or larger than half of B_{MSY}. If the stock size was lower than half of B_{MSY}, the relative fishing impact is linearly reduced to zero ($F_{reduced}$) with decrease in biomass as shown in the following equation:

$$F_{reduced} = \frac{B_t}{B_{MSY}}F \tag{8}$$

(iii) 0.8 scenario: as the *ii* scenario but it considered a relative fishing impact of $0.8F_{MSY}$.

(iv) $F_{current}$ scenario: as the *ii* scenario but it considered $F_{current}/F_{MSY}$ estimation of the last year of the temporal series. This scenario is very close to the $0.95F_{MSY}$ one proposed by Froese et al. (2018).

For the forecast scenarios, an *ad hoc* script based on the modified methodology proposed by Froese et al. (2018) was applied. Specifically, the script was modified to calculate the prediction of B/B_{MSY} and catches for just a single stock. As in the methodology of Froese et al. (2018), the uncertainty was calculated by means Monte Carlo simulations based on 1,000 samples expressed as 90% of the confidence interval.

RESULTS

Main Features of Fisheries

Figure 1 shows the landing trend by fishery for the time series from 2004 to 2018. In the investigated period, *L. caudatus* was exploited mainly by spatolara fishery accounting for about 68% of the total landing, followed by bottom trawler and other fisheries (longliners and purse seiners) with about 22 and 10%, respectively. Overall, the total landings increased from 2004 to 2011 with a maximum of 1,150 tons, followed by a progressive reduction reaching 168 tons in 2018. The fishing effort of spatolara, expressed as the number of days at the sea, highlighted a similar dome-shaped pattern with the highest value in 2007. In addition, some information on the spatolara fishery and gear features are shown in **Supplementary Table 1**.

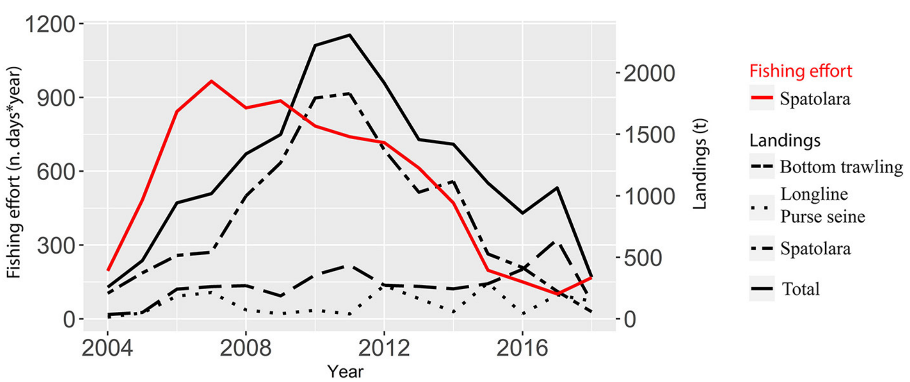


FIGURE 1 | The left *y*-axis indicates the value of fishing effort expressed as the number of days at sea per year whereas the right *y*-axis indicates the landings by fishery typologies expressed in tons. Specifically, fishery typologies are graphically indicated as follows: bottom trawling (long dash black line), longline and purse seine (dotted black line), and spatolara (two dashed black line). The solid black line and solid red line represent the total landing and spatolara fishing effort, respectively.

CMSY and BSM Results

The outputs of CMSY and BSM were very similar (**Table 1**) in terms of r and k estimations, stock size trend, and exploitation rate (**Figure 2**). Both models estimated an overexploited level for stock size ($B/B_{MSY} < 1$) since 2011 and an overfishing condition ($F/F_{MSY} > 1$) since 2009, although in the last year, the F/F_{MSY} value dropped below 1 (**Table 1** and **Figure 2**). The estimated stock size (0.54 and 0.63 for BMS and CMSY, respectively, **Table 1**) indicated an overfished condition of the stock according to Palomares et al. (2018) (**Supplementary Table 2**). Moreover, the Kobe plot based on BSM estimations showed a probability of 44.8 and 55.1% that the status stock fell in the overfished (red part) or recovering status (yellow part) of the graph, respectively (**Figure 2**).

AMSY Results

Outputs of the AMSY model are shown in **Supplementary Figure 2** and **Table 1**. The biomass index from 1994 to 2018 showed a decreasing trend (**Supplementary Figure 2**) even if in 2009 a peak of biomass, due likely to a good recruitment, was recorded, as confirmed by the highest density index and lower average weight in the time series (**Supplementary Figure 3**). The model outputs (**Supplementary Figure 2** and **Table 1**) underlined that the stock is both overfished ($F/F_{MSY} > 1$) and, according to Palomares et al. (2018), "grossly overexploited" ($B/B_{MSY} < 0.5$) from 2012 to 2018, with the stock productivity being severely impaired ($0.5 \leq C/C_{MSY} < 1$). The reference point of the last year of the time series was 0.27 for B/B_{MSY} (95% CI 0.15–0.49) and 2.02 (95% CI 0.66–4.18) for F/F_{MSY}.

The overall dynamics of the stock, showed by the Kobe plot (**Supplementary Figure 2**), outlined a progressive worsening of the stock status from 1994 to 1998, followed by a high exploitation level associated to a low standing stock biomass for most of the examined period, with the exception of 2008, 2009, and 2010, during which a recovery of the stock occurred.

Sensitivity Analysis

The sensitivity analysis showed that the B/B_{MSY} estimations were more affected by B_{end}/k prior variation for both CMSY and BSM. Conversely, B_{start}/k influenced mostly the B/B_{MSY} estimation of the AMSY model (**Supplementary Table 2**). In light of the above, to perform trusted estimations of stock size by CMSY and BSM, a reliable prior of biomass range at end of time series is crucial. On the other side, for AMSY, the choice of biomass range relative to unexploited biomass at the start of the time series is of paramount importance.

TABLE 1 | Main output of three models in terms of stock size (B/B_{MSY}), exploitation rate (F/F_{MSY}), and r-k prior. Median value ($\tilde{x}$), lower (lci), and upper (uci) confidential interval are shown.

Model	Item	lci	$\tilde{x}$	uci
BSM	B/B_{MSY} (2018)	0.28	0.53	0.87
	F/F_{MSY} (2018)	0.53	0.94	3.29
	r	0.3	0.44	0.64
	k	4.09	5.91	8.53
CMSY	B/B_{MSY} (2018)	0.32	0.63	0.79
	F/F_{MSY} (2018)	0.29	0.37	0.72
	r	0.33	0.44	0.6
	k	4.53	6.51	9.36
AMSY	B/B_{MSY} (2018)	0.15	0.27	0.48
	F/F_{MSY} (2018)	0.66	2.02	4.19

Forecast Results

B/B_{MSY} and the predicted cumulative catches of *L. caudatus* under the different exploitation scenarios of F are shown in **Figure 3**. By reducing the relative fishing impact to 0.5, 0.6, and 0.8 of F_{MSY}, *L. caudatus* stock could reach the B_{MSY} level over a period between 5 and 8 years. While maintaining the F current, which is very close to the F_{MSY} estimated by BSM, the stocks need 12 years to reach a value of 0.94 B/B_{MSY} (**Figure 3**).

An increasing trend of catches throughout the years for all considered scenarios was predicted, with only the scenario 0.5 showing a catch decrease in the first year (**Figure 3**). Overall, an average increase of catches of about three times more than those of 2018 was expected according to all scenarios. The highest values of catches were predicted for the scenarios 0.8 and $F_{current}$ with about 555 and 617 tons, respectively. However, both predicted B/B_{MSY} and catches showed a high uncertainty.

DISCUSSION

Unlike other Mediterranean areas, in the Strait of Sicily, the spatolara fishery, a specific midwater trawl fishery targeted to *L. caudatus*, has been developed from the early 90s. This fishery started in Sciacca harbor and proved a sudden increase in yield and fishing effort followed by a progressive decline through time. The trend in yield and fishing effort was followed, with a shift of about 4 years, by the reaction of stock in terms of biomass, which declined considerably after 2011.

According to Palomares et al. (2018), who classified the fish stock status basing on B/B_{MSY} in the final year of a time series, results of BSM and CMSY suggested an overfished status of *L. caudatus* stock of the Strait of Sicily, while AMSY indicated a condition of "grossly overfished" (0.2–0.5), being close to "collapsed" (<0.20). The stock size estimations by the three models highlighted a very similar trend, even if the AMSY depicts a more severe overfished condition (**Supplementary Figure 4**). The differences between AMSY and the other two models might be due to the different periods analyzed. Indeed, the decrease of biomass index from trawl surveys that have occurred from 1994 to 2004 further stresses the importance of having an independent estimate of stock abundance since the beginning of fisheries exploitation. The estimated stock size was below B_{MSY} since the end of the 1990s, with the exception of the years 2009 and 2010, during which signals of strong recruitment events were recorded (**Supplementary Figure 3**). Likewise, the BSM and CMSY estimated a similar trend of B/B_{MSY} for the same period of AMSY, 2004–2018 (**Supplementary Figure 4**).

The results of the sensitivity analysis showed that $B_{start/k}$ prior setting for BSM and CMSY affected poorly the B/B_{MSY} estimation, ranging from 0.50 to 0.63. Conversely, $B_{end/k}$ prior

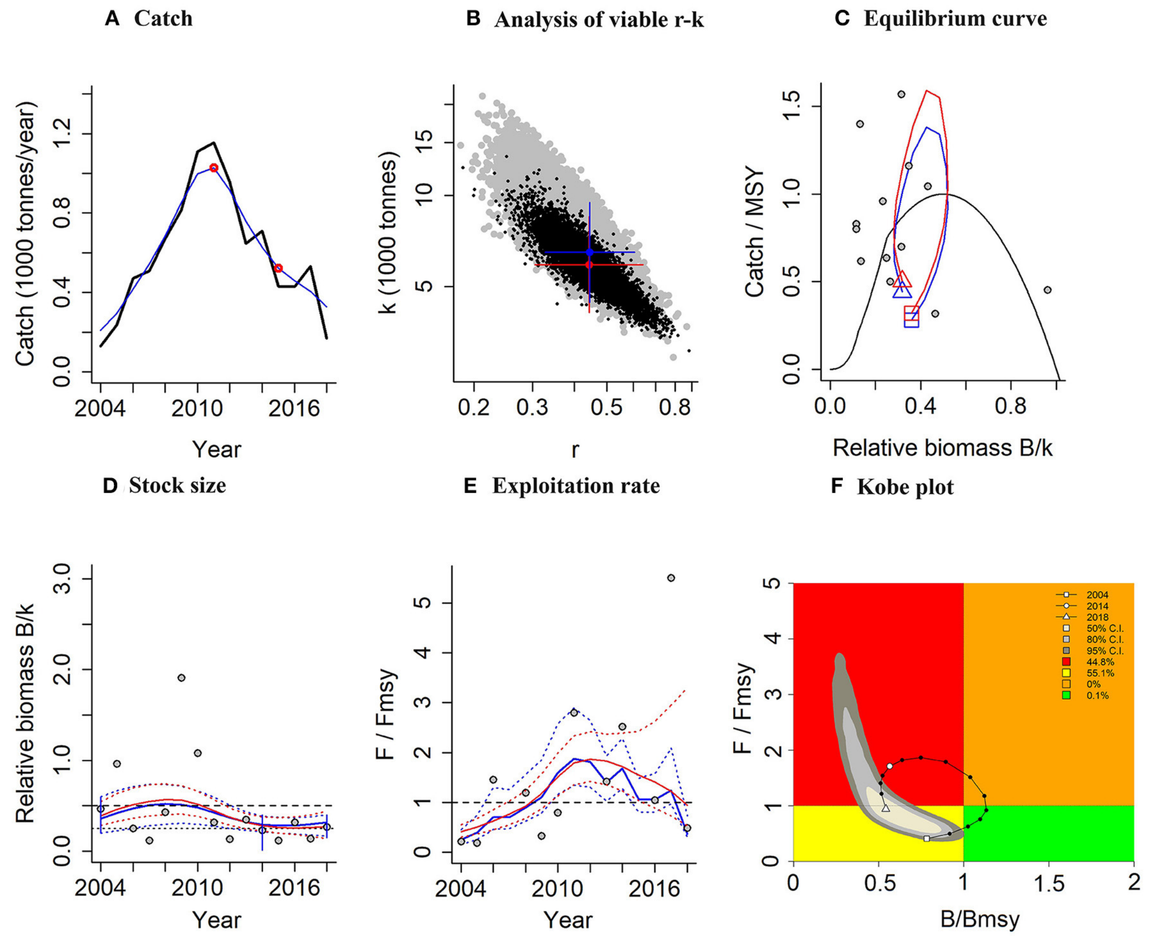


FIGURE 2 | Graphical output of the CMSY (blue lines) and BSM (red lines): **(A)** catch; **(B)** Monte Carlo simulations of the best combination of *r* and *k*; **(C)** Equilibrium curve estimated through Schaefer model, where square and triangle symbols represent the estimates of initial and final years, respectively; **(D)** stock size (dashed lines indicate confidence interval); **(E)** exploitation rate (dashed lines indicate confidence interval); **(F)** Kobe plot showing B/B_{MSY} against F/F_{MSY} ratios estimated by BSM. In the Kobe plot, shaded areas indicate the confidence interval at 50% (light gray), 80% (gray), and 95% (dark gray) and quadrants are color-coded, i.e., green (not overfished, no overfishing), red quadrant (overfished and overfishing), or yellow (recovering status).

setting showed the biggest effect on the outcome of B/B_{MSY}, ranging from 0.21 to 0.79.

The only configuration tested for AMSY ($B_{start/k}$ ranging for 0.4–0.8) indicated a collapsed condition of the stock according to Palomares et al. (2018). However, this last assessment could be neglected because that high initial biomass (0.7–1 nearly unexploited) was deemed highly reliable on the basis that in the first year of the biomass index, only one spatolara vessel was active and the fishery was not yet fully developed.

Regarding the exploitation rates, high differences among the models were recognized. Specifically, although at different level, CMSY and BSM depicted a no overfishing condition ($F/F_{MSY} < 1$) in the last year, with the fishing pressure lower than that giving the maximum sustainable yield. Conversely, AMSY estimated a condition of high overfishing even in the last year, with the F/F_{MSY} being equal to 2.02. In this regard, it should be recalled that estimation of exploitation by AMSY should be used with caution since this method does not use the information on catch or fishing effort. Conversely, relative stock size could be considered suitable for management advice (Froese et al., 2020).

According to the forecast model, the stock depletion is so heavy that the recovery of stock biomass to level compatible with MSY is expected in 2030 if the fishing effort is maintained at the 2018 level, which is very close to F_{MSY}. The scenarios 0.5 and 0.6 provide fast rebuilding of the stock reaching a value of biomass higher to that maximum sustainable yield but providing the lowest levels of catches. Although with high uncertainty in model estimation, a good compromise between production and conservation objectives is provided by the scenario reducing fishing mortality at 80% of F_{MSY}. This scenario produces the fastest rebuilding of the stock and a minimal loss in catch in a period of 5–8 years.

Although the data input used to run the models are from official statistics, the estimation provided in this study may have some uncertainty due to the lack of discard data. Indeed,

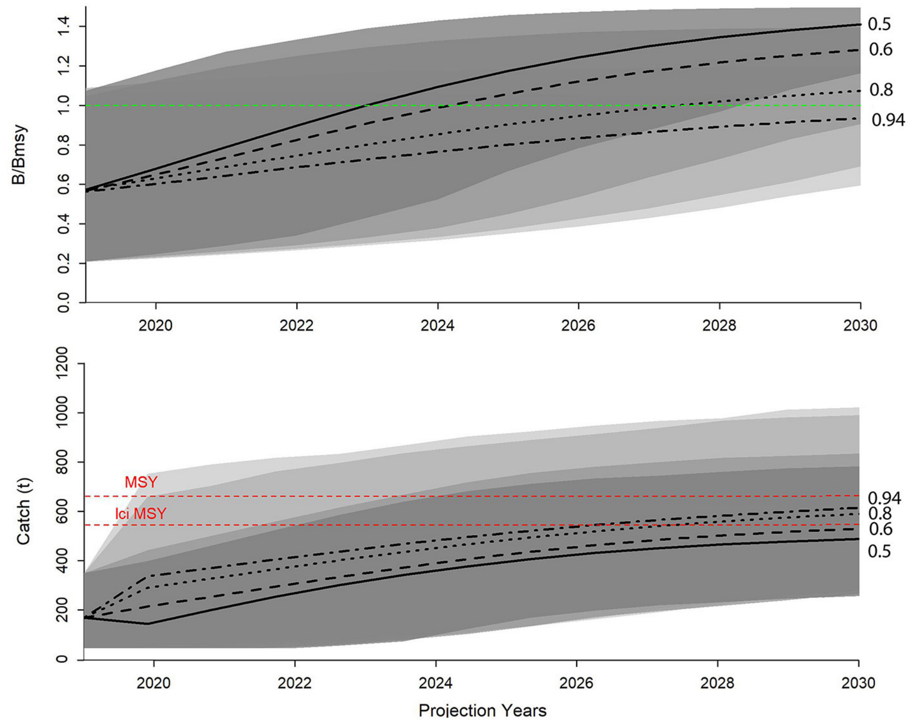


FIGURE 3 | In the upper panel, B/B_{MSY} trends, while in the lower panel, the predictive catch trends (expressed in tons) both under four different exploitation *F* scenarios: 0.5 (solid line), 0.6 (long dash line), 0.8 (dotted line), and 0.94 (two dashed black line). The shaded areas indicate the range of uncertainty. The dashed green line represents B/B_{MSY} equal to 1 and the dashed red lines represent the value of MSY and its lower confidence interval (lci MSY).

no studies on discard for this species are available in the investigated area.

Across the Mediterranean Sea, the knowledge on discarding of *L. caudatus* is scattered and scarce (e.g., Sánchez et al., 2004; Tzanatos et al., 2007; Soykan et al., 2016; Carbonnel and Mallol 2012). The discard rates are affected by gears, target species, fishing ground depth, as well as the request of the local market. Tzanatos et al. (2007) in the Aegean Sea and Sánchez et al. (2004) in the Catalan Sea reported that the whole catch of *L. caudatus* was discarded by gillnet and by trawlers, respectively. Conversely, Carbonell and Mallol (2012) provided discard rate estimation by trawlers of 7% in Catalonia waters and 100% in Balearic island, while Soykan et al. (2016) estimated a discard rate of about 30% in Turkish waters.

Considering the lack of discard data in the investigated area, the CMSY and BSM assessments were performed using only official landing data. This might affect the stock status estimation, giving a more optimistic state of the exploited stock. However, the absence of discard does not affect the stock perception by the AMSY, which used only fishery independent data and showed a clear overfished and overfishing condition of the *L. caudatus* stock.

The described pattern of the spatolara fishery, together with the modeled trajectories of the biomass and the exploitation rate, reflect the typical phases of development of an uncontrolled fishery (Hilborn and Walters, 1992). The fast decline of the stock has been due to the development of specific gear, the spatolara net, which likely increased the fishery catchability together with a rapid increase of the fishing effort. These features ensured high catches and revenues in the short term but, on the other side, resulted in a progressive decrease in fish abundance and, finally, fishery collapse. All this happened within a context of lack of specific management measures for *L. caudatus* fishery in terms of catch or fishing effort quota and technical measures such as the establishment of a minimum conservation reference size. In the near future, due to its monospecific nature, it would be advisable to implement the spatolara fishery management measures based on the Total Allowable Catches (TAC). A management based on TAC was quite successful in the recovery and maintenance of the North-East Atlantic stocks (Cardinale et al., 2017) such as the similar species *Aphanopus carbo* (ICES., 2020). The effectiveness of management measure based on TAC for *L. caudatus* has also been demonstrated in New Zealand as described by (Bentley et al., 2014).

Considering that the juveniles of silver scabbardfish represent an abundant fraction caught by trawling (D'Onghia et al., 2000), a further management measure to ensure the recovery of silver scabbardfish could concern the development and adoption of more selective trawling net, including the use of devices able to improve the size at first capture of this species.

Eventually, the present study provides a further example on how the absence of adequate management measures can lead to a rapid depletion of the resource and, consequently, unprofitable fishery. Learning from the history of *L. caudatus* fishery in the

Strait of Sicily, it would be important to monitor both stock size and fishery pressure and to adopt a multiannual species-specific management plan to guarantee the fishery sustainability according to the United Nations sustainable development goals (United Nations., 2015).

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

Ethical review and approval was not required for the animal study because no tests or experiments were performed on vertebrate animals.

AUTHOR CONTRIBUTIONS

FFi and SV: conceptualization and validation. FFa and VG: formal analysis. FFa, DS, MG, and VG: data curation and data collection and figures. FFi and FFa: writing—original draft. FFi, FFa, DS, MG, SV, and VG: writing—review and editing. All authors contributed to the article and approved the submitted version.

FUNDING

This work was supported by European Data Collection Framework (DCF)–Transversal Variables and MEDITS survey modules funded by the European Union and the Italian Ministry for Agricultural, Food and Forestry Policies.

ACKNOWLEDGMENTS

This study was carried out within the framework of Italian National Programs developed according to the European Data Collection Framework. The authors warmly thank all the technical staff of the CNR of Mazara del Vallo who collected data during the MEDITS trawl surveys. A special thank you to Henning Winker (Department of Statistical Sciences, University of Cape Town) for his help in developing the modified script and also for his useful advice.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2020.584601/full#supplementary-material

Supplementary Figure 1 | Map showing the study area.

Supplementary Figure 2 | Graphical output of the AMSY model: **(A)** Biomass index; **(B)** Monte-Carlo simulations of the best combination of r and k, **(C)** Catch/MSY (dashed lines indicate confidence interval); **(D)** F/FMSY trend (dashed lines indicate confidence interval); **(E)** B/BMSY trend (dashed lines indicate confidence interval), **(F)** Kobe plot showing B/BMSY against F/FMSY ratios. In the Kobe plot shaded areas indicate the confidence interval at 50% (light grey), 80% (grey) and 95% (dark grey) and quadrants are color-coded i.e. green (not overfished, no overfishing), red quadrant (overfished and overfishing) or yellow (recovering status).

Supplementary Figure 3 | The left y-axis indicates density index expressed as number of fish caught on square kilometres (grey line) whereas the right y-axis indicates the average weight of fish caught per year expressed in grams (black line).

Supplementary Figure 4 | Stock size (B/BMSY) trends estimated applying AMSY (blue), BSM (red) and CMSY (green). The coloured areas represent the confidence interval for each model.

REFERENCES

Anonymous. (2017). *MEDITS Handbook, Version n. 9*. MEDITS Working Group, 106. Available online at: http://www.sibm.it/MEDITS%202011/principaledownload.htm (accessed July 30, 2020).

Bentley, N., Kendrick, T. H., and MacGibbon, D. J. (2014). *Fishery Characterisation and Catch-per-unit-effort Analyses for Sea Perch (Helicolenus Spp.) in New Zealand, 1989–90 to 2009–10*. Wellington: Ministry for Primary Industries.

Carbonell, A., and Mallol, S. (2012). Differences between demersal fisheries discards: high and low productivity zones of the Northwestern Mediterranean Sea. *Boll. Soc. Hist. Nat. Balears*, 55, 25–45.

Cardinale, M., Osio, G. C., and Scarcella, G. (2017). Mediterranean Sea: a failure of the European fisheries management system. *Front. Mar. Sci*. 4, 72. doi: 10.3389/fmars.2017.00072

Cingolani, N., Coppola, S. R., and Mortera, J. (1986) *Studio di fattibilità per un sistema di rilevazione campionaria delle statistiche della pesca (PESTAT). Parte II – Statistiche di cattura e sforzo di pesca.* Quad. Ist. Ric. Pesca Marittima. Ancona

Cope, J. M. (2013). Implementing a statistical catch-at-age model (Stock Synthesis) as a tool for deriving overfishing limits in data-limited situations. *Fish. Res*. 142, 3–14. doi: 10.1016/j.fishres.2012.03.006

Demestre,. M., Moli,. B., Recasens,. L., and Sánchez, P. (1993). Life history and fishery of Lepidopus caudatus (Pisces: *Trichiuridae*) in the Catalan Sea (Northwestern Mediterranean). *Mar. Biol*. 115, 23–32. doi: 10.1007/BF00349382

Dick, E. J., and MacCall, A. D. (2011). Depletion-based stock reduction analysis: a catch-based method for determining sustainable yields for data-poor fish stocks. *Fish. Res*. 110, 331–341. doi: 10.1016/j.fishres.2011.05.007

D'Onghia, G., Mastrototaro, F., and Maiorano, P. (2000). Biology of silver scabbard fish, Lepidopus caudatus (*Trichiuridae*), from the Ionian Sea (Eastern-central Mediterranean). *Cybium* 24,249–262.

FAO Fisheries and aquaculture software. (2016). "FishStatJ - Software for Fishery and Aquaculture Statistical Time Series," in *FAO Fisheries and Aquaculture Department*. Rome. Avaiolable onlibe at: http://www.fao.org/fishery/ (accessed April 12, 2020)

FAO. (2018). *The State of Mediterranean and Black Sea Fisheries. General Fisheries Commission for the Mediterranean*. Rome: FAO, 172.

Figueiredo, C., Diogo, H., Pereira, J. G., and Higgins, R. M. (2015). Using information-based methods to model age and growth of the silver scabbardfish, Lepidopus caudatus, from the mid-Atlantic Ocean. *Mar. Biol. Res*. 11, 86–96. doi: 10.1080/17451000.2014.889307

Fiorentini, L., Cosimi, G., Sala, A., Leonori, I., and Palombo, V. (1999). Efficiency of the bottom trawl used for Mediterranean international trawl survey (MEDITS). *Aquat. Living Resour*. 12, 187–205. doi: 10.1016/S0990-7440(00)88470-3

Froese, R., Demirel, N., Coro, G., Kleisner, K. M., and Winker, H. (2017). Estimating fisheries reference points from catch and resilience. *Fish Fish*. 18, 506–526. doi: 10.1111/faf.12190

Froese, R., and Pauly, D. (2019). *FishBase*. World Wide Web electronic publication. www.fishbase.org.

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2018). Status and rebuilding of European fisheries. *Mar. Policy* 93, 159–170. doi: 10.1016/j.marpol.2018.04.018

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2020). Estimating stock status from relative abundance and resilience. *ICES J. Mar. Sci.* 77, 527–538. doi: 10.1093/icesjms/fsz230

Hilborn, R., and Walters, C. J. (1992). *Quantitative Fisheries Stock Assessment. Choice, Dynamics and Uncertainty*. New York, NY: Springer Science & Business Media. doi: 10.1007/978-1-4615-3598-0

ICES. (2020). "Black scabbardfish (*Aphanopus carbo*) in subareas 1, 2, 4–8, 10, and 14, and divisions 3.a, 9.a, and 12.b (Northeast Atlantic and Arctic Ocean)," in *Report of the ICES Advisory Committee, 2020* (ICES Advice 2020, bsf.27.nea).

Karlovac, J., and Karlovac, O. (1976). Apparition de Lepidopus caudatus (Euphr.) dans totutes les phases de sa vie en Adriatique. *Rapp. P. V. Comm. Int. Explor. Scient. Mer Médit*. 23, 67–68.

MacCall, A. D. (2009). Depletion-corrected average catch: a simple formula for estimating sustainable yields in data-poor situations. *ICES J. Mar. Sci*. 66, 2267–2271. doi: 10.1093/icesjms/fsp209

Molí, R., Lombarte, A., and Morales-Nin, B. (1990). Age and growth of Lepidopus caudatus on the Northwestern Mediterranean Sea. *Rapp. Comm. int. Mer Médit*. 32:269.

Myers, R. A., Barrowman, N. J., Hutchings, J. A., and Rosenberg, A. A. (1995). Population dynamics of exploited fish stocks at low population levels. *Science* 269, 1106–1108. doi: 10.1126/science.269.5227.1106

Nakamura, I., and Parin, N. V. (1993). *FAO Species Catalogue. Snake Mackerels and Cutlassfishes of the World (Families Gempylidae and Trichiuridae).* Kyoto: FAO Fish. Synop.

Orsi Relini, L., Fida, B., and Palandri, G. (1989). Osservazioni sulla riproduzione di *Lepidopus caudatus* (Euphrasen, 1788), Osteichthyes, Trichiuridae, del mar Ligure. *Oebalia* 15, 715–723.

Palomares, M. L. D., Froese, R., Derrick, B., Nöel, S.-L., Tsui, G., Woroniak, J., et al. (2018). *A Preliminary Global Assessment of the Status of Exploited Marine Fish and Invertebrate Populations. A Report Prepared by the Sea Around Us for OCEANA*. Vancouver, BC: The University of British Columbia.

Punt, A. E. (2003). Extending production models to include process error in the population dynamics. *Can. J. Fish. Aquat. Sci.* 60, 1217–1228. doi: 10.1139/f03-105

Robertson, D. A. (1980). Spawning of the frostfish, Lepidopus caudatus (Pisces: Trichuridae), in New Zealand waters. *New Zealand J. Mar. Freshwater Res*. 14, 129–136. doi: 10.1080/00288330.1980.9515853

Sánchez, P., Demestre, M., and Martin, P. (2004). Characterisation of the discards generated by bottom trawling in the northwestern Mediterranean. *Fish. Res*., 67, 71–80. doi: 10.1016/j.fishres.2003.08.004

Soykan, O. Z. A. N., Akgül, S. A., and Kinacigil, H. T. (2016). Catch composition and some other aspects of bottom trawl fishery in Sigacik Bay, central Aegean Sea, eastern Mediterranean. *J. Appl. Ichthyol*, 32, 542–547. doi: 10.1111/jai.13042

Spedicato, M. T., Massut,í, E., Mérigot, B., Tserpes, G., Jadaud, A., and Relini, G. (2019). The MEDITS trawl survey specifications in an ecosystem approach to fishery management. *Sci. Mar*. 83, 9–20. doi: 10.3989/scimar.04915.11X

Thorson, J. T., Minto, C., Minte-Vera, C. V., Kleisner, K. M., and Longo, C. (2013). A new role for effort dynamics in the theory of harvested populations and data-poor stock assessment. *Can. J. Fish. Aquat. Sci*. 70, 1829–1844. doi: 10.1139/cjfas-2013-0280

Torre, M., Kallianiotis, A., Sicuro, B., and Tsavalou, V. (2011). Geographical and bathymetric distribution of silver scabbardfish *Lepidopus caudatus* in North Aegean Sea. *Int. Aquat. Res.* 3, 217–226.

Torre, M., Sicuro, B., and Kallianiotis, A. (2019). Diet of Silver scabbardfish *Lepidopus caudatus* (Euphrasen, 1788) in the Northern Aegean Sea. *Cah. Biol. Mar*. 60, 31–40. doi: 10.21411/CBM.A.4C45C5BD

Tuset, V., González, J. A., Santana, J. I., Lopez, A. M., and Diaz, M. G. (2006). Reproductive pattern and growth in *Lepidopus caudatus* (*Osteichthyes*, *Trichiuridae*) from the Canary islands (Eastern-Central Atlantic). *Electron. J. Ichthyol*. 1, 26–37.

Tzanatos, E., Somarakis, S., Tserpes, G., and Koutsikopoulos, C. (2007). Discarding practices in a Mediterranean small-scale fishing fleet (Patraikos Gulf, Greece). *Fish. Manag. Ecol*. 14, 277–285. doi: 10.1111/j.1365-2400.2007.00556.x

United Nations. (2015). *Historic New Sustainable Development Agenda Unanimously Adopted by 193 UN Members*.

Vasconcellos, M., and Cochrane, K. (2005). "Overview of world status of data-limited fisheries: inferences from landing statistics," in *Fisheries Assessment and Management in Data-limited Situations*. eds G. H. Kruse, V. F. Gallucci, D. E. Hay, R. I. Perry, R. M. Peterman, T. C. Shirley, P. D. Spencer, B. Wilson, and D. Woodby (Alaska Sea Grant Programme; University of Alaska Fairbanks), 1–20. doi: 10.4027/famdls.2005.01

Whitehead, P. J., Bauchot, M. L., Hureau, J. C., Nielson, J., and Tortonese, E. (1986). *Fish of the North-Eastern Atlantic and the Mediterranean*. Vol. 2. Paris: UNESCO. doi: 10.2307/1444931

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 12 April 2021
doi: 10.3389/fmars.2021.646174

How Can Information Contribute to Management? Value of Information (VOI) Analysis on Indian Ocean Striped Marlin (*Kajikia audax*)

Meng Xia[1], Tom Carruthers[2], Richard Kindong[1], Libin Dai[1], Zhe Geng[1], Xiaojie Dai[1]* and Feng Wu[1]*

[1] College of Marine Sciences, Shanghai Ocean University, Shanghai, China, [2] Institute for the Oceans and Fisheries, The University of British Columbia, Vancouver, BC, Canada

OPEN ACCESS

Edited by:
Simone Libralato, National Institute of Oceanography and Experimental Geophysics (OGS), Italy

Reviewed by:
Valeria Mamouridis, Independent Researcher, Rome, Italy
Yuan Li, State Oceanic Administration, China

****Correspondence:***
Xiaojie Dai
xjdai@shou.edu.cn
Feng Wu
fwu@shou.edu.cn

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: *25 December 2020*
Accepted: *17 February 2021*
Published: *12 April 2021*

Citation:
Xia M, Carruthers T, Kindong R, Dai L, Geng Z, Dai X and Wu F (2021) How Can Information Contribute to Management? Value of Information (VOI) Analysis on Indian Ocean Striped Marlin (Kajikia audax). Front. Mar. Sci. 8:646174. doi: 10.3389/fmars.2021.646174

Fisheries researchers have focused on the value of information (VOI) in fisheries management and trade-offs since scientists and managers realized that information from different resources has different contribution in the management process. We picked seven indicators, which are log-normal annual catch observation error (Cobs), annual catch observation bias (Cbias), log-normal annual index observation error (Iobs), maximum length observation bias (Linfbias), observed natural mortality rate bias (Mbias), observed von Bertalanffy growth parameter K bias (Kbias), and catch-at-age sample size (CAA_nsamp), and built operating models (OMs) to simulate fisheries dynamics, and then applied management strategy evaluation (MSE). Relative yield is chosen as the result to evaluate the contribution of the seven indicators. Within the parameter range, there was not much information value reflected from fisheries-dependent parameters including Cobs, Cbias, and Iobs. On the other hand, for fisheries-independent parameters such as Kbias, Mbias, and Linfbias, similar tendency of the information value was showed in the results, in which the relative yield goes down from the upper bound to the lower bound of the interval. CAA_nsamp had no impact on the yield after over 134 individuals. The VOI analysis contributes to the trade-offs in the decision-making process. Information with more value is more worthy to collect in case of waste of time and money so that we could make the best use of scientific effort. But we still need to improve the simulation process such as enhancing the diversity and predictability in an OM. More parameters are on the way to be tested in order to collect optimum information for management and decision-making.

Keywords: value of information, fisheries management, simulation test, striped marlin, management strategy evaluation

INTRODUCTION

Uncertainty is pervasive in natural systems and manifests itself in many forms (Morgan and Henrion, 1990; Regan et al., 2002). The role of science in conservation and management of natural resources is generally to reduce uncertainty (Halpern et al., 2006). In fisheries, managing fisheries quantitatively eventually becomes a popular tendency with adaptive management

(Hilborn and Walters, 1992). The promise of adaptive management is that learning in the short term will improve management in the long term, which is best kept if the focus of learning is on those uncertainties that impede the most the achievement of management objectives (Runge et al., 2011).

Fisheries management falls into the category of decision-making under uncertainty due to the growth of adapted management. Inherent in such a task is the problem of investing in new information (Mantyniemi et al., 2009). Information comes with a cost, basically; as a result, we should find an optimum amount of valuable information in the decision-making process. The cost savings from reduced information collecting may outweigh the small potential loss in the decision accuracy of the results (Walters and Pearse, 1996; de Bruin and Hunter, 2003; Ling et al., 2006).

Fisheries management is plagued with various kinds of uncertainties, but not all uncertainties are equally important to resolve. Nevertheless, we still need a massive amount of information to conduct our conservation and management work. Experts in resource management continue to advocate for more resources for information collecting to support science-based decision-making (NOAA, 2001). This should facilitate the consideration of trade-offs that exist between resources allocated to information collecting and those allocated to other management activities. Information collecting in natural resource management can include fundamental research, monitoring, and the analytical processing of data gathered from these tasks (Hansen and Jones, 2008).

Unfortunately, experience with commercial fisheries worldwide during recent decades suggests that allocating considerable resources to data collection and stock assessments has not prevented overexploitation and collapse (Walters and Maguire, 1996; Pauly et al., 2002; Myers and Worm, 2003).

So we ask ourselves, is the data collecting extent not wide enough? Is the direction of our collecting correct? Or are the data we collected really helping with the analysis? Therefore, the problem of the value of information (VOI) has been recognized and discussed in basic fisheries stock assessment textbooks (Hilborn and Walters, 1992) and journal papers (e.g., Hansen and Jones, 2008), but examples where the VOI has been explicitly quantified in a fisheries context are scarce (Hansen and Jones, 2008; Mantyniemi et al., 2009).

In the language of classical decision theory, there is a high expected VOI reflected from important uncertainty. The value of new information is the difference between the expected value of an optimal action after the new information has been collected and the value before the new information has been collected. Therefore, Raiffa and Schlaifer (1961) described the central concept through the expected value of perfect information (EVPI):

$$EVPI = E_s[max_a U(a, s)] - max_a E_s[U(a, s)]$$

where U is a utility function that we want to maximize by implementing some action a in the presence of system uncertainty s.

Many researchers have examined the value of reducing uncertainty or the value of increased surveys in commercial fisheries using operating models (OMs) designed to maximize given objectives (e.g., McAllister et al., 1999; Punt and Smith, 1999; Moxnes, 2003) by using techniques including Monte Carlo simulations (e.g., Bergh and Butterworth, 1987; Powers and Restrepo, 1993; Punt et al., 2002) and Bayesian approaches (McAllister and Pikitch, 1997; McDonald and Smith, 1997). Punt and Smith (1999) also evaluated the VOI but neglected the parameter uncertainty and relative credibility of alternative model structures. Quantifying the VOI is more common in the fields of decision-making under uncertainty other than fisheries. The concept of the VOI belongs naturally to the theory of information economics, a branch of microeconomic theory (Quirk, 1976). Basically, the value is understood as a measure of the economic VOI, but there is no need to be so restrictive; any quantitative measure of utility can be used, such as the number of fish landed or a perception of happiness on a scale of 0–100 (Mantyniemi et al., 2009).

Ignoring the opportunity costs of information collecting can lead to overly optimistic predictions of the value of increased assessment effort, which occurs at the expense of various management activities. The value of an assessment program should be measured not by the precision of the estimates it generates but rather in how well fishery management objectives are met in a broader sense (Hansen and Jones, 2008). This requires our models to approach the situation that is happening under water as efficiently as possible. Hence, the most valuable information should be provided in order to improve the model fit and also make the best use of grants and funding.

As mentioned above, we conducted a study on the VOI analysis using Indian Ocean striped marlin (*Kajikia audax*) as a case study in the purpose of detecting information contribution in management strategy evaluation (MSE) process. MSE process was conducted within a simulation test. Meanwhile, relative yield was used to mature the contribution of information. Striped marlin is a common bycatch species in distant water fisheries such as tuna longline fishery (Dai and Xu, 2007). Management of bycatch species especially data-limited species is fairly necessary, and information value will provide valuable guidance to data collection for researchers and managers of these bycatch species.

MATERIALS AND METHODS

Simulation of fishery dynamics was carried out using state-space age-structured OMs included in DLMtool (Carruthers and Hordyk, 2018) and MSEtool (Carruthers et al., 2018), an open-source package developed within the R environment for efficient closed-loop evaluation of fishery management procedures. MSE closed-loop testing is presented here basically following the guidelines of Punt et al. (2016).

Operating Model (OM)

A state-space age-structured model is used in the OM (Carruthers et al., 2018). This model is fitted to an index of biomass and catch-at-age composition data (for details on how these data are simulated in closed-loop testing, see Carruthers and Hordyk, 2018) and estimates time-invariant selectivity and process error in the form of recruitment deviations.

Operating model is set up based on the stock assessment materials from 2017 IOTC 15th Working Party on Billfish (WPB15) (Wang, 2017). All errors from the original assessment are moved to make a "clean" base case OM and we assume that this situation is the best case that we can achieve in the real world.

Life history and fishing parameters were based on the maximum-likelihood estimates from the stock assessments, with modifications to provide greater generality in the interpretation of results. Where values were estimated for both sexes, the female parameters were used.

Catch and index information is the most common input as the fisheries-independent data in fisheries study; hence, we set up the OM with modified catch and index error and bias, which are as follows: log-normal annual catch observation error σ_C (Cobs), log-normal annual index observation error σ_I (Iobs), and bias factor for annual catch observations b_C (Cbias). We also chose the bias factor for the observed natural mortality rate b_M (Mbias), the bias factor in the observed von Bertalanffy growth parameter K b_K (Kbias), and the bias factor in the observed maximum length b_{Linf} (Linfbias) as representing fisheries-dependent data in the study. The sample size of catch-at-age observation (CAA_samp) is also chosen to be tested as it is informative on stock structure and could provide special information in MSE.

Where we focus on in this study is

$$\hat{C}_{i,y} = b_{C,i}\varepsilon_{C,i,y}C_{i,y}$$

$$\varepsilon_C \sim rlnorm\,(1, \sigma_C)$$

$$\hat{I}_{i,y} = b_{I,i}\varepsilon_{I,i,y}I_{i,y}$$

$$\varepsilon_I \sim rlnorm\,(1, \sigma_I)$$

where $\hat{C}_{i,y}$ and $C_{i,y}$ are the observed and simulated catch of simulation i in year y, respectively. b_C is the bias factor in the catch, and $\varepsilon_{C,i,y}$ is a log-normal distributed catch observation error of simulation i in year y. $\hat{I}_{i,y}$ and $I_{i,y}$ are the observed and simulated catch of simulation i in year y, respectively. b_I is the bias factor in the index, and $\varepsilon_{I,i,y}$ is a log-normal distributed index observation error of simulation i in year y.

For natural mortality M, maximum body length Linf, and growth parameter K, biases were just implemented as a factor similar to b_C, simulated as follows:

$$\hat{M}_i = b_M M_i$$

$$\hat{K}_i = b_K K_i$$

$$\hat{C}_i = b_C C_i$$

$$\widehat{Linf}_i = b_{Linf} Linf_i$$

where M_i, K_i, C_i, and $Linf_i$ are the simulated natural mortality, the von Bertalanffy growth parameter K, the annual catch, and the maximum length in simulation i, and $\hat{M}_i$, $\hat{K}_i$, $\hat{C}_i$, and $\widehat{Linf}_i$ are the corresponding observations. Bias b is a factor (**Figure 1B**), and the error is a log-normal error term with mean 1 and coefficient of variation (CV) determined by M, K, C, and Linf.

Parameter Settings

Seven parameters are tested for the VOI in this case study including Cobs, Iobs, Cbias, Mbias, Kbias, Linfbias, and CAA_nsamp. All parameters are expressed with their lower and upper bounds (**Table 1**).

(0.05, 0.15) is applied to σ_C and σ_I, (4/5, 5/4) is applied to b_C and b_{Linf}, and (2/3, 3/2) is applied to b_M and b_K. (10, 1000) is applied to CAA_nsamp. Low error/bias represents the lower bound of the parameters, while high error/bias represents the upper bound of the parameters. Real catch is a stochastic time-series catch with a rising trend. Yields with errors or biases applied are shown in **Figure 1**.

Parameters are tested independently, which means there is only one changing variable in each MSE run without other errors in the simulation system so that VOI results are generated in a "clean" environment.

Management Strategy Evaluation (MSE)

For VOI testing, management procedures SCA_MSY, SCA_75MSY, and SCA_4010 were applied to run the MSE in this study. These three data-rich management procedures are based on statistical catch-at-age (SCA) stock assessment with MSY, 75%MSY, and 40–10 harvest control rules, respectively (Carruthers et al., 2018), in which catch = MSY, catch = 75%MSY, and 40–10 HCRs are used in fisheries management. These assessment-based MPs were chosen from nine data-rich MPs based on SCA, delay difference, and surplus production methods as catch-at-age data generated from the observation model were used when running SCA-based MPs. Nine iterations of parameter values between lower and upper bounds were applied with 128 simulations when running the MSE. Long-term yield was calculated under a 50-year projection. The average yield was rescaled as the relative yield using the yield in the last 10 years. The mean trend of each simulation for every individual MP was calculated, and the trend of each simulation was also calculated in terms of the three MPs.

RESULTS

Different observations could be seen when MSE runs were performed with different parameter settings associated with the three data-rich MPs.

Cobs and Iobs

Simulation tests of Cobs and Iobs converged well, and the patterns showed that not much information value was necessary. When the parameter Cobs was tested, the majority of simulations with all three MPs were concentrated around the line representing a relative yield equal to 1 with only a

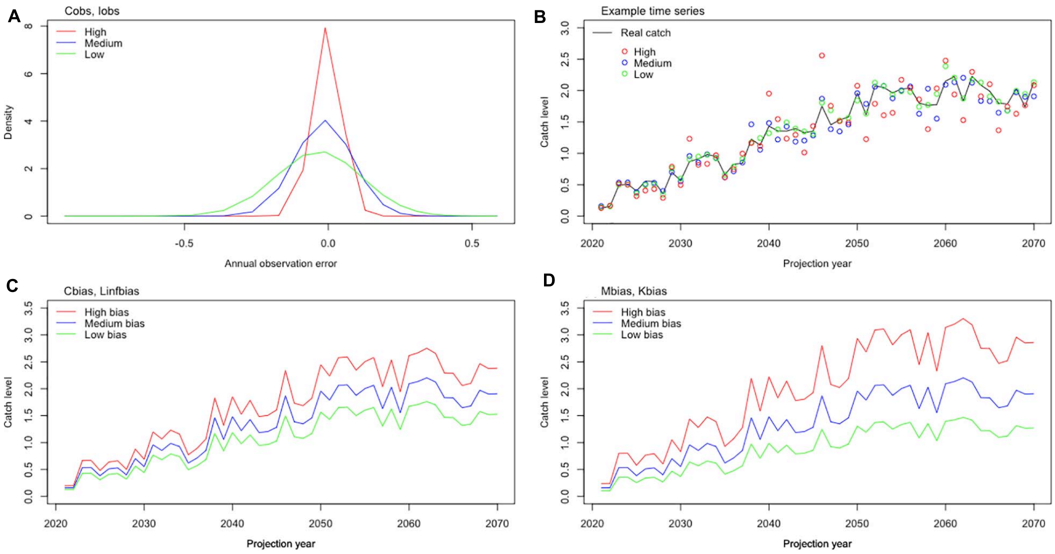


FIGURE 1 | Parameter performance with time-series data. **(A)** Annual catch/index observation error distribution in low (0.05), medium (0.1), and high (0.15) level. **(B)** Simulated real catch with low (0.05), medium (0.1), and high (0.15) level observation error. **(C)** Catch level with low (4/5), medium (1), and high (5/4) level bias in Cbias and Linfbias. **(D)** Catch level with low (2/3), medium (1), and high (3/2) level bias in Mbias and Kbias.

TABLE 1 | Parameter settings in striped marlin case study.

Parameters	Code	Description	Low	Medium	High
σ_C σ_I	Cobs Iobs	Log-normal annual observation error (expressed as a coefficient of variation)	0.05	0.1	0.15
b_C b_{Linf}	Cbias Linfbias	Bias factor in observed catch (all simulations, all years)	4/5	1	5/4
b_M b_K	Mbias Kbias	Bias factor in observed catch (all simulations, all years)	2/3	1	3/2
CAA_nsamp	CAA_nsamp	Number of catch-at-age observation per time step	10	500	1000

Cbias, bias factor for annual catch observations; Mbias, bias factor for observed natural mortality rate; Kbias, bias factor in observed von Bertalanffy growth parameter K; Linfbias, bias factor in observed maximum length; Cobs, log-normal annual catch observation error; Iobs, log-normal annual index observation error.

few noise bumps mostly between 0.5 and 1.5 (**Figure 2**, upper row). Compared with Cobs, there were even less noises when parameter Iobs was run; almost all 128 simulations converged toward yield equal to 1 (**Figure 2**, lower panel). Above all, simulations in testing of parameters Cobs and Iobs are stationary and concentrated and hence had no influence on the final relative yield. We could barely get any useful VOI from Cobs and Iobs since the relative yield did not change a lot within the parameter range.

Cbias and Linfbias

Contrary to the parameters Cobs and Iobs that had tendency to converge toward yield equal to 1 after simulation runs, Cbias and Linfbias apparently had a broader distribution range diverging in most simulation cases from yield equal to 1. In fact, parameter Cbias had higher values of relative yield for lower bias factors (<0.9), in most simulations, then gradually converging toward the yield range (0.6–1) for bias factors greater than 0.9 (**Figure 3**, upper row). Regarding the parameter Linfbias, simulation runs showed fluctuating changes in the relative yield; very high yields were seen at lower bias values for most simulations and for all three MPs, then dropping drastically and staying constant to yield ranges between 0.5 and 1, for bias values superior to 0.95. The three MPs looked alike for most cases except for the noises observed at the beginning of SCA_4010 representing the lower bias values. For both parameters, we observed the necessity of more information value for higher relative yields when parameter values are low.

Mbias and Kbias

The results of these two bias factors, Mbias and Kbias, were quite similar with that of Linfbias. With a similar high relative yield at the beginning, it gradually drops to a relative yield equal to 1 then below 1 and constant in the range between 0.5 and 1 for both parameters Mibas and Kbias (**Figure 4**). Looking into details, simulations with the three MPs in Mbias are nearly exactly the same as that in Kbias.

CAA_nsamp

The parameter of the catch-at-age sample size was a bit different from the other parameters tested in this study. It is not controlled throughout a bias nor error but directly by the number of the

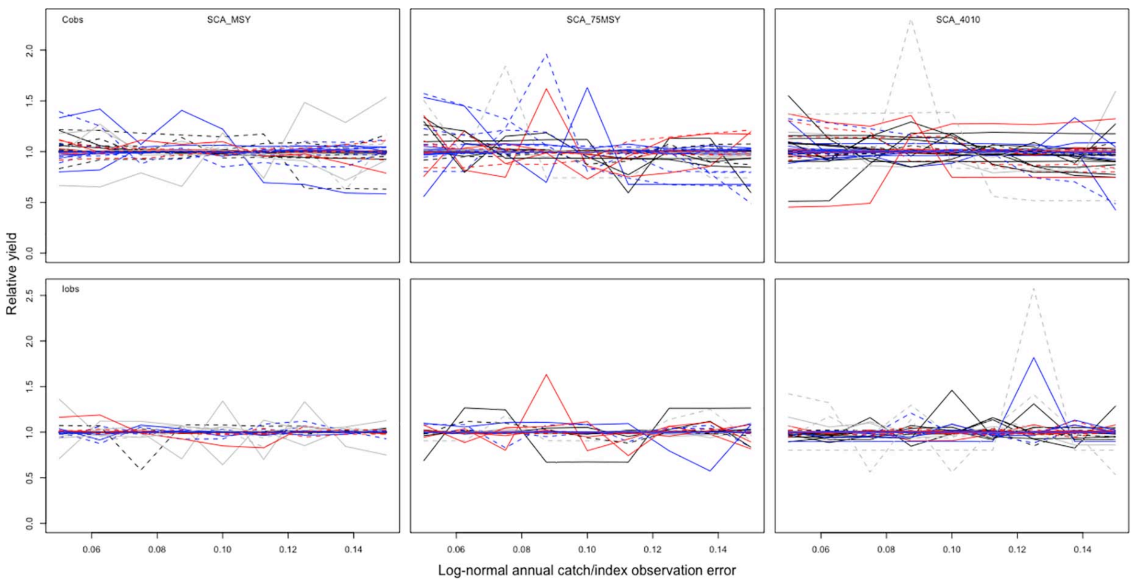


FIGURE 2 | Results of 128 simulations of the parameters Cobs and Iobs with three MPs.

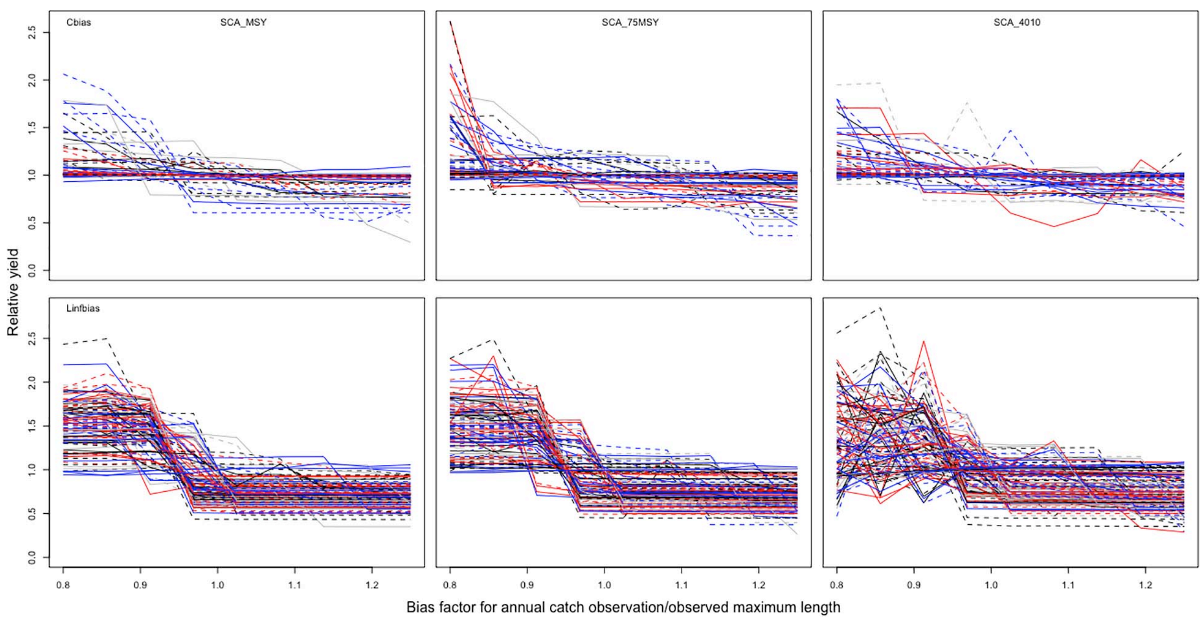


FIGURE 3 | Results of 128 simulations of the parameters Cbias and Linfbias with three MPs.

catch-at-age sample. The result shows that the relative yield was very sensitive to CAA_nsamp at the first iteration, especially at the very beginning of the interval (**Figure 5**). Then the relative yield goes back to 1 and stays stationary at 1 until the end of the interval. It converged well after the first interval at a relative yield equal to 1.

Mean Trend

The mean trends of the seven parameters over MPs SCA_MSY, SCA_75MSY, and SCA_4010 are summarized in **Figure 6**.

Generally, the mean trend of Cbias, Cobs, CAA_nsamp, and Iobs looks similar, whereas Linfbias, Mbias, and Kbias share a similar shape. These three parameters (Linfbias, Mbias, and Kbias) as observed in **Figure 6** simply show their impact on the final relative yield, since they cause the yield to drop from their expected values to lower values (relative yield < 1). For Cbias, Cobs, CAA_nsamp, and Iobs, the mean trend goes flat and smoothly within the interval. Especially, an obvious drop was observed at the beginning of CAA_nsamp, and we also noticed that this drop started slightly above 1 in Cbias and

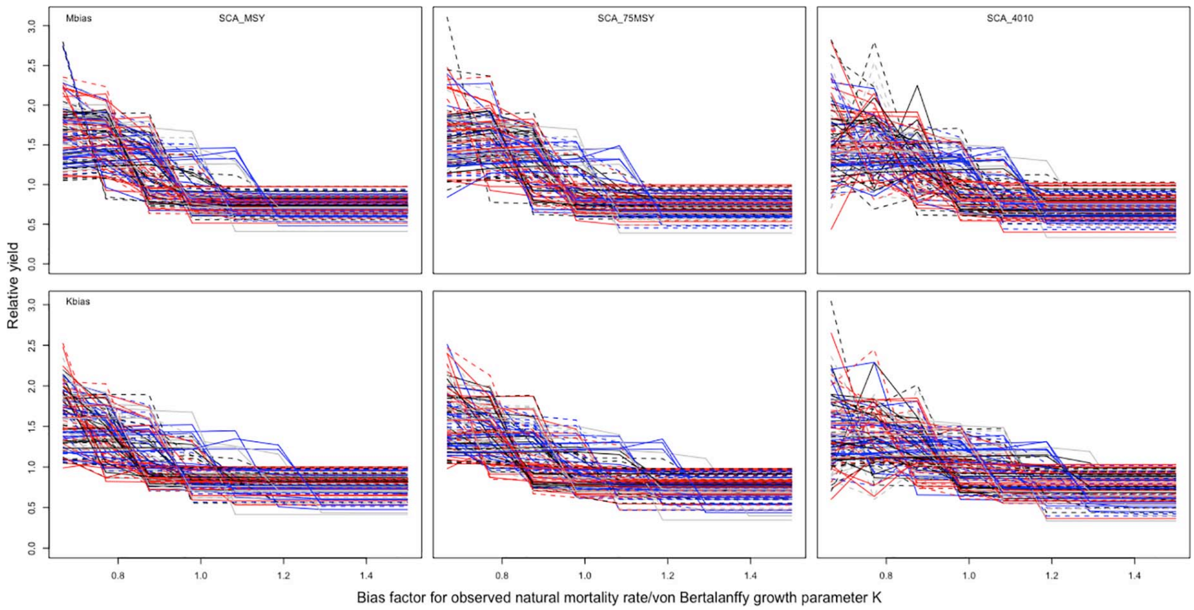


FIGURE 4 | Results of 128 simulations of the parameters Mbias and Kbias with three MPs.

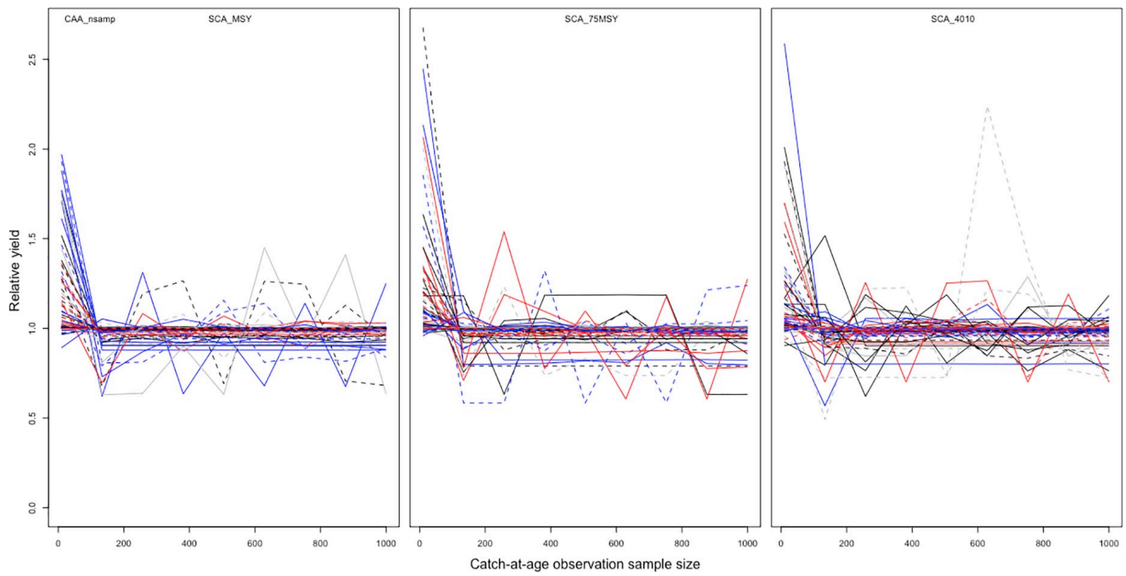


FIGURE 5 | Results of 128 simulations of the parameter CAA_nsamp with three MPs.

stayed constantly smooth throughout as from 1.2. Similar to what it shows in simulation-specific plots, the mean trends of Cobs and Iobs were quite flat and followed the line of a relative yield equal to 1.

It is not surprising that the relative yield results of parameters Mbias and Kbias were very close; both parameters started around 1.5 and then dropped slowly and converged around 0.75. Especially, there is a platform at the beginning of Linfbias in contrast to the rapid drop at the start interval of Mbias and Kbias.

DISCUSSION

We notice that catch- and index-related parameters, including Cbias, Cobs, and Iobs, provide a few information values as the relative yield does not have distinct change within the parameter interval. Similarly, but slightly different, there is a significant but small signal in the first iteration, which reflects a strong information value as the relative yield goes completely flat in the following iterations. In the other three biases, Mbias, Kbias, and Linfbias, it is clear that a great information value was

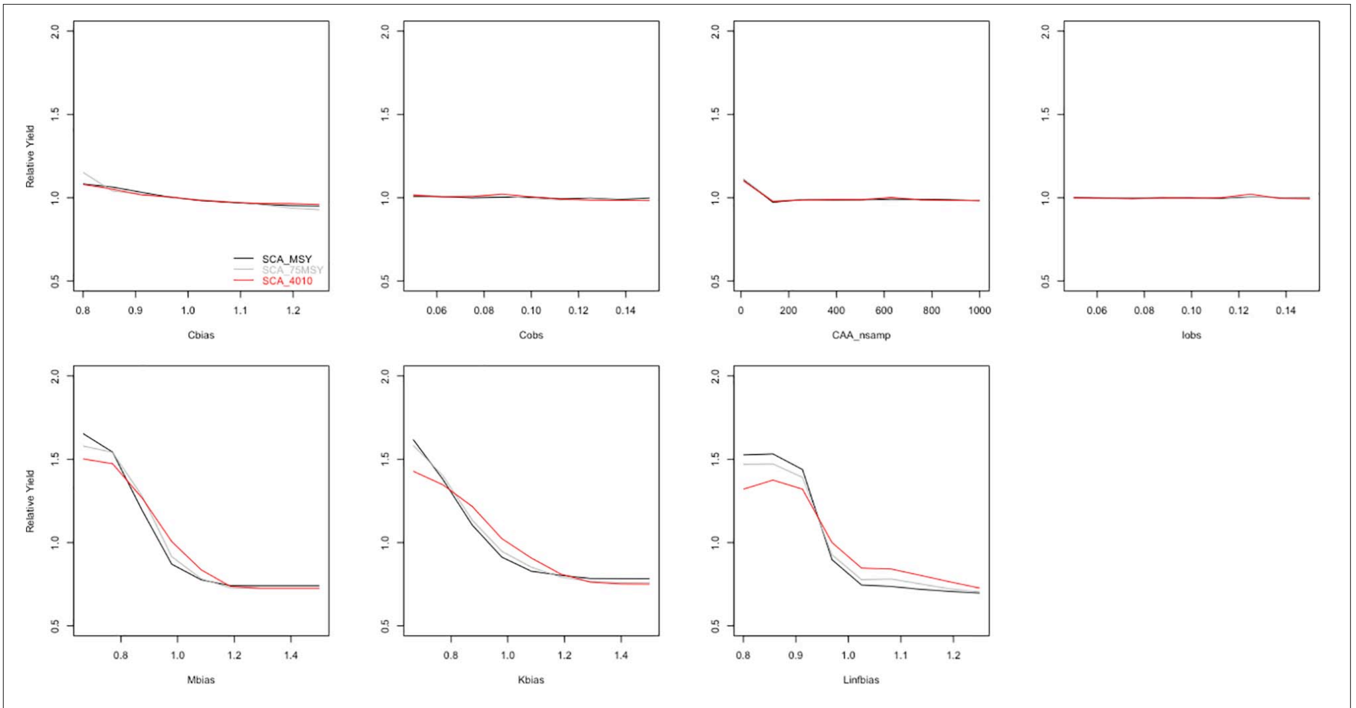


FIGURE 6 | Mean trend of all parameters conducted with three MPs.

reflected as we can see in the mean trend plot (**Figure 6**). Consequently, fisheries-dependent parameters, including Cobs, Cbias, CAA_nsamp, and Iobs, tend to a flat trend of the relative yield under the three MPs. Thus, there is a special interval in CAA_nsamp that indicates a relatively huge information value at the beginning. We also found a significant information value in fisheries-independent parameters, such as Mbias, Kbias, and Linfbias. Interestingly, with almost the same tendency from the lower bound to the upper bound, the parameter value pulls the relative yield from the very top at around 1.5 and then drops rapidly and goes flat to the bottom.

Base-Case OM Settings

The base-case OM was set to represent the "best" data available situation that we can achieve in reality. Simulation studies conducted on a non-noised parameter will indicate the impact of the changing variable. However, there could always be debates on the ideal base-case OM. Questions may arise including the following: Is it really the "best" available situation? How far is it from our reality? What else can be the noise in our study based on this model structure? There are lots of questions for us to answer.

In our base-case OM, natural mortality (M) was set to 0.45 and steepness (h) to 0.86. In the stock assessment performed by Wang (2017), sensitivity analysis of M and h was conducted with M values of 0.35 and 0.55, and h values of 0.75 and 0.95. However, another stock assessment on striped marlin was performed by Wang (2018) using the Stock Synthesis package in the Indian Ocean; the author conducted a sensitivity analysis based on h values of 0.4 and 0.5 and M values of 0.25, and an age-specific M (controlled by the average M value).

In other studies, for instance, Parker et al. (2018) conducted a stock assessment of striped marlin in IOTC-WPB16 using the Bayesian State-Space Surplus Production Model software, JABBA. In their study, the reference steepness used was 0.5 with a sensitivity analysis of lower value 0.4 and higher value 0.86, while admitting reasonable uncertainty about the natural mortality M.

In the present study, for simulation test progress, individual values of information of each parameter were tested under the environment denoted "clean" and "perfect" operation models. So the results obtained are based on the assumption that the OM settings are constantly perfect. As a result, we only tested a single parameter at one time without any noises from other parameters, which is obviously non-existent in real fisheries. Nevertheless, in this preliminary study, we are still using the single-parameter testing system, as what we actually focus on is the impact of a single parameter rather than the synergistic effect. And we clearly got the valuable result that individual fisheries-independent parameters and the catch-at-age sample size are more informative than fisheries-dependent information. This could be the fundamental theory in VOI study in fisheries, and more studies on the information from other aspects could be done based on our research.

As we all know, uncertainties are glued together and always appear at the same time. Thus, future works should be geared toward multi-impact parameter simulation tests to detect interactions within uncertainties.

Impacts of Information Values

The importance of the quantity of fisheries data has been increasingly realized in fisheries stock assessments and

MSEs (Restrepo and Powers, 1999). As an analysis on VOI for management, we focused mostly on the most effective information contributing to the management process. The parameters in our simulation tests, which provided large efforts in management, could also be important in stock assessment works, especially fisheries-independent parameters such as Mbias, Kbias, and Linfbias. The information brought from these parameters would be helpful in life history, growth, and species movement studies. A study by Johnson et al. (2015) suggested that in order to design better studies using simulation tests, accurate estimates of sample sizes would be more helpful than conventional power analysis and be reasonably straightforward to use so as to justify the extra time and effort required for the simulation.

Obviously, an optimum sample size is necessarily important in management case studies. Using an appropriate sample size will effectively save effort put in data collection, such as money and time. In the perspective of fisheries management, we suggest that more effort should be put on data reporting and information collection for a fisheries-independent sampling approach. Apparently, Mbias, Kbias, and Linfbias are relatively more important derivers on yield compared with Cobs, Cbias, Iobs, and CAA_nsamp. Therefore, some actions should be done in the current data collecting system, for instance, cut down the number of catch-at-age data and set a lower bound of 134 individuals due to the inflection point in the study (**Figure 5**). We found that Mbias, Kbias, and Linfbias derived yields in exactly the same way, that is, a half higher yield with low bias and, on the other hand, a quarter lower yield with high bias (**Figure 6**).

Chen et al. (2003) evaluated the impact of data quantity to fisheries and reported that the lack of sufficient data may lead to relatively higher steepness with higher uncertainty (wider distribution). According to Chen et al. (2003), a difference index of parameter mean reached +40.5% and a difference index of standard deviation reached extremely high values of +778.5%, which could definitely bring the yield to a completely different level, such as hyperdepletion or hyperstability. However, in Chen et al. (2003), natural mortality estimation was also driven by data quality, which, in turn, fluctuated the mean value (from -18 to +50%) with a wide standard deviation distribution (+3.3 to 112.0%). From the perspective of yield-expected management, this variance would drop the yield by 50% from the highest estimation to the lowest.

Regarding the use of abundance index data, Schnute (1985) and Maunder and Punt (2004) raised debates as to what type of data is appropriate to use; questions such as whether to use fisheries-independent data such as surveys or to use fisheries-dependent data such as information from commercial or recreational fisheries were raised. From our point of view, we observed that catch or abundance index data did not cause yield results to fluctuate. Therefore, we suggest that both fisheries-independent and -dependent data may be used for stock assessment and management, and that these data types may not bring severe impact on yield results. However, our study showed that bias in catch and index data were not the main drivers of yield fluctuations; it could probably also depend on the fisheries type and MPs.

The number of catch-at-age samples is always a huge challenge for bycatch species (Pelletier and Gros, 1991). The final result, i.e., the yield, is emphasized, rather than the intermediate VPA result, i.e., the fishing mortality, as stressed in a previous study by Pelletier and Gros (1991); the yield per recruit is less sensitive to catch than the VPA result. Hence, the CV of fishing mortality is approximately equal to those of catch estimators, whereas the yield variance is lower than the input catch-at-age error. Consequently, the uncertainty due to catch is moderate, and the CVs of the yield range are between 8 and 15%.

Fournier and Archibald (1982) suggested that catch-at-age data should not be produced without considering the final use to which they will be put. If the final use is an age-structured model, then aging a large number of older fish accurately may not only be a waste of money and effort but could also degrade the quality of the estimates obtained from the age-structured model. Similarly, in our study, age-structured catch data are necessary but only in a relatively low level. Too much effort put on catch-at-age data collection could be a waste of both money and time, as mentioned by Fournier and Archibald (1982).

In our base-case OM, the number of catch-at-age samples was set between 500 and 600 with the aim to remove the impact of the lacking age-structured catch data. On the other hand, in Wang's stock assessment (Wang, 2017), the catch-at-age number was set between 100 and 200, which is quite close to the result we got at 134. Consequently, a large sample size of catch-at-age data is determined to be a waste of time and effort. However, this could also depend on age-based selectivity and vulnerability of the stock (Linton and Bence, 2011).

Future Data Collection

As computer-intensive technology and statistical methods evolve, an increase in attention is now being paid on the quality of the data collected for fisheries analyses. There are huge efforts put on global marine fisheries catch reconstruction. Pauly and Zeller (2016) described the source of catch into three contents: foreign fishing, industrially catch, and small-scale fisheries and suggested to put more effort on small-scale fisheries data collection. Based on the VOI analysis results obtained in this study, Cbias and Cobs show that the huge effort put on data collection could possibly have tiny contribution to our management. Nevertheless, Pauly and Zeller (2016) also found that reconstructed global catches between 1950 and 2010 were 50% higher than the FAO dataset and are declining rapidly since catches peaked in the 1990s, which also indicates that data collecting is still necessary in the perspective of global fishing status analysis.

The quantity of fisheries data can have a profound impact on the quality of stock assessment (Chen et al., 2003). Realistically, information has various availabilities in terms of data type or even fisheries status. A valuable fishery tends to have fisheries-independent and -dependent information collected for many fisheries variables with long time series, while a less valuable fishery, however, often has limited information collected. The optimum data size for the two fisheries could be very different, so we should implement this VOI analysis on more different types of fishery to find the best guidance of fishery-specific data collection.

Data collected from commercial fishery represent different characteristics of the stock than data collected by scientific surveys. Data collected from a well-defined fisheries-independent survey tend to be unbiased and representative of the targeted fish stock and are thus considered more reliable than the data collected from commercial fisheries (Hilborn and Walters, 1992). It is thus important to improve data quantity and collect fisheries-independent data, which often are more reliable than data collected from commercial fisheries. In our case study, fisheries-independent data such as Kbias, Mbias, Linfbias, etc., bring more impact on yield than fisheries-dependent information including Cbias, Cobs, and Iobs, which support the point of view above.

More complex cost models of observation processes are needed by managers to account for overhead costs of certain operations (survey boats, launches, and crew) and then account for prorated data collection costs (e.g., survey days at sea).

DATA AVAILABILITY STATEMENT

The data analyzed in this study are subject to the following licenses/restrictions: The dataset is correlated to the conference document "Stock assessment of Striped marlin (Tetrapturus audax) in the Indian Ocean using the Stock Synthesis" in Indian Ocean Tuna Commission 15th Working Party on Billfish and is provided by the author directly. Requests to access these datasets should be directed to Shengping Wang, wsp@mail.ntou.edu.tw.

ETHICS STATEMENT

Ethical review and approval was not required for the animal study because only simulation and computing work was done on the species.

AUTHOR CONTRIBUTIONS

MX and TC conceived of the presented idea. MX, TC, and RK developed the theory and performed the computations. XD verified the analytical methods. MX, TC, RK, and LD designed the model and the computational framework and analyzed the data. MX, LD, and ZG carried out the implementation. MX, TC, RK, and FW wrote the manuscript with input from all authors. XD and FW provided funding for the research and study. All authors discussed the results and contributed to the final manuscript.

FUNDING

This study was supported by the National Observer Program from the Ministry of Agriculture and Rural Affairs of the People's Republic of China.

ACKNOWLEDGMENTS

We sincere thanks to researchers from the Institute for Oceans and Fisheries in the University of British Columbia and from the College of Marine Sciences in Shanghai Ocean University, which greatly facilitated this study. We thank Observer Program from Ministry of Agriculture and Rural Affairs (MARA) to provide funding and support this study. We also thank Rémi Letestu, Sylvain Le Jeune, and Amélie Beaugrand for their collaboration.

REFERENCES

Bergh, M. O., and Butterworth, D. S. (1987). Towards rational harvesting of the South African anchovy considering survey imprecision and recruitment variability. *S. Afr. J. Mar. Sci.* 5, 937–951. doi: 10.2989/025776187784522702

Carruthers, T. R., and Hordyk, A. R. (2018). The Data-Limited Methods Toolkit (DLM tool): an R package for informing management of data-limited populations. *Methods Ecol. Evol.* 9, 2388–2395. doi: 10.1111/2041-210x.13081

Carruthers, T. R., Huynh, Q., and Hordyk, A. H. (2018). *Management Strategy Evaluation toolkit (MSEtool): an R Package for Rapid MSE Testing of Data-Rich Management Procedures*.

Chen, Y., Chen, L., and Stergiou, K. I. (2003). Impacts of data quantity on fisheries stock assessment. *Aquat. Sci.* 65, 92–98. doi: 10.1007/s000270300008

Dai, X. J., and Xu, L. X. (2007). *A Color Atlas of Global Tuna Fishery Catch*. Beijing: China Ocean Press.

de Bruin, S., and Hunter, G. J. (2003). Making the trade-off between decision quality and information cost. *Photogram. Eng. Rem. Sens.* 69, 91–98. doi: 10.14358/pers.69.1.91

Fournier, D., and Archibald, C. P. (1982). A general theory for analyzing catch at age data. *Can. J. Fish. Aquat. Sci.* 39, 1195–1207. doi: 10.1139/f82-157

Halpern, B. S., Regan, HM., Possingham, H. P., and McCarthy, M. A. (2006). Accounting for uncertainty in marine reserve design. *Ecol. Lett.* 9, 2–11. doi: 10.1111/j.1461-0248.2005.00827.x

Hansen, G. J., and Jones, M. L. (2008). The value of information in fishery management. *Fisheries* 33, 340–348. doi: 10.1577/1548-8446-33.7.340

Hilborn, R., and Walters, C. (1992). *Quantitative Fisheries Stock Assessment: Choice, Dynamics and Uncertainty*. London: Chapman and Hall.

Johnson, P. C., Barry, S. J., Ferguson, H. M., and Müller, P. (2015). Power analysis for generalized linear mixed models in ecology and evolution. *Methods Ecol. Evol.* 6, 133–142.

Ling, J. M., Aughenbaugh, J. M., and Paredis, C. J. J. (2006). Managing the collection of information under uncertainty using information economics. *Trans. Am. Soc. Mech. Eng.* 128, 980–990. doi: 10.1115/1.2205878

Linton, B. C., and Bence, J. R. (2011). Catch-at-age assessment in the face of time-varying selectivity. *ICES J. Mar. Sci.* 68, 611–625. doi: 10.1093/icesjms/fsq173

Mantyniemi, S., Kuikka, S., Rahikainen, M., Kell, L. T., and Kaitala, V. (2009). The value of information in fisheries management: north Sea herring as an example. *ICES J. Mar. Sci.* 66, 2278–2283. doi: 10.1093/icesjms/fsp206

Maunder, M. N., and Punt, A. E. (2004). Standardizing catch and effort data: a review of recent approaches. *Fish. Res.* 70, 141–159. doi: 10.1016/j.fishres.2004.08.002

McAllister, M. K., and Pikitch, E. K. (1997). A Bayesian approach to choosing a design for surveying fishery resources: application to the eastern Bering Sea trawl survey. *Can. J. Fish. Aquat. Sci.* 54, 301–311. doi: 10.1139/f96-286

McAllister, M. K., Starr, P. J., Restrepo, V. R., and Kirkwood, G. P. (1999). Formulating quantitative methods to evaluate fishery-management systems: what fishery processes should be modelled and what trade-offs should be made? *ICES J. Mar. Sci.* 56, 900–916. doi: 10.1006/jmsc.1999.0547

McDonald, A. D., and Smith, A. D. M. (1997). A tutorial on evaluating expected returns from research for fishery management using Bayes' theorem. *Nat. Resour. Model.* 10, 185–216. doi: 10.1111/j.1939-7445.1997.tb00106.x

Morgan, G., and Henrion, M. (1990). *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*. Cambridge: Cambridge University Press.

Moxnes, E. (2003). Uncertain measurements of renewable resources: approximations, harvesting policies and value of accuracy. *J. Environ. Econ. Manag.* 45, 85–108. doi: 10.1016/s0095-0696(02)00011-6

Myers, R. A, and Worm, B. (2003). Rapid worldwide depletion of predatory fish communities. *Nature* 423, 280–283. doi: 10.1038/nature01610

NOAA (2001). *Marine Fisheries Stock Assessment Improvement Plan. Report of the National Marine Fisheries Service National Task Force for Improving Fish Stock Assessments*. Washington, DC: U.S. Department of Commerce.

Parker, D., Winker, H., da Silva, C., and Kerwath, S. E. (2018). *Bayesian State-Space Surplus Production Model JABBA Assessment of Indian Ocean Striped Marlin (Tetrapturus audax*), IOTC-2018-WPB16-16_-_MLS_JABBA_Final. Available online at: https://iotc.org/documents/WPB/16/16-MLS_JABBA (accessed August 27, 2018).

Pauly, D., Christensen, V., Guenette, S., Pitcher, T. J., Sumaila, U. R., Walters, C. J., et al. (2002). Towards sustainability in world fisheries. *Nature* 418, 689–695. doi: 10.1038/nature01017

Pauly, D., and Zeller, D. (2016). Catch reconstructions reveal that global marine fisheries catches are higher than reported and declining. *Nat. Commun.* 7:10244.

Pelletier, D., and Gros, P. (1991). Assessing the impact of sampling error on model-based management advice: comparison of equilibrium yield per recruit variance estimators. *Can. J. Fish. Aquat. Sci.* 48, 2129–2139. doi: 10.1139/f91-252

Powers, J. E., and Restrepo, V. R. (1993). Evaluation of stock assessment research for Gulf of Mexico king mackerel: benefits and costs to management. *North Am. J. Fish. Manag.* 13, 15–26. doi: 10.1577/1548-8675(1993)013<0015:eosarf>2.3.co;2

Punt, A. E., Butterworth, D. S., de Moor, C. L., De Oliveira, J. A. A., and Haddon, M. (2016). Management strategy evaluation: best practices. *Fish Fish.* 17, 303–334.

Punt, A. E., and Smith, A. D. M. (1999). Harvest strategy evaluation for the eastern stock of gemfish (*Rexea solandri*). *ICES J. Mar. Sci.* 56, 860–875. doi: 10.1006/jmsc.1999.0538

Punt, AE, Walker, TI., and Prince, J. D. (2002). Assessing the management-related benefits of fixed-station fishery-independent surveys in Australia's southern shark fishery. *Fish. Res.* 55, 281–295. doi: 10.1016/s0165-7836(01)00276-4

Quirk, J. P. (1976). *Intermediate Microeconomics*. Chicago, IL: Science Research Associates, 359.

Raiffa, H., and Schlaifer, R. O. (1961). *Applied Statistical Decision Theory*. Cambridge, MA: Harvard University.

Regan, HM, Colyvan, M., and Burgman, M. A. (2002). A taxonomy and treatment of uncertainty for ecology and conservation biology. *Ecol. Appl.* 12, 618–628. doi: 10.1890/1051-0761(2002)012[0618:atatou]2.0.co;2

Restrepo, V. R., and Powers, J. E. (1999). Precautionary control rules in US fisheries management: specification and performance. *ICES J. Mar. Sci.* 56, 846–852. doi: 10.1006/jmsc.1999.0546

Runge, M. C., Converse, S. J., and Lyons, J. E. (2011). Which uncertainty? Using expert elicitation and expected value of information to design an adaptive program. *Biol. Conserv.* 144, 1214–1223. doi: 10.1016/j.biocon.2010.12.020

Schnute, J. (1985). A general theory for analysis of catch and effort data. *Can. J. Fish. Aquat. Sci.* 42, 414–429. doi: 10.1139/f85-057

Walters, C., and Maguire, J. J. (1996). Lessons for stock assessment from the northern cod collapse. *Rev. Fish Biol. Fish.* 6, 125–137.

Walters, C., and Pearse, P. H. (1996). Stock information requirements for quota management systems in commercial fisheries. *Rev. Fish Biol. Fish.* 6, 21–42. doi: 10.1007/bf00058518

Wang, S. P. (2017). *Stock Assessment of Striped marlin (Tetrapturus audax) in the Indian Ocean using the Stock Synthesis, IOTC-2017-WPB15-32_Rev1*. Available online at: https://iotc.org/documents/stock-assessment-striped-marlin-tetrapturus-audax-indian-ocean-using-stock-synthesis (accessed August 31, 2017).

Wang, S. P. (2018). *Stock assessment of Striped marlin (Tetrapturus audax*) in the Indian Ocean using the Stock Synthesis, IOTC-2018-WPB16-19-TWN_SA_MLS_rev1. Available online at: https://iotc.org/documents/WPB/16/19-MLS_SS3 (accessed August 30, 2018).

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 19 May 2021
doi: 10.3389/fmars.2021.662942

Adapting Simple Index-Based Catch Rules for Data-Limited Stocks to Short-Lived Fish Stocks' Characteristics

Sonia Sánchez-Maroño, Andrés Uriarte, Leire Ibaibarriaga and Leire Citores*

Marine Research, AZTI, Basque Research and Technology Alliance (BRTA), Pasaia, Spain

Most of the methods developed for managing data-limited stocks have been designed for long-lived species and result in a poor performance when applied to short-lived fish due to their high interannual variability of stock size (IAV). We evaluate the performance of several catch rules in managing two typical short-lived fish (anchovy-like: characterized by high natural mortality, and hence, IAV, and full maturity at age 1; and sprat/sardine-like: with medium natural mortality and IAV, being fully mature at age 2). We followed the management strategy evaluation approach implemented in FLBEIA software to test several model-free harvest control rules, where the Total Allowable Catch (TAC) is yearly modified according to the recent trends in an abundance index (n-over-m rules: means of the most recent *n* values over the precedent *m* ones). The performance of these rules was assessed across a range of settings, such as time-lags between the index availability and management implementation, and alternative restrictions on TACs' interannual variability (the uncertainty caps, UC). Moreover, we evaluated the sensitivity of the rule performance to the operating model assumptions (stock type, productivity, recruitment variability and initial depletion level) and to the observation error of the index. In general, the shorter the lag between observations, advice and management, the bigger the catches and the smaller the biological risks. For in-year management, 1-over-m rules are reactive enough to stock fluctuations as to gradually reduce risks. The 1-over-2 rule with symmetric 80% UCs reduces catches and risks toward precautionary levels in about 10 years, faster than if applied unconstrained (i.e., without UC), whilst the ICES default 2-over-3 rule with symmetric 20% UC is not precautionary. We prove that unconstrained rules gradually reduce the fishing opportunities, with amplified effects with increasing IAV. This property explains the stronger reductions of catches and risks achieved for the anchovy compared to the sprat/sardine-like stocks for any rule and the balance between catches and risks as the index CV increases. However, to avoid unnecessary long-term losses of catches from such reduction properties, it is suggested that the rules should be applied provisionally until a better assessment and management system is set up.

Keywords: data-limited, management strategy evaluation, FLBEIA, short-lived fish, model-free harvest control rules

OPEN ACCESS

Edited by:
Giuseppe Scarcella,
National Research Council (CNR), Italy

Reviewed by:
Sanja Matic-Skoko,
Institute of Oceanography and Fisheries (IZOR), Croatia
Brett W. Molony,
Oceans and Atmosphere (CSIRO), Australia

****Correspondence:***
Sonia Sánchez-Maroño
ssanchez@azti.es

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: *02 February 2021*
Accepted: *21 April 2021*
Published: *19 May 2021*

Citation:
Sánchez-Maroño S, Uriarte A, Ibaibarriaga L and Citores L (2021) Adapting Simple Index-Based Catch Rules for Data-Limited Stocks to Short-Lived Fish Stocks' Characteristics. Front. Mar. Sci. 8:662942. doi: 10.3389/fmars.2021.662942

INTRODUCTION

The majority of the stocks exploited worldwide are from fisheries that lack formal stock assessments (Beddington et al., 2007; Costello et al., 2012; Ricard et al., 2012). These are usually low value resources (Bentley and Stokes, 2009b), often corresponding to by-catch, small-scale, recreational and/or artisanal fisheries. But there are also cases in which the quality of the data hinders its use for assessment purposes or there is insufficient capacity to conduct stock assessments (Dowling et al., 2019). In an attempt to decrease the number of stocks with unassessed status and to provide management advice for the largest number of species as possible, several jurisdictions have developed hierarchical tier systems that categorize stocks based on the data available or the ability to estimate key assessment parameters (Dichmont et al., 2015). Aiming at reducing risks to sustainability, but still maintaining profitable fleets and addressing food security issues (United Nations, 2019).

The International Council for the Exploration of the Sea (ICES), that provides management advice for many European fisheries, started to develop its tier system, the so-called data-limited framework, in 2012 (ICES, 2012a). Since then, this framework has evolved over time through several expert working groups that have validated and refined many of the methods proposed (ICES, 2012b, 2020c). Nowadays ICES classifies stocks into six categories based on the available information (ICES, 2019). Category 1 comprises stocks with full analytical stock assessment and forecasts. Category 2 refers to stocks with analytical assessments and forecasts that are only treated qualitatively as indicative of trends in stock metrics such as recruitment, fishing mortality and biomass. Category 3 includes stocks for which one or more indices (from surveys, from exploratory assessments or from elsewhere) are available and indicative of trends in stock metrics. Categories 4, 5 and 6 are increasingly data-limited stocks for which only catch and/or landing data are available. For each stock, if there is an agreed management plan that has been evaluated to be consistent with the precautionary approach, ICES provides advice based on that plan. Otherwise, ICES provides advice for stocks in categories 1 and 2 based on the ICES maximum sustainable yield (MSY) advice rule that aims at maximizing the average long-term yield while maintaining productive fish stocks, whereas for stocks in categories 3–6 the advice is based on empirical harvest control rules that aim at maintaining the stocks within safe biological limits in accordance with the precautionary approach. In 2014, the majority of the stocks fell in category 3 (ICES, 2014; Dichmont et al., 2015). The empirical harvest control rule used for these stocks adjusts the most recent advised catch according to the ratio of average stock size indices over the last years. In addition, to account for the inherent uncertainty of the index, the interannual change in the catch advice is capped by a maximum change limit called uncertainty cap (UC).

Despite the fact that numerous methods to assess data-limited stocks have been developed in the last years (MacCall, 2009; Dick and MacCall, 2011; Wetzel and Punt, 2011), empirical harvest control rules are emerging as an alternative for data-limited stocks (Bentley and Stokes, 2009a; Dowling et al., 2015). These rules set the management actions based on directly observable indicators rather than from stock assessment models and are readily applicable. Ideally, the performance of these harvest control rules, and more generally the management procedures encompassing them, should be tested by simulation before implementation (Punt et al., 2016). Whenever possible, the simulation testing should be done specifically for each case (Bentley and Stokes, 2009a). However, developing management plans is not trivial, since it demands expertise and can sometimes be resource consuming (Dowling et al., 2019). And it is even more difficult for data-limited stocks, for which information is scarce or less reliable. In these cases, Bentley and Stokes (2009a) argued that generic approaches might not be optimal but can be better than not taking any approach at all. Furthermore, they noted that evaluating generic approaches for a variety of stock characteristics and fishery types could allow to discern which are the most influential factors and gain understanding about concrete circumstances under which the management plans satisfy the objectives.

Generic harvest control rules are usually evaluated for generic stocks (Geromont and Butterworth, 2014; Carruthers et al., 2016) or for specific species (Jardim et al., 2015; Fischer et al., 2020). Often, different species representing contrasting life-traits are selected (Carruthers et al., 2014; Wetzel and Punt, 2015; Walsh et al., 2018). Various simulation studies have shown that the performance of the harvest control rules might change depending on the life history-traits, the productivity of the stock and the depletion level. In particular, in many cases, the performance of the harvest control rules worsened for short-lived fish stocks (those with a lifespan restricted to 4–6 years (ICES, 2017) and becoming fully mature between 1 or 2 years-old). Walsh et al. (2018) showed that choosing an ineffective harvest control rule could have much more dramatic and negative outcomes for short-lived fish species. For Carruthers et al. (2014) butterfish proved to be the most challenging stock due to its short life-span and highly variable recruitment. In a recent paper Fischer et al. (2020) evaluated the performance of the empirical harvest control rule for ICES category 3 stocks for 29 stocks with contrasting life-history parameters. They concluded that the rule performed worse for the more productive stocks (growth parameter of the von Bertalanffy model, k, larger than 0.32 year^{-1}). Stocks with higher k have larger natural mortality (Gislason et al., 2010) and are inherently more variable. This can lead to quick stock recovery, but in this case the rule was not reactive enough to avoid stock collapse.

Some small pelagic fish are good examples of short-lived fish species and of the most common difficulties encountered. Their short life-span, the highly variable recruitment dynamics, the aggregative behaviour of many of them and the quick response to environmental drivers make them vulnerable to exploitation (Freón et al., 2005). The most effective management plans are based on close monitoring with fishery-independent surveys (Barange et al., 2009), short time lag between the stock assessment and the management decision (Freón et al., 2005; Sánchez et al., 2018), pre-recruitment surveys (Dichmont et al., 2006a; Sánchez et al., 2018) or the use of flexible harvest control rules to accommodate the management to the population oscillations, for example setting an initial conservative TAC with a within season adjustment when year-class strength is known (Plagányi et al., 2007).

Representative small pelagics are anchovy, sprat, and sardine. These species are commercially important species and essential in the ecosystem due to their situation in the food-chain, as they are food source for fish, marine mammals, and birds. Maximum anchovy length is around 15–19 cm (corresponding to age of 2 to 5 years) and all individuals are mature at 1 year-old (Barange et al., 2009). Whereas maximum sprat and sardine lengths range between 15–18 cm and 23–40 cm (corresponding to 4 to10 year-old fish), respectively. Having these stocks also a later age of first spawning, generally at ages 2 and 3 (Barange et al., 2009). Anchovies are characterised by higher natural mortality values (Gislason et al., 2010; ICES, 2020a,b) and earlier maturity (Checkley et al., 2017; ICES, 2020a,b) than those for sprat and sardine. This leads to lower survival rates for anchovies, which consequently implies higher interannual variability of stock size (IAV), as a higher fraction of the population is sustained by recruits.

The objective of this work is to evaluate by simulation-testing the performance of simple empirical harvest control rules for short-lived fish stocks. In particular, we focus on stocks in ICES category 3, for which catch advice is based on the previous advice multiplied by an estimation of the recent trend of the population obtained from a biomass index. The rules tested differ in the number of years used to infer the trend in the population, the uncertainty caps that set the maximum allowable interannual variability in the catch advice and the time lag between the biomass index and the year for which the advice is provided. Additionally, we evaluate the inclusion of a biomass safeguard level in the rules. We consider two types of short-lived small pelagic fish, anchovy-like and sprat/sardine-like, which are simulated based on their life history characteristics (Jardim et al., 2015; Fischer et al., 2020) under different exploitation levels. Finally, we test the sensitivity of the results to the precision of the biomass index and to the productivity of the stock and the variability of the recruitment, by changing the steepness and the process error of the stock-recruitment model, respectively. The results are discussed to provide guidelines on the best empirical harvest control rules for short-lived data-limited fish stocks.

MATERIALS AND METHODS

Management Strategy Evaluation

We evaluated the performance of advice rules for ICES category 3 stocks using a Management Strategy Evaluation (MSE) simulation framework (Punt et al., 2016). The simulations were carried out using the FLBEIA software (García et al., 2017), which is a tool to perform bio-economic impact assessment of fisheries management strategies based on FLR tools (Kell et al., 2007).

The simulation framework has two main components: the operating model (OM), which represents the *real world* (i.e., the fish stocks and the fleets targeting them); and the management procedure (MP), representing the advice process (i.e., assessment and advice rule). Both components are connected through the observation model that feeds the MP with information on the OM (e.g., observation of catches, biological parameters and/or abundance indices) and the implementation model, that alters the OM given the advice from the MP. Each of these components is described in detail below.

Operating Model Based on Life-History Parameters

We simulated two types of short-lived fish stocks: an anchovy-like stock (STK1) and a sprat/sardine-like stock (STK2). The anchovy-like stocks are characterised by high natural mortality (above 0.8 $year^{-1}$), full maturity at age 1 and large interannual fluctuations (>40% among years), whereas sprat/sardine-like stocks are stocks with medium natural mortality (between 0.4 and 0.7) that are fully mature at age 2 and have intermediate interannual variability. For each stock, the biological OM was based on an age-structured (ages $0–6^{+}$) model by semester. Spawning was assumed to occur at the beginning of the second semester (1st July), so that recruits (age 0 individuals) entered the population on 1st July. Birthdate was assumed on 1st January, which implies that age 0 group only lasts for 6 months in the population, becoming afterward age 1. The operating model for each type of stock was based on their life-history parameters (Jardim et al., 2015; Kell et al., 2017; Fischer et al., 2020). Growth was based on the von Bertalanffy growth model and lengths were converted to weight-at-age using a length-weight model. Annual natural mortality rates by age group were derived from length-at-age based on the Gislason's model (Gislason et al., 2010). Maturity-at-age was 1 for individuals aged 1 and older in the case of the anchovy-like stock and for individuals aged 2 and older for sprat/sardine-like stocks. For the latter stock, maturity-at-age 1 was assumed equal to 0.5. Annual recruitments were generated according to the Beverton and Holt stock-recruitment model with steepness equal to 0.75 that represented a medium productivity (Jardim et al., 2015), virgin biomass (B0) equal to 100 000 tonnes and a standard deviation (σ_{REC}) at 0.75 without autocorrelation in residuals. More details are provided in **Supplementary Annex I**.

Reference points for each of the stocks were estimated based on the above dynamics and presuming 50% of the catches occurred in each semester. The limit biomass (B_{lim}) was set as 20% of the virgin biomass B0 (Mace and Sissenwine, 1993; Smith et al., 2009) and the biomass at which the stock had collapsed ($B_{collapse}$) was set as 10% of the virgin biomass B0 (Punt et al., 2016). A proxy for F_{MSY} ($F_{MSYproxy}$) was based on $F_{40\%\ B0}$ (Punt et al., 2014), i.e., the fishing mortality rate associated with a biomass of 40% B0 at equilibrium. All the estimated values are given in **Supplementary Annex I (Table I.4)**.

The historical trajectory of each stock was simulated for 30 years. Each stock started from a virgin population. During the first 10 years the exploitation increased linearly up to a constant level of fishing mortality (F_{hist}) that was kept constant for the next 20 years. Three levels of F_{hist} leading to different depletion levels (FAO, 2011; Geromont and Butterworth, 2015) at the beginning of the simulation period were tested: (i) underexploited, $F_{hist} = 0.5 \cdot F_{MSYproxy}$; (ii) fully exploited, $F_{hist} = F_{MSYproxy}$; and (iii) overexploited, $F_{hist} = 2 \cdot F_{MSYproxy}$. Variability in the historical fishing mortality (F) was included through a log-normal distribution with a coefficient of variation (CV_F) of 10%. The percentage of fishing mortality in each semester was kept constant at the value that leaded to 50% of the catches in each semester (0.3 for anchovy-like stock and 0.4 for sprat/sardine-like stock in the first semester).

Observation Model

In each year y, the observed abundance index of biomass at age 1+ (I_y) followed a log-normal distribution as follows:

$$I_y = q \cdot B_{y,s,1+} \cdot e^{\varepsilon_y}, \text{ with } \varepsilon_y \sim N\left(0, \sqrt{\ln\left(1 + CV_I^2\right)}\right),$$

where q is the catchability of the survey, which was set equal to 1, $B_{y,s,1+}$ is the biomass at age 1+ at the beginning of the semester s in year y and CV_I is the coefficient of variation of the index in normal scale that was assumed equal to 0.25. The specific time-instant in which the abundance index is observed will change depending on the management calendar, as explained below.

Management Procedure

The management procedure was based on an empirical harvest control rule (HCR) of type n-over-m. This means that the TAC was based on the previous year TAC adjusted to the trend in the stock size indices for the values in the most recent n years relative to the values in the preceding m years.

In the usual management calendar, which is known as interim year advice (int), the TAC from January to December in year ($y+1$) was based on the indices on B1+ in the interim year y (at the beginning of the second semester) as follows:

$$TAC_{Jan_{y+1}Dec_{y+1}} = TAC_{Jan_yDec_y} \cdot \frac{\frac{\sum_{i=y-(n-1)}^{i=y} I_i}{n}}{\frac{\sum_{i=y-(n+m-1)}^{i=y-n} I_i}{m}}.$$

This means that there was no indication of age 1 in the TAC year, which for short-lived fish might be the bulk of the population (**Figure 1A**).

Following a similar approach to Sánchez et al. (2018), we evaluated two alternative management calendars than shortened the time lag between the biomass index and the management advice: in-year advice (iny) and full population advice (fpa). In the in-year advice, the management calendar was moved to July-June, and the TAC was set as soon as the biomass index on B1+ at the beginning of the second semester was available. So, the TAC from July (y) to June ($y+1$) was based on the index up to year y as follows:

$$TAC_{Jul_yJun_{y+1}} = TAC_{Jul_{y-1}Jun_y} \cdot \frac{\frac{\sum_{i=y-(n-1)}^{i=y} I_i}{n}}{\frac{\sum_{i=y-(n+m-1)}^{i=y-n} I_i}{m}}.$$

This implies that the biomass index provided indications on the abundance of the age 1 group during the second semester in year y, but not during the first semester of year ($y+1$) (**Figure 1B**).

In the full population advice, the management calendar was the calendar year, but the biomass index was available up to year ($y+1$) and provided information on all the age classes that were going to be exploited (i.e., B1+ at the beginning of the first semester). The TAC from January to December ($y+1$) was:

$$TAC_{Jan_{y+1}Dec_{y+1}} = TAC_{Jan_yDec_y} \cdot \frac{\frac{\sum_{i=y-(n-2)}^{i=y+1} I_i}{n}}{\frac{\sum_{i=y-(n+m-2)}^{i=y-(n-1)} I_i}{m}}.$$

This is the usual case when a recruitment index is available, and the TAC is set based on indications on all the age classes (**Figure 1C**). But it also applies to cases where a survey at the beginning of year y on B1+ will be used to set the TAC of the entire year y (even if the TAC is set once the management year has started).

Regarding the values of n and m, we tested the 2-over-3 rule that is the default ICES harvest control rule for category 3 stocks, and we compared it with respect to other rules that could potentially react faster to the high IAV of the short-lived fish stock dynamics, namely, 1-over-2, 1-over-3 and 1-over-5. In the first year of application of the rule, the rule depended on a reference TAC value, which was calculated as an average of the catch in the most recent m years, being m the number of preceding years in the denominator of the harvest control rule.

In the ICES framework for stocks in categories 3–6, to avoid large oscillations in the TAC advice from year to year, due to noise in the indices, the interannual changes in TAC advice are capped, so that only changes up to a maximum limit are allowed. The so-called Uncertainty Cap level (UC) has a default value of ±20%. This means that the TAC change from year to year cannot be larger than 20%, or if defined by the ratio of the consecutive TACs they must lie between 0.8 and 1.2. In general, if we denote UC(L,U) the uncertainty caps with L lower and U upper levels, the ratio of the consecutive TACs from year to year will be within the interval (1-L, 1+U). We considered the following alternative UCs: (i) no UCs denoted as UC(NA,NA); (ii) symmetric UCs at ± 20% UC(0.2,0.2), ± 50% UC(0.5,0.5) and ± 80% UC(0.8,0.8); and (iii) asymmetric UCs at 20% lower and 25% upper caps UC(0.2,0.25), 50% lower with 100% upper, UC(0.5,1.0), or with a 150% upper caps, UC(0.5,1.5), and 80% lower with 275% upper, UC(0.8,2.75), or with 400% upper UC(0.8,4) or with 525% upper caps, UC(0.8,5.25). In the case of the symmetric UCs, even when a decreasing change is followed by an increasing change of the same magnitude, the TAC does not achieve the same level, so that continuously applying the symmetric UCs up and down would lead to a continuous decrease in the TAC. The asymmetric UCs aimed at overcoming this by allowing larger upper than lower uncertainty caps to allow recovering to the same or larger TAC levels after a reduction. The UC values considered allow recoveries of the initial TAC levels up to: 75% for UC(0.5,0.5) and UC(0.8,2.75); 100% for UC(0.2,0.25), UC(0.5,1.0) and UC(0.8,4); and 125% for UC(0.5,1.5) and UC(0.8,5.25).

It is important to note that the n-over-m rules, without and with uncertainty caps, have intrinsic properties that determine the performance of the rule. As shown in **Supplementary Annex II**, for an abundance index in stationary conditions that fluctuated around its mean according to a log-normal error (σ^2) distribution (accounting for both observation and process

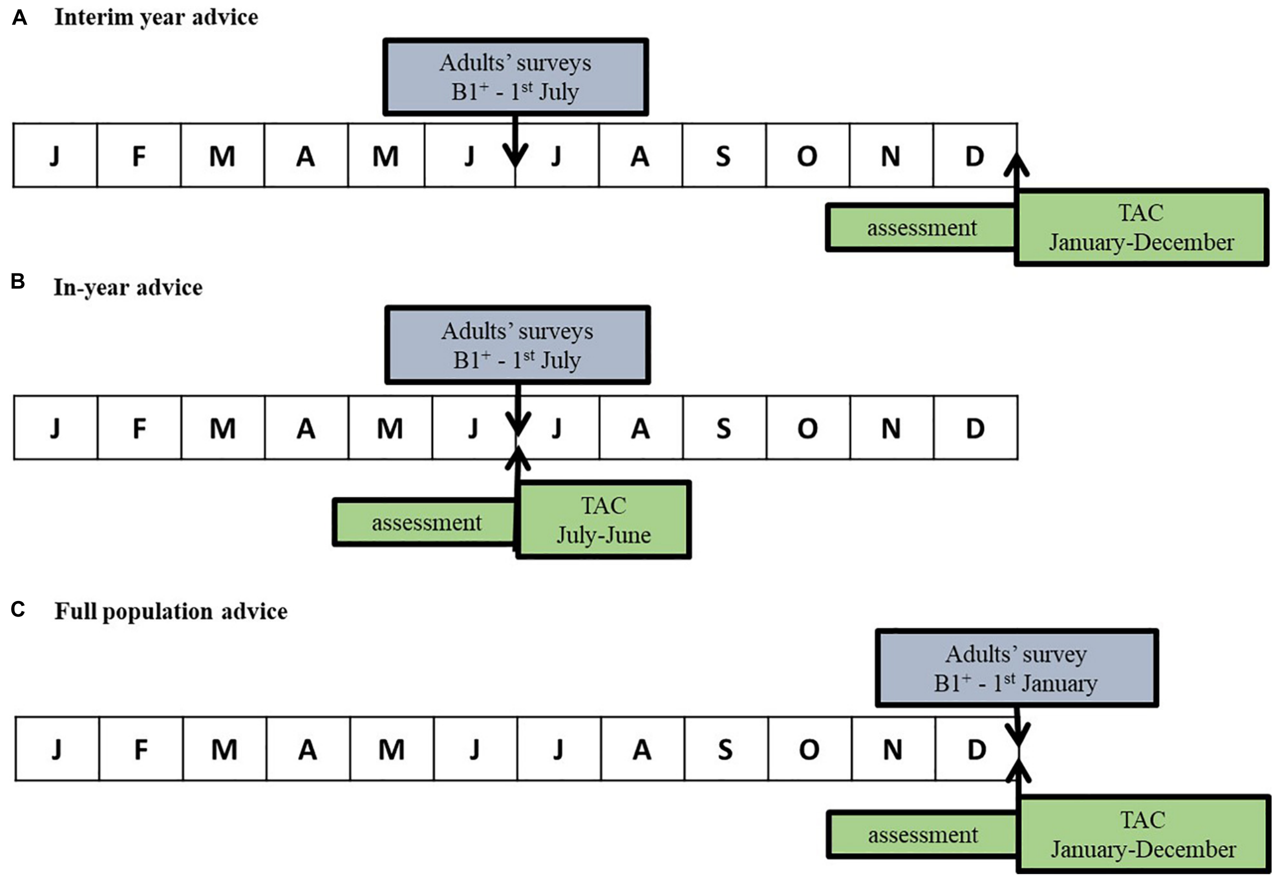


FIGURE 1 | Graphical representation of the timings of abundance surveys, stock assessment and management period for each management calendar. From top to bottom, interim year advice, in-year advice and full population advice.

errors), any n-over-m ratio $\left(r_{n,m}\right)$ with $n < m$ resulted in a median value <1 with the following expected value:

$$med\left(r_{n,m}\right) = \exp\left(\frac{1}{2}\ln\left(\frac{nm + n(\exp\left(\sigma^2\right) - 1)}{mn + m(\exp\left(\sigma^2\right) - 1)}\right)\right).$$

This means that these rules tended to reduce the fishing opportunities along time. In general, the larger the difference between n and m, the larger would be the reduction properties of the rule. In addition, the greater the interannual variability of the index, the greater the reduction properties of the n-over-m rule would be (up to an asymptotic value). The application of uncertainty caps generally modified the reduction properties of the rules. When symmetric uncertainty caps were incorporated (i.e., $L = U$), the reduction property was kept though its magnitude was modified and it could almost be vanished for small symmetric uncertainty caps (~0.2). Alternatively, for asymmetric UCs, given a lower cap value (L), as the upper value (U) increased the change factor of the rule increased and large differences between the lower and upper value (U-L) turned over the rule properties from a reduction to an increase of the fishing opportunities. In fact, given the variability of the index and the parameters of the rule n, m and L, it would be possible to calculate what upper uncertainty cap level (U) is required to make the median change trend factor equal to either (i) the median change factor obtained without uncertainty caps, or (ii) to 1 (i.e., the inflexion point, where the factor turns from a reduction to an increasing factor).

For a subset of rules, we also evaluated the effect of including a biomass safeguard (Fischer et al., 2020). This consisted in a multiplicative factor that reduced the TAC advice when the observed index was below a threshold value ($I_{trigger}$):

$$TAC_{y+1} = TAC_{y+1} \cdot min\left(1, \frac{I_l}{I_{trigger}}\right),$$

where I_l is the last available index and the biomass safeguard $I_{trigger}$ can adopt three alternative values: $I_{min} = min\left(I_{hist}\right)$; $I_{minpa} = 1.64 \cdot min\left(I_{hist}\right)$ or $I_{norm} = exp\left(mean\left(log\left(I_{hist}\right)\right) - 1.645 \cdot sd\left(log\left(I_{hist}\right)\right)\right)$. The biomass safeguard was included in the 1-over-2 rule with (i) no UCs: UC(NA,NA); (ii) symmetric UCs at ± 20%: UC(0.2,0.2) and ± 80%: UC(0.8,0.8); and (iii) asymmetric UCs at 80% lower with 400% upper caps: UC(0.80, 4.00).

Implementation Model

No implementation error was simulated. All the TAC was taken as far as the population supported it. Catches were not allowed to be larger than 90% of the numbers at age in the population. The percentage of the TAC taken in each semester was set to 50%. When the semester quota was not taken, it was transferred to the next semester within the same management calendar.

Scenarios

For each combination of stock type and historical fishing pattern (2 stock types × 3 fishing patterns) we evaluated the performance of 120 variants of the advice rule (corresponding to 4 variants of the n-over-m advice rule, 10 sets of UCs and 3 management calendars). Simulated scenarios were the combination of the alternatives for the different components listed in **Table 1**.

Projections

Dynamics were simulated forward for 30 years and run for 1000 iterations for each scenario. Uncertainty in the projection period was introduced through: (i) recruitment process error from a Beverton and Holt stock-recruitment relationship; and (ii) the log-normal observation error on the B1+ index used to establish the TAC.

Performance Statistics

For each stock and starting depletion level, we calculated the interannual variation (IAV) of biomass as the average of the IAV of each iteration (IAV_{iter}):

$$IAV_{iter} = \sqrt{\frac{\sum_{y=1}^{N-1} \left(\ln(B_{y+1,\ iter}) - \ln(B_{y,\ iter})\right)^2}{N-1}},$$

where $B_{y,\ iter}$ is the total abundance in mass at the beginning of year y and iteration $iter$ and N is the number of years in the selected period. This statistic was calculated for the historical period (years 0–30), the short-term of the projection years (first five projection years; years 31–35) and the long-term of the projection years (last ten projection years; years 51–60).

TABLE 1 | List of alternative scenarios simulated for the different components.

Variable	Description	scenario	Scenario description
STKN	Stock type	STK1	Anchovy like
		STK2	Sprat/sardine like
LHSC	Life-history scenario	bc	See **Supplementary Annex I, Table I.1**
SIGR	Standard deviation for the recruitment log-normal error	0.75	
FHIST	F target in the historical period	fopt	$F_{target} = F_{40\%B0}$
		flow	$F_{target} = 0.5 \cdot F_{40\%B0}$
		fhigh	$F_{target} = 2 \cdot F_{40\%B0}$
CVFH	CV for the FHIST error	0.10	
IDXT	Index type	b1p	Biomass index on individuals age 1 or older
CVID	Coefficient of variation of the error term for the B1+ index	low	$CV = 0.25$
ADVT	Advice type	int	Interim-year advice
		iny	In-year advice
		fpa	Full population advice
HCRT	HCR type	2o3, 1o2, 1o3, 1o5	n-over-m type rules
UCPL	Uncertainty cap (lower bound)	0	No uncertainty cap
		0.2, 0.5, 0.8	Minimum increase in TAC of 20, 50, and 80% from previous year
UCPU	Uncertainty cap (upper bound)	0	No uncertainty cap
		0.2, 0.5, 0.8	Maximum increase in TAC of 20, 50, and 80 % from previous year (symmetric to lower bound)
		1.25 (only UCPL = 0.2)	Maximum increase in TAC of 125% for UCPL = 0.2
		1, 2 (only UCPL = 0.5)	Maximum increase in TAC of 100, 200 % for UCPL = 0.5
		2, 3.5, 5 (only UCPL = 0.8)	Maximum increase in TAC of 200, 350, 500 % for UCPL = 0.8
BSAFE	Biomass safeguard $min\left(1, \frac{I_i}{I_{irigger}}\right)$	Imin	$I_{irigger} = min\ (I_{hist})$
		Iminpa	$I_{irigger} = 1.64 \cdot min\ (I_{hist})$
		Inorm	$I_{irigger} = e^{mean(log(I_1 hist)) - 1.645 \cdot sd(log(I_{hist}))}$
HCRI	HCR initialisation (i.e., reference TAC in the 1st simulation year)	nin	$\frac{\sum_{i=y-m}^{y-1} C_i}{m}$ (for n-over-m rule)

For analysing the performance of the different rules under the alternative operating models, the biological risks (maximum probability of SSB being below the biomass limit B_{lim} in the projection period) and the relative yields (ratio between catches and maximum sustainable yield MSY) were calculated in the short, medium and in the long-term. It must be noted that, according to the ICES precautionary criteria, biological risks are considered acceptable at or below 0.05.

Sensitivity Analysis

We tested the sensitivity of the rules' performance to the coefficient of variation of the survey index (CV_I). As an alternative to the assumed value of 0.25 that was considered a low CV, we considered a high CV equal to 0.5, a CV equal to the IAV in the historical period and a CV twice the IAV in the historical period. These last two cases aimed at exploring the signal-to-noise between the abundance index and the inherent variability of the population itself. The sensitivity analysis was carried out for the following subset of rules: (i) all the rules without any UC, to test the impact of the error in the index observation without any constraints in the TAC changes; and (ii) the 1-over-2 and the 2-over-3 rules with symmetric 80% UCs.

Robustness of the results with respect to the assumptions on the stock productivity and recruitment variability were also tested. Regarding the productivity, the steepness of the Beverton and Holt stock-recruitment model was changed to 0.5 (corresponding to low productivity) and to 1 (for high productivity). For the recruitment variability, values of the standard deviation of the recruitment model were set at 0.5 and 1. This sensitivity analysis was carried out for the following subset of rules: (i) the 1-over-2 rule without any UC; (ii) the 1-over-2 and the 2-over-3 rules with symmetric 80% UCs; and (iii) the 1-over-2 rule with 80% lower and 400% upper UCs.

RESULTS

Life History Characteristics

The two types of stocks simulated had markedly different IAVs (**Figure 2**). Anchovy-like stocks (STK1) had significatively larger IAV than the sprat/sardine-like stocks (STK2). However, the IAV of a given stock was also a function of the initial depletion level (FHIST), the recruitment variability (SIGR) and to a lesser extent of the stock productivity. The IAV tended to increase as exploitation levels, recruitment variability or stock productivity increased.

Given the alternative historical exploitation levels considered, the initial population status for the two stock-types was very different in terms of risks at the beginning of the projection period (**Table 2**). Initial risks were higher for the anchovy-like stocks. For the presumed optimum level of exploitation (F_{proxy} leading to 40%B0), the anchovy-like stock (STK1) had a high initial risk of falling below B_{lim} (equal to 0.12), while for the sprat/sardine-like stock (STK2) this risk was 0.01. For the case of overexploitation initial risks increased to 0.4 and 0.3 respectively, while for the case of under exploitation initial risks were below 0.05 for both types of stocks. If the stocks were allowed to evolve without fishing during the projection period, short term risk for the anchovy was at or above 0.05 for the fully exploited and overexploitation trajectories, while for the sprat/sardine short term risk was above the threshold of 0.05 only for the historical overexploitation trajectory. These risks levels, in the absence of fishery, dropped to zero in the long-term for all the cases.

Rules Comparison Under Base Case (Median Productivity and SIGR = 0.75)

For any given rule, the timing of the advice and management was a major factor in the performance of the rule, both in terms of yield and biological risks. The shorter the lag between observation and management (int > iny > fpa), the bigger were the expected relative yields and the smaller the risks (**Figure 3**). Generally, in-year advice (iny) outperformed the interim year advice (int) and full population advice (fpa) performed better than the other two, by resulting in smaller biological risks and larger relative yields. Although the differences between the iny and fpa advices were minor in comparison to their differences with the int. These effects were clearer in the long than in the short-term. Only in a few cases (mainly for anchovy-like stocks) the shortest time lag (fpa) did not improved the performance of the rules in comparison with the iny in the long-term. Most of these cases corresponded to the 1-over-m rules with lower 20% UC or the 2-over-3 rule without any UC, while for the few remaining cases differences were negligible. All the results from now on will be analysed for the in-year advice.

Figure 4 shows the median trajectories for the two simulated stocks for the standard advice rule for ICES category 3 stocks, namely the 2-over3 rule with a 20% uncertainty cap. During the projection period, median SSB increased, except for historically overexploited (fhigh) sprat/sardine-like stock for which the stock showed a high and increasing probability of collapse during the projection period (**Figure 4**). However, in all the cases, the variability of the SSB trajectories was very high, leading to large biological risks in the short-term (between 0.16 and 0.46 for anchovy-like stocks and between 0.01 and 0.44 for sprat/sardine-like stocks, depending on the initial exploitation status) which were reduced in the long-term for the anchovy-like stocks (to values between 0.09 and 0.27), but were increased for the sprat/sardine-like stocks (to values between 0.02 and 0.52). In all the cases, catch decreased through the time series with the median always remaining below MSY during the projection period (**Figure 4**).

In comparison to the other rules, for the same UC levels, advice rule 2-over-3 resulted in higher risks in the long term (**Figure 5**), and generally above 0.05 (with the only exception for both stocks of using UC(0.8,0.8)). Moreover, the 20% symmetric uncertainty cap, used as a standard in ICES, resulted in risks above 0.05 at historical exploitation levels at or above F_{MSY} for both stock-types and for any trend rule.

In the short-term, differences in the rules' performance were small both in terms of in terms of risks (**Figures 5**, **6**) and yield (**Figure 7**). For all the rules tested, initial depletion levels were the major drivers of risks in the short-term. As historical fishing mortality increased, risks increased. For the historical

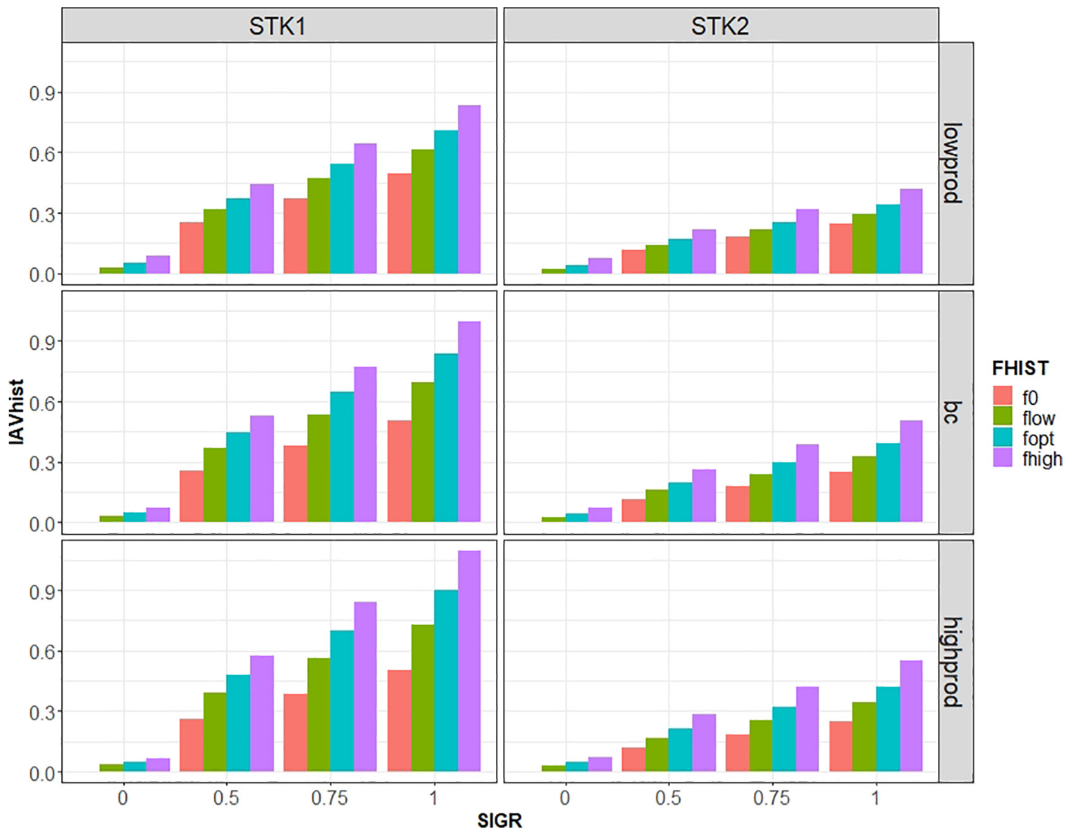


FIGURE 2 | Interannual variation in the historic period (IAVhist) by standard deviation for the recruitment log-normal error (SIGR, x-axis) as a function of the stock type: anchovy-like (STK1) and sprat/sardine-like (STK2); stock productivity: low (lowprod), medium (bc) and high (highprod); and the exploitation level: zero catch (f0), under exploitation (flow), fully exploited (fopt) and overexploitation (fhigh). Interactive version of the figure is available online at https://aztigps.shinyapps.io/Sanchezetal2021_FMS/.

exploitation levels above F_{MSY} all the rules resulted in short-term risks well above the 0.05 precautionary level. This was also seen for the anchovy-like stock (STK1) exploited at an optimum exploitation level, where short-term risks were also above 0.05. In the long term, for every UC level and historical exploitation, rule 2-over-3 had equal or larger relative yield than the 1-over-m respective rules but always with higher risks. Differences among the other rules (1-over-m rules) were smaller in terms of catches and risks at equal UC and historical exploitation level, though in general for the 1-over-m rules, there was a small reduction of catches and risks for the anchovy-like stocks as *m* increased and just the contrary (increased with *m*) for the sprat/sardine-like stocks. In most cases, the 1-over-m rules reduced the risks along time (**Figure 6**), except when applied to fully or overexploited sprat/sardine-like stocks coupled with the UC(0.2,0.25) or UC(0.5,1.5). Alternatively, the 2-over-3 rule did not reduce risks as much as the 1-over-2 rule, and could even result in increased risks particularly for the sprat/sardine-like stocks (except for UC(0.8,0.8) or UC(NA,NA)).

Regarding the effect of the different UCs, for every rule asymmetric UCs had higher relative yields and risks in the short term compared to those with symmetric UC. For the same lower uncertainty cap, the larger the upper uncertainty cap (i.e., the larger the asymmetry), the larger the risks for similar or larger catches. However, differences were small in terms of relative yields for the lower UC (UCL) at 80% (**Figure 7**). Largest risks were usually seen for the UC(0.5,1.5) as it tended to result in the largest allowed catches (**Figure 5**). These effects were amplified in the long term: for all scenarios defined by stock

TABLE 2 | Biological risks for the different OM conditionings (combination of stock -STKN- and initial depletion level -FHIST-) for base case productivity and recruitment standard deviation at 0.75.

STKN	FHIST	Initial risks	Short-term risks (F = 0)	Long-term risks (F = 0)
STK1	flow	0.02	0.01	0.00
	fopt	0.12	0.05	0.00
	fhigh	0.40	0.13	0.00
STK2	flow	0.00	0.00	0.00
	fopt	0.01	0.00	0.00
	fhigh	0.30	0.14	0.00

Initial risks correspond to the probability of falling below B_{lim} in the last historical year and short-term and long-term risks (F = 0) correspond to the maximum expected risks in the absence of catches, in the first 5 and last 10 projection years, respectively.

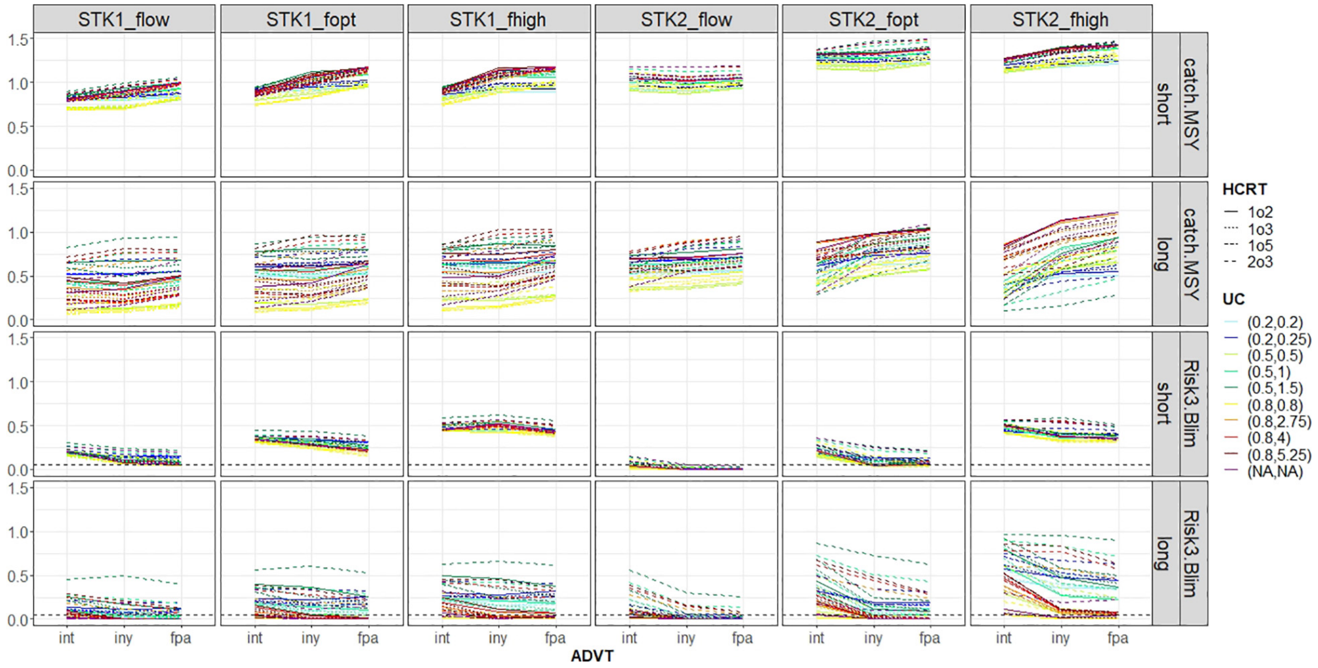


FIGURE 3 | Relative yields (catch/MSY) and biological risks (Risk3.Blim: maximum probability of falling below B_{lim}) by calendar type (ADVT, x-axis) and alternative operating models (in columns). The harvest control rules (HCRT) are represented by line types and uncertainty caps limits (UC) by line colours. See **Table 1** for definitions of abbreviations. The horizontal black dashed line represents the 0.05 biological risk. Interactive version of the figure is available online at https://aztigps.shinyapps.io/Sanchezetal2021_FMS/.

type, historical exploitation level and trend rule, the asymmetric UCs had higher risks than those with symmetric UC and were not always accompanied with higher relative yields. Among the symmetric UCs, UC(0.2,0.2) is the one resulting in highest risks (not always with highest relative yields). UC(0.2,0.2) was non-precautionary regardless the type of HCR (**Figure 5**) for all the OMs, except for the sprat/sardine-like stocks with low historical exploitation levels. For the symmetrical UCs, long-term results showed that in general the larger the interannual percentage of change allowed, the smaller were the risks and, to a lesser extent, the catches, up to the 80% UC. If unconstrained (no UCs), risks showed a sharp decrease along with a relatively minor decrease in catches. The differences in terms of risks between the performance of the rules 1-over-m with 80% symmetric UC and without any UC was minor compared to the increase of catches of the latter case (no UCs). If focusing only on the symmetric UCs, the only rule that was precautionary in the long-term for all simulated OMs was the 1-over-2 rule without any UC or with a symmetric 80% UC. However, the 1-over-2 rule without UC (unconstrained changes) resulted in similar risks for substantially higher catches.

When comparing across all rules in terms of the trade-off between yields and risks, the best rule was the 1-over-2 without any uncertainty cap, as for all OMs it resulted in the highest levels of catches for sustainable risk levels in the long term (**Figure 8**). Subtle differences between stocks might be seen, as for the anchovy-like stocks (STK1) the 1-over-2 rule with UC(0.8,2.75) resulted in slightly higher catches for precautionary level of risks, while for the sprat/sardine-like stocks (STK2) the 1-over-2 rule without any uncertainty cap was the rule producing highest yields for slightly smaller risks. The figure also shows that if in the long-term risks below 0.1 would be acceptable, then 1-over-2 rule with UC(0.8, 4) would result in the largest catches for all OMs keeping risks below 0.1. Overall, this means that for these short-lived fish stocks with base case population dynamics 1-over-2 rule was preferred and should be applied with a large uncertainty cap (as large as UC(0.8,2.75) or UC(0.8,4)) or without setting it, UC(NA,NA), to achieve the best compromises between risks and catches in the long term.

The inclusion of a biomass safeguard in the rules remarkably reduced the risks in the medium and long terms by slightly reducing the relative yields for the fully or overexploited stocks (**Figure 9**). However, the 1-over-2 rule without UC and without biomass safeguard was still among the rules showing the best compromise in catches over risks in the long term for all OMs, complying always with the ICES precautionary criteria. The Inorm biomass safeguard lead to the smallest reduction in relative yields with similar benefits in the reduction of risks as Imin, whilst Iminpa implied bigger loses in yield for very similar risks. In the long term, the asymmetric UC(0.8,4) turned to be precautionary regardless the initial exploitation level when combined with a biomass safeguard. Additionally, the biomass safeguard made the UC(0.2,0.2) precautionary in the long-term. Notably the major differences were driven by the uncertainty cap limits, whereby the symmetric UC(0.8,0.8) implied greater reduction of risks than the others (particularly

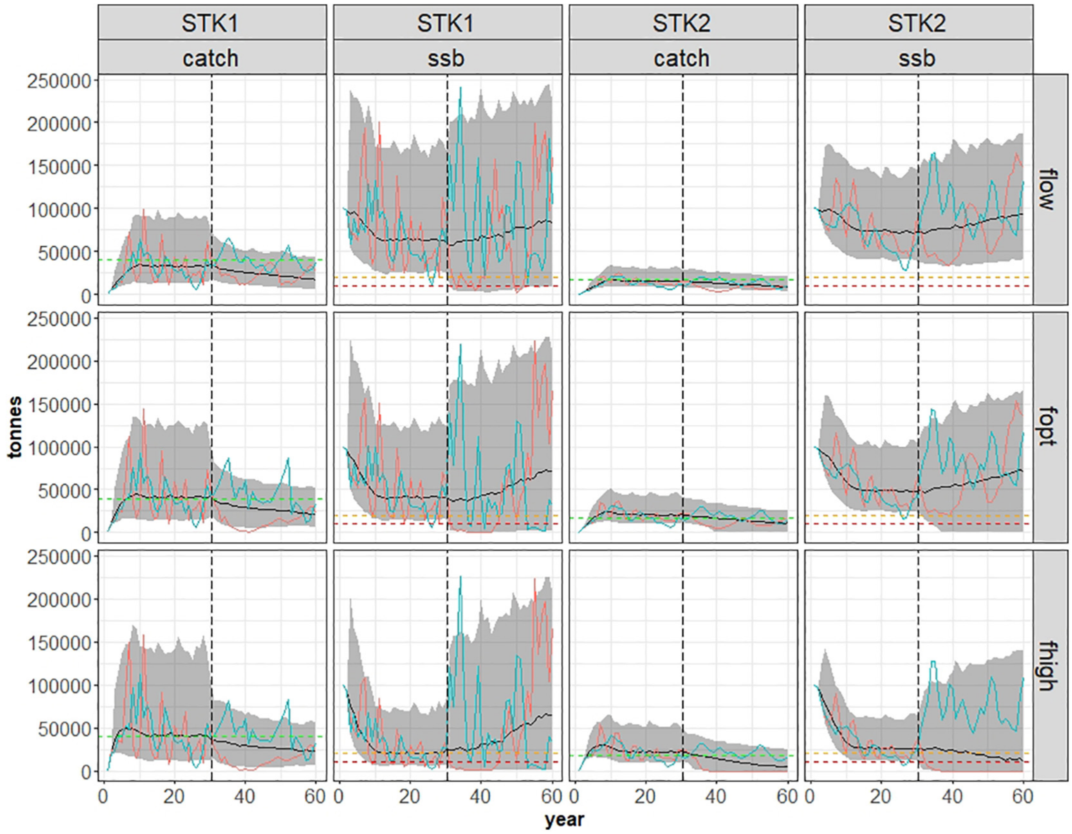


FIGURE 4 | Trajectories of catch and SSB in tonnes along years (x-axis) for the 2-over-3 rule with a 20% uncertainty cap and under an in-year advice for different life histories: stock-types in columns and historical exploitation levels in rows. The solid line represents the median and the shaded area the 90% confidence intervals computed from the 5th and 95th percentiles and coloured lines represent specific iterations. The dashed vertical line is located before year 31, which is the first year of the projection. The dashed horizontal lines represent the different reference points: the green line in catch plots correspond to MSY and orange and red lines in SSB plots to B_{lim} (20% B_0) and $B_{collapse}$ (10% B_0), respectively. Interactive version of the figure is available online at https://aztigps.shinyapps.io/Sanchezetal2021_FMS/.

clear in the medium term). Focussing on the medium term the faster reduction of risks was achieved by rule 1-over-2 with UC(0.8,0.8) and a biomass safeguard of Iminpa.

Sensitivity to Coefficient of Variation of the Survey Index

For all the n-over-m rules without any UC and the 1-over-2 and 2-over-3 rules with symmetric 80% UCs, when the CV of the index increased, the relative yield decreased (**Figure 10**). While, in the case of risks, different patterns were observed depending on stock type and rules. For underexploited anchovy-like stocks and under- or fully exploited sprat/sardine-like stocks, risk increased as CV increased, whereas for the rest of operating models risks decreased or stayed almost unchanged as CV increased. This pattern was more marked for the 2-over-3 rule without UC. However, observed small reduction in risks in the long-term occurred at the expense of a significant reduction in catches. All these effects must be related to the fact that observation errors in surveys implied increased perceived variability of the population (actually $IAV_{obs}^2 = IAV_{OM}^2 + 2 \cdot log\left(CVID^2 + 1\right)$, where IAV_{obs} is the observed IAV, IAV_{OM} is the IAV in the population and *CVID* is the index CV) and this perceived IAV increase induced more pronounced reduction properties of the rules (**Supplementary Annex I**). If the reductions in risks were less relevant than reduction in catches, it was probably related to a poorer signal to noise ratio in the observations of the population when CV of the survey (CVID) increased. In summary, the increase in CVs tended to decrease expected catches because they amplified the reduction properties of the rules through increased perceived IAV, but did not necessarily reduce risks because of the poorer signal to noise information (particularly evident in the sprat/sardine like stock).

Risks increased almost linearly with the IAV (**Figure 11**). In general, the sprat/sardine-like stocks had smaller IAVs than anchovy-like stocks, but at similar IAVs anchovy-like stocks had smaller risks than sprat/sardine-like stocks (**Figure 11**). This was due to the fact that sprat/sardine-like stocks had similar IAVs as anchovy-like stocks only after being historically overexploited (i.e., when the stock was at rather low levels and risks were high), whereas anchovy-like stocks were underexploited (at flow, high biomass levels and low risks). The close relationship between risk and IAV by stocks was very clear in the short term, but in the long

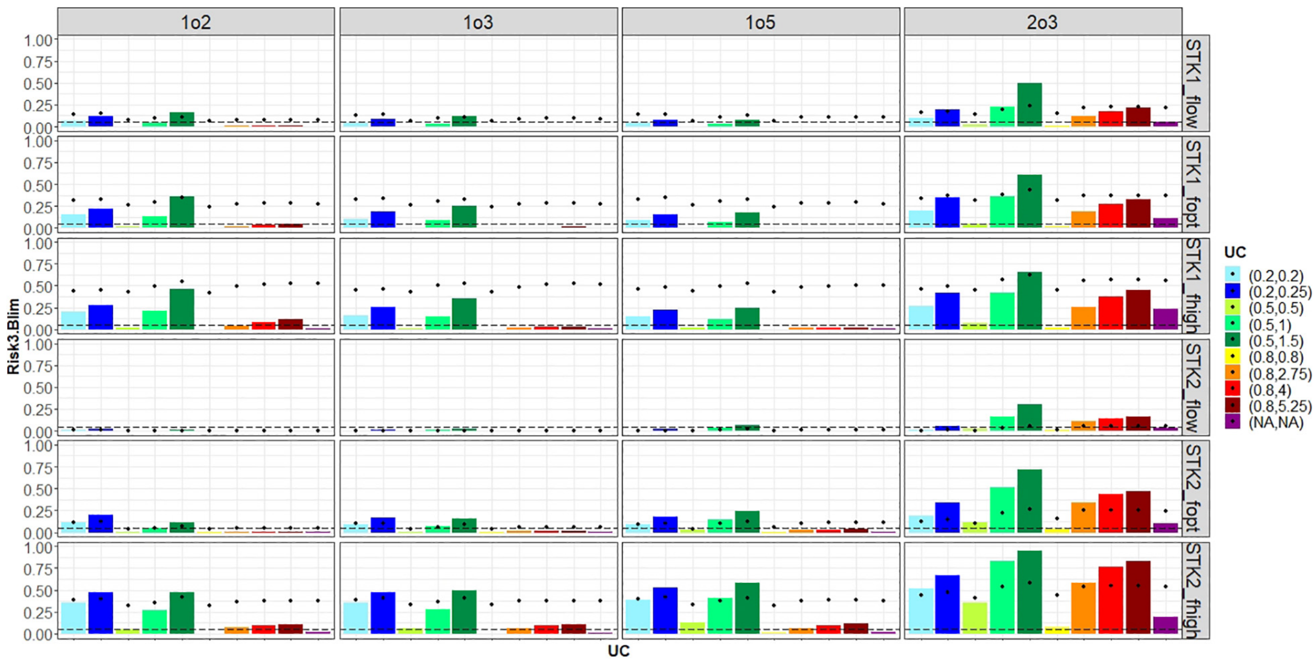


FIGURE 5 | Biological risks (Risk3.Blim: maximum probability of falling below B_{lim}) for the different configurations of the rule in an in-year advice. The rows correspond to the operating models (combination of stock type and the historical exploitation level) and the columns to the harvest control rule type. The uncertainty cap lower and upper limits combinations are represented on the x-axis for alternative timeframes: the black dots represent the risks in the short-term (first 5 projection years) and the colour bars represent the risk in the long-term (last 10 projection years). The horizontal dashed line corresponds to the 0.05 risk. See **Table 1** for definitions of abbreviations. Interactive version of the figure is available online at https://aztigps.shinyapps.io/Sanchezetal2021_FMS/.

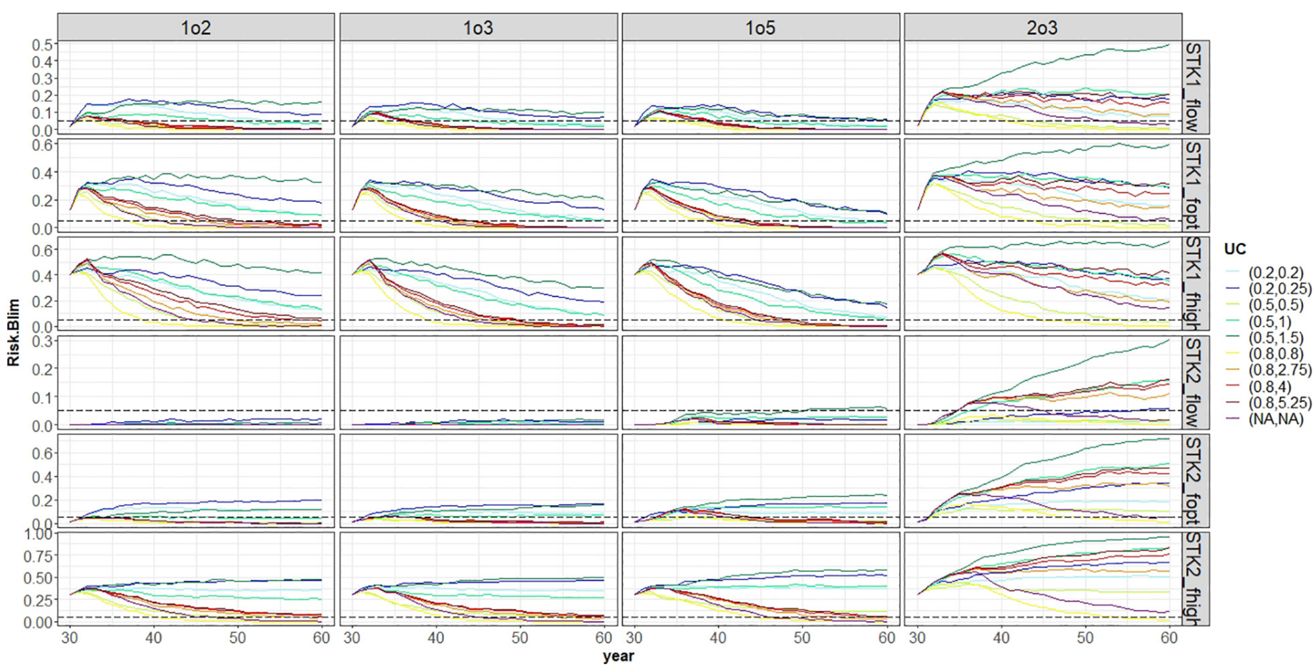


FIGURE 6 | Trajectories of biological risks (Risk3.Blim: maximum probability of falling below B_{lim}) along years (x-axis) under an in-year advice. The rows correspond to the operating models (combination of stock type and the historical exploitation level) and the columns to the harvest control rule type. The uncertainty cap lower and upper limits combinations are represented by different coloured lines. The horizontal dashed line corresponds to the 0.05 risk. See **Table 1** for definitions of abbreviations. Interactive version of the figure is available online at https://aztigps.shinyapps.io/Sanchezetal2021_FMS/.

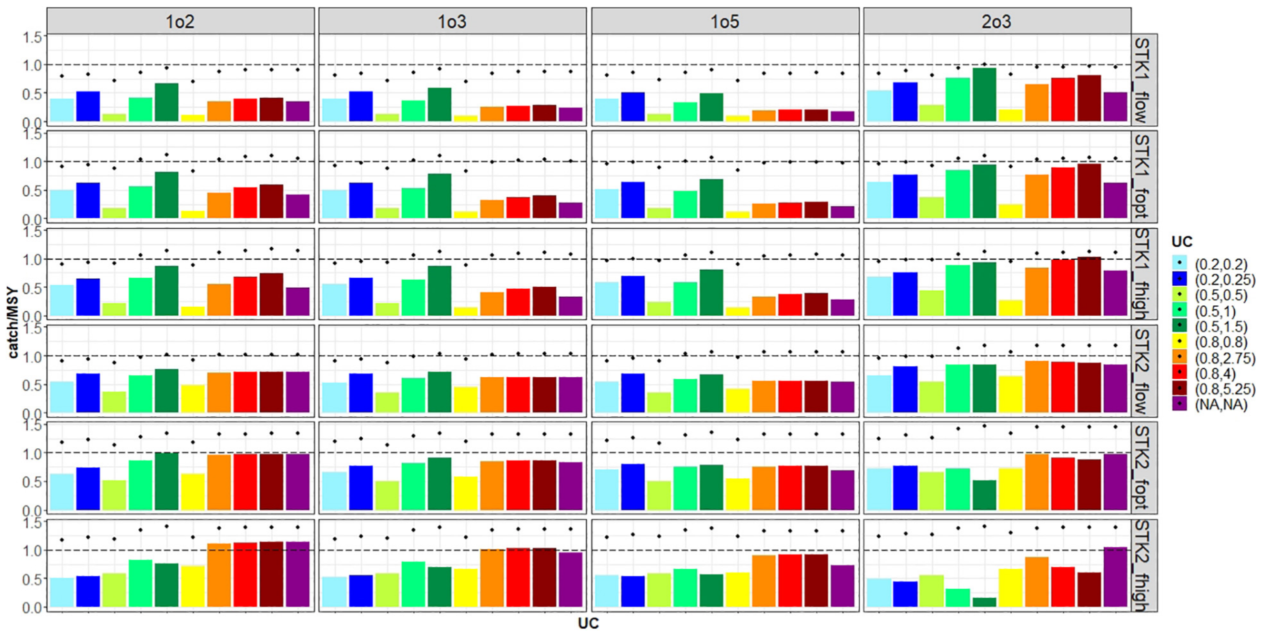


FIGURE 7 | Relative yields (catches/MSY) for the different configurations of the rule in an in-year advice. The rows correspond to the operating models (combination of stock type and the historical exploitation level) and the columns to the harvest control rule type. The uncertainty cap lower and upper limits combinations are represented on the x-axis for alternative timeframes: black dots represent the relative yields in the short-term (first 5 projection years) and the colour bars represent the relative yields in the long-term (last 10 projection years). The horizontal dashed line corresponds to catches at MSY. See **Table 1** for definitions of abbreviations. Interactive version of the figure is available online at https://aztigps.shinyapps.io/Sanchezetal2021_FMS/.

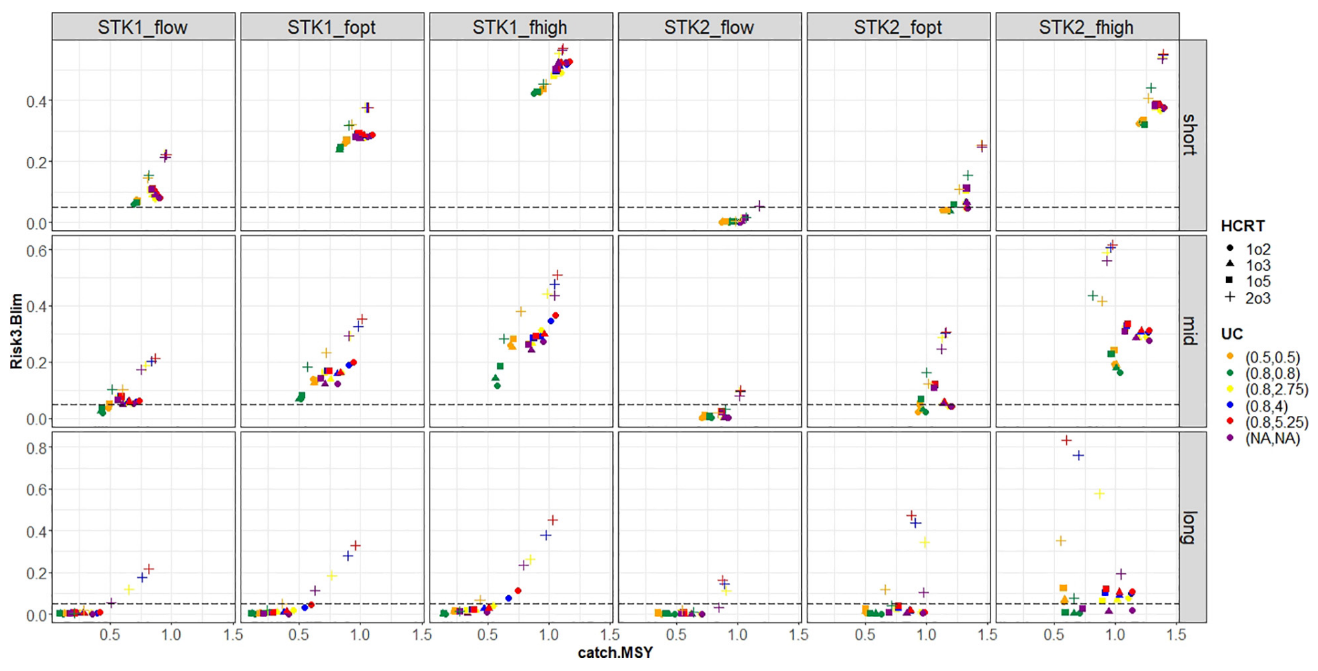


FIGURE 8 | Biological risks (Risk3.Blim: maximum probability of falling below B_{lim}) versus the relative yields (catches/MSY) (x-axis) by rule type (symbols) and uncertainty cap lower and upper limits (colours). The columns correspond to the different OMs (as combination of the stock-type and historical exploitation) and the rows to the temporal scales: the short-term (first 5 projection years), medium-term (next 5 projection years) and the long-term (last 10 projection years). Dashed line corresponds to the 0.05 risk. See **Table 1** for definitions of abbreviations. Interactive version of the figure is available online at https://aztigps.shinyapps.io/Sanchezetal2021_FMS/.

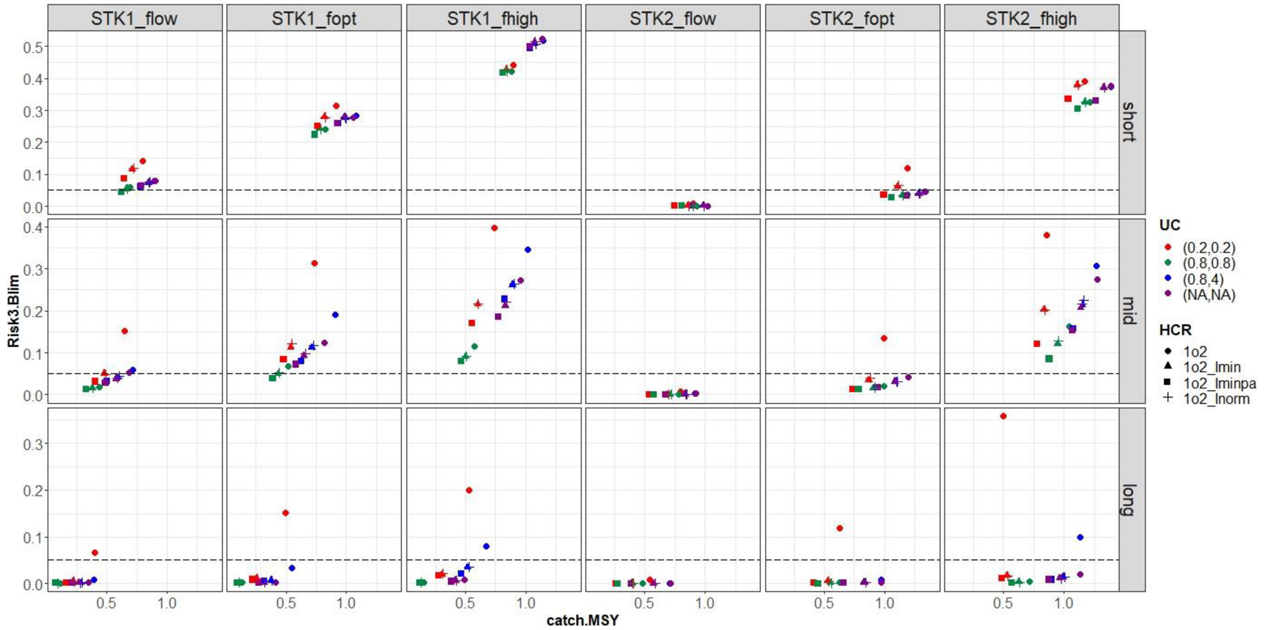


FIGURE 9 | Biological risks (Risk3.Blim: maximum probability of falling below B_{lim}) versus the relative yields (catches/MSY) (x-axis) for the 1-over-2 rule by uncertainty cap lower and upper limits (colours) and biomass safeguards (colours). The columns correspond to the different OMs (as combination of the stock-type and historical exploitation) and the rows to the temporal scales: the short-term (first 5 projection years), medium-term (next 5 projection years) and the long-term (last 10 projection years). Dashed line corresponds to the 0.05 risk. See **Table 1** for definitions of abbreviations. Interactive version of the figure is available online at https://aztigps.shinyapps.io/Sanchezetal2021_FMS/.

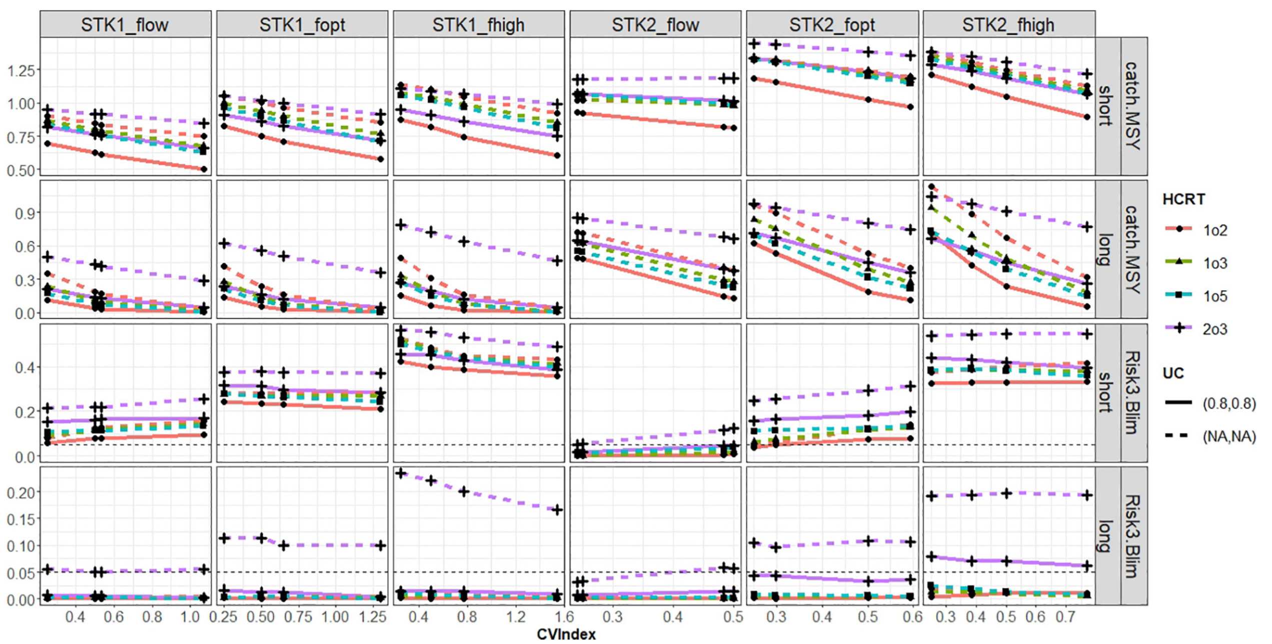


FIGURE 10 | Relative yields (catch/MSY) and biological risks (Risk3.Blim: maximum probability of falling below B_{lim}) in the short- and long-terms (in rows) under an in-year advice for the different CV values of the index (x-axis). The columns correspond to the operating models (combination of stock type and the historical exploitation level). The harvest control rule types are represented by the coloured lines and the uncertainty cap lower and upper limits combinations are represented by the line types (solid line: 80% symmetric uncertainty cap; and dashed line: 20% symmetric uncertainty cap). The horizontal dashed line corresponds to the 0.05 risk. See **Table 1** for definitions of abbreviations. Interactive version of the figure is available online at https://aztigps.shinyapps.io/Sanchezetal2021_FMS/.

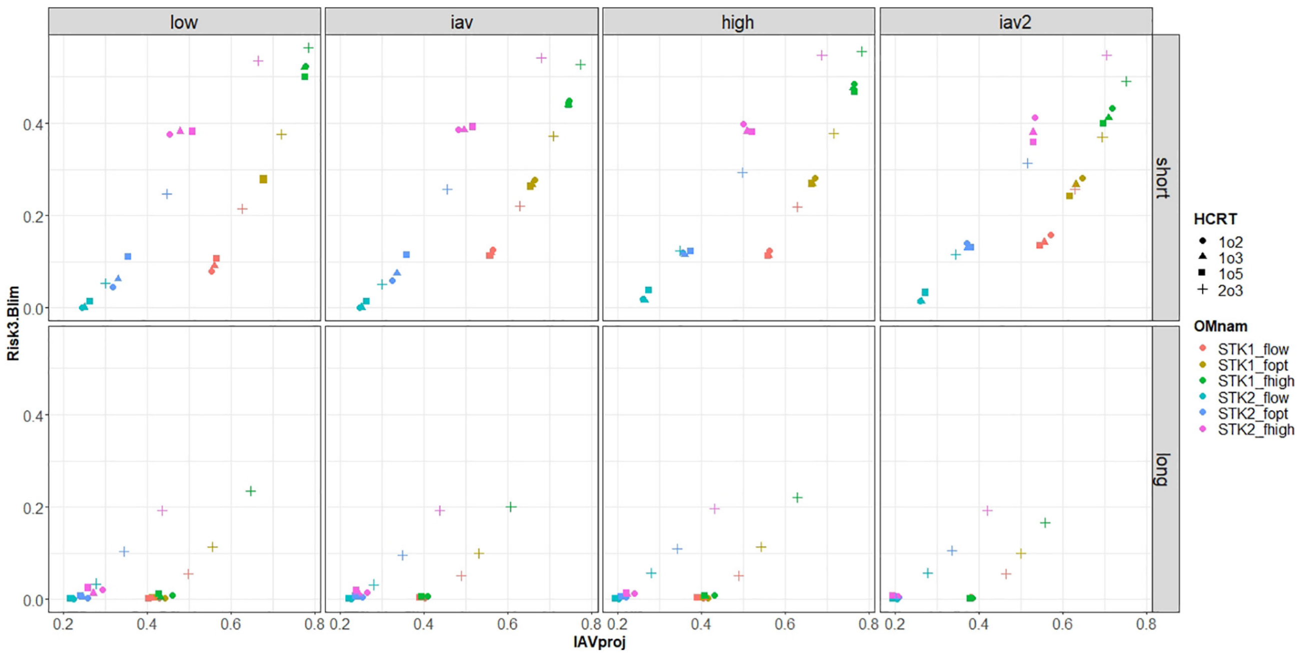


FIGURE 11 | Biological risks (Risk3.Blim: maximum probability of falling below B_{lim}) versus the interannual variability (x-axis) under an in-year advice. The columns correspond to the CVs of the index and the rows to the timeframes: the short-term (first 5 projection years) and the long-term (last 10 projection years). The harvest control rule types without any uncertainty cap are represented by the dot types and the operating models (combination of stock-type and historical exploitation level) are represented by the dot colours. See **Table 1** for definitions of abbreviations. Interactive version of the figure is available online at https://aztigps.shinyapps.io/Sanchezetal2021_FMS/.

term and as a result of a large reduction in the catches, fishing mortality and IAV were greatly reduced.

Sensitivity to the OM Assumptions

For the selected harvest control rules (2-over-3 UC(0.8,0.8) and 1-over-2 rule UC(0.8,0.8), UC(0.8,4.0) and UC(NA,NA)), when the standard deviation of the recruitment increased, risks in the long-term increased for under- or fully exploited stocks; whilst, for overexploited stocks, risks decreased as the standard deviation increased (**Figure 12**). Regarding catches, relative yields tended to decrease, at any historical exploitation level, as the standard deviation of the recruitment increased, except for the case of sprat/sardine-like stocks under the 1-over-2 rule with either UC(0.8,4) or UC(NA,NA), where the relative yields increased (**Figure 13**).

Regarding the sensitivity to the productivity level, in the long-term, relative yields and risks decreased as productivity levels increased. The reduction in risks was greater than those observed in catches (**Figures 12**, **13**).

DISCUSSION

In this work we have tested by simulation the performance of the ICES advice rules for category 3 stocks for the case of short-lived fish. The default 2-over-3 rule with 20% UC (ICES, 2012a) resulted to be not precautionary as it implied long term biological risks above 5%. As an alternative, 1-over-2 rule unconstrained by any uncertainty cap or the 1-over-2 rule including a biomass safeguard with 80% lower and 400% upper uncertainty caps accommodated better to the highly fluctuating nature of the short-lived stocks, resulting in precautionary risk levels in the long term.

In the last years, empirical harvest control rules that set the management actions based on directly observable indicators rather than from stock assessment models are increasingly being proposed for data-limited stocks (Bentley and Stokes, 2009a; Dowling et al., 2015). In particular, empirical rules that included an abundance index providing a precise estimate on stock status have been shown to perform better than those that lack such an index (Carruthers et al., 2014; Geromont and Butterworth, 2014). The catch trend rules considered in this work, including the ICES advice rule for category 3 stocks, are within this type of empirical harvest control rules and they aim at managing the stocks by modifying the advice according to changes in stock status obtained from an abundance index. However, for a short-lived fish the value of any index would be limited in time as the populations are largely renewed year after year according to the strength of recruitment. For this reason, the guidance provided by any index on the target managed population degrades with time and can become misleading if the fraction of the managed population informed by the index is not sufficiently representative. This explains why a key factor determining the performance of the rules for short-lived fish was the time lag between the abundance index and the management calendar. From the three management calendars evaluated, the shorter the

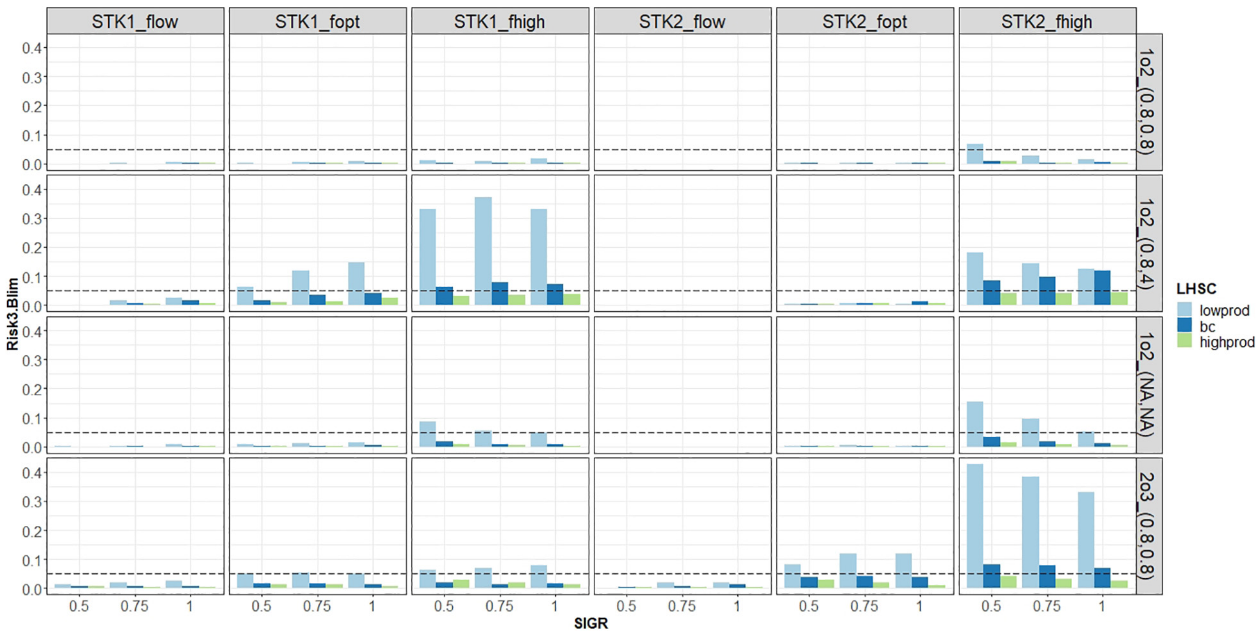


FIGURE 12 | Biological risks (Risk3.Blim: maximum probability of falling below B_{lim}) in the long-term (last 10 projection years) versus the standard deviation of recruitment (x-axis) and stock productivity (colours) under an in-year advice. The columns correspond to the alternative OMs (as combination of the stock-type and historical exploitation) and the rows to the configurations of the rule (harvest control rule type and uncertainty cap lower and upper limits). Dashed line corresponds to the 0.05 risk. See **Table 1** for definitions of abbreviations. Interactive version of the figure is available online at https://aztigps.shinyapps.io/Sanchezetal2021_FMS/.

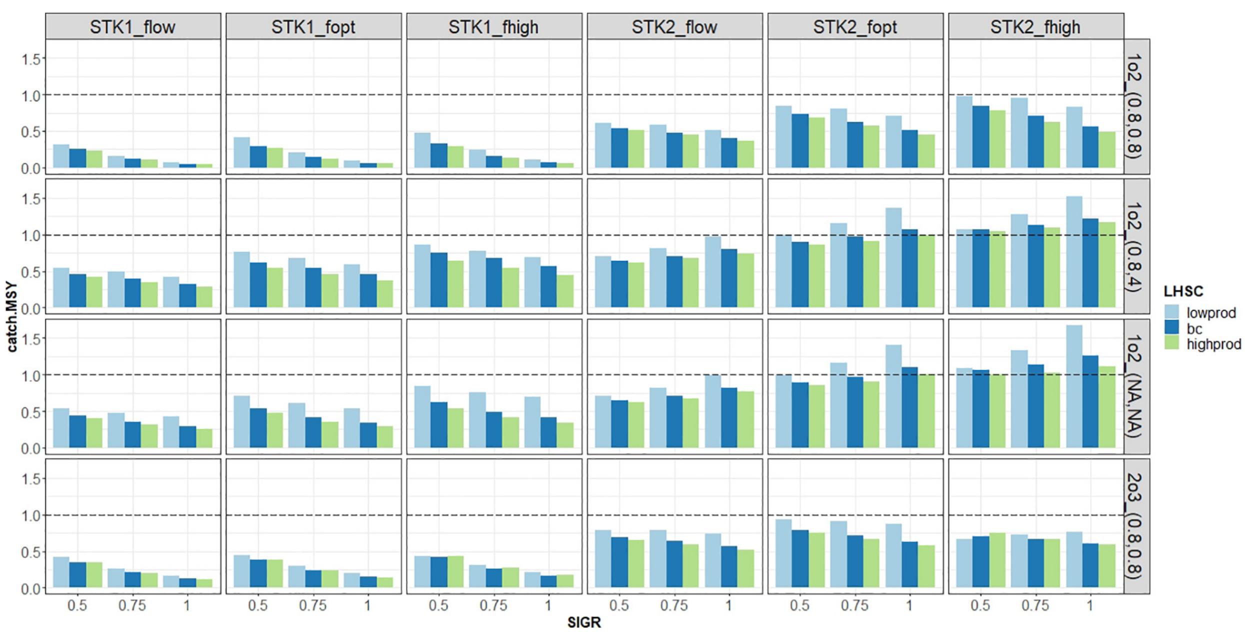


FIGURE 13 | Relative yields (catches/MSY) in the long-term (last 10 projection years) versus the standard deviation of recruitment (x-axis) and stock productivity (colours) under an in-year advice. The columns correspond to the different OMs (as combination of the stock-type and historical exploitation) and the rows to the configurations of the rule (harvest control rule type and uncertainty cap lower and upper limits). Dashed line corresponds to catches equal to MSY. See **Table 1** for definitions of abbreviations. Interactive version of the figure is available online at https://aztigps.shinyapps.io/Sanchezetal2021_FMS/.

time lag between the observed index and the application of the management advice, the bigger were the catches and the smaller were the biological risks. In the interim year advice, there was a time lag of about a year between the index and the management calendar, so that the TAC was set without any indication of the age 1 class which would form the bulk of the population. Moving the management calendar to July-June, as soon as the abundance indices were available, allowed for the in-year management to reduce this time lag to just half a year and allowed gaining information on all age classes sustaining the second half of the year catches and all except age 1 of the next (first) half of the following year catches. This in-year management procedure has been applied successfully in the case of the Bay of Biscay anchovy where, after the stock collapse in 2005, such a change in the management calendar allowed to reopen the fishery with a management plan based on the most recent biomass estimates from the spring fishery independent surveys (Sánchez et al., 2018). Other successful applications are the joint management procedure for the multispecies South African pelagic fishery where a within-season revision of the anchovy TAC based on the most recent surveys allowed a better utilisation of the anchovy resource (De Oliveira and Butterworth, 2004) or the Australia's Prawn Fisheries where the timing of the fishing season was adjusted during the year based on the assessed status of one of the tiger prawn species (Dichmont et al., 2006b; Anon, 2014, 2018). Interim and in-year advices have been also compared by Fischer et al. (2020), who found that including more recent data and setting the TAC yearly improved the performance of the empirical catch rule. The full-population advice calendar, in which the abundance index provides information on all exploited age classes over the entire management year, as for instance when a pre-recruit survey index is available, entailed further improvements with respect to the other management calendars. Early indication of recruitment strength have already been demonstrated to be beneficial in other works (Dichmont et al., 2006a; Le Pape et al., 2020). However, the improvement over the in-year procedure was smaller than that between the interim and the in-year advice procedures. For the Bay of Biscay anchovy, Sánchez et al. (2018) showed that the benefit of the full population advice procedure over the in-year advice was also moderate, as catches increased by 15% for the same level of allowable risks.

In relation with the former considerations, we expected that the 1-over-m rules would have a better performance (compromise between risks and relative yields) in managing these short-lived fish than the 2-over-m rules, as the later would incorporate in the numerator the obsolete index of year (*y-1*), hence not improving the information on the managed population. Furthermore, the 2-over-3 rules had lesser reduction properties of fishing opportunities in time than the 1-over-m rules. This was confirmed when comparing the rule 2-over-3 by UCs with any of the 1-over-m rule for the same stock and historical exploitation, as the latter achieved a substantial reduction of risks for lesser reductions of catches in all cases. The poor performance of this rule for the simulated stocks was in agreement with (Fischer et al., 2020) who demonstrated that the 2-over-3 rule performed very poorly for more productive stocks (i.e., with $k > 0.32$ year^{-1}), which was the case of our simulated short-lived fish stocks (with $k = 0.89$ and $k = 0.56$ for anchovy-like and sprat/sardine-like stocks, respectively). By definition, the 2-over-3 rule smooths interannual changes in the stock indicator to obtain stock trends over the last five years, but for short lived species interannual changes are usually far larger than the medium-term trends in the stock and therefore 1-over-m rules have the power of better updating to the interannual changes conditioned to in-year advice management procedure. Rule 2-over-3 with UC(0.2,0.2) was devised at preventing the advice to push the exploitation to unlikely high or low levels because of abnormally high noisy observations. However, it was developed for stocks with lower interannual variability (stocks with longer lifespans which have substantial inertia over time) and therefore was not able to accommodate the high natural interannual fluctuations characteristic of the short-lived fish stocks (Barange et al., 2009; Checkley et al., 2017). As an alternative, the 1-over-m rules (those which select only the latest survey index in the numerator) were more reactive to the biomass fluctuations.

In general, the performance of the three 1-over-m rules tested were very similar within stocks, with some tendency of faster reduction of catches as m increased leading in the long term to smaller catches for both stocks for the larger m rules for all UCs (less intense in the sprat/sardine-like stocks) and to decreased risks but only for the anchovy-like stocks. The reasons for the different behaviour of the rules was partly related to the reduction properties of the rules (**Supplementary Annex II**). For instance, the tendency among the 1-over-m rules to produce smaller catches as m increased for slightly smaller levels of risks was a direct result of such mechanistic reduction properties, because the reduction effects for a fixed n became more pronounced as m increased. In addition, the stronger reduction of relative catches and risks for anchovy than for sardine/sprat like stocks for the same harvest control rules was a direct effect of the larger IAV of the anchovy-like stocks, because the larger the IAV the larger the reduction of the fishing opportunities in time produced by the rules.

Among these rules, we have seen that those with more restrictive UC (i.e., UC(0.2, 0.2) or UC(0.2, 0.25)) or with asymmetrical lower 50% UC (that is UC(0.5,1) or UC(0.5,1.5)) resulted in the poorest performance in terms of risks. The asymmetric rules with UCL of 50% (with UCU > UCL as tested here) were much more restrictive in reducing the catch options (as a maximum reduction of 50% was allowed) compared to facilities to increasing catches (with allowed increase up to 100% or 150%), diminishing the decreasing properties of the 1-over-m rules in comparison with the unconstrained application of the rules (i.e., UC(NA,NA)) or with the rest of the rules. The UC(0.5,0.5) resulted in lower catches and risks since such UC range increased the reduction properties of the rule compared to the unconstrained application (see further evidence in **Supplementary Annex II**). In general, larger UCs were expected to have an increased capability to accommodate the advice to rapid stock fluctuations. Our results supported this conclusion as for all rules of the type 1-over-m, the widest UC ranges (UC(0.8,*)) resulted in smallest risks in the long term (always below 0.11) with the highest relative yields (i.e., catches/MSY). It is remarkable that no application of any uncertainty cap, UC(NA,NA), resulted in a robust rule which was sustainable in the long term for the two stocks or for any past historical exploitation of the stock, with allowable catches in the long-term as high as those allowed by UC(0.8,2.75). This result questions the need of any UC for short-lived fish species.

The addition of a biomass safeguard to the rules increased the reduction properties of the rules: faster with the Iminpa in the medium term, but with better balance between catch options for precautionary risk levels with the Inorm in the long term. The inclusion of the Inorm biomass safeguard allowed increasing the upper UC limit up to 400% (1-over-2 with UC(0.8,4) and Inorm), still precautionary for all the stocks independently of their starting depletion level, but not overcoming the balance showed in the long term by the unconstrained 1-over-2 (UC(NA,NA)).

Consequently, the balance between catches and risks (or risk per ton caught) favoured the adoption of the rule 1-over-2 rule, versus the 1-over-3 and 1-over-5 rules. Furthermore, in the medium term the best uncertainty caps associated to that rule were those with UC(0.8,0.8), while in the long term performed best with no UC (unconstrained, UC(NA,NA)) or with UC(0.8,4) when coupled with the Inorm biomass safeguard. The former indications are applicable to any short-lived fish as we have shown them to be robust to the different stock types and historical exploitation levels of the stock before management. However, we have seen that the optimum combination of rule type and UCs depended partly on the stock life-history characteristics. This means that, when possible, it would be desirable to identify which is the best harvest control rule for each case study by simulation testing (as defined by the combination of the trend rule, the UC and the biomass safeguard). Therefore, our current work serves for providing general guidelines, but it is still recommended, when available knowledge on the stocks allows it, to fine-tune the rules, as suggested by several authors (Walsh et al., 2018; Fischer et al., 2020). Carruthers et al. (2016) suggested that often tuning MPs for specific stocks is important, though this may not be viable in data-poor assessment scenarios because of insufficient data and analysis resources, as for instance in Sagarese et al. (2019).

None of the trend rules we have tested can assure in the short and medium terms that biological risks will be lower than 5%, as this would basically depend upon the initial depletion levels, though in the long term many of these rules became precautionary. Therefore, the selection of any rule should be based more on the relative performance of these rules in time (i.e., on the speed of reducing risks to precautionary levels relative to the final catches which would be allowed). Clarifying the time framework (medium or long) over which a specific reduction of risk is required and the potential or real frequency of biomass assessments, can guide the selection of a specific rule.

Different IAV for the two types of stocks modelled was an important factor to explain the distinct behaviour of the tested rules. As we have shown theoretically, the larger the IAV the larger the reduction of the fishing opportunities through time produced by the rules. Actually, the theoretical inverse relationship between IAV and risks for a given rule was evidenced by our simulations. Anchovy-like stocks had significatively larger IAV than the sprat/sardine-like stocks, something probably related to the higher M of anchovies (i.e., higher dependence on recruitment variability and lesser inertia of the stock). Therefore, the reduction properties of any rule were increased for anchovy-like species compared to sprat/sardine-like stocks and consequently the initial risks would be more rapidly reduced in time for the anchovy-like stocks. And, in general, same outcome is expected for stocks with high natural mortality like anchovies. In addition, for each stock, IAV was demonstrated to be a function of the recruitment variability, the productivity, and the historical exploitation level, among other factors, being positively correlated with these three factors. In addition, it is evident that the CV of the surveys impacted the observed interannual variability of the stock through the monitoring system, so that the larger the IAV in the population, the larger will be the observed IAV in the indices and consequently this will amplify the reduction properties of the rules. Fischer et al. (2020) demonstrated that both the variability of the stock and of survey indices were important factors in determining the performance of catch rules. This is in accordance with our observed different performance of the rules for the two defined stock types, leading to slightly different selection of the optimal management strategy in each case. Cost-benefit analysis of reducing the index CV or adding new surveys could be conducted in the future. We have shown for the two stocks that risk and IAV are positively related; this is explained by the fact that high F implies higher risks and larger variability (lesser inertia of the stocks), for the same reason as exploitation declined, risk decreased as F and IAV decreased. This also explains why for the same IAV the risks were not the same for the two stocks, as they were associated with quite different exploitation levels for each stock type.

Barange et al. (2009) concluded that the most effective monitoring programmes for small pelagic fish were based on fishery-independent surveys that provided precise information of the state of the stocks. The precision of the survey index was shown to impact the performance of the rules. As an increase in the precision of the index lead to higher catches during the whole projection period (relationship inverse to CV for the two stocks). At the same time, we have seen that for the 1-over-m rules risks were relatively insensitive to the CV of surveys. This was probably due to the fact that we had two contrasting effects as CV increased. On the one hand, the observed IAV increased and catches decreased so risks should in principle decrease. But, on the other hand, as CV increased the signal to noise ratio decreased and therefore the risks should increase. In summary, we obtained for overexploited stocks that the highest relative catches over MSY were only obtained at low CV for the indices, as higher CV would imply significant reductions of catches for similar levels of risks in the long term. Therefore, investments to improve survey precision (CV) could be justified on the basis of allowing sustainable and relatively high yields (with low biological risks to B_{lim}), while avoiding undue losses of catch options.

In this work, F_{MSY} was approximated by $F_{40\%B0}$, the fishing mortality leading to 40% of the virgin biomass (Punt et al., 2014). However, the depletion level at the beginning of the simulation period was not as intended for anchovy-like stocks. Under full exploitation ($F_{40\%B0}$) the biological risks for the anchovy-like stocks were around 12% and the catch was 1.02 MSY. Therefore, the F_{MSY} proxy adopted for this stock seemed to be too high and hence, some lower levels (e.g., $F_{50\%B0}$) could have been adopted as applied in some small pelagic populations (Barange et al., 2009). The starting depletion level was a major factor driving the risks, especially in the short term (at the beginning of the management period), but often still noticeable in the long-term. In fact, the identification of most suitable HCR may change according to the initial depletion level of the stock. Therefore, an early indication of the actual exploitation level of the stock is of importance in identifying optimal HCRs. Furthermore, if an initial assessment of the current exploitation levels relative to F_{MSY} were available, the currently used reference TAC could be corrected with this F_{MSY} indicator. That is, for a n-over-m rule, a reference TAC could be calculated as the mean catches in the last *m* years multiplied by the inverse of the ratio between the mean fishing mortality in the last *m* years over $F_{MSY.}$ As if the initial harvest rate was set to appropriate levels that reduced the risks in the short-term, the rules were expected to reach sustainable levels in a shorter timeframe. Dowling et al. (2019) recommend embedding data-limited assessment methods (DLMs) within data-limited harvest strategies since precautionary HCRs can compensate for poor estimates of stock status by DLMs.

The selected n-over-m rules do not always seem to be optimal in terms of catches, as yields often fall below MSY as in Jardim et al. (2015) and Fischer et al. (2020). Our study reveals the strengths and limitations of the trend-based catch rules of the type n-over-m (with n < m) when applied to short lived stocks. In order to reduce risks these rules should be of the type 1-over-m to be reactive enough to the relatively rapid increases and falls of these stocks, otherwise they can easily tend to increase risks as happened with many of the 2-over-3 rules. Among the 1-over-m rules, those with symmetric wide UCs (UC(0.8,0.8)) will reduce harvest rates and risks toward precautionary levels in about 10 years (medium term), faster than those with asymmetric UCs or unconstrained (UC(NA,NA)), whilst the later unconstrained rules are those achieving highest catches relative to those expected for the F_{MSY} (or relative yields) at precautionary risk levels in the long term (30 years). For these reasons, ICES is considering recommending the application of the former (1-over-2 with UC(0.8,0.8)) over the unconstrained 1-over-2 rule for managing short-lived data-limited fish stocks (ICES, 2020d). However, these rules achieve these goals due to their mechanistic properties of gradually reducing yields, shown here theoretically and by simulation. The reduction effects on catches and risks are continuous in time and basically independent from the historical exploitation of the stock, not necessarily leading or stabilizing them at sustainable levels (around F_{MSY}). In our simulations, this implied for all exploitation levels that the application of these rules would successfully reduce catches and risks to precautionary levels in the medium term, but if applied for too long will reduce yields below F_{MSY} accompanied by unnecessary further reductions of risks. For underexploited stocks, unnecessary loses of catches will also occur. Therefore, the application of these rules should be considered as interim provisional approaches for the management of short-lived data-limited fish until a better assessment of stock status and of harvest levels relative to F_{MSY} are available. To move the exploitation toward F_{MSY}, an alternative approach to an assessment could be to complete the rule with a multiplier relative to an indicator of F_{MSY} obtained from the catches, as in Fischer et al. (2020). However, the latter authors were not successful in the tunning the rule for stocks with high growth (von Bertalanffy's parameter *k*), typical for shorter lived species. Another alternative approach to a complete assessment of F_{MSY}, could be the search for a precautionary harvest rate for these short-lived data-limited fish according to their particular life-history. This harvest rate should be robust to the suspected variability and catchability of the survey monitoring system (if one exists). In this way, such a constant harvest rate (1-over-1 rule) could be applied annually to the stock index to provide the catch advice for the subsequent management year (Dichmont and Brown, 2010; ICES, 2020d). This strategy could be convenient for species that live less than 2 years old.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://github.com/ssanchezAZTI/WKDLSSLS_paperFRONTIERS.

AUTHOR CONTRIBUTIONS

AU conceived the research. SS-M carried out the simulation work, completed the first draft. LC solved the equations in **Supplementary Annex II**. SS-M and LI developed the Shiny App with the interactive version of the figures. All authors contributed to the definition of the theoretical framework of present work and structure of the manuscript, discussed the results, contributed to the final manuscript, and approved the submitted version.

FUNDING

This work was funded by the Dirección de Pesca del Gobierno Vasco (Spain), through PELAGICOS ("Small pelagics: asessment, biology and stocks dynamics") and IMPACPES ("Developing tools to estimate the bio-economic impact of the fisheries management") projects.

ACKNOWLEDGMENTS

The authors would like to thank the productive discussions with the members of the ICES Workshop on Data-limited Stocks of Short-lived Species (WKDLSSLS) and the work of the two reviewers that has contributed to improve our work. Special thanks to María Korta and Guillermo Boyra for their help to build the Shiny app with the interactive figures. This manuscript is contribution No. 1030 from AZTI, Marine Research, Basque Research and Technology Alliance (BRTA).

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2021.662942/full#supplementary-material

REFERENCES

Anon (2014). *Shark Bay Prawn Managed Fishery Harvest Strategy 2014 – 2019*. Version 1.1 (November 2014). Fisheries Management Paper 265. Perth WA: Department of Fisheries.

Anon (2018). *Exmouth Gulf Prawn Managed Fishery Harvest Strategy 2014 – 2019*. Version 1.1 (July 2018). Fisheries Management Paper 265. Perth, WA: Department of Primary Industries and Regional Development.

Barange, M. A., Bernal, M., Cergole, M. C., Cubillos, L. A., Cunningham, C. L., Daskalov, G. M., et al. (2009). "Current trends in the assessment and management of stocks," in *Climate Change and Small Pelagic Fish*, eds D. Checkley, J. Alheit, Y. Oozeki, and C. Roy (New York, NY: Cambirdge University Press), 191–255.

Beddington, J. R., Agnew, D. J., and Clark, C. W. (2007). Current problems in the management of marine fisheries. *Science* 316, 1713–1716. doi: 10.1126/science.1137362

Bentley, N., and Stokes, K. (2009a). Contrasting paradigms for fisheries management decision making: how well do they serve data-poor fisheries? *Mar. Coast. Fish.* 1, 391–401. doi: 10.1577/c08-044.1

Bentley, N., and Stokes, K. (2009b). Moving fisheries from data-poor to data-sufficient: evaluating the costs of management versus the benefits of management. *Mar. Coast. Fish.* 1, 378–390. doi: 10.1577/c08-045.1

Carruthers, T. R., Kell, L. T., Butterworth, D. D. S., Maunder, M. N., Geromont, H. F., Walters, C., et al. (2016). Performance review of simple management procedures. *ICES J. Mar. Sci.* 73, 464–482. doi: 10.1093/icesjms/fsv212

Carruthers, T. R., Punt, A. E., Walters, C. J., MacCall, A., McAllister, M. K., Dick, E. J., et al. (2014). Evaluating methods for setting catch limits in data-limited fisheries. *Fish. Res.* 153, 48–68. doi: 10.1016/j.fishres.2013.12.014

Checkley, D. M. Jr., Asch, R. G., and Rykaczewski, R. R. (2017). Climate, anchovy, and sardine. *Annu. Rev. Mar. Sci.* 9, 469–493. doi: 10.1146/annurev-marine-122414-033819

Costello, C., Ovando, D., Hilborn, R., Gaines, S. D., Deschenes, O., and Lester, S. E. (2012). Status and solutions for the world's unassessed fisheries. *Science* 338, 517–520. doi: 10.1126/science.1223389

De Oliveira, J. A. A., and Butterworth, D. S. (2004). Developing and refining a joint management procedure for the multispecies South African pelagic fishery. *ICES J. Mar. Sci.* 61, 1432–1442. doi: 10.1016/j.icesjms.2004.09.001

Dichmont, C. M., and Brown, I. W. (2010). A case study in successful management of a data-poor fishery using simple decision rules: the queensland spanner crab fishery. *Mar. Coast. Fish.* 2, 1–13. doi: 10.1577/c08-034.1

Dichmont, C. M., Deng, A., Punt, A. E., Venables, W., and Haddon, M. (2006a). Management strategies for short-lived species: the case of Australia's Northern Prawn Fishery. 1. Accounting for multiple species, spatial structure and implementation uncertainty when evaluating risk. *Fish. Res.* 82, 204–220. doi: 10.1016/j.fishres.2006.06.010

Dichmont, C. M., Deng, A., Punt, A. E., Venables, W., and Haddon, M. (2006b). Management strategies for short lived species: the case of Australia's Northern Prawn Fishery. 2. Choosing appropriate management strategies using input controls. *Fish. Res.* 82, 221–234. doi: 10.1016/j.fishres.2006.06.009

Dichmont, C. M., Punt, A. E., Dowling, N., De Oliveira, J. A. A., Little, L. R., Sporcic, M., et al. (2015). Is risk consistent across tier-based harvest control rule management systems? A comparison of four case-studies. *Fish Fish.* 17, 731–747. doi: 10.1111/faf.12142

Dick, E. J., and MacCall, A. D. (2011). Depletion-Based Stock Reduction Analysis: a catch-based method for determining sustainable yields for data-poor fish stocks. *Fish. Res.* 110, 331–341. doi: 10.1016/j.fishres.2011.05.007

Dowling, N. A., Dichmont, C. M., Haddon, M., Smith, D. C., Smith, A. D. M., and Sainsbury, K. (2015). Empirical harvest strategies for data-poor fisheries: a review of the literature. *Fish. Res.* 171, 141–153. doi: 10.1016/j.fishres.2014.11.005

Dowling, N. A., Smith, A. D. M., Smith, D. C., Parma, A. M., Dichmont, C. M., Sainsbury, K., et al. (2019). Generic solutions for data-limited fishery assessments are not so simple. *Fish Fish.* 20, 174–188. doi: 10.1111/faf.12329

FAO (2011). *Review of The State of World Marine Fishery Resources*. Fao Fisheries And Aquaculture Technical Paper 569. Rome: FAO, 334.

Fischer, S. H., De Oliveira, J. A. A., and Kell, L. T. (2020). Linking the performance of a data-limited empirical catch rule to life-history traits. *ICES J. Mar. Sci.* 77, 1914–1926.

Freón, P., Cury, P., Shannon, L., and Roy, C. (2005). Sustainable exploitation of small pelagic fish stocks challenged by environmental and ecosystem changes: a review. *Bull. Mar. Sci.* 76, 385–462.

García, D., Sánchez, S., Prellezo, R., Urtizberea, A., and Andrés, M. (2017). FLBEIA: A simulation model to conduct Bio-Economic evaluation of fisheries management strategies. *SoftwareX* 6, 141–147. doi: 10.1016/j.softx.2017.06.001

Geromont, H. F., and Butterworth, D. S. (2014). Generic management procedures for data-poor fisheries: forecasting with few data. *ICES J. Mar. Sci.* 72, 251–261.

Geromont, H. F., and Butterworth, D. S. (2015). Generic management procedures for data-poor fisheries: forecasting with few data. *ICES J. Mar. Sci.* 72, 251–261. doi: 10.1093/icesjms/fst232

Gislason, H., Daan, N., Rice, J. C., and Pope, J. G. (2010). Size, growth, temperature and the natural mortality of marine fish. *Fish Fish.* 11, 149–158. doi: 10.1111/j.1467-2979.2009.00350.x

ICES (2012a). *ICES Implementation of Advice for Data-limited Stocks in 2012 in its 2012 Advice*. Lisbon: ICES, 40.

ICES (2012b). *Report of the Workshop on the Development of Assessments based on LIFE History Tratits and Exploitation Characteristics (WKLIFE)"*. Lisbon: ICES.

ICES (2014). *Report of the Workshop on the Development of Quantitative Assessment Methodologies Based on Life-History traits, Exploitation Characteristics and Other Relevant Parameters for Data-limited Stocks (WKLIFE IV)"*. Lisbon: ICES.

ICES (2017). ICES fisheries management reference points for category 1 and 2 stocks. *ICES Ad. Tech. Guid.* doi: 10.17895/ices.pub.3036

ICES (2019). Advice basis. *ICES Ad. Basis.* doi: 10.17895/ices.advice.5757

ICES (2020a). Baltic fisheries assessment working group (WGBFAS). *ICES Sci. Rep.* 2:643. doi: 10.17895/ices.pub.6024

ICES (2020b). Herring assessment working group for the area south of 62° N (HAWG). *ICES Sci. Rep.* 2:1151. doi: 10.17895/ices.pub.6105

ICES (2020c). Ninth workshop on the development of quantitative assessment methodologies based on life-history tratis, exploitation characteristics, and other relevant parameters for data-limited stocks (WKLIFE IX). *ICES Sci. Rep.* 1:131.

ICES (2020d). Workshop on data-limited stocks of short-lived species (WKDLSSLS2). *ICES Sci. Rep.* 2:119. doi: 10.17895/ices.pub.5984

Jardim, E., Azevedo, M., and Brites, N. M. (2015). Harvest control rules for data limited stocks using length-based reference points and survey biomass indices. *Fish. Res.* 171, 12–19. doi: 10.1016/j.fishres.2014.11.013

Kell, L. T., Mosqueira, I., and fromentin, J.-M. (2017). FLife: an R package for modelling life history relationships and population dynamics. *Col. Vol. Sci. Pap. ICCAT* 73, 3009–3024.

Kell, L. T., Mosqueira, I., Grosjean, P., Fromentin, J.-M., Garcia, D., Hillary, R., et al. (2007). FLR: an open-source framework for the evaluation and development of management strategies. *ICES J. Mar. Sci.* 64, 640–646. doi: 10.1093/icesjms/fsm012

Le Pape, O., Vermard, Y., Guitton, J., Brown, E. J., van de Wolfshaar, K. E., Lipcius, R. N., et al. (2020). The use and performance of survey-based pre-recruit abundance indices for possible inclusion in stock assessments of coastal-dependent species. *ICES J. Mar. Sci.* 77, 1953–1965. doi: 10.1093/icesjms/fsaa051/5861726

MacCall, A. D. (2009). Depletion-corrected average catch: a simple formula for estimating sustainable yields in data-poor situations. *ICES J. Mar. Sci.* 66, 2267–2271.

Mace, P., and Sissenwine, M. P. (1993). "How much spawning per recruit is enough?," in *Risk Evaluation and Biological Reference Points*, eds S. J. Smith, J. J. Hunt, and D. Rivard (Ottawa, ONT: National Research Council), 101–125.

Plagányi, ÉE., Rademeyer, R. A., Butterworth, D. S., Cunningham, C. L., and Johnston, S. J. (2007). Making management procedures operational—innovations implemented in South Africa. *ICES J. Mar. Sci.* 64, 626–632. doi: 10.1093/icesjms/fsm043

Punt, A. E., Butterworth, D. S., de Moor, C. L., De Oliveira, J. A. A., and Haddon, M. (2016). Management strategy evaluation: best practices. *Fish Fish.* 17, 303–334. doi: 10.1111/faf.12104

Punt, A. E., Smith, A. D. M., Smith, D. C., Tuck, G. N., and Klaer, N. L. (2014). Selecting relative abundance proxies for BMSY and BMEY. *ICES J. Mar. Sci.* 71, 469–483. doi: 10.1093/icesjms/fst162

Ricard, D., Minto, C., Jensen, O. P., and Baum, J. K. (2012). Examining the knowledge base and status of commercially exploited marine species with the RAM Legacy Stock Assessment Database. *Fish Fish.* 13, 380–398. doi: 10.1111/j.1467-2979.2011.00435.x

Sagarese, S. R., Harford, W. J., Walter, J. F., Bryan, M. D., Isely, J. J., Smith, M. W., et al. (2019). Lessons learned from data-limited evaluations of data-rich reef fish species in the Gulf of Mexico: implications for providing fisheries management advice for data-poor stocks. *Can. J. Fish. Aquatic Sci.* 76, 1624–1639. doi: 10.1139/cjfas-2017-0482

Sánchez, S., Ibaibarriaga, L., Uriarte, A., Prellezo, R., Andrés, M., Abaunza, P., et al. (2018). Challenges of management strategy evaluation for small pelagic fish: the Bay of Biscay anchovy case study. *Mar. Ecol. Prog. Ser. View* 617-618, 245–263. doi: 10.3354/meps12602

Smith, D., Punt, A., Dowling, N., Smith, A., Tuck, G., and Knuckey, I. (2009). Reconciling approaches to the assessment and management of data-poor species and fisheries with Australia's harvest strategy policy. *Mar. Coast. Fish.* 1, 244–254. doi: 10.1577/c08-041.1

United Nations (2019). *The Sustainable Development Goals Report 2019*. New York, NY: United Nations.

Walsh, J. C., Minto, C., Jardim, E., Anderson, S. C., Jensen, O. P., Afflerbach, J., et al. (2018). Trade-offs for data-limited fisheries when using harvest strategies based on catch-only models. *Fish Fish.* 19, 1130–1146. doi: 10.1111/faf.12316

Wetzel, C. R., and Punt, A. E. (2011). Model performance for the determination of appropriate harvest levels in the case of data-poor stocks. *Fish. Res.* 110, 342–355. doi: 10.1016/j.fishres.2011.04.024

Wetzel, C. R., and Punt, A. E. (2015). Evaluating the performance of data-moderate and catch-only assessment methods for US west coast groundfish. *Fish. Res.* 171, 170–187. doi: 10.1016/j.fishres.2015.06.005

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 15 June 2021
doi: 10.3389/fmars.2021.679299

Using the LBB Method for the Assessments of Seven Fish Stocks From the Yangtze Estuary and Its Adjacent Waters

Yuanchao Wang[1,2,3], *Cui Liang*[1,2]*, *Weiwei Xian*[1,2,3,4,5]* *and Yibang Wang*[1,6]

[1] Key Laboratory of Marine Ecology and Environmental Sciences, Institute of Oceanology, Chinese Academy of Sciences, Qingdao, China, [2] Laboratory for Marine Ecology and Environmental Science, Qingdao National Laboratory for Marine Science and Technology, Qingdao, China, [3] University of Chinese Academy of Sciences, Beijing, China, [4] Center for Ocean Mega-Science, Chinese Academy of Sciences, Qingdao, China, [5] CAS Engineering Laboratory for Marine Ranching, Institute of Oceanology, Chinese Academy of Sciences, Qingdao, China, [6] Qingdao University of Science and Technology, Qingdao, China

OPEN ACCESS

Edited by:
Giuseppe Scarcella,
National Research Council (CNR), Italy

Reviewed by:
Yuan Li,
Third Institute of Oceanography, State Oceanic Administration, China
Valeria Mamouridis,
Independent Researcher, Rome, Italy

***Correspondence:**
Weiwei Xian
wwxian@qdio.ac.cn
Cui Liang
liangc@qdio.ac.cn

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: *11 March 2021*
Accepted: *05 May 2021*
Published: *15 June 2021*

Citation:
Wang YC, Liang C, Xian W and Wang YB (2021) Using the LBB Method for the Assessments of Seven Fish Stocks From the Yangtze Estuary and Its Adjacent Waters. Front. Mar. Sci. 8:679299. doi: 10.3389/fmars.2021.679299

The status of fishery resources in the Yangtze estuary and its adjacent waters is still unclear for the effective implementation of fishery management strategies. To help address this gap, a new method especially for data-limited fish stocks (LBB) was applied to assess seven commercially and ecotrophically important fish stocks. Fish specimens were collected in the estuary by bottom trawling quarterly from May 2018 to February 2019. Two historical datasets were collected with the same method in the same area for Indian perch (*Jaydia lineata*) and sickle pomfret (*Pampus echinogaster*). To explore the growth features and resilience of fish stocks, auximetric plots and growth performance indices (Φ') were used. Results showed that common hairfin anchovy (*Setipinna tenuifilis*) in 2018 and Indian perch in 2018 showed a healthy stock biomass status with complete length structures under a sustainable fishing pressure. The others were outside of safe biological limits or overfished. The $L_{\mathrm{mean}}/L_{\mathrm{opt}} < 0.9$ in six (67%) of nine LBB models for seven fish stocks suggested that most of the stocks were truncated in length structures. This contribution provides the main fishery reference points regarding stock status that can inform managers and form the basis for various management strategies.

Keywords: LBB, stock status, data limited, growth patterns, Yangtze estuary

INTRODUCTION

Despite the fact that China has the largest capture production worldwide with the insight of the distortion in catches (Watson and Pauly, 2001; Pauly and Le Manach, 2015; FAO, 2019), effective fishery management remains a huge challenge. In fact, there are various fishery management strategies in China, including input control, output control, technical control and management measures, economic instruments, management of aquaculture, distant water fisheries management, and international cooperation mechanisms (Cao et al., 2017; Huang and Tang, 2019). Nevertheless, the effects of these strategies regarding fishery conservation are limited. For example, the fishery licensing system (input control) has been in force since 1979. Numerous acts have amended the Fisheries Law of People's Republic of China since 1986, continuously reinforcing the fishery licensing system. However, there is a noticeable gap between reality and expectation regarding the licensing system's implementation process because the prerequisite, namely the status of fishery resources, is often neglected (Huang and Tang, 2019). In China, such a gap along with the lack of fishery reference points and raw data precludes the possibility of optimizing management and conserving fishery resources.

The Yangtze estuary and its adjacent waters (YE), the most representative estuarine fishing ground in China, also faces such a challenge. Traditional fishery resources are experiencing serious depletions. Yellow croaker (*Larimichthys polyactis*) is an essential commercial fish species in the YE. There could be two populations, namely the northern and the southern in nearshore Chinese waters. In particular, the southern population, which is found in the Southern Yellow Sea and East China Sea, contributes to approximately 70–80% of the total catch of this fish stock. In 2000, this stock reached the highest landing ever (7,059 tonnes) in the YE (Xu and Chen, 2010). Its asymptotic length and age at which the probability of maturing is 95% (years) have been decreasing over time, as shown *via* biological parameters analysis (Shan et al., 2017). Osbeck's grenadier anchovy (*Coilia mystus*) is an amphidromous and neritic fish with three local populations in China, i.e., in the YE, the Minjiang River, and the Pearl River (Zhang, 2001). It is a traditional and commercial fish species, and it is a brackish species in the YE (Yang et al., 2019). Its catch had reached the peak at 5,282 tonnes in the YE in 1974, constituting about 48.6% of the total catch. However, it is unable to form the fishing season in recent years (Zhuang et al., 2018). Common hairfin anchovy (*Setipinna tenuifilis*) is a bycatch species in the YE. The Latin name of this species was misapplied as *Setipinna taty* based on the Taiwan Fish Database (Shao, 2021). With severe depletions of traditional targets, common hairfin anchovy accounted for a relatively larger fraction of landings in the early 2000s (Zhuang et al., 2006). Bombay duck (*Harpadon nehereus*) is a major target of commercial fisheries in the YE in recent years. It was the only all-year-round dominant species in this area from 2012 to 2013 (Sun et al., 2015). The records of the so-called silver pomfret (*Pampus argenteus*) in the Bohai Sea, Yellow Sea, and East China Sea of China are those of sickle pomfret (*Pampus echinogaster*) based on morphological and molecular analyses (Li et al., 2017). It has been further utilized since the 1960s and became the main fishing target gradually after the 1970s. The fishing season for sickle pomfret was from late April to early June (He et al., 2006; Zhuang et al., 2006). However, it was severely depleted due to heavy fishing pressure in the 1990s. Previous research showed that the summer fishing moratorium in the East China Sea seemed to benefit this stock (Yan et al., 2019). Kammal thryssa (*Thryssa kammalensis*) and Indian perch (*Jaydia lineata*) are essential forage and bycatch species. These small fish species play an important role in the energy flow process of the estuarine ecosystem. Previous studies have often ignored the biological and ecological information for these small species due to their limited economic value and historical data. Apparently, there is an urgent situation in getting the pictures of stocks status of these resources and relative reference points for existing policies and managements.

Sustainable fisheries around the world require science-based management of all exploited fish species (MSA, 2007; CFP, 2013; Melnychuk et al., 2016; Cao et al., 2017; Rudd and Thorson, 2018). This highlights the need for stock assessment methods suitable for data-limited situations. One such method is the length-based Bayesian biomass estimator (LBB), a newly developed method to estimate relative biomass level (B/B_0) and other reference points, such as L_{mean}/L_{opt}, using length frequency (LF) data (Froese et al., 2018a). The ratio B/B_0 is an indicator of current biomass level relative to unexploited stock size, which is also treated as a basic input in other assessment models. The ratio L_{mean}/L_{opt} describes whether the age and size composition of an exploited stock is appropriate or not. LBB requires only representative LF data, which is usually easy to measure and collect, while other similar methods require more demanding input [length-based spawning potential ratio model (LB-SPR): Hordyk et al., 2015a,b, 2016; catch-curve stock reduction analysis model (CC-SRA): Thorson and Cope, 2015; length-based, integrated, mixed-effects model (LIME): Rudd and Thorson, 2018]. LBB assumes that mortality, growth, and recruitment should fluctuate around mean values over the range of ages in the respective LF samples, and stocks have typical growth and mortality patterns (Froese et al., 2018a).

In this study, we applied the LBB approach to estimate the status of seven common fish species in the YE. These consist of two forage species (kammal thryssa and Indian perch) and five valuable commercial species (yellow croaker, Osbeck's grenadier anchovy, common hairfin anchovy, Bombay duck, and sickle pomfret), thus covering the spectrum from forage species to predators and therefore being a more representative dataset/analysis. This paper aims to provide a case study of exploring the stock status as well as essential reference points for these seven fish stocks in the YE. These results make the policy implementations more effective and can also be used as priors for other assessment models.

MATERIALS AND METHODS

Survey Area

The YE (**Figure 1**), in the north of the East China Sea, is the biggest estuarine fishing ground in China. It is an essential habitat, supporting approximately 50 brackish and marine exploited fish populations (Zhuang et al., 2018). The sea surface temperature ranges from 7.16 to 30.12°C (Hou et al., 2013). The proportion of diatoms in the YE was declining, while that of pfiesteria was rising especially after the 2000s (Yang and Xu, 2014). Due to anthropogenic activities, the cumulative reduction of sediment discharge to the YE was up to 44.44×10^8 tonnes from 1997 to 2015 (Guo et al., 2019).

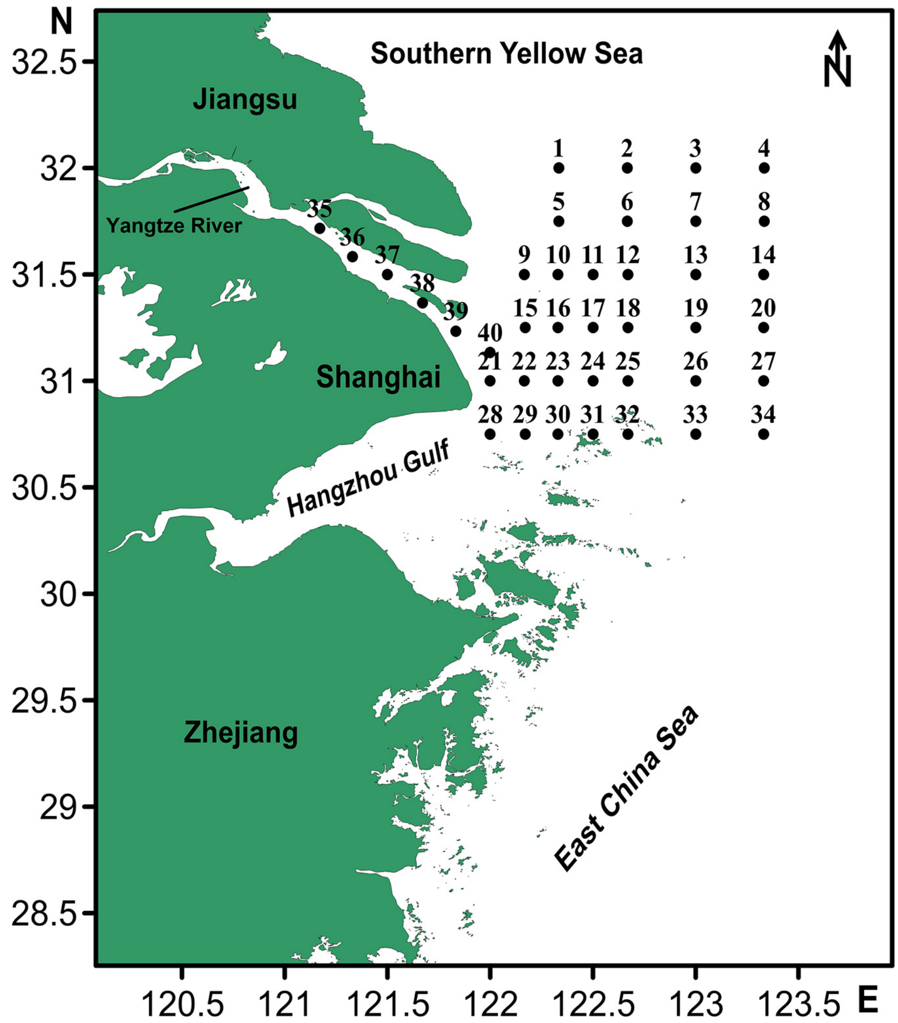


FIGURE 1 | The survey area and sampling sites in the Yangtze estuary and its adjacent waters, China.

Sampling Method

The sampling area ranged from 30°30′N to 32°20′N and 122°E to 123°30′E (**Figure 1**). Fish specimens were collected quarterly in May 2018, August 2018, November 2018, and February 2019 by bottom trawling with a cod end mesh size of 25 mm. Two historical LF datasets had been collected by the same gear of the same selectivity in the same area (Indian perch 1984: collected monthly from June 1984 to November 1984; sickle pomfret 1999: collected in November 1998 and May 1999; sickle pomfret 2012: May 2012). All specimens were identified to the species level and their scientific names were checked according to FishBase (Froese and Pauly, 2019). For each fish stock in question, its entire catch was collected and measured to the nearest 0.1 cm (standard length, SL). The detailed information of the seven stocks covered here are given in **Table 1** and **Supplementary Table S1**. One species was tentatively identified as Kammal thryssa (*T. kammalensis*), although it is described by Whitehead et al. (1988) as a strictly tropical species of Southeast Asia (see also Munroe and Nizinski, 1999).

Growth Pattern

To explore the growth features among respective families and proxies for resilience in this study, auximetric plots and growth performance indices (Φ') were used (Pauly, 1979, 1981, 1991; Munro and Pauly, 1983; Pauly and Munro, 1984; Murua et al., 2017). This study assumed that a family growth space could be treated as a reasonable range for fluctuations of growth parameters in this family. These seven fish species belong to five families (**Table 1**), with their growth spaces determined by two von Bertalanffy growth parameters (L_{inf} and K). The records of Φ' value for each fish species in question were extracted from FishBase. The L_{inf} (SL) estimated by LBB was transferred into L_{inf}' (TL) according to length–length relationships, and then the K_{LBB} and Φ'_{LBB} for seven fish stocks in this study were estimated by the empirical equation in FishBase. This calculation assumed that a species would grow rapidly toward a small size when it faced with the risk of depletion. Relative parameters can be found in **Supplementary Tables S2, S3**.

TABLE 1 | Basic information for the seven studied fish stocks.

Family	Common name (scientific name)	Year	*N*	Class interval	Min (cm)	Max (cm)	Length type
Sciaenidae	Yellow croaker (*Larimichthys polyactis*)	2018	650	10	7.4	23.0	SL
Engraulidae	Kammal thryssa (*Thryssa kammalensis*)	2019	297	4	4.4	11.4	SL
	Osbeck's grenadier anchovy (*Coilia mystus*)	2018	541	10	4.9	18.8	SL
	Common hairfin anchovy (*Setipinna tenuifilis*)	2018	564	5	1.2	18.0	SL
Synodontidae	Bombay duck (*Harpadon nehereus*)	2018	1,389	20	3.6	26.5	SL
Apogonidae	Indian perch (*Jaydia lineata*)	2018	355	2	2.6	6.5	SL
		1984	999	2	1.4	7.6	SL
Stromateidae	Sickle pomfret (*Pampus echinogaster*)	2012	146	10	3.8	20.5	SL
		1999	315	10	8.1	23.3	SL

SL, standard length.

Length-Based Bayesian Biomass Estimation

The LBB method could be used in the assessments of fish stocks, for estimating their relative stock size and other reference points. First of all, LBB approximates asymptotic length L_{inf}, length at first capture L_{c}, M/K, and F/K over the past years. Reliable "true" values from other independent sources can be used to improve estimations. Taking these parameters as priors, LBB then gives the B/B_0 for relative stock size and $L_{\mathrm{mean}}/L_{\mathrm{opt}}$ for current size and age composition of health state (Froese et al., 2018a). The R-code can be found on http://oceanrep.geomar.de/43182/.

The LBB method assumes that growth can be described by the standard von Bertalanffy (von Bertalanffy, 1938; Beverton and Holt, 1957) growth equation, i.e.,

$$L_{\mathrm{t}} = L_{\mathrm{inf}}[1 - e^{-K(t-t_0)}] \tag{1}$$

where L_{t} is the length at age t, L_{inf} is the asymptotic length, K is the rate by which L_{inf} is approached, and t_0 is the theoretical age at zero length. The growth parameters L_{inf} and K are used in several equations in this study.

The fully selected part of the commercial catch in numbers-at-length can be described as a function of total mortality rate relative to somatic growth rate (Z/K) (Quinn and Deriso, 1999), i.e.,

$$N_L = N_{L_{\mathrm{start}}}\left(\frac{L_{\mathrm{inf}} - L}{L_{\mathrm{inf}} - L_{\mathrm{start}}}\right)^{Z/K} \text{for } L > L_{\mathrm{start}} \text{ and } L < L_{\mathrm{inf}} \tag{2}$$

where N_L is the number of survivors to length L, and $N_{L_{\mathrm{start}}}$ is the number at length L_{start}, which indicates the start size of full selection by gears. Z/K could be divided into M/K and F/K, and unfished state could be illustrated by setting F/K as 0 and $N_{L_{\mathrm{start}}}$ as 1 in Eq. 2.

The catch in numbers that is subject to partial selection is a function of gear selectivity (here assumed trawl-like), which could be used as a complement to Eq. 2 and is described by Eq. 3, i.e.,

$$S_L = \frac{1}{1 + e^{-\alpha(L-L_c)}} \tag{3}$$

where S_L is the fraction of individuals that are retained by the gear at length L, L_{c} is the length at first capture, and α describes the steepness of the ogive (Sparre and Venema, 1998; Quinn and Deriso, 1999).

Rearranging and combining Eqs. 2 and 3 leads to Eq. 4 (Froese et al., 2018a), which can be fitted to the whole catch in numbers-at-length and, thus, used to estimate L_{inf}, the ratios M/K and F/K, and the selectivity parameters L_{c} and α. Eq. 4 has the form,

$$N_{L_{\mathrm{i}}} = N_{L_{\mathrm{i}-1}}\left(\frac{L_{\mathrm{inf}} - L_{\mathrm{i}}}{L_{\mathrm{inf}} - L_{\mathrm{i}-1}}\right)^{\frac{M}{K} + \frac{F}{K}S_{L_{\mathrm{i}}}} \text{ and } C_{L_{\mathrm{i}}} = N_{L_{\mathrm{i}}}S_{L_{\mathrm{i}}} \tag{4}$$

where $N_{L_{\mathrm{i}}}$ is the number of individuals in length class L_{i}, $N_{L_{\mathrm{i}-1}}$ is the number in the previous length class, $C_{L_{\mathrm{i}}}$ represents the individuals that are vulnerable to the gear, and all other parameters are as described above. Dividing both sides of Eq. 4 by their respective sums yields the version of the LBB equation that is actually fitted to the catch in numbers curve (Eq. 5) (Froese et al., 2018a):

$$\frac{C_{L_{\mathrm{i}}}}{\sum C_{L_{\mathrm{i}}}} = \frac{N_{L_{\mathrm{i}}}\ S_{L_{\mathrm{i}}}}{\sum N_{L_{\mathrm{i}}}\ S_{L_{\mathrm{i}}}} \tag{5}$$

The following work is mainly about the Bayesian calculation of LBB within the Bayesian Gibbs sampler software JAGS (Plummer, 2003) and its execution using the statistical language R (R Core Team, 2013). Details of start values and priors for the Bayesian estimation are presented in Froese et al. (2018a). A Dirichlet-multinomial distribution is assumed in the fitting process of observed $p_{L_{\mathrm{i}}}$, and $\hat{p}_{L_{\mathrm{i}}}$ are predicted from Eq. 6:

$$p_{L_{\mathrm{i}}} = \frac{N_{L_{\mathrm{i}}}}{\sum N_{L_{\mathrm{i}}}} \text{ and } \hat{p}_{L_{\mathrm{i}}} = \frac{\hat{N}_{L_{\mathrm{i}}}}{\sum \hat{N}_{L_{\mathrm{i}}}} \tag{6}$$

where $\hat{N}_{L_{\mathrm{i}}}$ is a function of the estimable population dynamic based on Bayesian algorithm which finds the best fitting L_{inf}, M/K, F/K, L_{c}, and α values in the process of fitting $p_{L_{\mathrm{i}}}$ and $\hat{p}_{L_{\mathrm{i}}}$. With the estimation of L_{inf}, M/K, and F/K, the value of L_{opt} maximizing the unexploited cohort biomass can be calculated by

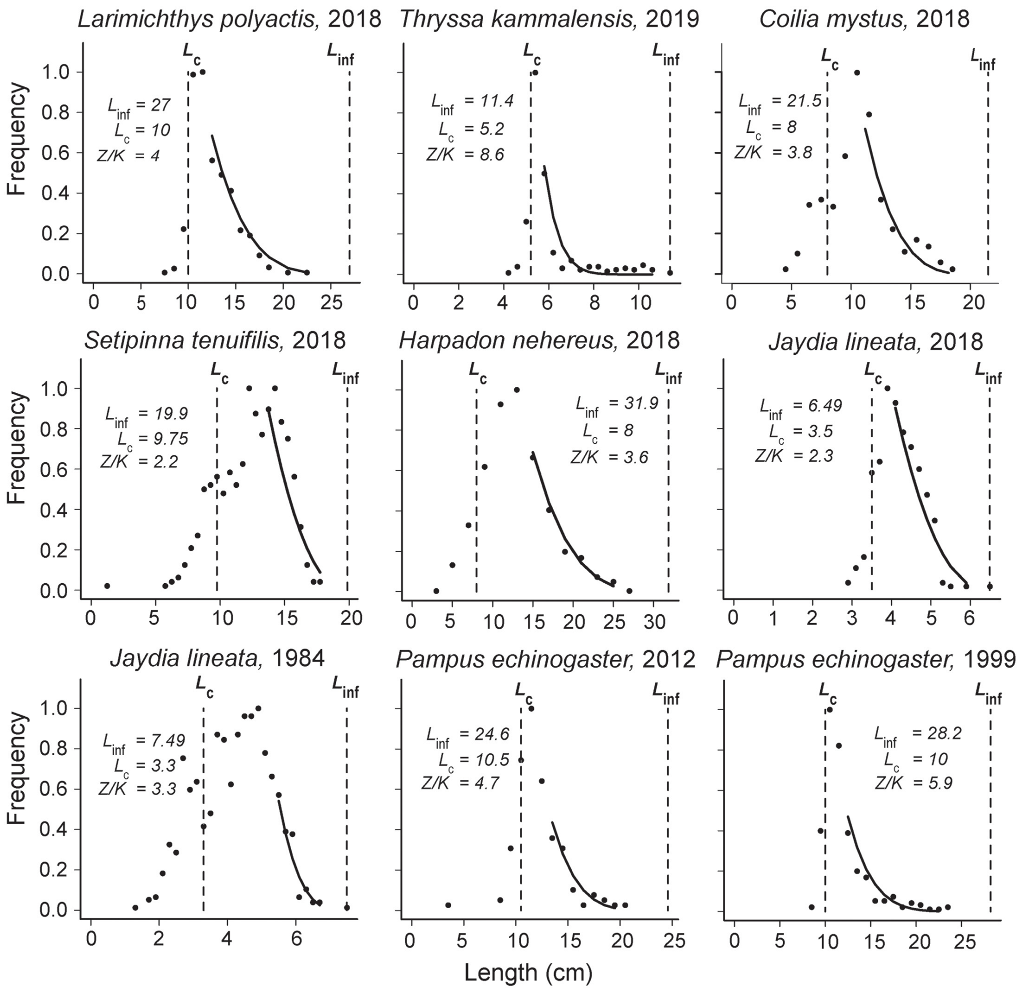


FIGURE 2 | Fitness to the fully selected part of the catch in the numbers curve used to obtain L_{inf} (cm), L_c (cm), and Z/K priors for the seven studied fish stocks. Black dots indicated the observed LF data.

Eq. 7 (Holt, 1958) and the L_{c_opt} value that leads to L_{opt} could be obtained by Eq. 8 (Froese et al., 2016):

$$L_{opt} = L_{inf}\left(\frac{3}{3+\frac{M}{K}}\right) \tag{7}$$

$$L_{c\_opt} = \frac{L_{inf}\left(2+3\frac{F}{M}\right)}{\left(1+\frac{F}{M}\right)\left(3+\frac{M}{K}\right)} \tag{8}$$

Eq. 9 gives the yield-per-recruit (Beverton and Holt, 1966) formula, which uses the parameters estimated by LBB, i.e., L_{inf}, L_c, F/K, M/K, and F/M:

$$\frac{Y'}{R} = \frac{F/M}{1+F/M}(1-L_c/L_{inf})^{M/K} \left(1-\frac{3\,(1-L_c/L_{inf})}{1+\ \frac{1}{M/K+F/K}}+\frac{3\,(1-L_c/L_{inf})^2}{1+\ \frac{2}{M/K+F/K}}-\frac{(1-L_c/L_{inf})^3}{1+\ \frac{3}{M/K+F/K}}\right) \tag{9}$$

An index of catch per unit effort ($CPUE'/R$), representing the relative stock status, is then calculated by dividing Eq. 9 by F/M as a proxy of fishing effort in Eq. 10:

$$\frac{CPUE'}{R} = \frac{Y'/R}{F/M} = \frac{1}{1+F/M}(1-L_c/L_{inf})^{M/K} \left(1-\frac{3\,(1-L_c/L_{inf})}{1+\ \frac{1}{M/K+F/K}}+\frac{3\,(1-L_c/L_{inf})^2}{1+\ \frac{2}{M/K+F/K}}-\frac{(1-L_c/L_{inf})^3}{1+\ \frac{3}{M/K+F/K}}\right) \tag{10}$$

By setting F as 0, the relative biomass level of unexploited state could be obtained in Eq. 11:

$$\frac{B_0' > L_c}{R} = (1-L_c/L_{inf})^{\frac{M}{K}} \left(1-\frac{3\,(1-L_c/L_{inf})}{1+\ \frac{1}{M/K}}+\frac{3\,(1-L_c/L_{inf})^2}{1+\ \frac{2}{M/K}}-\frac{(1-L_c/L_{inf})^3}{1+\frac{3}{M/K}}\right) \tag{11}$$

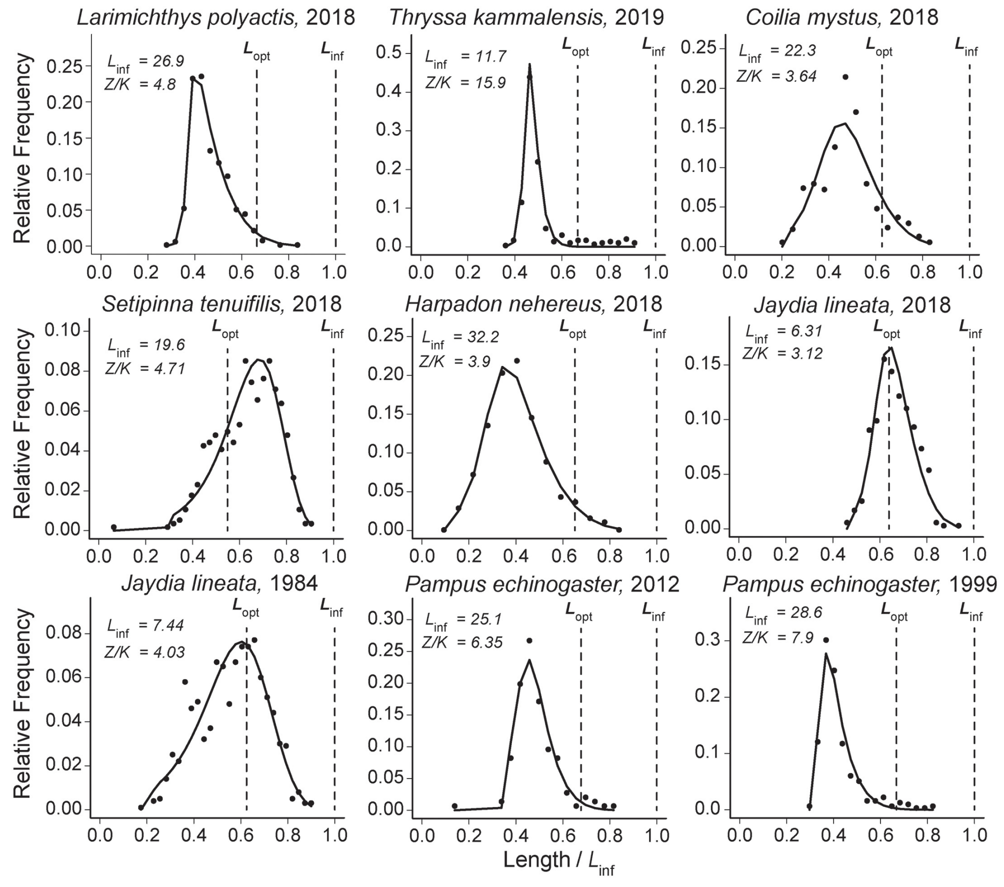


FIGURE 3 | Graphical outputs of LBB analyses, showing the fit of the main LBB equation. Black dots indicated the observed LF data. L_{opt} and L_{inf} were illustrated by two dash lines.

where $B_0^{'} > L_c$ indicated the exploitable fraction ($>L_c$) of the unfished biomass (B_0).

Finally, an index of relative biomass depletion for the exploited part of the population B/B_0 is then obtained from Beverton and Holt (1966) *via* Eq. 12:

$$\frac{B}{B_0} = \frac{\frac{CPUE^{'}}{R}}{\frac{B_0^{'}>L_c}{R}} \tag{12}$$

The assumption of knife-edge selection in Eqs. 9 and 11 causes the overestimation of yield per recruit when the selection ogive overlaps with most of the life span of short-lived species (Pauly and Soriano, 1986; Pauly and Greenberg, 2013). To deal with this bias, LBB calculates the yield per recruit separately for each length group. The uncertainty in the estimation of B/B_0 assumes to be related with that of F/K, M/K, F/M, and L_{inf} (Froese et al., 2018a).

RESULTS

In this contribution, nine LBB models were constructed for seven fish stocks from the YE. LF datasets of each stock from 2018 to 2019 were combined to increase sample size and representativeness. All LF data exhibited good patterns to reflect resource status and met the requirements of LBB (**Figures 2**, **3**). **Figure 2** shows the accumulated LF data used to estimate priors. The black curve in **Figure 3** shows the fit of the LBB master equation (Eq. 5) for each stock, providing estimates for fishery reference points, i.e., M/K, F/M, B/B_{MSY}, B/B_0, L_{mean}/L_{opt}, and L_c/L_{c_opt}, which are given in **Table 2**, along with their 95% confidence intervals. The L_{opt} dash lines indicated relatively good stock status or good length structures if they were at the middle or left of the peak of the curves (**Figure 3**), which implied that only three stocks had relatively good length structures in this study.

Of the nine LBB models for seven fish stocks, only two (22%) had appropriate fishing mortalities with $F/M < 1$, suggesting an overall overfishing phenomenon. The ratios of L_{mean}/L_{opt} and L_c/L_{c_opt} were lower than 0.9 in six (67%) of these stocks, suggesting truncated length structure and fishing of too small individuals. **Figure 4** depicts the narrow confidence intervals of L_{inf} and points out that Kammal thryssa, yellow croaker, and sickle pomfret had severe decreases in biomass. By comparing the results from two distinct periods, the sickle pomfret and Indian perch showed apparently reduced L_{inf} values in recent years; however, their B/B_0 values, an indicator of depletion, seemed to increase.

TABLE 2 | Essential reference points from LBB estimates for the fish stocks in question.

Common name	Year	M/K	F/M	B/B_{MSY}	B/B_0	L_{mean}/L_{opt}	L_c/L_{c_opt}
Yellow croaker	2018	1.52 (1.25–1.77)	2.2 (1.76–2.92)	0.35 (0.26–0.5)	0.13 (0.094–0.18)	0.71	0.6
Kammal thryssa	2019	1.49 (1.27–1.76)	9.64 (7.92–11.8)	0.079 (0.059–0.1)	0.029 (0.022–0.037)	0.78	0.68
Osbeck's grenadier anchovy	2018	1.79 (1.54–2.04)	1.05 (0.749–1.41)	0.81 (0.51–1.1)	0.289 (0.18–0.408)	0.84	0.74
Common hairfin anchovy	2018	2.47 (2.15–2.69)	0.904 (0.593–1.35)	1.6 (0.8–2.5)	0.548 (0.272–0.869)	1.5	1.7
Bombay duck	2018	1.61 (1.32–1.89)	1.43 (1.07–2.04)	0.47 (0.31–0.73)	0.171 (0.111–0.262)	0.65	0.5
Indian perch	2018	1.7 (1.47–1.99)	0.849 (0.492–1.14)	1.2 (0.54–1.7)	0.43 (0.19–0.61)	1.1	1.1
	1984	1.8 (1.43–2.05)	1.25 (0.857–1.93)	1 (0.58–1.7)	0.363 (0.206–0.599)	1.2	1.2
Sickle pomfret	2012	1.43 (1.1–1.69)	3.48 (2.66–4.47)	0.23 (0.15–0.31)	0.0845 (0.0558–0.115)	0.73	0.65
	1999	1.49 (1.19–1.79)	4.25 (3.52–5.76)	0.14 (0.1–0.2)	0.0507 (0.0369–0.0718)	0.63	0.53

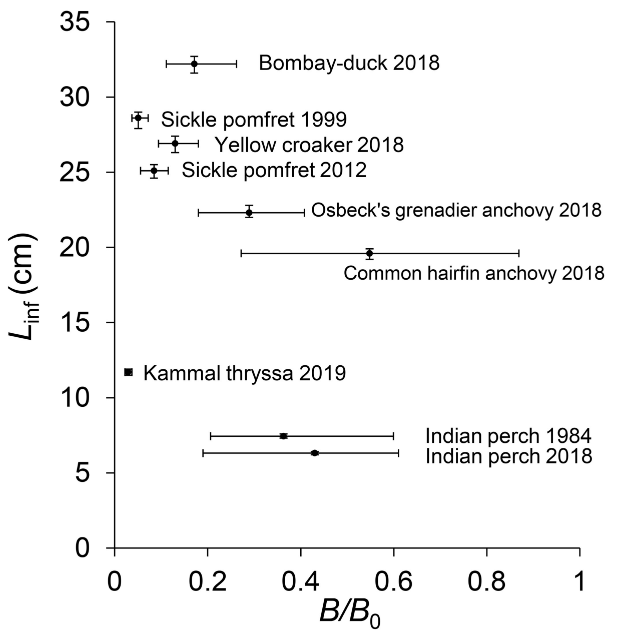


FIGURE 4 | The scatter plot of L_{inf} (cm) and B/B_0 estimated from LBB with uncertainties.

Growth spaces of five families formed five distinct ellipsoid clouds in **Figure 5**. All ellipsoid clouds showed a downward trend, which indicated that in each family, smaller fishes tended to higher K and vice versa. Sciaenidae and Synodontidae tended to bigger size relative to the other three families, and Engraulidae species occupy a larger range of L_{inf}. Apogonidae have relatively smaller body size and higher growth rate. Indian perch and kammal thryssa, as two forage species in this study, tended to faster growth with their smaller L_{inf} and higher K relatively.

The L_{inf} values estimated by LBB for Bombay duck and sickle pomfret, illustrated in **Figure 6A** by a cross, were close to the third quartile of the L_{inf} records from FishBase. The L_{inf} values of two anchovies were bigger than related records from FishBase, while the estimates for the two forage species were close to the respective medians. **Figure 6B** shows the growth performance indices (Φ') of seven fish stocks (cross) based on L_{inf} estimates from LBB. The Φ' value of sickle pomfret was larger than the median of other populations of this same species, while that of Indian perch was lower than the median of relative records. The $L_{mean}/L_{opt} < 0.9$ in six (67%) of nine stocks, suggesting that most of the stocks were truncated in length structures (**Figure 7**). Only two stocks were subject to sustainable fishing pressure and of a healthy stock biomass. The others were outside of safe biological limits or overfished.

DISCUSSION

Stock Status Criteria

Punt et al. (2014) stated that B_{MSY} is generally approximated between $0.35B_0$ and $0.4B_0$. Actually, FAO (Ye, 2011: 328) started to use $B/B_0 < 0.4$ as the limit for overfishing since 2011. Based on the FAO definition of stocks status ($B/B_0 > 0.6$: under fished; $0.4 < B/B_0 < 0.6$: fully fished; $B/B_0 < 0.4$: overfished), Rosenberg et al. (2017) provided the stock status criteria based on B/B_{MSY} with $B_0 = 2B_{MSY}$, suggesting that overfishing occurs when $B < 0.8B_{MSY}$. Froese et al. (2018b) suggested that stocks were well managed and in good condition when $F \leq F_{MSY}$ and $B \geq B_{MSY}$, and if $B < 0.5B_{MSY}$, treated as outside of safe biological limits or depleted, corresponding with Opitz et al. (2016).

The biomass level below which a stock may be considered "collapsed" or deep-depleted is used to defining by B_0, B_{MSY}, or *Max.catch* (see **Table 1** in Garcia et al., 2018), and there is no general agreement about this limit. The arbitrary $B/B_0 < 0.2$ was widely used in conventional assessments to indicate the delaying depensation phenomena (Petitgas et al., 2010; Garcia et al., 2018). In this study, $B/B_{MSY} < 0.2$ (i.e., $B/B_0 < 0.1$ with $B_0 = 2B_{MSY}$) was accepted in **Table 3**. Collapse means the loss of spawning and feeding areas and types of migrants and residents in addition to decreases in biomass and truncated length structure (Petitgas et al., 2010; Garcia et al., 2018). This indicated that $B/B_{MSY} < 0.2$ in this study was more conservative than the widely used $B/B_0 < 0.2$ and showed more positive expectation of stock resilience in lower biomass level. Even so, it should be kept in mind that this biomass limit was just an approximation, and this positive expectation did not mean a lot. It would be more appropriate to concentrate on the dynamic of fisheries (Garcia et al., 2018).

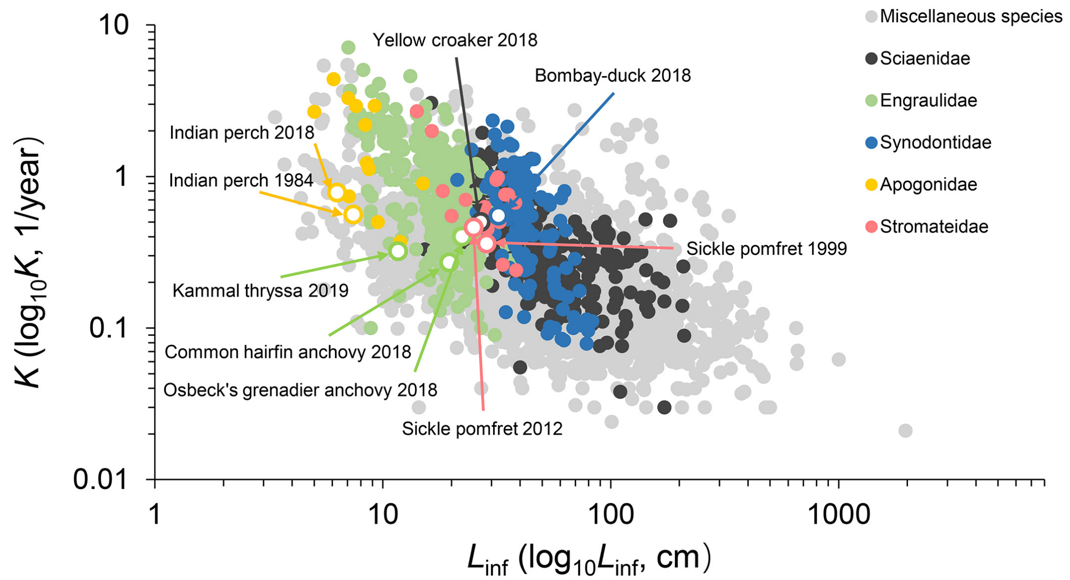


FIGURE 5 | The auximetric plot with the growth spaces of five families (filled circles) and the growth position estimates for the seven fish stocks in question (hollow circles).

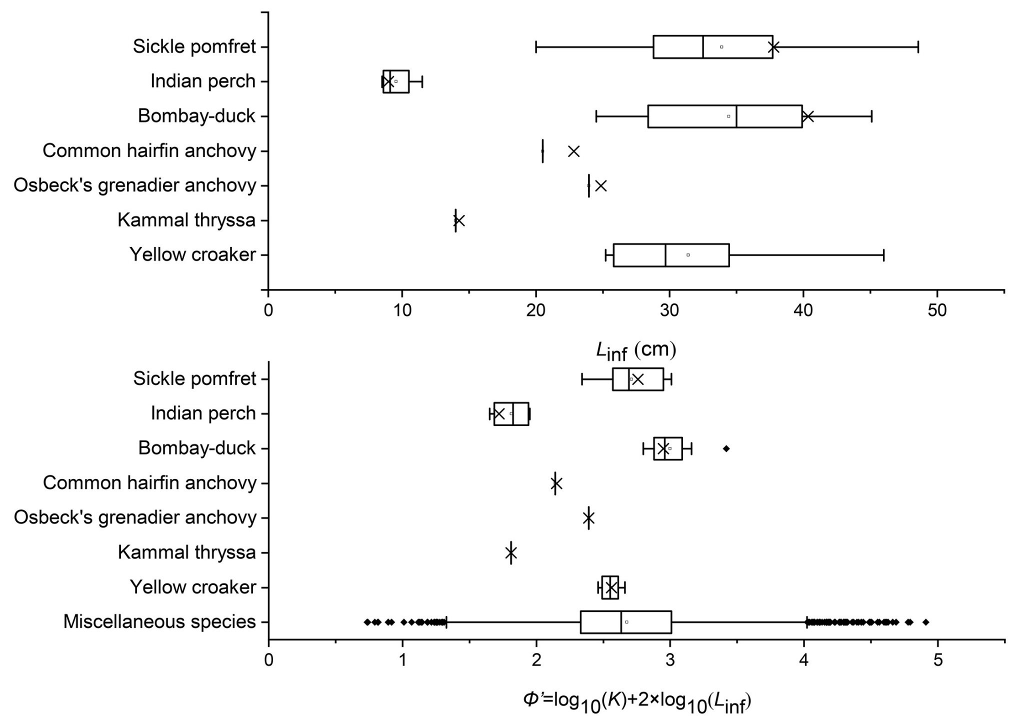


FIGURE 6 | (A) The L_{inf} (cm, total length) estimated by LBB for six fish species [cross; the L_{inf} value of yellow croaker from LBB was not shown because of its unsuitable standard length (SL) and the lack of length–length correlation coefficients]. The box plots depict the records of L_{inf} values collected from FishBase with mean values depicted by tiny squares. **(B)** The growth performance index (Φ') of the seven fish species in question estimated by the L_{inf} values from LBB (cross). The box plots show the growth performance index (Φ') for these fish stocks with data collected from FishBase.

A scatter diagram of F/F_{MSY} and B/B_{MSY} is usually used to illustrate exploitation status of a relevant fishery stock (such as Figure 3 in Froese et al., 2018b). The LBB model does not estimate F/F_{MSY} but F/M, which represents the average value over the past year (Froese et al., 2018a). F/M can be considered as a proxy of F/F_{MSY} for the related stock in the given year just because the covering duration of every LF dataset in this study was 1 year. $F/M > 1.0$ was used to imply the unsustainable fishing pressure in this study. Note that nine LBB models for these seven fish species used NA for M/K priors, assuming a normally distributed prior for M/K with mean = 1.5 and SD = 0.15 (Froese et al., 2018a). This assumption may bring deviations into F/M values, considering that M/K is not an LHI (life history invariants) and not conserved across species (Thorson et al., 2017). It would be noteworthy and necessary to use species-specific priors of natural mortalities for future LBB applications if available.

Forage Species

Kammal Thryssa (*T. kammalensis*)

The species we tentatively identified as *T. kammalensis* is a common, pelagic-neritic and brackish fish species along Chinese coastal waters (Zhang et al., 2019). As a forage species in the YE, Kammal thryssa plays an important role in the estuarine food web (Yu and Xian, 2009). Kammal thryssa belongs to Engraulidae (Froese and Pauly, 2019). The low estimate of B/B_{MSY} and its high F/M indicated that the stock was outside of safe biological limits in 2019 (**Figure 7**). The L_c/L_{c_opt} (<0.9) and F/M (>1) suggested that high fishing pressure contributed to its deep-depleted state. The stock in this study was in the bottom left corner of the green space in **Figure 5**, and its K value was similar to two anchovies in question and even lower than that of sickle pomfret, which indicated that this forage stock was hard to recover from severe depletion relatively. A high Φ' implies that a species grows fast to a large body size, something that corresponds to a "high growth performance" and has implications for population productivity and resilience (Murua et al., 2017). The Φ' value of this species was similar with its record in FishBase (**Figure 6B**) and belonged to the cohort of low Φ' values, i.e., "low growth performance" or with low resilience. Oscillations tended to be important for generating a high risk of a collapse for shorter-lived species just like this species with lower resilience (Garcia et al., 2018).

Indian Perch (*J. lineata*)

Indian perch is a small-sized demersal forage species of Apogonidae (yellow space in **Figure 5**; Li et al., 2013). It is abundant on sandy and muddy bottoms from coastal inlets to deeper waters (Zhuang et al., 2006). The stock in this study was located at the bottom left corner of the yellow space, and it became smaller in size and faster in growth in 2018 (**Figure 5**). To a certain extent, this implies its adaptation to environmental factors (such as seasonal variation, Jin et al., 2012) by growing rapidly toward a small size and which may contribute to the bigger B/B_0 value in 2018 than that in 1984 (**Figure 4**). The low Φ' value of Indian perch (**Figure 6B**) belonged to the cohort of low Φ' values among miscellaneous species, and the lower mean Φ' value of these two stocks in question depicted its relative lower resilience among different populations of this species. Two stocks of this fish species had good biomass levels, and the fishing pressure decreased to an appropriate level in 2018. This may take it into the safe biological limit.

Commercial Species

Yellow Croaker (*L. polyactis*)

Yellow croaker is a benthopelagic and oceanodromous fish species of the family Sciaenidae, illustrated with black dots in **Figure 5**. This fish stock is an essential commercial target of fishing activities currently in the YE. It had a relative lower L_{inf} and higher K in this family (**Figure 5**), and its Φ' value was close to the average level among the recorded populations in FishBase (**Figure 6B**), suggesting a relative faster growth rate in its family and a normal resilience. This stock was grossly overfished with truncated length structure in 2018 (**Figure 7**). The ratio of the 95th percentile length to asymptotic length $L_{95\mathrm{th}}/L_{\mathrm{inf}} = 0.84$ (**Supplementary Material**), indicating the lack of large individuals (Froese et al., 2018b). Its low relative biomass ($B/B_0 = 0.13$) indicated the severe depletion of this stock, which was similar to the situation of the species ($B/B_0 = 0.15$) in Liaodong Bay in 2012–2013 (Zhai and Pauly, 2019), suggesting the overall overfished status of this species in coastal China.

Osbeck's Grenadier Anchovy (*C. mystus*)

Osbeck's grenadier anchovy is one of the commercial species in the YE. The catch of this stock reached the peak of 5,281.8 tonnes in 1974 and decreased to 40 tonnes in recent years (Zhao et al., 2020). Its B/B_0 value in 2018 was reduced to 0.29 (**Figure 4**), lower than that of the same stock in 2009 ($B/B_0 = 0.32$ from Liang and Pauly, 2017; Zhai and Pauly, 2019), which implied that its status had gotten worse. This stock had a relatively larger L_{inf} estimated by LBB than the record in FishBase, suggesting the more complete length structure of this species than that from 2006 to 2007 in the YE and a signal of population recovery (**Figure 6A**; He et al., 2008; Froese and Pauly, 2019). It is distributed in the lower and right of the growth pattern of Engraulidae (**Figure 5**), having the same Φ' value with the record in FishBase (**Figure 6B**), showing no abnormal changes in growth pattern and resilience. This indicated that it has a good restoration potentiality, although out of safe biological limits (**Figure 7**).

Common Hairfin Anchovy (*S. tenuifilis*)

Common hairfin anchovy is an amphidromous and schooling fish species living mainly in coastal waters (Froese and Pauly, 2019). This stock occupied 11.64% of the total abundance among fish species in the YE from 1998 to 2001 (Yu and Xian, 2009). It had a larger L_{inf} value (22.8 cm in total length) than the record (20.5 cm in total length) in FishBase (**Figure 6A**). Its L_{inf} and K values in 2018 were both lower than those in East China Sea in 2000–2002 ($L_{\mathrm{inf}} = 23.6$ cm in total length and $K = 0.3288$) from Liu et al. (2006). This stock showed a healthy status with a good length structure and a high biomass level in 2018 (**Figure 7**).

Bombay Duck (*H. nehereus*)

Bombay duck is a benthopelagic, oceanodromous, and carnivorous fish species (Froese and Pauly, 2019). It belongs to the small size cohort and the middle level in growth rate in Synodontidae (blue space in **Figure 5**). This species was a competitive predator in comparison with the others

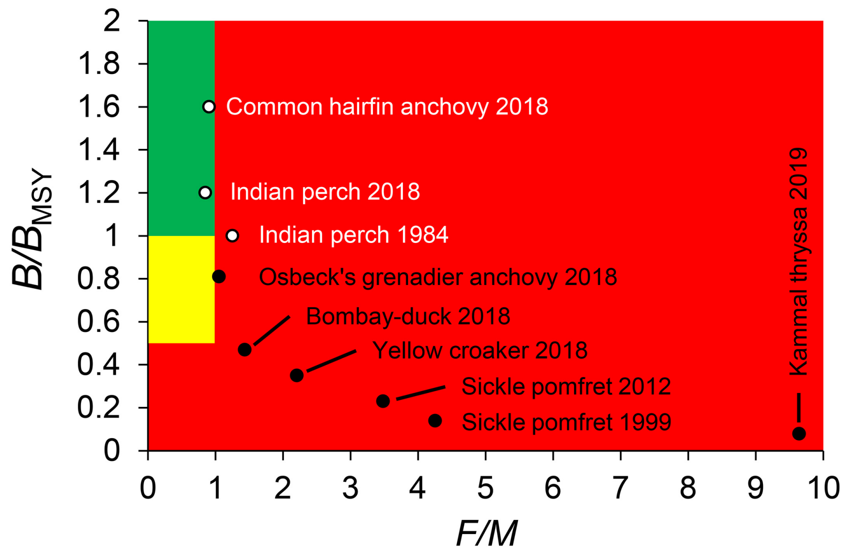


FIGURE 7 | The scatter plot of B/B_{MSY} and F/M for the nine LBB models of seven fish stocks in question. Red area, stocks that are being overfished or are outside of safe biological limits; yellow area, recovering stocks; green area, stocks subject to sustainable fishing pressure and of a healthy stock biomass. White dots mean $L_{mean}/L_{opt} > 0.9$.

TABLE 3 | Definition of fish stock status, based on B/B_{MSY}.

B/B_{MSY}	Stock status	Notes
≥1	Healthy	Froese et al. (2018b), $B > B_{MSY}$: in good condition
0.8–1.0	Slightly overfished	Punt et al. (2014), B_{MSY} is generally approximated between $0.35B_0$ and $0.4B_0$
0.5–0.8	Overfished	FAO (Ye, 2011: 328) and Rosenberg et al. (2017), $B/B_{MSY} < 0.8$: overfished
0.2–0.5	Grossly overfished	Froese et al. (2018b), $B < 0.5B_{MSY}$: outside of safe biological limits or depleted; Opitz et al. (2016), $B < 0.5B_{MSY}$: outside of safe biological limits
<0.2	Collapsed	Worm et al. (2009) and Froese et al. (2018b), $B < 0.2B_{MSY}$: overfishing or being severely depleted or unsustainable exploitation

in this study, according to its relatively higher K values and resilience (**Figures 5**, **6B**). Although with a relatively high L_{inf} value from LBB, this stock was outside of safe biological limits and grossly overfished in 2018 (**Figure 7**). It was a dominant species in the YE for years (Sun et al., 2015); however, the length structure of this stock was severely truncated by fishing activities. This result was consistent with the estimate for the same stock in 2008–2009 (Zhai and Pauly, 2019), suggesting its overfished status for at least 10 years.

Sickle Pomfret (*P. echinogaster*)

Sickle pomfret is a benthopelagic and oceanodromous fish species of Stromateidae (pink space in **Figure 5**). Its L_{inf} estimate for the year 2012 from LBB was lower than that in 1999 and was close to the third quartile of records in FishBase (**Figure 6A**). This stock appeared to have a slight increase in biomass (**Figure 4**) and tended to a higher growth rate in 2012 (**Figure 5**), which may be related with its relative higher resilience (**Figure 6B**). Yan et al. (2019) showed that the index of relative importance (IRI) of this species increased from 51 in 2014 to 753 in 2017 and its recruitment per spawning increased from 112.50 in 2014 to 183.13 in 2017, suggesting a signal of stock recovery after prolonging the summer fishing moratorium in East China Sea in 2017. The stock in question was already collapsed in 1999, corresponding with He et al. (2006) and Zhuang et al. (2006), and its stock status had turned to grossly overfished in 2012, although still out of its safe biological limit (**Figure 7**). Our study provided a signal of its recovery in the YE. However, there is no doubt that its stock status was still in bad conditions with truncated length structure and this recovery was limited. For better conservation of sickle pomfret and other commercial species, stricter and specific fishery policies and implementations are required.

CONCLUSION

In this paper, the LBB was used to perform stock assessments for seven common fish species based on representative length frequencies collected from the YE. The status and fishery reference points of these fish stocks were estimated, respectively. Auximetric plots and growth performance indices (Φ') were used to reveal the growth features and imply resilience of the studied stocks, which can be useful when formulating scientific advice. The L_{mean}/L_{opt} <0.9 in six (67%) of nine stocks suggested that most of the stocks were truncated in length structures. Common hairfin anchovy in 2018 and Indian perch in 2018 showed a healthy stock biomass status with complete length structures under a sustainable fishing pressure. The others were outside of safe biological limits or overfished.

This study assumed that a species would grow rapidly toward a small size when it faced with depletions (a positive feedback) for the historical comparison in auximetric plots. The real $\Delta K/\Delta L_{\text{inf}}$ ratio, for a fish stock in different historical stages, could reveal the real feedback to environmental changes more accurately. This paper did not take environmental factors (e.g., temperature but also the presence of predators) into considerations, which may play an essential role in the life history of a fish stock, especially for forage species. This study might serve as basis for future studies and fishery management plans, which could focus on the overall assessments of all exploited fishery stocks and integrations and tradeoffs between species-specific information and ecosystem-based managements.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

ETHICS STATEMENT

Ethical review and approval was not required for the animal study because our manuscript was based on survey cruise data, and no live vertebrates or higher invertebrates were involved, thus we believe an ethical review process was not required for our study.

AUTHOR CONTRIBUTIONS

YCW and WX conceived and designed the study. YCW performed the data analysis and wrote the first draft of the manuscript, with insights from WX, CL, and YBW. All authors contributed to the revisions of the manuscript.

FUNDING

This research was funded by grants from the National Natural Science Foundation of China (31872568 and 41976094) and Natural Science Foundation of China-Shandong Joint Fund for Marine Ecology and Environmental Sciences (U1606404).

ACKNOWLEDGMENTS

We acknowledge Daniel Pauly and Maria Lourdes Palomares from *Sea Around Us*, University of British Columbia, Canada, for their contributions in the workshop of the assessment of Chinese stocks held in Qingdao, China.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2021.679299/full#supplementary-material

REFERENCES

Beverton, R. J. H., and Holt, S. J. (1957). *On the Dynamics of Exploited Fish Populations. Fishery Investigations Series II, XIX*. London: Ministry of Agriculture, Fisheries and Food, 533.

Beverton, R. J. H., and Holt, S. J. (1966). *Manual of Methods for Fish Stock Assessment, Part II-Tables of Yield Functions*. FAO Fisheries Technical Paper No. 38 (Rev. 1). Rome: FAO, 10.

Cao, L., Chen, Y., Dong, S., Hanson, A., Huang, B., Leadbitter, D., et al. (2017). Opportunity for marine fisheries reform in China. *Proc. Natl. Acad. Sci. U.S.A.* 114, 435–442. doi: 10.1073/pnas.1616583114

CFP (2013). Regulation (EU) No 1380/2013 of the European parliament and of the council of 11 December 2013 on the common fisheries policy, amending council regulations (EC) No 1954/2003 and (EC) No 1224/2009 and repealing council regulations (EC) No 2371/2002 and (EC) No 639/2004 and council decision 2004/585/EC. *Off. J. Eur. Union* L354, 22–61.

FAO (2019). *FAO Yearbook. Fishery and Aquaculture Statistics 2017*. Rome: FAO, 28–30.

Froese, R., and Pauly, D. (2019). *FishBase. World Wide Web Electronic Publication*. Available online at: www.fishbase.org (accessed December 31, 2019).

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2018a). A new approach for estimating stock status from length frequency data. *ICES J. Mar. Sci.* 75, 2004–2015. doi: 10.1093/icesjms/fsy078

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2018b). Status and rebuilding of European fisheries. *Mar. Policy* 93, 159–170. doi: 10.1016/j.marpol.2018.04.018

Froese, R., Winker, H., Gascuel, D., Sumaila, U. R., and Pauly, D. (2016). Minimizing the impact of fishing. *Fish Fish.* 17, 785–802. doi: 10.1111/faf.12146

Garcia, S. M., Ye, Y., Rice, J., and Charles, A. (2018). *Rebuilding of Marine Fisheries Part 1: Global Review*. FAO Fisheries and Aquaculture Technical Paper, 630/1. Rome: FAO.

Guo, W. X., Li, Y., and Wang, H. X. (2019). Driving factors analysis of the evolution of runoff and sediment at Datong station in resent 60 years. *China Rural Water and Hydropower* 7, 60–65. doi: 10.1057/9781403944023_4

He, Z. K., Sun, Z. Z., and Hong, B. (2006). Monitor on dynamics of adult and young white pomfret *Pampus argenteus* in south bank waters of the mouth of the Changjiang River. *Fish. Sci. Technol. Inf.* 33, 81–83. doi: 10.3969/j.issn.1001-1994.2006.02.010

He, W., Li, Z., Liu, J., Li, Y., Murphy, B. R., and Xie, S. (2008). Validation of a method of estimating age, modelling growth, and describing the age composition of *Coilia mystus* from the Yangtze Estuary, China. *ICES J. Mar. Sci.* 65, 1655–1661. doi: 10.1093/icesjms/fsn143

Holt, S. J. (1958). The evaluation of fisheries resources by the dynamic analysis stocks, and notes on the time factors involved. *ICNAF Spec. Publ.* 1, 77–95.

Hordyk, A., Ono, K., Sainsbury, K., Loneragan, N., and Prince, J. (2015a). Some explorations of the life history ratios to describe length composition, spawning-per-recruit, and the spawning potential ratio. *ICES J. Mar. Sci.* 72, 204–216. doi: 10.1093/icesjms/fst235

Hordyk, A., Ono, K., Valencia, S., Loneragan, N., and Prince, J. (2015b). A novel length-based empirical estimation method of spawning potential ratio (SPR), and tests of its performance, for small-scale, data-poor fisheries. *ICES J. Mar. Sci.* 72, 217–231. doi: 10.1093/icesjms/fsu004

Hordyk, A. R., Ono, K., Prince, J. D., and Walters, C. J. (2016). A simple length-structured model based on life history ratios and incorporating size-dependent selectivity: application to spawning potential ratios for data-poor stocks. *Can. J. Fish. Aquat. Sci.* 73, 1787–1799. doi: 10.1139/cjfas-2015-0422

Hou, W. F., Yu, C. G., and Chen, X. Q. (2013). Temperature distribution in Zhoushan Fishing Ground. *J. Ningbo Univ.* 26, 31–34.

Huang, S. L., and Tang, Y. (2019). Review and prospect of theories of fisheries management and China's practice. *J. Fish. China.* 43, 211–231. doi: 10.11964/jfc.20181011512

Jin, W. H., Xue, L. J., Zhu, Z. J., and Pan, G. L. (2012). Feeding habits of *Apogon lineatusin* the East China Sea and southern Yellow Sea. *Mar. Fish.* 34, 361–370. doi: 10.13233/j.cnki.mar.fish.2012.04.003

Li, X. S., Yu, Z. H., Sun, S., and Jin, X. S. (2013). Ecological niche breadth and niche overlap of dominant species of fish assemblage in Yangtze River estuary and its adjacent waters. *Chin. J. Appl. Ecol.* 24, 2353–2359. doi: 10.13287/j.1001-9332.2013.0394

Li, Y., Zhang, Y., Gao, T. X., Han, Z. Q., Lin, L. S., and Zhang, X. M. (2017). Morphological characteristics and DNA barcoding of *Pampus echinogaster* (Basilewsky, 1855). *Acta Oceanol. Sin.* 36, 18–23. doi: 10.1007/s13131-017-1124-x

Liang, C., and Pauly, D. (2017). Growth and mortality of exploited fishes in China's coastal seas and their uses for yield-per-recruit analyses. *J. Appl. Ichthyol.* 33, 746–756. doi: 10.1111/jai.13379

Liu, Y., Cheng, J. H., and Li, S. F. (2006). Utilization status of *Setipinna taty* in the East China Sea and its rational exploitation. *J. Fish. Sci. China* 13, 485–491.

Melnychuk, M. C., Peterson, E., Elliott, M., and Hilborn, R. (2016). Fisheries management impacts on target species status. *Proc. Natl. Acad. Sci. U.S.A.* 114, 178–183. doi: 10.1073/pnas.1609915114

MSA. (2007). *Magnuson-Stevens Fishery Conservation and Management Act, Public Law 94-265. As Amended by the Magnuson-Stevens Fishery Conservation and Management Reauthorization Act (P.L. 109-479)*. Available online at: http://www.nmfs.noaa.gov/msa2005/docs/MSA_amended_msa%20_20070112_FINAL.pdf (accessed 19 December 2014)

Munro, J. L., and Pauly, D. (1983). A simple method for comparing the growth of fishes and invertebrates. *Fishbyte* 1, 5–6.

Munroe, T. A., and Nizinski, M. (1999). "Engraulidae. Anchovies," in *FAO Species Identification Guide for Fishery Purposes. The Living Marine Resources of the WCP. Batoid fishes, Chimaeras and Bony Fishes Part 1 (Elopidae to Linophrynidae)*, Vol. 3, eds K. E. Carpenter and V. H. Niem (Rome: FAO), 1698–1706.

Murua, H., Rodriguez-Marin, E., Neilson, J. D., Farley, J. H., and Juan-Jordá, M. J. (2017). Fast versus slow growing tuna species: age, growth, and implications for population dynamics and fisheries management. *Rev. Fish Biol. Fish.* 27, 733–773. doi: 10.1007/s11160-017-9474-1

Opitz, S., Hoffmann, J., Quaas, M., Matz-Lück, N., Binohlan, C., and Froese, R. (2016). Assessment of MSC-certified fish stocks in the Northeast Atlantic. *Mar. Policy* 71, 10–14. doi: 10.1016/j.marpol.2016.05.003

Pauly, D. (1979). *Gill Size and Temperature as Governing Factors in Fish Growth: a Generalization of von Bertalanffy's Growth Formula*. Berichte aus dem Instituts für Meereskunde an der Universität Kiel, No. 63. Kiel: Universität Kiel, 156.

Pauly, D. (1981). The relationships between gill surface area and growth performance in fish: a generalization of von Bertalanffy's theory of growth. *Ber. Dtsch. Wissenschaftlichen Kommission Meeresforschung* 28, 251–282.

Pauly, D. (1991). Growth performance in fisheries: rigorous description of patterns as a basis for understanding causal mechanisms. *Aquabyte Newsl. Netw. Trop. Aquac. Sci.* 4, 3–6.

Pauly, D., and Greenberg, A. (2013). *ELEFAN in R: A New Tool for Length-Frequency Analysis*. Fisheries Centre Research Reports 21(3). Vancouver: University of British Columbia, 52.

Pauly, D., and Le Manach, F. (2015). *Tentative Adjustments of China's Marine Fisheries Catches (1950–2010)*. Fisheries Centre Working Paper 2015-28. Vancouver: University of British Columbia.

Pauly, D., and Munro, J. L. (1984). Once more on the comparison of growth in fish and invertebrates. *Fishbyte Newsl. Netw. Trop. Fish. Sci.* 2:21.

Pauly, D., and Soriano, M. L. (1986). "Some practical extensions to Beverton and Holt's relative yield-per-recruit model," in *the First Asian Fisheries Forum*, eds J. L. Maclean, L. B. Dizon, and L.-V. Hosillos (Manila: Asian Fisheries Society), 491–495.

Petitgas, P., Secor, D. H., McQuinn, I., Huse, G., and Lo, N. (2010). Stock collapses and their recovery: mechanisms that establish and maintain lifecycle closure in space and time. *ICES J. Mar. Sci.* 67, 1841–1848. doi: 10.1093/icesjms/fsq082

Plummer, M. (2003). "JAGS: a program for analysis of Bayesian graphical models using Gibbs sampling," in *Proceedings of the 3rd International Workshop on Distributed Statistical Computing (DSC 2003), Vienna*, eds K. Hornik, F. Leisch, and A. Zeileis (Vienna: Vienna Technical University), 20–22.

Punt, A. E., Smith, A. D. M., Smith, D. C., Tuck, G. N., and Klaer, N. L. (2014). Selecting relative abundance proxies for BMSY and BMEY. *ICES J. Mar. Sci.* 71, 469–483. doi: 10.1093/icesjms/fst162

Quinn, T. J., and Deriso, R. B. (1999). *Quantitative Fish Dynamics*. New York, NY: Oxford University Press, 560.

R Core Team (2013). *R: A Language and Environment for Statistical Computing*. Vienna: R Foundation for Statistical Computing.

Rosenberg, A. A., Kleisner, K. M., Afflerbach, J., Anderson, S. C., Dickey-Collas, M., Cooper, A. B., et al. (2017). Applying a new ensemble approach to estimating stock status of marine fisheries around the world. *Conserv. Lett.* 11:e12363. doi: 10.1111/conl.12363

Rudd, M. B., and Thorson, J. T. (2018). Accounting for variable recruitment and fishing mortality in length-based stock assessments for data-limited fisheries. *Can. J. Fish. Aquat. Sci.* 75, 1019–1035. doi: 10.1139/cjfas-2017-0143

Shan, X. J., Li, X. S., Yang, T., Sharifuzzaman, S. M., Zhang, G. Z., Jin, X. S., et al. (2017). Biological responses of small yellow croaker (*Larimichthys polyactis*) to multiple stressors: a case study in the Yellow Sea, China. *Acta Oceanol. Sin.* 36, 39–47. doi: 10.1007/s13131-017-1091-2

Shao, K. T. (2021). *Taiwan Fish Database*. Available online at: http://fishdb.sinica.edu.tw (accessed April 22, 2021)

Sparre, P., and Venema, S. C. (1998). *Introduction to Tropical Fish Stock Assessment. Part 1. Manual*. FAO Fisheries Technical Paper No. 306.1, Rev. 2. Rome: FAO, 407.

Sun, P. F., Dai, F. Q., Chen, Y. L., Shan, X. J., and Jin, X. S. (2015). Seasonal variations in structure of fishery resource in the Yangtze River Estuary and its adjacent waters. *Prog. Fish Sci.* 36, 8–16. doi: 10.11758/yykxjz.20150602

Thorson, J. T., and Cope, J. M. (2015). Catch curve stock-reduction analysis: an alternative solution to the catch equations. *Fish. Res.* 171, 33–41. doi: 10.1016/j.fishres.2014.03.024

Thorson, J. T., Munch, S. B., Cope, J. M., and Gao, J. (2017). Predicting life history parameters for all fishes worldwide. *Ecol. Appl.* 27, 2262–2276. doi: 10.1002/eap.1606

von Bertalanffy, L. (1938). A quantitative theory of organic growth (inquiries on growth laws. II.). *Hum. Biol.* 10, 181–213. doi: 10.2307/41447359

Watson, R., and Pauly, D. (2001). Systematic distortions in world fisheries catch trends. *Nature* 414, 534–536. doi: 10.1038/35107050

Whitehead, P. J. P., Nelson, G. J., and Wongratana, T. (1988). FAO Species Catalogue. Vol. 7. Clupeoid fishes of the world (Suborder Clupeoidei). An annotated and illustrated catalogue of the herrings, sardines, pilchards, sprats, shads, anchovies and wolf-herrings. *FAO Fish. Synop.* 7, 305–579.

Worm, B., Hilborn, R., Baum, J. K., Branch, T. A., Collie, J. S., Costello, C., et al. (2009). Rebuilding global fisheries. *Science* 325, 578–585. doi: 10.1126/science.1173146

Xu, Z., and Chen, J. (2010). Population division of *Larimichthys polyactis* in China Sea. *Chin. J. Appl. Ecol.* 21, 2856–2864.

Yan, L. P., Liu, Z. L., Jin, Y., and Cheng, J. H. (2019). Effects of prolonging summer fishing moratorium in the East China Sea on the increment of fishery resources. *Mar. Fish.* 41, 513–519. doi: 10.13233/j.cnki.mar.fish.2019.05.001

Yang, Q., Zhao, F., Song, C., Zhang, T., Zhuang, P., Jiang, T., et al. (2019). Habitat history reconstruction of *Coilia mystus* from the Yangtze River Estuary and its adjacent sea area. *J. Fish. Sci. China* 26, 1175–1184. doi: 10.3724/SP.J.1118.2019.19073

Yang, Y., and Xu, R. (2014). The environment variation trend in the Changjiang River estuary in the past 30a. *Mar. Sci.* 39, 101–107. doi: 10.11759/hykx20141124001

Ye, Y. (2011). *Review of the State of the World Marine Fishery Resources*. FAO Fisheries and Aquaculture Technical Paper. Rome: FAO, 569.

Yu, H. C., and Xian, W. W. (2009). The environment effect on fish assemblage structure in waters adjacent to the Changjiang (Yangtze) River estuary (1998–2001). *Chin. J. Oceanol. Limnol.* 27, 443–456. doi: 10.1007/s00343-009-9155-6

Zhai, L., and Pauly, D. (2019). Yield-per-recruit, Utility-per-recruit, and relative biomass of 21 exploited fish species in China's coastal seas. *Front. Mar. Sci.* 6:724. doi: 10.3389/fmars.2019.00724

Zhang, J., Zhang, N., Li, Y., Xiao, J. G., Zhang, R., and Gao, T. X. (2019). Population genetic structure of *Thryssa kammalensis* in the Chinese seas inferred from control region sequences. *Mar. Biodivers.* 49, 2621–2632. doi: 10.1007/s12526-019-00995-3

Zhang, S. Y. (2001). *Fauna Sinica*. Beijing: Science Press.

Zhao, F., Yang, Q., Song, C., Zhang, T., and Zhuang, P. (2020). Biological characteristics and resource utilization of *Coilia mystus* in the Yangtze Estuary. *Mar. Fish.* 42, 110–119. doi: 10.13233/j.cnki.mar.fish.2020.01.012

Zhuang, P., Wang, Y. H., Li, S. F., Deng, S. M., Li, C. S., and Ni, Y. (2006). *Fishes of the Yangtze Estuary*. Shanghai: Shanghai Scientific & Technical Publishers.

Zhuang, P., Zhang, T., and Li, S. F. (2018). *Fishes of the Yangtze Estuary*, 2nd Edn. Beijing: China Agriculture Press, 125–126.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 22 June 2021
doi: 10.3389/fmars.2021.552076

Check for updates

Data Poor Approach for the Assessment of the Main Target Species of Rapido Trawl Fishery in Adriatic Sea

Enrico Nicola Armelloni[1,2], *Martina Scanu*[1,2]*, *Francesco Masnadi*[1,2], *Gianpaolo Coro*[3], *Silvia Angelini*[1] *and Giuseppe Scarcella*[1]

[1] Department of Biological, Geological, and Environmental Sciences (BiGeA), Alma Mater Studiorum - University di Bologna, Bologna, Italy, [2] Institute for Marine Biological Resources and Biotechnology, National Research Council (IRBIM-CNR), Ancona, Italy, [3] Institute of Information Science and Technologies "A. Faedo", National Research Council of Italy (ISTI-CNR), Pisa, Italy

OPEN ACCESS

Edited by:
Hui Zhang,
Institute of Oceanology, Chinese Academy of Sciences (CAS), China

Reviewed by:
Nazli Demirel,
Istanbul University, Turkey
Kui Zhang,
Chinese Academy of Fishery Sciences (CAFS), China

***Correspondence:**
Martina Scanu
martina.scanu@irbim.cnr.it

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: 15 April 2020
Accepted: 14 May 2021
Published: 22 June 2021

Citation:
Armelloni EN, Scanu M, Masnadi F, Coro G, Angelini S and Scarcella G (2021) Data Poor Approach for the Assessment of the Main Target Species of Rapido Trawl Fishery in Adriatic Sea. Front. Mar. Sci. 8:552076. doi: 10.3389/fmars.2021.552076

Information on stock status is available only for a few of the species forming the catch assemblage of rapido fishery of the North-central Adriatic Sea (Mediterranean Sea). Species that are caught almost exclusively by this gear, either as target (such as *Pectinidae*) or accessory catches (such as flatfishes apart from the common sole), remain unassessed mainly due to the lack of data and biological information. Based on cluster analysis, the catch assemblage of this fishery was identified and assessed using CMSY model. The results of this data-poor methodology showed that, among the species analyzed, no one is sustainably exploited. The single-species CMSY results were used as input to an extension of the same model, to test the effect of four different harvest control rule (HCR) scenarios on the entire catch assemblage, through 15-years forecasts. The analysis showed that the percentage of the stocks that will reach B_{msy} at the end of the projections will depend on the HCR applied. Forecasts showed that a reduction of 20% of fishing effort may permit to most of the target and accessory species of the rapido trawl fishery in the Adriatic Sea to recover to B_{msy} levels within 15 years, also providing a slight increase in the expected catches.

Keywords: catch assemblage, flatfishes, Mediterranean sea, harvest control rule, CMSY

INTRODUCTION

Single Species Fishery Management (SSFM) has many limitations since it does not consider the effects of fishing on non-target species and the effect of species interaction on the fisheries (Link, 2010). Typically, in an SSFM context, advice given for a few species is the unique information used to control the whole fishery (Moffitt et al., 2016), and this might lead to over-pressured bycatch species (Browman et al., 2004). Nevertheless, when applying management measures specifically developed for one species (e.g., introduction of quotas), they will affect the entire catch assemblage ("technical interaction"; Punt et al., 2002). Although few practical experiments are available, intergovernmental marine science organizations strongly advise about the limited view given by single-stock management on multiple stocks caught in mixed fisheries (ICES., 2017). To avoid this situation, and under the government's recommendation, in recent years fishery science has been focused on developing a multi-species approach (Link, 2010; Hilborn, 2011; Froese et al., 2018; Howell and Subbey, 2019). However, to date management advices for the Mediterranean Sea mostly rely on single-species stock assessment methodologies (FAO-GFCM, 2019).

Above all, considering the intrinsic multi-specific nature of the fishery, there is a strong need to move forward to more comprehensive management of stocks in the Mediterranean Sea (Colloca et al., 2013; Cardinale et al., 2017). Sophisticated assessment models able to give insights into ecosystem complexity have been proposed, though they are limited by the large amount of data required (Maunder and Punt, 2013). As such, these models are not easy to fit data-poor environments such as the Mediterranean Sea (Maravelias and Tsitsika, 2008). To find an alternative solution, we tested an advanced surplus production model implementation that assess the status of multiple species at once in data-poor scenarios (Froese et al., 2018). Surplus production models calculate fisheries parameters at Maximum Sustainable Yield (MSY) (e.g., biomass, exploitation, catch) based on the estimates of the intrinsic rate of growth (r) and the carrying capacity (k) parameters that are specific and tailored to the stock, rather than referring to the species in general.

This paper presents the first attempt to analyze and to project in the medium-term future the state of exploitation of the catch assemblage caught by rapido trawlers in the North Adriatic Sea (General Fisheries Commission for the Mediterranean – GFCM, Geographical Sub-Area – GSA 17), one of the most impacting fisheries in the Mediterranean Sea (Colloca et al., 2017). Based on the Annual Economic Report of the Scientific, Technical and Economic Committee for Fisheries (STECF), 64 vessels belonging to this segment were active in 2018, accounting for about 270 engaged crew and a gross value of landing estimated around 20 million € (STECF, 2019). This fishery represents an interesting case study, because—thanks to the gear conformation—rapido trawlers are able to catch some species that are difficult to get with other gears. Many species that are almost exclusively caught by this gear—either as target (such as *Pectinidae*) or accessory catches (such as flatfishes other than sole)—remain unassessed mainly due to lack of data and biological information. Therefore, it could be difficult to implement an ecosystem approach to fishery management and there is a high risk of underestimating the impact of this fishery. The catch assemblages of the most important demersal gears in GSA 17 were first reconstructed and clustered through multivariate analysis, to detect leading species for rapido fishery. At a second stage, the status of these stocks was evaluated through a Bayesian state-space implementation of the Schaefer production Model (BSM) of the CMSY software (Froese et al., 2017). Finally, the BSM estimates were used to run a CMSY extension on the entire rapido trawl catch assemblage (Froese et al., 2018), to estimate rebuilding time and to forecast expected catches. This extension considers fisheries' inter-dependencies to predict the overall status of the stocks under four different harvest control rule (HCR; Berger et al., 2012) scenarios up to 15 years in the future (2033). The main novelty of this study is the application of data-poor methodologies to jointly assess the status of the entire catch assemblage, while also assessing how rebuilding time depends on the level of future exploitation.

MATERIALS AND METHODS

Rapido Fishery

The rapido trawl fishery has been in place for more than 50 years in the western side of the north-central Adriatic Sea (**Figure 1**), where it is carried out all year round on the soft bottoms outside three nautical miles offshore (Scarcella et al., 2007). This gear is constituted by a cone-shaped net with a rigid metallic mouth opening up to 4 m wide, which slides on the seafloor aided by sleds. The mouth is equipped with a wooden plank on the top, acting as a depressor that allows the iron teeth in the lower edge to penetrate the sediment (Hall-Spencer et al., 1999). The gear shape enables trawlers to target flatfishes and species that live buried in the sediments, which are usually difficult to catch with otter trawling. As a result, catch composition forms a specific assemblage, mainly constituted by *Pectinidae*, in the sandy offshore areas of the North-East Adriatic (Giovanardi et al., 1998), and by flatfishes in the muddy inshore areas of central Adriatic (Pranovi et al., 2000). The penetration of the iron teeth in the sediment makes this gear particularly invasive to the sea-bottom, especially affecting the macro and meiobenthic communities (Pranovi et al., 2000; Petović et al., 2016; Santelli et al., 2017). Indeed, since many fish species, such as flatfish and gobies, feed on meiofaunal species (Schückel et al., 2013) this fishing gear acts not only as direct pressure on demersal fish stocks but also as an indirect pressure interfering with the distribution of stocks' preys.

Multivariate Analyses to Define Catch Assemblages

Data used to reconstruct the catch assemblages for main demersal gears in the GSA 17 were gathered from the STECF Annual Economic Report (STECF, 2019), which contains catch amount by species at gear and nation levels. The dataset was manually filtered to exclude pelagic species and taxonomic categories higher than the family level. Fishing gears representing small-scale fishery were grouped under the polyvalent passive gears (PGP) category. The yearly time frame considered was 2012–2017, due to data gaps in STECF (2019), namely Croatian data before 2012 and Italian data for 2018. The species list was sorted by magnitude of total catches and those falling within the 99% of the cumulative distribution were retained for the successive analysis. Then, for each selected species a vector was constructed, with each element representing mean catch by gear and by country. The obtained data were normalized by applying the *chord* transformation—i.e., scaling each vector to norm 1 (Legendre and Gallagher, 2001). The vectors obtained were assembled into a matrix (MC, **Supplementary Table 1**), where rows represented species, columns represented gears, and cells included normalized values of catches. Then, a multivariate analysis was applied to verify, firstly, if there were differences between catch assemblages of gears considered and if there were species strictly affected by rapido trawl fishery rather than

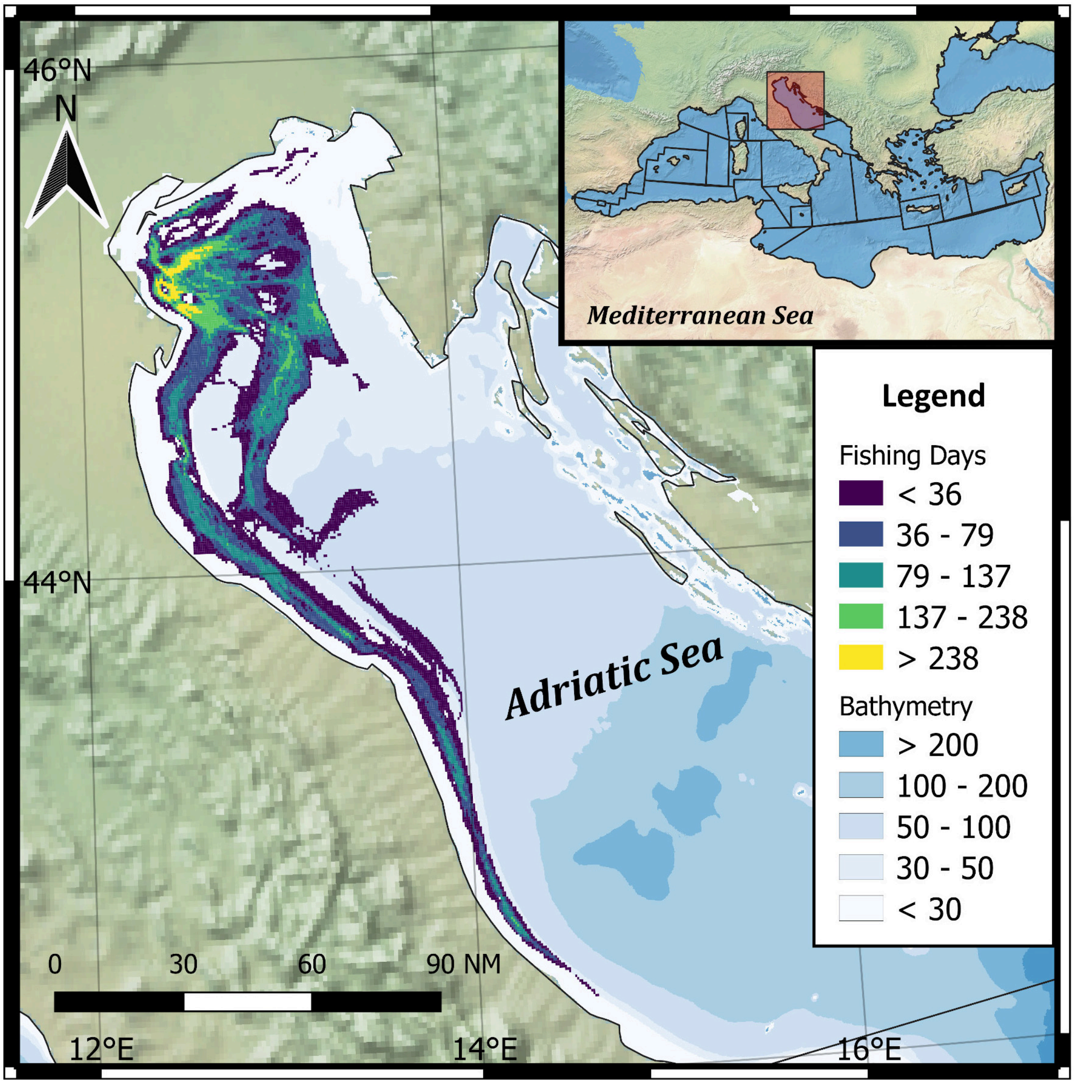


FIGURE 1 | Rapido trawl fishery effort distribution in GSA 17 North Adriatic sea, obtained with AIS data analysis based on Galdelli et al. (2019).

by other gears. Differences between catch assemblages of gears were assessed through a one-way permutational multivariate analysis of variance (PERMANOVA) with 9,999 permutations (Oksanen et al., 2016) applied to a matrix of Euclidean distances computed over the MC columns. A pairwise analysis (Arbizu, 2017) was used to explore the gear contribution to the difference. Then, to identify species strictly affected by specific gears, the species list was partitioned through a hierarchical cluster analysis—based on the Ward method (Ward, 1963)—applied to the matrix of Euclidean distance computed over the MC rows. As a result, this process identified a group of species that were mostly correlated (i.e., targeted) with rapido trawling on which a joint HCR test would be more meaningful. Multiscale bootstrap resampling (Borcart et al., 2018)—from the "pvclust" R package (Suzuki and Shimodaira, 2015)—was used to verify the statistical robustness of the identification of these species. To understand the contribution of each gear and nation to the cluster definition, MC rows were aggregated on the clusters identified, then mean values by MC column were computed for each group and represented through radar plots (Bion, 2021).

Stock Assessment

The stock assessments of the species identified through cluster analysis were performed using the CMSY software. CMSY includes a BSM, which fits catch and—optionally—biomass (or catch-per-unit-of-effort) data through a Markov Chain Monte Carlo method based on the Schaefer function for biomass dynamics. The model estimates fisheries reference points (MSY, F_{msy}, B_{msy}) as well as relative stock size (B/B_{msy}) and exploitation (F/F_{msy}) from catch data and broad priors for "resilience" (approximated by r) and stock's relative biomass (B/k) at the beginning and the end of the catch time series. For the scopes of this paper, BSM was executed on landing data and biomass indices. The biomass indices were obtained from the SoleMon project (Grati et al., 2013), a trawl survey carried out from 2005 up to the present with rapido trawl in a 36,742-km^2 area of the Northern and Central Adriatic Sea (Scarcella et al., 2014). To improve the indices estimates, data were smoothed through the "BCrumb" routine, a state-space model for trend analysis of ecological time series that is part of the JABBA (Winker et al., 2018) and JARA (Winker and Sherley, 2019) models. This tool treats relative biomass as an unobservable state variable that follows a log-linear Markovian process to reduce the influence of observation error on the CMSY estimates (Winker et al., 2018). As input for the catch data, the longest series of landings in GSA17 available for each species were used (see **Table 1** and **Supplementary Table 2**; Fortibuoni et al., 2018; STECF, 2019; DCF-ITA). Missing data of Croatian and Slovenian landings were reconstructed through a mean proportion, derived from the years in which they were available for all GSA17 bordering countries. Priors for r were either taken from previous specific studies in this area (Froese et al., 2018) or inferred from their averages in FishBase and SeaLifeBase (Palomares and Pauly, 2018; Froese and Pauly, 2019).

The choice of an increasing pattern from the initial to the final depletion prior in the reference models was supported by an overall increase in the fishing pressure in the Adriatic Sea (Colloca et al., 2017) followed by a reduction of the productivity of the commercial fishery over the study period (Marini et al., 2017). A sensitivity analysis was conducted to test the effect of different sets of viable depletion priors (B_{start}/k and B_{end}/k) on the final B/B_{msy} value. A Feed-Forward Artificial Neural Network was used to estimate these viable prior ranges of relative biomass for each studied species, based on characteristics of the catch time series such as minimum and maximum catch, length, slope in the final years, and shape (Froese et al., 2021 submitted). The network was trained with the data of 400 stock to detect interplay patterns of catch and abundance and predict relative biomass priors directly from the catch time series. Following the procedure described in Falsone et al. (2021), the accuracy of the final result was calculated through the percent difference between the reference model's values and the Artificial Neural Network model's values.

Stock Projections

The outputs of single-species stock assessments were used to run an advanced implementation of CMSY (Froese et al., 2018). This model uses a rewrite of the Schaefer function to predict next year's status of the biomass, based on the parameters estimated by the CMSY model:

$$\frac{B_{t+1}}{B_{msy}} = \frac{B_t}{B_{msy}} + 2\,F_{msy}\,\frac{B_t}{B_{msy}}\left(1 - \frac{B_t}{2\,B_{msy}}\right) - \frac{B_t}{B_{msy}}\,F_t$$

In the equation, B_t and F_t, respectively, represent the biomass and the fishing effort in a certain year (t), while B_{t+1} is the biomass in the following year. The model assumes that the estimated r and k CMSY parameters remain constant over the projection time. The catch assemblage analysis iteratively uses the above formula under different relative effort scenarios, i.e., as different ratios of fishing mortality (F) over the fishing mortality in the last estimation year (F_{last_year}). In particular, for the stocks identified in the cluster analysis, the following HCR scenarios, based on the F of every single stock, were used:

- Scenario (1): 0.5 F_{2018} simulating a reduction of 50%,
- Scenario (2): 0.6 F_{2018} simulating a reduction of 40%,
- Scenario (3): 0.8 F_{2018} simulating a reduction of 20%,
- Scenario (4): 0.95 F_{2018} simulating a reduction of 5%,

where F_{2018} is the F value of the last year of each stock time series. The advanced implementation of CMSY is a non-Bayesian statistical algorithm that builds on the Bayesian estimates of CMSY. Based on the F scenarios, the algorithm cycles through the following steps for each scenario:

1. For each stock, produce 1,000 iterations of the biomass in time, starting from values in the neighborhoods of B/B_{msy};
2. Average all the generated B/B_{msy} time series of each stock;
3. Average the averaged B/B_{msy} time series of all stocks;
4. Estimate confidence intervals and plot the forecasts.

Step 1 of the algorithm is necessary to account for uncertainty around the estimate of B/B_{msy}, also due to a random error term used in the Schaefer function in CMSY.

Since CMSY accounts for stock depletion at very low biomass levels, the effort scenarios consider also different effects of the exploitation level on low-biomass stocks. In particular, during the projections, the following rules are applied:

1. In Scenario (1), the fishing mortality of a stock is set equal to zero when $B < 0.5\,B_{msy}$;
2. In the other scenarios, when $B < 0.5\,B_{msy}$, F is linearly decreased with biomass, according to the relation $F = \frac{(2Bt)}{Bmsy}\ Fmsy$.

TABLE 1 | Input data of the CMSY analysis.

FAO 3-Alpha Code	Scientific name	Common name	Start year	End year	r. low	r. high	stb.low	stb.hi	Endb.low	Endb.hi	Smoothed index
BLL	*Scophtalmus rhombus*	Brill	1972	2018	0.31	0.71	0.4	0.8	0.01	0.2	Y
BOY	*Bolinus brandaris*	Purple dye murex	1972	2018	0.64	1.46	0.7	1	0.4	0.8	N
SJA	*Pecten jacobaeus*	Mediterranean scallop	1972	2018	0.25	0.74	0.4	0.8	0.1	0.3	Y
SOL	*Solea solea*	Common sole	1972	2018	0.33	0.76	0.4	0.8	0.1	0.5	N
SCX- > QSC	*Aequopecten opercularis*	Queen scallop	2004	2008	0.37	0.84	0.2	0.6	0.01	0.4	Y

Stocks are presented by FAO 3-Alpha code, scientific and common name of the species. Start year, first year of the analysis; End year, last year of the analysis; r.high/r.low, range specified for resilience; stb.low/stb.high, prior biomass range relative to the unexploited biomass (B/k) at the beginning of the time series; Endb.low/Endb.hi, prior relative biomass (B/k) range at the end of the catch time series; Smoothed index, smooth to the biomass index.

Rule number 2 comes from a $\frac{2B_t}{B_{msy}}$ linearly decreasing multiplier of F_{msy} used in CMSY to account for repopulation hysteresis for low relative biomasses (Froese et al., 2018, 2020).

Projecting biomass after fixing relative fishing mortality to the one in the last year for each stock, allows accounting for the real and different effects of the fisheries on each stock. Indeed, this assumption proportionally reduces the effort on each stock, assuming that the fishing strategies and gears do not change. Thus, in this way, a uniform reduction of the fishing hours in a certain year will affect each stock differently.

RESULTS

The taxonomic list analyzed with the multivariate analysis was composed of 87 species (**Supplementary Table 3**). The PERMANOVA test highlighted a significant difference between the catch assemblages of the nation-gear combination (**Table 2**). Further, pairwise contrast indicated that rapido (ITA_TBB) column was statistically different from the majority of the gears (**Table 3**), except for Italian polyvalent passive gears (ITA_PGP) and Croatian bottom trawlers (HRV_DTS).

The cluster analysis partitioned the species list into 11 groups, nine of which statistically confirmed (**Figure 2**). DTS was the main driver for three clusters (1, 2, and 3), which contrast was due to different contributions of ITA and HRV catches. ITA_PGP was the major driver of three clusters (4, 5, and 6) that were differentiated for the degree of contribution of ITA_DTS. Group 7 was driven by ITA_PGP, while it accounted for large contributions of ITA_DTS and ITA_TBB. One group (8) was entirely driven by ITA_DRB. The last group (9) was almost exclusively driven by ITA_TBB, which therefore was our target group. This latter assemblage of species was composed of *Pecten jacobaeus, Scophtalmus rhombus, Solea solea, Bolinus brandaris,* and *Aequopecten opercularis* (SJA, BLL, SOL, BOY, and SCX; **Table 2**). Even if the SCX FAO 3-Alpha Code stands for the *Pectinidae* family, the species selected for the stock assessment was *Aequopecten opercularis,* since this species constitutes the majority of the *Pectinidae* catches in the north Adriatic basin.

Based on the data series and priors in **Table 1**, the results of the single species assessments are reported in **Figure 3**. The majority of the stocks assessed in the present study were considered to be in a data-limited situation due to the lack of information, except for common sole (SOL) for which stock assessment was also available from age-based approaches (GFCM, 2018). For this reason, the most recent common sole estimates (FAO-GFCM, 2019) were used to validate the BSM model.

The BSM analysis highlighted several observations: for what regards biomass, the analyzed stocks showed a value lower than B_{msy} from the year 2000 onward, whereas common sole (**Figure 3D**) and purple dye murex (**Figure 3B**) were over the reference point in last years. As for the common sole, in the last twenty years, biomass was estimated to range between B_{msy} and B_{lim} (50% B_{msy}). Purple dye murex was the only species for which values of biomass never went under B_{msy}. For what regards fishing mortality, F was estimated to go under F_{msy} in the last years for three stocks. On the contrary, brill (**Figure 3A**) was in a strong overexploitation status due to a continuous increase of fishing mortality (F/F_{msy} in 2018 was $\sim$2). As for the common sole, fishing mortality cycled around F_{msy} during the time series, and F showed an increasing trend that reached a F/F_{msy} ratio of about 1 in 2018, consistently to the age-based assessment (FAO-GFCM, 2019). The F pace of purple dye murex was a counter-trend: it remained below the reference point until recent times and reached it only in the last year.

To sum up, the stock trajectories of the Mediterranean scallop (**Figure 3C**) and queen scallop (**Figure 3E**) reported in the Kobe plot (Maunder and Aires-da-Silva, 2011) passed from red to yellow area, i.e., there was a slight decrease in fishing mortality while the state of biomass was still below the reference point. As for brill, the stock trajectory remained in the red quadrant, with low biomass and a high level of F. The trajectory of

TABLE 2 | Results of One-Way PERMANOVA analysis.

Source	Df	SS	MS	F	R^2	Pr (> F)
Gear	8	19.46	4.11	16.34	0.22	0.001***
Residuals	464	62.27	0.25		0.78	
Total	472	81.72				

*Df, degrees of freedom; SS, sum of square; MS, mean of square; F, Fisher value; R^2, R square; Pr, significance; ***, highly significant.*

TABLE 3 | Results of pairwise PERMANOVA analysis, *p*-values corrected with the Bonferroni method.

	HRV_DTS	HRV_PGP	HRV_RMP	ITA_DRB	ITA_DTS	ITA_PGP	ITA_TBB	SVN_DTS
HRV_PGP	**0.036**							
HRV_RMP	**0.036**	1						
ITA_DRB	**0.036**	**0.036**	**0.036**					
ITA_DTS	**0.036**	**0.036**	**0.036**	**0.036**				
ITA_PGP	1	**0.036**	**0.036**	**0.036**	**0.036**			
ITA_TBB	1	0.18	**0.036**	**0.036**	**0.036**	1		
SVN_DTS	**0.036**	1	1	**0.036**	**0.036**	**0.036**	0.108	
SVN_PGP	**0.036**	0.072	0.864	1	**0.036**	**0.036**	**0.036**	0.72

The gears code is composed, by a first group three letters representing the nation (HRV, Croatia; ITA, Italy; SVN, Slovenia) and a second referring to the fleet segment (DTS, bottom trawl; PGP, polyvalent passive gears; RMP, rampon; DRB, towed dredge; TBB, rapido beam trawl).
Significant contrasts are reported in bold.

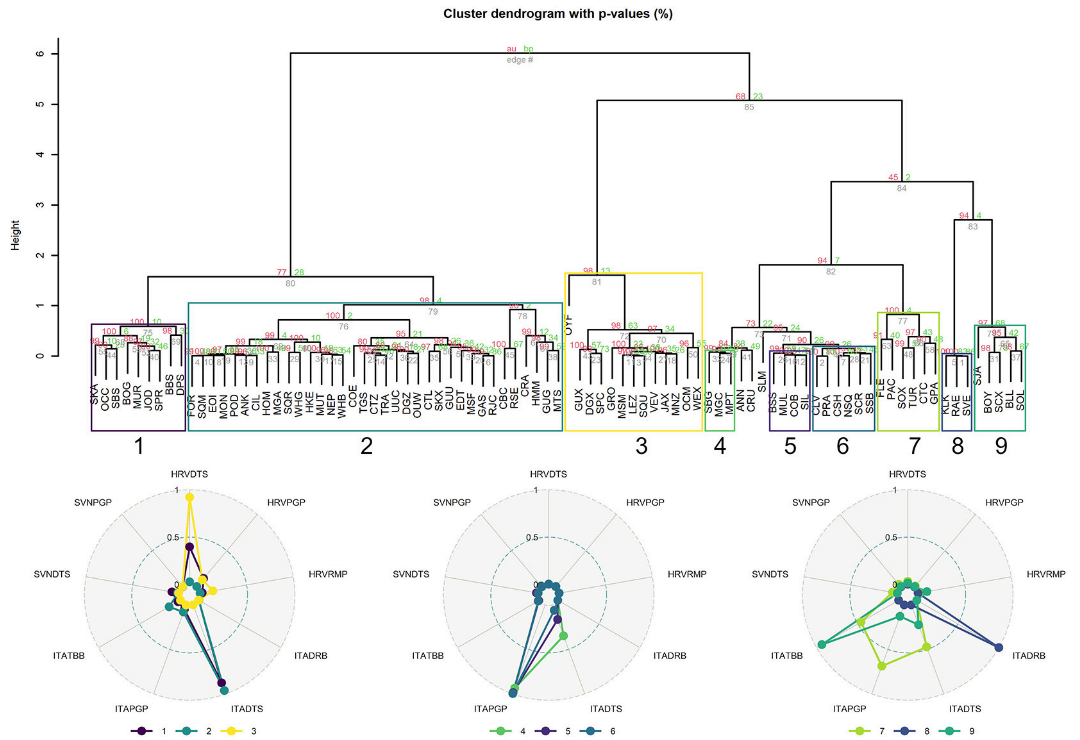


FIGURE 2 | Hierarchical cluster analysis with the Ward method (Ward, 1963) applied to the gear-by-country table. AU *p*-value (printed in red color in default) is the abbreviation of "approximately unbiased" *p*-value, which is calculated by multiscale bootstrap resampling. BP value (printed # in green color by default) is "bootstrap probability" value, which is less accurate than AU value as *p*-value. Clusters with high AU values (e.g., 95%) are indicated with blue edges and are strongly supported by data.

the purple dye murex stock indicated sustainable exploitation during the majority of the time series, however, it went into an overfishing status in the last years. Common sole trajectory oscillated around the reference point during the last years and finally stabilized around MSY.

The Artificial Neural Network-based sensitivity analysis showed that a moderate alteration of the relative biomass priors did not affect the final B/B_{msy} estimation substantially. The difference between our results and those obtained through the Artificial Neural Network was always under 20% for all studied species, ranging from a 6% minimum for the Mediterranean scallop to a 19% maximum for common sole (**Table 4**).

Based on these assessments, the CMSY extended analysis, performed on the entire catch assemblage, produced different projections depending on the applied HCR (**Figure 4**). In Scenarios (1) and (2), 80% of the stocks reached B_{msy} in 2030, whereas in Scenario (3) a few more years were required to reach B_{msy}. On the contrary, in Scenario (4), under a more permissive HCR, only 60% of the stocks were observed to reach B_{msy} in 2033. Catch projections showed an opposite pattern to biomass, with an initial decrease whose steepness depended on the HCR (**Figure 5**). Overall, scenarios showed an initial drop of the catches followed by a recovery and stabilization. In the long-term, Scenario (3) and (4) stabilized at a higher level than the initial estimates.

DISCUSSION

This was the first extensive assessment-based meta-analysis of the main target and accessories species of rapido trawl fishery in the Adriatic Sea. In the case of mixed fisheries, formulating policies for management and conservation requires the use of models capable of predicting how catch assemblages change in response to fishing effort (Welcomme, 1999). However, when management objectives point toward fishing at reference points of the main target species, the overpressure of accessory species of the same catch assemblage is very plausible (Punt et al., 2002). These considerations fit well the Mediterranean context where demersal fisheries are commonly multispecific (Colloca et al., 2003). Within this context, identifying clusters of commercially important species might help to define conservation units in management plans (Rogers and Pikitch, 1992). In the case of the demersal fishery in the Adriatic Sea, the cluster analysis highlights that a few resources were characterizing the catch assemblages of each gear, except for ITA_PGP and ITA/HRV_DTS, which resulted to be the more generalists. The fact that these fleets showed the most diversified assemblage compared with the other gears reflected the *modus operandi* of these fisheries: ITA_PGP seasonally switches gears and grounds following resource availability (Grati et al., 2018), while the DTS footprint is by far the larger in the area (Russo et al., 2020), spreading across the spatial range of many different species. In contrast,

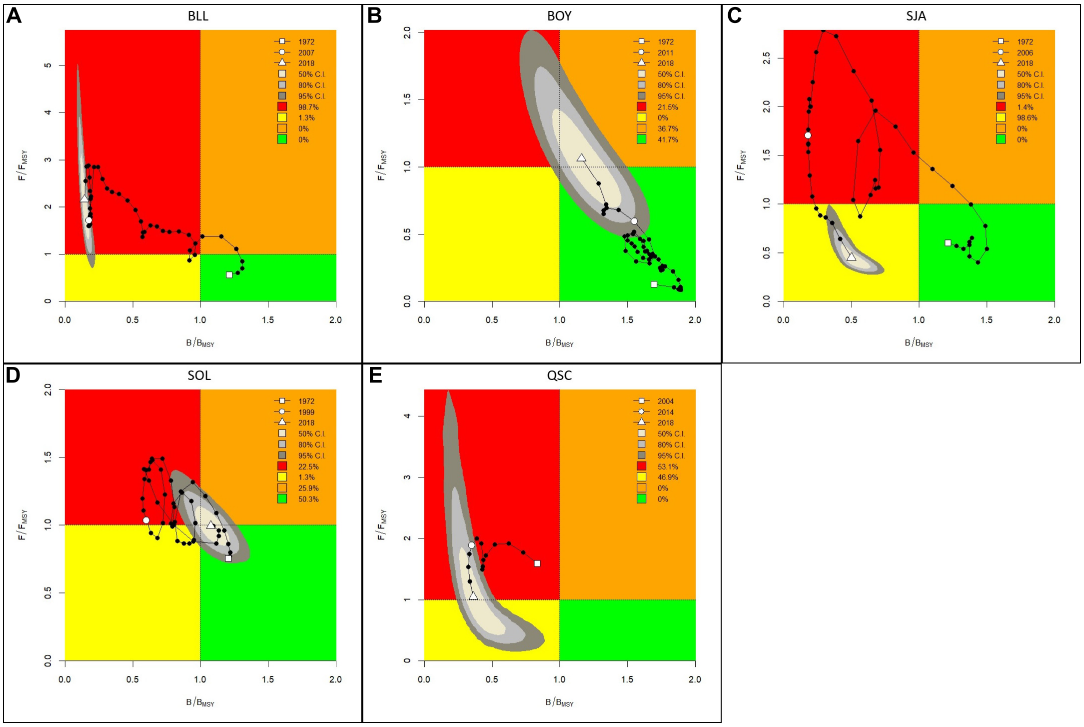


FIGURE 3 | Kobe plots resulting from the single species stock assessment: **(A)** Brill, **(B)** Purple dye murex, **(C)** Mediterranean scallop, **(D)** Common sole, and **(E)** Queen scallop.

some of the most landed resources were mainly targeted by one specific gear, such as the group formed by clams (SVE: *Chamelea gallina*, KLK: *Callista chione*, RAE: *Solen marginatus*) targeted by Italian DRB, and the cluster made by *Pectinidae* (SJA, SCX) and flatfishes (SOL: *Solea solea*, BLL: *Scophtalmus rhombus*, TUR: *Scophthalmus maximus*) targeted by Italian TBB. These findings allowed us to consider the assemblage of species analyzed as representative of the exploitation exerted by the rapido fishery.

Although the Adriatic sea is one of the most intensively trawled area of the Mediterranean sea (Eigaard et al., 2017; Ferrà et al., 2018) and in the entire world (Amoroso et al., 2018), some of the stocks analyzed showed an increase in biomass at the end of the analysis time-scale (evident in the single-species Kobe plot trajectory toward the recovery area). A possible explanation may be found in the management measures adopted in the last decades: current regulation includes a summer ban to the trawling activity—total closure for 1 month (EC, 2006), extending temporary spatial restrictions up to 4 or 6 nm depending on vessel length since 2012. These measures might have had relevant consequences for recruitment success in coastal areas (Scarcella et al., 2014) leading to a general improvement in the overall status of stocks exploited by rapido fishery. However, species respond in different manners to effort reduction due to different resilience, competition, and recruitment impairment (Gamble and Link, 2009), and those species for which biomass levels have fallen below 0.5 B/B_{msy}, a threshold that characterizes impaired stocks (Froese et al., 2016), remained in alarming status. Nevertheless, literature reports that flatfishes recruitment success does not strictly depend on stock size (Iles, 1994; Maunder, 2012; Van der Hammen et al., 2013), therefore additional work is required to explain the alarming status of brill. Environmental characteristics of the study area may have a large effect on the resources: organic matter input from rivers and the resulting nutrient enrichment can lead to a high rate of primary productivity, particularly in the Northern and the Central Adriatic (Cognetti et al., 2000), which helps to maintain recruitment capacity in marine fish stocks (Britten et al., 2016), mainly for species with high resilience such as common sole. On the other hand, North Adriatic is a recognized key area for seasonal low oxygen depletion, whether it be eutrophication or climate change-related (Kollmann and Stachowitsch, 2001), and has been repeatedly affected over the last three decades by bottom anoxia and benthic mortalities (e.g., *Pectinidae* family; Mattei and Pellizzato, 1996). This facilitates detritus-feeding group establishment, such as purple-dye murex, that can make a stand to the recovery of the suspension feeders, i.e., *Pectinidae*, by consuming and smothering the potential recruits (Riedel et al., 2010). These dynamics, together with continuous trawling, might have led scallops to such low biomass. Nevertheless, it is important to underline that the biomass of the Mediterranean scallop was estimated to have recently increased over 0.5 B_{msy}.

The aggregated forecast analysis showed that the percentage of the stocks that will reach B_{msy} at the end of the projections will depend on the HCR applied. Scenario (1) and (2) were the fastest in reaching B_{msy} (80% of the stocks by 2030), however, they required the biggest drop in catches in the short period; this

TABLE 4 | Summary table of the sensitivity analysis over the B/B_{msy} estimation that compares the results obtained from reference model (ref) against the one computed with priors estimated by an Artificial Neural Network (ANN).

Species	Prior B_{start}/k ref.	Prior B_{end}/k ref.	Prior B_{start}/k ANN	Prior B_{end}/k ANN	B/B_{msy} ref	B/B_{msy} ANN	Δ %
QSC	0.2–0.6	0.01–0.4	0.25–0.72	0.07–0.33	0.36	0.40	−11.5
BOY	0.7–1	0.4–0.8	0.73–0.98	0.17–0.55	1.15	1.01	12.77
SJA	0.4–0.8	0.1–0.3	0.13–0.46	0.04–0.26	0.50	0.47	5.82
BLL	0.4–0.8	0.01–0.2	0.17–0.54	0.02–0.23	0.14	0.13	6.71
SOL	0.4–0.8	0.1–0.5	0.35–0.77	0.23–0.67	1.07	1.28	−19.02

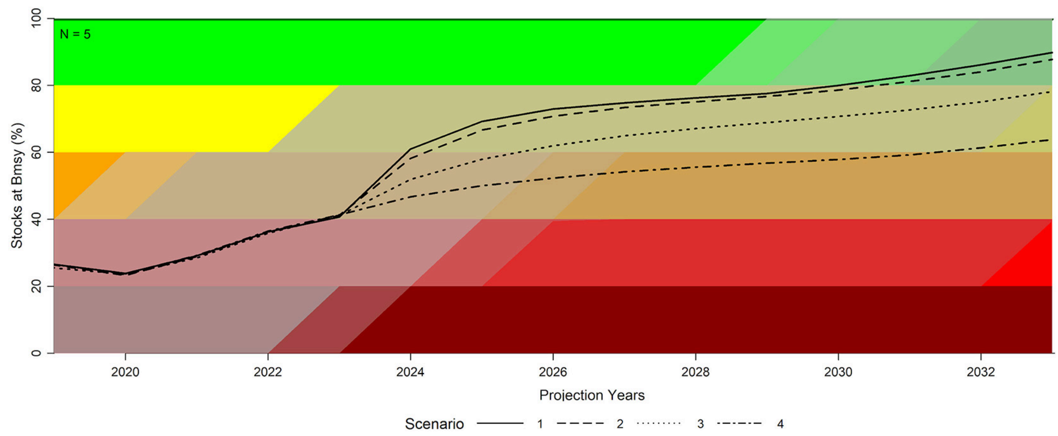


FIGURE 4 | Forecast of alternative HCRs from the CMSY extended analysis on the catch assemblage: percentage of stocks at B_{msy}. Stronger the effort reduction, shorter the range of time in which 80% of the stocks will reach the Bmsy. Scen. (1): 50% of effort reduction; Scen. (2): 40% of effort reduction; Scen (3): 20% of effort reduction; Scen. (4): 5% of effort reduction.

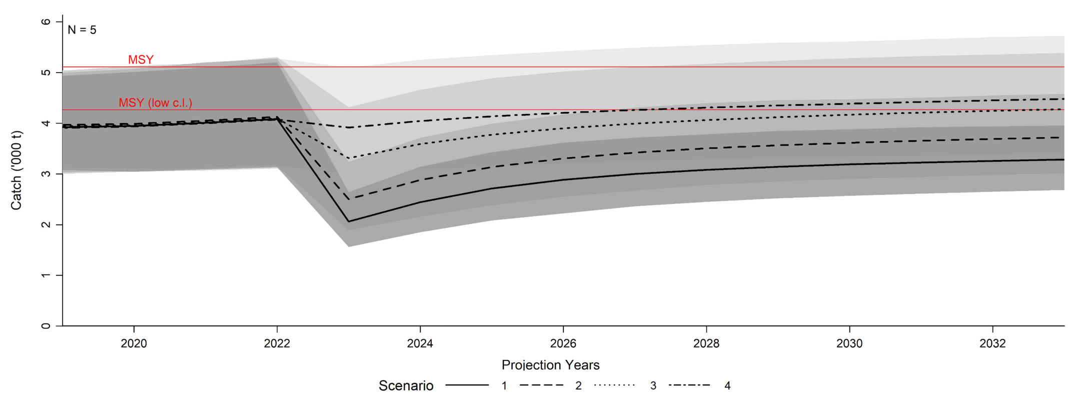


FIGURE 5 | Forecast of alternative HCRs from the CMSY extended analysis on the catch assemblage: projections of catch time series. After a first decrease, all the scenarios, independently from the strength of the control rule, will figure a stabilization in catches.

sudden reduction would be probably economically and socially unsustainable for the Adriatic fishing sector. On the opposite, Scenario (4) could be preferable from an economic point of view due to higher catches in the long term, but it would allow fewer stocks to reach B_{msy} by 2033 (only 60%), breaching the sustainability principles of the EU Common Fisheries Policy (European Parliament, 2013). Scenario (3) foreseen that 80% of the stocks will reach B_{msy} in 15 years if the F will be reduced by 20% providing a possible compromise between long-term environmental and social sustainability (relatively high expected catch and reasonably fast and good rebuilding in stock biomass). Scenario (3) was therefore more sustainable and compatible with the fundamental principles of CFP, which is to match sustainable exploitation of the fish stocks with socio-economic sustainability (Reg EU No. 1380/2013).

Despite simulation of HCRs showed a biomass recovery for the majority of the stocks regardless of the scenario (>60% of the stocks reach for all the rebuilding strategies B_{msy}), it may be less reliable for brill and Mediterranean scallop, which were classified in critical status. In fact, in forecast analyses, an increase in the total biomass of the considered species might have been driven by those stocks that were already in a recovering phase.

Therefore, other management measures should be combined with a reduction of fishing effort to allow for stocks' recovering (Demirel et al., 2020), especially in the most depleted cases. Considering that the areas of persistency of these species are well known (AdriaMed, 2011), specific adaptive measures for rapido trawl fishery should be implemented, such as spatio-temporal closures to protect the stocks (Hall-Spencer et al., 1999): guaranteeing protected areas might allow stocks to be more resilient to local depletions (Kritzer and Liu, 2014). Furthermore, effort reduction by itself does not imply a concomitant overall reduction of the fishing mortality for all stocks (Cardinale et al., 2017). Thus, even if the actual management plan (Recommendation GFCM/43/2019/5) already envisages a fishing effort reduction comparable to scenario (3), other management measures may be necessary to avoid the depletion of the most pressured commercial and accessory species.

The presented approach and the used models implicate strong assumptions on the stocks' life-history traits as well as in exploitation status that should be carefully considered. In addition, the CMSY model does not account for the size and age structure of the stock and therefore tends to overestimate sustainable productivity in stocks where excessive fishing pressure has truncated the population structure (Froese et al., 2018). Moreover, the forecasting algorithm assumes that fishing strategies and gears do not change in time. Thus, the estimates coming from the present study should not be taken as a detailed reproduction of reality. Nevertheless, they were sufficient to produce an overall sound snapshot of the performance of different future inter-correlated fisheries scenarios, which would have required many years of data preparation and data gap-filling if data-rich approaches had been used.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

ACKNOWLEDGMENTS

FM, MS, and EA thank those who contribute to their training with specific courses. Also, all authors want to thank the DRuMFISH project (EASME/EMFF/2014/.1.3.2.4/SI2.721116), in which this work was initialized. The research leading to these results has been conceived under the International Ph.D. Program "Innovative Technologies and Sustainable Use of Mediterranean Sea Fishery and Biological Resources" (www.FishMed-PhD.org). This study represents partial fulfillment of the requirements for the Ph.D. thesis of FM and EA. Anonymous reviewer are thanked for their comments on an earlier version of this paper.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2021.552076/full#supplementary-material

REFERENCES

AdriaMed (2011). *Report of the Technical Meeting on Solemon Survey Activities, GCP/RER/010/ITA/SR-01.* AdriaMed Scientific Reports N. 01. Rome: FAO AdriaMed. 21.

Amoroso, R. O., Pitcher, C. R., Rijnsdorp, A. D., McConnaughey, R. A., Parma, A. M., Suuronen, P., et al. (2018). Bottom trawl fishing footprints on the world's continental shelves. *Proc. Natl. Acad. Sci. U.S A.* 115, E10275–E10282. doi: 10.1073/pnas.1802379115

Arbizu, M. (2017). Pairwiseadonis: Pairwise Multilevel Comparison Using Adonis. R Package. Version 0.0. doi: 10.1109/IROS.2007.4399402

Berger, A., Harley, S., Pilling, G., Davies, N., and Hampton, J. (2012). "Introduction to harvest control rules for WCPO tuna fisheries," in *Proceedings of the Eighth Scientific Committee Meeting for the WCPFC* Nouméa.

Bion, R. (2021). *ggradar: Create Radar Charts Using ggplot2.*

Borcart, D., Gillet, F., and Legendre, P. (2018). *Numerical Ecology with R*, 2nd Edn. New York, NY: Springer International Publishing AG.

Britten, G. L., Dowd, M., and Worm, B. (2016). Changing recruitment capacity in global fish stocks. *Proc. Natl. Acad. Sci.U.S.A.* 113, 134–139.

Browman, H., and Stergiou, K. (2004). Perspectives on ecosystem-based approaches to the management of marine resources. *Mar. Ecol. Prog. Ser.* 274, 269–303.

Cardinale, M., Osio, G. C., and Scarcella, G. (2017). Mediterranean Sea: a Failure of the European fisheries management system. *Front. Mar. Sci.* 4:72. doi: 10.3389/fmars.2017.00072

Cognetti, G., Lardicci, C., Abbiati, M., and Castelli, A. (2000). The Adriatic sea and the Tyrrhenian sea. *Seas Millenn. Environ. Eval.* 1, 267–284.

Colloca, F., Cardinale, M., Belluscio, A., and Ardizzone, G. (2003). Pattern of distribution and diversity of demersal assemblages in the central Mediterranean sea. *Estuar. Coast. Shelf Sci.* 56, 469–480. doi: 10.1016/S0272-7714(02)00196-8

Colloca, F., Cardinale, M., Maynou, F., Giannoulaki, M., Scarcella, G., Jenko, K., et al. (2013). Rebuilding Mediterranean fisheries: a new paradigm for ecological sustainability. *Fish Fish.* 14, 89–109. doi: 10.1111/j.1467-2979.2011.00453.x

Colloca, F., Scarcella, G., and Libralato, S. (2017). Recent trends and impacts of fisheries exploitation on mediterranean stocks and ecosystems. *Front. Mar. Sci* 4:244. doi: 10.3389/fmars.2017.00244

Demirel, N., Zengin, M., and Ulman, A. (2020). First large-scale eastern mediterranean and black sea stock assessment reveals a dramatic decline. *Front. Mar. Sci.* 7:103. doi: 10.3389/fmars.2020.00103

EC (2006). *Council Regulation (EC) No 1967/2006 of 21 December2006 Concerning Management Measures for the Sustainable Exploitation of Fishery Resources in the Mediterranean Sea, amending Regulation (EEC) No 2847/93 and repealing Regulation (EC) No 1626/94.*

Eigaard, O. R., Bastardie, F., Hintzen, N. T., Buhl-Mortensen, L., Buhl-Mortensen, P., Catarino, R., et al. (2017). The footprint of bottom trawling in European waters: distribution, intensity, and seabed integrity. *ICES J. Mar. Sci.* 74, 847–865. doi: 10.1093/icesjms/fsw194

European Parliament (2013). European Parliament and Council. regulation (EU) No. 1380/2013 of the European Parliament and of the Council of 11 December 2013 on the common fisheries policy. *Off. J. Eur. Union* 354, 22–61.

Falsone, F., Scannella, D., Geraci, M. L., Gancitano, V., Vitale, S., and Fiorentino, F. (2021). How fishery collapses: the case of *Lepidopus caudatus* (Pisces: Trichiuridae) in the Strait of Sicily (Central Mediterranean). *Front. Mar. Sci.* 7:584601. doi: 10.3389/fmars.2020.584601

FAO-GFCM (2019). *Working Group on Stock Assessment of Demersal Species (WGSAD) 19–24 November 2018 Final Report*. Rome: FAO.

Ferrà, C., Tassetti, A. N., Grati, F., Pellini, G., Polidori, P., Scarcella, G., et al. (2018). Mapping change in bottom trawling activity in the Mediterranean sea through AIS data. *Mar. Policy* 94, 275–281. doi: 10.1016/j.marpol.2017.12.013

Fortibuoni, T., Libralato, S., Arneri, E., Giovanardi, O., Solidoro, C., and Raicevich, S. (2018). Erratum: fish and fishery historical data since the 19th century in the Adriatic Sea, Mediterranean. *Sci. Data* 5:180144. doi: 10.1038/sdata.2018.144

Froese, R., Demirel, N., Coro, G., Kleisner, K. M., and Winker, H. (2017). Estimating fisheries reference points from catch and resilience. *Fish Fish.* 18, 506–526. doi: 10.1111/faf.12190

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2018). Status and rebuilding of European fisheries. *Mar. Policy* 93, 159–170. doi: 10.1016/j.marpol.2018.04.018

Froese, R., and Pauly, D. (2019). *FishBase*. Version (02/2018).

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2020). Estimating stock status from relative abundance and resilience. *ICES J. Mar. Sci.* 77, 527–538. doi: 10.1093/icesjms/fsz230

Froese, R., Winker, H., Coro, G., Palomares, M.-L. D., Tsikliras, A. C., Dimarchopoulou, D., et al. (2021). Catch time series as the basis for fish stock assessments: the CMSY++ method and its worldwide applications. *Submitt Fish Fish*

Froese, R., Winker, H., Gascuel, D., Sumaila, U. R., and Pauly, D. (2016). Minimizing the impact of fishing. *Fish Fish.* 17, 785–802. doi: 10.1111/faf.12146

Galdelli, A., Mancini, A., Tassetti, A. N., Ferrà Vega, C., Armelloni, E., Scarcella, G., et al. (2019). "A cloud computing architecture to map trawling activities using positioning data," in *Proceeddings of the 15th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications*, Vol. 9, (New York; NY: American Society of Mechanical Engineers). doi: 10.1115/DETC2019-97779

Gamble, R. J., and Link, J. S. (2009). Analyzing the tradeoffs among ecological and fishing effects on an example fish community: a multispecies (fisheries) production model. *Ecol. Model.* 220, 2570–2582. doi: 10.1016/j.ecolmodel.2009.06.022

GFCM (2018). *Scientific Advisory Committee on Fisheries (SAC) Working Group on Stock Assessment of Demersal Species (WGSAD)* 13 – 18 November 2017 Final Report, Vol. 1. Rome: GFCM and FAO. 13–18.

Giovanardi, O., Pranovi, F., and Franceschini, G. (1998). "Rapido" trawl-fishing in the Northern Adriatic: preliminary observations on effects on macrobenthic communities. *Acta Adriat.* 39, 37–52.

Grati, F., Aladzuz, A., Azzurro, E., Bolognini, L., Carbonara, P., ?obani, M., et al. (2018). Seasonal dynamics of small-scale fisheries in the Adriatic sea. *Mediterr. Mar. Sci.* 19:21. doi: 10.12681/MMS.2153

Grati, F., Scarcella, G., Polidori, P., Domenichetti, F., Bolognini, L., Gramolini, R., et al. (2013). Multi-annual investigation of the spatial distributions of juvenile and adult sole (Solea solea L.) in the Adriatic Sea (northern Mediterranean). *J. Sea Res.* 84, 122–132. doi: 10.1016/j.seares.2013.05.001

Hall-Spencer, J., Froglia, C., Atkinson, R. J. A., and Moore, P. G. (1999). The impact of Rapido trawling for scallops,*Pecten jacobaeus*(L.), on the benthos of the Gulf of Venice. *ICES J. Mar. Sci.* 56, 111–124. doi: 10.1006/jmsc.1998.0424

Hilborn, R. (2011). Future directions in ecosystem based fisheries management: a personal perspective. *Fish. Res.* 108, 235–239. doi: 10.1016/j.fishres.2010.12.030

Howell, D., and Subbey, S. (2019). "Multispecies considerations in stock assessments: "yes we can"," in *Proceedings of the ICES Annual Science Conference ICES C. 2013/E07*, (Bergen: IMR).

ICES. (2017). *WGMIXFISH – Report of the Working Group on Mixed Fisheries Advice for the North Sea*. Copenhagen: ICES. 128.

Iles, T. C. (1994). A review of stock-recruitment relationships with reference to flatfish populations. *Neth. J. Sea Res.* 32, 399–420. doi: 10.1016/0077-7579(94)90017-5

Kollmann, H., and Stachowitsch, M. (2001). Long-term changes in the benthos of the northern adriatic sea: a phototransect approach. *Mar. Ecol.* 22, 135–154. doi: 10.1046/j.1439-0485.2001.01761.x

Kritzer, J. P., and Liu, O. R. (2014). "Fishery management strategies for addressing complex spatial structure in marine fish stocks," in *Stock Identification Methods*, (Cambridge, MA: Academic Press), 29–57. doi: 10.1016/B978-0-12-397003-9.00003-5

Legendre, P., and Gallagher, E. D. (2001). Ecologically meaningful transformations for ordination of species data. *Oecologia* 129, 271–280. doi: 10.1007/s004420100716

Link, J. S. (2010). *Ecosystem-Based Fisheries Management: Confronting Tradeoffs*. New York, NY: Cambridge University Press, doi: 10.1017/CBO9780511667091

Maravelias, C. D., and Tsitsika, E. V. (2008). Economic efficiency analysis and fleet capacity assessment in Mediterranean fisheries. *Fish. Res.* 93, 85–91. doi: 10.1016/j.fishres.2008.02.013

Marini, M., Bombace, G., and Iacobone, G. (2017). *Il Mare Adriatico e le Sue Risorse*. Palermo: Carlo Saladino Editore.

Mattei, N., and Pellizzato, M. (1996). A population study on three stocks of a commercial Adriatic pectinid (*Pecten jacobaeus*). *Fish. Res.* 26, 49–65. doi: 10.1016/0165-7836(95)00413-0

Maunder, M. N. (2012). Evaluating the stock-recruitment relationship and management reference points: application to summer flounder (*Paralichthys dentatus*) in the U.S. mid-Atlantic. *Fish. Res.* 125–126, 20–26. doi: 10.1016/j.fishres.2012.02.006

Maunder, M. N., and Aires-da-silva, A. (2011). *Evaluation of the Kobe Plot and Strategy Matrix and Their Application to Tuna in the EPO*. Iattc, 191-211. La Jolla, CA. Available online at: https://www.iattc.org/Meetings/Meetings2011/SAC-02/Docs/_English/SAC-02-11_Evaluation-of-Kobe-plot-and-matrix.pdf (accessed May 9-12, 2011)

Maunder, M. N., and Punt, A. E. (2013). A review of integrated analysis in fisheries stock assessment. *Fish. Res.* 142, 61–74. doi: 10.1016/j.fishres.2012.07.025

Moffitt, E. A., Punt, A. E., Holsman, K., Aydin, K. Y., Ianelli, J. N., and Ortiz, I. (2016). Moving towards ecosystem-based fisheries management: options for parameterizing multi-species biological reference points. *Deep Res. Part II Top. Stud. Oceanogr.* 134, 350–359. doi: 10.1016/j.dsr2.2015.08.002

Oksanen, A. J., Blanchet, F. G., Friendly, M., Kindt, R., Legendre, P., Mcglinn, D., et al. (2016). *Vegan: Community Ecology Package*. doi: 10.4135/9781412971874.n145

Palomares, M., and Pauly, D. (2018). *SeaLifeBase. Version (02/2018)*.

Petović, S., Markoviæ, O., Ikica, Z., Ðuroviæ, M., and Joksimoviæ, A. (2016). Effects of bottom trawling on the benthic assemblages in the south Adriatic Sea (Montenegro). *Acta Adriat.* 57, 81–92.

Pranovi, F., Raicevich, S., Franceschini, G., Farrace, M. G., and Giovanardi, O. (2000). Rapido trawling in the northern Adriatic Sea: effects on benthic communities in an experimental area. *ICES J. Mar. Sci.* 57, 517–524. doi: 10.1006/jmsc.2000.0708

Punt, A. E., Smith, A. D. M., and Cui, G. (2002). Marine Freshwater of technical interactions. *Mar. Freshw. Res.* 53, 615–629.

Riedel, B., Stachowitsch, M., and Zuschin, M. (2010). "Low dissolved oxygen impacts in the northern Adriatic: critical thresholds for benthic assemblages," in *Proceedings of the ICES Annual Science Conference* Vienna. 1–17.

Rogers, J. B., and Pikitch, E. K. (1992). Numerical definition of groundfish assemblages caught off the coasts of oregon and washington using commercial fishing strategies. *Can. J. Fish. Aquat. Sci.* 49, 2648–2656. doi: 10.1139/f92-293

Russo, E., Monti, M. A., Mangano, M. C., Raffaetà, A., Sarà, G., Silvestri, C., et al. (2020). Temporal and spatial patterns of trawl fishing activities in the Adriatic Sea (Central Mediterranean sea, GSA17). *Ocean Coast. Manag.* 192:105231. doi: 10.1016/j.ocecoaman.2020.105231

Santelli, A., Cvitkoviæ, I., Despalatoviæ, M., Fabi, G., Grati, F., Marèeta, B., et al. (2017). Spatial persistence of megazoobenthic assemblages in the Adriatic Sea. *Mar. Ecol. Prog. Series* 566, 31–48. doi: 10.3354/meps12002

Scarcella, G., Fabi, G., and Grati, F. (2007). Rapido trawl fishery in the north-central Adriatic Sea. *Rapp. Commun. Int. Mer. Mèditerr* 38:591.

Scarcella, G., Grati, F., Raicevich, S., Russo, T., Gramolini, R., Scott, R. D., et al. (2014). Common sole in the northern and central Adriatic sea: spatial management scenarios to rebuild the stock. *J. Sea Res.* 89, 12–22. doi: 10.1016/j.seares.2014.02.002

Schückel, S., Sell, A. F., Kihara, T. C., Koeppen, A., Kröncke, I., and Reiss, H. (2013). Meiofauna as food source for small-sized demersal fish in the southern North Sea. *Helgol. Mar. Res.* 67, 203–218. doi: 10.1007/s10152-012-0316-1

STECF (2019). *The 2019 Annual Economic Report on the EU Fishing Fleet (STECF 19-06) EUR 28359 EN*, eds N. Carvalho and M. Keatinge and J. Guillen Garcia (Luxembourg: Publications Office of the European Union). doi: 10.2760/911768

Suzuki, R., and Shimodaira, H. (2015). *Package ' Pvclust .' R Topic Document*.

Van der Hammen, T., Poos, J. J., Van Overzee, H. M. J., Heessen, H. J. L., Magnusson, A., and Rijnsdorp, A. D. (2013). Population ecology of turbot and brill: what can we learn from two rare flatfish species? *J. Sea Res.* 84, 96–108. doi: 10.1016/j.seares.2013.07.001

Ward, J. H. (1963). Hierarchical grouping to optimize an objective function. *J. Am. Stat. Assoc.* 58, 236–244. doi: 10.1080/01621459.1963.10500845

Welcomme, R. L. (1999). A review of a model for qualitative evaluation of exploitation levels in multi−species fisheries. *Fish. Manag. Ecol.* 6, 1–19. doi: 10.1046/j.1365-2400.1999.00137.x

Winker, H., Carvalho, F., and Kapur, M. (2018). JABBA: just another bayesian biomass assessment. *Fish. Res.* 204, 275–288. doi: 10.1016/j.fishres.2018.03.010

Winker, H., and Sherley, R. B. (2019). JARA: 'just another red-list assessment. *bioRxiv* [Preprint] 1–27. doi: 10.1101/672899

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The reviewer ND declared a past co-authorship with several of the authors, GC and GS, to the handling editor.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 30 July 2021
doi: 10.3389/fmars.2021.718052

Length-Based Assessment of Fish Stocks in a Data-Poor, Jointly Exploited (China and Vietnam) Fishing Ground, Northern South China Sea

Kui Zhang[1,2,3]**, *Jiajun Li*[1,2], *Gang Hou*[4], *Zirong Huang*[1,2], *Dengfu Shi*[1], *Zuozhi Chen*[1,2,3] *and Yongsong Qiu*[1,2]

[1] *South China Sea Fisheries Research Institute, Chinese Academy of Fishery Sciences, Guangzhou, China,* [2] *Key Laboratory of Open-Sea Fishery Development, Ministry of Agriculture and Rural Affairs, Guangzhou, China,* [3] *Southern Marine Science and Engineering Guangdong Laboratory, Guangzhou, China,* [4] *College of Fisheries, Guangdong Ocean University, Zhanjiang, China*

OPEN ACCESS

Edited by:
Giuseppe Scarcella,
National Research Council (CNR), Italy

Reviewed by:
Chongliang Zhang,
Ocean University of China, China
Yuan Li,
Third Institute of Oceanography, State Oceanic Administration, China

***Correspondence:**
Kui Zhang
zhangkui@scsfri.ac.cn

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: 31 May 2021
Accepted: 12 July 2021
Published: 30 July 2021

Citation:
Zhang K, Li J, Hou G, Huang Z, Shi D, Chen Z and Qiu Y (2021) Length-Based Assessment of Fish Stocks in a Data-Poor, Jointly Exploited (China and Vietnam) Fishing Ground, Northern South China Sea. Front. Mar. Sci. 8:718052. doi: 10.3389/fmars.2021.718052

The Beibu Gulf is one of the most important fishing grounds in the South China Sea (SCS), and the fisheries resources in this area are exploited by both China and Vietnam. In recent decades, some indications of overfishing have appeared, including declining catch rates, frequently changing catch composition, and shrinking body sizes in main commercial fish species. Due to limited data availability, only a small subset of exploited fish stocks in this area has been assessed. Here, we applied two length-based methods, electronic length frequency analysis (ELEFAN) and length-based Bayesian biomass estimation (LBB), to stock assessment of nine exploited fish species in the Beibu Gulf. There were total 53, 652 length records of 30 target stocks used in this study during the survey period from 1960 to 2015. The results showed that the two length-based methods presented different ability in estimating exploitation rate (E), and the estimated E ranged from 0.34 to 0.87 using ELEFAN method while ranged from 0.26 to 0.86 using LBB method. The prior information from ELEFAN method was effective for LBB method, as there were significant differences in 66.7% of the 30 target stocks in estimated L_{inf}, and 93.3% in estimated B/B_{MSY}, using LBB method with and without prior information. The estimated L_c/L_{c_opt} and B/B_{MSY} of LBB method suggest a pressing situation for the fisheries in the Beibu Gulf, as 86.7% of the 30 target stocks had been suffering from growth overfishing ($L_c/L_{c\_opt} < 1$), and 83.3% had been overexploited or fully exploited ($B/B_{MSY} \leq 1.2$). In addition, we suggest using both ELEFAN and LBB methods to fit length-frequency data of data-poor fish stocks because they are complementary in estimating management reference points. We also emphasize collaboration mechanism should be established by China and Vietnam for the sustainability and recovery of fishery resources in the Beibu Gulf.

Keywords: Beibu Gulf, electronic length frequency analysis, length-based Bayesian estimation, prior information, exploitation rate, management

INTRODUCTION

Marine fisheries resources are an important source of animal protein and micronutrients, and provide employment opportunities and income for people worldwide [Food and Agriculture Organization (FAO) (2016); Pauly and Zeller, 2016]. As a result of widespread overfishing leading to sequential depletion of exploited stocks, global fishery catch has been stagnating, then gradually decreasing since the late 1980s (Kleisner et al., 2013). Stock assessment is a basic work to carry out modern management and maintain fishery sustainability. With the improvement of computer simulation ability and multi-disciplinary collaboration, stock assessment methods have been developed rapidly. The stock assessment models tend to be more diversified, and their structures become more complicated (Maunder and Punt, 2013). The classical assessment models always need a large amount of statistical and survey data, including catch, abundance index and even age structure. However, most of exploited fisheries, especially in developing countries, do not have the data required for traditional methods and are considered data-poor. Consequently, only 20% of global catch comes from assessed species, and less than 1% of species have been assessed (Costello et al., 2012). The severity of this problem has been gradually realized, and increasing alternative methods for data-poor fisheries have been building in recent years (Dick and Maccall, 2011; Martell and Froese, 2013; Cadrin and Dickey-Collas, 2015; Hordyk et al., 2015; Froese et al., 2018).

At present, two types of methods are commonly used in data-poor fisheries, the catch-based methods and the length-based methods (Liang et al., 2020). The catch-based methods estimate sustainable yield or maximum sustainable yield (MSY) of the target population using catch time series and auxiliary data, e.g., intrinsic rate of increase, natural mortality, and age at maturity. The length-based methods can use length-frequency data to estimate growth, mortality and development status, e.g., exploitation rate, and relative stock size (B/B_{MSY}). Electronic length frequency analysis (ELEFAN) is widely used to fit von Bertalanffy growth function and estimate growth and mortality parameters for data-poor fisheries (Pauly and David, 1981). It enables users to formulate some management options for fisheries, especially in data-poor, tropical areas. Recently, a new length-based method, length-based Bayesian biomass estimation (LBB), was developed to estimate B/B_{MSY}, and the current exploited biomass relative to the unexploited biomass (B/B_0) for data-poor fish stocks (Froese et al., 2018). Compared to statistical catch data, length-frequency data is more convenient to collect due to the lower time and economic cost. Size-related measures (e.g., mean length, length at first sexual maturity) have long been used as indicators of response to population decline, especially in tropical waters where fish age are difficult to be identified, and data poor areas where historical catch data are not counted accurately. The length-based methods avoids relying on this incomplete dataset and instead used size composition data gathered from a range of sources to generate species-level assessments (Nadon et al., 2015), which obviously improves fisheries management in developing countries (Baldé et al., 2019). In addition, the assessment efficiency of catch-based methods largely depends on the accuracy of statistical catch data. However, marine fisheries catch data were distorted due to neglected small-scale fisheries, illegal fisheries, and discarded bycatch (Watson and Pauly, 2001; Pauly and Zeller, 2016). The systematic distortions in catch trends will impact the assessment results and prevent effective management.

The South China Sea (SCS) is located at the center of the Indo-West Pacific region, and is a representative sea of data-poor fisheries (Zhang et al., 2017). Despite its vast sea area, most of the fishing efforts and landings from the People's Republic of China (here after referred to as 'China') are concentrated in the northern continental shelf (Qiu et al., 2008). The northern SCS are important spawning and feeding grounds for commercial fish stocks, as well as marine fishing grounds. Since China's reform and opening up, the demand for seafood has increased with fast growth in the economy of coastal areas. Rapid growth in the number of marine fishing vessels and catches from the 1970s to 1990s had resulted in the decline of offshore fishery resources in the northern SCS (Zhang et al., 2017), especially in typical semi-closed bays (Zhang et al., 2020a,b). The Beibu Gulf covers an area of 12.8×10^3 km^2, and is surrounded by the land territories of China and Socialist Republic of Vietnam (here after referred to as 'Vietnam') (**Figure 1**). It is highly productive and rich in fishery resources, and has been one of China's four major fishing grounds (Qiu et al., 2008). The Chinese and Vietnamese governments signed a Fishery Cooperative Agreement in 2000 (Qiu et al., 2008), and designed a joint fishing zone (**Figure 1**) in the Beibu Gulf (allow fishing for both countries). In recent six decades, fish community structure in Beibu Gulf has changed observably, from demersal to pelagic species and from high-trophic-level to low-trophic-level species (Su et al., 2021). The major commercial fish stocks, e.g., threadfin porgy *Evynnis cardinalis*, tend to be smaller body size, and earlier sexual maturity (Zhang et al., 2020a). It is commonly agreed that for risk avoidance and economic benefits, biomass (B) of fish stocks must be above the MSY level (B_{MSY}) and fishing pressure (F) must be below the MSY level (F_{MSY}) based on the MSY framework (Froese et al., 2020). However, limited research on fish stock assessment based on the MSY framework has been undertaken (Zhang et al., 2017), so it is necessary to establish alternative methods in the Beibu Gulf.

In this paper, we applied the two above-mentioned length-based methods (ELEFAN and LBB) to stock assessment for nine exploited fish stocks in the Beibu Gulf. ELEFAN is widely used in fish stock assessment in Chinese waters, and many of the main commercial species have been assessed by this method, e.g., largehead hairtail *Trichiurus japonicus* (Zhou et al., 2002), small yellow croaker *Larimichthys polyactis* (Liu et al., 2012). LBB is a newly developed method and has been recently introduced to stock assessment in Chinese waters (Liang et al., 2020; Zhang et al., 2021b). The assumptions and computational procedures of the two methods are quite different (Pauly and David, 1981; Froese et al., 2018). Until now, how prior information affect the performance of LBB method and comparison of assessment results with ELEFAN method in data-poor fisheries have not been

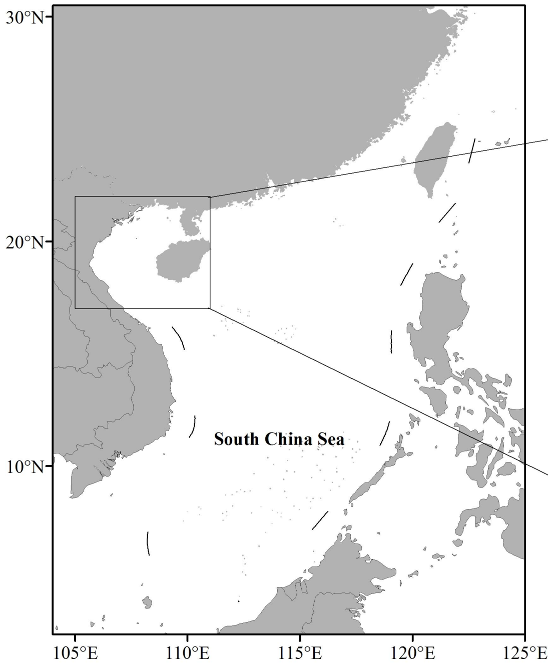


FIGURE 1 | Map of Beibu Gulf, including the joint fishing zone (grids) between China and Vietnam, and sampling stations (dots).

documented. The objectives of this study were to: (1) provide an overview of exploitation status of exploited fish stocks in the Beibu Gulf; (2) compare the assessment results of the two length-based methods; and (3) compare the performance of LBB method with and without prior information. The results may contribute to providing a scientific basis to assist sustainable utilization and management of fish stocks in data-poor areas.

MATERIALS AND METHODS

Data Collection

Length data analyzed in this study were from bottom-trawl surveys (1960–2015) conducted by the SCS Fisheries Research Institute. The sampling stations (**Figure 1**) were predetermined before the surveys and consistent from year to year. Each station was investigated once and trawled for 1 h, with an average hauling speed of 3–4 knots in all surveys. The mesh size of the bottom-trawl nets ranged from 120 to 200 mm, with 30–40 mm cod-end mesh size in all the surveys. Surveys were conducted monthly in the 1960s and quarterly in other periods (**Table 1**). All captured fishery samples were identified to the species level, and biological data including length, weight, sexual maturity and stomach fullness for main commercial species were measured. The individuals were randomly sampled for measurement and laboratory bioassays. For each species, if fewer than 50 individuals were caught in a station, all were cryopreserved for laboratory bioassays; otherwise, 50 individuals were sampled randomly and measured. For each fish, the standard length was measured to the nearest millimeter.

Nine exploited fish stocks, including Japanese scad (*Decapterus maruadsi*), threadfin porgy (*Evynnis cardinalis*), yellowbelly threadfin bream (*Nemipterus bathybius*), golden threadfin bream (*Nemipterus virgatus*), red bigeye (*Priacanthus macracanthus*), purple-spotted bigeye (*Priacanthus tayenus*), brushtooth lizardfish (*Saurida undosquamis*), Japanese jack mackerel (*Trachurus japonicus*), and largehead hairtail (*Trichiurus japonicus*), were selected in this study regarding their high economic values and large catches in the northern SCS (Qiu et al., 2008; Zhang et al., 2017; Su et al., 2021). There were total 53, 652 length records of the nine fish species during different sampling years used in this study (total 30 assessment sequences in **Table 1**). Anal length was used for *T. japonicas*, fork length for *D. maruadsi* and *T. japonicas*, and body length for the other six fish species.

ELEFAN Method

The growth of the fish stocks was modeled by the von Bertalanffy equation (von Bertalanffy, 1938):

$$L_t = L_{\text{inf}}(1 - \exp(-K(t - t_0))) \tag{1}$$

where L_t is length (cm) at age t, L_{inf} the asymptotic length, K is the von Bertalanffy growth coefficient, and t_0 is the theoretical age at length zero. The ELEFAN I routines incorporated in the FiSAT II (Gayanilo and Pauly, 1997) software were used to fit growth curves to the restructured length-frequency data. Using both the "automatic search routine" and the "response surface analysis" within ELEFAN, it was possible to achieve the best fit for the growth curve (best-fitting combination of L_{inf} and K) to the length-frequency data.

TABLE 1 | Summary of samplings and length data for nine fish stocks collected during 1962–2012 for stock assessment in Beibu Gulf, South China Sea.

Species	Sequence	Sampling year	Standard length range (mm)	Numbers of individuals measured	Sampling intervals
Decapterus maruadsi	1	1992	90–270	635	Quarterly
	2	1998	32–300	1714	Quarterly
	3	2006	76–264	1049	Quarterly
	4	2007	67–250	1028	Quarterly
	5	2009	86–235	1226	Quarterly
	6	2010	96–215	465	Quarterly
	7	2012	75–256	1318	Quarterly
Evynnis cardinalis	8	1962	40–240	5201	Monthly
	9	1999	57–230	1120	Quarterly
	10	2006	41–196	2055	Quarterly
	11	2015	23–202	2783	Quarterly
Nemipterus bathybius	12	1992	51–220	650	Quarterly
	13	1997	51–200	870	Quarterly
	14	2009	41–230	450	Quarterly
Nemipterus virgatus	15	1960	36–282	6781	Monthly
	16	1962	46–275	2356	Monthly
	17	1992	68–300	976	Quarterly
	18	1998	43–300	3168	Quarterly
	19	2006	60–316	1467	Quarterly
	20	2007	75–308	670	Quarterly
	21	2009	63–310	828	Quarterly
	22	2012	75–272	545	Quarterly
Priacanthus macracanthus	23	1999	55–300	1722	Quarterly
	24	2015	57–303	1295	Quarterly
Priacanthus tayenus	25	1999	55–287	421	Quarterly
Saurida undosquamis	26	1999	11–435	6467	Quarterly
Trachurus japonicus	27	1999	90–290	1170	Quarterly
Trichiurus japonicus	28	1982	132–605	432	Quarterly
	29	1999	20–670	3662	Quarterly
	30	2015	61–528	1128	Quarterly

The parameter t_0 were calculated using the empirical equation (Pauly, 1983):

$$\log_{10}(-t_0) = -0.3922 - 0.275\log_{10} L_{\inf} - 1.038\log_{10} K \quad (2)$$

Total mortality (Z) was estimated by the length-converted catch curve procedure (Pauly, 1983):

$$\ln(N_i/\Delta t_i) = c - Zt_i^{'} \quad (3)$$

where N_i is the number of fish caught in a given length class i, t_i' is the relative age corresponding to length class i, Δt_i is the time needed for growing through the length class i, and c is the intercept of the linear equation, respectively.

The instantaneous natural mortality (M) was calculated (Pauly, 1983) by:

$$\ln M = -0.0152 - 0.279\ln L_{\inf} + 0.654\ln k + 0.463\ln T \quad (4)$$

where T is the mean environmental temperature. Fishing mortality (F) was calculated by subtracting M from Z, and the exploitation ratio (E) was obtained from F/Z.

LBB Method

Growth in body length is also assumed to follow the von Bertalanffy growth function (von Bertalanffy, 1938) in the LBB method (Froese et al., 2018).

Most of commercially exploited fish species grow throughout their lifetime, and their body size would approach the asymptotic length L_{inf} if mortality were zero, which can be expressed by:

$$P_{L/L_{\inf}} = (1 - \frac{L}{L_{\inf}})^{M/K} \quad (5)$$

where $P_{L/Linf}$ is the probability to survive to length L/L_{inf}, which is solely a function of the M/K ratio.

The LBB method assumes that the selectivity of fishing gear is trawl-like, i.e., small individuals (length $< L_x$) can not be caught, all individuals will be caught if exceed a certain body size (length $> L_{start}$), and part of the individuals are caught when length between L_x and L_{start}. The gear selectivity can be expressed by the following equation:

$$S_L = \frac{1}{1 + e^{-\alpha(L - L_c)}} \quad (6)$$

where S_L is the fraction of individuals that are retained by the gear at length L, L_c is the length where 50% of the individuals are retained by the gear, and α represents the steepness of the ogive (Quinn and Deriso, 1999).

Combining the equations (1), (5), and (6), and rearranging lead to:

$$N_{L_i} = N_{L_{i-1}} \left(\frac{L_{\text{inf}} - L_i}{L_{\text{inf}} - L_{i-1}}\right)^{\frac{M}{K} + \frac{F}{K} S_{L_i}} \tag{7}$$

$$C_{L_i} = N_{L_i} S_{L_i} \tag{8}$$

where N_{Li} and N_{Li-1} are the numbers of individuals in length class L_i and the previous length class L_{i-1}, respectively. To minimize the required parameters, the ratios M/K and F/M are estimated, instead of the absolute values of F, M, and K in the LBB analysis. In other words, the increase in fish body length can be used as a proxy for its life time, and by using ratios instead of absolute values the units of time and biomass cancel out (Froese et al., 2018).

The Bayesian Gibbs sampler JAGS within R statistical language (version 4.0.3) was used to fit the observed proportions at-length to their expected values:

$$\hat{p}_{L_i} = \frac{\hat{N}_{L_i}}{\sum \hat{N}_{L_i}} \tag{9}$$

where p_{Li} is the observed proportions-at-length,$\hat{p}_{L_i}$ is the mean values for p_{Li}, $\hat{N}_{L_i}$ denotes the mean values for N_{Li}, which has been mentioned in equation (7).

The observed and predicted length distributions were then fitted by assuming Dirichlet-multinomial distribution (Thorson et al., 2017), which was proposed for fitting size and age composition in stock assessment models using a Bayesian framework. Proportions-at-length assume Dirichlet-multinomial distribution with an effective sample size of 1,000, which was chosen based on desirable performance across various simulation-testing trial scenarios (Froese et al., 2018).

The following equations are used to approximate the population status through the estimated quantities L_{inf}, L_c, M/K, and F/K. First, the length L_{opt} representing the maximum biomass of unexploited cohort is obtained from:

$$L_{\text{opt}} = L_{\text{inf}} \left(\frac{3}{3 + \frac{M}{K}}\right) \tag{10}$$

With a given fishing pressure F/M, the length at first capture L_{c_opt} that maximizes catch and biomass can be obtained from:

$$L_{\text{c\_opt}} = \frac{L_{\text{inf}}(2 + 3\frac{F}{M})}{(1 + \frac{F}{M})(3 + \frac{M}{K})} \tag{11}$$

An index catch per unit of effort ($CPUE'/R$) is obtained as dividing relative yield-per-recruit (Y'/R) by F/M, which can be described as:

$$\frac{CPUE'}{R} = \frac{\frac{Y'}{R}}{\frac{F}{M}} = \frac{1}{1+F/M}(1 - L_c/L_{\text{inf}})^{M/K} \left(1 - \frac{3(1-L_c/L_{\text{inf}})}{1+1/(M/K+F/K)} + \frac{3(1-L_c/L_{\text{inf}})^2}{1+2/(M/K+F/K)} - \frac{(1-L_c/L_{\text{inf}})^3}{1+3/(M/K+F/K)}\right) \tag{12}$$

The relative biomass in the exploited phase of the fish population if no fishing takes place is given by:

$$\frac{B_0' > L_c}{R} = (1 - L_c/L_{\text{inf}})^{M/K} \left(1 - \frac{3(1-L_c/L_{\text{inf}})}{1+\frac{1}{M/K}} + \frac{3(1-L_c/L_{\text{inf}})^2}{1+\frac{2}{M/K}} - \frac{(1-L_c/L_{\text{inf}})^3}{1+\frac{3}{M/K}}\right) \tag{13}$$

where $B_0' > L_c$ denotes the exploitable fraction ($> L_c$) of the unfished biomass (B_0).

The ratio of fished to unfished biomass is described as:

$$\frac{B}{B_0} = \frac{\frac{CPUE'}{R}}{\frac{B_0' > L_c}{R}} \tag{14}$$

A proxy for the relative biomass that can produce B_{MSY}/B_0 was obtained by re-running Equations (12–14) with $F/M = 1$ and $L_c = L_{c\_opt}$ (Froese et al., 2018).

Hordyk et al. (2019) indicated that the LBB analysis did not correct for the pile-up effect (pile-up of abundance observations in length classes used as bins in length-frequency analyses), and may result in a biased estimate of F and M/K. Therefore, we applied other two modified LBB model (Froese et al., 2019) on the length data of the 9 exploited fish species from Beibu Gulf. The two models, LBB-1 (full correction for the pile-up effect), and LBB-2 (let the Bayesian model determine the degree of correction based on the best fit to the available data) were based on the original LBB equation, and corrected for the pile-up effect.

In this study, we also analyzed the performance of LBB method with and without prior information. The prior information of parameters L_{inf} and Z/K were from the output of ELEFAN method. All the analysis was implemented using LBB_33a.R, an R-code algorithm presented by Froese et al. (2018, 2019). Fish stocks were classified to three exploitation statuses based on the estimates of B/B_{MSY}, overexploited status was assigned where $B/B_{MSY} < 0.8$, fully exploited status where $0.8 \leq B/B_{MSY} \leq 1.2$, and underdeveloped status where $B/B_{MSY} > 1.2$ (Amorim et al., 2019). Besides, the stocks are considered as suffering from growth overfishing when the estimated $L_c/L_{c\_opt} < 1$ (Liang et al., 2020; Zhang et al., 2021b).

RESULTS

Comparison of Assessment Results Between ELEFAN and LBB Method

The estimated asymptotic lengths for all assessment sequences ranged from 22.0 to 70.0 cm using ELEFAN method while ranged from 22.0 to 70.3 cm using LBB method. There were not significant differences in estimated L_{inf} between ELEFAN method and LBB method, in all assessment sequences ($p > 0.05$), except *D. maruadsi* stock of 2006 ($t = 5.37$, $p < 0.05$), and *T. japonicas* stock of 1982 ($t = 3.12$, $p < 0.05$). The estimated Z/K for all assessment sequences ranged from 3.36 to 11.19 using ELEFAN method while ranged from 2.3 to 12.0 using LBB method. There

TABLE 2 | Comparison of estimated parameters between ELEFAN method and LBB method with prior information.

Species	Sequence	Sampling years	ELEFAN method			LBB method		
			L_{inf} (cm)	Z/K	E	L_{inf} (cm)	Z/K	E
Decapterus maruadsi	1	1992	29.7	4.26	0.70	30.3 (29.8–30.8)	4.4 (4.1–4.7)	0.76
	2	1998	32.0	4.35	0.72	31.7 (31.1–32.2)	4.5 (4.1–5.2)	0.79
	3	2006	**30.5**	**5.48**	**0.76**	**27.5 (27.0 –28.0)**	**2.7 (2.5–2.9)**	**0.64**
	4	2007	32.9	3.57	0.73	32.9 (32.3–33.4)	3.6 (3.3–3.7)	0.78
	5	2009	26.8	5.33	0.78	27.7(27.2–28.1)	4.9 (4.4–5.3)	0.80
	6	2010	25.5	**4.09**	**0.71**	26.3 (25.8–26.6)	**12 (11–13)**	**0.86**
	7	2012	23.9	3.36	**0.63**	24.2 (23.9–24.5)	3.2 (2.9–3.5)	**0.73**
Evynnis cardinalis	8	1962	27.6	4.89	**0.49**	27.9 (27.4–28.4)	5 (4.6–5.2)	**0.58**
	9	1999	25.9	**6.92**	0.62	22.0 (22.4–23.1)	**5.6 (5.4–5.8)**	0.58
	10	2006	23.0	5.94	**0.60**	22.7 (22.3–23.2)	6.3 (5.9–6.7)	**0.69**
	11	2015	23.5	**5.79**	**0.58**	23.4 (23.1–23.9)	**6.8 (6.5–7.3)**	**0.70**
Nemipterus bathybius	12	1992	24.2	**5.67**	**0.57**	24.4 (24.1–24.8)	**3.1 (2.9–3.3)**	**0.51**
	13	1997	22.0	**6.29**	0.62	22.1 (22.0–22.3)	**2.6 (2.5–2.7)**	0.61
	14	2009	23.6	**5.54**	0.58	24.1 (23.8–24.5)	**4.9 (4.6–5.1)**	0.62
Nemipterus virgatus	15	1960	32.6	**4.08**	**0.34**	32.1 (31.5–32.6)	**2.3 (2.1–2.4)**	**0.26**
	16	1962	33.5	4.37	**0.47**	33.1 (32.4–33.6)	4.3 (4–4.8)	**0.58**
	17	1992	34.1	**6.85**	**0.62**	34.6 (34.1–35.2)	**9.3 (8.4–10)**	**0.73**
	18	1998	32.9	**6.89**	0.61	33.6 (33.1–34.4)	**4.1 (3.9–4.4)**	0.56
	19	2006	32.1	**6.63**	0.60	32.8 (32.3–33.4)	**6 (5.7–6.3)**	0.62
	20	2007	31.5	**8.45**	0.71	31.5 (30.9–32.1)	**11 (10–12)**	0.77
	21	2009	31.2	9.40	0.74	31.4 (30.8–32)	8.9 (8.3–9.4)	0.75
	22	2012	32.0	**7.07**	**0.56**	32.5 (32.0–33.0)	**12 (11–13)**	**0.77**
Priacanthus macracanthus	23	1999	29.3	**5.06**	**0.68**	28.5 (28.2–29.2)	**2.8 (2.6–3.1)**	**0.58**
	24	2015	29.1	**6.53**	**0.70**	29 (28.4–29.4)	**3.5 (3.3–3.8)**	**0.59**
Priacanthus tayenus	25	1999	29.4	5.72	0.68	29.4 (29.3–29.7)	5.8 (5.5–6.1)	0.67
Saurida undosquamis	26	1999	45.5	**5.07**	**0.56**	45.5 (44.4–46.3)	**8.7 (8.2–9.5)**	**0.77**
Trachurus japonicus	27	1999	31.2	5.12	**0.58**	31.6 (31.1–32.0)	5.3 (4.9–5.5)	**0.67**
Trichiurus japonicus	28	1982	**62.2**	**4.57**	**0.71**	**58.2 (57.2–59.3)**	**3.7 (3.4–4.3)**	**0.80**
	29	1999	70.0	**11.19**	0.87	70.3 (68.5–71.6)	**7.8 (7.5–8.2)**	0.84
	30	2015	58.5	**5.86**	0.59	58.3 (57.3–59.1)	**5.3 (5–5.5)**	0.63

The bold numbers represent significantly different results ($p < 0.05$) between ELEFAN and LBB method. The numbers between brackets represent 95% credible intervals for the parameters.

were not significant differences in estimated Z/K between ELEFAN method and LBB method in 11 assessment sequences (No. 1, 2, 4, 5, 7, 8, 10, 16, 21, 25, and 27, **Table 2**).

The estimated exploitation rates for all assessment sequences ranged from 0.34 to 0.87 using ELEFAN method while ranged from 0.26 to 0.86 using LBB method. The lowest value of exploitation rate occurred in *N. virgatus* stock of 1960 using both the two method. The highest value of exploitation rate occurred in *T. japonicus* stock of 1999, and *D. maruadsi* stock of 2010 for ELEFAN method and LBB method, respectively. There were significant differences in estimated E between ELEFAN method and LBB method in 16 assessment sequences (**Table 2**). Estimated exploitation rates for three assessment sequences, *E. cardinalis* stock of 1962 and *N. virgatus* stock of 1960 and 1962 were below 0.5 using LBB method, and only *N. virgatus* stock of 1960 were below 0.5 using LBB method (**Table 2**). Therefore, most of the fish stocks faced with overfishing during the assessment years.

LBB Method With and Without Prior Information

There were significant differences in 20 assessment sequences ($p < 0.05$) in estimated L_{inf} using LBB method with and without prior information, and 10 assessment sequences (No. 5, 7, 12, 18, 20, 23, 24, 25, 26, and 28) were insensitive to the prior information (**Table 3**). As for estimated B/B_{MSY}, there were not significant differences using LBB method with and without prior information in only 2 assessment sequences (No. 6 and 17). In terms of exploitation statuses (B/B_{MSY}), 9 assessment sequences (No. 3, 4, 8, 13, 14, 16, 18, 23, and 24) showed different exploitation status using LBB method with and without prior information. For example, *D. maruadsi* stock of 2006 and 2007 were in overexploited status using LBB with

TABLE 3 | Comparison of assessment results of LBB method with and without prior information.

Species	Sequence	Sampling years	With prior information			Without prior information		
			L_{inf} (cm)	L_c/L_{c_opt}	B/B_{MSY}	L_{inf} (cm)	L_c/L_{c_opt}	B/B_{MSY}
Decapterus maruadsi	1	1992	30.3 (29.8–30.8)	0.65	0.33 (0.27–0.41)	31.6 (31.1–32.2)	0.68	0.4 (0.28–0.56)
	2	1998	31.7 (31.1–32.2)	0.79	0.33 (0.24–0.45)	30.7 (30.3–31.1)	0.84	0.47 (0.31–0.74)
	3	2006	27.5 (27.0–28.0)	0.75	**0.88 (0.63–1.2)**	26.1 (25.8 –26.6)	0.93	**1.7 (0.36–3)**
	4	2007	32.9 (32.3–33.4)	0.46	**0.24 (0.18–0.3)**	29.9 (29.3–30.6)	0.64	**0.98 (0.48–1.7)**
	5	2009	27.7 (27.2–28.1)	0.75	0.31 (0.23–0.41)	27.5 (27.1–27.9)	0.87	0.58 (0.38–0.84)
	6	2010	26.3 (25.8–26.6)	0.85	0.13 (0.098–0.16)	29.6 (29.3–30.2)	0.84	0.13 (0.091–0.16)
	7	2012	24.2 (23.9–24.5)	0.95	0.58 (0.43–0.77)	23.9 (23.6–24.3)	0.86	0.38 (0.22–0.56)
Evynnis cardinalis	8	1962	27.9 (27.4–28.4)	0.74	**0.86 (0.62–1)**	25.4 (25–25.8)	0.63	**0.54 (0.33–0.86)**
	9	1999	22.0 (22.4–23.1)	0.54	2.5 (1–4.4)	21.0 (20.8–21.3)	0.38	1.6 (0.51–2.7)
	10	2006	22.7 (22.3–23.2)	0.82	0.56 (0.44–0.65)	23.7 (23.4–24.1)	0.6	0.16 (0.11–0.23)
	11	2015	23.4 (23.1–23.9)	0.78	0.53 (0.45–0.64)	21.2 (20.8–21.4)	0.7	0.36 (0.25–0.48)
Nemipterus bathybius	12	1992	24.4 (24.1–24.8)	**1.2**	2.1 (0.82–3.7)	23.9 (23.6–24.3)	**0.94**	1.3 (0.81–2)
	13	1997	22.1 (22.0–22.3)	**1.5**	**3 (0.55–8.8)**	25.0 (24.7–25.5)	**0.83**	**0.52 (0.35–72)**
	14	2009	24.1 (23.8–24.5)	0.9	**0.89 (0.68–1.1)**	27.6 (27.1–28.2)	0.61	**0.2 (0.14–0.3)**
Nemipterus virgatus	15	1960	32.1 (31.5–32.6)	**1.0**	2.7 (1.1–5.5)	27.7 (27.5–28)	**0.74**	2 (0.68–6.3)
	16	1962	33.1 (32.4–33.6)	0.86	**0.96 (0.74–1.2)**	30.7 (30.1–31.2)	0.7	**0.5 (0.26–0.76)**
	17	1992	34.6 (34.1–35.2)	1.1	0.59 (0.46–0.73)	31.7 (31.2–32.2)	1.1	0.54 (0.39–0.7)
	18	1998	33.6 (33.1–34.4)	0.92	**1.5 (1.1–2.2)**	32.8 (32.2–33.4)	0.69	**0.68 (0.46–1)**
	19	2006	32.8 (32.3–33.4)	0.76	0.7 (0.59–0.83)	29.9 (29.3–30.3)	0.65	0.42 (0.27–0.6)
	20	2007	31.5 (30.9–32.1)	0.81	0.27 (0.23–0.31)	31.1 (30.6–31.6)	0.64	0.1 (0.069–0.14)
	21	2009	31.4 (30.8–32.0)	0.73	0.33 (0.27–0.39)	38.1 (37.4–38.8)	0.46	0.052 (0.035–0.077)
	22	2012	32.5 (32.0–33.0)	0.89	0.4 (0.33–0.47)	26.5 (25.9–26.9)	0.78	0.29 (0.2–0.39)
Priacanthus macracanthus	23	1999	28.5 (28.2–29.2)	0.73	**1.1 (0.8–1.7)**	27.8 (27.3–28.2)	0.77	**1.4 (0.67–2.3)**
	24	2015	29 (28.4–29.4)	0.66	**0.96 (0.64–1.2)**	29.8 (29.3–30.4)	0.55	**0.47 (0.31–0.64)**
Priacanthus tayenus	25	1999	29.4 (29.3–29.7)	0.62	2.3 (0.72–4.1)	29.3 (29.2–29.5)	0.56	1.9 (0.47–3.6)
Saurida undosquamis	26	1999	45.5 (44.4–46.3)	0.55	0.21 (0.17–0.24)	44.2 (43.6–44.9)	0.46	0.085 (0.57–0.12)
Trachurus japonicus	27	1999	31.6 (31.1–32.0)	0.94	0.72 (0.57–0.87)	34.8 (34.2–35.3)	0.69	0.22 (0.15–0.32)
Trichiurus japonicus	28	1982	58.2 (57.2–59.3)	0.87	0.42 (0.29–0.59)	58.1 (57.4–59.1)	0.67	0.096 (0.03–0.24)
	29	1999	70.3 (68.5–71.6)	0.3	0.067 (0.057–0.082)	67.0 (65.8–68.3)	0.33	0.1 (0.079–0.13)
	30	2015	58.3 (57.3–59.1)	0.5	0.54 (0.45–0.66)	63.1 (62.1–64)	0.35	0.12 (0.085–0.17)

The bold numbers represent inconsistent results (B/B_{MSY} determining the exploitation status and L_c/L_{c_opt} determining whether growth overfishing) by LBB method with and without prior information. The numbers between brackets represent 95% credible intervals for the parameters.

prior information, but in fully exploited and underdeveloped status without prior information. Four assessment sequences (No. 12, 13, 15, and 17) showed growth overfishing were not happening using LBB method with prior information, and only 1 assessment sequence (No. 17) showed the same results without prior information (**Table 3**).

Model Performance of Three Types of LBB Methods

Reference point outputs (**Table 4**) showed that the three types of LBB methods (original LBB, LBB-1, and LBB-2) produced the same results when detecting the occurrence of growth overfishing, i.e., 86.7% of the 30 target stocks were facing growth overfishing ($L_c/L_{c\_opt} < 1$), except for 4 assessment sequences (No. 12, 13, 15, and 17). The original LBB and LBB-2 models produced the same decisions if the stocks had been overfished (B/B_{MSY}). LBB-1 model produced similar results with the other two models, except for 5 assessment sequences (No. 3, 8, 18, 23, and 24). The underestimation of estimated B/B_{MSY} for the 5 assessment sequences made their exploitation status negatively, i.e., the original LBB and LBB-2 models indicated 4 stocks (No. 3, 8, 23, and 24) were fully exploited while LBB-1 showed they

TABLE 4 | Comparison of assessment results of LBB method and two modified methods.

Species	Sequence	Sampling years	L_c/L_{c_opt}			B/B_{MSY}		
			LBB	LBB-1	LBB-2	LBB	LBB-1	LBB-2
Decapterus maruadsi	1	1992	0.65	0.63	0.64	0.33 (0.27–0.41)	0.23 (0.18–0.28)	0.27 (0.22–0.34)
	2	1998	0.79	0.75	0.77	0.33 (0.24–0.45)	0.23 (0.18–0.27)	0.27 (0.18–0.38)
	3	2006	0.75	0.71	0.74	0.88 (0.63–1.2)	**0.5 (0.38–0.61)**	0.82 (0.55–1.1)
	4	2007	0.46	0.44	0.45	0.24 (0.18–0.3)	0.15 (0.11–0.18)	0.21 (0.16–0.29)
	5	2009	0.75	0.72	0.74	0.31 (0.23–0.41)	0.22 (0.18–0.27)	0.28 (0.21–0.35)
	6	2010	0.85	0.83	0.85	0.13 (0.098–0.16)	0.11 (0.083–0.14)	0.12 (0.093–0.15)
	7	2012	0.95	0.92	0.92	0.58 (0.43–0.77)	0.4 (0.32–0.5)	0.41 (0.31–0.53)
Evynnis cardinalis	8	1962	0.74	0.7	0.75	0.86 (0.62–1)	**0.58 (0.48–0.7)**	0.86 (0.66–1.1)
	9	1999	0.54	0.63	0.54	2.5 (1–4.4)	2.5 (0.85–4.5)	2.5 (1.1–4.6)
	10	2006	0.82	0.79	0.8	0.56 (0.44–0.65)	0.42 (0.36–0.49)	0.45 (0.38–0.55)
	11	2015	0.78	0.75	0.77	0.53 (0.45–0.64)	0.39 (0.34–0.44)	0.48 (0.39–0.59)
Nemipterus bathybius	12	1992	1.2	1.0	1.1	2.1 (0.82–3.7)	1.3 (0.95–1.5)	2.1 (0.71–3.8)
	13	1997	1.5	1.2	1.3	3 (0.55–8.8)	1.4 (1–1.9)	2 (0.48–3.2)
	14	2009	0.9	0.87	0.89	0.89 (0.68–1.1)	0.83 (0.75–0.94)	0.84 (0.72–0.91)
Nemipterus virgatus	15	1960	1.0	1.0	1.0	2.7 (1.1–5.5)	2.6 (0.79–5.7)	2.6 (0.67–5.6)
	16	1962	0.86	0.82	0.82	0.96 (0.74–1.2)	0.87 (0.75–0.91)	0.85 (0.83–0.91)
	17	1992	1.1	1.1	1.1	0.59 (0.46–0.73)	0.48 (0.41–0.58)	0.58 (0.47–0.7)
	18	1998	0.92	0.85	0.91	1.5 (1.1–2.2)	**0.99 (0.81–1.2)**	1.5 (0.86–2)
	19	2006	0.76	0.74	0.76	0.7 (0.59–0.83)	0.54 (0.46–0.62)	0.7 (0.57–0.85)
	20	2007	0.81	0.79	0.8	0.27 (0.23–0.31)	0.22 (0.19–0.25)	0.24 (0.2–0.29)
	21	2009	0.73	0.72	0.72	0.33 (0.27–0.39)	0.28 (0.24–0.32)	0.31 (0.26–0.35)
	22	2012	0.89	0.86	0.89	0.4 (0.33–0.47)	0.32 (0.28–0.36)	0.39 (0.34–0.46)
Priacanthus macracanthus	23	1999	0.73	0.67	0.72	1.1 (0.8–1.7)	**0.59 (0.46–0.73)**	1.1 (0.7–1.6)
	24	2015	0.66	0.62	0.67	0.96 (0.64–1.2)	**0.57 (0.42–0.71)**	0.93 (0.71–1.3)
Priacanthus tayenus	25	1999	0.62	0.76	0.63	2.3 (0.72–4.1)	2.5 (0.7–5)	2.3 (0.68–7.5)
Saurida undosquamis	26	1999	0.55	0.54	0.54	0.21 (0.17–0.24)	0.17 (0.15–0.2)	0.17 (0.15–0.2)
Trachurus japonicus	27	1999	0.94	0.91	0.93	0.72 (0.57–0.87)	0.55 (0.47–0.67)	0.62 (0.47–0.76)
Trichiurus japonicus	28	1982	0.87	0.84	0.85	0.42 (0.29–0.59)	0.3 (0.22–0.39)	0.3 (0.23–0.37)
	29	1999	0.30	0.30	0.30	0.067 (0.057–0.082)	0.052 (0.044–0.061)	0.067 (0.055–0.08)
	30	2015	0.50	0.49	0.49	0.54 (0.45–0.66)	0.38 (0.31–0.46)	0.46 (0.33–0.61)

Three length-based methods presented by Froese et al. (2019) are original LBB equation (LBB), correct for the pile-up effect (LBB-1), and let the Bayesian model determine the degree of correction based on the best fit to the available data (LBB-2). The bold numbers are inconsistent results (exploitation status) by LBB-2 comparing with other two models. The numbers between brackets represent 95% credible intervals for the parameters.

were overexploited; the original LBB and LBB-2 models showed *N. virgatus* stock of 1998 (No. 18) were underdeveloped while LBB-1 indicated it was fully exploited. The estimated B/B_{MSY} showed 83.4% of the 30 target stocks were in overexploited status or fully exploited status while *E. cardinalis* stock of 1999, *N. bathybius* of 1992 and 1997, *N. virgatus* of 1960, and *P. tayenus* of 1999 were in underdeveloped status (**Table 4**). In summary, the original LBB and LBB-2 models produced similar results, indicating Bayesian model can help determine the degree of correction.

DISCUSSION

This study is the first attempt to apply both the traditional ELEFAN method and the newly developed LBB method across the main exploited fish stocks in the Beibu Gulf, and test the effect of prior information on LBB method. The results showed that the two length-based methods presented different ability in estimating exploitation rates, and the prior information from ELEFAN method was effective for LBB method. The estimated L_c/L_{c_opt} and B/B_{MSY} of LBB method suggest a pressing situation for the fisheries in Beibu Gulf, as 86.7% of the 30 target stocks had been suffering from growth overfishing, and 83.3% had been overexploited or fully exploited.

Model Performance

There have been burgeoning literatures on the use of relatively simple methods to evaluate data-poor fisheries status. These approaches range from using life history characteristics as a guide to the vulnerability of fishing (Goodwin et al., 2006; Punt et al., 2011; McCully Phillips et al., 2015), to more holistic evaluations for obtaining management reference points and harvest control rules (Cope and Punt, 2009), or extensive assessment-based meta-analysis (Armelloni et al., 2021) using

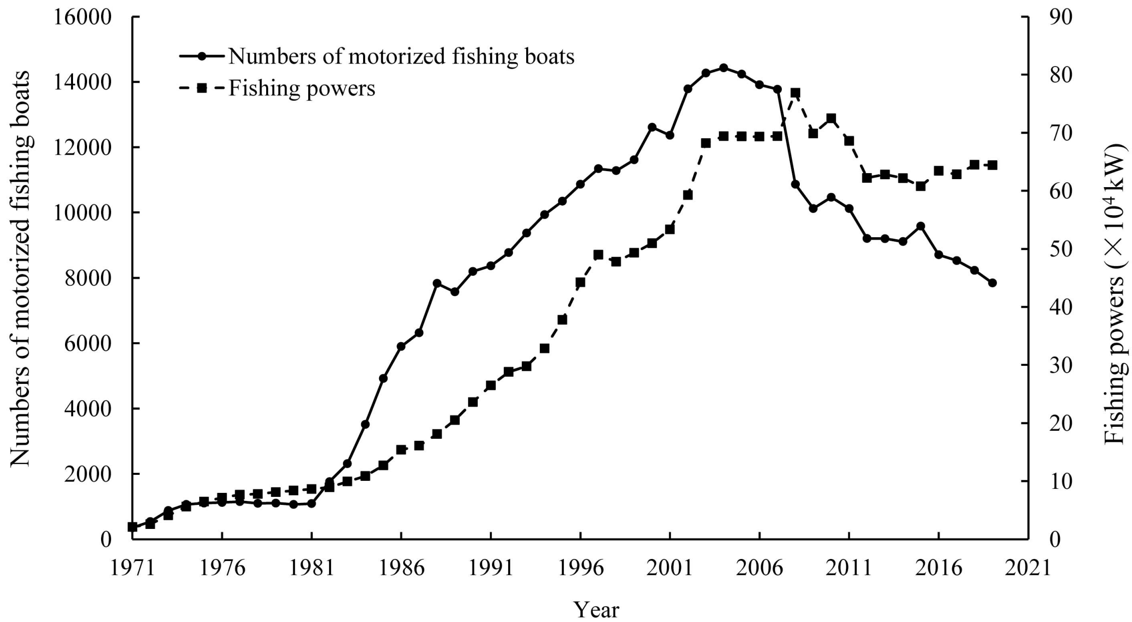


FIGURE 2 | Numbers of motorized fishing boats and total fishing powers of Guangxi Province.

catch data, and auxiliary information (e.g., age-length data, life history parameters). Among the various data, fish growth in body length is discrepant by species and convenient to access.

Fish growth in body length of ELEFAN and LBB method both are assumed to follow von Bertalanffy equation (Pauly and David, 1981; Froese et al., 2018). However, the parameters in the two methods are estimated in different ways: the growth and mortality parameters (i.e., M, F, and K) in ELEFAN method can be directly calculated from empirical formulas or procedures while the ratios M/K and F/M are estimated, instead of the absolute values of F, M, and K in the LBB method. Compared with LBB method, ELEFAN method can provide the estimated growth and mortality parameters which are essential in full stock assessment or ecosystem based assessment, but relatively limited management reference points. Gulland (1983) recommend that 0.5 may be the suitable exploitation rate for fish stocks in temperate water. However, fish stocks in tropical and subtropical areas (e.g., the Beibu Gulf) have short life-cycles and rapid growth, and they can sustain high exploitation rates (Wang et al., 2012). Therefore, the exploitation rate may be insufficient for the fishery management in Beibu Gulf while L_c/L_{c_opt} and B/B_{MSY} provided by LBB method are commonly used management reference points (Zhang et al., 2021b). Our study showed the prior information from ELEFAN method was effective for LBB method (**Supplementary Figure 1**) because most of the assessment sequences produced significantly different results with and without prior information.

The parameters of LBB method are calculated by a Bayesian Monte Carlo Markov Chain (MCMC) approach (Cowles and Carlin, 1996), which has been widely used in fishery data analysis (Haddon, 2010). With this Bayesian framework, it is straightforward to calculate credible intervals for multiple parameters. In this study, 95% credible intervals of B/B_{MSY} and L_c/L_{c_opt} were calculated, and these results can provide alternative information sources which can support decision-making. Besides, we also applied two modified LBB models (LBB-1 and LBB-2) with corrections for the pile-up effect (Froese et al., 2019; Hordyk et al., 2019). The results (**Table 4**) showed estimations of the original LBB method have been little affected by the pile-up effect for most of the assessment sequences.

In addition, we suggest using both ELEFAN and LBB methods to fit length-frequency data of data-poor fish stocks because they are complementary in estimating management reference points.

Challenges in Fisheries Management for the Beibu Gulf

The Beibu Gulf has multiple ecosystems with estuaries, mangroves, coral reefs, and shelves, which provide comfortable habitats for spawning, feeding, and nursery areas for abundant fish species (Qiu et al., 2008). As reported to date, 960 fish species inhabit this embayment, which belonging to 162 fish families. The main fishing gears are trawl, purse seine, gill net, hook and set nets, and the trawl fishery accounts for more than 70% of the total catch (Zou et al., 2013). There are not available statistical catch data in the Beibu Gulf because catch data are gathered by administrative districts (e.g., provinces in China), instead of sea areas. Therefore, it was considered to be a data-poor fishing ground, and the length-based methods used in this study may fill a gap in knowledge of biomass levels and exploitation status of main fish stocks in the Beibu Gulf.

Zou et al. (2013) has estimated the fishery catch of the Beibu Gulf to be 85.7 × 10^4 t in 2012, including 65.7 × 10^4 t caught by China, and 20.0 × 10^4 t caught by Vietnam. The numbers of motorized fishing boats and total fishing powers of Guangxi Province were selected to represent the long-term trend of fishing efforts in the Beibu Gulf (**Figure 2**). Before China's reform and opening up in 1978, the number of motorized fishing boats in Guangxi Province was less than 1200, and total fishing powers was no more than 8.5 × 10^4 kW. In 1980s and 1990s, the fishing efforts had been rapidly increasing and some indications of overfishing have appeared, e.g., catch rates trend downward (Qiu et al., 2008), catch composition has changed significantly (Chen et al., 2011), and miniaturization, early sexual maturity and accelerated growth have occurred in main commercial fish species (Zhang et al., 2020a). The indications of overfishing were consistent with our assessment results, which showed the assessed fish stocks had been overexploited in the 1990s.

In the recent two decades, a series of conservative management measures have been implemented by Chinese government in the SCS, including "double control" system, summer fishing moratorium, "zero-growth" and "negative-growth" strategies (Shen and Heino, 2014; Cao et al., 2017). Benefiting from the management measures, the fishing efforts had been stabilized and then decreased (**Figure 2**). Recent studies have shown that the management measures to reduce fishing pressure had been playing an important role for fishery resources recovery, e.g., the average daily yields of fishing boats and output values have increased after the summer fishing moratorium (Su et al., 2019), and these measures have a positive influence on the biological characteristics of this commercial fish species (Zhang et al., 2021a). However, our results showed the main commercial fish stocks were still in overexploited status in recent years (**Table 4**). Beibu Gulf is a co-developed area of fishery resources by both China and Vietnam, but until now, only China makes policy efforts to reduce fishing pressure. For example, during the 3.5-months summer fishing moratorium, all fishing gears (except for rod fishing) of China stopped fishing in the Beibu Gulf, but the fishing boats of Vietnam were still active in this sea area. Therefore, we emphasize collaboration mechanism should be established by the two countries for management and sustainability of fishery resources in the Beibu Gulf.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The animal study was reviewed and approved by South China Sea Fisheries Research Institute Animal Welfare Committee.

AUTHOR CONTRIBUTIONS

KZ conceived the study and wrote the first draft. JL, GH, and DS performed the data analyses and prepared the graphs. ZH, ZC, and YQ provided the original length data and revised the manuscript. All the authors contributed to the article and approved the submitted version.

FUNDING

This work was supported by the Key Research and Development Project of Guangdong Province (2020B1111030001), the National Natural Science Foundation of China (31602157), and the Central Public-Interest Scientific Institution Basal Research Fund (2020TD05 and 2021SD01).

ACKNOWLEDGMENTS

The authors are grateful to our colleagues, Youwei Xu, Mingshuai Sun, Xin Liang, and Yuezhong Wang, who have been working at the forefront of marine fishery resources surveys, and crew of R/V *Beiyu60011* for sample collection and measurement.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2021.718052/full#supplementary-material

REFERENCES

Amorim, P., Sousa, P., Jardim, E., and Menezes, G. M. (2019). Sustainability status of data-limited fisheries: global challenges for snapper and grouper. *Front. Mar. Sci.* 6:654. doi: 10.3389/fmars.2019.00654

Armelloni, E. N., Scanu, M., Masnadi, F., Coro, G., Angelini, N., and Scarcella, G. (2021). Data poor approach for the assessment of the main target species of rapido trawl fishery in Adriatic Sea. *Front. Mar. Sci.* 8:552076. doi: 10.3389/fmars.2021.552076

Baldé, B. S., Fall, M., Kantoussan, J., Sow, F. N., Diouf, M., and Brehmer, P. (2019). Fish-length based indicators for improved management of the sardinella fisheries in Senegal. *Reg. Stud. Mar. Sci.* 31:100801. doi: 10.1016/j.rsma.2019.100801

Cadrin, S. X., and Dickey-Collas, M. (2015). Stock assessment methods for sustainable fisheries. *ICES J. Mar. Sci.* 72, 1–6. doi: 10.1093/icesjms/fsu228

Cao, L., Chen, Y., Dong, S., Hanson, A., Huang, B., Leadbitter, D., et al. (2017). Opportunity for marine fisheries reform in China. *Proc. Natl. Acad. Sci. U.S.A.* 114, 435–442.

Chen, Z., Qiu, Y., and Xu, S. (2011). Changes in trophic flows and ecosystem properties of the Beibu Gulf ecosystem before and after the collapse of fish stocks. *Ocean Coast. Manage.* 54, 601–611. doi: 10.1016/j.ocecoaman.2011.06.003

Cope, J. M., and Punt, A. E. (2009). Length-based reference points for data-limited situations: applications and restrictions. *Mar. Coast. Fish.* 1, 169–186. doi: 10.1577/c08-025.1

Costello, C., Ovando, D., Hilborn, R., Gaines, S. D., Deschenes, O., and Lester, S. E. (2012). Status and solutions for the world's unassessed fisheries. *Science* 338, 517–520. doi: 10.1126/science.1223389

Cowles, M. K., and Carlin, B. P. (1996). Markov chain Monte Carlo convergence diagnostics: a comparative review. *J. Am. Stat. Assoc.* 91, 883–904. doi: 10.1080/01621459.1996.10476956

Dick, E. J., and Maccall, A. D. (2011). Depletion-Based Stock Reduction Analysis: a catch-based method for determining sustainable yields for data-poor fish stocks. *Fish. Res.* 110, 331–341. doi: 10.1016/j.fishres.2011.05.007

Food and Agriculture Organization (FAO) (2016). *The State of World Fisheries and Aquaculture (SOFIA) Report 2016*. Rome: FAO.

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2018). A new approach for estimating stock status from length frequency data. *ICES J. Mar. Sci.* 75, 2004–2015. doi: 10.1093/icesjms/fsy078

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2019). On the pile-up effect and priors for L_{inf} and M/K: response to a comment by Hordyk et al. on "A new approach for estimating stock status from length frequency data". *ICES J. Mar. Sci.* 76, 461–465. doi: 10.1093/icesjms/fsy199

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2020). Estimating stock status from relative abundance and resilience. *ICES J. Mar. Sci.* 77, 527–538. doi: 10.1093/icesjms/fsz230

Gayanilo, F. C., and Pauly, D. (eds) (1997). "FAO-ICLARM stock assessment tools: reference manual," in *FAO Computerized Information Series (Fisheries)*, eds F. C. Gayanilo and D. Pauly (Rome: FAO), 8.

Goodwin, N. B., Grant, A., Perry, A. L., Dulvy, N. K., and Reynolds, J. D. (2006). Life history correlates of density-dependent recruitment in marine fishes. *Can. J. Fish. Aquat. Sci.* 63, 494–509. doi: 10.1139/f05-234

Gulland, J. A. (1983). *Fish Stock Assessment: A Manual of Basic Methods*. New York, NY: Wiley Online Library.

Haddon, M. (2010). *Modelling and Quantitative Methods in Fisheries*, 2nd Edn. New York, NY: Chapman and Hall.

Hordyk, A. R., Loneragan, N. R., and Prince, J. D. (2015). An evaluation of an iterative harvest strategy for data-poor fisheries using the length-based spawning potential ratio assessment methodology. *Fish. Res.* 171, 20–32. doi: 10.1016/j.fishres.2014.12.018

Hordyk, A. R., Prince, J. D., Carruthers, T. R., and Walters, C. J. (2019). Comment on "A new approach for estimating stock status from length frequency data" by Froese et al. (2018). *ICES J. Mar. Sci.* 76, 457–460. doi: 10.1093/icesjms/fsy168

Kleisner, K., Zeller, D., Froese, R., and Pauly, D. (2013). Using global catch data for inferences on the world's marine fisheries. *Fish. Fish.* 14, 293–311. doi: 10.1111/j.1467-2979.2012.00469.x

Liang, C., Xian, W., Liu, S., and Pauly, D. (2020). Assessments of 14 exploited fish and Invertebrate stocks in Chinese waters using the LBB method. *Front. Mar. Sci.* 7:314. doi: 10.3389/fmars.2020.00314

Liu, Q., Xu, B., Ye, Z., and Ren, Y. (2012). Growth and mortality of small yellow croaker (*Larimichthys polyactis*) inhabiting Haizhou bay of China. *J. Ocean Univ. China* 11, 557–561. doi: 10.1007/s11802-012-2099-z

Martell, S., and Froese, R. (2013). A simple method for estimating MSY from catch and resilience. *Fish. Fish.* 14, 504–514. doi: 10.1111/j.1467-2979.2012.00485.x

Maunder, M. N., and Punt, A. E. (2013). A review of integrated analysis in fisheries stock assessment. *Fish. Res.* 142, 61–74. doi: 10.1016/j.fishres.2012.07.025

McCully Phillips, S. R., Scott, F., and Ellis, J. R. (2015). Having confidence in productivity susceptibility analyses: a method for underpinning scientific advice on skate stocks? *Fish. Res.* 171, 87–100. doi: 10.1016/j.fishres.2015.01.005

Nadon, M. O., Ault, J. S., Williams, I. D., Smith, S. G., and DiNardo, G. T. (2015). Length-based assessment of coral reef fish populations in the main and northwestern Hawaiian Islands. *Plos One* 10:e0133960. doi: 10.1371/journal.pone.0133960.g003

Pauly, D. (1983). *Some Simple Methods for the Assessment of Tropical Fish Stocks*. FAO Fisheries Technical Paper No. 234. Rome: FAO.

Pauly, D., and David, N. (1981). ELEFAN I, a BASIC program for the objective extraction of growth parameters from length-frequency data. *Meeresforschung* 28, 205–211.

Pauly, D., and Zeller, D. (2016). Catch reconstructions reveal that global marine fisheries catches are higher than reported and declining. *Nat. Commun.* 7:10244.

Punt, A. E., Smith, D. C., and Smith, A. D. M. (2011). Among-stock comparisons for improving stock assessments of data-poor stocks: the "Robin Hood" approach. *ICES J. Mar. Sci.* 68, 972–981. doi: 10.1093/icesjms/fsr039

Qiu, Y., Zeng, X., Chen, T., Yuan, W., and Wang, Y. (2008). *Fishery Resources and Management in South China Sea*. Beijing: The Ocean Press.

Quinn, T. J., and Deriso, R. B. (1999). *Quantitative Fish Dynamics*. New York, NY: Oxford University Press.

Shen, G., and Heino, M. (2014). An overview of marine fisheries management in China. *Mar. Policy* 44, 265–272. doi: 10.1016/j.marpol.2013.09.012

Su, L., Chen, Z., Zhang, K., Xu, Y., Xu, S., and Wang, K. (2021). Decadal-scale variation in mean trophic level in Beibu Gulf based on bottom-trawl survey data. *Mar. Coast. Fish.* 13, 174–182. doi: 10.1002/mcf2.10144

Su, Y., Chen, G., Zhou, Y., Ma, S., and Wu, Q. (2019). Assessment of impact of summer fishing moratorium in South China Sea during 2015-2017. *South China Fish. Sci.* 15, 20–28.

Thorson, J. T., Johnson, K. F., Methot, R. D., and Taylor, I. G. (2017). Model-based estimates of effective sample size in stock assessment models using the Dirichlet-multinomial distribution. *Fish. Res.* 192, 84–93. doi: 10.1016/j.fishres.2016.06.005

von Bertalanffy, L. (1938). A quantitative theory of organic growth (inquiries on growth laws II). *Hum. Biol.* 10, 181–213.

Wang, X., Qiu, Y., Du, F., Lin, Z., Sun, D., and Huang, S. (2012). Population parameters and dynamic pool models of commercial fishes in the Beibu Gulf, northern South China Sea. *Chin. J. Oceanol. Limn.* 30, 102–117.

Watson, R., and Pauly, D. (2001). Systematic distortions in world fisheries catch trends. *Nature* 414, 534–536. doi: 10.1038/35107050

Zhang, K., Cai, Y., Liao, B., Jiang, Y., Sun, M., Su, L., et al. (2020a). Population dynamics of threadfin porgy *Evynnis cardinalis*, an endangered species on IUCN red list in the Beibu Gulf, South China Sea. *J. Fish Biol.* 97, 479–489. doi: 10.1111/jfb.14398

Zhang, K., Guo, J., Xu, Y., Jiang, Y., Fan, J., Xu, S., et al. (2020b). Long-term variations in fish community structure under multiple stressors in a semi-closed marine ecosystem in the South China Sea. *Sci. Total Environ.* 745:140892. doi: 10.1016/j.scitotenv.2020.140892

Zhang, K., Geng, P., Li, J., Xu, Y., Kalhoro, M. A., Sun, M., et al. (2021a). Influences of fisheries management measures on biological characteristics of threadfin bream (*Nemipterus virgatus*) in the Beibu Gulf, South China Sea. *Acta Oceanol. Sin.* (in press).

Zhang, K., Zhang, J., Shi, D., and Chen, Z. (2021b). Assessment of coral reef fish stocks from the Nansha Islands, South China Sea, using length-based Bayesian biomass estimation. *Front. Mar. Sci.* 7:610707. doi: 10.3389/fmars.2020.610707

Zhang, K., Liao, B., Xu, Y., Zhang, J., Sun, M., Qiu, Y., et al. (2017). Assessment for allowable catch of fishery resources in the South China Sea based on the statistical data. *Haiyang Xuebao* 39, 25–33.

Zhou, Y., Xu, H., Liu, Z., and Xue, L. (2002). A study on variation of stock structure of hairtall, *Trichiurus haumela* in the East China Sea. *J. Zhejiang Ocean Univ.* (*Nat. Sci.*). 21, 314–320.

Zou, J., Lin, P., and Wang, Q. (2013). Evaluation of catch in Beibu Gulf of South China Sea in 2012. *South Chin. Fish. Sci.* 9, 75–81.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 11 August 2021
doi: 10.3389/fmars.2021.663375

Methods for Identifying Species Complexes Using a Novel Suite of Multivariate Approaches and Multiple Data Sources: A Case Study With Gulf of Alaska Rockfish

Kristen L. Omori[1]*, Cindy A. Tribuzio[2], Elizabeth A. Babcock[3] and John M. Hoenig[1]

[1] Department of Fisheries Science, Virginia Institute of Marine Science, William & Mary, Gloucester Point, VA, United States, [2] Auke Bay Laboratories, Alaska Fisheries Science Center, National Marine Fisheries Service, National Oceanic and Atmospheric Administration, Juneau, AK, United States, [3] Department of Marine Biology and Ecology, Rosenstiel School of Marine and Atmospheric Sciences, University of Miami, Miami, FL, United States

OPEN ACCESS

Edited by:
Natalie Anne Dowling,
Oceans and Atmosphere (CSIRO), Australia

Reviewed by:
José Lino Vieira De Oliveira Costa,
University of Lisbon, Portugal
Lyall Bellquist,
The Nature Conservancy, United States

***Correspondence:**
Kristen L. Omori
komori@vims.edu

Specialty section:
This article was submitted to Marine Ecosystem Ecology, a section of the journal Frontiers in Marine Science

***Received:** 02 February 2021*
***Accepted:** 16 July 2021*
***Published:** 11 August 2021*

Citation:
Omori KL, Tribuzio CA, Babcock EA and Hoenig JM (2021) Methods for Identifying Species Complexes Using a Novel Suite of Multivariate Approaches and Multiple Data Sources: A Case Study With Gulf of Alaska Rockfish. Front. Mar. Sci. 8:663375. doi: 10.3389/fmars.2021.663375

International and national laws governing the management of living marine resources generally require specification of harvest limits. To assist with the management of data-limited species, stocks are often grouped into complexes and assessed and managed as a single unit. The species that comprise a complex should have similar life history, susceptibility to the fishing gear, and spatial distribution, such that common management measures will likely lead to sustainable harvest of all species in the complex. However, forming complexes to meet these standards is difficult due to the lack of basic biological or fisheries data to inform estimates of biological vulnerability and fishery susceptibility. A variety of cluster and ordination techniques are applied to bycatch rockfish species in the Gulf of Alaska (GOA) as a case study to demonstrate how groupings may differ based on the multivariate techniques used and the availability and reliability of life history, fishery independent survey, and fishery catch data. For GOA rockfish, our results demonstrate that fishing gear primarily defined differences in species composition, and we suggest that these species be grouped by susceptibility to the main fishing gears while monitoring those species with high vulnerabilities to overfishing. Current GOA rockfish complex delineations (i.e., Other Rockfish and Demersal Shelf Rockfish) are consistent with the results of this study, but should be expanded across the entire GOA. Differences observed across species groupings for the variety of data types and multivariate approaches utilized demonstrate the importance of exploring a diversity of methods. As best practice in identifying species complexes, we suggest using a productivity-susceptibility analysis or expert judgment to begin groupings. Then a variety of multivariate techniques and data sources should be used to identify complexes, while balancing an appropriate number of manageable groups. Thus, optimal species complex groupings should be determined by commonality and consistency among a variety of multivariate methods and datasets.

Keywords: stock complex, species assemblage, cluster analysis, ordination analysis, data-limited fisheries

INTRODUCTION

The requirement to implement catch limits for data-limited and previously unassessed stocks resulting from recent international policies, such as the Magnuson-Stevens Reauthorization Act of 2006 (MSRA, 2007) and Common Fisheries Policy (CFP, 2013), presents scientific and management challenges for regional fishery management entities. Managing an aggregation of fish stocks or species as a single unit is one approach utilized by fisheries managers in an attempt to comply with international and federal laws (Jiao et al., 2009), reduce the number of required stock assessments (Koutsidi et al., 2016), and create manageable harvest regulations. These aggregations, also known as stock or species complexes, are often determined by similarity in life history characteristics, vulnerability to the fishery, and geographic distributions (USOFR, 2009). Multiple stocks of a single species being managed together are likely to have strong similarities in life history and susceptibility, whereas complexes consisting of multiple species have more diverging characteristics in productivity (i.e., life history traits), behavior, and habitat preference. Species in a complex are typically caught in a multispecies fishery and often lack adequate data for a single species assessment (USOFR, 2009).

Assigning species to complexes can be a difficult, but critical task for implementing sustainable management of data-limited species. Complexes are often formed using a combination of life history traits, trophic roles, and fishing pressure (Shertzer and Williams, 2008). However, rarely is the full extent of this information available to adequately determine the appropriateness of a complex grouping, and there can be a mismatch in groupings when using life history traits compared to fishery susceptibility (i.e., species caught together by the same gear types). Grouping species based on life history characteristics, which represent the population's productivity, is important because species with similar growth and maturity often demonstrate similar responses to fishing pressure (e.g., Farmer et al., 2016; DeMartini, 2019). From a management perspective, grouping by susceptibility to fishing gear (e.g., multispecies fisheries) is often simpler than grouping by life history traits, because management by gear type is less easily enforceable for complexes harvested by a variety of gears. Yet, the potential for disproportionate impacts on the species within the complex exists when complexes are formed using gear susceptibility and when selectivity or availability differs by species (DeMartini, 2019).

Aggregating species exclusively based on either life history or fishery traits can lead to unsuitable groupings. For example, a complex formed on fishing vulnerability may group species with divergent life history characteristics, and species that reproduce at earlier ages and are more fecund (i.e., have a higher productivity) are more resilient to fishing pressure compared to species that have lower fecundity and reproduce later in life (i.e., have a lower productivity). Alternatively, grouping species only on similarities in life history may be futile if the species are not vulnerable to the same fishing gear (e.g., Pikitch, 1991; Vinther et al., 2004).

Reconciling the need to balance fishery vulnerability and biological considerations for establishing species complexes remains a difficult scientific problem. No single method has proven robust for all species complex grouping approaches, and often development of species complexes relies on a combination of qualitative (i.e., expert judgement) and quantitative measures. Productivity-susceptibility analysis (PSA) has been proposed as a tool for grouping data-limited species based primarily on expert judgment (Patrick et al., 2010; Cope et al., 2011). A PSA bins information (i.e., life history values and impact by fisheries indicators) in productivity or susceptibility categories based on expert judgement. The rankings within each category are calculated into an overall vulnerability score, which is thereby used to summarize species into groups. However, PSA may not be as useful when forming complexes with closely related species with poor quality data, because vulnerability rankings are likely to be too similar despite having the possibility of scoring differently in the susceptibility categories. For example, Cope et al. (2011) determined that vulnerability rankings from a PSA could not alone be used to establish complexes for rockfish species in the United States West Coast groundfish fishery. A hierarchical tiered approach was implemented by applying clustering analyses first using ecological distribution (i.e., depth and latitude), followed by using the vulnerability scores. Yet, the use of expert judgment for scoring vulnerability was considered problematic for species with such poor quality data.

Alternately, multivariate techniques (e.g., cluster analyses and ordination methods) are a quantitative tool used for identifying similarities among species when adequate species-specific data are available. Of the few quantitative studies that have developed species complexes, the combination of expert judgment and multiple data sources or multivariate approaches (or both) have typically been used to assign species to appropriate groups. For example, both ordination and clustering methods can be used to examine species assemblages using one data source (e.g., Lee and Sampson, 2000; Williams and Ralston., 2002), or multiple data sources with each dataset being analyzed separately, summarized and compared to determine species groupings (e.g., Shertzer and Williams, 2008; Pennino et al., 2016). Other studies have developed methods to quantitatively synthesize findings of species co-occurrence when using multiple datasets. For example, Farmer et al. (2016) combined analysis of multiple catch data matrices along with a life history matrix to assign species to complexes by amalgamating the results from individual hierarchical cluster analyses into a weighted mean cluster association index. However, the weighted mean cluster association index depended on each cluster analyses from each data source to produce clear, sensible results (i.e., no chaining, which is when single units branch and form their own cluster). The array of quantitative studies used to identify species complexes have focused primarily on associations or similarities among species.

Conversely, other studies examining potential species complexes have grouped together similar catch units (i.e., within a specified area and temporal scale) based on similar species composition. Grouping species based on vulnerability to particular fishing gears allowed analysts to determine how different factors, such as depth (Rogers and Pikitch, 1992), influenced the species composition, while providing potential species assemblages based on fishery susceptibility that many east management and enforcement. Koutsidi et al. (2016) developed a unique method that combined biological traits with fishing operation data to examine how the different fishing sectors tended to catch species with similar biological traits. This study concluded that it could be advantageous to consider functional biological traits in management decisions for data-limited species that lack traditional assessments. The method that Koutsidi et al. (2016) applied required knowledge of a variety of life history, behavior, distribution, ecology and habitat attributes in addition to species-specific catch data from the fisheries, which may not be available for data-limited species.

Management of several of the Gulf of Alaska (GOA) rockfish species (**Figure 1**) is an example where managers have identified species complexes, but further quantitative analysis would be desirable to validate these assignments. GOA rockfish (genus *Sebastes*) are caught as bycatch (i.e., unintended catch that is either discarded or retained) in a variety of fisheries. Rockfish in the GOA pose a unique challenge due to their range in life history values, habitat preferences, and behavior. Optimally, the rockfish in each complex should withstand similar fishing pressures, have comparable distributions, and common productivity levels. Currently, most of the non-targeted rockfish in the GOA are assessed in two complexes: the Other Rockfish complex, which consists of species that are classified as the "slope," "pelagic shelf," and "demersal shelf" rockfish assemblages; and the Demersal Shelf Rockfish complex, which separates the group of seven "demersal shelf" species from the remaining rockfish species in one management area (North Pacific Fishery Management Council (NPFMC), 2019). These complex delineations often combine species with different habitat preferences, which ultimately affects their spatial distributions (i.e., based on gear selectivity and availability). Additionally, the species compositions of the GOA rockfish complexes have undergone multiple changes throughout their management history. In 2011, a PSA indicated that select GOA rockfish had high vulnerability scores due to their low productivity and medium susceptibility level in the fisheries (Ormseth and Spencer, 2011), which implies that the rockfish assemblages should be carefully monitored and managed judiciously. However, further quantitative analysis is warranted to identify whether current GOA complexes should be restructured.

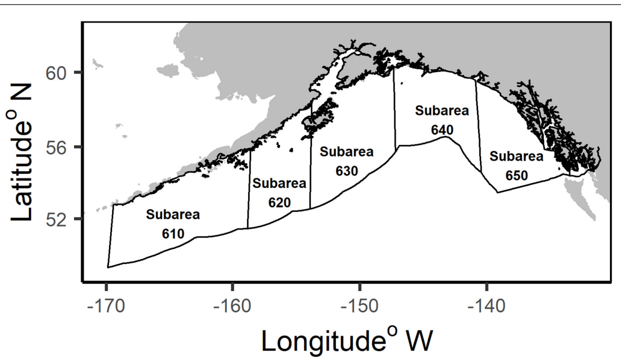


FIGURE 1 | Map of the National Marine Fisheries Service (NMFS) management subareas in the Gulf of Alaska.

In this study, the goal is to explore the consistency of various quantitative methods for identifying species complexes, while also providing an approach to aggregate data across different spatial areas and gear types. The GOA Other Rockfish and Demersal Shelf Rockfish species are used as a case study, because identifying consistent species groupings has proven difficult for these species. Most of the GOA rockfish species are generally not targeted and have high discard rates due to little economic value. A combination of life history traits, fishery dependent, and fishery independent data sources are used to assemble species complexes with hierarchical and non-hierarchical clustering methods and ordination techniques. Two modes of analyses were implemented to the catch data for the clustering methods: (1) aggregate similar species together based on catch presence and abundance; (2) group similar sampling units based on common catch composition. The species assemblages are compared across multivariate techniques and data types to explore patterns of consistency and identify species complexes for management. These results provide new insight into how the data quality and quantitative methodology utilized may influence groupings for implementing species complexes. Additionally, this is the first quantitative analysis to identify species complexes in the GOA.

MATERIALS AND METHODS

Management Units and Species

The GOA is partitioned into the National Marine Fisheries Service (NMFS) subareas: 610, 620, 630, 640 and 650 (**Figure 1**). These subareas are used in the analyses to examine differences in the species composition by area. The GOA Other Rockfish complex comprises 25 *Sebastes* species in the GOA management area. Seven of the 25 species are managed in a separate complex (**Table 1**), Demersal Shelf Rockfish, in subarea 650, but are included in the Other Rockfish complex in all other subareas in the GOA. The State of Alaska assesses the Demersal Shelf Rockfish in subarea 650, and manages their catch in parallel with state waters fisheries for these species. Additionally, northern rockfish (*S. polyspinis*) are only included in the Other Rockfish complex in subareas 640 and 650 for management, but they are assessed as part of a single species stock assessment for the entire GOA. Northern rockfish catch data from all subareas are included in our analyses for comparison, but are not a candidate for reassignment.

Other Rockfish species vary widely in their distribution, habitat selection, and life history traits. With an exception of harlequin (*S. variegatus*), these rockfish in the GOA are at the northern limits of their distribution, which span the U.S. West Coast from Southern California to Alaska (Love et al., 2002). Harlequin are found primarily in northern waters from British

Columbia to Alaska (Tribuzio and Echave, 2019). Species in the Other Rockfish complex occur in depths up to 800 m, but typical are found in depths ranging from 100 to 275 m (Love et al., 2002). Adult habitats include high relief rocks, reefs or crevices, low relief rocky bottoms, mudflats, vegetative areas, and mixed habitat (Johnson et al., 2003; Conrath et al., 2019). Some individuals are more solitary, whereas others tend to aggregate in mixed-species assemblages (Johnson et al., 2003). In general, rockfish species are characterized by their late maturity, longevity, and their ability to bear live young (Love et al., 2002; Beyer et al., 2015). However, there is a wide range of life history values within the Other Rockfish complex (**Table 1**; see section "Life History Data").

The Other Rockfish complex consist of bycatch species captured in more lucrative rockfish and other groundfish fisheries using trawl and longline gear. More than half of the species belonging to the Other Rockfish complex are rarely caught (<1% of the total catch of the Other Rockfish complex). These rockfish have a low economic value (B. Fissel, AFSC, pers. comm.) resulting in a high discard rate estimated at 56% over the entire time series (Tribuzio and Echave, 2019). Based on biomass, most of the Other Rockfish are caught in the trawl fisheries. Within the complex, some species tend to be caught more on longline gear (e.g., yelloweye rockfish in in subarea 630), and others across gear types (e.g., redbanded rockfish), highlighting the variability within the complex. Species in the Demersal Shelf Rockfish complex managed in subarea 650 are commonly found in rocky, high relief habitats (Tribuzio and Echave, 2019), where trawling fishing gear is prohibited. Demersal Shelf Rockfish species are primarily caught by longline gear fisheries (i.e., hook-and-line and jig) targeting sablefish (*Anoplopoma fimbria*) and Pacific halibut (*Hippoglossus stenolepis*; **Table 1**).

Data Sources

Life History Data

The life history parameters were assembled from peer-reviewed articles, gray literature, assessment data from NMFS, and global predictions using *FishLife* (Thorson et al., 2017). Although species data from the GOA or northern ranges were used when available, most life history studies examining maximum age or age/length at maturity were completed in lower latitudes. When no data were available from the GOA, life history information from southern areas were utilized, despite the potential for differential growth rates by latitude (e.g., splitnose rockfish [*S. diploproa*]; Gertseva et al., 2010). Depending on data availability, the included life history data for the analyses were: age and length at maturity (A_{mat} and L_{mat}, respectively), maximum age recorded (as a proxy for longevity, A_{max}), mean maximum length from the von Bertalanffy growth curve (L_{∞}), and von Bertalanffy growth parameter (k; **Table 1**). Natural mortality, M, was not included in the life history analysis, because M is frequently derived from other life history traits, such as maximum age, for these species, and is thus directly correlated.

Fishery Catch Data

Fishery catch information from 2010 to 2018 was used to estimate presence/absence and catch-per-unit-effort (CPUE) for each of the species. Other Rockfish species are incidentally caught in other groundfish fisheries by five gear types including non-pelagic trawl (NPT), pelagic trawl (PTR), longline hook and line (LL), pot (POT), and jig (JIG). The majority of the rockfish bycatch species by biomass are caught in the trawling gear (NPT and PTR), which primarily targets pollock, Pacific cod, flounders, and target rockfish species, in all subarea except 650. They are also caught in fishery longline gear types (LL and JIG) in all subareas that target sablefish and Pacific halibut. Fisheries species-specific catch information is gathered from the Alaska Regional Office Catch Accounting System (CAS) using data from 2010 (when quality data were first available for these rockfish species) to 2018. The sampling unit for the catch data is determined by each unique vessel trip identifier each week for each subarea as reported by fishermen, ranging from < 10 to over 8,000 vessel trips for each gear type and subarea over the entire time period. The CPUE input data used for the analyses are defined as biomass (mt) caught per vessel trip for each species based on available fisheries data.

Survey Data

The NMFS Alaska Fisheries Science Center (AFSC) bottom trawl survey (von Szalay and Raring, 2018) and annual longline survey (Malecha et al., 2019) were used as fishery independent data sources. Other Rockfish species information has been collected on the Alaska bottom trawl survey in the GOA since 1980. The bottom trawl survey used a triennial time scale from 1984 - 1996, followed by a biannual basis (1999 - current). Years included in this dataset range from 1984 to 2017. The trawl survey covers depths up to 1000 m, sampling around 320,000 km^2 from late May - early August using a stratified-random design including an average of 235 hauls that catch at least one species in the Other Rockfish complex. The sampling unit for the trawl survey is biomass (kg) per km^2 calculated by the biomass caught per area swept by the trawl net. General habitat types (i.e., gully, shelf, and slope), depth and latitude and longitude are recorded.

The NMFS annual longline survey targets sablefish (*Anoplopoma fimbria*), but also catches Other Rockfish species. The longline survey can sample areas that are deemed untrawlable (e.g., areas with high relief and rocky habitat), providing catch information for species that might not be susceptible to the trawl gear. Data on rockfish from the longline survey used in this study range from 1995 to 2017. The sampling unit for the longline survey is number of individuals caught per set of hooks. Other factors that influence survey catch, such as depth bins, latitude and longitude, are available.

Multivariate Analyses Background

A variety of quantitative multivariate clustering and ordination methods were implemented to explore potential alternative species groupings. We considered a species complex 'appropriate' for management advice if there was high consistency in clustering among different multivariate methods and types of data. Two clustering methods and one ordination technique were applied to each data type as suggested by Lee and Sampson (2000) and Shertzer and Williams (2008). The two clustering methods conducted in this study are Ward's minimum variance and

TABLE 1 | Life history characteristics for each Gulf of Alaska Other Rockfish (GOA OR) and Demersal Shelf Rockfish (DSR) species.

Common name	*Sebastes* sp.	Assessment Group	A_{max}	A_{mat}	L_{mat} (mm)	L_{∞} (mm)	*k*
blackgill	*S. melanostomus*	GOA OR	90 (OR/CA; 1)	21 (OR/CA; 1)	350 (OR/CA; 1)	548 (OR/CA; 1)	0.04 (OR/CA; 1)
bocaccio	*S. paucispinis*	GOA OR	45 (WA; 2)	4 (CA; 12)	450 (CA; 12)	909 (BC; 22)	0.088 (BC; 22)
canary	*S. pinniger*	DSR	71 (CA; 3)	9 (CA; 12)	480 (BC; 20)	580 (BC/WA/OR/CA; 23)	0.16 (BC/WA/OR/CA; 23)
Chilipepper	*S. goodie*	GOA OR	35 (OR/CA; 4)	2.5 (OR/CA; 4)	260 (OR/CA; 4)	575 (OR/CA; 4)	0.252 (OR/CA; 4)
China	*S. nebulosus*	DSR	78 (AK; 5)	4 (CA; 12)	270 (CA; 12)	450 (AK; 28)	0.19 (WA/OR/CA; 31)
copper	*S. caurinus*	DSR	50 (AK; 5)	6 (CA; 12)	340 (CA; 12)	400 (AK; 28)	0.13 (WA/OR/CA; 31)
darkblotched	*S. crameri*	GOA OR	105 (6)	8.4 (OR; 13)	365 (OR; 13)	455 (OR; 24)	0.185 (6)
greenstriped	*S. elongates*	GOA OR	54 (AK; 5)	8.5 (WA/OR/CA; 14)	230 (CA; 12)	355 (BC; 25)	0.115 (BC; 25)
harlequin	*S. variegatus*	GOA OR	34 (AK; 7)	9.0*	230 (AK; 20)	323 (AK; 7)	0.110 (AK; 7)
northern	*S. polyspinis*	Subareas: 640,650	72 (AK; 7)	13 (AK; 15)	360 (AK; 15)	404 (AK; 7)	0.155 (AK; 7)
pygmy	*S. wilsoni*	GOA OR	26 (BC; 5)	6.0*	183.9*	230 (AK; 28)	0.180*
quillback	*S. maliger*	DSR	90 (AK; 8)	5 (AK; 16)	260 (CA; 12)	610 (AK; 28)	0.113*
redbanded	*S. babcocki*	GOA OR	106 (AK; 5)	4 (CA; 12)	420 (BC; 20)	698 (BC; 22)	0.042 (BC; 22)
redstripe	*S. proriger*	GOA OR	55 (BC; 5)	8 (16)	290 (BC; 20)	420 (BC; 22)	0.15 (BC; 22)
rosethorn	*S. helvomaculatus*	DSR	87 (AK; 5)	8 (CA; 12)	210 (AK; 20)	319 (BC; 22)	0.079 (BC; 22)
sharpchin	*S. zacentrus*	GOA OR	58 (AK; 7)	10 (16)	270 (AK; 16)	350 (AK; 7)	0.122 (AK; 7)
silvergray	*S. brevispinis*	GOA OR	75 (AK; 7)	10 (BC; 17)	460 (BC; 16)	623 (AK; 7)	0.093 (AK; 7)
splitnose	*S. diploproa*	GOA OR	103 (BC; 9)	7 (CA; 12)	218 (WA/OR/CA; 21)	314 (BC; 9)	0.155 (BC; 9)
stripetail	*S. saxicola*	GOA OR	38 (30)	4 (CA; 18)	200 (BC; 20)	327 (CA; 18)	0.147 (CA; 18)
tiger	*S. nigrocinctus*	DSR	116 (AK; 5)	15.0*	391.1*	610 (AK; 28)	0.083*
vermilion	*S. miniatus*	GOA OR	60 (AK; 5)	6 (CA; 18)	330 (CA; 18)	688 (CA; 18)	0.164 (CA; 27)
widow	*S. entomelas*	GOA OR	60 (BC; 5)	5 (CA; 12)	370 (CA; 12)	516 (OR; 26)	0.15 (OR; 26)
yelloweye	*S. ruberrimus*	DSR	117 (AK; 10)	22 (AK; 16)	475 (AK; 16)	644 (AK; 10)	0.046 (AK; 10)
yellowmouth	*S. reedi*	GOA OR	99 (BC; 5)	11 (BC; 32)	380 (BC; 20)	469 (BC; 32)	0.12 (BC; 32)
yellowtail	*S. flavidus*	GOA OR	64 (BC; 11)	9 (WA/OR/CA; 19)	410 (WA/OR/CA; 19)	530 (BC; 22)	0.20 (BC; 22)

Assessment Group indicates the current species complex assignment. Life history values included are: maximum age (A_{max}), age-at-maturity (A_{mat}), length-at-maturity (L_{mat}), average maximum length (L_{∞}) and von Bertalanffy growth parameter, k. Regions or states (i.e., CA, California; OR, Oregon; WA, Washington; BC, British Columbia; AK, Alaska) and citation (in ***Appendix 1****) are listed in parentheses.*

k-mediods; the ordination technique that is implemented is either canonical correspondence analysis (CCA) or non-metric multidimensional scaling (NMDS). These methods are described in Manly (2005); Zuur et al. (2007) and Legendre and Legendre (2012). All analyses were conducted in the R software language (R Core Team, 2020).

Both hierarchical (Ward's minimum variance) and non-hierarchical (*k*-mediods) cluster analysis are implemented to identify and compare consistency in species groupings. Ward's minimum variance analysis is a hierarchical, agglomerative clustering technique, which uses the centroid method to iteratively group closest objects together (Ward, 1963). Ward's analyses were conducted in R package "stats" (R Core Team, 2020), and a bootstrap resampling method was applied to determine the stability of each grouping with 1000 bootstrap samples in R package "fpc" (Hennig, 2007; Hennig, 2020). For each bootstrap sample, the new dataset was formed by drawing samples from the original dataset with replacement and applying the Ward's clustering analysis. The Jaccard coefficient, J, was calculated to examine the similarity in the cluster membership between the original cluster with each bootstrap cluster. The mean Jaccard coefficient values, $\bar{J}$, were computed for each cluster, where a higher value indicated more stability in the cluster. A value of 0.75 or greater implies that the original cluster is stable; values ranging from 0.6 to 0.75 suggest there are patterns in the data, but uncertainty in the cluster (Hennig, 2007). Dendrograms were used to aid in the interpretation of the results. The non-hierarchical cluster method, *k*-mediods, is a more robust variant of the traditional *k*-means (Kaufman and Rousseeuw, 1990). This *k*-mediods method finds optimal groupings by minimizing the distance between all objects and their nearest cluster center (mediod). The *k*-mediods analyses were conducted using R package "stats" (R Core Team, 2020). The optimal number of desired groupings for *k*-mediods was determined *a priori* using the average silhouette width (Rousseeuw, 1987) in R package "factoextra" (Kassambara and Mundt, 2020). The silhouette width is the measure of quality of the clustering by examining the (dis)similarities of an object to the other objects within the same cluster compared to objects belonging to other clusters (Rousseeuw, 1987), where the number of k clusters selected is based on the highest average silhouette width. An average silhouette width less than 0.25 signifies that there is not enough structure in the data to support natural clusters (Kaufman and Rousseeuw, 1990).

Additionally, for either method it is possible to use either of two different clustering techniques: R-mode (comparing variables or descriptors) or Q-mode (comparing objects; see **Figure 2**; described in Legendre and Legendre, 2012). R-mode directly identifies relationships among species (variables) by examining species similarities based on the catch in each sampling unit, whereas Q-mode identifies clusters by grouping units based on commonality in species composition. Q-mode is particularly useful for identifying groupings of sampling units (e.g., year and gear combinations) in multispecies catch data, but requires further analysis to examine species composition groupings within sampling units (e.g., Rogers and Pikitch, 1992).

The ordination techniques that were utilized to identify relationships among species are CCA and NMDS. The CCA technique is commonly used to examine species relationships and environmental variables that influence community composition. This analysis uses a set of weighted linear regressions to describe the relationship among species catch and explanatory variables (e.g., gear, depth, or location). It assumes that the species data are unimodal and vary along the gradients of the explanatory variables. Here, depth or depth bins, general substrate type, gear, and NMFS subarea were included as factors in CCA when applicable. In contrast to CCA, NMDS accommodates different magnitudes in the data, because it preserves the order of the distances rather than the magnitude of the distances. The NMDS technique also does not assume an underlying response model (Legendre and Legendre, 2012). Both ordination methods were conducted using R package "vegan" (Oksanen et al., 2019) and the first two dimensions of ordination space were used for visual representation.

Application of Multivariate Analyses

Analyses of Life History Characteristics

Both Ward's and *k*-mediods analyses were applied to identify species groupings based on life history characteristics using R-mode. The input life history table used in the analysis had species as the rows and life history characteristics as the columns with entries being the associated life history values. Three versions of the life history table were used for the analyses: species-specific values for each characteristic when data were available (species with no information were removed from this table, $n = 21$), species-specific values with missing values estimated from *FishLife* (Thorson et al., 2017, **Table 1**), and binned data based on four percentile bins (0–25, 26–50, 51–75, and 75–100%). Binned data allowed for data gaps and data uncertainty. The data in the species-specific life history tables were standardized by dividing each characteristic value by the mean for each life history characteristic. The standardization process ensures the magnitude of the data are similar so that the life history values are weighted the same in the analyses. The Euclidean distances were then calculated to develop the final dissimilarity matrix before Ward's and *k*-mediods analyses were implemented. Lastly, NMDS was applied to the dissimilarity matrix to assist in visualizing the species groupings and show any relationships among species and life history characteristics.

Sub-Unit Matrices of Catch and Survey Data

There are two scales of aggregation of the data, sub-unit and a more aggregated 'unit' scale (**Figure 2**). At the 'sub-unit' scale, input data matrices had entries of presence/absence or CPUE of a species (represented in the rows) for a given sampling unit (i.e., the smallest sampling unit of either haul, tow, or set in the columns). A matrix was created for every area and gear combination for all years combined. The application of the multivariate methods for each individual data sub-unit matrix ensured that each gear in the fisheries and surveys and each area are treated independently.

Ward's analysis, *k*-mediods and CCA were applied to the commercial catch and survey matrices. The R-mode for

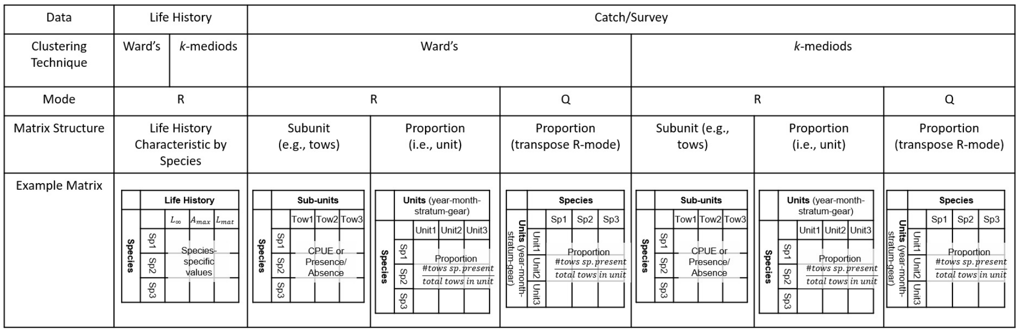


FIGURE 2 | Design of the model analyses identifying data, clustering technique and input matrix structure for each aspect of the cluster analyses.

the cluster analyses was implemented for the sub-unit data matrices. The multivariate analyses using R-mode allowed direct identification of species groupings for each gear type and NMFS subarea in the GOA when using the sub-unit matrix. Once the data matrices were created, the CPUE sub-unit matrices were standardized using a root-root transformation to down-weight highly abundant and prevalent species. Subsequently, the dissimilarity matrices were computed using Sorensen distance for presence/absence data matrix and chi-square measure of distance for the standardized CPUE sub-unit matrix prior to the application of cluster analyses. Other data standardizations and distance measures were implemented, but did not change the results. The sub-unit CPUE input data matrices were assembled with the sub-units as rows and species as columns for the CCA. A chi-square transformation was applied on the data matrices before implementing a CCA. External factors, such as depth, latitude, longitude and substrate type, were included in the survey catch analyses for each sub-unit.

Proportion Matrix of Catch and Survey Data

The second scale of aggregation was the aggregated 'unit' scale, which developed an input 'proportions' matrix. This proportions matrix consolidated the individual sub-unit matrices into a combined matrix. While in the 'sub-unit' matrices the columns represented the smallest sampling unit (i.e., haul, tow, or set), the columns of the proportions matrix were defined as a 'unit', which encompassed a temporal, spatial, and gear component. Here, each column was a unique combination of year, month, subarea, and gear while rows were species. The gear indicates the gear types used in the commercial catch and fishery-independent surveys, such that the gear categories are: NPT, PTR, LL, POT, and JIG for the fisheries gear and "trawl survey" and "longline survey" for the NMFS surveys. The entries were the proportion of tows that a species was present within that unit (i.e., the sum of tows with a species present divided by the total number of tows within the unit). The proportions matrix combined data for all gear categories (i.e., commercial and survey gears) into a single matrix, which allowed the exploration of similarity in the species catch composition among different gears and areas. The proportions matrix can also be useful to limit the impact of abundant and frequently caught species by reducing the difference between the number of null or zero catches for less common species and high valued positive catches for prevalent species.

Ward's analysis and k-mediods were applied to the proportions matrix using both R-mode and Q-mode. Similar to the R-mode application of the cluster analyses on the sub-unit matrices, the R-mode allows direct comparison of species relationships. The Q-mode, which used the transpose of the proportions matrix as the input data, required more detailed investigation to identify species groupings because clustering was by unit, not species. The species groupings that comprised each cluster were visually examined to determine which characteristics (i.e., gear, subarea, month, season, and year) influenced the clustering. The proportions matrix (or transpose thereof) already reduced the catch of species to comparable scales, thus, no standardization was necessary. Chord distances were calculated to obtain the dissimilarity matrices for the proportions matrix prior to applying the cluster analyses. The Chord distance is a type of Euclidean distance measure that can accommodate non-normalized data and is not sensitive to outliers (Shirkhorshidi et al., 2015). For the CCA, the proportions input matrix was assembled with the units as rows and species in the columns. A chi-square transformation was applied before implementing a CCA. Gear and subarea for each unit in the proportions matrix was included as external factors.

RESULTS

Analyses of Life History Characteristics

The rockfish in the GOA have a wide range of life history values (**Table 1**). Results for Ward's analysis and k-mediods on the life history tables differed slightly, but provided the same general conclusion. The multivariate analyses on the life history table supplemented with *FishLife* values are reported here; results based on the life history table with missing values and binned data are similar and reported in the **Supplementary Material** (**Supplementary Figures 1**, **2**).

Results from Ward's analysis had weakly supported groupings based on the bootstrap resampling for species with mid to lower values of length and ages associated with maturity, growth, and longevity ($\bar{J}$ values ranging from 0.63 to 0.69). The bootstrap resampling suggested patterns in the data for the grouping of three or four clusters with similar $\bar{J}$-values ranging from 0.63 to 0.83, but the clusters lack stability. Only the low productive species (i.e., tiger, blackgill, and yelloweye) remained in their own grouping in both k = 3 or 4 clusters in Ward's analysis with $\bar{J}$ values of 0.73 and 0.83, respectively. The NMDS plot with results from Ward's analysis represents three clusters, one with the low productivity group (i.e., high length and age values), one with relatively higher productivity (i.e., lower length and age values), and the third group with varying levels of productivity (**Figure 3A**). When k = 4 clusters, two species, redbanded and bocaccio, separate into their own group; these two species have low A_{max} and high L_{mat} and L_{∞} compared to the other species in their cluster when k = 3.

Results from k-mediods split the rockfish into two clusters based on the highest silhouette width of 0.30. The first cluster contained rockfish with life history values with high length and age values (i.e., low productivity). The second cluster consisted of rockfish with medium to high productivity (**Figure 3B**).

Comparing the results from the different clustering methods, the methods tended to group species by large or small lengths ($L_{\infty}$and L_{mat}) and younger or older maximum age (A_{max}) and age at maturity (A_{mat}), but most clusters were weakly supported. There were a few species that were placed in the same group regularly. These species tend to fall on the ends of the rockfish productivity spectrum (i.e., all high or low values for age and length associated with maturity, growth, and longevity). For example, tiger, blackgill, and yelloweye rockfishes all have high L_{mat}, A_{mat}, L_{∞}, and A_{max} values (i.e., low productivity) and were consistently clustered together for k-mediods and Ward's analysis. There are other rockfish species that have opposing life history characteristics. For example, splitnose has a high A_{max}, but low L_{∞}, while bocaccio has low A_{max} and A_{mat} and high L_{∞} and L_{mat}. These species tended to waver between clusters depending on the method and suggested number of clusters. Overall, larger, older rockfish tended to cluster together, but there is a wide variation and spread of life history values among and within the clusters resulting in no distinct support for clusters.

Sub-Unit Matrices of Catch and Survey Data

Exploratory runs were performed with all methods applied to the catch and survey data to determine whether results were robust to the inclusion of rare species (i.e., species comprising less than 1% of total catch). Due to poor performance (i.e., lack of clustering and chaining in Ward's analyses) in exploratory runs when rare species were included, it was determined that these species should be removed from further analyses of the catch and survey data. Species removal varied considerably for sub-unit analyses (see **Supplementary Material 1** and **Supplementary Figure 3** for species composition and sparseness across gears and subareas).

When each gear and area were analyzed separately using the sub-unit matrix, some analyses demonstrated poor performance (e.g., high prevalence of chaining or lack of clustering). Generally, results demonstrated that the more abundant and more frequently caught species tended to group together, while the less abundant species also commonly clustered together (**Supplementary Figure 4**). This pattern is demonstrated in both types of cluster analyses for all subareas of the GOA and all gear types for both presence/absence and CPUE data matrices. However, these results should be interpreted with care, given the performance issues encountered. The ordination analyses (CCA) did not yield discernable groupings nor strong associations with the additional explanatory information (e.g., depth, longitude, latitude, and substrate type; **Supplementary Figure 5**). Thus, the analyses using the sub-unit matrix were of limited insight for grouping of species complexes.

Proportions Matrix of Catch and Survey Data

The exploratory runs with the proportions matrix indicated that rare species should be excluded to provide better clustering performance. A total of 14 species remained in the unit proportions matrix after rare species were excluded. The total number of species remained the same across analyses and modes.

Aggregating the data into units (i.e., by year, month, subarea, and gear) in the proportions matrix enabled the cluster analyses to find stronger relationships among the species using R-mode. Although the groupings from the k-mediods analysis using the unit aggregation led to similar results as using the sub-unit matrix, Ward's analyses tended to aggregate species by co-occurrence. The bootstrap resampling method indicated that k = 2 or 3 clusters were supported with $\bar{J}$ values ranging from 0.69 to 0.84. For the two-cluster output, one stable cluster ($\bar{J}$ = 0.84) contained species that are only within the Other Rockfish complex with the exception of rosethorn (**Figure 4**). The other cluster aggregated species predominately found in the Demersal Shelf Rockfish group ($\bar{J}$ = 0.82). For the three-cluster output, the clustering data suggested that two species (i.e., canary and yellowtail could be weakly separated into their own group ($\bar{J}$ = 0.69), whereas these species are aggregated with the Demersal Shelf Rockfish cluster when k = 2 (**Figure 4**).

The clustering and ordination analyses indicated that gear and occasionally subarea influenced the groupings using Q-mode. There did not appear to be any seasonal or temporal trends. Ward's analysis performed poorly due to the common chaining issue and there was no appropriate number of groupings found based on the bootstrapping. Conversely, the k-mediods method provided discernable groupings. The optimal number of clusters (k) for k-mediods was 5 based on the average silhouette width of 0.32. However, the optimal number of clusters based on where the average silhouette width first reaches its asymptote was k = 2 at a silhouette width value of 0.29 (**Figure 5**). Thus, results from the k = 2 and k = 5 clusters are presented.

Results from k-mediods with k = 2 clusters yielded clearly defined groups differentiated primarily by gear type (**Figure 6A**). The first cluster contained trawling gears (i.e., NPT, PTR, and the trawl survey), as well as the pot gear (POT). The second cluster consisted of longline gear types (i.e., LL, JIG, and the longline survey). Differences in subareas could also be discerned (**Figure 6B**); the first cluster mostly contained subareas 610, 620, and 630, whereas cluster 2 comprised all subareas. The division of subareas can be attributed to specific fishing gear in

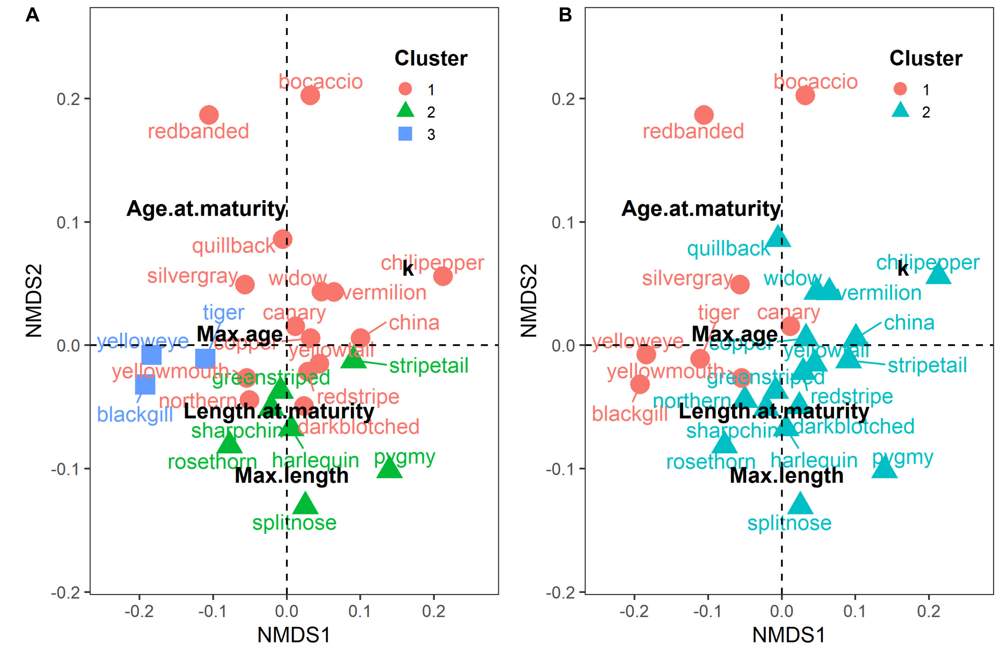


FIGURE 3 | NMDS plot of species' clusters identified from life history values estimated from *FishLife* for missing values from **(A)** Ward's hierarchical cluster analysis and **(B)** *k*-mediods. In Ward's analysis three or four clusters were supported by the bootstrapping resampling method; results with four clusters separated redbanded and bocaccio into their own cluster.

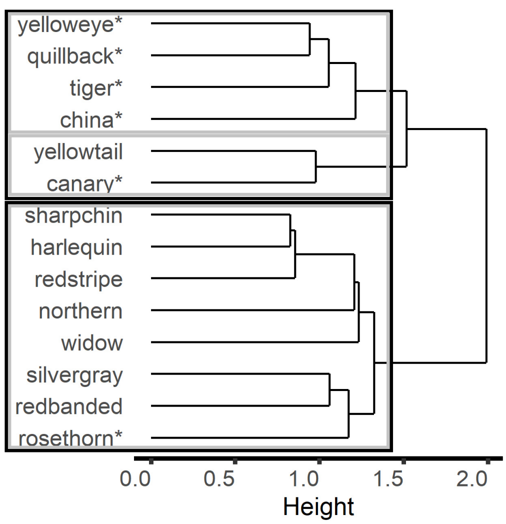


FIGURE 4 | Results from Ward's hierarchical cluster analysis using the proportions matrix with "units" (year-month-subarea-gear) in R-mode where 2 (black lines) or 3 (gray lines) clusters are supported by the bootstrap resampling method. The "*" indicates species that currently belong to the Demersal Shelf Rockfish complex.

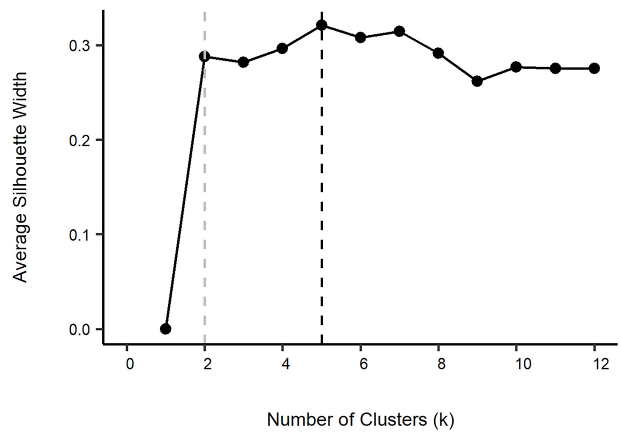


FIGURE 5 | Average silhouette width from Q-mode *k*-mediods cluster analysis using the proportions matrix with "units" (year-month-subarea-gear). The suggested optimal number of clusters is $k = 5$ (black dashed line), but the average silhouette width plateaus at $k = 2$ (gray dashed line).

certain subareas (**Supplementary Figure 3**). For example, NPT and PTR gear types do not fish in subarea 650, whereas JIG gear is primarily used in subareas 630 and 650.

The majority of the species belonging to the Demersal Shelf Rockfish complex (i.e., China, yelloweye, tiger, rosethorn, quillback and canary) had a higher proportion of presence in the cluster associated with the longline gear (cluster 2; **Figure 6C**). In comparison, most of the species that only belong to the Other Rockfish complex (i.e., widow, sharpchin, redstripe and harlequin) were present in higher proportion in the cluster that contained mostly all trawl gear and subareas 610, 620 and 630 (cluster 1; **Figure 6C**). For comparison, northern rockfish are caught in almost 100% of the units in cluster 1 (**Figure 6C**), which is as expected because the northern rockfish is a target

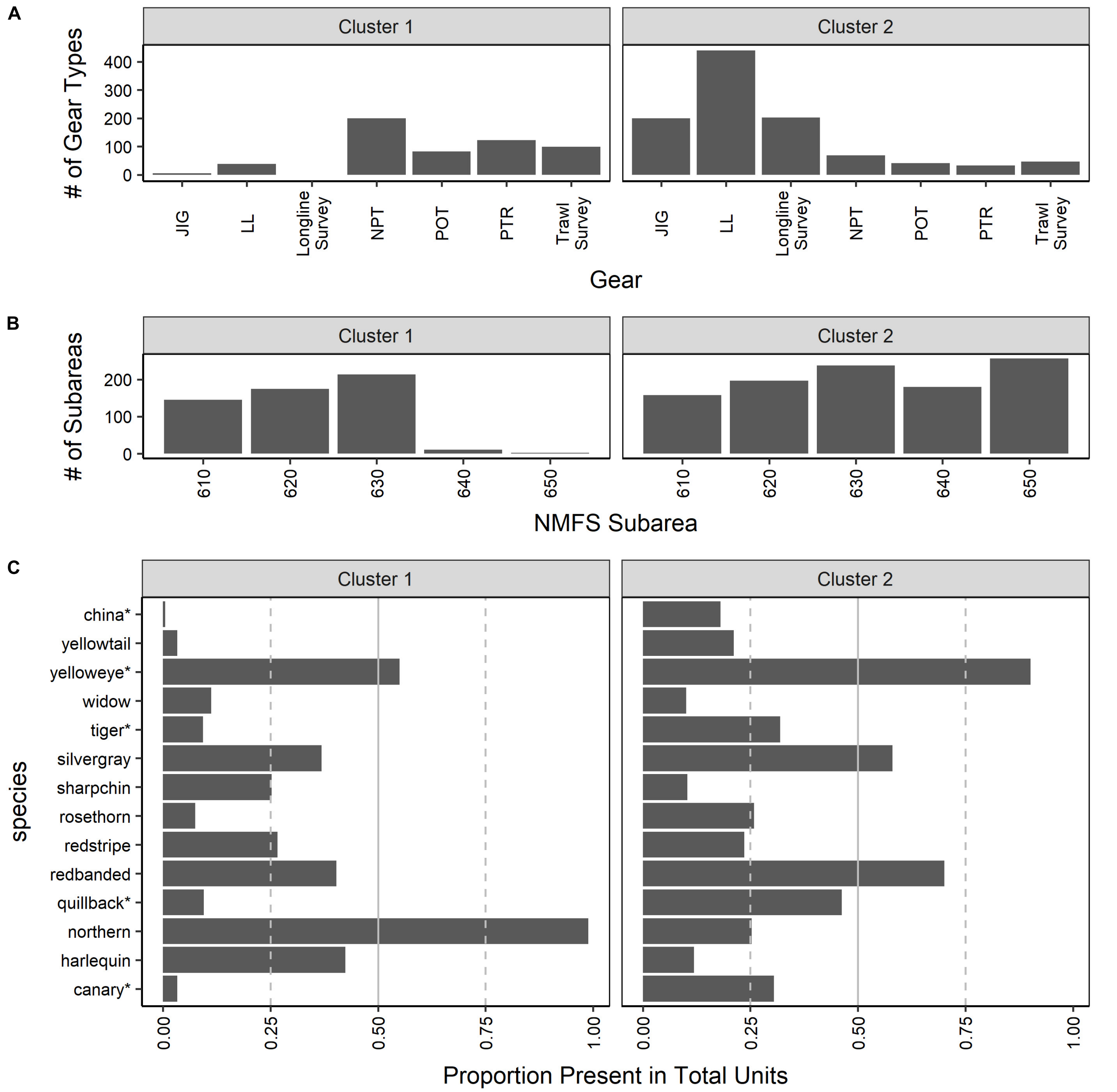


FIGURE 6 | Results from Q-mode *k*-mediods using the proportions matrix with "units" (year-month-subarea-gear) to synthesize all gear types (fishing gear: jig [JIG], longline hook and line [LL], non-pelagic trawl [NPT], pot [POT], and pelagic trawl [PTR]; and surveys: longline and trawl) and subareas into one dataset when $k = 2$ clusters. In **(A)** the number of units where each gear type was present in each cluster is shown. In **(B)** the number of units where each subarea were present in each cluster is illustrated. In **(C)** the proportion of units (year-month-subarea-gear) that a species is present out of the total number of units assigned to each cluster is provided to represent the species composition in each suggested cluster when $k = 2$. Species that currently belong to the Demersal Shelf Rockfish complex are indicated by "*".

species, assessed separately, and caught solely by trawl gears in subareas 610, 620, and 630. The northern rockfish results suggest that the clustering is accurately reflecting the data. There were some species that did not follow this pattern. Two species (i.e., silvergray and redbanded) that were commonly found in all gear types (**Supplementary Figure 3**), but belong only to the Other Rockfish complex, were found in 41% and 46%, respectively, of the total units in cluster 1 (affiliated with trawl gear; **Figure 6C**), whereas these two species were in 56% and 68% of the units in cluster 2 (affiliated with longline gear; **Figure 6C**). Additionally, yellowtail was present more frequently in the units in the cluster associated with longline gear (cluster 2; **Figure 6C**) than the cluster associated with trawl gear (cluster 1; **Figure 6C**), despite the species only being assigned to the Other Rockfish complex.

Although the results when $k = 5$ clusters generated more mixed groupings compared to $k = 2$, there was some separation among gear types (**Figure 7A**). The major fishery gears (i.e., NPT, JIG, and LL) each separated into their own clusters with some overlap between LL and JIG gear (i.e., clusters 3, 4, and 5, respectively, in **Figure 7A**). Cluster 1 consisted of a mix of all trawl gear (fishery and survey), while cluster 2 included mostly all longline survey and LL units (**Figure 7A**). The separation of subareas in the clusters followed a similar pattern to the $k = 2$ cluster results. Most clusters contained a mix of subareas (**Figure 7B**); however, some gear types do not fish in specific subareas.

There were several species that were abundant in most clusters and some species that were specific to a few clusters when $k = 5$ (**Figure 7C**). For example, yelloweye was present in 75% or more of the units in all but cluster 1 (**Figure 7C**). In contrast, harlequin was generally associated only with trawling gear types and subareas 610, 620 and 630 (i.e., clusters 1 and 3; **Figure 7C**). Similar to the species composition when $k = 2$ clusters, many of the Demersal Shelf Rockfish species were found in higher proportion in clusters associated with longline gear (LL, JIG, and longline survey in clusters 2, 4, and 5 covering all subareas; e.g., quillback). Yellowtail was found in higher proportion in clusters with JIG and LL (i.e., clusters 4; **Figure 7C**) and in low presence (i.e., < 10%) in clusters linked with longline survey and all trawl gear (**Figure 7C**).

Although CCA results from the proportions matrix did not reveal any species aggregations in ordination space, the results did reveal general groupings primarily by gear (**Figure 8**) and secondarily by subarea (**Supplementary Figure 6**). The groupings indicated that there were underlying differences in the species composition by gear and subarea. The other variables (i.e., year, month, and temporal factors) did not influence the groupings and were excluded from further CCA analyses. About a third (36%) of the variation could be explained by the gear and subarea variables, which suggested that these variables were correlated with the species composition. The first axis, CCA1, represented a strong gradient and explained ∼40% of the CCA variation. The second axis, CCA2, explained ∼25% of the CCA variation (**Supplementary Table 1**). Based on CCA1 and CCA2, the longline survey, LL and JIG all separated (**Figure 8**). The various trawl gear units (NPT, PTR and trawl survey) appeared to be mixed in ordination space along the CCA axes. The POT fisheries gear overlapped with both the trawl gears and LL (**Figure 8**). A few species are moderately associated to specific gears according to the CCA results, such as yellowtail, canary and China rockfish to JIG, longline survey, and LL. Axis CCA1 separated subarea 650 from the other subareas (**Figure 8**). However, all the other subareas were not affiliated with the CCA axes, indicating that gear types contributed to most of the variation.

DISCUSSION

Our analyses demonstrate the importance of exploring a variety of quantitative methods for determining species complexes based on both life history and catch or survey data. Although each multivariate approach has associated pros and cons, utilizing multiple methods can help identify consistent trends across data and statistical approaches. The use of multiple data types and methods for identifying species complexes should be considered best practice for the management of data-limited fisheries. Our results demonstrate that reliance on single methods or a single type of data may provide limited interpretations that may lead to suboptimal species groupings and, ultimately, poor management performance.

Specific to our case study, our analyses indicate that an alteration in the complexes for management of these species may be warranted. We suggest that the Demersal Shelf Rockfish species should be separated from the remainder of the Other Rockfish complex in all subareas in the GOA for assessment purposes. The remaining bycatch rockfish from this study can be grouped together as one complex. There were no clear divisions of species based on the life history characteristics due to the uncertainty and diversity in values, and unstable clustering among methods. The application of multiple methods (clustering and ordination techniques, R- and Q-mode, and data structure) and examination of the catch and survey data provided a basis to develop possible complexes. Some methods were unsuccessful (e.g., sub-unit analyses), while others delivered sensible groupings (k-mediods in Q-mode for proportions matrix). The rockfish groupings separated mainly by gear in our analyses, which suggested that the assessment models providing management advice for these complexes should incorporate the associated survey gear.

GOA Bycatch Rockfish Results and Study Limitations

Wide ranges in productivity and resilience of species' populations are not uncommon when applying methods to identify species complexes (DeMartini, 2019). The life history cluster analysis results indicated that rockfish in the GOA tended to group by higher (i.e., earlier age and smaller size at maturation) and lower (i.e., older age and larger size at maturation) productivity levels, but generally demonstrated a wide range in life history values. A few rockfish species had conflicting levels of productivity with different life history characteristics (e.g., long-lived with early age-at-maturity), which made it challenging to define a species with high or low productivity compared to other rockfish. The uncertainty in the life history values limits interpretation of the results. One source of uncertainty is that life history values were borrowed from outside of the GOA when data were not available and research suggests that there can be regional differences in values (Boehlert and Kappenman, 1980; Gertseva et al., 2010; Keller et al., 2012). Additionally, studies for a given species often showed variability, making it difficult to place a species into high or low productivity groupings. Given the uncertainties in the data, the results did not yield definitive groups and were deemed less reliable than the outputs of the cluster analysis using catch and survey data. Yet, based on PSA results, GOA rockfish, as a genus, fall in the lower productivity spectrum (Ormseth and Spencer, 2011). Rockfish results from Ormseth and Spencer

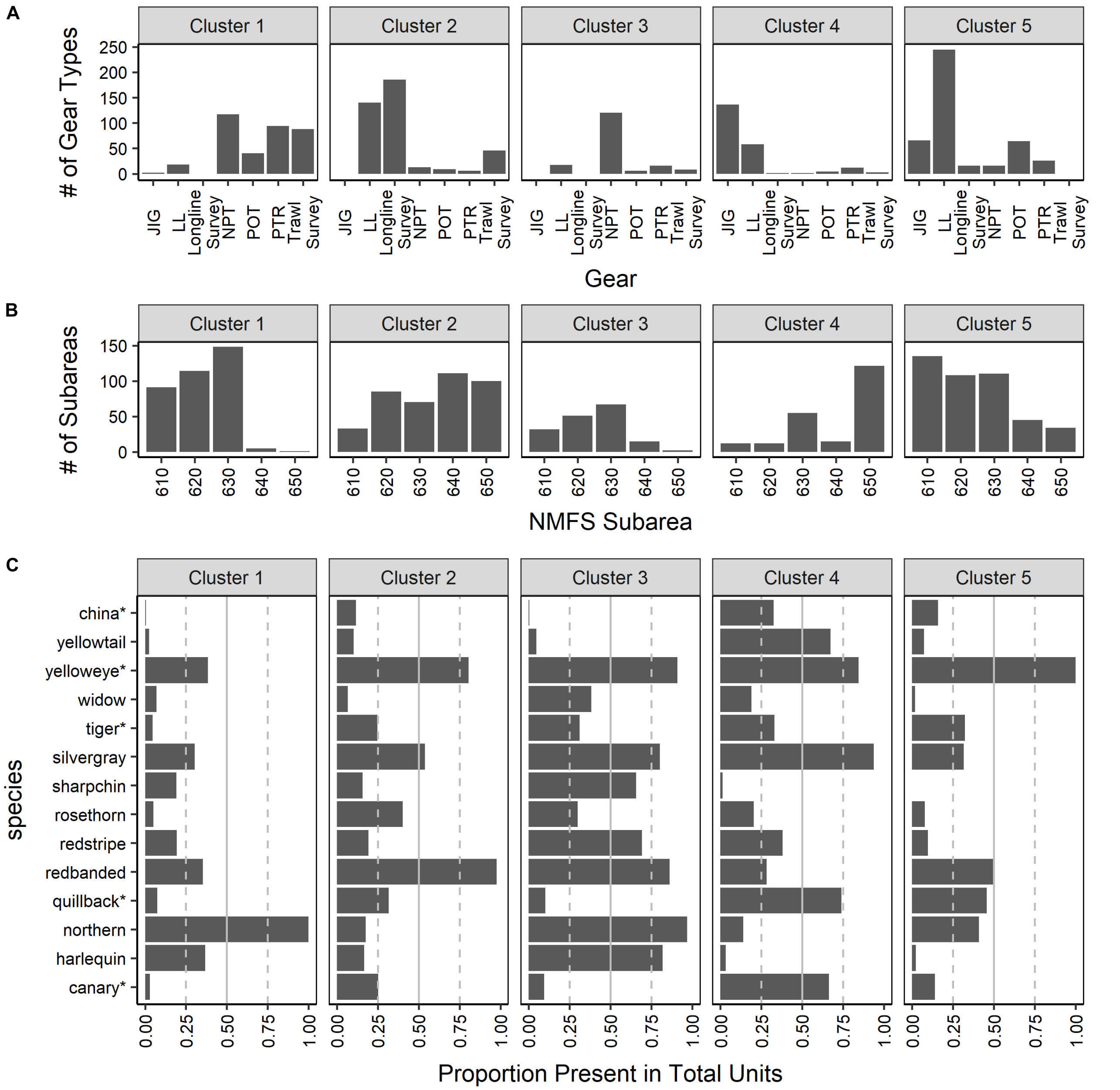


FIGURE 7 | Results from Q-mode *k*-mediods using the proportions matrix with "units" (year-month-subarea-gear) to synthesize all gear types (fishing gear: jig [JIG], longline hook and line [LL], non-pelagic trawl [NPT], pot [POT], and pelagic trawl [PTR]; and surveys: longline and trawl) and subareas into one dataset when $k = 5$ clusters. In **(A)** the number of units where each gear type was present in each cluster is shown. In **(B)** the number of units where each subarea were present in each cluster is illustrated. In **(C)** the proportion of units (year-month-subarea-gear) that a species is present out of the total number of units assigned to each cluster is provided to represent the species composition in each suggested cluster when $k = 5$. Species that currently belong to the Demersal Shelf Rockfish complex are indicated by "*".

(2011) concur with the United States West Coast groundfish PSA results (Cope et al., 2011) that included more rockfish species. Given that rockfish are generally less productive compared to the other species in the GOA, they tend to be more vulnerable to fishing pressure.

Each rockfish species faces different susceptibility to the widely varying fisheries that operate in the GOA, but one particular challenge is the placement of rare or ubiquitous species into a species group using cluster analyses. We had a range of 3 to 13 species included in the sub-unit cluster analyses depending on the gear type and subarea due to the exclusion of rare species (species with < 1% of total catch). There were 11 of the 25 species that made up < 1% of the units (year-month-subarea-gear) with positive catch for the proportions matrix. The multivariate

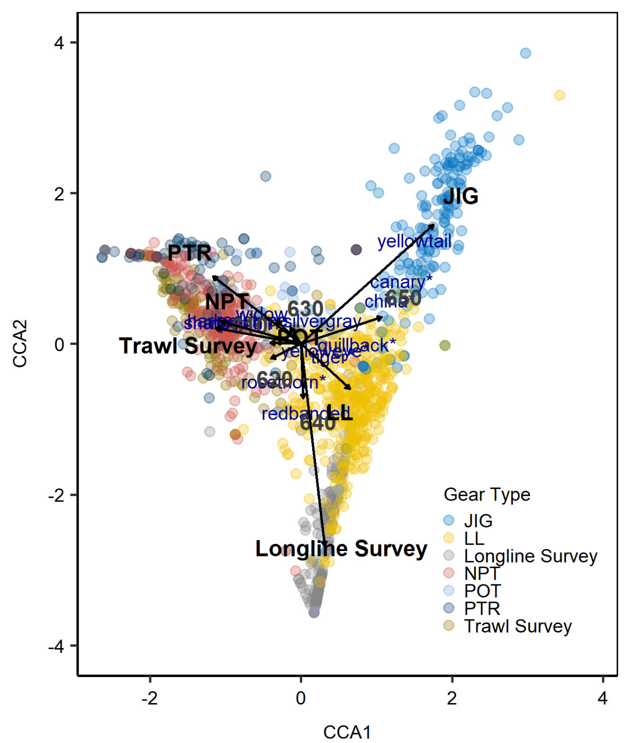


FIGURE 8 | CCA results using the proportions matrix with units (year-month-subarea-gear) plotted on the first two CCA axes. Gear type is color coded, species are marked in blue text (with species currently assigned to the Demersal Shelf Rockfish marked with "*") and factors (i.e., gear and subarea) provided in black bold text. Gear types include fishing gear (jig [JIG], longline hook and line [LL], non-pelagic trawl [NPT], pot [POT], and pelagic trawl [PTR]) and surveys (longline and trawl surveys).

methods in this study were unable to provide species association or coexistence relationships for these rare species. Likewise, species that are captured across many gear types and areas are difficult to assign to groups. The clustering results did not indicate specific species associations for these abundant rockfish.

Most of the clustering analyses also failed to provide consistent or reliable results when applied to each gear and subarea dataset separately through application to the sub-unit matrix. When the various methods were applied to the sub-unit matrices there were no clearly delineated relationships of commonly caught species or rarer species. We had anticipated that the finer-scale approach might provide insight into the co-occurrence among species. However, the lack of identified co-occurrence relationships (i.e., similarities among species) with the sub-unit matrices was likely because the R-mode groups by similar catch in each unit or sub-unit. As a result, the more abundant and more frequently caught species are commonly grouped. Thus, the differences in magnitude and frequency of the catch mask the less obvious relationships among species.

Aggregating all the datasets into a single data matrix enabled gears, subareas, and temporal components to be compared, while major categories that influenced the groupings could be identified. The challenge is determining logical and biologically informed clusters (e.g., balancing too few or too many clusters that may result in a narrow or wide range of species productivity), while balancing the practical management of species that are exploited across varying gear types and subarea. Using the k-mediods analysis, either two or five clusters were recommended. The suggested $k = 5$ clusters identified specific relationships among different gear types and occasionally subareas. Some species appeared to be associated with only a specific cluster (or clusters), whereas other species were commonly found in all clusters. The rockfish that occur in medium to high frequency in all or most of the clusters are species that are found ubiquitously in the GOA and are caught by most gear types. The results with $k = 2$ clusters indicated that the species composition caught by longline gear types clearly separated from trawling gear types. Overall, the analysis of the catch and survey data indicated that gear was the biggest contributing factor in grouping similar units of rockfish species composition. NMFS management subarea could have influenced the cluster results, as there was a strong interaction between fishery gear and subarea (i.e., certain gears only operate in specific subarea). These analyses suggest that rockfish species that are only predominately caught by a specific gear could be assigned to a rockfish complex that commonly associates with that gear for assessment and management purposes.

These analyses, particularly the proportions matrix analyses, provided a way to examine the species composition from the fishery catch with the survey data. Our results indicated that the trawl survey and trawl fisheries gear tended to be grouped together more frequently than the longline gear types (i.e., the longline survey, LL, and JIG). Williams and Ralston. (2002) found that the bottom trawl survey reflects the trawl fishery sector well off the coast of California and Oregon, United States, which includes non-pelagic and pelagic trawl, because it catches species that are typically found at the bottom (e.g., Keller, 2008) or distributed in the water column (e.g., widow rockfish, Wilkins, 1986). In contrast, the longline survey is a fixed station survey that targets primarily commercially important sablefish (Malecha et al., 2019). The longline survey did not always catch species typically caught in the longline fishery gear types (**Supplementary Figure 3**). Of the top five Other Rockfish species caught in the longline survey by numbers, only three are designated in the Demersal Shelf Rockfish complex. This result suggests that the longline survey alone is not representative of the populations within the complex or caught by the longline gear fisheries. If the Demersal Shelf Rockfish complex is extended to all subareas of the GOA, other data resources will be needed to assess this assemblage. For example, the Demersal Shelf Rockfish assessment utilizes submersibles to estimate abundance trends to set quotas in NMFS subarea 650 (Olson et al., 2018). Studies have identified that commercial catch data do not necessarily reflect the species composition in the survey data (i.e., species composition in the ecosystem; Lee and Sampson, 2000; Pennino et al., 2016), but surveys should include a broader diversity of species than that found in the commercial catch. Given the diversity of gear types utilized in the GOA, as well as specific gears fishing in habitat-specific areas (e.g., Rooper and Martin, 2012) and habitat-specific preferences of some rockfish (Laidig et al., 2009; Conrath et al., 2019), it is not surprising that the longline survey does not perfectly reflect the species composition of the various longline gear fisheries. Yet, the paucity of data available for the bycatch rockfish species in the GOA requires that any data on catch rates and composition should be utilized. We suggest the incorporation of the longline survey data in the analysis of species complexes in the GOA, despite some limitations in the overlap of the survey catch composition compared to the longline gear species composition. In the future, other survey types, such as submersibles, which are used in the current Demersal Shelf Rockfish assessment (Olson et al., 2018), should be investigated when survey data underrepresent the species composition of the fishery.

GOA Bycatch Rockfish Management Recommendations

The management of the bycatch of GOA rockfish poses a challenge because these species have a diverse range in life history values, habitat preferences, spatial distribution, and fishing vulnerability. Based on the summary of our analyses, as well as consideration of previous work with GOA rockfish complexes (e.g., the PSA of Ormseth and Spencer, 2011), we propose an alteration for management of the rockfish complexes in the GOA (**Table 2**). The current GOA Other Rockfish complex consists of species that are classified as the "slope," "pelagic shelf," and "demersal shelf" rockfish assemblages and the group of seven "demersal shelf" species are separated into the Demersal Shelf Rockfish complex in subarea 650. Our results indicated that the current delineation that split the GOA Other Rockfish and Demersal Shelf Rockfish complexes is appropriate. The analysis of catch and survey data indicated that these two complexes tended to separate by the main fishing gear types, trawl and longline, gulf-wide with the Demersal Shelf Rockfish more closely associated with the latter gear. We suggest that the Demersal Shelf Rockfish species be placed into their own complex for all subareas in the GOA.

Some alterations and considerations may be warranted, particularly for highly prevalent or rare species. For instance, silvergray and redbanded rockfish were commonly found in all gear types and were equally common in both the longline and trawl groupings. We suggest that the few species that are caught in high prevalence by all gear types should be placed in the group of species that associates with the gear that catches the species in the highest abundance (see **Table 2** for these assignments). Although these bycatch rockfish are frequently caught, they do not have enough data to warrant a single-species assessment. Similar approaches will likely be appropriate for rare species, which were excluded from this analysis (but included in **Table 2** based on gear association). We suggest placing rare species in the species group associated with the gear in which they are most commonly caught. By doing so will help ensure that the rare species are managed consistent with the fishing pressure that they encounter. However, rare species may be more prone to localized depletion or other conservation concerns and should be carefully monitored.

TABLE 2 | Suggested assemblages for species complexes based on the analysis of all available data and clustering techniques.

GOA Other Rockfish	GOA Shelf Rockfish
blackgill	canary
bocaccio	China
chili*pepper*	*copper*
darkblotched	quillback
greenstriped	rosethorn
harlequin	tiger
northern	**yelloweye***
pygmy	
redbanded*	
redstripe	
sharpchin	
silvergray*	
splitnose	
stripetail	
vermilion	
widow	
yellowmouth	
yellowtail	

These complexes should be assessed and managed as such throughout the entire GOA. Species in bold italics are assigned based on occurrence in gear types, but should be carefully monitored. Species in bold are commonly caught in all gears and have been assigned to the complex that is associated with the gear, in which they are most commonly caught. Rare species (species that comprise < 1% of total catch) are provided in italics and are similarly assigned to the complex related to the gear in which they are most frequently caught. Other management considerations (e.g., enforcement issues) might be warranted to reassign common and rare species to different complexes. An "" is used to identify suggested precautionary indicator species for each complex based on the low productivity from the life history cluster analyses.*

Further specific alterations to the current complexes also should be investigated. One species, yellowtail rockfish, which is assigned to the "pelagic shelf" assemblage by the North Pacific Fishery Management Council (North Pacific Fishery Management Council (NPFMC), 2019) and assessed in the Other Rockfish complex, was associated more closely with the longline gear grouping. However, this species was caught in both main fishery gear types, trawl and longline, but only caught in the trawl survey. We suggest that yellowtail rockfish remain in the Other Rockfish complex, but should be monitored due to its association with species from the Demersal Shelf rockfish complex (**Table 2**). Careful consideration should be applied to all species belonging to the "pelagic shelf" assemblage classified by the North Pacific Fishery Management Council (North Pacific Fishery Management Council (NPFMC), 2019), because results from this analysis split the "pelagic shelf" rockfish into opposing groups based on species association, but have different gear associations.

One method to help provide guidance for the management and sustainability of species in complexes is to identify indicator species. An indicator species should be commonly observed in the gear types associated with the clusters, demonstrate similar population trends, and share similar life history traits (e.g., reproductive success) as other species, and not have a noticeable competitive relationship with the rest of the species in the group (Landres et al., 1988; Simberloff, 1998; Zacharias and Roff, 2001). Additionally, they should exhibit the highest vulnerability or be near the lower end of the productivity spectrum for the complex (i.e., be a "weakest link" species; Shertzer and Williams, 2008). The community structure must also be relatively stable to manage a complex based on an indicator species; yet, studies often show large marine ecosystem shifts (Shertzer et al., 2009). Thus, these assumptions are often violated or no species is able to fulfill all the requirements for an appropriate indicator species (Niemi et al., 1997). However, an indicator species can still be useful by providing supplementary precautions and buffers for the complex by demonstrating potential instability within the group if the variation in the population of the indicator species increases or there are drastic changes to the population.

To help ensure sustainability for all rockfish in the complexes, it may be useful to select one or two precautionary indicator species that are on the lower end of the productivity spectrum for the complex, but are commonly observed by the predominant gear type (i.e., they are not rare species). Based on the PSA results from Ormseth and Spencer (2011); Cope et al. (2011), and our analyses on the life history characteristics, we suggest that redbanded and silvergray in the Other Rockfish complex and yelloweye in the Demersal Shelf rockfish complex may be appropriate indicator species given their low productivity and relatively high frequency of observation (**Table 2**). We believe that these general groupings are both practical for management advice (i.e., bycatch quotas can be enforced because groupings align by common gear types) and biologically relevant (i.e., all rockfish genus fall on the lower end of the productivity spectrum). We suggest that future research explore the possibility of identifying indicator species for the GOA Other Rockfish complex and whether redbanded and silvergray might be appropriate representatives.

Given the data limitations for the GOA Other Rockfish species (e.g., lack of consistent life history data, a number of diverse gear types, and the high occurrence of rare species that are seldom observed), the groupings for the complexes should be re-evaluated when new or updated data are available. In particular, the uncertainty in life history values used in these analyses hindered the ability to develop clusters based on productivity. For example, length data are not collected for many species in this study, but length data collection could inform key life history values. To be able to adequately represent these data-limited species, particularly rare species, improved data collection will be the only reliable solution to implement the type of species clustering approaches used in this study. Future focus on the collection of biological data from discards of rare species would be a helpful for better managing bycatch rockfish species.

In the current study, we were unable to include environmental or habitat features to the proportions matrix analyses due to the lack of data from the various fishery sectors, as well as, the problematic issue of identifying broad-scale features for entire management subareas. However, many studies examining species association or identifying species complexes have determined depth (Rogers and Pikitch, 1992; Lee and Sampson, 2000; Gomes et al., 2001; Williams and Ralston., 2002; Rooper, 2008), broad substrate or habitat structure (Anderson et al., 2009) or a combination of factors (Tolimieri and Levin, 2006) affect the species composition. Additionally, when multiple fishing gears are included in analyses to examine species composition in a given area, it is often found that different combinations of gear type, environmental, and spatial features influence the species catch (e.g., Vinther et al., 2004; Pennino et al., 2016; Tuda et al., 2016). Nonetheless, most of these studies focus on only one gear type or utilize survey data collected by submersibles, which enables researchers to determine main environmental or habitat features influencing the grouping. Further work is warranted to collect data and determine if habitat or environmental variables might help to better identify rockfish species complexes.

General Species Complex Recommendations

Appropriate methods for identifying species complexes are likely to vary on a case-by-case basis because each region and fishery has different attributes that need to be evaluated. Oftentimes, life history characteristics are unknown or complexes formed based on productivity do not necessarily align with vulnerability to the fishery or spatial distribution of the species. When there are conflicting results on groupings, managers must consider alternative options. A PSA or other risk assessment methods (e.g., Sustainability Assessment for Fishing Effects, Zhou et al., 2016) can help guide groupings for management as a preliminary tool (Cope et al., 2011), but this method may not accurately depict fishing dynamics in the susceptibility scores for all species (Hordyk and Carruthers, 2018). As previously discussed, Cope et al. (2011) recommend a step-wise method for assigning species to complexes using commonalities among species in depth preferences, spatial distribution, and vulnerability scores (i.e., based on levels of productivity and susceptibility to exploitation). Based on our analyses, we recommend that gear type needs to be considered in this step-wise grouping method, because certain species are more susceptible to specific gears than others. Incorporating gear types enables the comparison of species' vulnerability to different fishing pressures due to differences in spatial distribution (McCully Phillips et al., 2015), patchy distributions (Silva et al., 2012), and habitat preferences (e.g., Jagielo et al., 2003; Conrath et al., 2019).

The use of a variety of multivariate methods helps validate the appropriateness of the suggested groupings. We recommend using a combination of multiple data types, data aggregation scales, and the application of several multivariate analyses to develop species complexes. Each data-limited situation requires context-specific methods tailored to intricacies of the species and fishery being managed. For example, the inadequacies of our analyses using the sub-unit matrices to identify species co-occurrence demonstrates the importance of applying multiple analyses at multiple data aggregation scales to develop robust groupings. Likewise, we suggest that exploring both R-mode and Q-mode multivariate methods is warranted, especially when fishery and survey catch are the primary sources of data. Although not as widely used for analysis of species complexes, Q-mode can be valuable to identify commonalities in species groupings across gear types and management subareas. R-mode analysis provides a more direct clustering approach by species, which is useful when reliable life history data are available or a limited number of gear types (or a single multispecies fleet) harvest the primary species of concern (e.g., reef fishes that are fished using longline gear types along the southeastern coast of the U.S. [Shertzer and Williams, 2008] and Gulf of Mexico [Farmer et al., 2016]). However, it can be difficult to get reliable outputs from R-mode when a variety of gears differentially exploit the diversity of species under consideration across a broad spatial range (i.e., management subareas). In our study, Q-mode analysis proved to be useful when determining manageable species complexes. Ultimately, there is not a single universal approach to determining species complexes that is robust to all species traits and data availability situations. Our study demonstrates that a diversity of quantitative multivariate approaches is warranted when exploring potential species complexes, while Q-mode analysis should be more widely explored, especially for situations where there are multiple gear types. Thus, the optimal groupings should be determined by commonality and consistency among a variety of different multivariate methods and datasets.

Conclusion

Managing data-limited species as a complex can be a practical approach for reducing the number of required stock assessments when insufficient data and ecological knowledge exists to perform individual stock assessments (Koutsidi et al., 2016), but the management of the complex is only as good as the information used to define the groupings (Fujita et al., 1998). We provide one of the first explorations of species complex groupings based on the combination of clustering from multiple data types (e.g., life history, catch, and survey data), multiple data aggregation scales (e.g., by sub-unit and at an aggregated "unit" scale), and a wide variety of multivariate methods (e.g., Ward's analysis, *k*-mediods, CCA, and NMDS), as well as, different modes (e.g., R-mode and Q-mode). Exploration of each of these approaches was important for making management recommendations for the GOA Other Rockfish complex, because certain approaches (i.e., analyzing sub-unit matrices for the catch and survey data) failed their diagnostics of model adequacy, and data (i.e., life history characteristics) had varying levels of quality. By analyzing all of these approaches, we were able to address consistency and reliability across methods, thereby developing species complex advice that is likely more robust compared to using any single approach.

We found that the species designations for the Other Rockfish and Demersal Shelf Rockfish complexes appear to be appropriate, but these complexes should be extended across all management subareas in the GOA (i.e., the Demersal Shelf Rockfish complex is currently only delineated in subarea 650). Despite our methodology being more resource intensive and providing the same complex assignment as existing, less analytically thorough, approaches, these results are likely specific to this case study. We would expect that in other situations, using our suite of quantitative methods would result in different species assignment compared to more commonly used qualitative approaches. However, our approach does require increased resources, including both funding and personnel, which needs to be weighed against the desire to improve species assignment, assessment, and management of species complexes.

Although these results are based on the best data currently available, there is a clear need for improved data collection on bycatch species in the GOA. Collection and incorporation of other data could improve clustering analysis in the future by providing improved data on species distributions, habitat associations, and co-occurrence. As fish move poleward and into deeper depth subareas due to changing climactic conditions (e.g., Perry et al., 2005; Pinsky et al., 2013; Kleisner et al., 2017), there is likely to be a northward shift in the center of gravity for many of the GOA rockfish species examined here, which are at the northern extent of their range in the GOA. Improved data collection will be paramount for identifying changing distributions, which are likely to alter the frequency and abundance of rockfish catch by fisheries and surveys. Thus, the combination of new data collection approaches and further refinement of methods for identifying species complex groupings will be crucial to detect changes in species composition and abundance and implementing sustainable fisheries management.

DATA AVAILABILITY STATEMENT

The data analyzed in this study is subject to the following licenses/restrictions: The raw survey data supporting the conclusions of this article will be made available by the author, without undue reservations. Data from the fisheries sector cannot be disclosed due to confidentiality regulations. Requests to access these datasets should be directed to afsc.webmaster@noaa.gov. Analyses and code available at: https://github.com/klomori/Multivariate-Analyses-Species-Complexes.

AUTHOR CONTRIBUTIONS

KO and CT conceived the study. KO analyzed and interpreted the data with the help and support of CT, EB, and JH and wrote the manuscript with contributions from all authors. All the authors contributed to the article and approved the submitted version. The statements, findings, conclusion, and recommendations are those of the authors and do not necessarily reflect the views of Virginia Sea Grant, NOAA, or the United States Department of Commerce.

FUNDING

This article was prepared by KO using Federal funds under award NMFS-Sea Grant Population Dynamics Fellowship (Award NA18OAR4170322), Virginia Sea Grant College Program Project [VASG project 721691], and from the National Oceanic and Atmospheric Administration's (NOAA) National Sea Grant College Program, United States Department of Commerce. This

article is Contribution No. 4035 of the Virginia Institute of Marine Science (VIMS), William & Mary.

ACKNOWLEDGMENTS

We express our gratitude to AFSC Bottom Trawl and Longline Survey Team for collecting the data, and the database management team for making the data assessible. We also thank Daniel Goethel, Andrew Scheld, Paul Spencer, Craig Faunce and reviewers for providing helpful comments and reviews on the manuscript.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2021.663375/full#supplementary-material

REFERENCES

Anderson, T. J., Syms, C., Roberts, D. A., and Howard, D. F. (2009). Multi-scale fish–habitat associations and the use of habitat surrogates to predict the organisation and abundance of deep-water fish assemblages. *J. Exp. Mar. Biol. Ecol.* 379, 34–42. doi: 10.1016/j.jembe.2009.07.033

Andrews, A. H., Cailliet, G. M., Coale, K. H., Munk, K. M., Mahoney, M. M., and O'Connell, V. M. (2002). Radiometric age validation of the yelloweye rockfish (*Sebastes ruberrimus*) from southeastern Alaska. *Mar. Freshwater Res.* 53, 139–146.

Andrews, A. H., Kerr, L. A., Cailliet, G. M., Brown, T. A., Lundstrom, C. C., and Stanley, R. D. (2007). Age validation of canary rockfish (*Sebastes pinniger*) using two independent otolith techniques: lead-radium and bomb radiocarbon dating. *Mar. Freshwater Res.* 58, 531–541. doi: 10.1071/mf07074

Bechtol, W. R. (1998). *A synopsis of life history and assessment of Cook Inlet rockfish. Regional Information Report No. 2A98-40*. Anchorage, AK: Alaska Dept. of Fish and Game.

Beyer, S. G., Sogard, S. M., Harvey, C. J., and Field, J. C. (2015). Variability in rockfish (*Sebastes* spp.) fecundity: species contrasts, maternal size effects, and spatial differences. *Environ. Biol. Fishes* 98, 81–100. doi: 10.1007/s10641-014-0238-7

Boehlert, G. W., and Kappenman, R. F. (1980). Variation of growth with latitude in two species of rockfish (*Sebastes pinniger* and *S. diploproa*) from the northeast Pacific Ocean. *Mar. Ecol. Prog. Ser* 3, 1–10. doi: 10.3354/meps003001

CFP (2013). Regulation (EU) No 1380/2013 of the European Parliament and of the Council of 11 December 2013 on the Common Fisheries Policy. *Official J. Eur. U.* 354, 22–61.

Chilton, D. E., and Beamish, R. J. (1982). *Age Determination Methods for Fishes Studied by the Groundfish Program at the Pacific Biological Station*. Ottawa: Dept. of Fisheries and Oceans, 102.

Conrath, C. L., Rooper, C. N., Wilborn, R. E., Knoth, B. A., and Jones, D. T. (2019). Seasonal habitat use and community structure of rockfishes in the Gulf of Alaska. *Fish. Res.* 219:105331. doi: 10.1016/j.fishres.2019.105331

Cope, J., Dick, E. J., MacCall, A., Monk, M., Soper, B., and Wetzel, C. (2015). *Data-Moderate Stock Assessments for Brown, China, Copper, Sharpchin, Stripetail, and Yellowtail Rockfishes and English and Rex Soles in 2013*. Portland, OR: Pacific Fishery Management Council, 298.

Cope, J. M., DeVore, J., Dick, E. J., Ames, K., Budrick, J., Erickson, D. L., et al. (2011). An approach to defining stock complexes for US West Coast groundfishes using vulnerabilities and ecological distributions. *North Am. J. Fish. Manage.* 31, 589–604. doi: 10.1080/02755947.2011.591264

DeMartini, E. E. (2019). Hazards of managing disparate species as a pooled complex: a general problem illustrated by two contrasting examples from Hawaii. *Fish Fish.* 20, 1246–1259. doi: 10.1111/faf.12404

Echeverria, T. W. (1987). Thirty-four species of California rockfishes: maturity and seasonality of reproduction. *Fish. Bull. U.S.* 85, 229–250.

Edwards, A. M., Haigh, R., and Starr, P. J. (2012). *Stock Assessment and Recovery Potential Assessment for Yellowmouth Rockfish (Sebastes reedi) Along the Pacific Coast of Canada. DFO Can. Sci. Advis. Sec. Res. Doc. 2012/095*. Ottawa, ON: Fisheries and Oceans Canada, iv+188.

Farmer, N. A., Malinowski, R. F., McGovern, M. F., and Rubec, P. J. (2016). Stock complexes for fisheries management in the Gulf of Mexico. *Mar. Coast. Fish.* 8, 177–201. doi: 10.1080/19425120.2015.1024359

Field, J. C. (2007). *Status of the Chilipepper Rockfish, Sebastes Goodei, in 2007*. Santa Cruz, CA.

Froese, R., and Pauly, D. (2010). *FishBase*. Available online at: https://fishbase.org (accessed May 25, 2020).

Fujita, R. M., Foran, T., and Zevos, I. (1998). Innovative approaches for fostering conservation marine fisheries. *Ecol. Appl.* 8, S139–S150. doi: 10.1007/978-3-319-78622-3_6

Gertseva, V. V., and Cope, J. M. (2011). Population dynamics of splitnose rockfish (*Sebastes diploproa*) in the Northeast Pacific Ocean. *Ecol. Model.* 222, 973–981. doi: 10.1016/j.ecolmodel.2010.12.003

Gertseva, V. V., Cope, J. M., and Matson, S. E. (2010). Growth variability in the splitnose rockfish *Sebastes diploproa* of the northeast Pacific Ocean: pattern revisited. *Mar. Ecol. Prog. Ser.* 413, 125–136. doi: 10.3354/meps08719

Gomes, M. C., Serrao, E., and de Fátima Borges, M. (2001). Spatial patterns of groundfish assemblages on the continental shelf of Portugal. *ICES J. Mar. Sci.* 58, 633–647. doi: 10.1006/jmsc.2001.1052

Gunderson, D. R., Zimmermann, M., Nichol, D. G., and Pearson, K. (2003). Indirect estimates of natural mortality rate for arrowtooth flounder (*Atheresthes stomias*) and darkblotched rockfish (*Sebastes crameri*). *Fish. Bull., U.S.* 101, 175–182.

Heifetz, J., Ianelli, J. N., and Clausen, D. M. (1997). *Slope Rockfish. Stock Assessment and Fishery Evaluation (SAFE) Report for the Groundfish Resources of the Gulf of Alaska*. Anchorage AK: North Pacific Fisheries Management Council, 247–288.

Hennig, C. (2007). Cluster-wise assessment of cluster stability. *Comput. Stat. Data An.* 52, 258–271. doi: 10.1016/j.csda.2006.11.025

Hennig, C. (2020). *fpc: Flexible Procedures for Clustering. R package version 2.2-5*. Available online at: https://CRAN.R-project.org/package=fpc (accessed December 06, 2020).

Hicks, A. C., Haltuch, M. A., and Wetzel, C. (2009). *Status of Greenstriped Rockfish (Sebastes elongatus) Along the Outer Coast of California, Oregon, and Washington. Northwest Fishery Science Center, 2725 Montlake, Blvd. E*. Seattle, WA: Northwest Fishery Science Center.

Hordyk, A. R., and Carruthers, T. R. (2018). A quantitative evaluation of a qualitative risk assessment framework: examining the assumptions and predictions of the Productivity Susceptibility Analysis (PSA). *PLoS One* 13:e0198298. doi: 10.1371/journal.pone.0198298

Jagielo, T., Hoffmann, A., Tagart, J., and Zimmermann, M. (2003). Demersal groundfish densities in trawlable and untrawlable habitats off Washington: implications for the estimation of habitat bias in trawl surveys. *Fish. Bull., U.S.* 101, 545–565.

Jiao, Y., Hayes, C., and Cortes, E. (2009). Hierarchical Bayesian approach for population dynamics modeling of fish complexes without species-specific data. *ICES J. Mar. Sci.* 66, 367–377. doi: 10.1093/icesjms/fsn162

Johnson, S. W., Murphy, M. L., and Csepp, D. J. (2003). Distribution, habitat, and behavior of rockfishes, *Sebastes* spp., in nearshore waters of southeastern Alaska: observations from a remotely operated vehicle. *Environ. Biol. Fishes* 66, 259–270. doi: 10.1023/a:1023981908146

Kassambara, A., and Mundt, F. (2020). *Factoextra: Extract and Visualize the Results of Multivariate Data Analyses. R package version 1.0.7*. Available online at: https://CRAN.R-project.org/package=factoextra (accessed April 1, 2020).

Kaufman, L. R., and Rousseeuw, P. J. (1990). *Finding Groups in Data: An Introduction to Cluster Analysis*. Hoboken NJ: John Wiley & Sons Inc, 725.

Keller, A. A. (2008). *The 2005 US West Coast Bottom Trawl Survey of Groundfish Resources off Washington, Oregon, and California: Estimates of Distribution, Abundance, and Length Composition*. Washington DC: NOAA.

Keller, A. A., Molton, K. J., Hicks, A. C., Haltuch, M., and Wetzel, C. (2012). Variation in age and growth of greenstriped rockfish (*Sebastes elongatus*) along the U.S. west coast (Washington to California). *Fish. Res.* 119–120, 80–88. doi: 10.1016/j.fishres.2011.12.012

Kerr, L. A., Andrews, A. H., Munk, K., Coale, K. H., Frantz, B. R., Cailliet, G. M., et al. (2005). Age validation of quillback rockfish (*Sebastes maliger*) using bomb radiocarbon. *Fish. Bull. U.S.* 103, 97–107.

Kleisner, K. M., Fogarty, M. J., McGee, S., Hare, J. A., Moret, S., Perretti, C. T., et al. (2017). Marine species distribution shifts on the US Northeast Continental Shelf under continued ocean warming. *Prog. Oceanogr.* 153, 24–36. doi: 10.1016/j.pocean.2017.04.001

Koutsidi, M., Tzanatos, E., Machias, A., and Vassilopoulou, V. (2016). Fishing for function: the use of biological traits to evaluate the effects of multispecies fisheries on the functioning of fisheries assemblages. *ICES J. Mar. Sci.* 73, 1091–1103. doi: 10.1093/icesjms/fsw006

Kramer, D. E., and O'Connell, V. M. (1988). *Guide to Northeast Pacific Rockfishes: Genera Sebastes and Sebastolobus, Marine Advisory Bulletin 25. Alaska Sea Grant College Program*. Fairbanks, AK: University of Alaska.

Laidig, T. E., Watters, D. L., and Yoklavich, M. M. (2009). Demersal fish and habitat associations from visual surveys on the central California shelf. *Estuar. Coast. Shelf Sci.* 83, 629–637. doi: 10.1016/j.ecss.2009.05.008

Landres, P. B., Verner, J., and Thomas, J. W. (1988). Ecological uses of vertebrate indicator species: a critique. *Cons. Biol.* 2, 316–328. doi: 10.1111/j.1523-1739.1988.tb00195.x

Lee, Y., and Sampson, B. (2000). Spatial and temporal stability of commercial groundfish assemblages off Oregon and Washington as inferred from Oregon trawl logbooks. *Can. J. Fish. Aquat. Sci.* 57, 2443–2454. doi: 10.1139/f00-223

Legendre, P., and Legendre, L. F. (2012). *Numerical Ecology*, 3rd Edn. Amsterdam: Elsevier.

Lenarz, W. (1987). *Ageing and Growth of Widow Rockfish, pp. 31-35. In Widow Rockfish, Proceedings of a Workshop, Tiburon, California, December 11-12, 1980. U.S. Dep. Commer., NOAA Tech. Rep. NMFS-48*. Tiburon CA: NOAA.

Love, M. S., Yoklavich, M., and Thorsteinson, L. (2002). *The Rockfishes of the Northeast Pacific*. Berkeley CA: Univ. Calif. Press.

MacCall, A. D. (2005). *Assessment of Vermilion Rockfish in Southern and Northern California*. Portland, OR: Pacific Fishery Management Council.

Malecha, P. W., Hanselman, D. H., and Heifetz, J. (2007). *Growth and Mortality of Rockfishes (Scorpaenidae) from Alaska Waters. U.S. Dep. Commer., NOAA Tech. Memo. NMFS-AFSC-172, 61*. Washington, D.C: NOAA.

Malecha, P. W., Rodgveller, C. J., Lunsford, C. R., and Siwicke, K. A. (2019). *The 2018 Longline Survey of the Gulf of Alaska and Eastern Aleutian Islands on the FV Alaskan Leader: Cruise Report AL-18-01. AFSC Processed Rep. 2019-02, 30 p. Alaska Fish. Sci. Cent., NOAA, Natl. Mar. Fish. Serv., 7600 Sand Point Way NE*. Seattle WA: NOAA, 98115.

Manly, B. F. J. (2005). *Multivariate Statistical Methods: a Primer*, 3rd Edn. London: Chapman & Hall and CRC Press.

McCully Phillips, S. R., Scott, F., and Ellis, J. R. (2015). Having confidence in productivity susceptibility analyses: A method for underpinning scientific advice on skate stocks? *Fish. Res.* 171, 87–100. doi: 10.1016/j.fishres.2015.01.005

MSRA (Magnuson-Stevens Fishery Conservation and Management Reauthorization Act of 2006) (2007). *Public Law no. 109-479, 120 Stat. 3575*. Available online at: https://www.fisheries.noaa.gov/resource/document/magnuson-stevens-fishery-conservation-and-management-act.

Munk, K. M. (2001). Maximum ages of groundfishes in waters off Alaska and British Columbia and considerations of age determination. *AK Fish. Bull.* 8, 12–21.

Nichol, D. G. (1990). *Life History Examination of Darkblotched Rockfish (Sebastes crameri) off the Oregon Coast.* Master's Thesis. Corvallis: Oregon State University.

Nichol, D. G., and Pikitch, E. K. (1994). Reproduction of darkblotched rockfish off the Oregon Coast. *Trans. Am. Fish. Soc.* 123, 469–481. doi: 10.1577/1548-8659(1994)123<0469:rodrot>2.3.co;2

Niemi, G. J., Hanowski, J. M., Lima, A. R., Nicholls, T., and Weiland, N. (1997). A critical analysis on the use of indicator species in management. *J Wildl. Manage.* 61, 1240–1252. doi: 10.2307/3802123

North Pacific Fishery Management Council (NPFMC) (2019). *North Pacific Fisheries Management Plan for Groundfish of the Gulf of Alaska, 605 W. 4th Ave, Suite 306, Anchorage, AK 99501*. Anchorage, AK: NPFMC, 130.

Oksanen, J., Blanchet, F. G., Friendly, M., Kindt, R., Legendre, P., McGlinn, D., et al. (2019). *vegan: Community Ecology Package. R package version 2.5-6*. Available online at: https://CRAN.R-project.org/package=vegan (accessed November 28, 2020).

Olson, A., Williams, B., and Jaenicke, M. (2018). *Assessment of the Demersal Shelf Rockfish Stock Complex in the Southeast Outside Subdistrict of the Gulf of Alaska. In Stock Assessment and Fishery Evaluation Report for the Groundfish Resources of the Gulf of Alaska, North Pacific Fishery Management Council, 605 W 4th Ave, Suite 306. Anchorage, AK 99501*. Anchorage, AK: North Pacific Fishery Management Council, 47.

Ormseth, O. A., and Spencer, P. D. (2011). An assessment of vulnerability in alaska groundfish. *Fish. Res.* 112, 127–133. doi: 10.1016/j.fishres.2011.02.010

Patrick, W. S., Spencer, P., Link, J., Cope, J., Field, J., Kobayashi, D., et al. (2010). Using productivity and susceptibility indices to assess the vulnerability of United States fish stocks to overfishing. *Fish. Bull. U.S.* 108, 305–322.

Pennino, M. G., Thomé-Souza, M. J. F., Carvalho, A. R., da Silveira Fontes, L. C., Parente, C., and Lopes, P. F. M. (2016). A spatial multivariate approach to understand what controls species catch composition in small-scale fisheries. *Fish. Res.* 175, 132–141. doi: 10.1016/j.fishres.2015.11.028

Perry, A. L., Low, P. J., Ellis, J. R., and Reynolds, J. D. (2005). Climate change and distribution shifts in marine fishes. *Science* 308, 1912–1915. doi: 10.1126/science.1111322

Phillips, J. B. (1964). *Life History Studies on ten Species of Rockfish (genus Sebastodes). Cal. Dep. Fish Game Fish Bull. 126*. San Diego CA: University of California.

Pikitch, E. K. (1991). Technological interactions in the U.S. West Coast groundfish fishery and their implications for management. *ICES Mar. Sci. Symp.* 193, 253–263.

Piner, K. R., Wallace, J. R., Hamel, O. S., and Mikus, R. (2006). Evaluation of ageing accuracy of bocaccio (Sebastes paucispinis) rockfish using bomb radiocarbon. *Fish. Res.* 77, 200–206. doi: 10.1016/j.fishres.2005.10.003

Pinsky, M. L., Worm, B., Fogarty, M. J., Sarmiento, J. L., and Levin, S. A. (2013). Marine taxa track local climate velocities. *Science* 341, 1239–1242. doi: 10.1126/science.1239352

R Core Team (2020). *R: A Language and Environment for Statistical Computing*. Vienna: R Foundation for Statistical Computing.

Rogers, J. B., and Pikitch, E. K. (1992). Numerical definition of groundfish assemblages caught off the coasts of Oregon and Washington using commercial fishing strategies. *Can. J. Fish. Aquat. Sci.* 49, 2648–2656. doi: 10.1139/f92-293

Rooper, C. N. (2008). An ecological analysis of rockfish (*Sebastes* spp.) assemblages in the North Pacific Ocean along broad-scale environmental gradients. *Fish. Bull. U.S.* 106, 1–11.

Rooper, C. N., and Martin, M. H. (2012). Comparison of habitat-based indices of abundance with fishery-independent biomass estimates from bottom trawl surveys. *Fish. Bull. U.S.* 110, 21–35.

Rousseeuw, P. J. (1987). Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *J. Comput. Appl. Math.* 20, 53–65. doi: 10.1016/0377-0427(87)90125-7

Shertzer, K. W., Williams, E. H., and Taylor, J. C. (2009). Spatial structure and temporal patterns in a large marine ecosystem: exploited reef fishes of the southeast United States. *Fish. Res.* 100, 126–133. doi: 10.1016/j.fishres.2009.06.017

Shertzer, K. W., and Williams, E. W. (2008). Fish assemblages and indicator species: reef fishes off the southeastern United States. *Fish. Bull., U.S.* 106, 257–269.

Shirkhorshidi, A. S., Aghabozorgi, S., and Wah, T. Y. (2015). A comparison study on similarity and dissimilarity measures in clustering continuous data. *PLoS One* 10:e0144059. doi: 10.1371/journal.pone.0144059

Silva, J. F., Ellis, J. R., and Catchpole, T. L. (2012). Species composition of skates (Rajidae) in commercial fisheries around the British Isles and their discarding patterns. *J. Fish Biol.* 80, 1678–1703. doi: 10.1111/j.1095-8649.2012.03247.x

Simberloff, D. (1998). Flagships, umbrellas, and keystones: is single-species management passé in the landscape era? *Biol. Conserv.* 83, 247–257. doi: 10.1016/s0006-3207(97)00081-5

Stanley, R. D., and Kronlund, A. R. (2005). Life history characteristics for silvergray rockfish (*Sebastes brevispinis*) in British Columbia waters and the implications for stock assessment and management. *Fish. Bull. U.S.* 103, 670--684.

Stevens, M. M., Andrews, A. H., Cailliet, G. M., Coale, K. H., and Lundstrom, C. C. (2004). Radiometric validation of age, growth, and longevity for the blackgill rockfish (*Sebastes melanostomus*). *Fish. Bull., U.S.* 102, 711–722.

Tagart, J., Wallace, F., and Ianelli, J. N. (2000). *Status of the Yellowtail Rockfish Resource in 2000*. Portland, OR: Pacific Fishery Management Council.

Thorson, J. T., Munch, S. B., Cope, J. M., and Gao, J. (2017). Predicting life history parameters for all fishes worldwide. *Ecol. Appl.* 27, 2262–2276. doi: 10.1002/eap.1606

Tolimieri, N., and Levin, P. S. (2006). Assemblage structure of eastern Pacific groundfishes on the US continental slope in relation to physical and environmental variables. *Trans. Am. Fish. Soc.* 135, 317–332. doi: 10.1577/t05-092.1

Tribuzio, C. A., and Echave, K. B. (2019). *Assessment of the Other Rockfish Stock Complex in the Gulf of Alaska. In.... Stock Assessment and Fishery Evaluation Report for the Groundfish Resources of the Gulf of Alaska, North Pacific Fishery Management Council, 605 W 4th Ave, Suite 306. Anchorage, AK 99501*. Anchorage, AK: North Pacific Fishery Management Council, 49.

Tuda, P. M., Wolff, M., and Breckwoldt, A. (2016). Size structure and gear selectivity of target species in the multispecies multigear fishery of the Kenyan South Coast. *Ocean Coast. Manage.* 130, 95–106. doi: 10.1016/j.ocecoaman.2016.06.001

USOFR (U.S. Office of the Federal Register) (2009). *Magnuson–Stevens Act provisions; Annual Catch Limits; National Standard Guidelines. Code of Federal Regulations, Title 50, Part 600. U.S.* Washington, D.C: Government Printing Office.

Vinther, M., Reeves, S. A., and Patterson, K. R. (2004). From single-species advice to mixed species management: taking the next step. *ICES J. Mar. Sci.* 61, 1398–1409. doi: 10.1016/j.icesjms.2004.08.018

von Szalay, P. G., and Raring, N. W. (2018). *Data Report: 2017 Gulf of Alaska Bottom Trawl Survey. U.S. Dep. Commer., NOAA Tech. Memo. NMFS-AFSC-374*. Washington, D.C: NOAA.

Ward, J. H. Jr. (1963). Hierarchical grouping to optimize an objective function. *J. Am. Stat. Assoc.* 58, 236–244. doi: 10.1080/01621459.1963.10500845

Westrheim, S. J. (1975). Reproduction, maturation, and identification of larvae of some Sebastes (*Scorpaenidae*) species in the northwest Pacific Ocean. *J. Fish. Res. Bd Can.* 32, 2399–2411. doi: 10.1139/f75-277

Westrheim, S. J., and Harling, W. R. (1975). *Age-Length Relationships for 26 Scorpaenids in the Northeast Pacific Ocean. Fisheries and Marine Service Research and Development Technical Report 565*. Nanaimo BC: Department of Fisheries and Oceans Resource Services.

Wilkins, M. E. (1986). Development and evaluation of methodologies for assessing and monitoring the abundance of widow rockfish, *Sebastes entomelas*. *Fish. Bull.* 84, 287–310.

Williams, E. H., and Ralston, S. (2002). Distribution and co-occurrence of rockfishes (family: Sebastidae) over trawlable shelf and slope habitats of California and southern Oregon. *Fish. Bull., U.S.* 100, 836–855.

Wilson, C. D., and Boehlert, G. W. (1990). The effects of different otolith ageing techniques on estimates of growth and mortality for the splitnose rockfish, *Sebastes diploproa*, and canary rockfish, *S. pinniger*. *Cal. Fish Game* 76, 146--160.

Zacharias, M. A., and Roff, J. C. (2001). Use of focal species in marine conservation and management: a review and critique. *Aquat. Cons. Mar. Freshwater Ecosyst.* 11, 59–76. doi: 10.1002/aqc.429

Zhou, S., Hobday, A. J., Dichmont, C. M., and Smith, A. D. M. (2016). Ecological risk assessment for the effects of fishing: a comparison and validation of PSA and SAFE. *Fish. Res.* 183, 518–529. doi: 10.1016/j.fishres.2016.07.015

Zuur, A. E., Ieno, E. N., and Smith, G. M. (2007). *Analyzing Ecological Data*. Berlin: Springer.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

APPENDIX

Life History Parameter Value Sources

TABLE A1 | Reference number with associated source from the life history parameters of rockfish from **Table 1**.

Reference number	Source
1	Stevens, M.M., Andrews, A.H., Cailliet, G.M., Coale, K.H., Lundstrom, C.C., 2004. Radiometric validation of age, growth, and longevity for the blackgill rockfish (*Sebastes melanostomus*). Fish. Bull., U.S. 102, 711–722.
2	Piner, K.R., Wallace, J.R., Hamel, O.S., Mikus, R., 2006. Evaluation of ageing accuracy of bocaccio (*Sebastes paucispinis*) rockfish using bomb radiocarbon. Fish. Res. 77, 200–206.
3	Andrews, A.H., Kerr, L.A., Cailliet, G.M., Brown, T.A., Lundstrom, C.C., Stanley, R.D., 2007. Age validation of canary rockfish (*Sebastes pinniger*) using two independent otolith techniques: Lead-radium and bomb radiocarbon dating. Mar. Freshwater Res. 58, 531–541.
4	Field, J.C., 2007. Status of the chilipepper rockfish, *Sebastes goodei*, in 2007. Santa Cruz, CA.
5	Munk, K.M., 2001. Maximum ages of groundfishes in waters off Alaska and British Columbia and considerations of age determination. AK Fish. Bull. 8, 12–21.
6	Gunderson, D.R., Zimmermann, M., Nichol, D.G., Pearson, K., 2003. Indirect estimates of natural mortality rate for arrowtooth flounder (Atheresthes stomias) and darkblotched rockfish (*Sebastes crameri*). Fish. Bull., U.S. 101, 175–182.
7	Malecha, P.W., Hanselman, D.H., Heifetz, J., 2007. Growth and mortality of rockfishes (Scorpaenidae) from Alaska Waters. U.S. Dep. Commer., NOAA Tech. Memo. NMFS-AFSC-172, 61 pp.
8	Kerr, L.A., Andrews, A.H., Munk, K., Coale, K.H., Frantz, B.R., Cailliet, G.M., Brown, T.A., 2005. Age validation of quillback rockfish (*Sebastes maliger*) using bomb radiocarbon. Fish. Bull., U.S. 103, 97–107.
9	Gertseva, V.V., Cope, J.M., Matson, S.E., 2010. Growth variability in the splitnose rockfish *Sebastes diploproa* of the northeast Pacific Ocean: Pattern revisited. Mar. Ecol. Prog. Ser. 413, 125–136.
10	Andrews, A.H., Cailliet, G.M., Coale, K.H., Munk, K.M., Mahoney, M.M., O'Connell, V.M., 2002. Radiometric age validation of the yelloweye rockfish (*Sebastes ruberrimus*) from southeastern Alaska. Mar. Freshwater Res. 53, 139–146.
11	Chilton, D.E., Beamish, R.J., 1982. Age Determination Methods for Fishes Studied by the Groundfish Program at the Pacific Biological Station. 102 pp.
12	Echeverria, T.W., 1987. Thirty-four species of California rockfishes: maturity and seasonality of reproduction. Fish. Bull., U.S. 85, 229–250.
13	Nichol, D.G., Pikitch, E.K., 1994. Reproduction of darkblotched rockfish off the Oregon Coast. Trans. Am. Fish. Soc.,123, 469–481.
14	Hicks, A.C., Haltuch, M.A., Wetzel, C., 2009. Status of greenstriped rockfish (*Sebastes elongatus*) along the outer coast of California, Oregon, and Washington. Northwest Fishery Science Center, 2725 Montlake, Blvd. E., Seattle, WA.
15	Heifetz, J., J.N. Ianelli, Clausen., D.M., 1997. Slope rockfish. Stock assessment and fishery evaluation (SAFE) report for the groundfish resources of the Gulf of Alaska, pp. 247-288. North Pacific Fisheries Management Council, Anchorage.
16	Bechtol, W.R., 1998. A synopsis of life history and assessment of Cook Inlet rockfish. Regional Information Report No. 2A98-40. Alaska Dept. of Fish and Game, 333 Raspberry Road, Anchorage, AK. Available at: http://www.adfg.alaska.gov/FedAidPDFs/RIR.2A.1998.40.pdf.
17	Stanley, R.D., Kronlund, A.R., 2005. Life history characteristics for silvergray rockfish (*Sebastes brevispinis*) in British Columbia waters and the implications for stock assessment and management. Fish. Bull., U.S. 103, 670–684.
18	Phillips, J.B., 1964. Life history studies on ten species of rockfish (genus *Sebastodes*). Cal. Dep. Fish Game Fish Bull. 126.
19	Tagart, J., Wallace, F., Ianelli, J.N., 2000. Status of the yellowtail rockfish resource in 2000. Pacific Fishery Management Council, 7700 NE Ambassador Pl #101, Portland, OR.
20	Westrheim, S.J., 1975. Reproduction, maturation, and identification of larvae of some *Sebastes* (Scorpaenidae) species in the northwest Pacific Ocean. J. Fish. Res. Bd Can. 32, 2399–2411.
21	Gertseva, V.V., Cope, J. M., 2011. Population dynamics of splitnose rockfish (*Sebastes diploproa*) in the Northeast Pacific Ocean. Ecol. Model. 222, 973–981.
22	Westrheim, S.J., Harling, W.R., 1975. Age-length relationships for 26 Scorpaenids in the Northeast Pacific Ocean. Fisheries and Marine Service Research and Development Technical Report 565.
23	Wilson, C.D., Boehlert, G.W., 1990. The effects of different otolith ageing techniques on estimates of growth and mortality for the splitnose rockfish, *Sebastes diploproa*, and canary rockfish, *S. pinniger*. Cal. Fish Game 76, 146–160.
24	Nichol, D.G., 1990. Life History Examination of Darkblotched Rockfish (*Sebastes crameri*) off the Oregon Coast. [Master's thesis, Oregon State University, Corvallis] Available at: http://ir.library.oregonstate.edu/xmlui/handle/1957/11341.
25	Keller, A.A., Molton, K.J., Hicks, A.C., Haltuch, M., Wetzel, C., 2012. Variation in age and growth of greenstriped rockfish (*Sebastes elongatus*) along the U.S. west coast (Washington to California). Fish. Res. 119–120, 80-88.
26	Lenarz, W., 1987. Ageing and growth of widow rockfish, pp. 31-35. In Widow rockfish, proceedings of a workshop, Tiburon, California, December 11-12, 1980. U.S. Dep. Commer., NOAA Tech. Rep. NMFS-48.
27	MacCall, A.D., 2005. Assessment of Vermilion Rockfish in Southern and Northern California. Pacific Fishery Management Council, 2130 SW Fifth Ave, Suite 224, Portland, OR 97220. 128 pp.

(Continued)

TABLE A1 | Continued

Reference number	Source
28	Kramer, D.E., O'Connell, V.M., 1988. Guide to northeast Pacific rockfishes: genera *Sebastes* and *Sebastolobus*, Marine Advisory Bulletin 25. Alaska Sea Grant College Program, University of Alaska, Fairbanks, AK.
29	Froese, R., Pauly, D., 2010. FishBase. *Assessed*: 5/25/2020. https://fishbase.org
30	Love, M.S., Yoklavich, M., Thorsteinson, L., 2002. The rockfishes of the northeast Pacific. Univ. Calif. Press, Berkeley, CA.
31	Cope, J., Dick, E.J., MacCall, A., Monk, M., Soper, B., Wetzel, C. 2015. Data-moderate stock assessments for brown, china, copper, sharpchin, stripetail, and yellowtail rockfishes and English and rex soles in 2013. Pacific Fishery Management Council, 7700 Ambassador Place NE, Suite 200, Portland, OR 97220. 298 pp.
32	Edwards, A.M., Haigh, R., Starr, P.J., 2012. Stock assessment and recovery potential assessment for yellowmouth rockfish (*Sebastes reedi*) along the Pacific coast of Canada. DFO Can. Sci. Advis. Sec. Res. Doc. 2012/095. iv + 188 p.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 17 August 2021
doi: 10.3389/fmars.2021.663554

Check for updates

Catch and Length Models in the Stock Synthesis Framework: Expanded Application to Data-Moderate Stocks

Merrill B. Rudd[1], Jason M. Cope[2], Chantel R. Wetzel[2] and James Hastie[2]*

[1] *Scaleability LLC, Seattle, WA, United States,* [2] *Fishery Resource Analysis and Monitoring Division, Northwest Fisheries Science Center, National Marine Fisheries Service, National Oceanic and Atmospheric Administration, Seattle, WA, United States*

OPEN ACCESS

Edited by:
Natalie Anne Dowling, Oceans and Atmosphere (CSIRO), Australia

Reviewed by:
Henning Winker, Department of Agriculture, Forestry and Fisheries, South Africa
Valeria Mamouridis, Independent Researcher, Rome, Italy

***Correspondence:**
Merrill B. Rudd
merrillrudd@gmail.com

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: *03 February 2021*
Accepted: *21 July 2021*
Published: *17 August 2021*

Citation:
Rudd MB, Cope JM, Wetzel CR and Hastie J (2021) Catch and Length Models in the Stock Synthesis Framework: Expanded Application to Data-Moderate Stocks. Front. Mar. Sci. 8:663554. doi: 10.3389/fmars.2021.663554

Many fisheries in the world are data-moderate, with data types (e.g., total removals, abundance indices, and biological composition data) of varied quality (e.g., limited time series or representative samples) or available data. Integrated stock assessments are useful tools for data-moderate fisheries as they can include all available information, can be updated due to the availability of more information over time, and can directly test the inclusion and exclusion of specific data types. This study uses the simulation testing and systematic data reduction from the US West Coast benchmark assessments to examine the performance of Stock Synthesis with catch and length (SS-CL) compositions only. The simulation testing of various life histories, recruitment variabilities, and data availability scenarios found that the correctly specified SS-CL can estimate unbiased key population quantities such as stock status with as little as 1 year of length data although 5 years or more may be more reliable. The error in key population quantities is decreased with an increase in years and the sample size of length data. The removal of the length compositions from benchmark assessments often caused large model deviations in the outputs compared to the removal of other data sources, indicating the importance of length data in integrated models. Models with catch and length data, excluding abundance indices and age composition, generally provided informative estimates of the stock status relative to the reference model, with most data scenarios falling within the CIs of the reference model. The results of simulation analysis and systematic data reduction indicated that SS-CL is potentially viable for data-moderate assessments in the USA, thus reducing precautionary buffers on catch limits for many stocks previously assessed in a lower tier using catch-only models. SS-CL could also be applied to many stocks around the world, maximizing the use of data available *via* the well tested, multifeature benefits of SS.

Keywords: fisheries stock assessment, integrated models, age-structured models, data-limited models, US west coast fisheries

INTRODUCTION

Fisheries vary in data quantity and quality, which affect the amount of information used for stock status information. An integrated stock assessment framework can include all the available information and can be updated due to the availability of more information available over time. Stock Synthesis (SS; Methot and Wetzel, 2013) is an example of an integrated stock assessment framework that allows for flexible approaches to data treatment. This ranges from "data-rich" applications, with a full complement of catch, abundance index, and biological data (mainly length and/or age compositions), to "data-limited" applications, which typically include only one of the abovementioned information inputs. Many fisheries worldwide fall in the "data-moderate" category, where one of catch, abundance index, or biological compositions is unavailable (Thorson and Cope, 2015; Wetzel and Punt, 2015; Dichmont et al., 2021). Each category may be further limited if the available data types cover only a limited time series, have only a limited sample size, or are not fully representative of the stock (Booth and Quinn, 2006). Data type, data quality, and the representativeness of the stock affect the type of model that could reasonably be applied to infer stock status, the degree of uncertainty in the estimates of stock status, and the consideration of the level of a precautionary buffer when making management decisions.

Data-moderate cases often lean on the data-limited approaches that require specific, limited inputs, which may ignore auxiliary data types or make unnecessary simplifying assumptions leading to high uncertainties in population estimates. Important data such as biological composition may be ignored to fit the mold of specific data-limited modeling approaches when an abundance index is not available. Length compositions are a key input to most stock assessments as the information is easier to obtain compared to ages, and thus being a main source of recruitment and spawning potential information (Thorson et al., 2019). It is also typically believed that many fisheries use a length-selective gear, therefore lengths are essential for estimating gear selectivity and fishing intensity (Parma and Deriso, 1990; Punt et al., 2014). Some catch-only methods have been extended to include biological compositions as they become available (Thorson and Cope, 2015), and length-only methods have explored the inclusion of catch data if available to estimate population size (Rudd and Thorson, 2018). The amount of length composition needed is not well understood and may also depend on life history characteristics (Minte-Vera et al., 2017), thus assessments with catch and length and with no abundance index are not widely used in management jurisdictions where catch limits are required.

When stock assessments are based on limited data, a precautionary approach to management would warrant additional buffers to catch limits and other management options. To address this issue, the Scientific and Statistical Committee (SSC) of the Pacific Fishery Management Council defined three broad assessment categories, each with an associated allowable biological catch (ABC) buffer defined by a model uncertainty. This ABC buffer defines the percentage reduction of the overfishing limit (OFL), which is a catch level that corresponds to the maximum sustainable yield of the stock. The OFL is meant to be a level beyond the catch threshold, which would likely to result in overfishing (NOAA, 2021). Category 1 ("data-rich" or "full") assessments estimate the OFL using a mixture of data types, including total catch, abundance indices or surveys, and length and/or age composition data. On the other side of the data spectrum, category 3 ("data limited") stock assessment methods estimate the OFL using catch, life history parameters, and a prior on relative stock abundance in a specific year of the time series (Dick and MacCall, 2011; Cope, 2013). Current data-limited methods for category 3 stocks do not include abundance indices or biological compositions that would inform stock status over time (Thorson and Cope, 2015). To date, category 2 ("data-moderate") assessments approved by the Pacific Fishery Management Council SSC were developed using specific data-moderate approaches for the West Coast groundfish stocks. These data-moderate assessments are to combine catch-based methods using an abundance index, excluding biological composition data (Cope et al., 2013; Wetzel and Punt, 2015). A key difference between categories 3 and 2 assessments is that category 3 assessments are meant as an objective approach to set sustainable catch limits based on catch-only approaches without estimating stock status. With the inclusion of an abundance index, category 2 assessments may track stock responses to management intervention. Therefore, category 2 assessments may also include prior information on relative stock abundance that should be updated from the data (if not, then they are functionally a category 3 assessment in which the data are not used to inform current stock status). Data-moderate models also may not necessarily estimate recruitment deviations due to the lack of information on age classes typically held within biological compositions (Cope et al., 2015).

To date, stocks with catch or length and with no abundance index would be relegated to data-limited assessments with additional uncertainty buffers that may not be necessary if biological composition data could be included in an integrated model with catch data. This is important because category 3 assessments have higher uncertainty buffers than category 2 assessments. However, abundance indices are not always informative about the population. In some cases, data-rich stock assessment results may show a little change to the reference model outputs with the exclusion of an abundance index (Wetzel et al., 2017). These assessment sensitivity results observationally suggest a reliance mainly on catch and compositional data only for some data-rich stock assessments, and thus offering evidence that catch and length only models can be adequate to inform management metrics. Further, in situations of assessing more stocks than possible at one time, it may be of a strategic interest to perform catch and length assessments for the stocks that are minor targets or are believed to be at high abundance, rather than spending limited resource capacity to prepare data types and perform a full assessment with every available data source.

This study focuses on the performance of estimating key population quantities such as stock status in SS models with catch and length (SS-CL) data only in a maximum likelihood context. Firstly, we used the simulation testing to evaluate the performance of SS-CL under a variety of life histories

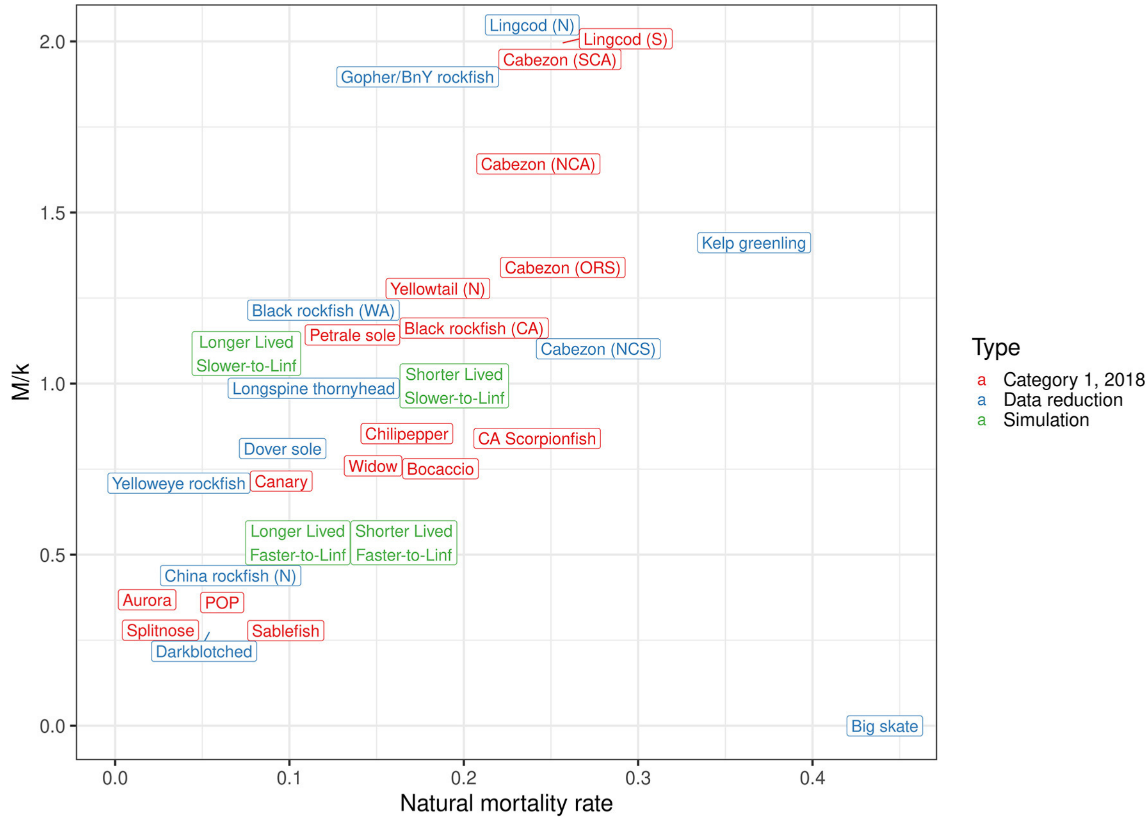


FIGURE 1 | Natural mortality rate (*M*) compared with the ratio of *M* to von Bertalanffy growth coefficient *k* (*M/k*) for various groundfish species.

and data permutations. We then removed data from current U.S. West Coast groundfish benchmark stock assessments to explore how sensitive the benchmark assessments are to the removal of different data types reducing down to catch and length data only, specifically focusing on the amount of length composition data used. Removing data sources is a commonly applied approach in stock assessment analyses to understand the influence and or potential contradictory information providing a way of measuring how data conditioning affects the model outputs (Cope et al., 2015). Both approaches, simulation and conducting sensitivities to benchmark stock assessments, provide unique ways to evaluate the use of different applications of length and catch models for consideration as an additional data-moderate stock assessment method for application to stocks off the U.S. West Coast, and for the general use of integrated stock assessment models worldwide in data-moderate contexts.

MATERIALS AND METHODS

The use of SS with catches and length composition only requires a very few adjustments from the applications that include an abundance index. Models may include multiple fleets, sexes, or other dynamics that have been already included as the features in SS. Catches range from the first to the last year of the model and are assumed known without error. Length compositions are assumed to be representative of their respective fleet, sex, etc. Life history values such as the productivity of stock (steepness), growth parameters, natural mortality, fecundity, and maturity are generally prespecified rather than being estimated though the estimation could be possibly dependent on the length data quantity and/or quality. Recruitment can be estimated by following standard bias correction procedures. Selectivity parameters can be estimated or fixed. Data weighting is needed for models with multiple fleets and would follow the standard procedures for other SS models (Punt, 2017).

Simulation Testing

Operating Model

We used SS as an operating model to simulate "true" populations and generate data based on the approach developed in the R package *ss3sim* (Anderson et al., 2014). The *ss3sim* approach involves inputting a set of "true" life history values, fishing mortality time series, and recruitment deviations, then generating population trajectories by running the SS model without calculating the Hessian matrix for SDs. This serves to include age-structured population dynamics and stochasticity to generate all true values for the population.

TABLE 1 | Parameter values used to develop life history scenarios in the operating model.

Parameter	Description	Life history			
		Short-lived, slow-growing	**Short-lived, fast-growing**	**Long-lived, slow-growing**	**Long-lived, fast-growing**
Amax	Maximum age (years)	30	30	60	60
M	Natural mortality (1/year)	0.18	0.18	0.09	0.09
k	Von Bertalanffy growth coefficient (1/year)	0.17	0.3	0.09	0.15
Linf	Asymptotic length (cm)	55	55	55	55
t0	Length at age = 0 (cm)	−1	−1	−1	−1
L50	Length at 50% maturity (cm)	36.3	36.3	36.3	36.3
M/k	Ratio of *M* to *k*	1.06	0.6	1.02	0.6
F_{MSY}	Fishing mortality expected to produce maximum sustainable yield (MSY)	0.16	0.17	0.08	0.08
h	Steepness	0.7	0.7	0.7	0.7
last_recdev	Last year of estimated recruitment deviates based on age at 5% selectivity	97	98	94	96

We developed four life history scenarios based on the West Coast groundfish stocks that varied in longevity (e.g., how long they live) and the individual growth rate (e.g., how much of their lives are spent at their maximum size). The shorter-lived life history type had a natural mortality rate (M) of 0.18 for an approximately maximum age of 30 years, whereas the longer-lived life history type had an M of 0.09 for an approximately maximum age of 60 years (Hamel, 2015). We considered slower- and faster-growing options for the shorter- and longer-lived life history types by adjusting the von Bertalanffy growth coefficient (k). We chose the values of k associated with reaching the asymptotic length at 90% of the maximum age (slower-growing) and 50% of the maximum age (faster-growing). We confirmed that the M/k ratios were close to 1.0 and 0.60 for the slower-growing life history types and for the faster-growing life history types, respectively as these M/k ratios are representative for the West Coast groundfish stocks assessed through 2018 (**Figure 1**, **Supplementary Table 1**). We kept the asymptotic length constant at 55 cm and assumed that the length at 50% maturity was equal to 66% of the asymptotic length (i.e., 36.3 cm) for all life history types (Cope and Punt, 2009). Selectivity was constant over scenarios and time using the double-normal selectivity function to represent logistic selectivity assuming a peak selectivity at 42 cm. Parameter values used for each of the four life history types are available in **Table 1**, and growth curves are shown in **Supplementary Figure 1**.

We input the fishing mortality time series based on a time series of the ratio of the fishing mortality rate to the fishing mortality rate associated with *MSY* (F/F_{MSY}) shared across life history types. After reviewing the fishing mortality rate time series from the US West Coast stocks, we identified a general pattern of low exploitation before World War II, then the exploitation rate increases after World War II until the 1980s or 1990s. After remaining at a high exploitation rate in the 1990s, the exploitation rate declines through the present (**Figure 2**). To mimic this pattern, we assumed that the F/F_{MSY} ratio remained relatively low for the first 25 years, increasing from 0.01 to 0.05, then increased more rapidly from 0.05 to 2 over the next 30 years. The F/F_{MSY} ratio remained at 2 for 5 years, then decreased from 2 to 0.6 over the next 20 years, and remained at 0.6 for the last 20 years of the time series. We then scaled this F/F_{MSY} ratio using the F_{MSY} for each life history type. F_{MSY} was calculated by finding the constant F-value that maximizes long-term catch. F_{MSY} was 0.08 for both longer-lived life histories, whereas F_{MSY} was 0.17 and 0.16 for the shorter-lived, faster-growing life history type and the shorter-lived, slower-growing life history type, respectively (**Table 1**). The catch time series was calculated within the operating model based on the input fishing mortality rate time series and the scale of the population (**Supplementary Figure 2**).

Recruitment followed an underlying Beverton–Holt stock-recruit curve with steepness (h) equal to 0.7 and a recruitment SD of 0.8, on the higher side for West Coast species (**Supplementary Table 1**). We compared a high recruitment variability scenario to a lower recruitment variability scenario, with the SD of 0.4. The log of equilibrium recruitment was assumed to be constant at 10.0. Simulation replicates were varied by the input recruitment deviates; the time series of recruitment deviates for each simulation replicate was identical across life history types (**Supplementary Figures 3**, **4**).

Data Scenarios

Each true population determined by a life history type, a recruitment variability, and a simulation replicate was then subjected to data availability scenario tests based on the number of samples of length data annually and the number of years of length data included in the model. We generated the observation

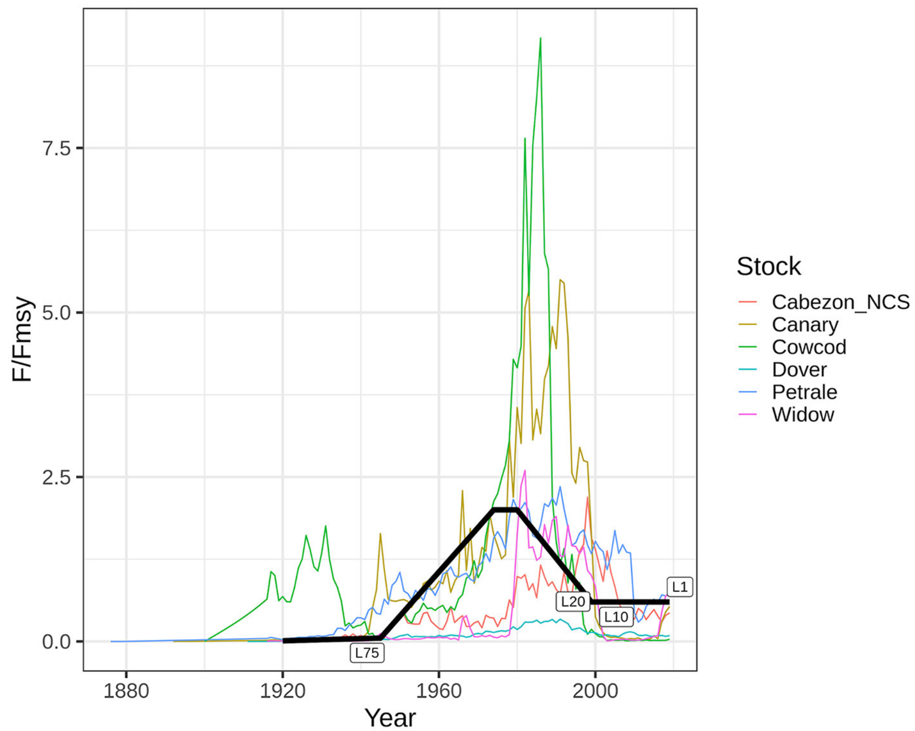


FIGURE 2 | Ratio of estimated fishing mortality rate to F_{MSY} for the six West Coast stocks, which informed the shape of our chosen F/F_{MSY} time series on which the simulated fishing mortality rate scenario is based. The simulated F/F_{MSY} series is labeled where the length data are included: for 75, 20, 10, and 1 year of data.

data from the operating model population by sampling of the expected data.

To test the ability of SS to estimate the key parameters of interest with catch and length data alone, we included a "perfect" catch and length scenario. The "perfect" scenario assumed that the length composition data was known perfectly over 100 years with an input sample size of 1,000 lengths per year. The "perfect" scenario was used to make sure that any biases in scenarios with catch and length data only were due to the limitation of sample size or recruitment variability, rather than structural inconsistencies between the observation and estimation models. For all other length data scenarios of interest, we used the samples from the length composition with either 200 samples (representing a moderate sample size) or 50 samples (representing a limited sample size) per year using a multinomial distribution. We tested an additional scenario where the length data sample size decreased over time, specifying 200 samples per year before the year 88 and 50 samples from the years 88–100.

For each sample size scenario, we also explored the number of years of length data included in the model. From the sampled data, we considered the inclusion of the final (a) 75, (b) 20, (c) 10, (d) 5, and (e) 1 year of the sampled length data. We tested a decline in the sample size over time only with the 20-year length data scenario. The approach of a subset of the number of years after the data were generated allowed us to directly compare the number of years of length data included in the model, rather than any stochastic association with the resampling of the length composition for each independent scenario.

Estimation Model

For all scenarios, we assumed that the catch was known without any error based on the input fishing mortality time series. We used SS 3.30.14 to test the model under various simulation scenarios. The estimated parameters included the recruitment deviations, log of equilibrium recruitment $\log(R_0)$, and two selectivity parameters governing the shape and peak of the left side of the double-normal selectivity curve. We fixed natural mortality, growth parameters, steepness, and the recruitment SD to their true values.

We also ran sensitivity tests assuming that the natural mortality rate was 10% lower and higher than the truth (0.081 and 0.099 compared with the true value of 0.09), the asymptotic length was 10% lower and higher than the truth (49.5 and 60.5 cm compared with the true value of 55 cm), and the coefficient of variation (CV) around the growth curve was 25% lower and higher than the truth (0.075 and 0.125 compared to the true value of 0.1) for the "perfect" scenario to understand the expected patterns.

The first year of estimated recruitment deviates was the maximum age subtracted from the first year of length data, starting in year 1 if length data is available before year 29 (based on the longevity of the short-lived life history being 30 years). To determine the final year of estimated recruitment deviates, we identified the age associated with 5% selectivity for each life history type, and subtracted that age from the final year in the model. For example, the short-lived, slow-growing life history type reached 5% selectivity at age three, so the final year of estimated recruitment deviates was 97 out of 100 (**Table 1**). To prevent the biased estimates of the spawning output in the early years of the time series, we allowed for the estimation of early recruitment deviates starting 30 years before the first year of removals by the fishery.

We used the iterative procedure developed by Methot and Taylor (2011) to account for the bias adjustment in estimated recruitment deviates. We first ran SS to calculate the Hessian matrix, then the bias ramp parameters were estimated based on the model estimates from the first run. We then input the bias ramp parameter estimates and reran the model without calculating the Hessian matrix to speed up the simulation model runs. We used the bias-adjusted model estimates to compare across scenarios to mimic the model parameter estimation that would take place using SS-CL in practice. In subsequent steps, the Hessian matrix on the second run could be estimated to explore the characterization of the uncertainty of individual model runs for length data scenarios.

Performance Metrics

We determined the convergence rate of each scenario defined by the maximum final parameter gradient <1.0 and the maximum likelihood estimate of the log of unfished recruitment $\log(R_0)$ <12.0 to ensure that the population is estimated to be a reasonable size (e.g., the failed model convergence that would likely to be due to the selection of a bad starting value *via* jitter rather than the inability to estimate the population size). From the converged runs, we calculated the relative error for key population quantities for each of 100 simulation replicates. Relative error was calculated as:

$$\mathrm{RE} = \frac{E_s - E_R}{E_R} \tag{1}$$

where E_S is the estimated value and E_R is the true value for the simulation study. We used "bias" to describe the accuracy of the estimator, calculated as the median relative error (MRE). We used "error" to describe the precision around a parameter estimate, which is calculated as the median absolute relative error (MARE; Ono et al., 2012).

Systematic Data Reduction in Benchmark Stock Assessments

A subset of West Coast groundfish stocks with the existing full assessments were selected for data explorations (**Table 2**). The selected stock encompasses a range of life histories (e.g., flatfishes, roundfishes, elasmobranchs, and rockfishes), exploitation (e.g., recreational or commercial fisheries), and data availability [e.g., catch-per-unit-effort (CPUE) indices, fishery-independent indices, and length and age compositions]. Each assessment also presents variable amounts of data quality and quantity within each data type, thus there is no ability to standardize the data within the data scenarios.

To generate appropriate data scenario comparisons to the full assessments, a number of steps were taken based on the data scenario. The archived assessment for each of the listed assessment years for each of the stocks in **Table 2** is used as a starting point for analysis. A select group of the archived assessment was then converted to SS v.3.30.15 (Dover sole, longspine thornyhead, and kelp greenling) for the ease of exploration with the converted model compared to the original model to ensure similar estimates and model performance. All biological parameters were fixed across the scenarios to limit the effects of an aberrant parameter estimation as it is possible to estimate those parameters outside the model while allowing selectivity and recruitment deviations (if estimated) to remain estimated (parameters not typically estimated outside the models). Additionally, in case of their presence in the model, the retention parameters governing the length of individuals were retained in case of capture and were fixed at the MLE estimates to avoid variances in the estimates of total mortality among the runs. Next, each of the full assessments was run with the full Hessian and reweighted according to the Francis data weighting approach (Francis, 2017). This step was performed due to the assessments ranging over a period of time when model weighting approaches were evolving. Additionally, because the scenarios were aimed to explore the sensitivity of the model to data, applying the appropriate data weighting within each scenario was considered as essential. The reweighted full assessment model was termed as the "reference" model.

Model Treatments

Seven data scenarios relative to the reference model were conducted. Each of the scenarios and the steps applied in their generation were as follows:

1. Removal of all indices ("-Indices"): The likelihood contribution for all indices in the model was set equal to zero. The data remaining in the model were the catches, lengths, and ages that were available in the reference model.
2. Removal of all lengths ("-Lengths"): The likelihood contribution for all length data in the model was set equal to zero. The data remaining in the model were the catches, indices, and ages that were available in the reference model.
3. Removal of all ages ("-Ages"): The likelihood contribution for all age data in the model was set equal to zero. The data remaining in the model were the catches, indices, and lengths that were available in the reference model.
4. "Only lengths": The likelihood contribution for all indices and age data in the model was set equal to 0. The data remaining in the model were the catches and lengths that were available in the reference model.
5. "Lengths 20 years": The likelihood contribution for all indices and age data in the model was set equal to zero and all length data prior to 20 years before the final model year were

TABLE 2 | List of West Coast groundfish stock assessments evaluated.

Species	Model years	Fleets	References
Dover sole	1910–2010	3 fishery and 4 survey	Hicks and Wetzel, 2013
Big skate	1916–2018	4 fishery and 2 survey	Taylor et al., 2019
Cabezon (NCS)	1916–2018	5 fishery and 2 (1) survey	Cope et al., 2019
Lingcod (North)	1889–2016	4 (4) fishery and 4 survey	Haltuch et al., 2017
Kelp greenling	1915–2014	5 fishery and 3 (3) survey	Berger et al., 2015
Longspine thornyhead	1964–2012	1 fishery and 3 survey	Stephens and Taylor, 2013
Yelloweye rockfish	1889–2016	7 (3) fishery and 5 (2) survey	Gertseva and Cope, 2017
Black rockfish (WA)	1940–2017	3 fishery and 2 (2) survey	Cope et al., 2016
China rockfish (North)	1900–2014	3 (1) fishery	Dick et al., 2016
Gopher and black and yellow rockfish	1916–2018	3 fishery and 7 (3) survey	Monk and He, 2019

The fleet column indicates the fleet structure in the reference model showing the number of fishing fleets with removals (fishery) and the number of survey fleets (independent and fishery-dependent), where the number inside parenthesis indicates the number of fishery-dependent indices.

removed. The data remaining in the model were the catches from all years and length data from the last 20 years of the model. If the reference model had selectivity blocks applied to fleet selectivity (could be a survey or fishery) that were outside the new length data range, those parameters were fixed at the reference model MLE estimate.

6. "Lengths 10 years": It exhibited the same setup as described above for the "Lengths 20 years" scenario but its lengths were reduced to the value in the last 10 years of the model.
7. "Lengths 1 year": It exhibited the same setup as described above in the previous two length-based scenarios but with only retaining the final year length data.

Performance Metrics

The performance of each data scenario was evaluated using the measure of relative error in the four estimated quantities: (1) unfished spawning output, (2) spawning output in the final year, (3) stock status (i.e., the fraction of an unfished spawning output) in the final year, and (4) the OFL value for the first projection year calculated within SS due to the association of the catch with F_{MSY}. The relative error was calculated from Equation (1), where E_s is the estimated quantity from the data scenario s and $E_R$is the estimate from the full reference model. The 95% CI of the relative error is also provided to indicate whether a given scenario would be found within the estimated uncertainty of reference models. Those scenarios that do fall outside those bounds would be indicative of a more significant departure from the reference model.

RESULTS

Simulation Testing

Stock Synthesis models with catch and length data converged at high rates across scenarios. The highest rates of non-convergence occurred for scenarios with a single year of length composition, particularly with only 50 samples of length per year (**Supplementary Table 2**). We verified that 100 simulation replicates were enough to quantify the bias and error by checking that the MRE reached an asymptote after 100 simulation replicates (**Supplementary Figure 5**).

The "perfect information" scenario, where the length composition was known perfectly for all 100 years, confirmed that SS estimated unbiased and precise key population quantities across 100 simulation replicates with both a high and low recruitment variability when excluding an abundance index and age composition (**Figure 3**, **Supplementary Tables 3–6**). The unbiased perfect information scenario under a high and low recruitment variability led us to assume that any breakdown in the bias or error under alternative sampling scenarios was due to the limited number of samples and the number of years of length data included in the model.

The bias increased only marginally with a decrease in the years of length data and sample size. Under the lower recruitment variability scenario, the bias in the terminal year fraction unfished was mostly affected with a single year of length data for the longer-lived life history types, or with a low sample size and single year of length data across life history types (**Supplementary Table 3**). With a higher recruitment variability, the bias pattern with a decrease in years of length data was more ambiguous; compared with fewer years of length data, some scenarios with 75 years of length data were more biased in the terminal year of fraction unfished (**Figure 3**, **Supplementary Table 4**).

The error increased with a decrease in years and a lower sample size of length data, and was higher with a higher recruitment variability (**Figure 3**, **Supplementary Tables 5**, **6**). The error increased the most when paring down from 5 to 1 year of length data for low recruitment variability scenarios, and a high recruitment variability with a sample size of 200 lengths per year (**Figure 3**, **Supplementary Tables 5**, **6**). With a higher recruitment variability and a low sample size, the increase in error

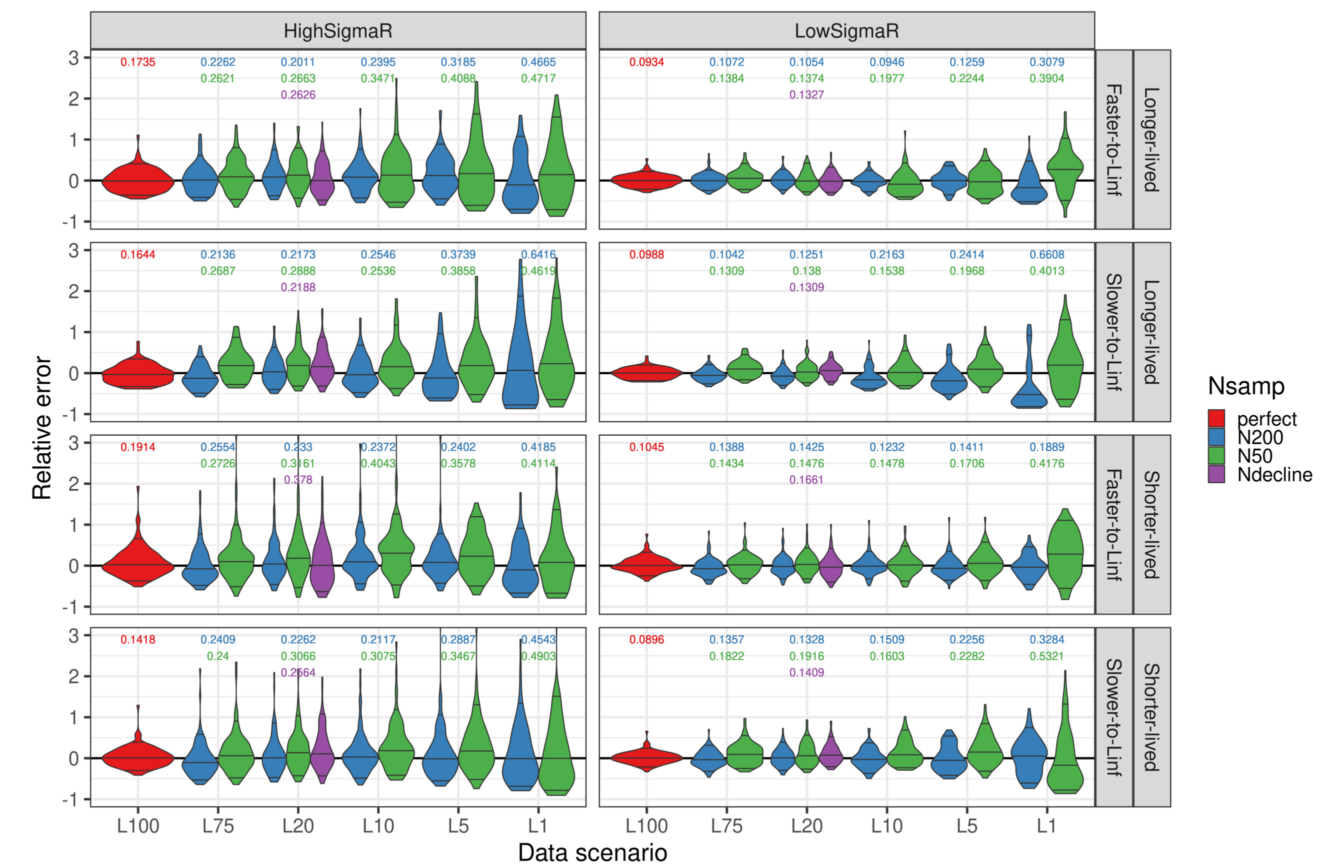


FIGURE 3 | Distribution of relative err or *(estimated – true)/true* for the fraction unfished in the terminal year across simulation replicates, life history, and recruitment variability scenarios, with the number of years of length data on the *x*-axis and color indicating the sample size of length data ("perfect" indicates the length data that is known without error and "Ndecline" is a decline from 200 to 50 samples over the last 20 years of the series). Lines in the violin plots show the median and 90th quantiles, which are generally centered at zero with some variabilities with fewer years of length data. The values above each violin plot show the median absolute relative error (MARE), where there are multiple values, the top value corresponds to $N = 200$ samples annually, the next corresponds to $N = 50$ samples annually and with 20 years of length data, and the third value corresponds to a declining N from 200 to 50 samples over the time series of length compositions.

was most pronounced with 5 or 10 years of length data (**Figure 3**, **Supplementary Table 6**).

A decline in the sample size from 200 to 50 samples over 20 years had an intermediate bias and error to the scenarios with constantly 200 or 50 samples per year. The bias was <16% with a high recruitment variability and <10% with a low recruitment variability for all life history scenarios in a decline of the sample size scenario (**Supplementary Tables 3**, **4**). The error was <38% with a high recruitment variability and <17% with a low recruitment variability across life history scenarios (**Supplementary Tables 5**, **6**).

There were no significant patterns in the bias or error between life history scenarios. The shorter-lived, and particularly faster-growing, life history types had some higher rates of model non-convergence with fewer years of length data compared with the longer-lived life history types (**Supplementary Table 2**). While the bias and error were higher for some combinations of life history type, recruitment variability, sample size of lengths, and the number of years of length data, none of the patterns held constant across scenarios to properly tease apart the impacts directly related to the life history type (**Supplementary Tables 3–6**).

When the natural mortality rate was assumed to be 10% lower than the truth, the estimates of a fraction of unfished were biased to be lower than the truth (i.e., the stock assessment would be conservative in the estimates of stock status). The opposite was true when the natural mortality rate was assumed to be 10% higher than the truth (i.e., the stock assessment would assume that the stock biomass was higher than the truth). When the asymptotic length was assumed to be 10% greater than the truth, the fraction unfished in the last year of data was estimated to be lower than the truth. In this case, the stock assessment would be conservative in the estimates of stock status. Conversely, when the asymptotic length was assumed to be 10% less than the truth, the fraction unfished was estimated to be greater than the truth, overestimating the view of stock status (**Figure 4**). However, in this case, 54% of the model runs did not converge, a phenomenon that did not occur when the asymptotic length was mis-specified

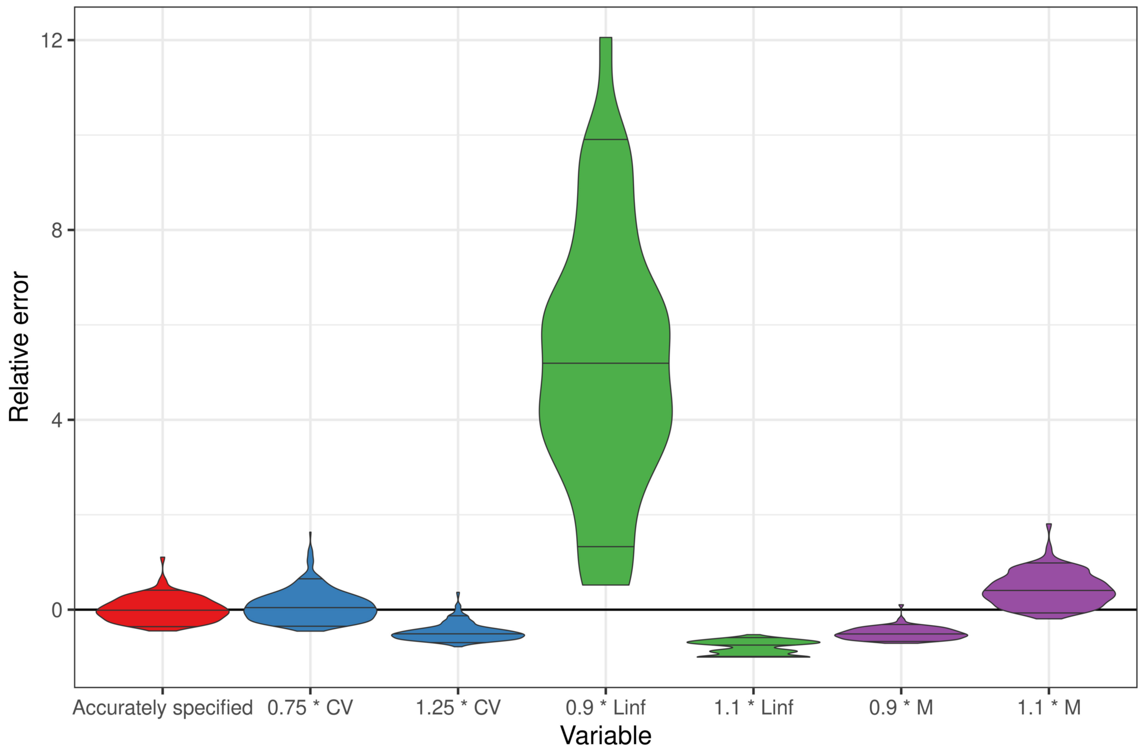


FIGURE 4 | Distribution of relative error *(estimated – true)/true* for the fraction unfished in the terminal year across simulation replicates for the longer-lived, faster-growing life history scenario under a high recruitment variability. All models assume 100 years of length data are perfectly specified, comparing a bias and an error when the CV of the growth curve is mis-specified by ±25%, the asymptotic length (Linf) is mis-specified by ±10%, and the natural mortality rate is mis-specified by ±10%.

higher than the truth. Issues on model convergence would indicate to analysts that some fixed values, such as asymptotic length, may not be correct. Mis-specifying the CV around the growth curve to be lower than the truth did not impact the bias or error in the estimates of the fraction unfished in the last year of data. However, assuming that more variation around the growth curve led to underestimates of the fraction unfished and more conservative estimates of stock status (**Figure 4**).

Systematic Data Reduction in Benchmark Stock Assessments

There are several caveats to be mindful of when interpreting these results. Each data inclusion scenario is within an assessment that shows variable levels of a consistent or inconsistent signal among data types, as well as how much each data type in the reference model is weighted. Each truncated length scenario represents a different amount of the total available length data. Additionally, the level of sampling in the most recent years of data is also highly variable among the stocks. Lastly, the model structure assumed across data scenarios (e.g., estimated vs. fixed parameters) likely do not fully reflect the decisions an assessment author may possibly make when faced with the data remaining for a real world assessment. The results are structured first within species categories as those often share common data issues, then general result patterns are provided and the relative error for the unfished spawning output, the final spawning output, the final fraction unfished, and the OFL are shown for all species in **Figures 5**, **6**.

The performance and stability of models with only length and catch data were better with fewer fleets. Most data scenarios fell within the CIs of the reference benchmark assessment model considered by management as the availability of the best scientific information. Spawning output in the last year of the model and the OFL tended to be most sensitive to the data removal of all model outputs considered. The removal of length composition from the assessment often caused large model deviations in the outputs compared to the removal of other data sources. Models with only length compositions tended to provide informative outputs relative to the reference benchmark assessment, especially for the fraction unfished.

The estimates of recent fraction unfished and the OFL were conservative (biased low) for 7 of the 10 stocks in comparison with the reference model. The lack of length data most often led to the lower estimates of the spawning output, the fraction unfished, and the OFL in comparison to the reference model. The possession of either 1 year or 10 years of length data often led to the most variable results. The inclusion of only 1 year

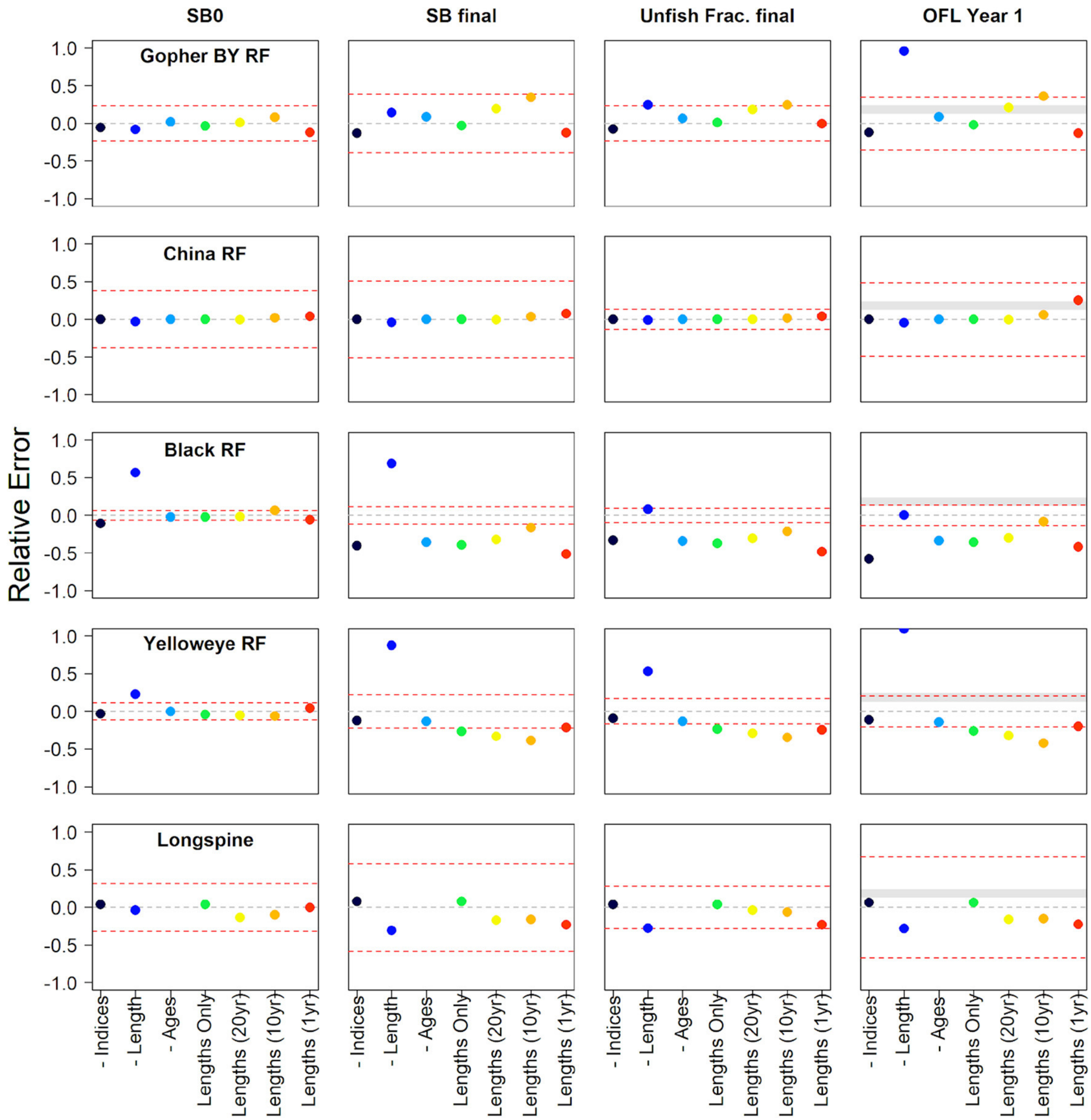


FIGURE 5 | The relative error of unfished spawning biomass, final model year spawning biomass, final model year fraction of unfished spawning biomass, and the first overfishing level estimated from each data scenario compared against the reference model for nearshore rockfish, slope rockfish, and slope scorpaenids. The data scenarios either remove specific data from the assessment model indicated by "-" (e.g., -Indices are model results with all indices removed) or only use specific amounts of length data (e.g., "Lengths (20yr)" has the 20 years of length data at the end of the modeled period). The dashed gray line identifies the zero line and the dashed red lines identify the 95% confidence interval from the reference model for each of the estimated quantities. The gray banded area on the OFLs indicates the area between a category 2 sigma of 1.0 and either a *P** (called P-star) value of 0.45 or 0.45 (buffer = 0.874 vs. 0.761) translated into relative error (0.126–0.238) where the resulting Acceptable Biological Catch if based on the estimated OFL would be greater than the OFL of the reference model.

of length data led to more conservative estimates of the model output in 7 out of 10 models. Only one of the higher estimates, kelp greenling, was outside the CIs of the reference model. In the following sections, we offer specific insights and details into the results of each case study.

Gopher and Black-and-Yellow Rockfish

The gopher and black-and-yellow rockfish complex comprises two shallow nearshore demersal species that are a minor target for recreational and commercial fisheries. They are mostly taken by hook-and-line, and the live-fishery nature of the commercial fishery makes length collection a more suitable sampling option. The model covers the waters of California up to Cape Mendocino. The catch time series begins over 100 years ago, with both fishery-dependent and fishery-independent abundance indices and length compositions beginning around 35 years before the end of the model (2019, **Figure 7**). Age compositions are very limited. Likelihood profiling indicated a weak but

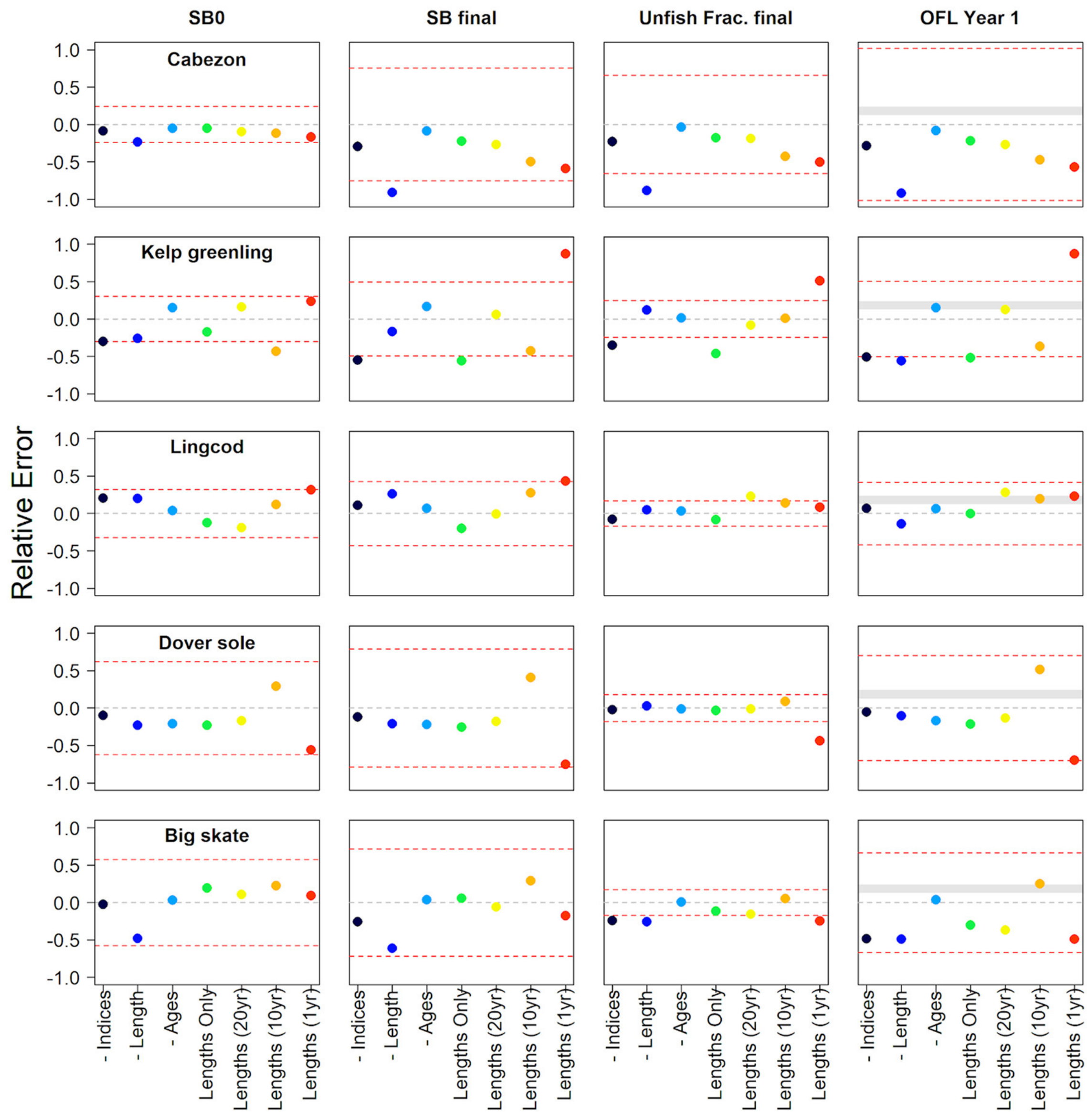


FIGURE 6 | The relative error of unfished spawning biomass, final model year spawning biomass, final model year fraction of unfished spawning biomass, and the first overfishing level estimated from each data scenario compared against the reference model for nearshore roundfishes, flatfish, and elasmobranch. The data scenarios either remove specific data from the assessment model indicated by "-" (e.g., -Indices are model results with all indices removed) or only use specific amounts of length data (e.g., "Lengths (20yr)" has the 20 years of length data at the end of the modeled period). The dashed gray line identifies the zero line and the dashed red lines identify the 95% confidence interval from the reference model for each of the estimated quantities. The gray banded area on the OFLs indicates the area between a category 2 sigma of 1.0 and either a p^* (called P-star) value of 0.45 or 0.45 (buffer = 0.874 vs. 0.761) translated into relative error (0.126–0.238) where the resulting Acceptable Biological Catch if based on the estimated OFL would be greater than the OFL of the reference model.

generally consistent signal in the length and age compositions, and to a lesser extent, in the indices (Monk and He, 2019). The six indices of abundance in the model show stark contradictions in the information content for various model parameters (Monk and He, 2019). Meanwhile, there are several indices, which do not provide a consistent signal within the model. The reference model exhibits a high uncertainty in the spawning output, and lower uncertainty in the current fraction unfished. Biologically, gopher and black-and-yellow rockfish would be more similar to the lower growing life history in the simulation study.

The removal of the length compositions demonstrated the largest effect on the model outputs relative to the reference model although that effect was minimal (**Figure 8**). The truncation of length data time series to 20 or 10 years of data show notable changes in the terminal year spawning output and current fraction unfished (**Figure 8**). These changes tended to be higher in the spawning output and subsequently more in the optimistic fraction unfished. Relative changes across the model outputs and data scenarios were within the CIs of the model, with the exception being the high positive relative error of the estimated OFL value in case of the removal of all length compositions (**Figure 5**).

China Rockfish

China rockfish is a deeper nearshore demersal species that is a minor target for recreational and commercial fisheries. It is mostly taken by hook-and-line, and the live-fishery nature of the commercial fishery makes the length collection a more suitable sampling option. The northern model covers the waters of Washington State. The catch time series begins just over 50 years ago, with a single fishery-dependent abundance index beginning in the early 1980s, and the majority of length and age composition data from the catch present during approximately the last 20 years of the model (**Supplementary Figure 6**). Likelihood profiling indicated a weak but generally consistent signal in the index and length and age compositions (Dick et al., 2016). The reference model exhibits a high uncertainty in the spawning output but a low uncertainty in the current fraction unfished. Biologically, China rockfish would be more similar to the faster-growing life history in the simulation study. Recruitment deviations are not estimated in the reference model.

There is a very little effect on model outputs with any of the data scenarios (**Supplementary Figure 7**). All model outputs were within the CIs of the reference model (**Figure 5**). The biggest deviation from the reference model was found in the estimate of OFL for the 1 year of length data scenario.

Black Rockfish

Black rockfish is a mostly nearshore, pelagic schooling species that is a major recreational target. It is therefore limited in the net-based catches and is mostly taken by a hook-and-line gear. The Washington State black rockfish stock assessment catch time series begins roughly 80 years ago, with the fishery-dependent abundance indices, length and age composition beginning mostly around 40 years prior to the final model year (2015, **Supplementary Figure 8**). Likelihood profiling indicated that indices and the length composition data show some agreement despite often in contradiction to the age composition data (Cope et al., 2015). The reference model exhibits low uncertainty and very little retrospective patterns. Biologically, black rockfish would be more similar to the slower growing life history in the simulation study.

The removal of the length composition data demonstrated the largest effect on model outputs, especially on the population scale estimate (**Supplementary Figure 9**). The removal of indices or ages had a little effect on the estimate of the initial spawning output and across the majority of the time series, but both data scenarios had departures in the estimates during the final years of the model resulting in the estimates of a more depleted stock relative to the reference model (**Supplementary Figure 9**). The truncation of lengths shows significant decreases in the terminal year spawning output and current fraction unfished (**Supplementary Figure 9**). Most data scenarios demonstrated lower terminal spawning output and current fraction unfished estimates compared to the small CIs of the reference model (**Figure 5**). While the reference model was near the target-relative spawning output level, the length scenarios tended to be closer to the minimum stock size threshold (**Supplementary Figure 9**).

Yelloweye Rockfish

The yelloweye rockfish stock assessment is a two-area model containing submodels for California and Oregon/Washington with both fishery-dependent and fishery-independent abundance indices, length compositions, and age-at-length compositions (Gertseva and Cope, 2017). Yelloweye rockfish typically inhabit deep rocky habitat, and is difficult to sample using a trawl gear but is effectively sampled using a hook-and-line gear. The large size of yelloweye rockfish has made the species a target of recreational fisheries though they were believed overfished for many years, and thus have been under strict harvest guidelines since the mid-2000s. The restrictions had also decreased the availability of the amount of data to subsequent stock assessments.

The catch time series is about 130 years, with the data sources starting around 40 years ago (**Supplementary Figure 10**). Likelihood profiling indicated that indices and the length composition data are generally in agreement despite of their opposition to age data. Sensitivity analysis shows the removal of lengths that caused issues in the estimation of the initial spawning output and current relative stock abundance (Gertseva and Cope, 2017). Overall, uncertainty in the model is relatively low. This low uncertainty in the asymptotic estimates may be due to the model being one sex as female and male life history parameters are very similar. While natural mortality and recruitment compensation (i.e., steepness) parameters are fixed (a common approach for a West Coast groundfish stock assessment), growth, recruitment, and many selectivity parameters are estimated, providing an ample space for uncertainty in parameter estimation in case of data lacking information. Biologically, yelloweye rockfish is more similar to the slower growing life history in the simulation study.

The removal of the length compositions demonstrated the largest effect on model outputs (**Supplementary Figure 11**) as the model estimated a very different stock abundance throughout the time series, indicating that the length data are a primary source of information in the reference model. The removal of indices or ages had a little effect, which results in very similar spawning output trajectories and fraction unfished over time (**Supplementary Figure 11**). The truncation of length data had small and consistent effects on the model output despite enough to be outside the small CIs of the reference model (**Figure 5**).

Longspine Thornyhead

Longspine thornyhead are a deep water species off the West Coast that are primarily targeted by commercial trawl fishing and are frequently sampled by fishery-independent trawl surveys (**Supplementary Figure 12**). The most recent assessment for longspine thornyhead was conducted in 2013 and accepted as a data-limited stock assessment (category 2) because no age data were included due to the current inability in aging this species.

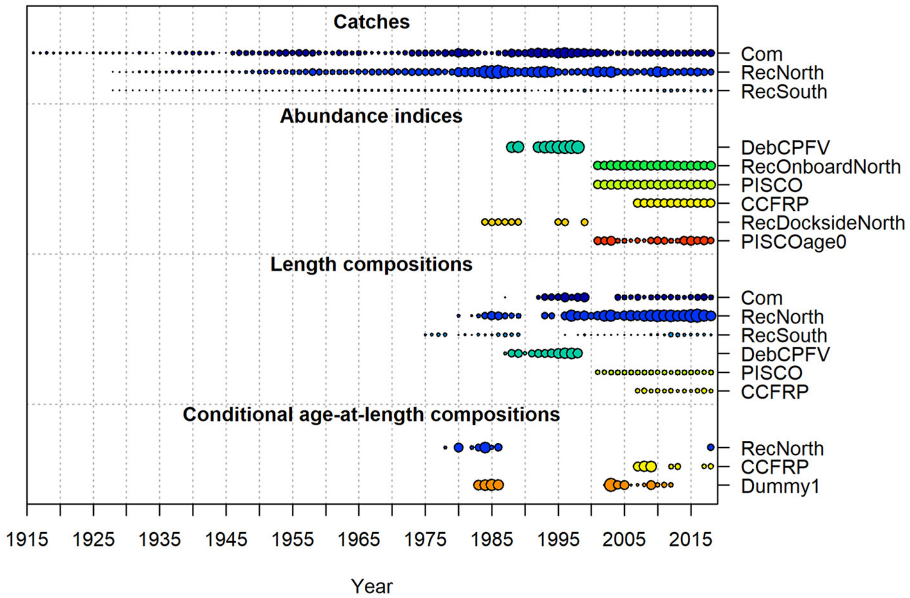


FIGURE 7 | Summary of the data type, the length of data time series, and the quantity for gopher and black-and-yellow rockfish. The size of the bubble by year is based on the sample size (e.g., larger bubbles indicate higher sample sizes). The bubble size for the indices is equal to the inverse of the mean SE for the survey. Catches are both commercial (Com) and recreational (RecNorth and RecSouth). Abundance indices are either fishery-dependent from onboard observers (DebCPFV, RecOnboardNorth, and RecDocksideNorth) or from fishery-independent surveys (PISCO, CCFRP, and PISCOage0). Length compositions come from the catch, one fishery-dependent survey (DebCPFV) and two fishery-independent surveys (PISCO and CCFRP). Conditional age-at-length compositions come from the recreational catch, a fishery-independent survey (CCFRP), and a dummy fleet representing a number of sampling techniques.

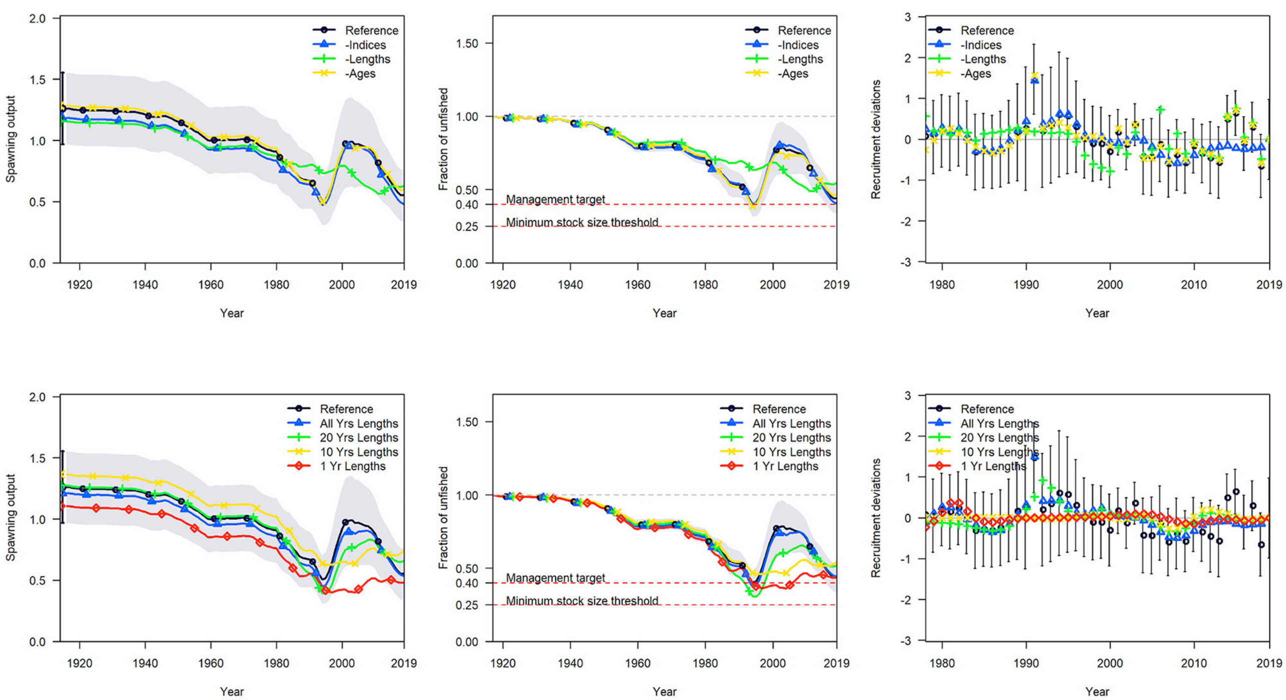


FIGURE 8 | Comparison of model estimates of spawning output, the fraction unfished, and annual recruitment deviations relative to the reference model (black) for gopher and black-and-yellow rockfish. The top row are comparisons between the reference model and when all indices (blue), all lengths (green), or all ages (yellow) are removed. The bottom row are comparisons between the reference model and when only catches and all lengths (blue), 20 years of lengths (green), 10 years of length (yellow), or only 1 year of lengths (red) are used in the model.

For comparing the two data scenarios that included either catch plus index only data or catch and length data, the estimate was nearly identical to the reference model in case of the presence of only lengthy data (**Figure 5**, **Supplementary Figure 13**). This indicates that the indices in the reference model have a little influence on the model estimates. For examining the model estimates in case of the use of variable amounts of length data, the model performance in terms of the fraction unfished was similar to the reference model in case of the use of either 20 or 10 years of data (**Figure 5**, **Supplementary Figure 13**). The relative error across data scenarios to the OFL estimates were well within the reference model 95% CI (**Figure 5**).

Cabezon

The northern California substock of cabezon was used in this example, with a range from Point Conception to the California-Oregon border. The catch time series is also very long, with length compositions starting in earnest 40 years ago, and a fishery-dependent index of abundance that stretches back 60 years, terminating 25 years ago, though also with another fishery-independent index in the most recent years (**Supplementary Figure 14**). Age composition data was limited to fishery-independent samples only. Likelihood profiling indicated that indices and the length composition data are generally in agreement, and the sensitivity analysis shows the removal of either caused issues on estimating the final spawning output and fraction unfished (Cope et al., 2019). This is also reflected in the levels of asymptotic uncertainty in the reference model spawning output being highest for the final year. Biologically, cabezon would be more similar to the faster-growing life history in the simulation study.

The removal of the length compositions demonstrated the largest effect on model outputs (**Supplementary Figure 15**) as the model had a hard time converge without lengths, with the highest uncertainty in the final year stock abundance. The removal of indices or ages had a little effect. However, even 1 year of length data allowed the model to provide reasonable results (**Supplementary Figure 15**). For scenarios lacking indices and ages, there is a linear trend downward in the spawning output and subsequently the lower relative stock abundance as the time series of lengths decreases (**Figure 6**). While the estimates without indices and ages are lower than the reference model, all results are within the reference confidence intervals for each metric under all length scenarios.

Kelp Greenling

Kelp greenling is a nearshore species that experience both recreational and commercial exploitation and is not sampled by the existing West Coast trawl surveys (**Supplementary Figure 16**). The data available in the reference model consists primarily of fishery-dependent CPUE indices, length, and age composition data after the year 2000. The reference model included three CPUE indices that in case of their removal from the model ("-Indices") caused the estimated spawning output to decline, with the stock trajectory at the lower 95% CI of the reference model (**Figure 6**, **Supplementary Figure 17**). However, the relative stock trajectory was similar to the reference model until the end of the time series where the data scenario sharply declined. When all length data were dropped from the model, the spawning output was lower than the reference model with changes in the pattern of the stock trajectory over time but estimated a similar unfished fraction at the end of the time series. The data scenario removing only the age data resulted in the most similar stock estimates of stock sizes and fraction unfished (**Supplementary Figure 17**).

The suite of scenarios examining the model performance relative to the reference model when only the catch and length data that were available were highly variable (**Figure 6**, **Supplementary Figure 17**). The scenario that retained all length data had a similar trajectory post-1980, but then diverged from the reference model at the end of the time series. The difference in the recent year estimates indicates that the CPUE indices in the reference model have a large influence in recent year estimates that the length data did not support. However, when only the last 20 years of lengths were used, the stock trajectory over time differs, but ultimately estimates a similar fraction unfished in recent years. The estimates of stock size, status, and the trajectories differed greatly from the reference model when only limited data were available (10 or 1 year, **Supplementary Figure 17**). The relative error of the estimated final spawning output and fraction unfished were well outside the reference model CI for the 1-year data sensitivity (**Figure 6**).

Lingcod

The lingcod north substock comprises the areas of the Oregon and Washington coast. The substock has a long catch time series, with most fishery-dependent abundance indices and length compositions starting in the early 1980s with some fishery-independent abundance indices in recent years (**Supplementary Figure 18**). The age composition data are available for the final 20–30 years of the model (**Supplementary Figure 18**). Likelihood profiling indicated indices and the length composition data show some agreement despite often in contradiction to the age composition data (Haltuch et al., 2018). The reference model exhibits the most uncertainty in the initial abundance though the last 20 years of the spawning output also show an increase in uncertainty. Biologically, lingcod, especially women, would be more similar to the slower growing life history in the simulation study. Recruitment deviations are estimated in the reference model.

The removal of the length compositions or indices demonstrated the largest and most similar effects on the model outputs (**Supplementary Figure 19**). The removal of ages had a little effect given the growth was fixed. The length-only models show a divergence in models with varying degrees of data showing reduced absolute abundance with the most length data and a higher abundance with lower years of length data (**Supplementary Figure 18**). Larger departures from the reference model occurred with less sampled years. All data scenarios demonstrated consistent estimates of the fraction unfished with even 1 year of length data scenario resulting in an informative estimate in the final year. There was a linear trend upward in the spawning output and overall steady and slightly larger fraction unfished as the time series of lengths decreased (**Figure 6**). The estimates were all within the reference model CIs for each metric under each length scenario.

Dover Sole

Dover sole is a primarily exploited commercial trawl gear of the West Coast. The co-occurrence of this species with sablefish, a highly valuable stock, along with its own marketability have resulted in a long exploitation history. The reference assessment has a large number of length and age composition data from both commercial fleets and survey fleets, with the four fishery-independent surveys that were relatively flat across the sampled years (1980–2010, **Supplementary Figures 20**, **21**).

The model was relatively insensitive to the removal of the index data ("- Indices", **Figure 6**, **Supplementary Figure 21**) with only a small decline in the spawning output across time. The reference model estimated a relatively stable spawning output time series with limited impacts to the stock size due to removals. The indices in the model were relatively flat across time, especially the most recent index from 2003 to 2010, and the limited change in the model estimates when the indices were removed highlights the lack of information in these data. The data scenarios that removed either all the length ("-Lengths") or the age data ("- ges") resulted in downward shifts in the estimated spawning output but were similar to the reference model in terms of scale.

The data scenarios that were explored using only catch and length data generally varied based on the amount of available length data. The scenario that included either all or 20 years of length data were comparable with the "-Ages" data scenario, which used all the lengths and indices in the reference model (**Figure 6**, **Supplementary Figure 21**). The scale of the population from these scenarios were lower than the reference model but resulted in similar population scale estimates. However, when a larger amount of length data, either only 10 or 1 year of length data, were removed, the estimates varied to a greater extent from the reference model and in the 1-year scenario resulted in the fraction unfished that was outside the 95% CI from the reference model.

Big Skate

The big skate assessment is an example of a stock with a long catch history but mostly limited to data within the last 20 years (**Supplementary Figure 22**). While the fishery-independent indices of abundance had small average slopes upward across time, the fits to the indices are mostly flat, indicating a very little influence or the information content. The age data also seem to be weakly informative and contradictory to the signal in the index. Likelihood component analyses (Taylor et al., 2019) indicate length compositions to be the most informative data source. The estimates of spawning output are highly largely uncertain. Biologically, a big skate growth is slow to reach asymptotic size, thus having relatively more informative length compositions. Recruitment was not estimated in this model.

The removal of the length compositions demonstrated the largest effect on model outputs (**Supplementary Figure 23**) though given the already large uncertainty in the reference model spawning output was just within the confidence bound (**Figure 6**). Further examination of altering the available length composition data showed mostly conservative deviations from the reference model in case of the inclusion of no indices or age data, with even 1 year of length data being informative of model scale and relative abundance (**Figure 6**). The OFL estimate demonstrated the largest deviation from the reference model.

DISCUSSION

This study used two types of experiments to explore the possible use of catch and length data in age-structured models when reliable abundance indices and age composition are unavailable. The simulation study demonstrated that we can expect the unbiased estimates of key population quantities on average when including only catch and length data. The probability of an accurate parameter estimate for any given stock assessment generally increases with more years of length composition data, a higher sample size of length data, and for the stocks with a lower recruitment variability. A single year of length data was typically most biased and with the highest error, but 5 years of length data decreased the bias and error.

These results are applicable to data-moderate stocks worldwide. When stocks are lacking an abundance index, one option may be to compare the estimates of the stock status or an exploitation rate with catch- or length-only approaches, leaning on an ensemble of models to make management decisions. Pons et al. (2020) compared the bias and error of catch- and length-only methods in the estimation of their common output, exploitation rate if both catch and length are available without an abundance index. One takeaway of this exploration was that catch and length would ideally be used together in an integrated model. While the length-based integrated mixed effects model integrated catch and length data to estimate fishing mortality and recruitment deviations over time (Rudd and Thorson, 2018), the important features of age-structured populations such as multiple fleets, multiple sexes, and alternate selectivity functions (e.g., dome-shaped selectivity) are not implemented or thoroughly tested (Pons et al., 2019). Meanwhile, SS has a wide range of important features for modeling age-structured population dynamics that are well tested with an ongoing technical support from NOAA. Further, many catch-only approaches simply approximate a sustainable catch limit rather than model population dynamics (Carruthers et al., 2014). In cases of using catch-only methods to estimate stock status, they generally do not perform well (Free et al., 2020). With a few years of length data, SS-CL would likely improve the assessments previously relying on catch-only approaches.

In addition to improvements in the estimates of stock status, the integrated SS framework allows for the ability to consider model goodness of fit, residual analysis, retrospective analysis, and other diagnostics useful for considering the model choice and uncertainty. The ability to model the key aspects of abovementioned age-structured population dynamics along with statistical diagnostics makes it reasonable to relax the precautionary buffer between the OFL (e.g., MSY) and ABC (i.e., recommended catch limit). In the USA, only 11% of the OFLs and ABCs are calculated using data-moderate methods, compared with 30% using data-rich assessments and 59% using data-limited approaches (Newman et al., 2015). This may be due to the lack of approved data-moderate assessment approaches. With the approval of SS-CL for use in data-moderate assessments for the stocks managed by the Pacific Fishery Management Council, a large proportion of OFLs and ABCs set using data-limited approaches may upgrade to the data-moderate category, particularly when OFLs are approximated using catch-only approaches and recent length compositions are becoming available.

While SS may be used to model multiple fleets, areas, and sexes, the simulations in this study represent the simplified versions of fish stocks with only a single fleet operating in a homogenous area. Length compositions must be representative of the entire fishery to accurately inform the fraction unfished, and this task becomes more complicated with multiple fleets and selectivity (Sharma et al., 2014; Pons et al., 2020). Future simulation testing could help inform the potential issues using length and catch data only by exploring mis-specified selectivity forms, sex-specific growth rates for species with sexual dimorphism, and more life history scenarios. Comparison of simulation testing with systematic data reduction allows us to understand the impact of catch and length-only models from multiple practical angles.

The systematic data reduction study demonstrated that the length composition data proved a critical input to a variety of West Coast groundfish stock assessments. Length data were not just ancillary to other data types as models reduced to only length and catch histories, including those with short time series (10 years or less) of length compositions that retained much of the information of reference models. A big reason for this is that the length composition is a key input to estimating both fleet selectivity and recruitment variability in an age-structured stock assessment (Minte-Vera et al., 2017; Thorson et al., 2019). Shorter time series of length compositions would often offer simplified views of the past population dynamics but could still provide the informed estimates of the fraction unfished in the final model years (Thorson and Cope, 2015; Rudd and Thorson, 2018). The results here are encouraging for the use of length and catch models as viable data-moderate stock assessment candidates.

Meanwhile, it is most desirable to have all forms of data that are integrated and working together in a stock assessment, it is not unusual that different data types show weak and/or conflicting contributions of indices of abundance. Many stocks do not have scientifically designed abundance indices available; the fishery-dependent CPUE time series that are available subsequently suffer from a systematic bias or an insufficient contrast leading to large uncertainties, and thus a weak influence on model outputs. For stocks with a low-contrast standardized trawl survey index, the index had a limited influence on the model estimates. These stock assessments tend to behave similarly to length-only models, so there is a precedent for length-driven models to inform the West Coast fisheries management.

In instances where data sources such as abundance indices or length compositions are more influential, contradictory signals present real problems (Maunder et al., 2017). Data weighting is an important, nontrivial aspect of developing reference stock assessment models, and there is no way to do it (Francis, 2017; Punt, 2017). Thus, decisions are necessary to resolve contradictory data. Down weighting of certain likelihood components in favor of others is common but may instead mask important model misspecifications (Maunder and Piner, 2017; Wang and Maunder, 2017). The inclusion of multiple data types in an integrated model may cause additional challenges as data may have an influence on unrelated model processes (Piner et al., 2016), thus arguing for the specification of model parameters outside the model. One example is the establishment of life history values such as natural mortality or growth external to the model to better establish selectivity parameters, and subsequently exploring the model misspecification through sensitivity analyses. The decision to fix the life history parameters in these model comparisons is therefore a common practice, and also provided one level of experimental control in separating the effects of data exclusion rather than life history misspecification. This decision likely decreased the influence of age, and possibly length, composition to a certain extent, but was a trade-off to gain the interpretability of results. It is also possible that size compositions may hold limited information about the population trend, especially given the uncertainty in life history parameters (Minte-Vera et al., 2017) or should be down weighted to only inform selectivity (Sharma et al., 2014).

When length compositions were the only source of data, they tend to offer more conservative OFL estimates due to the changes in either the initial or final estimates of the stock size. The most conservative estimates generally arose in case of the availability of limited years of length data though the degree of this difference varies. The basic argument of including length compositions is that they provide the information on length-based selectivity, the fishing intensity, recruitment deviations, and the current fraction unfished. When the indices of abundance or age compositions are either unavailable or too resource-intensive to process, length plus catch models show the capacity to provide suitable estimates of sustainable catch. In most cases, length-only models were more conservative than the reference model in all examined model outputs, decreasing the chance that such models will lead to overfishing in the short term.

The stripping back of stock assessment data does not presume simpler models. Most of the model complexities were maintained across these data scenarios, and are not likely how one would specify a stock assessment model if truly faced with limited data. When data are sparse, parsimony is beneficial as the estimation of numerous selectivity parameters with little data may complicate the model convergence. How this would influence the comparisons that were not explored though keeping the model complexity high still resulted in reasonable results for the length-only models. Likewise, other simplifications were made, such as fixing life history parameters to the reference model, thus possibly reducing the amount of deviance from the reference model.

Similar to many stock assessments, future applications of SS-CL will be limited due to the difficulties in making the assumptions about fixed parameters and model structure. Misspecifying key life history values, such as natural mortality, asymptotic length, or the CV in the growth curve, demonstrates the expected biases. Applications will turn to external studies or meta-analyses to inform the fixed values of growth, natural mortality, or steepness parameters. However, biases associated with fixing the life history values or potential estimation biases from confounding parameters would also be potential issues in any stock assessment and should always be considered. Analysts would also be alerted about the potential issues of parameter and model misspecification through convergence issues, as seen with the parameter misspecification in the simulation study, as well as likelihood profiling, residual diagnostics, and retrospective analysis (Carvalho et al., 2017).

The use of SS-CL, a viable application, as a stock assessment tool for fisheries with life history information, time series of removals, and as little as a snapshot or short time series of representative length compositions. A flow chart for using the SS-CL approach is given in the **Supplementary Material**. The technical support behind SS, well-tested features such as multiple fleets and sexes, and an integrated nature to include all data as they become available make SS-CL a viable stock assessment option for data-moderate stocks worldwide.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

MR ran the simulation analysis and contributed to writing the paper. JC and CW consulted in the simulation analysis, ran the systematic data reduction, and contributed to writing the paper. JH consulted in the simulation and systematic data reduction analyses and secured funding for the project. All authors contributed to the article and approved the submitted version.

FUNDING

This study was funded by the NOAA Fishery Resource Analysis and Monitoring Division, Requisition number NFFP7410-19-03274, contract number 1333MF19PNFFP0245.

ACKNOWLEDGMENTS

We thank Owen Hamel and Melissa Haltuch for reviews of this draft, Andre Punt for chairing the SSC review of this work, and the Pacific Fishery Management Council SSC Groundfish subcommittee for reviewing this research.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2021.663554/full#supplementary-material

REFERENCES

Anderson, S. C., Monnahan, C. C., Johnson, K. F., Ono, K., and Valero, J. L. (2014). ss3sim: an R package for fisheries stock assessment simulation with Stock Synthesis. *PLoS ONE* 9:e92725. doi: 10.1371/journal.pone.0092725

Berger, A. M., Arnold, L., and Rodomsky, B. T. (2015). *Status of Kelp Greenling (Hexagrammos decagrammus) Along the Oregon Coast in 2015*. Portland, OR: Pacific Fishery Management Council.

Booth, A. J., and Quinn, T. J. II. (2006). Maximum likelihood and Bayesian approaches to stock assessment when data are questionable. *Fish. Res.* 80, 169–181. doi: 10.1016/j.fishres.2006.05.003

Carruthers, T. R., Punt, A. E., Walters, C. J., MacCall, A., McAllister, M. K., Dick, E. J., et al. (2014). Evaluating methods for setting catch limits in data-limited fisheries. *Fish. Res.* 153, 48–68. doi: 10.1016/j.fishres.2013.12.014

Carvalho, F., Punt, A. E., Chang, Y. J., Maunder, M. N., and Piner, K. R. (2017). Can diagnostic tests help identify model misspecification in integrated stock assessments? *Fish. Res.* 192, 28–40. doi: 10.1016/j.fishres.2016.09.018

Cope, J., Dick, E. J., MacCall, A., Monk, M., Soper, B., and Wetzel, C. (2013). *Data-Moderate Stock Assessments for Brown, China, Copper, Sharpchin, Stripetail, and Yellowtail Rockfishes and English and Rex Soles in 2013*. Portland, OR: Pacific Fishery Management Council.

Cope, J. M. (2013). Implementing a statistical catch-at-age model (Stock Synthesis) as a tool for deriving overfishing limits in data-limited situations. *Fish. Res.* 142, 3–14. doi: 10.1016/j.fishres.2012.03.006

Cope, J. M., Berger, A. M., Whitman, A. D., Budrick, J. E., Bosley, K. M., Tsou, T. S., et al. (2019). *Assessing Cabezon (Scorpaenichthys marmoratus) Stocks in Waters off of California and Oregon, With Catch Limit Estimation for Washington State*. Portland, OR: Pacific Fishery Management Council.

Cope, J. M., and Punt, A. E. (2009). Length-based reference points for data-limited situations: applications and restrictions. *Mar. Coast. Fish.* 1, 169–186. doi: 10.1577/C08-025.1

Cope, J. M., Sampson, D., Stephens, A., Key, M., Mirick, P. P., Stachura, M., et al. (2016). *Assessments of California, Oregon, and Washington Stocks of Black Rockfish (Sebastes melanops) in 2015*. Portland, OR: Pacific Fishery Management Council.

Cope, J. M., Thorson, J. T., Wetzel, C., and Devore, J. D. (2015). Evaluating a prior on relative stock status using simplified age-structured models. *Fish. Res.* 171, 101–109. doi: 10.1016/j.fishres.2014.07.018

Dichmont, C. M., Deng, R. A., Dowling, N., and Punt, A. E. (2021). Collating stock assessment packages to improve stock assessments. *Fish. Res.* 236:105844. doi: 10.1016/j.fishres.2020.105844

Dick, E. J., and MacCall, A. D. (2011). Depletion-Based Stock Reduction Analysis: a catch-based method for determining sustainable yields for data-poor fish stocks. *Fish. Res.* 110, 331–341. doi: 10.1016/j.fishres.2011.05.007

Dick, E. J., Monk, M., Taylor, I., Haltuch, M., Tsou, T. S., and Mirick, P. (2016). *Status of China Rockfish off the U.S. Pacific Coast in 2015*. Portland, OR: Pacific Fishery Management Council.

Francis, R. I. C. C. (2017). Revisiting data weighting in fisheries stock assessment models. *Fish. Res.* 192, 5–15. doi: 10.1016/j.fishres.2016.06.006

Free, C. M., Jensen, O. P., Anderson, S. C., Gutierrez, N. L., Kleisner, K. M., Longo, C., et al. (2020). Blood from a stone: Performance of catch-only methods in estimating stock biomass status. *Fish. Res.* 223:105452. doi: 10.1016/j.fishres.2019.105452

Gertseva, V., and Cope, J. M. (2017). *Stock Assessment of the Yelloweye Rockfish (Sebastes ruberrimus) in the State and Federal Waters off California, Oregon, and Washington*. Portland, OR: Pacific Fishery Management Council.

Haltuch, M. A., Wallace, J., Allen Akselrud, C., Nowlis, J., Barnett, L. A. K., Valero, J. L., et al. (2017). *2017 Lingcod Assessment*. Portland, OR: Pacific Fishery Management Council.

Haltuch, M. A., Wallace, J., Allen Akselrud, C., Nowlis, J., Barnett, L. A. K., Valero, J. L., et al. (2018). *2017 Lingcod Stock Assessment*. Portland, OR: Pacific Fishery Management Council.

Hamel, O. S. (2015). A method for calculating a meta-analytical prior for the natural mortality rate using multiple life history correlates. *ICES J. Mar. Sci.* 72, 62–69. doi: 10.1093/icesjms/fsu131

Hicks, A. C., and Wetzel, C. R. (2013). *The Status of Dover Sole (Microstomus pacificus) Along the U.S. West Coast in 2011.* Portland, OR: Pacific Fishery Management Council.

Maunder, M. N., Crone, P. R., Punt, A. E., Valero, J. L., and Semmens, B. X. (2017). Data conflict and weighting, likelihood functions and process error. *Fish. Res.* 192, 1–4. doi: 10.1016/j.fishres.2017.03.006

Maunder, M. N., and Piner, K. R. (2017). Dealing with data conflicts in statistical inference of population assessment models that integrate information from multiple diverse data sets. *Fish. Res.* 192, 16–27.

Methot, R. D., and Taylor, I. G. (2011). Adjusting for bias due to variability of estimating recruitments in fishery assessment models. *Can. J. Fish. Aquat. Sci.* 68, 1744–1760. doi: 10.1139/f2011-092

Methot, R. D., and Wetzel, C. R. (2013). Stock synthesis: a biological and statistical framework for fish stock assessment and fishery management. *Fish. Res.* 142, 86–99. doi: 10.1016/j.fishres.2016.04.022

Minte-Vera, C. V., Maunder, M. N., Aires-da-Silva, A. M., Satoh, K., and Uosaki, K. (2017). Get the biology right, or use size-composition data at your own risk. *Fish. Res.* 192, 114–125. doi: 10.1016/j.fishres.2017.01.014

Monk, M. H., and He, X. (2019). *The Combined Status of Gopher (Sebastes carnatus) and Black-and-Yellow Rockfishes (Sebastes chrysomelas) in U.S. Waters off California in 2019*. Portland, OR: Pacific Fishery Management Council.

Newman, D., Berkson, J., and Suatoni, L. (2015). Current methods for setting catch limits for data-limited fish stocks in the United State. *Fish. Res.* 164, 86–93. doi: 10.1016/j.fishres.2014.10.018

NOAA (2021). *Setting an Annual Catch Limit*. Available online at: https://www.fisheries.noaa.gov/insight/setting-annual-catch-limit (accessed June 11, 2021).

Ono, K., Punt, A. E., and Rivot, E. (2012). Model performance analysis for Bayesian biomass dynamics models using bias, precision and reliability metrics. *Fish. Res*. 125–126, 173–183. doi: 10.1016/j.fishres.2012.02.022

Parma, A. M., and Deriso, R. B. (1990). Dynamics of age and size composition in a population subject to size-selective mortality: effects of phenotypic variability in growth. *Can. J. Fish. Aquat. Sci.* 47, 274–289. doi: 10.1139/f90-030

Piner, K. R., Lee, H.-H., and Maunder, M. N. (2016). Evaluation of using random-at-length observations and an equilibrium approximation of the population age structure in fitting the von Bertalanffy growth function. *Fish. Res.* 180, 128–137. doi: 10.1016/j.fishres.2015.05.024

Pons, M., Cope, J. M., and Kell, L. T. (2020). Comparing performance of catch-based and length-based stock assessment methods in data-limited fisheries. *Can. J. Fish. Aquat. Sci.* 77, 1026–1037. doi: 10.1139/cjfas-2019-0276

Pons, M., Kell, L., Rudd, M. B., Cope, J. M., and Fredou, F. L. (2019). Performance of length-based data-limited methods in a multi-fleet context: application to small tunas, mackerels, and bonitos in the Atlantic Ocean. *ICES J. Mar. Sci.* 76, 960–973. doi: 10.1093/icesjms/fsz004

Punt, A. E. (2017). Some insights into data weighting in integrated stock assessments. *Fish. Res.* 192, 52–65. doi: 10.1016/j.fishres.2015.12.006

Punt, A. E., Hurtado-Ferro, F., and Whitten, A. R. (2014). Model selection for selectivity in fisheries stock assessments. *Fish. Res.* 158, 124–134. doi: 10.1016/j.fishres.2013.06.003

Rudd, M. B., and Thorson, J. T. (2018). Accounting for variable recruitment and fishing mortality in length- based stock assessments for data-limited fisheries. *Can. J. Fish. Aquat. Sci.* 75, 1019–1035. doi: 10.1139/cjfas-2017-0143

Sharma, R., Langley, A., Herrera, M., Geehan, J., and Hyun, S.-Y. (2014). Investigating the influence of length-frequency data on the stock assessment of Indian Ocean bigeye tuna. *Fish. Res.* 158, 50–62. doi: 10.1016/j.fishres.2014.01.012

Stephens, A., and Taylor, I. G. (2013). *Stock Assessment and Status of Longspine Thornyhead (Sebastolobus altivelis) off California, Oregon, Washington in 2013*. Portland, OR: Pacific Fishery Management Council.

Taylor, I. G., Gertseva, V., Stephens, A., and Bizzarro, J. (2019). *Status of Big Skate (Beringraja binoculata) Off the U.S. Pacific Coast in 2019*. Portland, OR: Pacific Fishery Management Council.

Thorson, J. T., and Cope, J. M. (2015). Catch curve stock-reduction analysis: an alternative solution to the catch equations. *Fish. Res*. 171, 33–41. doi: 10.1016/j.fishres.2014.03.024

Thorson, J. T., Rudd, M. B., and Winker, H. (2019). The case for estimating recruitment variation in data-moderate and data-poor age-structured models. *Fish. Res.* 217, 87–97. doi: 10.1016/j.fishres.2018.07.007

Wang, S.-P., and Maunder, M. N. (2017). Is down-weighting composition data adequate for dealing with model misspecification, or do we need to fix the model? *Fish. Res.* 192, 41–51. doi: 10.1016/j.fishres.2016.12.005

Wetzel, C. R., Cronin-Fine, L., and Johnson, K. F. (2017). *Status of Pacific Ocean Perch (Sebastes alutus) Along the U.S. West Coast in 2017.* Portland, OR: Pacific Fishery Management Council.

Wetzel, C. R., and Punt, A. E. (2015). Evaluating the performance of data-moderate and catch-only assessment methods for U.S. west coast groundfish. *Fish. Res.* 171, 170–187. doi: 10.1016/j.fishres.2015.06.005

Conflict of Interest: MR was employed by the company Scaleability LLC, a single-member LLC in which she is the owner and sole member, and under where she consults as an independent scientific researcher.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 12 October 2021
doi: 10.3389/fmars.2021.714250

A Comparison of Three Data-Poor Stock Assessment Methods for the Pink Spiny Lobster Fishery in Mauritania

Beyah Meissa[1]*, Mamadou Dia[1], Braham C. Baye[1], Moustapha Bouzouma[1], Ely Beibou[1] and Rubén H. Roa-Ureta[2]

[1] Laboratoire Evaluation des Ressources Vivantes Aquatiques, Institut Mauritanien de Recherches Océanographiques et des Pêches, Nouadhibou, Mauritania, [2] Centre of Marine Science (CCMAR), University of Algarve, Faro, Portugal

OPEN ACCESS

Edited by:
Simone Libralato,
Istituto Nazionale di Oceanografia e di Geofisica Sperimentale, Italy

Reviewed by:
Amy Schueller,
Southeast Fisheries Science Center (NOAA), United States
Jin Gao,
Memorial University of Newfoundland, Canada

***Correspondence:**
Beyah Meissa
bmouldhabib@gmail.com

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: 24 May 2021
Accepted: 07 September 2021
Published: 12 October 2021

Citation:
Meissa B, Dia M, Baye BC, Bouzouma M, Beibou E and Roa-Ureta RH (2021) A Comparison of Three Data-Poor Stock Assessment Methods for the Pink Spiny Lobster Fishery in Mauritania. Front. Mar. Sci. 8:714250. doi: 10.3389/fmars.2021.714250

Several data-poor stock assessment methods have recently been proposed and applied to data-poor fisheries around the world. The Mauritanian pink spiny lobster fishery has a long history of boom and bust dynamics, with large landings, stock collapse, and years-long fishery closures, all happening several times. In this study, we have used catch, fishing efforts, and length-frequency data (LFD) obtained from the fishery in its most recent period of activity, 2015–2019, and historical annual catch records starting in 2006 to fit three data-poor stock assessment methods. These were the length-based Bayesian (LBB) method, which uses LFD exclusively, the Catch-only MSY (CMSY) method, using annual catch data and assumptions about stock resilience, and generalised depletion models in the R package CatDyn combined with Pella-Tomlinson biomass dynamics in a hierarchical inference framework. All three methods presented the stock as overfished. The LBB method produced results that were very pessimistic about stock status but whose reliability was affected by non-constant recruitment. The CMSY method and the hierarchical combination of depletion and Pella-Tomlinson biomass dynamics produced more comparable results, such as similar sustainable harvest rates, but both were affected by large statistical uncertainty. Pella-Tomlinson dynamics in particular demonstrated stock experiencing wide fluctuations in abundance. In spite of uncertain estimates, a clear understanding of the status of the stock as overfished and in need of a biomass rebuilding program emerged as management-useful guidance to steer exploitation of this economically significant resource into sustainability.

Keywords: stock assessment, data-poor, LBB, CMSY, CatDyn, pink lobster, Mauritania

INTRODUCTION

The resilience of exploited marine species depends largely on their intrinsic capacity to react to increasing fishing pressure. In general, large slow-growing species with a high age at first maturity are more vulnerable to fishing, exhibiting a larger decrease in abundance for a given fishing pressure (Gislason, 2003; Reynolds et al., 2005; Meissa and Gascuel, 2014). Their exploitation can lead to a sudden collapse of the fishery as it has happened more than once in the pink spiny lobster fishery in Mauritania during its 50 years of exploitation.

After 20 years of closure, a new active exploitation phase started in 2015 with a fleet that targeted the stock, and yet formal stock assessment has not been implemented to ensure sustainability, leading to high risks of repeating the errors of the past. This is a data-poor fishery and the time series of information available for stock assessment is short, thus, it provides a challenging opportunity to examine the advantages of several stock assessment methods for data-poor fisheries that have been proposed in recent years (Roa-Ureta et al., 2015, 2019; Froese et al., 2017, 2018).

The species occur at depths of 50–400 m and reproduce all year round with a peak between August and December (Dia et al., 2021). Reproduction and growth are linked to the moulting cycle. Lobsters periodically shed their exoskeleton to allow their body size to increase and for mating to occur. Males copulate with newly moulted females and the sperm is then stored internally until egg extrusion, which can be delayed for up to 2 years. When extruded, the eggs are fertilised and attached to the underside of the female, where they are carried for 9–11 months before hatching. The pink spiny lobster of Mauritania is vulnerable to exploitation due to its biological characteristics, among these attaining sexual maturity at a relatively large size (140–160 mm total length) and low fertility (in the order of 10^5 eggs). Its high commercial value has led, however, to a rush for its exploitation by vessels previously targeting octopus (*Octopus vulgaris*) that transformed into lobster boats and by newly chartered vessels. As a result, the number of fishing vessels increased rapidly from 5 in 2014 to over 22 vessels in January 2015. Fishing for this species was initiated by the French boats in 1956, following the decline of the green lobster fishery (Maigret, 1978), which until that year was the main target species for French, Spanish, and Portuguese fishers. The high market value of the pink spiny lobster caused its exploitation to increase rapidly. Its fishery went through three phases: a phase of excessive yields and collapse of landings between 1963 and 1970, a phase of reconstruction between 1971 and 1987, and the second phase of collapse between 1987 and 1988 (Diop and Kojemiakine, 1990). This second phase was a result of fishing agreements with the EEC (EU), which led to the intensification of fishing effort, with vessel numbers rising from 10 to 25. A concurrent escalation of poaching rapidly led to a new collapse of the fishery, and French boats left in 1990. Since 1995, the pink spiny lobster has been a by-catch of boats targeting demersal fish and cephalopods in Mauritanian waters (Goñi and Latrouite, 2005).

In 2006, improvement of the abundance index was noted in data from regular scientific surveys. However, the sampling protocols and gear used in these surveys were not adequate for the assessment of the abundance of the pink lobster. Despite the positive turn of the survey abundance index, the stock was not exploited again until 2013 when initially only two boats were active in the area. In November 2013, a craze for this species started with certain operators transforming their cephalopod vessels into lobster boats and others bringing newly chartered vessels into the area. The lack of knowledge about the potential of the stock in 2015 led authorities to commission an experimental fishery. Unfortunately, the high number of vessels authorised for the experimental fishery (22 vessels) in the first year caused a severe deterioration in the condition of the stock. In 2016, management introduced a closed period of 6 months, from July to December. As a result, very few berried females have been encountered in samples from the commercial catch, unlike in 2015 when fishing continued throughout the year.

A large majority of data-poor and small-scale fisheries remain un-assessed and these comprise a substantial part of total fisheries catch (Costello et al., 2012) and employment in the fishing sector worldwide (The World Bank, 2012). This has led to the development of new stock assessment methods that use less data and seek to provide results useful for management leading to sustainability (Froese et al., 2017, 2018; articles in Thorson et al., 2015). These methods differ in the data they use: the rationale they are based on, the assumptions they make, and the results they produce. A recent example of comparative application of data-poor methods is in the study of Maynou et al. (2021), where authors compared two methods to estimate the Pella-Tomlinson surplus production model. In this work, we aimed at examining the potential of three data-poor stock assessment methods, the length-based Bayesian model (LBB, Froese et al., 2017), the Catch-only MSY model (CMSY, Froese et al., 2018), and generalised depletion models combined with Pella-Tomlinson surplus production models (Roa-Ureta et al., 2015, 2019) to determine the exploitation status of the pink lobster stock in Mauritania. The data collected on the fishing activity over the period 2015–2019, which allows application of the three methods, are used to estimate the exploitation status and productivity of this lobster fishery. Our results provide useful insights into their applicability in the vast realm of the stock assessment of data-poor and small-scale fisheries.

MATERIALS AND METHODS

Description of the Fishery

The fishery is conducted on four fishing grounds off the coast of Mauritania, West Africa (**Figure 1**) by licenced boats that operate under an agreement with the national research institute (IMROP) to collect fisheries and biological data. At the start of the experimental pink lobster fishery in 2015, the number of lobster boats operating in Mauritanian waters was 22, ranging in length from 14 to 26 m and with a power rating of between 150 and 500 hp. This number increased from 20 to 25 units from 2016 to 2017 before dropping significantly in 2018 and 2019 to 14 and 12 vessels, respectively, following the withdrawal of the majority of chartered units.

At the beginning of the monitoring of the experimental fishery, the pink lobster fishery was carried out by coastal and offshore vessels using bottom-set, drop gillnets, with 180 mm stretched mesh size, 2 m high, and 25–40 m long. Vessels carried 10–18 sets of 400 nets. At the end of the first monitoring year, some effort control measures were introduced. The maximum length of each net was set at 40 m, the length of the whole set of nets deployed was set at a maximum of 1,600 m, and the maximum number of nets was set at 800. The gear used in the pink lobster fishery resulted in significant bycatch dominated by various demersal fish, scorpion fish, and crabs. Thus, for 1 kg of lobster caught, the by-catch varied from 1.04 to 14.5 kg. The

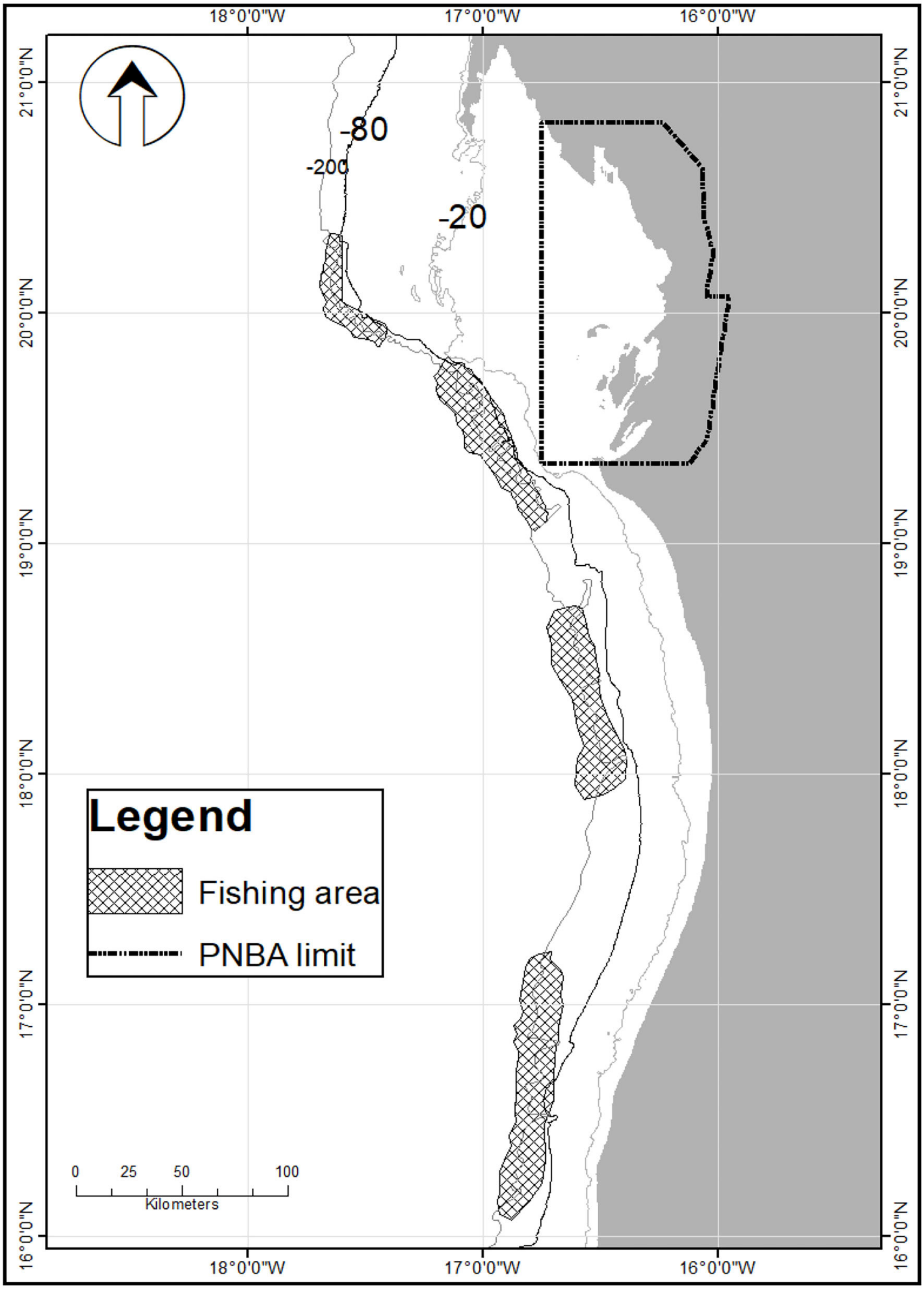


FIGURE 1 | Pink spiny lobster fishing areas off the coast of Mauritania. The National Park of Banc d'Arguin (PNBA) is a protected area where all fishing is banned.

pink spiny lobster is caught exclusively by vessels targeting this species and possessing a specific lobster-fishing licence, with little or no by-catch of pink spiny lobster in other fisheries. The pink lobster has been reported off Spain, Portugal, and Morocco, and it is also found in Senegal and Cabo Verde. In Mauritania, where this species was discovered and the only area where it is fished commercially, this species is found from north to south of the coastline (**Figure 1**).

Mauritanian regulations prohibit the capture and retention of gravid females and the retention of spiny lobsters whose total length is <23 cm. In addition, since 2016 a fishing ban extending from June to December each year was introduced to protect the main spawning seasons and to further restrict the magnitude of annual fishing effort. Catches at the start of the experimental fishery in 2015 were in the order of 704 tonnes and subsequently declined from 242 tonnes in 2016 to <200 tonnes in 2019.

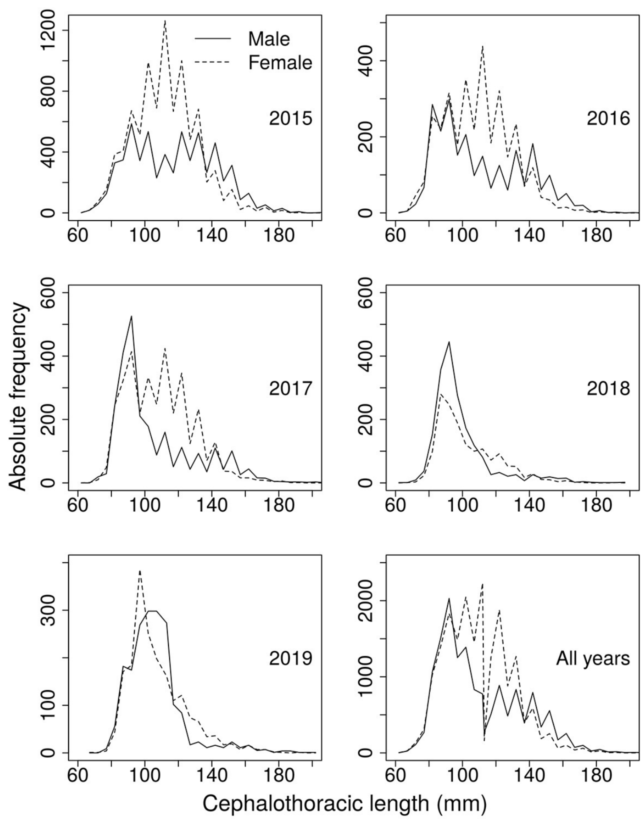


FIGURE 2 | Length frequency data collected over 5 years of fishing operations on the pink spiny lobster fishery in Mauritania.

Description of the Data

The data used in this study were collected during regular monitoring of fishing activities by scientific observers. These data consisted of total annual catch from 2006 to 2019, while from 2015 to 2019, the data included length composition of the annual catch (**Figure 2**), total monthly catch, total monthly fishing effort in days at sea, and mean monthly weight. Sampling was carried out by a cluster random method with ports, factories, and vessels as the three clusters in the population of fishing trips. The biological analyses were based on samples large enough (**Figure 2**) to secure a good representation of all size classes in the length range. Total length, measured from the origin of the inter-orbital spine to the end of the telson, and length of the cephalothorax, taken from the tip of the rostrum to the posterior border of the cephalothorax, were measured for each individual to the nearest millimetre. At the same time, all individuals were also weighed, their sex was noted, and the degree of sexual maturity of the females was recorded using the scale of macroscopic maturity proposed by Weinborn (1977) modified by Briones-Fourzan et al. (1997).

Data-Poor Stock Assessment Methods

Three data-poor stock assessment methods were implemented. The first method was the LBB method (Froese et al., 2018). The LBB method works with length-frequency data (LFD) in the catch. It makes the assumptions that recruitment is constant along with the time series and that growth follows von Bertalanffy's equation to analyse the descending slope of the LFD (Wang et al., 2020). It produces estimates of length at first capture that would maximise catch (L_C), the ratio of natural mortality to the rate parameter in von Bertalanffy's equation (M/k), and the ratio of fishing mortality to the growth rate parameter (F/k), while the value of the asymptotic length in von Bertalanffy's growth model is fixed at a value obtained from a separate biological analysis based on LFD in FISAT II (Dia et al., 2021).

In LBB, it is assumed that the growth in length follows Von Bertalanffy (1938) growth equation in the form given to it by Beverton and Holt (1957), i.e.,

$$L_t = L_\infty \left[1 - e^{-K(t-t_0)}\right] \tag{1}$$

where L_t is the length at age t, $L\infty$ is the asymptotic length, K is the rate at which L_{inf} is approached, and t_0 is the age at zero-length (Froese et al., 2018). When the fish are fully selected by the gear, the curvature of the right side of catch samples is a function of total mortality $(Z = M + F)$ relative to K. This curve is expressed by the equation

$$N_{\mathrm{Lstart}} \left(\frac{L_\infty - L}{L_\infty - Lstart}\right)^{\mathrm{Z/K}} \tag{2}$$

where N_L is the number of survivors to length L, N_{Lstart} is the number at length L_{start} with full selection, and Z/K is the ratio of the total mortality rate Z to the somatic growth rate (Froese et al., 2018). The lengths affected by partial selection are a function of the fishing gear (in this study assumed to be a trawl or another gear with a trawl-like selection curve), as given by the ogive described by Equation (3):

$$S_L = \frac{1}{1 + e^{-a(L-L_c)}} \tag{3}$$

where S_L is the fraction of individuals that are retained by the gear at length L, and α describes the steepness of the ogive (Froese et al., 2018). The parameters of the selection ogive are estimated at the same time as L_c, α, M/K, and F/K by fitting

$$N_{Li} = N_{Li-1} \cdot \left(\frac{L_\infty - L_i}{L_\infty - L_{i-1}}\right)^{\frac{M}{K} + \frac{FS_{Li}}{K}} \quad (4)$$

and

$$C_{Li} = N_{LI}\, S_{Li} \quad (5)$$

where L_i is the number of individuals at length i, L_{i-1} is the number at the previous length, C refers to the number of individuals vulnerable to the gear, and all other parameters are as described above (Froese et al., 2018). Finally, the following equation describes the framework for approximating stock status from $L\infty$, M/K, F/K, and L_c (Froese et al., 2017). First, given the estimates of $L\infty$ and M/K, L_{opt}, i.e., the size at which cohort biomass is at maximum, can be obtained from Equation (6):

$$L_{opt} = L_{\inf}\left(\frac{3}{3 + \frac{M}{K}}\right) \quad (6)$$

Based on Equation (6) and given fishing pressure (F/M), the mean length at first capture, which maximises catch and biomass (L_{c_opt}), can be obtained from

$$L_{c\_opt} = \frac{L_\infty\left(2 + 3\frac{F}{M}\right)}{\left(1 + \frac{F}{M}\right)\left(3 + \frac{M}{K}\right)} \quad (7)$$

Estimates of L_{c_opt} are used below to calculate a proxy for the relative biomass that can produce MSY (Froese et al., 2018). The relative biomass and the length at first capture estimated by LBB can then be used directly for management of data-poor stocks: if relative stock size B/B_0 is smaller than B_{MSY}/B_0, catches should be reduced; if, on the other hand, the mean length at first capture L_c is smaller than L_{c_opt}, fishing should start at larger sizes. The method was implemented within the Bayesian Gibbs sampler software JAGS (Plummer, 2003) and executed using the statistical language R (R Core Team, 2020) to fit observed proportions-at-length. This method was also used to generate current biomass priors as input to implement the second method, the catch-only CMSY method (Froese et al., 2017).

The CMSY method uses annual catch time series and previous knowledge of resilience to estimate parameters of Schafer's surplus production model, namely, the intrinsic rate of population growth r and the carrying capacity of the environment K. The basic biomass dynamics are governed by Equation (8):

$$B_{y+1} = B_y + r\left(1 - \frac{B_y}{K}\right)B_y - C_y \quad (8)$$

It assumes that r, the initial relative biomass (B_0/K), and the final relative biomass ($B_{current}/K$) are known in qualitative terms (high, intermediate, or low) and that the value of K varies between (maximum catch)/r and 4*(maximum catch)/r or between 2*(maximum catch)/r and 12*(maximum catch)/r depending on the level of biomass in the last year. Because the CMSY method can only be applied with Schaefer's model, it also assumes a symmetric production function, i.e., that the biomass that produces the MSY is $K/2$ and the MSY is $rK/4$. In Equation (8), B_{y+1} is the exploited biomass in the subsequent year $y + 1$, B_y is the current biomass, and C_y is the catch in year y. To account for depensation or reduced recruitment at severely depleted stock sizes, such as predicted by all common stock-recruitment functions (Beverton and Holt, 1957; Ricker, 1975; Barrowman and Myers, 2000), a linear decline of surplus production, which is a function of recruitment, somatic growth, and natural mortality (Schnute and Kronlund, 1996), is incorporated if biomass falls below ¼ k (Equation 9).

$$B_{t+1} = B_y + 4\frac{B_y}{K}r\left(1 - \frac{B_y}{K}\right)B_y - C_y\frac{B_y}{K} < 0.25 \quad (9)$$

The term (4*Bt/k) assumes a linear decline of recruitment below half of the biomass that is capable of producing MSY. The CMSY method is coded as an R script (CMSY_2019_5.R) and the version used here is a newer version than the one used in the original paper (Froese et al., 2017). The main differences are faster execution because of parallel processing and more emphasis on management, e.g., by adding an optional Kobe plot.

The third method was an implementation of the non-Bayesian hierarchical inference framework that combines a first stage of fitting generalised depletion models and a second stage of fitting the Pella-Tomlinson-generalised surplus production model (Roa-Ureta et al., 2015, 2019). This method employs catch, effort, and mean weight data at monthly time steps to fit open-population depletion models in the R package CatDyn (Roa-Ureta, 2019) and then uses annual biomass estimates from these depletion models as input to fit the Pella-Tomlinson surplus production model using a marginal-estimated likelihood function in Automatic Differentiation Model Builder (Fournier et al., 2011). The open-population nature of generalised depletion models consists of allowing for multiple exogenous inputs of abundance that occur during the fishing in multi-annual, monthly time series of data. This in turn allows consideration and estimation of the annual recruitment pulses that enter the vulnerable stock. Specifically, at the first stage of fitting the 72 months of catch and effort with a generalised depletion model, the model was a single-fleet process of the form:

$$C_t = kE_t^\alpha N_t^\beta = kE_t^\alpha\left(N_0e^{-Mt} - e^{\frac{-M}{2}}\left(\sum C_ie^{-M(t-i-1)}\right) + \sum R_je^{-M(t-p_j)}\right)^\beta e^{\frac{-M}{2}} \quad (10)$$

where t is the month (from January 2015 to December 2019), C is the predicted catch, k is the scaling (akin to catchability but for non-linear catch rate and abundance models), E is the observed fishing effort (in the number of days fishing per month),

N_0 is the initial abundance (at the end of December 2014), M is the natural mortality rate per month, and R_j is the magnitude of the recruitment pulse in year j (j = 1–5) due to growth of lobsters into the size retained by fishers. In this model, k, α, β, N_0, M, and the five R_j (totaling 10 parameters) are estimated by maximum likelihood by assuming that the observed catch χ_t has a normal distribution, with mean given by Equation (10) and variance estimated in the model from the data. Further details can be found in the study of Roa-Ureta (2015). The model is implemented in the R package CatDyn, currently on version 1.1-1 (Roa-Ureta, 2019). After estimation, it is possible to predict further results such as the time series of fishing mortality F_t for all months in the data by numerical solving for F at each time step using the Baranov catch equation. Furthermore, CatDyn also produces estimated time series of abundance N_t and biomass B_t for all months in the time series of data.

These biomass estimates can then be used, along with a longer time series of annual landings, to estimate a surplus production model much like absolute biomass estimates from surveys can be used to fit a surplus production model (Mueter and Megrey, 2006). Thus, in this third method for data-poor fisheries, we use 1 of the 12 monthly biomass estimates per year from the fit of the depletion model, particularly the monthly biomass estimate with the smallest average standard error, to fit a Pella-Tomlinson surplus production model. The Pella-Tomlinson model is the general case to which the Schaefer model is a particular case. We fitted a Pella-Tomlinson model of the form:

$$B_y = B_{y-1} + rB_{y-1}\left(1 - \left(\frac{B_{y-1}}{K}\right)^{p-1}\right) - \chi_{y-1},\ p > 1 \quad (11)$$

where y is the year (from 2006 to 2019), B is the biomass predicted by the model, r is the intrinsic rate of population growth, K is the carrying capacity of the environment, p is the symmetry of the production function, and χ is the observed annual catch. This model was fitted to biomass estimates from the depletion model for years 2015–2019 using a hierarchical inference method based on maximising a marginal likelihood function (Roa-Ureta et al., 2015).

The combined depletion and surplus production model does not make any assumption about population dynamics or life history, except for the mathematical forms in Equations (10) and (11). This method is not exclusively a data-poor method; it can be applied to long-time series of efforts and catch and samples of the mean weight in the catch at weekly or monthly time steps (Roa-Ureta et al. 2015, 2019). In this application, however, it is applied to just 5 years of data (2015–2019) to fit the depletion models at the first stage. At the second stage, the 5 years of data were supplemented with a longer time series of annual catch (2006–2019). So in this instance, the non-Bayesian hierarchical inference was implemented at the boundary of low information for the Pella-Tomlinson model.

At the first stage, when fitting open-population depletion models, this method needs to estimate the month of annual recruitment of each of the 5 years of monthly catch, effort, and mean weight data. We fitted 10 model variants by setting the 5 recruitment months at varying locations for each year along with the time series. These 10 variants were defined by examining, for each year, the few months with higher catch without a proportionate rise in fishing effort. The higher catch without concomitant raise in effort could be the result of recruitment to the size retained by fishers so that these months are good candidates. Each of the 10 variants was fitted with two likelihood functions, one was the full normal likelihood and the other was its adjusted profile approximation (Roa-Ureta, 2015), for a total of 20 model variants. We tried four numerical methods for optimization to maximise the likelihood function, namely, we used the spectral projected gradient (SPG), Conjugate-Gradient (CG), Broyden-Fletcher-Goldfarb-Shanno (BFGS), and the Nelder-Mead methods, which give a grand total of 80 model variant-optimization method combinations. The best variant-method combination was determined as the one with the least AIC and more conservative biomass estimate. A full description of this method can be found in the study of Roa-Ureta et al. (2019) and references therein.

RESULTS

LBB Method

According to this method, the relative fishing mortality F/M for the male individuals is 4.4 in the most current year, biomass in the same year is just 8% of initial biomass, and 21% of biomass at MSY (**Figure 3**). These indicators represent a stock that is severely overfished and still experiencing overfishing. Equivalent results were obtained when using aggregated length frequency (LF) data or males LF data.

Catch-Only MSY Method

Assumptions about the range of values for r determined a range of 95% credibility interval estimates for MSY, from a minimum of 71 tonnes to a maximum of 402 tonnes (**Table 1**). The largest spread of estimates occurs with r, four times higher when assuming r between 1 and 1.5 than when assuming r between 0.1 and 0.5. Interestingly, biomass in the last year is at about the same percentage of B_{MSY} under the three scenarios of r, i.e., around 40–50%.

Under the CMSY method, there is no objective manner to discern among results obtained from different assumptions of the range where the true r should lie, as is the case in the present study. However, here we present further results from the assumption that the true r should lie between 1 and 1.5 because the third stock assessment method employed, which does not make any assumption about the values of its parameters, estimated r between 1 and 1.5 (see below). Under this assumption, the stock was under fished until 2013, it experienced severe overfishing in 2015, and then removals have been closed to the MSY until 2019 (**Figure 4**, top left). The stock is still overfished, with biomass at just 50% of the B_{MSY} (**Figure 4**, top right), and still experiencing overfishing, with fishing mortality above F_{MSY} (**Figure 4**, bottom).

Hierarchical CatDyn and Pella-Tomlinson

Sixteen of 80 generalised depletion models fitted to the 60-month-long time series of catch and effort data achieved

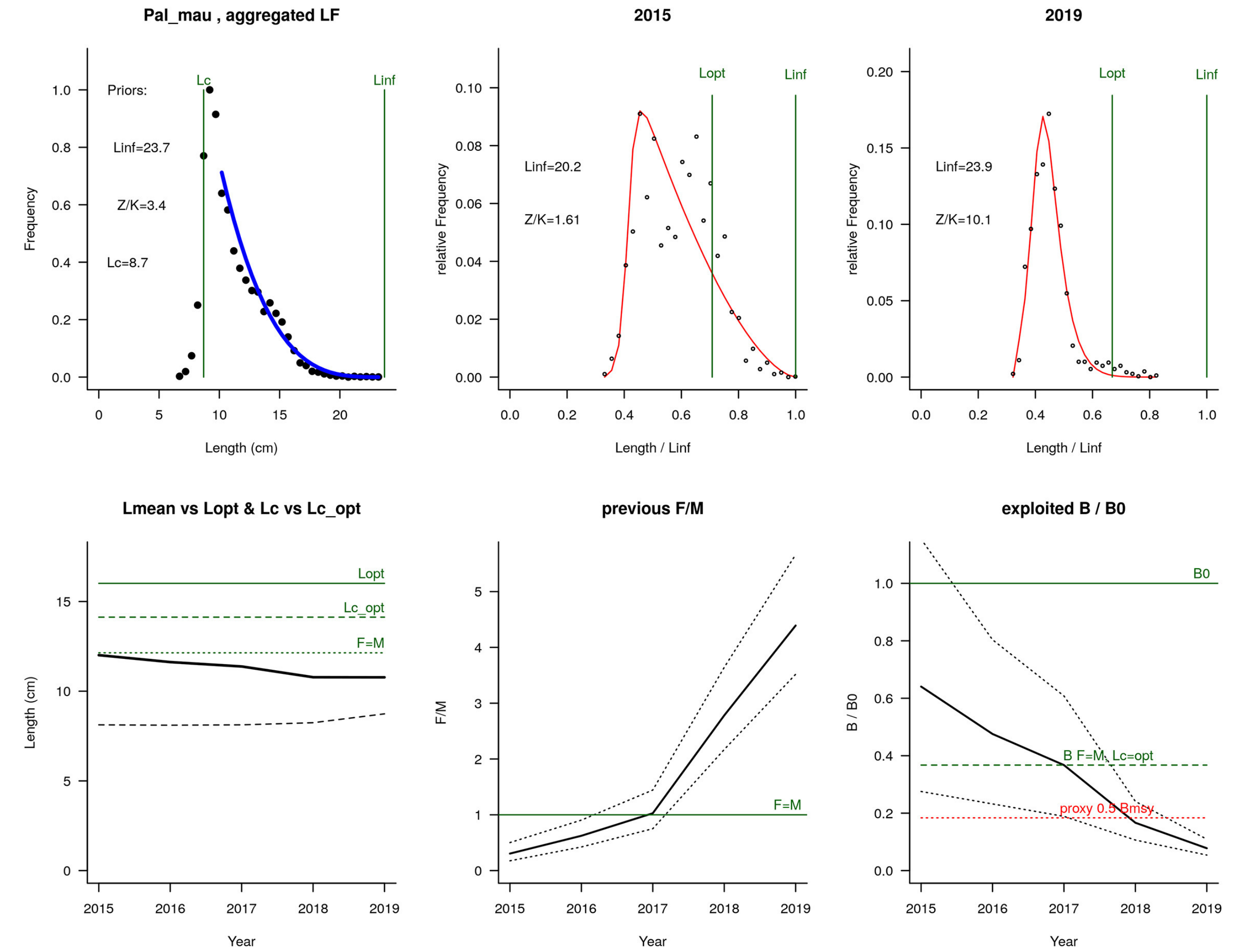


FIGURE 3 | Top-left: aggregated length frequency (LF) data and priors for L_c, L_{inf}, and Z/k. Top-mid and top-right: dots are the LF data for the first and last years, and the red line is the fit of the data to the LBB master equation. Bottom-left: mean length (L_{mean}, bold black curve) relative to L_{opt}, and L_c (dashed black curve) relative to L_{c_opt}. Bottom mid: relative fishing mortality F/M (black curve), with approximate 95% credibility limits (dotted lines), and reference level ($F = M$, green horizontal line). Bottom right: relative biomass B/B_0 (black curve) with approximate 95% credibility limits (dotted black curves), and a proxy for B_{MSY} (green dashed line), and a proxy for B_{pa} or 0.5 B_{MSY} (red dotted line).

TABLE 1 | Estimates and 95% credibility intervals (in parentheses) from a Schaeffer surplus production model fitted to annual catch data (14 years) of the pink spiny lobster of Mauritania with the CMSY method, under three assumptions about the range where the true *r* should lie.

Model	*r* (1/yr)	*K* (tonnes)	*MSY* (tonnes)	B_{2019} (tonnes)	B_{MSY} (tonnes)	$\frac{B_{2019}}{B_{MSY}}$	$\frac{F_{2019}}{F_{MSY}}$
$r = 0.1$–0.5	0.33	1,450	121 (71–206)	308	725 (376–1,400)	0.425	4.4
$r = 0.5$–1	0.84	967	203 (139–297)	192	483 (338–692)	0.398	3.01
$r = 1$–1.5	1.36	784	266 (176–402)	181	392 (289–532)	0.462	1.7

successful numerical convergence. These models differed in the timing of annual recruitment, the likelihood model, and the numerical optimization method. The lowest AIC model among those fitted with the full normal likelihood had recruitment pulses happening in November in all years (2015–2019), with 4 AIC units less than the next best normal-likelihood variant. Among those fitted with the adjusted profile normal likelihood, two were tied with the lowest AIC, with 2 AIC units less than the next best variant, and 1 of these 2 units had all recruitment pulses happening in October in all years, while the other had recruitment pulses on various other months. Considering that both the normal and adjusted profile normal variants had the best models with recruitment pulses in October each year and that the model with the normal likelihood (fitted with the SPG

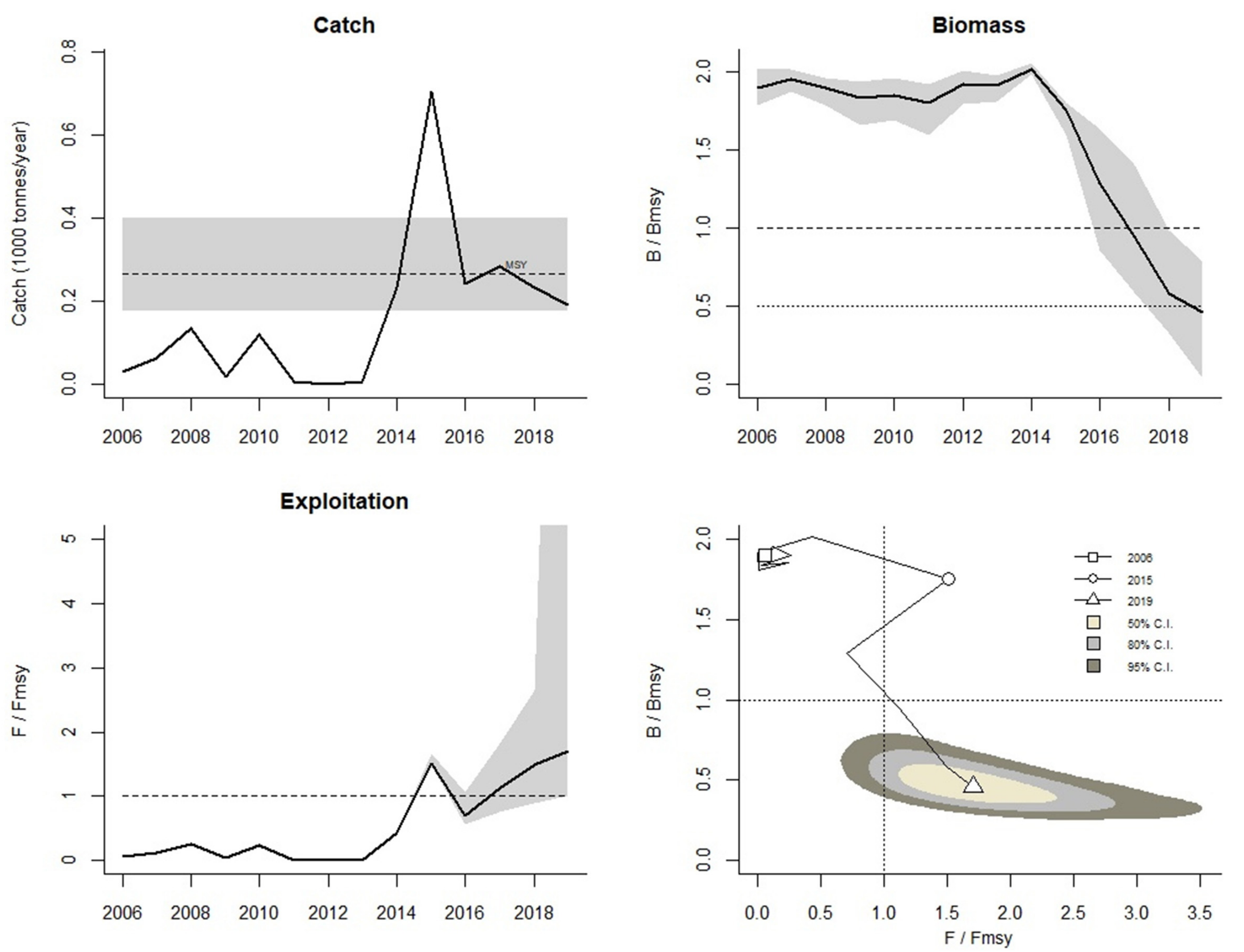


FIGURE 4 | The upper left panel shows catch relative to the 95% confidence interval of *MSY*, with an indication of 95% credibility limits in grey. The upper right panel shows the development of relative total biomass (B/B_{MSY}), with the grey area indicating uncertainty. The lower left graph shows relative exploitation (F/F_{MSY}), with F_{MSY} *corrected* for reduced recruitment below 0.5 B_{MSY}. The lower right panel shows the trajectory of relative stock size (B/B_{MSY}) as a function of fishing pressure (F/F_{MSY}).

numerical optimization method) was also the most conservative model (i.e., it estimated lower stock biomass) and had good numerical properties (all numerical gradients < 1), we selected the latter as the best working model.

The selected model fitted the observed monthly catch data well, with good residual diagnostics that include a symmetrical empirical distribution, a shapeless cloud, and a quantile-quantile plot falling on the 45° diagonal (**Figure 5**). Nevertheless, the short-time series resulted in the inability of the numerical method to calculate standard errors for most of the 11 parameters in the model, such as natural mortality and abundance parameters (**Table 2**).

The estimated monthly natural mortality rate implies an annual rate of 0.3228, which in turn implies longevity of 14 years according to Hoening's empirical relationship (Hoening, 2005). This agrees well with the previous results from Sow et al. (2019) which reported observing individual lobsters reaching 18 years and with Maigret (1978) where it is found that the pink lobster may live up to 21 years. Recruitment varies 5-fold and has an increasing trend towards the present while effort response and abundance response parameters correspond to fishing that is saturable (effort response < 1) and mildly over depleted (abundance response > 1; **Table 2**).

The monthly instantaneous exploitation rate has been decreasing slightly in 2019 but it has been high during the whole period, starting at 60% in 2015 and dropping to around 50% in 2019 (**Figure 6**, top panel). There appears to be an increase in recruitment following a year when the number of months without fishing increases (**Figure 6**, bottom panel).

Monthly pink spiny lobster biomass estimates from generalised depletion models are shown in **Figure 7** (green line). Among these, October estimates (green dots) had the

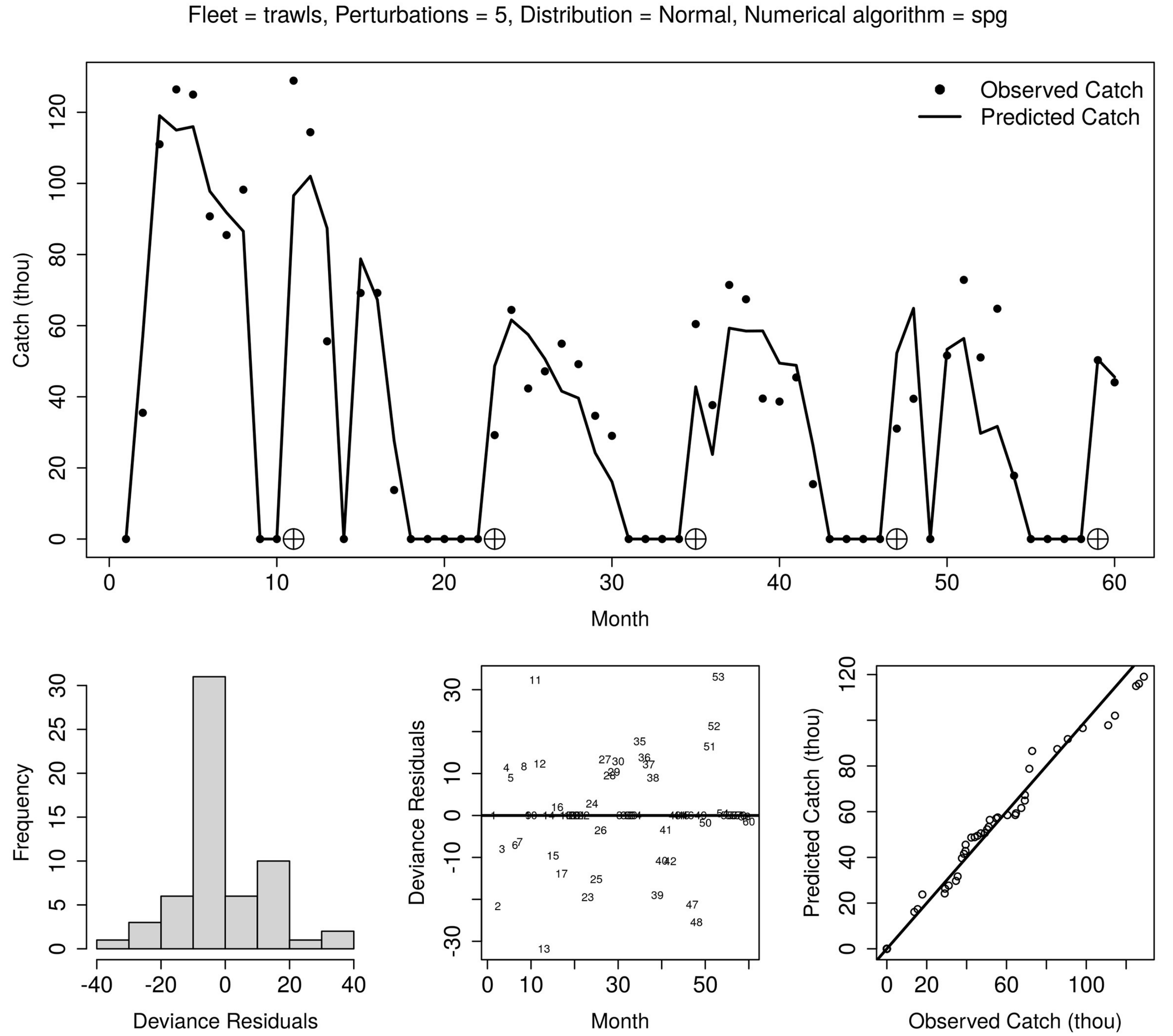


FIGURE 5 | The fit of the best variant of generalised depletion models to 60 months of catch and effort (2015–2019) of the Mauritanian pink spiny lobster fishery. Top panel: observed and predicted catch; lower panels, left to right: residual distribution, residual cloud, and q-q plot.

lowest standard errors so these estimates were used to fit the Pella-Tomlinson annual biomass dynamics.

The annual population dynamics as represented by the Pella-Tomlinson surplus production model has a tendency to strong fluctuations in abundance under fishing pressure (**Figure 7**). During periods of low annual landings, such as 2010–2013, the stock maintains a fairly stable size at ∼2,500 tonnes, but when landings increase as it happened from 2014 to 2019 the stock fluctuates widely.

The high value of the symmetry parameter p (**Table 3**) causes that the stock biomass maximising the growth rate is high biomass, much higher than $K/2$, and therefore stock productivity is low compared to stock biomass. This is reflected in a modest sustainable annual harvest rate, the mean latent productivity, amounting to just over 300 tonnes (**Table 3**). This sustainable annual harvest rate was substantially exceeded in 2015.

Although biomass fluctuations seem stable, with no increasing or decreasing trend in annually averaged biomass, they had a very wide amplitude in recent years. In fact, the lowest biomass was obtained in 2017, and it was close to the recorded catch. These wide fluctuations mean that despite annual catches close to the sustainable annual harvest since 2016, the stock still is overfished and needs to rebuild biomass to a level that produces narrower oscillations when the sustainable harvest rate is applied. All estimates from this model have poor precision, an expected outcome given the few years available to fit depletion models and then to inform Pella-Tomlinson population dynamics.

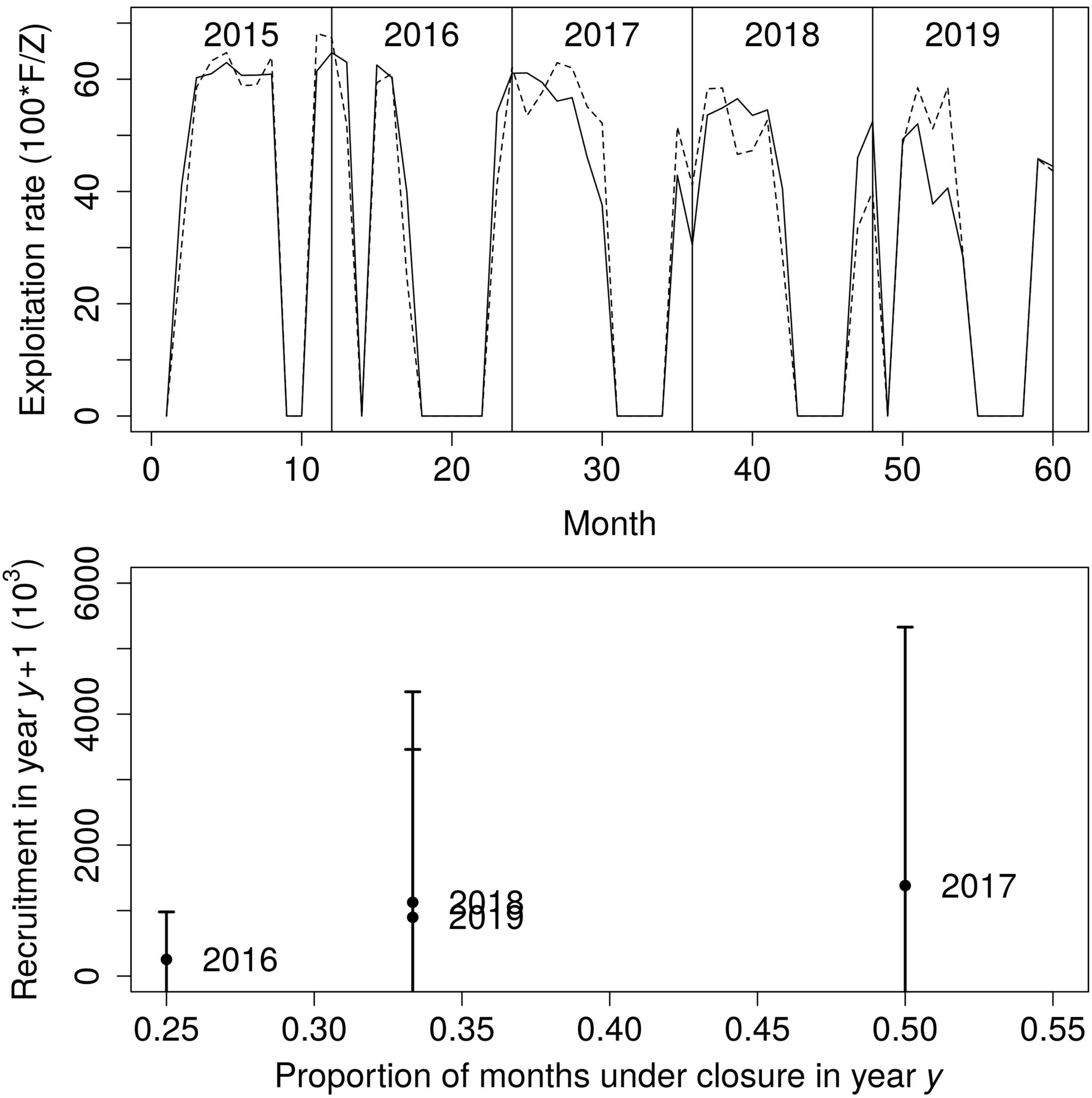


FIGURE 6 | Monthly instantaneous exploitation rate (top panel) and the relationship between months without fishing in a year and recruitment next year with estimated fishing mortality, total mortality, and recruitment from generalised depletion applied to the Mauritanian pink spiny lobster fishery.

DISCUSSION

The three methods found the stock overfished but they differed substantially in important aspects. The LBB method presented the stock in the worst condition. This method however assumes that recruitment is constant for all years in the time series of LFD. This is unlikely to be true considering the large catch spike of 2015, about three times higher than in any other year. Such a large spike in removals should have affected the spawning biomass. The depletion model does not make assumptions about recruitment, and it estimates a recruitment time series with a 55% coefficient of variation, the highest recruitment being five times the lowest recruitment and a trend of increasing recruitment from 2015 to 2019. Therefore, we consider that estimates from the LBB method are unreliable in this application.

The Catch-only MSY is a Bayesian model, so it is very important to present the independent knowledge about the stock (the history of the fishery) and derive from it the priors for

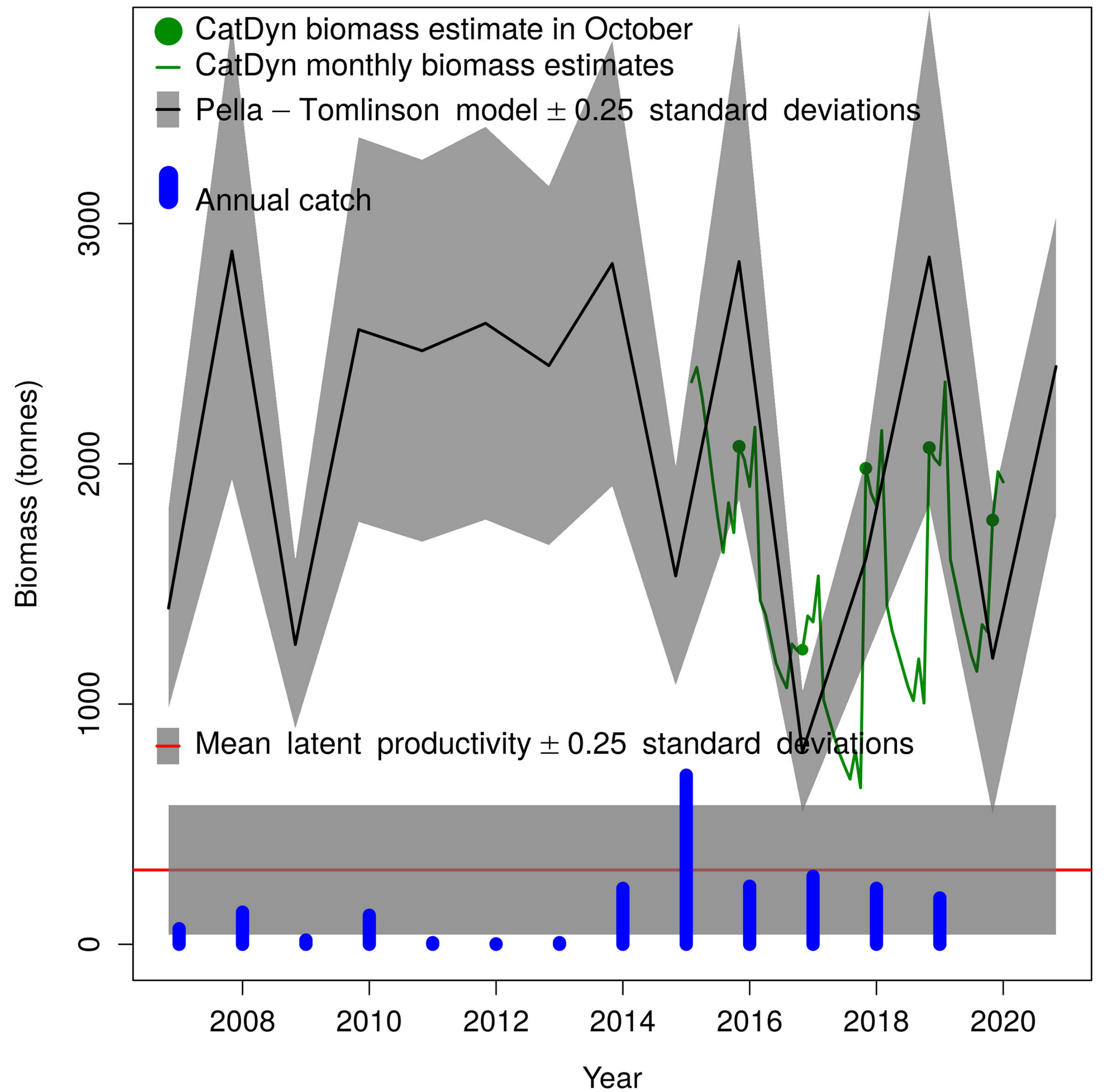


FIGURE 7 | Annual population dynamics of the pink spiny lobster stock in Mauritania according to the Pella-Tomlinson surplus production model. Note that CatDyn and Pella-Tomlinson biomass values are located in October of each year (10/12 fraction of a year) whole the catch bars are located in January.

relative biomass. In this case, that applies mostly to the start and intermediate biomass. The range of 0.9–1.0 for start biomass says the stock was practically unexploited in 2006. The range of 0.5–0.9 in 2015 indicates the start of the full fishery, probably already overexploiting the stock. The low biomass prior to 0.01–0.4 in 2019 is supported by the disappearance of larger lobsters and by the length-frequency analysis by LBB. The latter delivered the end biomass prior to CMSY.

The CMSY and the hierarchical CatDyn and Pella-Tomlinson fits resembled each other more in the diagnostics of stock status. Both methods found that catches of the last 4 years have been close to sustainable annual catches. They also produced close estimates of r (when the CMSY method assumed r between 1 and 1.5) and the sustainable annual harvest. The fact that MSY and latent productivity estimates were close is relevant because those estimates have direct management utility. The two

TABLE 2 | Maximum likelihood estimates of 11 parameters of the generalised depletion model with recruitment happening in October each year, fitted to catch and effort data of the pink spiny lobster fishery in Mauritania, in CatDyn R package.

Parameter	Estimates	Coefficient of variation (%)
Natural mortality (1/month)	0.0269	Not available
Initial abundance (10^3)	3,312	Not available
Recruitment 2015 (10^3)	481	Not available
Recruitment 2016 (10^3)	254	Not available
Recruitment 2017 (10^3)	1,382	Not available
Recruitment 2018 (10^3)	1,126	Not available
Recruitment 2019 (10^3)	897	Not available
Scaling (1/days)	5.543×10^{-6}	511.0
Effort response	0.5615	14.9
Abundance response	1.4380	29.5
Variance (10^6)	148	15.9

The likelihood function was the full normal and the optimization method was spg.

TABLE 3 | Maximum likelihood estimates of four free parameters of the Pella-Tomlinson surplus production model and derived estimate of mean latent productivity as a sustainable annual harvest rate.

Parameter	Estimate	Coefficient of Variation (%)
B_0 (tonnes)	1,399	118
K (tonnes)	2,540	126
r (1/yr)	1.370	160
p	3.62	93
Mean latent productivity (tonnes)	309	349

methods differed in other important respects. The CMSY method projected a still decreasing biomass and rising exploitation (F/F_{MSY}), while the hierarchical Pella-Tomlinson showed a stock experiencing stable biomass fluctuations with wide amplitude and slowly decreasing exploitation rate (F/Z). It should be noted that the CMSY has a tendency to overestimate fishing mortality and underestimate biomass when its results are tested against estimates from data-rich studies when depletion priors are not reliable (Bouch et al., 2020). Another aspect that resulted in similar results of these methods is statistical precision. Both CMSY and the hierarchical combination of CatDyn and Pella-Tomlinson yielded very imprecise estimates. On the one hand, the sustainable harvest rate from the CMSY method fell within a range of credibility intervals where the upper bound was nearly six times higher than the lower bound, considering all three assumptions for the range of r. The hierarchical combination of CatDyn and Pella-Tomlinson, on the other hand, yielded a sustainable harvest rate with a coefficient of variation close to 350%. These results confirm previous mythological studies with data-poor fisheries, which concluded that statistical precision of estimates will be a major shortcoming in the expansion of stock assessment techniques to data-poor fisheries (Maynou et al., 2021). One encouraging result though for the particular case studies in this work is that the CMSY method and the hierarchical combination of CatDyn and Pella-Tomlinson produced close estimates, albeit imprecise, of the sustainable harvest rate, 266 tonnes from the former and 309 tonnes from the latter. This coincidence notwithstanding, it appears that in general, the stock assessment of data-poor fisheries will require not just methods suited to fewer data but also, more efforts to collect data.

A biological reference point obtained for pelagic fish sets 40% as the maximum instantaneous exploitation rate (F/Z) that maintains spawning biomass at safe levels (Patterson, 1992). Generalised depletion models showed that the instantaneous exploitation rate has been decreasing since 2015 but this reduction is very gradual and slow, still well over Patterson's 40% empirical boundary. Since this biological reference point was developed for species that grow and reproduce rapidly, in just a few years, it is safe to assume that the bound is even lower for the long-lived pink spiny lobster stock. Thus, from the point of view of the instantaneous exploitation rate, the stock is most likely still overfished. The overfished status is also apparent in both, the dropping biomass presented by the CMSY method and the widely fluctuating biomass presented by the Pella-Tomlinson model. Therefore, in spite of the large statistical uncertainty in all estimates from CMSY and the hierarchical combination of CatDyn and Pella-Tomlinson, on account of the scarcity of data, it seems safe to conclude that the stock is overfished and there in need of a biomass rebuilding program.

Although the LBB method returned an apparently excessively pessimistic outlook for the status of the stock probably because it was affected by varying recruitment during the period of study, its estimate of the optimum size at first capture deserves consideration as a separate and potentially useful estimate. Regulations in Mauritania establish a minimum landing size of 83 mm of cephalothorax length, which is based on the smallest mature female observed. This is much lower than the estimated optimal size at first capture, which amounted to 140-mm cephalothorax length. Examination of the length-frequency data in **Figure 2** shows that establishing a 140 mm minimum landing size would leave most of the stock inaccessible to fishers, and it is probably also an overestimate of the true optimal entry size. Nevertheless, the large difference between the current regulation and the estimate of optimal entry size by the LBB method suggests that the current regulation could be too permissive. Rising entry size could also be considered along with other management measures that would seek to rebuild stock biomass. For instance, instead of the size of the smallest mature female, regulations may establish the female size at 50% maturity as the minimum landing size.

In 1958, the fishing effort was moderate, presumably around 1,800 fishing days per year. The total annual catch was then about 800 tonnes, giving a catch per day and per boat of almost 450 kg, more than enough to ensure the economic viability of the fishery. A development plan for the fishery was then set up in 1962, with the support of substantial international funding. The fishing effort was multiplied by seven (more than 12,000 boat days) and production reached 3,500 tonnes. In the following years (1963–1966) and following overexploitation of the stock, the catch-per-unit effort (CPUE), which had already been declining since 1959, was halved and then reduced to a quarter between 1967 and 1970 to reach 100 kg per boat per day, and total production fell to <200 tonnes. It was then necessary to wait about 10 years with a low fishing effort to allow the stock to recover and return to its original state. The quantities declared from 1968 to 1988 varied from 200 to 943 tonnes (in 1987). In 1988, the stock experienced its second overexploitation, and vessels targeting this species were converted to fish for other species. From 1992 to 2013, the reported catches were low or zero and originated from the by-catch of vessels targeting other species. Considering that the data from the last few years (2015–2019) and both the CMSY and the hierarchical method estimate around 300 tonnes as the sustainable harvest, it is apparent that the stock has become much less productive or that the exploitation has nearly always been either excessive or nil, a boom and bust dynamics. Indeed the CMSY showed a reduction by four of the biomass of the lobster over the last years. We hypothesise that it is possible to achieve a stable and sustainable fishery for the pink spiny lobster in Mauritania after rebuilding its biomass and then setting provisional catch limits that accord with the findings in this work while continuing the collection of catch, effort, and length-frequency data to reduce statistical uncertainty in stock assessment estimates.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

BM designed and planned the study. BM, MD, and RR-U drafted the manuscript. BM and RR-U analysed the data. BB, MB, and EB did field work. All authors contributed to the article and approved the submitted version.

ACKNOWLEDGMENTS

The authors thank their colleagues Seyidna Moussa, Ba Samba, and Sow Harouna for the data collection, Yeslem El Vally for the map, and Gianpaolo Coro, Nazli Dimerel, and Rainer Froese for assistance in improving this article. BM also thanks Ad Corten, Myriam Khalfallah, MLD Palomares, and two reviewers, who helped improve the writing of this study and thanks IMROP for supporting the data collection.

REFERENCES

Barrowman, N. J., and Myers, R. A. (2000). Still more spawner–recruitment curves: the hockey stick and its generalizations. *Cana. J. Fish. Aquat. Sci.* 57, 665–676. doi: 10.1139/f99-282

Beverton, R. J. H., and Holt, S. J. (1957). On the dynamics of exploited fish populations. *Fish. Investig.* 19, 1–533.

Bouch, P., Minto, C., and Reid, D. G. (2020). Comparative performance of data-poor CMSY and data-moderate SPiCT stock assessment methods when applied to data-rich, real-world stocks. *ICES J. Mar. Sci.* 78, 264–276. doi: 10.1093/icesjms/fsaa220

Briones-Fourzan, P., Lozano-Cabrera, E. M., and Arceo, P. (1997). "Biologia y ecologia de las langostas (crustacea:decapoda: Palinuridae)," in *Analisis y Diagnostico de los Recursos Pesqueros Criticos del Golfo de Mexico*, eds D. Flores-Harnandez, P. Sanchez-Gil, J. C. Seijo, F. Arreguin-Sandez (Universitad Autonoma de Campech. EPOMEX Serie Cientifica), 81–99

Costello, C., Ovando, D., Hilborn, R., Gaines, S. D., Deschenes, O., and Lester, S. E. (2012). Status and solutions for the worlds unassessed fisheries. *Science* 338, 517–520. doi: 10.1126/science.1223389

Dia, M., Meissa, B., Harouna, S. A., Alassane, B. S., Moustapha, B., Baye, B. C., et al. (2021). Pink lobster, *Palinurus mauritanicus* (Gruvel, 1911), from the Mauritanian Coast: elements of biology and exploitation. *Pakistan J. Zool.* 52, 1–11. doi: 10.17582/journal.pjz/20200722160708

Diop, M., and Kojemiakine, A. (1990). La langouste rose (*Panulirus mauritanicus*) de Mauritanie: Biologie, pêche et état de stock. *Bulletin scientifique du CNROP* 21, 15–21.

Fournier, D. A., Skaug, H. J., Ancheta, J., Ianelli, J., Magnusson, A., Maunder, M. N., et al. (2011): AD Model Builder: usingautomatic differentiation for statistical inference of highly parameterized complex nonlinearmodels. *Optim. Methods Softw.* 27, 233–249. doi: 10.1080/10556788.2011.597854

Froese, R., Demirel, N., Coro, G., Kleisner, K. M., and Winker, H. (2017). Estimating fisheries reference points from catch and resilience. *Fish Fish.* 18, 506–526. doi: 10.1111/faf.12190

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2018). A new approach for estimating stock status from length frequency data. *ICES J. Mar. Sci.* 76, 350–351 doi: 10.1093/icesjms/fsy139

Gislason, H. (2003). *The Effects of Fishing on Non-Target Species and Ecosystem Structure and Function*. Rome: Food & Agricultural Organization of the United Nations.

Goñi, R., and Latrouite, D. (2005). Biology, ecology and fisheries of *Palinurus spp*. species of European waters : *Palinurus elephas* (Fabricius, 1787) and *Palinurus mauritanicus* (Gruvel, 1911). *Cahiers de Biologie Marine* 46, 127–142.

Hoening, J. M. (2005). *Empirical Use of Longevity Data to Estimate Mortality Rates*. North Charleston, SC: SEDAR33-RD17. SEDAR, 8 p.

Maigret, J. (1978). *Contribution à l'étude des langoustes de la côte occidentale d'Afrique*. (Thèse de doctorat és Sciences Naturelles), Université d'Aix-Marseille, 264p.

Maynou, F., Demestre, M., Martín, P., and Sánchez, P. (2021). Application of a multi-annual generalized depletion model to the Mediterranean sandeel fishery in Catalonia. *Fish. Res.* 234:105814. doi: 10.1016/j.fishres.2020.105814

Meissa, B., and Gascuel, D. (2014). Overfishing of marine resources: some lessons from the assessment of demersal stocks off Mauritania. *ICES J. Mar. Sci.* 72, 414–427. doi: 10.1093/icesjms/fsu144

Mueter, F. J., and Megrey, B. A. (2006). Using multi-species surplus production models to estimate ecosystem-level maximum sustainable yields. *Fish. Res.* 81, 189–201. doi: 10.1016/j.fishres.2006.07.010

Patterson, K. (1992). Fisheries for small pelagic species: an empirical approach to management targets. *Rev. Fish Biol. Fish.* 2, 321–338. doi: 10.1007/BF00043521

Plummer, M. (2003). "JAGS: a program for analysis of Bayesian graphical models using Gibbs sampling," in *Proceedings of the 3rd International Workshop on Distributed Statistical Computing (DSC 2003), March 20-22, Vienna*, eds K. Hornik, F. Leisch, A. Zeileis (Vienna:Vienna Technical University), 20–22.

R Core Team (2020). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. Available online at: http://www.R-project.org/ (accessed September 23, 2021).

Reynolds, J. D., Dulvy, N. K., Goodwin, N. B., and Hutchings, J. A. (2005). Biology of extinction risk in marine fishes. *Proc. R. Soc. Lond. Series B* 272, 2337–2344. doi: 10.1098/rspb.2005.3281

Ricker, W. E. (1975). *Computation and Interpretation of Biological Statistics of Fish Populations*. Ottawa, Canada: Bulletin of the Fisheries Research Board of Canada 191, 382p.

Roa-Ureta, R. H. (2015). Stock assessment of the Spanish mackerel (Scomberomorus commerson) in Saudi waters of the Arabian Gulf with generalized depletion models under data-limited conditions. *Fish. Res.* 171, 68–77. doi: 10.1016/j.fishres.2014.08.014

Roa-Ureta, R. H. (2019). *CatDyn: Fishery Stock Assessment by Catch Dynamics Models*. Available online at: https://CRAN.R-project.org/package=CatDyn (accessed September 23, 2021).

Roa-Ureta, R. H., Molinet, C., Bahamonde, N., and Araya, P. (2015). Hierarchical statistical framework to combine generalized depletion models and biomass dynamic models in the stock assessment of the Chilean sea urchin (Loxechinus albus) fishery. *Fish. Res.* 171, 59–67. doi: 10.1016/j.fishres.2014.12.006

Roa-Ureta, R. H., Santos, M. N., and Leitão, F. (2019). Modelling long-term fisheries data to resolve the attraction versus production dilemma of artificial reefs. *Ecol. Model.* 407:108727. doi: 10.1016/j.ecolmodel.2019.108727

Schnute, J. T., and Kronlund, A. R. (1996). A management oriented approach to stock recruitement analysis. *Can. J. Fish. Aquat. Sci.* 53, 1281–1293. doi: 10.1139/f96-069

Sow, A., Zongo, B., and Kabre, T. J. (2019). Growth patterns and exploitation status of the spiny lobster species Palinurus mauritanicus (Gruvel 1911) in Mauritanian coasts. *Int. J. Agric. Policy Res.* 7, 17–31. doi: 10.15739/IJAPR.19.003

The World Bank (2012). *Hidden Harvest. The Global Contribution of Capture Fisheries. Report N0. 66469-GLB.* Available online at: https://openknowledge.worldbank.org/handle/10986/11873 (accessed June 11, 2021).

Thorson, J. T., Hicks, A. C., and Methot, R. D. (2015). Random effect estimation of time-varying factors in stock synthesis. *ICES J. Mar. Sci.* 72, 178–185. doi: 10.1093/icesjms/fst211

Von Bertalanffy, L. (1938). A quantitative theory of organic growth (inquiries on growth laws. ii). *Hum. Biol.* 10, 181–213.

Wang, Y., Wang, Y., Liu, S., Liang, C., Zhang, H., and Xian, W. (2020). Stock assessment using LBB method for eight fish species from the bohai and yellow seas. *Front. Mar. Sci.* 7:164. doi: 10.3389/fmars.2020.00164

Weinborn, J. A. (1977). Estudio prelimiar de la biología, ecología y semicultivo de los Palinúridos de Zihuatanejo, Gro., México, *Panulirus gracilis* Streets y Panulirus inflatus (Bouvier). *An. Centro Cienc. Mar. Limnol. Univ. Nal. Autón. México* 4, 27–78

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers in Marine Science

DATA REPORT
published: 04 November 2021
doi: 10.3389/fmars.2021.762610

From Past to Present: Construction of a Dataset Documenting Mother-of-Pearl Exports From a Pacific Island Nation, Papua New Guinea

Nittya S. M. Simard[1], Thane A. Militz[1], Jeff Kinch[2] and Paul C. Southgate[1]*

[1] Australian Centre for Pacific Islands Research and School of Science, Technology and Engineering, University of the Sunshine Coast, Sippy Downs, QLD, Australia, [2] National Fisheries College, National Fisheries Authority, Kavieng, Papua New Guinea

OPEN ACCESS

Edited by:
Simone Libralato,
Istituto Nazionale di Oceanografia e di Geofisica Sperimentale, Italy

Reviewed by:
Tomaso Fortibuoni,
Istituto Superiore per la Protezione e la Ricerca Ambientale (ISPRA), Italy
Melita Peharda,
Institute of Oceanography and Fisheries (IZOR), Croatia
Poul Holm,
Trinity College Dublin, Ireland

***Correspondence:**
Nittya S. M. Simard
nittya.simard@research.usc.edu.au

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: 22 August 2021
Accepted: 19 October 2021
Published: 04 November 2021

Citation:
Simard NSM, Militz TA, Kinch J and Southgate PC (2021) From Past to Present: Construction of a Dataset Documenting Mother-of-Pearl Exports From a Pacific Island Nation, Papua New Guinea. Front. Mar. Sci. 8:762610. doi: 10.3389/fmars.2021.762610

Keywords: historical data, fishery, time-series, pearl oyster, greensnail, trochus

INTRODUCTION

Inter-generational loss of information relating to marine resource exploitation leads to shifting baselines (Pauly, 1995; Pinnegar and Engelhard, 2007), which have direct consequences for fisheries management and livelihoods opportunities. Historical data provide a means of regaining that information (Jackson et al., 2011; Cardinale et al., 2015; Fortibuoni et al., 2017) and are increasingly incorporated into assessments of change (Lotze and Milewski, 2004; Eddy et al., 2010; Gianelli and Defeo, 2017). Through improved knowledge of past environmental states and resource use dynamics, there is demonstrable evidence that historical data brings value to modern marine policy and management in both national and regional contexts (Jackson et al., 2011; Engelhard et al., 2016; Fortibuoni et al., 2017).

Despite this, historical data are not commonly incorporated into such frameworks for several reasons. Most notably, historical data are difficult to collect. Records may exist in a variety of languages, accessible only as physical documents, widely dispersed among archives and institutions, require special permissions to access, or occur in obfuscating formats (Lotze and Milewski, 2004; Rose et al., 2009; McClenachan et al., 2012). Furthermore, the challenge of standardising unfamiliar data, such as non-metric weights and pre-decimal currencies, to enable interpretation in modern contexts, presents a barrier to their use (Lotze and Milewski, 2004; Bainbridge and Hulme, 2014; Tesfamichael et al., 2014). Funding barriers also exist, which hinder government agencies in addressing these challenges (McClenachan et al., 2012).

The inherent challenges of accessing and analysing historical data are particularly germane for agencies concerned with fisheries management in the Pacific region (Gillett and Tauati, 2018). Historical data of relevance to fisheries were rarely published or disseminated and, where extant, records are less accessible from within the region than from outside (Flores, 1984; Blanchet, 1990). Lack of coherent information policies (SPC, 1988; Blanchet, 1990) coupled with poor conservation of public records (Bell, 2003; Rose et al., 2009) has generated an abundance of isolated reports which are now only available from repositories of formal colonial authorities and international agencies. Compiling existing information into a usable, inter-operable data format, supporting multi-disciplinary use, has long been a regional priority, particularly for fisheries supporting livelihoods (SPC, 1988; Blanchet, 1990; Halford et al., 2021).

For a substantial part of the Pacific region, livelihoods are partly or wholly dependent on fishing for food security and income generation (Dalzell et al., 1996; Gillett and Tauati, 2018; Andrew et al., 2019). While artisanal fishing for subsistence has occurred for millennia (Swadling, 1976, 1977; Szabó and Amesbury, 2011), escalation of exploitation for both subsistence and export markets has occurred in the last several decades or centuries (Dalzell et al., 1996; Gillett and Lightfoot, 2001). Since the introduction of colonial capitalist economies to the region (ca. 1800s) (Cariño and Monteforte, 2009), export-driven mother-of-pearl (MoP) fisheries, which target pearl oysters (*Pinctada* spp.), greensnail (*Turbo marmoratus*), and trochus (*Rochia nilotica*) for their nacreous shells, have made and continue to make important contributions to household earnings (Hawes et al., 2011; Purdy et al., 2017; Vieira et al., 2017; Gillett et al., 2020; Purcell et al., 2021). With past exploitation inevitably influencing the status of present-day populations of these commodities (Berzunza-Sanchez et al., 2013), resulting in local depletion in some cases (Chesher, 1980; Kelso, 1996; Kile, 2000; Pakoa et al., 2014), there is scope for historical data to provide valuable insight into the scale, nature, and timing of human influences on MoP fisheries.

To support the use of historical data by agencies concerned with managing MoP fisheries, we present a quantitative, standardised, and quality-validated dataset covering over 130 years (1888–2019) of MoP exports from a key producer in the Pacific region; Papua New Guinea (PNG). Both the size and economic importance of MoP fisheries in PNG (Purdy et al., 2017; Vieira et al., 2017; Gillett et al., 2020) have motivated the collaborative effort presented here, which aims to raise awareness and expand access to existing historical information of consequence to national and regional marine policy and management (Anon, 2017; SPC, 2019). Specifically, weight, value, and value tonne^{-1} of MoP exports from PNG are presented as time-series from the onset of commercial fishing in 1888 to present (2019).

METHODS

Data Collection

Data were collected from two sources: (1) physical records and (2) the electronic data management system maintained by PNG National Fisheries Authority. A complete list of physical records from which data were collected appears in the Record Availability section.

Data pertaining to MoP exports were commonly reported as part of annual trade summaries representing a 12-month period. In 1903 and 1978, however, trade summaries represented a 21 and 16-month period, respectively, as a result of fiscal to calendar year transitions in reporting. For these years, data were discounted to a 12-month period through multiplication with the appropriate fraction (e.g., $^{12}/_{21}$ or $^{12}/_{16}$). In cases where data were reported monthly (e.g., government gazettes) or quarterly (e.g., statistical bulletins), data were summed to derive an annual datum for the corresponding reporting year. Similarly, where data were reported separately for past administrative divisions of PNG (colonial administrations of British New Guinea/Territory of Papua and German New Guinea/Territory of New Guinea), data were summed to derive an annual datum for the whole nation. Data pertaining to both weight and value of MoP exports were collected, when available. Where records contained both weight and value data, value tonne^{-1} was calculated.

The most definitive datum was chosen where multiple records reported data for a given reporting year with varying levels of precision (e.g., 2,797 cwt in one record was truncated to 140 tonnes in another). If data variability between records exceeded what could reasonably be attributed to truncation (evaluated using floor and ceiling functions), the mean $\pm$ 95% confidence interval (CI) of available data was calculated to represent the annual datum for the corresponding reporting year.

Taxonomic resolution of data was maintained where possible. Records commonly reported exports for pearl oysters, greensnail, and trochus separately, although some records reported the export of unspecified MoP in addition to, or in place of, the taxa-specific categories. The sum of all categories against which MoP exports were reported for a given reporting year was taken to represent the total MoP exported for that year.

Disaggregation of MoP exports based on processing (i.e., unprocessed shell or buttons) or origin (i.e., aquaculture or fisheries) was not possible as record specificity precluded such differentiation.

Interpolation

For some reporting years, data were unavailable for part or the entirety of PNG. Data pertaining to the value of MoP exports were available for 129 years (97.7% coverage) of the 132-year period covered by our dataset. Omissions were due to a loss of records associated with military occupations during WWI (1914) and WWII (1942 and 1946). Missing data were derived through linear interpolation, given by the equation

$$E = E_{Ya} + \frac{(E_{Yb} - E_{Ya}) \times (Y - Y_a)}{Y_b - Y_a} \tag{1}$$

where the value of exports (E) for a given year (Y) is linearly proportional to the nearest preceding (Y_a) and proceeding year (Y_b) for which the value of exports was known.

Data pertaining to the weight of MoP exports was available for 115 years (87.1% coverage) of the 132-year period. The difference in coverage between value and weight data was the result of annual trade summaries irregularly reporting the weight of MoP exports between 1900 and 1922. Where omitted, weight was calculated by dividing the value of exports for that year (a known value) by an estimate of their value tonne^{-1}, derived through linear interpolation (Equation 1). This approach, rather than interpolating weight directly, was chosen because the year-on-year variation in the value tonne^{-1} of exports was substantially less than the variation in weight (**Figure 1**), making value tonne^{-1} the more appropriate metric to interpolate.

Standardisation

The system of currency operating within PNG changed frequently (Mira, 1986), with values recorded in pound sterling

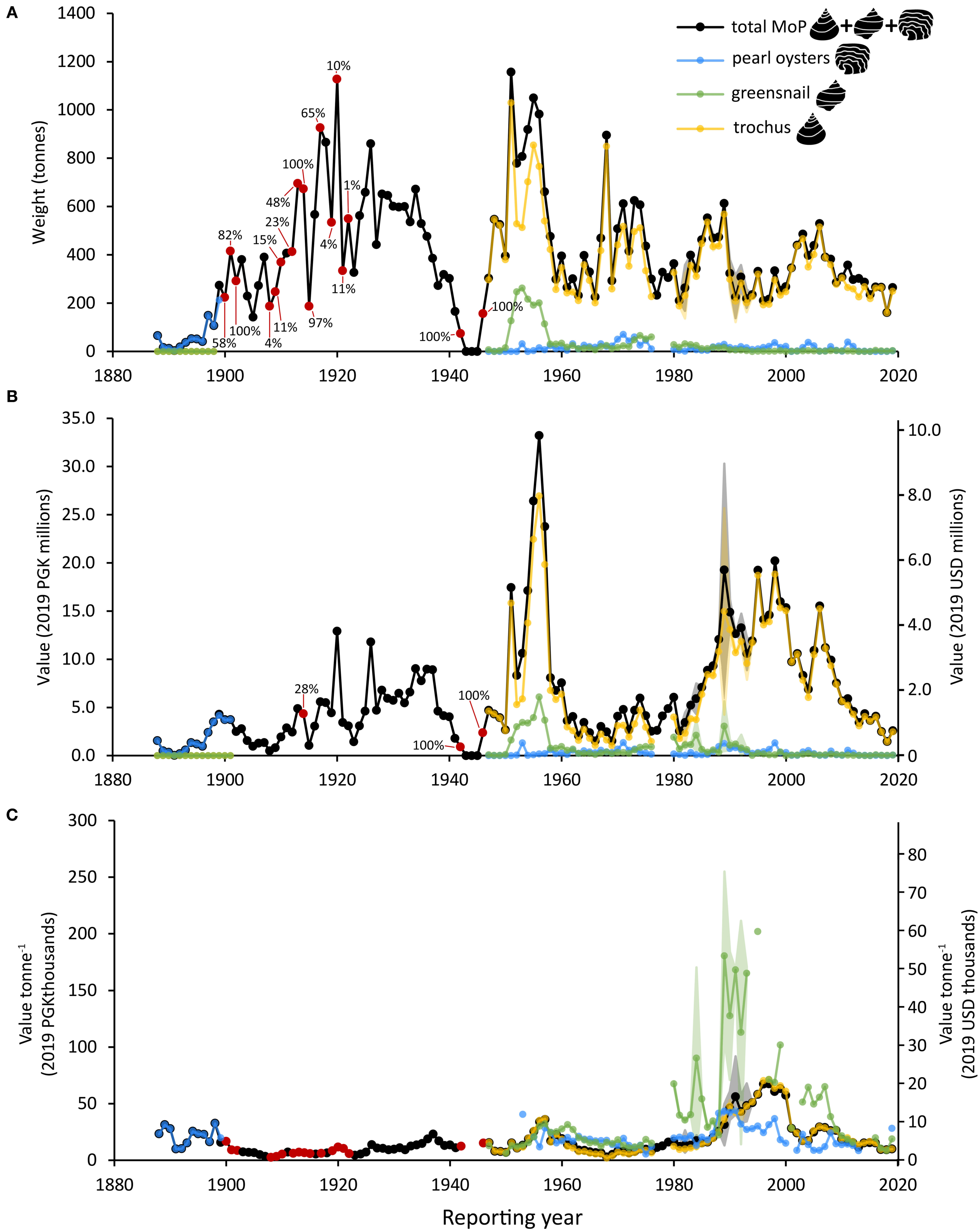


FIGURE 1 | Visualisation of the annual **(A)** weight, **(B)** value, and **(C)** value tonne^{-1} of mother-of-pearl (MoP) exports from Papua New Guinea between 1888 and 2019. Total MoP exports are differentiated as pearl oysters (*Pinctada* spp.), greensnail (*Turbo marmoratus*), and trochus (*Rochia nilotica*) for reporting years with a reasonable degree of accuracy (i.e., unspecified MoP accounted for <10% of exports). Shading identifies the 95% confidence interval. Data partly or entirely derived through interpolation are marked in red and the relative contribution of interpolated data to the weight and value of total MoP exports indicated as a percentage. Data can be accessed as described in the Dataset section.

(1888–1909), goldmark (1898–1913), Australian pound (1910–1966), Australian dollar (1966–1975), and kina (1975–2019). As these currencies were not directly comparable, values were converted and denominated in terms of a base currency. We adopted the current legal tender of PNG, kina (ISO 4217: PGK), as the base currency following precedent of prior studies (Glucksman and Lindholm, 1982; Wright, 1986).

Values recorded in demonetised currencies were expressed as PGK based on appropriate conversion rates. The Australian pound replaced the pound sterling at par, while the Australian pound replaced the goldmark at a conversion of 1 to 20.50 (Mira, 1986). Subsequently, the Australian dollar replaced the Australian pound at a conversion of 2 to 1, and then the PGK replaced the Australian dollar at par (Mira, 1986).

To standardise values across time, nominal values were adjusted for inflation using price indices representative of temporal changes in consumer prices in the local economy. Specifically, we used the Retail Price Index Numbers, Long-Term Linked Series (1888–1962) published by the Australian Bureau of Statistics (Castles, 1994), the Retail Price Index (1962–1971) published by the Australian Department of External Territories (Australia, 1972), and the Consumer Price Index (1971–2019) published by World Bank (2021) to adjust nominal values to 2019 PGK. Real values are reported as 2019 PGK alongside the 2019 United States dollar (ISO 4217: USD) equivalent, based on an exchange rate of 1 USD to 3.3875 PGK.

Weight was standardised as metric tonne, converting weights recorded in the imperial system of units as hundredweight (0.0508 tonne) or long ton (1.01605 tonne).

Dataset

Centralised reporting of MoP exports from PNG began in 1888, coinciding with the arrival of commercial pearling fleets (British New Guinea, 1889; Moore, 2000). Our dataset tabulates the standardised weight (tonnes), value (2019 PGK / USD) and value tonne^{-1} (2019 PGK/USD) of MoP exports annually from this point until 2019, on the basis of the reporting year (**Figure 1**). The relative contribution of interpolated data to a given reporting year is denoted as a percentage to indicate the extent data approximates actual exports. Similarly, the relative contribution of unspecified MoP exports to a given reporting year is denoted as a percentage to indicate the extent data for taxa-specific (i.e., pearl oysters, greensnail, trochus) categories may reflect actual exports.

The dataset is accessible through an unrestricted repository, USC Research Bank [DOI 10.25907/00080], and Research Data Australia [https://researchdata.edu.au/mother-of-pearl-1888-2019/1734519]. The source data underpinning the constructed dataset can also be retrieved, redacted as an XLS file, using the same accession link.

QUALITY-VALIDATION OF THE DATASET

In working with historical data, two aspects of selection bias must be addressed: (1) the degree to which collected data represent the wider record collection from which records were drawn; (2) the degree to which the collected data reflect actual history (Inwood and Maxwell-Stewart, 2020). Independently constructed time-series for MoP fisheries of PNG and neighbouring Pacific nations allows quantitative assessment of such biases, permitting quality-validation of our dataset.

Four-decades ago, Glucksman and Lindholm (1982) constructed time-series for MoP exports from PNG between 1948 and 1976. Their data, from undisclosed sources, were very highly correlated (Pearson's distances: $d_{cor} \leq 0.05$, $r > 0.99$, and $p < 0.001$) with our dataset for the period of overlap, showing near-identical trends and remarkably similar magnitudes (**Supplementary Figure 1**). Agreement between these two successive efforts demonstrates replicability and implies fairly homogenous data among records for this period.

In contrast, heterogeneous data among records for MoP exports from PNG between 1980 and 1993 is a known problem (Kailola, 1995). By presenting the mean $\pm$ 95% CI of collected data for this period, our dataset accurately reflects the variability among accessible records, thus, managing potential bias from record selection.

Comparison with the FAO Global Production database shows our dataset largely agrees with FAO's "best scientific estimates" (Garibaldi, 2012) of trochus and pearl oyster production for PNG (**Figure 2**). The reported weight of trochus production by FAO for periods 1953 to 1968 and 1985 to 2018 were highly correlated (Pearson's distance: $d_{cor}0.55$, $r = 0.85$, and $p < 0.001$) with the weight of trochus exports presented in our dataset. In comparison, the weight of pearl oyster production is reported by FAO for only a single period (1988–2018) and had a moderate correlation (Pearson's distance: d_{cor} 0.85, $r = 0.64$, and $p < 0.001$) with the weight of pearl oyster exports presented in our dataset. While disagreement with FAO estimates for missing data is understandable, the substantially greater weight of pearl oyster exports in 2011 and 2012 (**Figure 2B**) likely results from pearl oyster exports of aquaculture origin which should be excluded from the FAO data (Garibaldi, 2012).

To gauge whether our dataset accurately reflects the trends of MoP fisheries in the Pacific region, comparison was made to the Australian trochus fishery, which operated in the Great Barrier Reef region (Nash, 1985). The weight and value tonne^{-1} of trochus production from the Australian fishery was reported, almost continuously, from 1912 to 1962; these data show similar (Pearson's distances: $d_{cor} \leq 1.05$, $r \geq 0.45$, and $p \leq 0.002$) trends to those observed for MoP exports from PNG (**Supplementary Figure 2**).

The series of comparisons presented here, while not exhaustive, validate that our dataset provides a reliable indication of temporal change in MoP exports from PNG over many decades, consistent with past studies, international agency estimates, and regional trends in production and value tonne^{-1}. Since our dataset provides unprecedented coverage for MoP fisheries in the Pacific region, it is unreasonable to expect validation of each datum. By making the dataset freely available, however, we encourage further validation of our dataset as more information on MoP fisheries in the Pacific region becomes available.

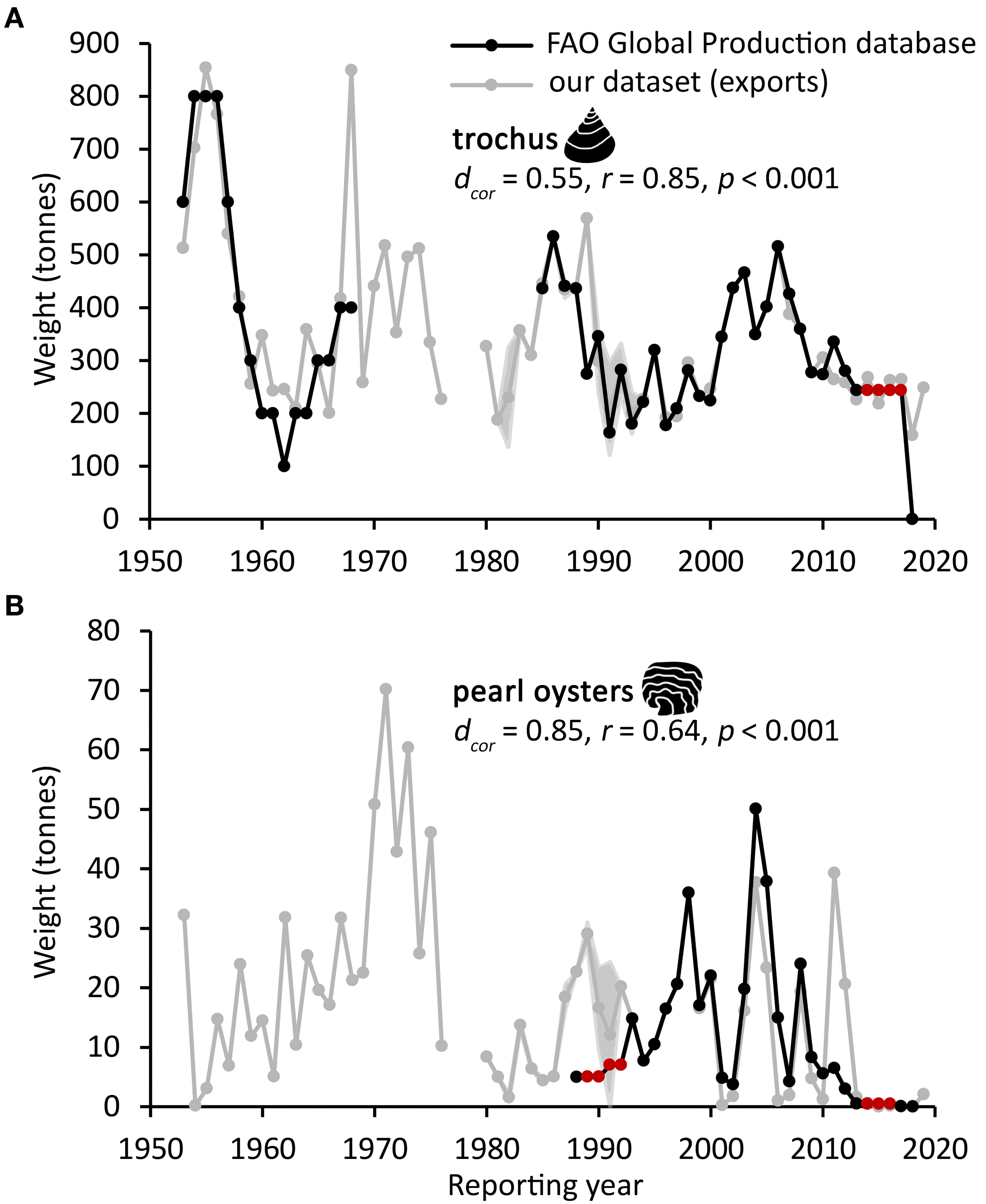


FIGURE 2 | Annual weight of **(A)** trochus (*Rochia nilotica*) and **(B)** pearl oysters (*Pinctada* spp.) production, based on data from FAO Global Production database (black lines), and exports, based on data from our dataset (grey lines), for Papua New Guinea since 1953. FAO estimates for missing data (red points) and the 95% confidence interval of exports (shading) are shown.

CONSIDERATIONS FOR INTERPRETATIONS AND USE OF THE DATASET

Effective management of commercial fisheries is of salience to the future of coastal communities in the Pacific region, where a substantial part of the population is partly or wholly dependent on fishing for income generation (Dalzell et al., 1996; Sulu et al., 2015). With extensive reef systems and abundant MoP resources, PNG is regarded as a main regional exporter of MoP (Gillett et al., 2020), where the harvest and sale of MoP is estimated to support 20–30% of the coastal population (Purdy et al., 2017), accounting for as much as 75% of income in some areas (Vieira et al., 2017). Expanding coastal human population and increasing pressure on marine resources emphasise the need for accessible fisheries information for analysis and to support effective fisheries management in the region (SPC, 2019). Since little attention has been given to MoP fisheries in the last 25 years (Gillett et al., 2020) and historical information is important in guiding appropriate policy (Jackson et al., 2011; Engelhard et al., 2016; Fortibuoni et al., 2017), our dataset provides a basis for raised awareness and improved management of MoP fisheries within both national (Anon, 2017) and regional contexts (SPC, 2019; Gillett et al., 2020). Our dataset presents and facilitates access to MoP trade information, which can be used to estimate and analyse fisheries production, bioeconomic trends, shocks, and their potential drivers (Gephart et al., 2017; Gianelli and Defeo, 2017). The dataset presented here could further be evaluated against other economic and social variables as well as ecological information (Barausse et al., 2011; Papetti et al., 2013; Haimovici and Cardoso, 2016; Gianelli and Defeo, 2017) to inform development of broader marine policy and management strategies. Considerations for the use and interpretation of our dataset in addressing the above opportunities are outlined below.

A concern in the use of historical data for monitoring fisheries is the existence of a latent bias arising from improvements in fisheries reporting systems and regulatory systems. This "presentist bias" (Zeller and Pauly, 2018) has potentially serious consequences when assessing the status of fisheries or in interpreting resource use dynamics. In the case of MoP exports from PNG, procedures for collection of export data have remained largely unchanged since their inception, relying on export declarations validated through visual inspection. Prior to 1899, however, we acknowledge that presentist bias led to underestimation of weight and value of MoP exports from PNG. This is partly because records contain minimal economic data before 1899, for German New Guinea, when a private company functioned as both the administrative authority and an economic competitor. With this conflict of interest, an accurate disclosure of trade information from economic rivals could not be expected and, understandably, such information is scant (Sack and Clark, 1979). Additionally, in British New Guinea, it was not until 1894 that inspectors were instated and ports of export constituted for MoP fisheries (British New Guinea, 1896). Prior to this, "considerable yields of pearl-oyster" appropriated from PNG went unreported, but it is impossible to fix the amount (British New Guinea, 1888, 1892). Caution is therefore advised when drawing conclusions from our dataset for MoP exports during the 19th century, because available data provides a known underestimation.

For most nations in the Pacific region, data on MoP fisheries production is virtually non-existent because artisanal fishing activities of coastal communities are generally not monitored by government agencies (Gillett and Lightfoot, 2001; Govan, 2013; Zeller et al., 2014). In lieu of definitive production data, export data are commonly used by management agencies to estimate production of MoP fisheries (e.g., Lasi, 2010; Gillett et al., 2020). Our analysis (**Quality-validation of the dataset** section) confirmed that MoP exports from PNG were reflective of national (**Figure 2**) and regional (**Supplementary Figure 2**) production trends validating such application, with the following considerations for unreported harvest. First, it must be recognised that pearl oysters, greensnail, and trochus are also harvested for subsistence (as a protein source) (Glucksman and Lindholm, 1982) and, to a small extent, for the domestic shell trade (Simard et al., 2019). Second, the proportion of MoP production ultimately exported is further reduced by shells rejected as part of quality control (i.e., undersized, oversized, or damaged shell) (Kelso, 1996). Third, export tariffs have incentivised commercial operators to under-declare export volumes (SPC, 1997; Gillett et al., 2020). Fourth, exports do not account for illegal, unreported, and unregulated (IUU) harvests by foreign fishing vessels, with poaching of MoP from territorial waters a known issue for much of the period covered by our dataset (Bach, 1955; Christensen, 2016). The extent to which these four factors contributed to a disparity between production and export of MoP in PNG is not precisely known; unreported harvest between 1980 and 1995 was approximated at 25–30% of the exported volume (ICECON, 1997; SPC, 1997) and a correction of 25% is currently adopted at a regional level when adjusting export data to estimate production (Gillett et al., 2020). Adoption of a similar correction when using our dataset to estimate MoP production should be given consideration until more precise estimates of error are established by clear scientific evidence (Garcia, 1994).

In addition to unreported harvest, the potential contribution of aquaculture to exports has implications for estimating fisheries production of pearl oysters. Neither greensnail nor trochus were ever cultured commercially in PNG (Kailola, 1995; Gillett et al., 2020), but pearl oysters were. During the 1960–70s, and more recently since 1997, pearl oysters were cultured commercially to support pearl production in PNG (George, 1978; IPA, 2021). Since records failed to identify the origin of pearl oyster exports, aquaculture could lead to an overestimation of fisheries production. The small volume of pearl oyster exports, however, suggests that aquaculture contributed, at most, only 4.9% of total MoP exports by weight during these periods (**Figure 1**), although actual contribution is likely less since the artisanal fishery was active and contributing to pearl oyster exports concurrently (Glucksman and Lindholm, 1982).

A limited aquaculture contribution would imply that export data provides a good indication of the minimal MoP fisheries production which has occurred in PNG, for reasons discussed above. Such information provides a much-needed overview in the case of data-poor fisheries (Govan, 2013), and several studies have demonstrated that export data provide an accurate understanding of relative temporal change in commercial fisheries production (e.g., Clarke, 2004; Schwerdtner Máñez and Ferse, 2010; Gianelli and Defeo, 2017; Plagányi et al., 2017). The significant correlation between Australian trochus production and MoP exports from PNG presented above certainly indicates that this holds true for MoP fisheries, as suggested elsewhere (ICECON, 1997; Gillett et al., 2020). It would be remiss, however, to not offer a few words of caution when relating export trends to production.

Trends in MoP exports, such as those shown in **Figure 1A**, can be difficult to interpret as they may reflect both biological and economic factors (Nash, 1985; Foale, 2008). For example, reduced export volume in a given year can reflect poor market price (SPC, 1960), rather than a depletion of stocks. Atypical of most commercial fisheries commodities, MoP is an inert product having a long-lasting (i.e., years) shelf-life (Glucksman and Lindholm, 1982; Foale, 2008). This permits stockpiling of MoP for liquidation when more favourable market prices arise and, thus, exports for any given year may reflect both current and past production. To better enable the users of our dataset to address potential economic factors influencing exports, the value tonne^{-1} of MoP exports was calculated and included in our dataset. Whilst in-country processing of MoP buttons would invariably impact the value tonne^{-1} of MoP exports, this is a relatively recent development, which occurred irregularly between 1992 and 2014 (ICECON, 1997; Gillett et al., 2020).

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: USC Research Bank [DOI 10.25907/00080] and Research Data Australia [https://researchdata.edu.au/mother-of-pearl-1888-2019/1734519].

Records catalogued by the National Library of Australia had the following accession numbers (Bib ID):

1. 395064: *New Guinea gazette*.
2. 1053953: *Annual report on British New Guinea*. Digitised and available from: https://nla.gov.au/nla.obj-82611572
3. 1282521: *Report to the Council of the League of Nations on the administration of the Territory of New Guinea*. Digitised and available from: https://nla.gov.au/nla.obj-324059207
4. 1293821: *Papua: annual report for the year ending 30th June*. Digitised and available from: https://nla.gov.au/nla.obj-268724687
5. 1293848: *Territory of Papua: Annual report for the period*. Digitised and available from: https://nla.gov.au/nla.obj-2060262652
6. 1293865: *Annual report of the Territory of Papua for the period....* Digitised and available from: https://nla.gov.au/nla.obj-2164593963
7. 1300182: *Territory of Papua: Annual report for the year*. Digitised and available from: https://nla.gov.au/nla.obj-1905139508
8. 1329016: *Report to the General Assembly of the United Nations on the administration of the Territory of New Guinea*. Digitised and available from: https://nla.gov.au/nla.obj-2059853295
9. 1758906: *Government gazette: British administration of German New Guinea*.
10. 2790423: *International trade*.
11. 2804807: *Report to the League of Nations on the administration of the Territory of New Guinea*. Digitised and available from: https://nla.gov.au/nla.obj-2590388577
12. 2804816: *Report to the Council of the League of Nations on the administration of the Territory of New Guinea*. Digitised and available from: https://nla.gov.au/nla.obj-228879604
13. 2816137: *Territory of Papua: Annual report for the period*. Digitised and available from: https://nla.gov.au/nla.obj-1905803422
14. 2851375: *Administration of Papua New Guinea*. Digitised and available from: https://nla.gov.au/nla.obj-1297995152
15. 2851382: *Administration of the Territory of New Guinea*. Digitised and available from: https://nla.gov.au/nla.obj-2765327678
16. 2851390: *Report to the General Assembly of the United Nations on the administration of the Territory of New Guinea*. Digitised and available from: https://nla.gov.au/nla.obj-1904874562
17. 2925185: *Amtsblatt für das Schutzgebiet Deutsch-Neuguinea*. Digitised and available from: https://nla.gov.au/nla.obj-48330386

Records catalogued by the Pacific Community (SPC) Library had the following accession numbers (Bib ID):

1. 18399: SPC (1997). *Workshop on trochus resource assessment, management and development report and selected papers*. Integrated Coastal Fisheries Management Project Technical Document No. 13. Noumea, New Caledonia: South Pacific Commission (SPC). Digitised and available from: http://opac.spc.int/cgi-bin/koha/opac-detail.pl?biblionumber=18399
2. 46314: Kailola, P. J. (1995). *Fisheries Resources Profiles: Papua New Guinea*. FFA Report No. 95/45. Honiara, Solomon Islands: Forum Fisheries Agency.
3. 53907: Wright, A. (1986). *An analysis of exports of marine produce from Papua New Guinea for the period 1980 to May 1986, with emphasis on produce collected by small-scale fishermen*. Fisheries Research Laboratory, Department of Primary Industry. Kavieng, Papua New Guinea: Department of Primary Industry (DPI).

Records catalogued by the Staats- und Universitätsbibliothek Bremen had the following accession numbers (Uniform Resource Locator):

1. urn:nbn:de:gbv:46:1-14372: *Jahresbericht über die Entwickelung der Schutzgebiete in Afrika und der Südsee:*

im Jahre (1899–1907). Digitised and available from: https://nbn-resolving.de/urn:nbn:de:gbv:46:1-14372.

AUTHOR CONTRIBUTIONS

NS, TM, and JK collected relevant records. NS extracted data from records and constructed the dataset. TM and JK verified the dataset. NS and TM performed the statistical analysis for validation. NS wrote the manuscript with support from TM, JK, and PS. All authors contributed to conception and design of the project, manuscript revision, read, and approved the submitted version.

FUNDING

This work was supported by the Australian Centre for International Agricultural Research (ACIAR) and the National Fisheries Authority (NFA) within ACIAR Projects FIS/2014/060 and FIS/2019/122 led by PCS at the University of the Sunshine Coast.

ACKNOWLEDGMENTS

We thankfully acknowledge: Margaret Kenna, for facilitating access to collections of the National Library of Australia and National Archives of Australia; Samuela Nakalevu (Pacific Community), for facilitating access to collections of the SPC library; John Kasu, Leban Gisawa, and Nerrie Leba (National Fisheries Authority), for provision of records from the National Fisheries Authority Electronic Data Management System; Daniel Mangano, Debra Gilmore, and Rebecca Cooke (University of the Sunshine Coast), for fulfilment of interlibrary loan requests and for coordinating research collections; the staff and volunteers of numerous institutions in Australia and abroad for assisting in the identification and digitisation of the published works utilised in construction of our dataset. Three Reviewers are also thanked for their thoughtful and constructive inputs to this manuscript and the corresponding dataset.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2021.762610/full#supplementary-material

Supplementary Figure 1 | Annual weight and value of **(A,B)** total mother-of-pearl (MoP) exports for Papua New Guinea differentiated as **(C,D)** trochus (*Rochia nilotica*), **(E,F)** pearl oysters (*Pinctada* spp.), and **(G,H)** greensnail (*Turbo marmoratus*), comparing data from Glucksman and Lindholm (1982) (black lines) with data from our dataset (grey lines).

Supplementary Figure 2 | Annual **(A)** weight and **(B)** value tonne^{-1} of trochus (*Rochia nilotica*) production from the Australian mother-of-pearl (MoP) fishery operating in the Great Barrier Reef region between 1912 and 1962 (Nash, 1985) compared with total MoP exports for Papua New Guinea.

REFERENCES

Andrew, N. L., Bright, P., de la Rua, L., Teoh, S. J., and Vickers, M. (2019). Coastal proximity of populations in 22 Pacific Island Countries and Territories. *PLoS One* 14:e0223249. doi: 10.1371/journal.pone.0223249

Anon (2017). *A Roadmap for Coastal Fisheries and Marine Aquaculture for Papua New Guinea: 2017-2026*. National Fisheries Authority. Papua New Guinea: Government of Papua New Guinea.

Australia (1972). *Papua New Guinea report for 1970-1971. No. 61.* Canberra, ACT: Government printer.

Bach, J. P. S. (1955). *The Pearling Industry of Australia: An Account of Its Social and Economic Development*. Newcastle, NSW: Commonwealth of Australia.

Bainbridge, I., and Hulme, P. (2014). PRACTITIONER'S PERSPECTIVE: how can ecologists make conservation policy more evidence based? Ideas and examples from a devolved perspective. *J. Appl. Ecol.* 51, 1153–1158. doi: 10.1111/1365-2664.12294

Barausse, A., Michieli, A., Riginella, E., Palmeri, L., and Mazzoldi, C. (2011). Long-term changes in community composition and life-history traits in a highly exploited basin (northern Adriatic Sea): the role of environment and anthropogenic pressures. *J Fish Biol* 79, 1453–1486. doi: 10.1111/j.1095-8649.2011.03139.x

Bell, J. (2003). Kerema Provincial archives burnt. *Pac. Manuscr. Bur. Newsl.* 5, 3–4. Available online at: https://asiapacific.anu.edu.au/pambu/pambu/Pambu16%2003Jun.pdf

Berzunza-Sanchez, M. M., Cabrera, M., d,. C. G., and Pandolfi, J. M. (2013). Historical patterns of resource exploitation and the status of Papua New Guinea coral reefs. *Pac. Sci.* 67, 425–440. doi: 10.2984/67.3.9

Blanchet, G. (1990). *Research and Development of Small-Scale Fisheries in the South Pacific*. National Centre for Development Studies, The Australian National University, Islands/Australia Working Paper No. 90/11, Socpac Printery.

British New Guinea (1888). *British New Guinea: Report for the year 1887*. No. 32. Victoria: Government Printer.

British New Guinea (1889). *British New Guinea: Report for the year 1888*. No. 31. Victoria: Government Printer.

British New Guinea (1892). *Annual Report on British New Guinea From 1st July, 1890 to 30th June, 1891 With Appendices*. Brisbane, QLD: Government Printer.

British New Guinea (1896). *Annual Report on British New Guinea from 1st July, 1894 to 30th June ,1895 With Appendices*. Brisbane, QLD: Government Printer.

Cardinale, M., Bartolino, V., Svedäng, H., Sundelöf, A., Poulsen, R. T., and Casini, M. (2015). A centurial development of the North Sea fish megafauna as reflected by the historical Swedish longlining fisheries. *Fish Fish.* 16, 522–533. doi: 10.1111/faf.12074

Cariño, M., and Monteforte, M. (2009). An environmental history of nacre and pearls: fisheries, cultivation and commerce. *Global Environ.* 2, 48–71. doi: 10.3197/ge.2009.020303

Castles, I. (1994). *Year book Australia 1995,* Vol. 77. Canberra, ACT: Australian Bureau of Statistics.

Chesher, R. H. (1980). *Stock Assessment Lapi, Black Lip and Gold Lip Oysters Near the Trobriand Islands*. Port Douglas, QLD: Marine Research Foundation. P193.

Christensen, J. (2016). "Illegal, unreported and unregulated fishing in historical perspective," in *Perspectives on Oceans Past*, eds. K. Schwerdtner Máñez, and B. Poulsen (Dordrecht: Springer), 133–153.

Clarke, S. (2004). Understanding pressures on fishery resources through trade statistics: a pilot study of four products in the Chinese dried seafood market. *Fish Fish.* 5, 53–74. doi: 10.1111/j.1467-2960.2004.00137.x

Dalzell, P., Adams, T. J. H., and Polunin, N. V. C. (1996). Coastal fisheries in the Pacific Islands. *Oceanogr. Mar. Biol. Annu. Rev*. 34, 395–531.

Eddy, T. D., Gardner, J. P., and Perez-Matus, A. (2010). Applying fishers' ecological knowledge to construct past and future lobster stocks in the Juan Fernandez Archipelago, Chile. *PLoS One* 5:e13670. doi: 10.1371/journal.pone.0013670

Engelhard, G. H., Thurstan, R. H., MacKenzie, B. R., Alleway, H. K., Bannister, R. C. A., Cardinale, M., et al. (2016). ICES meets marine historical ecology: placing the history of fish and fisheries in current policy context. *ICES J. Mar. Sci*. 73, 1386–1403. doi: 10.1093/icesjms/fsv219

Flores, B. (1984). A marine resource information system for the Pacific? *SPC Fish. Newsl*. 28, 26–30. doi: 10.1109/MAP.1984.27773

Foale, S. (2008). Appraising the resilience of trochus and other nearshore artisanal fisheries in the Western Pacific. *SPC Trochus Inf. Bull*. 14, 12–15. Available online at: https://spccfpstore1.blob.core.windows.net/digitallibrary-docs/files/3b/3b42459870b888dedcd017c9206de6e7.pdf?sv=2015-12-11&sr=b&sig=bxBtqvn9QEATg0%2FDZ8PhwRFpiqE3Dt3PA9rcdcd07Oo%3D&se=2022-04-23T06%3A49%3A37Z&sp=r&rscc=public%2C%20max-age%3D864000%2C%20max-stale%3D86400&rsct=application%2Fpdf&rscd=inline%3B%20filename%3D%22Trochus14_12_Foale.pdf%22

Fortibuoni, T., Libralato, S., Arneri, E., Giovanardi, O., Solidoro, C., and Raicevich, S. (2017). Fish and fishery historical data since the 19th century in the Adriatic Sea, Mediterranean. *Sci. Data* 4:170104. doi: 10.1038/sdata.2017.104

Garcia, S. M. (1994). The precautionary principle: its implications in capture fisheries management. *Ocean Coast. Manag*. 22, 99–125. doi: 10.1016/0964-5691(94)90014-0

Garibaldi, L. (2012). The FAO global capture production database: a six-decade effort to catch the trend. *Mar. Policy* 36, 760–768. doi: 10.1016/j.marpol.2011.10.024

George, C. D. (1978). *The Pearl. A Report to the Government of Papua New Guinea, the Food and Agriculture Organization of the United Nations and the Asian Development Bank on the Background and History of the Early and Present Day Development of the Cultivation of Pearl Shells and Pearls in the Indo-Pacific Region*. Samarai: Milne Bay Pearl Development. P403..

Gephart, J. A., Deutsch, L., Pace, M. L., Troell, M., and Seekell, D. A. (2017). Shocks to fish production: Identification, trends, and consequences. *Global Environ. Change* 42, 24–32. doi: 10.1016/j.gloenvcha.2016.11.003

Gianelli, I., and Defeo, O. (2017). Uruguayan fisheries under an increasingly globalized scenario: long-term landings and bioeconomic trends. *Fish. Res*. 190, 53–60. doi: 10.1016/j.fishres.2017.02.002

Gillett, R., and Lightfoot, C. (2001). *The Contribution of Fisheries to the Economies of Pacific Island Countries*. Pacific Studies Series, Asian Development Bank. Manila, PF: Asian Development Bank.

Gillett, R., McCoy, M., Bertram, I., Kinch, J., and Desurmont, A. (2020). *Trochus in the Pacific Islands: A Review of the Fisheries, Management and Trade*. Fisheries, Aquaculture and Marine Ecosystems Division, Secretariat of the Pacific Community. Noumea: Secretariat of the Pacific Community (SPC).

Gillett, R., and Tauati, M. I. (2018). *Fisheries of the Pacific Islands Regional and National Information*. FAO fisheries and aquaculture technical paper 625. Apia: Food and Agricultural Organization of the United Nations (FAO).

Glucksman, J., and Lindholm, R. (1982). A study of the commercial shell industry in Papua New Guinea since World War Two with particular reference to village production of trochus (Trochus niloticus) and green snail (Turbo marmoratus). *Sci. N. Guin*. 9, 1–10.

Govan, H. (2013). *Strategic Review of Inshore Fisheries Policies and Strategies in Melanesia: Fiji, New Caledonia, Papua New Guinea, Solomon Islands, and Vanuatu Part I: General Overview*. Noumea: Melanesian Spearhead Group, Secretariat of the Pacific Community.

Haimovici, M., and Cardoso, L. G. (2016). Long-term changes in the fisheries in the Patos Lagoon estuary and adjacent coastal waters in Southern Brazil. *Mar. Biol. Res*. 13, 135–150. doi: 10.1080/17451000.2016.1228978

Halford, A., Shedrawi, G., Bosserelle, P., Magron, F., and Vigga, B. (2021). "Supporting the integration of e-data systems into coastal fisheries across the Pacific Island Countries and Territories," in *4th SPC Regional Technical Meeting on Coastal Fisheries, Information paper 5. Noumea* [New Caledonia: Secretariat of the Pacific Community (SPC)].

Hawes, I., Lasiak, T., Smith, M. L., and Oengpepa, C. (2011). The status of silverlip pearl oyster *Pinctada maxima* (Jameson) (Mollusca, Pteridae) in the Solomon Islands after a 15-year export ban. *J. Shellfish Res*. 30, 255–260. doi: 10.2983/035.030.0209

ICECON (1997). *Aspects of the Industry, Trade, and Marketing of Pacific Island Trochus. Pacific Island Discussion Paper Series Number 2*. Reykjavic: World Bank.

Inwood, K., and Maxwell-Stewart, H. (2020). Selection bias and social science history. *So. Sci. Hist*. 44, 411–416. doi: 10.1017/ssh.2020.18

IPA (2021). *Opportunity Knocks: Pearl Farming in Samarai Island*. Business Advantage PNG, Investment Promotion Authority (IPA). Available online at: https://www.businessadvantagepng.com/promotions/opportunity-knocks-pearl-farming-in-samarai-island/ (accessed August 2, 2021).

Jackson, J. B. C., Alexander, K. E., and Sala, E. (2011). *Shifting Baselines: The Past and the Future of Ocean Fisheries*. Washington, DC: Island Press.

Kailola, P. J. (1995). *Fisheries Resource Profiles: Papua New Guinea*. FFA Report no. 95/45. Honiara: Forum Fisheries Agency.

Kelso, B. J. (1996). Warning signs unheeded in South Pacific invertebrate trade. *Naga ICLARM Q*. 19, 9–12.

Kile, N. (2000). Solomon Islands marine resources overview. *Pac. Econ. Bull*. 15, 143–147. Available online at: https://openresearch-repository.anu.edu.au/bitstream/1885/157579/1/151_soloman%20islands%20marine.pdf

Lasi, F. (2010). Trochus production in Solomon Islands from 1953 to 2006. *SPC Trochus Inf. Bull*. 15, 24–27. Available online at: https://www.spc.int/DigitalLibrary/Doc/FAME/InfoBull/TROC/15/TROC15_24_Lasi.html

Lotze, H. K., and Milewski, I. (2004). Two centuries of multiple impacts and successive changes in a North Atlantic food web. *Ecol. Appl*. 14, 1428–1447. doi: 10.1890/03-5027

McClenachan, L., Ferretti, F., and Baum, J. K. (2012). From archives to conservation: why historical data are needed to set baselines for marine animals and ecosystems. *Conserv. Letters* 5, 349–359. doi: 10.1111/j.1755-263X.2012.00253.x

Mira, W. J. D. (1986). *From Cowrie to Kina: The Coinages, Currencies, Badges, Medals, Awards and Decorations of Papua New Guinea*. Sydney, NSW: Spink.

Moore, C. (2000). Refocusing indigenous trade and power: the dynamics of early foreign contact and trade in Torres Strait, Cape York and Southeast New Guinea in the Nineteenth Century. *R. Hist. Soc. Qld J*. 17, 289–302. Available online at: https://search.informit.org/doi/abs/10.3316/ielapa.200101170

Nash, W. J. (1985). *Aspects of the Biology of Trochus niloticus and Its Fishery in the Great Barrier Reef Region: A Report Submitted to Fisheries Research Branch, Queensland Department of Primary Industries, and the Great Barrier Reef Marine Park Authority*. Northern Fisheries Research Centre. Cairns, QLD: Northern Fisheries Research Centre.

Pakoa, K., William, A., Neihapi, P., and Kikutani, K. (2014). *The Status of Green Snail (Turbo marmoratus) Resource in Vanuatu and Recommendations for Its Management*. Noumea: Secretarial of the Pacific Community (SPC).

Papetti, C., Di Franco, A., Zane, L., Guidetti, P., De Simone, V., Spizzotin, M., et al. (2013). Single population and common natal origin for Adriatic Scomber scombrus stocks: evidence from an integrated approach. *ICES J. Mar. Sci*. 70, 387–398. doi: 10.1093/icesjms/fss201

Pauly, D. (1995). Anecdotes and the shifting baseline syndrome of fisheries. *Tree* 10:430. doi: 10.1016/S0169-5347(00)89171-5

Pinnegar, J. K., and Engelhard, G. H. (2007). The 'shifting baseline' phenomenon: a global perspective. *Rev. Fish Biol. Fish*. 18, 1–16. doi: 10.1007/s11160-007-9058-6

Plagányi, É. E., McGarvey, R., Gardner, C., Caputi, N., Dennis, D., de Lestang, S., et al. (2017). Overview, opportunities and outlook for Australian spiny lobster fisheries. *Rev. Fish Biol. Fish*. 28, 57–87. doi: 10.1007/s11160-017-9493-y

Purcell, S. W., Tagliafico, A., Cullis, B. R., and Gogel, B. J. (2021). Socioeconomic impacts of resource diversification from small-scale fishery development. *Ecol. Soc*. 26:14. doi: 10.5751/ES-12183-260114

Purdy, D. H., Hadley, D. J., Kenter, J. O., and Kinch, J. (2017). Sea cucumber moratorium and livelihood diversity in Papua New Guinea. *Coast. Manage*. 45, 161–177. doi: 10.1080/08920753.2017.1278147

Rose, S., Quanchi, M., and Moore, C. (2009). *A National Strategy for the Study of the Pacific*. Brisbane, QLD: Australian Association for the Advancement of Pacific Studies.

Sack, P., and Clark, D. (eds.). (1979). *German New Guinea: The Annual Reports*. Canberra, ACT: The Australian National University.

Schwerdtner Máñez, K., and Ferse, S. C. (2010). The history of Makassan trepang fishing and trade. *PLoS One* 5:e11346. doi: 10.1371/journal.pone.0011346

Simard, N. S., Militz, T. A., Kinch, J., and Southgate, P. C. (2019). Artisanal, shell-based handicraft in Papua New Guinea: challenges and opportunities for livelihoods development. *Ambio* 48, 374–384. doi: 10.1007/s13280-018-1078-z

SPC (1960). *Note on the Pearl Shell Market in the South Pacific*. Noumea: South Pacific Commission (SPC).

SPC (1988). *Workshop on Pacific Inshore Fishery Resources (Noumea, New Caledonia, 14-25 March 1988). 687/88.* Noumea: South Pacific Commission (SPC).

SPC (1997). *Workshop on Trochus Resource Assessment, Management and Development: Report and Selected Papers*. Integrated Coastal Fisheries Management Project Technical Document No. 13. Noumea, New Caledonia: South Pacific Commission (SPC).

SPC (2019). *Division of Fisheries, Aquaculture and Marice Ecosystems - Business Plan 2016 - 2020 Version 3.0*. Noumea: Secretariat of the Pacific Community (SPC).

Sulu, R. J., Eriksson, H., Schwarz, A. M., Andrew, N. L., Orirana, G., Sukulu, M., et al. (2015). Livelihoods and fisheries governance in a contemporary Pacific Island setting. *PLoS One* 10:e0143516. doi: 10.1371/journal.pone.0143516

Swadling, P. (1976). Changes induced by exploitation in prehistoric shellfish populations. *Mankind* 10, 156–162. doi: 10.1111/j.1835-9310.1976.tb01146.x

Swadling, P. (1977). Central Province shellfish resources and their utilisation in the prehistoric past of Papua New Guinea. *Veliger* 19, 293–302.

Szabó, K., and Amesbury, J. R. (2011). Molluscs in a world of islands: the use of shellfish as a food resource in the tropical island Asia-Pacific region. *Quat. Int*. 239, 8–18. doi: 10.1016/j.quaint.2011.02.033

Tesfamichael, D., Pitcher, T. J., and Pauly, D. (2014). Assessing changes using fishers' knowledge to generate long time series of catch rates: a case study from the Red Sea. *Ecol. Soc*. 19:18. doi: 10.5751/ES-06151-190118

Vieira, S., Kinch, J., White, W., and Yaman, L. (2017). Artisanal shark fishing in the Louisiade Archipelago, Papua New Guinea: Socio-economic characteristics and management options. *Ocean Coast. Manage*. 137, 43–56. doi: 10.1016/j.ocecoaman.2016.12.009

World Bank (2021). *World Development Indicators: Consumer Price Index (2010 = 100)*. Available online at: https://data.worldbank.org/indicator/FP.CPI.TOTL?locations=PG (accessed July 30, 2021).

Wright, A. (1986). *An Analysis of Exports of Marine Produce From Papua New Guinea for the Period 1980 to May, 1986 With Emphasis on Produce Collected By Small-Scale Fishermen.* Fisheries Research Laboratory, Department of Primary Industry. Kavieng: Department of Primary Industry (DPI).

Zeller, D., Harper, S., Zylich, K., and Pauly, D. (2014). Synthesis of underreported small-scale fisheries catch in Pacific island waters. *Coral Reefs* 34, 25–39. doi: 10.1007/s00338-014-1219-1

Zeller, D., and Pauly, D. (2018). The 'presentist bias' in time-series data: implications for fisheries science and policy. *Mar. Policy* 90, 14–19. doi: 10.1016/j.marpol.2018.01.015

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

ORIGINAL RESEARCH
published: 23 November 2021
doi: 10.3389/fmars.2021.728948

Understanding the Dynamics of Ancillary Pelagic Species in the Adriatic Sea

Silvia Angelini[1,2], Enrico N. Armelloni[1,3], Ilaria Costantini[1], Andrea De Felice[1], Igor Isajlović[4], Iole Leonori[1], Chiara Manfredi[5], Francesco Masnadi[1,3], Giuseppe Scarcella[1], Vjekoslav Tičina[4] and Alberto Santojanni[1]*

[1] National Research Council, Institute for Marine Biological Resources and Biotechnology (CNR IRBIM), Ancona, Italy, [2] Fano Marine Center, The Inter-Institute Center for Research on Marine Biodiversity, Resources and Biotechnologies, Fano, Italy, [3] Department of Biological, Geological, and Environmental Sciences (BiGeA), Alma Mater Studiorum—University of Bologna, Bologna, Italy, [4] Institute of Oceanography and Fisheries, Split, Croatia, [5] Department of Biological, Geological, and Environmental Sciences (BiGeA), Marine Biology and Fisheries Laboratory, Alma Mater Studiorum—University of Bologna, Fano, Italy

OPEN ACCESS

Edited by:
Oscar Sosa-Nishizaki,
Center for Scientific Research and Higher Education in Ensenada (CICESE), Mexico

Reviewed by:
Emiliano García-Rodríguez,
Center for Scientific Research and Higher Education in Ensenada (CICESE), Mexico
Weiwei Xian,
Institute of Oceanology, Chinese Academy of Sciences (CAS), China

****Correspondence:***
Silvia Angelini
silvia.angelini@cnr.it

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: *22 June 2021*
Accepted: *25 October 2021*
Published: *23 November 2021*

Citation:
Angelini S, Armelloni EN, Costantini I, De Felice A, Isajlović I, Leonori I, Manfredi C, Masnadi F, Scarcella G, Tičina V and Santojanni A (2021) Understanding the Dynamics of Ancillary Pelagic Species in the Adriatic Sea. Front. Mar. Sci. 8:728948. doi: 10.3389/fmars.2021.728948

The status of fishery resources in the Mediterranean Sea is critical: most of the fish and shellfish stocks are in overexploitation and only half of them are routinely assessed. This manuscript presents the use of Surplus Production Models (SPMs) as a valid option to increase the number of assessed stocks, with specific attention to the Adriatic basin. Particularly, the stock of European sprat (*Sprattus sprattus*), Mediterranean horse mackerel (*Trachurus mediterraneus*), and Atlantic horse mackerel (*Trachurus trachurus*) living in the Adriatic Sea have been evaluated comparing three SPMs: Catch Maximum Sustainable Yields (CMSY), Stochastic surplus Production model in Continuous Time (SPiCT), and Abundance Maximum Sustainable Yields (AMSY). The different approaches present some variations; however, they generally agree on describing all the stocks close to the reference values for both biomass and fishing mortality in the most recent year. For the European sprat, AMSY results are the most robust model for this species' survey data allow depicting a clearer picture of the history of this stock. Indeed, for the horse mackerel species, CMSY or SPiCT results are the preferred models, since for these species landings are not negligible. Notwithstanding, age-structured assessments remain the most powerful approach for evaluating the status of resources, but SPMs have proved to be a powerful tool in a data-limited context.

Keywords: sprat, horse mackerel, Adriatic Sea, surplus production model, survey-based stock assessment

INTRODUCTION

The status of fishing resources in the Mediterranean Sea is critical: less than 50% of the fish and shellfish stocks inhabiting the basin are routinely assessed and the majority of them are considered overexploited (European Environment Agency (EEA), 2019). This fact underlines the need to improve the number of stocks assessed in order to have a complete picture of the status of fishing resources within the basin. Progress has been made to reach this objective as the last FAO report about the status of the resources in the Mediterranean and the Black Sea reveals a positive trend in the number of evaluated stocks. In particular, from 18 stocks assessed in 2006 to the highest peak of 85 in 2018, corresponding to ca. 80% of the total landing reported for the Mediterranean area (FAO, 2020). This fact is of relevant importance, particularly for this area in which the multispecies nature of Mediterranean fisheries (Lleonart and Maynou, 2003), the relatively recent history in fishery management (Colloca et al., 2013; Maunder and Piner, 2015), as well as the recent commitment of Mediterranean researchers in stock assessment (Colloca et al., 2013) have not facilitated the spreading of stock assessment applications.

Generally, one of the main reasons for the low number of stock evaluations is the lack of population structure data (Free et al., 2020), which are mainly represented by age information. The determination of age, when possible, represents a time-consuming task, thus generating a potential obstacle for the application of age-structured methodology. In reality, these models are widely diffused, this is due to the possibility of using statistical methods to convert lengths into ages, and also to the wide range of available approaches that can adapt to various requirements [e.g., XSA (Shepherd, 1999), SAM (Berg et al., 2014), SS (Methot and Wetzel, 2013)]. Moreover, age-structured models produce robust estimations, since age information offers the possibility of following cohorts' progression over time, as well as evaluating changes in fishing selectivity (Wang et al., 2014) and detecting fluctuation in spawning and recruitment (Aalto et al., 2015). In addition, these models are able to produce exhaustive results, e.g., trends of spawning stock biomass, recruitment, and fishing mortality at age, thus representing a powerful tool for evaluating the status of fisheries resources. However, to properly perform, age-based models need a wide range of input data, which are not always available. In these cases, Surplus Production Models (SPMs) represent a valid option to produce stock assessments. This type of model requires limited information, such as a time series of catch and, if available, an abundance index or effort data, and can estimate population biomass and produce evaluations of maximum sustainable yield (MSY), that is the maximum yield that the stock can sustain without affecting its long-term productivity (Sparre and Venema, 1998). These models provide also fishing mortality and biomass at the corresponding MSY level (F_{MSY} and B_{MSY}), which are useful to address the management objectives. Nevertheless, SPMs may be seen as a too simplistic approach that is not able to represent the complexity of population dynamics (e.g., Pedersen and Berg, 2017), as length or age data are not available or are not reliable (Punt, 2003). In these situations of data-limited context, the use of historical catch and survey or effort data is advisable (Jackson et al., 2001; Branch et al., 2011.); this will favor a truthful description of the status of the stock, as well as improving targets and limited reference points' estimates (Gabriel and Mace, 1999).

In the last two decades, SPMs have undergone important improvements (e.g., Punt, 2003; McAllister, 2014), like the inclusion of state-space factors, that allowed them to better account for real-world variability into the biomass dynamic modeling and favored further dissemination of these models (Meyer and Millar, 1999). The state-space formulation has the advantage of including uncertainties both in observed data and in the model process, in the form of, respectively, observation and process errors, thus resulting in improved parameter estimations (Ono et al., 2012). Also, these models allow the use of priors that can facilitate and address the estimation of reliable parameters. These priors can derive from literature or expert knowledge; thus, it is important to proceed with sensitivity tests or compare different approaches to select the most appropriate configuration (Pedersen and Berg, 2017). The Abundance Maximum Sustainable Yield model (AMSY; Froese et al., 2020), the Catch Maximum Sustainable Yield model (CMSY; Froese et al., 2017), and the Stochastic surplus Production model In Continuous Time (SPiCT; Pedersen and Berg, 2017), represent some of the most novel approaches among current SPMs. They summarize all the features and improvements listed before, representing at this time a solid option for developing stock assessments in data-poor contexts.

In this manuscript, these SPMs are used for evaluating the status of some pelagic stocks which were never previously assessed in the Adriatic Sea, such as European sprat (*Sprattus sprattus*), Mediterranean horse mackerel (*Trachurus mediterraneus*), and Atlantic horse mackerel (*Trachurus trachurus*). This area represents an important fishing ground for the Mediterranean Sea, accounting for 15% of the total landing coming from this basin (FAO, 2020) and is also one of the most intensively fished areas in Europe and the world (Eigaard et al., 2017; Amoroso et al., 2018). In the Adriatic Sea, small pelagics, specifically anchovy (*Engraulis encrasicolus*) and sardine (*Sardina pilchardus*) account for the highest landings (FAO, 2020). In a context of high fishing activity, the increase of assessed stocks can be helpful to understand the status of the entire basin and, in this case, specifically those of the pelagic domain. The three selected species can be considered as ancillary species of the small pelagic fishery occurring in the Adriatic basin. However, they assume a certain importance as traditional food and for their commercial value as well as in the ecological context (Barausse et al., 2009). Since data are not enough to develop age-structure approaches, these species represent a good case study for developing and comparing different SPMs.

MATERIALS AND METHODS

Study Area and Species Object of the Study

The study area is represented by the North Adriatic Sea, a semi-enclosed basin in the central Mediterranean Sea between Italy and the Balkan peninsula included in the Geographical Sub-Areas (GSA) 17 (General Fisheries Commission for the Mediterranean (GFCM), 2009; **Figure 1**). Anchovy and sardine represent the main target species of the fishing fleet operating in this area and are characterized by the use of pelagic trawlers and purse seiners. However, based on the information included in the European Union—Data Collection Framework (EU-DCF), which can be defined as the European database grouping fisheries data from all member states, the pelagic vessels fishing in the Adriatic Sea also report catches of other species, such as Mugilidae, European sprat (*Sprattus sprattus*), mackerels (*Scombrus* spp.), horse mackerels (*Trachurus* spp.), and others (source EU-DCF database 2019; European Commission (EC), 2017).

In this study European sprat, Mediterranean, and Atlantic horse mackerels are considered. European sprat (sprat, from here onward) is a pelagic species mainly fished by pelagic trawlers. In

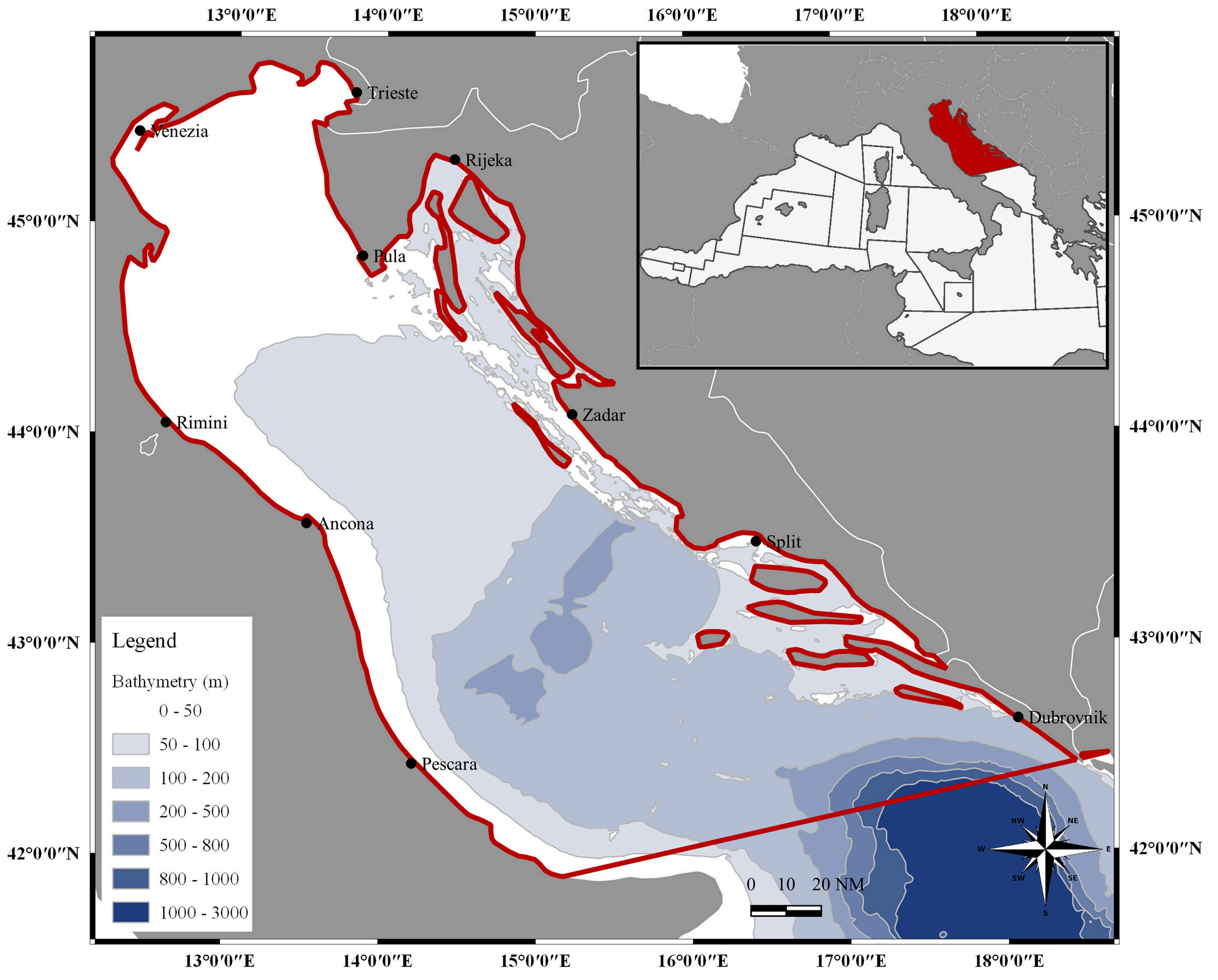


FIGURE 1 | Map of the study area, which is defined by the red line and corresponds to the GSA 17 (Northern Adriatic Sea).

the Adriatic Sea, this species is found mainly in the northwestern area (**Figure 2**), where it represents a traditional food. According to data availability, landing data includes years from 2004 to 2019 for both Italy and Croatia (**Figure 3**, top right panel); Italian data and Croatian data since 2013 correspond to those from the EU-DCF (European Commission (EC), 2017), whereas Croatian data from 2009 to 2012 refers to Eurostat (2021) and Croatian data from 2004 to 2008 were reconstructed through a mean proportion based on the years in which landing data were available for both countries. Historical total biomass estimates (**Figure 3**, bottom right panel) were obtained from Italian national acoustic surveys ECHOADRI carried out since 1976 up to 2008 in the Western Adriatic Sea, and from Croatian national acoustic survey PELMON carried out from 2003 up to 2012 in the eastern part of the Adriatic Sea (Azzali et al., 2002; Tičina et al., 2006; Leonori et al., 2012, 2017). Since 2009, European national acoustic surveys are internationally coordinated in the ambit of the EU MEDiterranean International Acoustic Surveys (MEDIAS) program (MEDIAS Handbook, 2019), and since 2013 the Croatian national survey has also been part of it. The MEDIAS coordinates acoustic surveys aimed at detecting the abundance and biomass of small pelagic species, their spatial distribution and demography together with oceanographic information. The survey period is in summer (June–September), although in some years and areas it has been shifted to early autumn. The ECHOADRI and the PELMON surveys represent the ancestors of the MEDIAS survey; before 2009, no acoustic common protocol was available in European waters, however at a national level research institutes carried out acoustic investigations using a methodology comparable to the one used in the MEDIAS surveys that was derived by the harmonization of the national protocols (Leonori et al., 2021).

Mediterranean and Atlantic horse mackerels (horse mackerels from here onward) are fished with different gears, mainly bottom trawlers, pelagic trawlers, and purse seiners. Although these species are semi-pelagic, they are found in surface waters but also close to the bottom, particularly the Mediterranean horse mackerel (Šantić et al., 2003; Piccinetti et al., 2012), and they are spread all over the GSA 17 (**Figure 4**). In this work, these two species are considered as a unique stock, since most of the

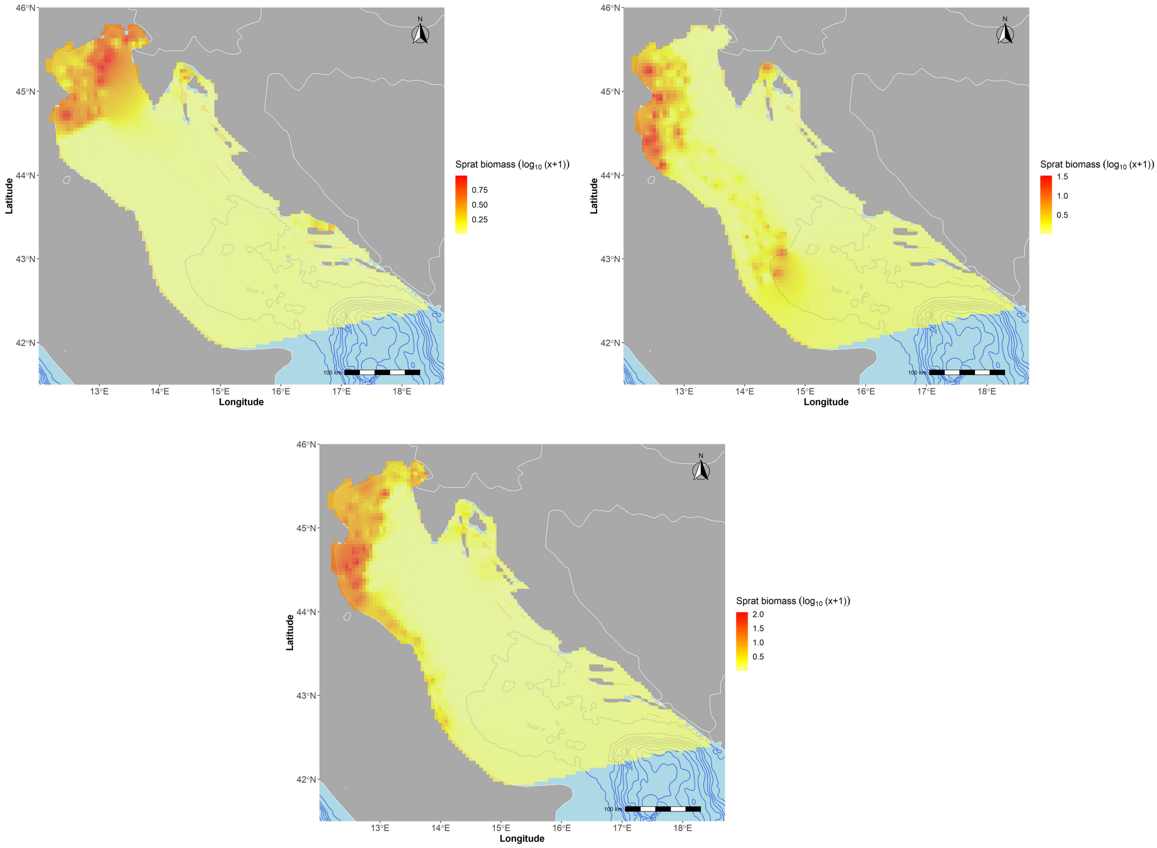


FIGURE 2 | European sprat. Biomass distribution expressed in $\log_{10}(x + 1)$ where x is the biomass index (tons/nm^2) related to the MEDIAS survey carried out in GSA 17 East and West for years 2014 in September (top left), 2018 (top right), and 2019 (bottom) in June–July.

landings are confounded: at the beginning of the time series, landings are reported at genus level without any indication on how to divide them by species. While in the most recent years, landings at the species level are available but unreliable, because only information relating to one of the two species is reported at year. Also, notwithstanding that these species show some differences in growth as well as in their depth distribution (Šantić et al., 2002, 2003; Piccinetti et al., 2012), these are not so relevant that they suggest avoiding this assumption. According to data availability, landing data includes years from 1970 to 2019 for both Italy and Croatia (**Figure 3**, top left panel). Italian data before 2004 are from Fortibuoni et al. (2018), while after this year they are derived from EU-DCF (European Commission (EC), 2017). Croatian data before 2013 correspond to those available from FishStatJ database (FAO-GFCM, 2019), whereas data from 2013 to 2019 are from EU-DCF (European Commission (EC), 2017). Survey data are from the MEDiterranean International Trawl Survey (MEDITS; Bertrand et al., 2002a). The MEDITS bottom trawl survey is a European program started in 1994 with the aim of collecting data on demersal communities to describe their distribution and demographic structure. Notwithstanding the MEDITS is focused on the demersal resources, the gear configuration used for this survey as well as the species behavior improve MEDITS trawl efficiency for horse mackerels (Dremière et al., 1999; Fiorentini et al., 1999; Bertrand et al., 2002b; Ragonese et al., 2004); given their semi-pelagic habit they could also be monitored with acoustic surveys, even if these surveys generally target more appropriately pure pelagic species. Sampling procedures, data collection, and management are standardized, according to a common protocol over GSAs and years, whose specific details can be found in the MEDITS handbook (Anonymous, 2017) and summarized in Spedicato et al. (2019). The survey is usually carried out in the late spring-summer period although in some years, and particularly in the west side of GSA 17, cruises were postponed to late summer or early autumn. The considered MEDITS time series extends from 1994 to 2019 and concerns annual biomass indices (kg/km^2) (**Figure 3**, bottom left panel). This index has been calculated by aggregating the two horse mackerel species and the two countries following the procedure of stratified mean and variance after raw abundance data were normalized by the trawl surface (Souplet, 1996).

Stock Assessment Models

Considering the data availability, three different stock assessment models are considered in this study. Models' priors for stock resilience were derived from the best available literature

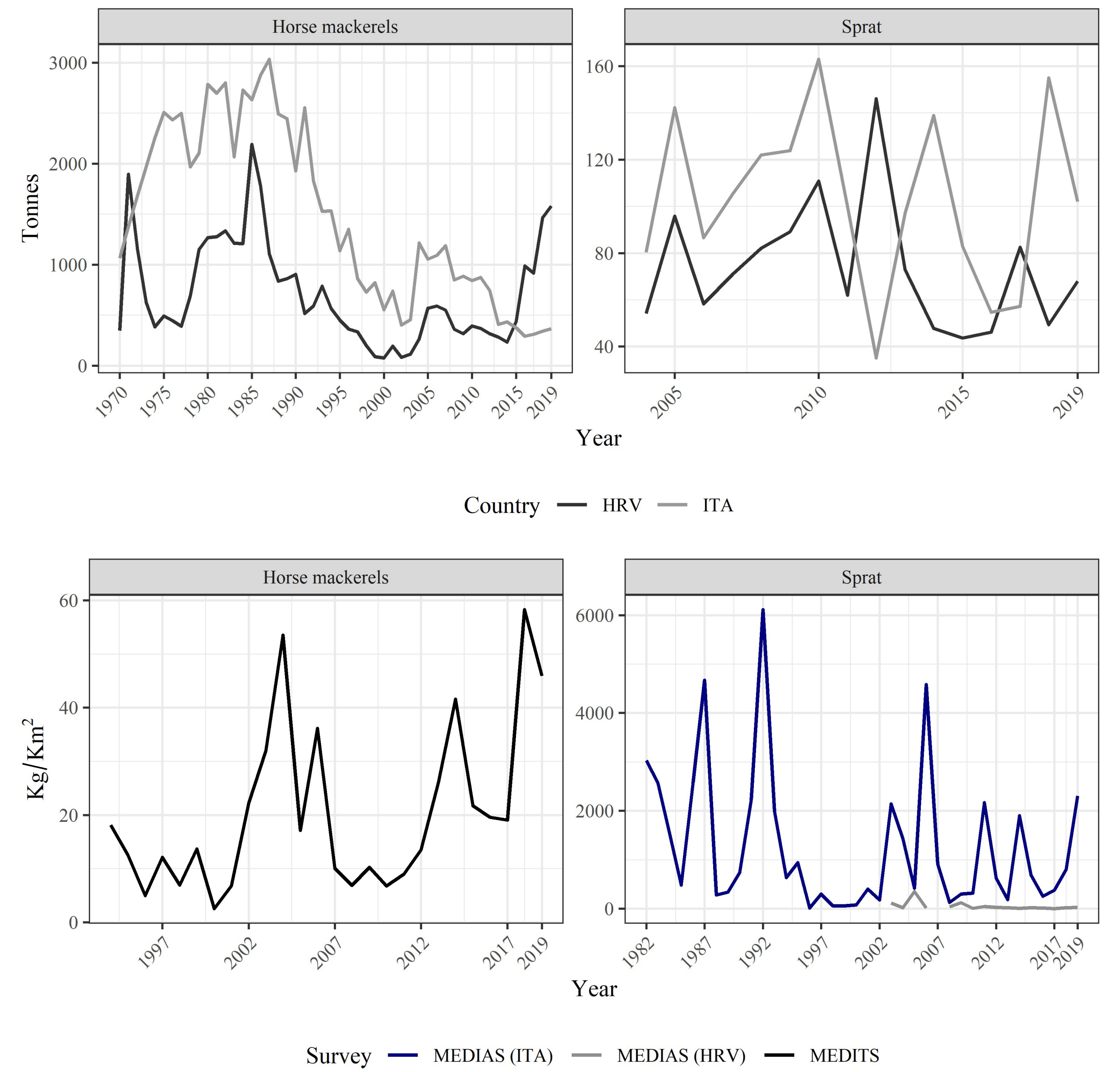


FIGURE 3 | Top panels: landing data in tons for horse mackerel species (left side) and sprat (right side) divided by country (Croatia = HRV, black line, Italy = ITA, gray line). Bottom left panel: survey index in kg/km^2 for horse mackerels from MEDITS survey (black line) including both Italy and Croatia from the year 1994 to the year 2019 (years 1994, 1995, and 1999 include only Italy). Bottom right panel: survey index in kg/km^2 for European sprat from acoustic surveys (Italy: ECHOADRI from 1982 to 2008 and MEDIAS from 2009 to 2019; Croatia: PELMON from 2003 to 2012 and MEDIAS from 2013 to 2019) divided by Italy [MEDIAS (ITA)—blue line] from the year 1982 to the year 2019 (years 1984, 1986, 2002, and 2003 have been estimated) and Croatia [MEDIAS (HRV)—gray line] from the year 2003 to the year 2019.

(Froese and Pauly, 2019), and revised after inspecting model diagnostics. Prior selection for exploitation status reflects the trend observed in the landings and the status of fishing capacity along the timeframe considered, which continuously increased during the 70s, peaked between the 80s and 90s, and then in the last 20 years was gradually reduced by the mean of management plans (Osio, 2012; Piroddi et al., 2015; Marini et al., 2017). After individuating credible ranges for the prior's distribution, a number of runs were done to test the sensitivity of the model to parameter variations. Runs diagnostics were compared in terms of priors-vs.-posterior distribution, residuals, stock trajectories, and retrospective patterns. For the SPiCT model, the guidelines for the acceptance of this type of model were also verified (Mildenberger et al., 2021).

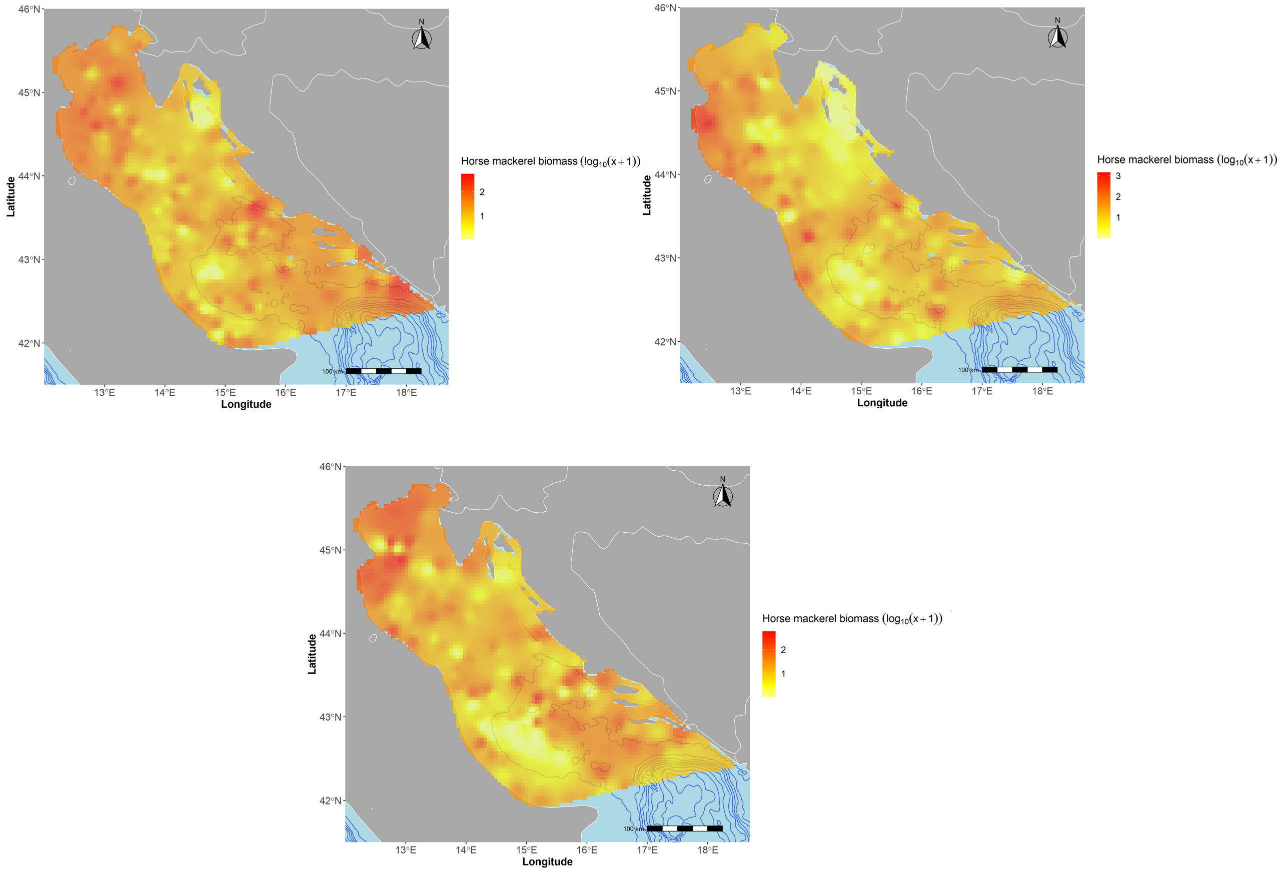


FIGURE 4 | Horse mackerels. Biomass distribution expressed in $\log_{10}(x + 1)$ where x is the biomass index (Kg/Km^2) related to the MEDITS survey carried out in GSA 17 East and West for years 2014 (top left), 2018 (top right), and 2019 (bottom).

TABLE 1 | Input data for the CMSY and the AMSY SPMs.

			CMSY				
Species	**Star year**	**Int. year**	**End year**	**r**	**Stb**	**Intb**	**Endb**
European sprat	2004	2010	2019	0.4–0.8 (Froese and Pauly, 2019)	0.2–0.8	0.2–0.8	0.2–0.6
Horse mackerels	1970 for landings; 1994 for the survey index	1996	2019	0.31–0.72 (Froese and Pauly, 2019)	0.6–0.9	0.1–0.4	0.2–0.6
			AMSY				
Species	**Star year**	**B/k year**	**End year**	**r**	**B/k prior**		
European sprat	1982	2011	2019	0.34–0.11 (Froese and Pauly, 2019)	Small		
Horse mackerels	1994	2004	2019	0.31–0.72 (Froese and Pauly, 2019)	About Half		

The following paragraphs are considering only the best-performing parameters.

Catch Maximum Sustainable Yields

The Catch Maximum Sustainable Yield model (CMSY; Froese et al., 2017) is an SPM that needs catch data, catch per unit effort (CPUE) or survey index, and priors on the maximum intrinsic rate of population increase (r) and depletion status (B/K) to estimate biomass, exploitation rate, MSY, and related reference points. The method is based on a two-step analysis that combines the CMSY model and a Bayesian state-space implementation of the Schaefer model (BSM). Within the CMSY model, catch data and r and K priors serve to estimate the carrying capacity (K) and biomass trajectories based on the population dynamics of the Schaefer model. Ranges of r and K priors are filtered with a Monte-Carlo algorithm to detect "viable" r-K pairs for which the corresponding biomass trajectories are compatible with the observed catches. Subsequently, the BSM model uses CPUE or survey index and catch data to estimate r and K-values. The output of the two models is compared to assess the robustness of the results, whereas final figures derive from the BSM model. The CMSY (version 9f) reported in this study is a further development of the one used in Froese et al. (2017) (information and R code available at http://oceanrep.geomar.de/33076/).

CMSY was applied to both sprat and horse mackerels; input data are summarized in **Table 1**. For the first species, landings were only available for the years from 2004 to 2019 and the same time series was also considered for the acoustic survey index. Only one survey index can be included in this model, thus considering that the bulk of the sprat population is localized in the western side of the Adriatic Sea (**Figure 2**), only the Italian survey index was taken into account. r was included in the range 0.32–0.74 (Froese and Pauly, 2019), and modified to 0.4–0.8 after inspecting the prior vs. posterior distribution. The B/K range for the initial and intermediate year (2011) was set as a medium to lo low depletion (0.2–0.8) and as a medium-to-strong depletion (0.2–0.6) at the end of the time series: we expect that the fishing pressure on this resource was not drastically changed along the short time-series, however, the priors for the initial and intermediate depletion status were set slightly higher than the final one in order to decrease the possibility of constraining the model. For horse mackerels, CMSY was developed including landing data for both Italy and Croatia, available for years from 1970 to 2019; while for the survey index the time series included years from 1994 to 2019. The r prior available in literature ranged between 0.31 and 0.72 for *Trachurs trachurus* and 0.33–0.76 for *Trachurus mediterranesus*, as suggested by Froese and Pauly (2019). We opted to adopt the more conservative r-values for both the two species and our choice was confirmed by model diagnostics. B/K priors were set as low depletion (0.6–0.9) at the beginning of the time-series, as strong depletion (0.1–0.4) in 1996, corresponding to a period when the fishing pressure was at its maximum, and as medium depletion (0.2–0.6) in the last year.

Surplus Production Model in Continuous Time

The Stochastic surplus Production model in Continuous Time (SPiCT, Pedersen and Berg, 2017) corresponds to a state-space version of the Pella-Tomlinson surplus production model (Pella and Tomlinson, 1969). This model is developed for incorporating the dynamics of both fisheries and biomass data including an observation error for both the input data. If available, SPiCT can work considering multiple survey indexes or effort data and offer the possibility to use seasonal information. Auxiliary information can be included in the Bayesian estimation framework, which allows the use of informative priors for helping the model to find parameter estimates in a closet range of values. Principal outputs of the model are the biomass reference points, B_{MSY} and B/B_{MSY}, and the fishing mortality reference points, F_{MSY} and F/F_{MSY}, together with estimates for r, K, and MSY. The model is developed using Template Model Builder (TMB, Kristensen et al., 2015), which is recently conceived to be used within the R framework.

In this study, SPiCT was developed for both the considered species. **Table 2** summarizes the input data. For sprat, SPiCT was set including both landing data and acoustic survey indexes from 2004 to 2019. These two sources of information reflect all the specimens targeted by the fishing activity; this is also valid for the horse mackerel stock. Considering the characteristics of SPiCT, the two survey data, the Italian and the Croatian acoustic surveys, have been included, and specify the season in which they occurred. Some priors were used, specifically the initial relative biomass was considered close to the B_{MSY} level, since the cyclic dynamic of the small pelagic species, represented also in the trend of landings, as well as the local commercial importance of this species does not suggest a strong depletion of this stock before the beginning of the time-series. However, a medium level of exploitation was assumed at the beginning of the time series due to a potentially important fishing capacity at the beginning of the 2000s mitigated by the start of management plans (Osio, 2012; Piroddi et al., 2015). A prior for r was included following the information included in FishBase (Froese and Pauly, 2019) for the same species, whereas the prior for the production curve was adjusted as suggested by Thorson et al. (2012) for the Clupeiformes. For horse mackerels, landing data has been included from the year 1970 to the year 2019, whereas the MEDITS index has been included from the year 1994 to the year 2019. SPiCT offers the possibility to specify the time of year when the survey was performed, thus MEDITS data have been included specifying the month in which the survey occurred. To help the convergence of the model, some priors have been set. Specifically, the initial relative biomass was considered close to the B_{MSY} level, whereas the initial exploitation level was considered negligible since the fishing activity at the beginning of the 70s' can be held as not as impactful as the present (Osio, 2012; Piroddi et al., 2015). Additionally, r was derived from the FishBase database (Froese and Pauly, 2019), whereas the prior for the production curve was adjusted as suggested by Thorson et al. (2012). Finally, considering the low value, which seems not to be consistent with the rest of the time series, for the landing data in 1970 compared to the following years, this value was scaled by a factor of 5 compared to the rest of the time series.

Abundance Maximum Sustainable Yields

Abundance Maximum Sustainable Yields (AMSY) is a SPM suitable for data-limited cases (Froese et al., 2020), that estimates fisheries reference points (F_{MSY}, F/F_{MSY}, B/B_{MSY}) of a stock combining its abundance (CPUE or total biomass), its resilience, and a prior for relative stock size (range of B/K, between 0 and 1). This method was specifically developed for situations for which total catch is unknown or unreliable or for bycatch species where abundances may be estimable only from survey data. AMSY takes information and tests a high number of combinations of productivity (r) and unexploited stock size or carrying capacity (K) for their compatibility with the input data through a Monte Carlo filtering process. AMSY estimates relative catches at year t with a rearranged form of the Schaefer equation that needs biomass at years t and $t + 1$; this implies that catches may be estimated up to the second last year in the time series, thus not estimating F for the last considered year. The lack of catch data also implies that catches and carrying capacity are estimated as relative values, thus AMSY does give an estimation of the relative carrying capacity (Kq). AMSY estimates of fishing

TABLE 2 | Input data for the SPiCT model.

	SPiCT					
Species	**Star year**	**End year**	**r**	**Initial relative biomass B/B$_{MSY}$**	**Initial depletion level**	**Parameter for the adjustment of the shape of the production curve**
European sprat	2004	2019	0.49 (Froese and Pauly, 2019)	1	0.6	0.599 (Thorson et al., 2012)
Horse mackerels	1970 for landings 1994 for the survey index	2019	0.51 (Froese and Pauly, 2019)	1	0.8	1.478 (Thorson et al., 2012)

pressure have wide margins of uncertainty, which may not be ideal for management purposes. Nevertheless, it seems to be well suited for estimating productivity as well as the relative stock size and may, therefore, be fundamental in the context of a data-poor stock.

AMSY was developed for both species; input data are summarized in **Table 1**. For sprat, a long time series (1982–2019) of estimated total biomass data belonging to the Italian acoustic surveys (ECHOADRI and MEDIAS) was available; *r* prior range was much wider than those used in the CMSY model (0.32–1.1 based on FishBase data and sensitivity analysis), this was needed to satisfy the large oscillations of this index and to identify enough viable *r-Kq* to reasonably accommodate the stock dynamic. The B/*K* prior was set as "Small" in 2011 based on the observation of the CPUE value for 2011 was ca. 30% of the maximum value observed in the longest time series (CPUE). For horse mackerels, AMSY was developed using the MEDITS index for the time series from 1994 to 2019; likewise, to the CMSY model, *r* was included in the range 0.31–0.72 (Froese and Pauly, 2019), and B/*K* priors were set in 2004, a year in which CPUE and catch data present important peaks. Considering this and taking into account the longer time series of landings, the corresponding prior was set as "About half," since the catch value for this year was ca. 40% of the maximum value observed in the longest time series.

RESULTS

European Sprat

Sprat is a migratory species mainly distributed on the western side of the north Adriatic Sea, as shown by the acoustic estimates available from both Italy and Croatia (**Figure 2**). Maps are shown only for the years 2014, 2018, and 2019, as an example of different periods.

Regarding the status of this stock, CMSY and SPiCT describe a similar situation: biomass results above the reference points for the first years, while since 2007 for CMSY and 2011 for SPiCT it moves below the reference point describing an increasing trend in the last years reaching the value of B/B$_{MSY}$ equal to 0.867 and 0.902 in 2019, respectively, for the CMSY and the SPiCT models (**Figure 5** bottom right panel and **Table 3**). Also, trends of F/F$_{MSY}$ for these two models are very similar, describing an overexploited stock for most of the time series and specifically since 2008 for CMSY and since 2009 for SPiCT; in 2019 F/F$_{MSY}$ is equal to 1.151 for CMSY and equal to 1.124 for SPiCT (**Figure 5** bottom left panel and **Table 3**).

TABLE 3 | European sprat—estimated parameters from the three SPMs.

Estimated parameters	CMSY	SPiCT	AMSY
F$_{2019}$	0.362	0.785	0.429*
B$_{2019\,(tons)}$	491.322	224.268	56,149
F$_{MSY}$	0.319	0.700	0.549
B$_{MSY\,(tons)}$	566.706	249	55,732
B/B$_{MSY}$	0.867	0.902	1.007
F/F$_{MSY}$	1.151	1.124	0.783*
r	0.638	0.508	1.097
K	1133.413	812	

This value refers to F 2018.

The longer time series considered by the AMSY model describes a fluctuating situation over the years (**Figure 5** bottom panels). At the beginning of the time series, this stock appears in good status being B and F, respectively, above and below the reference points (**Figure 5** bottom panels and **Table 3**). In the mid-90s, the high values of F/F$_{MSY}$ (equal to 5.05 in 1998) caused an important decay in biomass (**Figure 5** bottom left panels). In the following period, the stock trend is similar to the other two models, although more fluctuating. However, this model suggests a better stock's status since 2018, F/F$_{MSY}$ results equal to 0.78 and in 2019 B/B$_{MSY}$ results equal to 1.01 (**Figure 5** bottom panel and **Table 3**). *K* is not shown (**Table 3**), since AMSY only estimates relative carrying capacity, *Kq*.

Diagnostics (**Supplementary Figures 1A–9A**) present a good fitting for all the models, particularly for AMSY. Estimated parameters are summarized in **Table 3**: *r*-values are quite similar for the CMSY and the SPiCT models, while AMSY estimates a higher value; estimates of *K* are available only for SPiCT and CMSY with quite different values. These differences might be due to the diverse models' configuration and input data: CMSY comprises only the Italian acoustic index, whereas SPiCT offers the possibility to include both the Italian and the Croatian acoustic indexes. Considering the quite stable trend of the Croatian acoustic index accounting for lower values

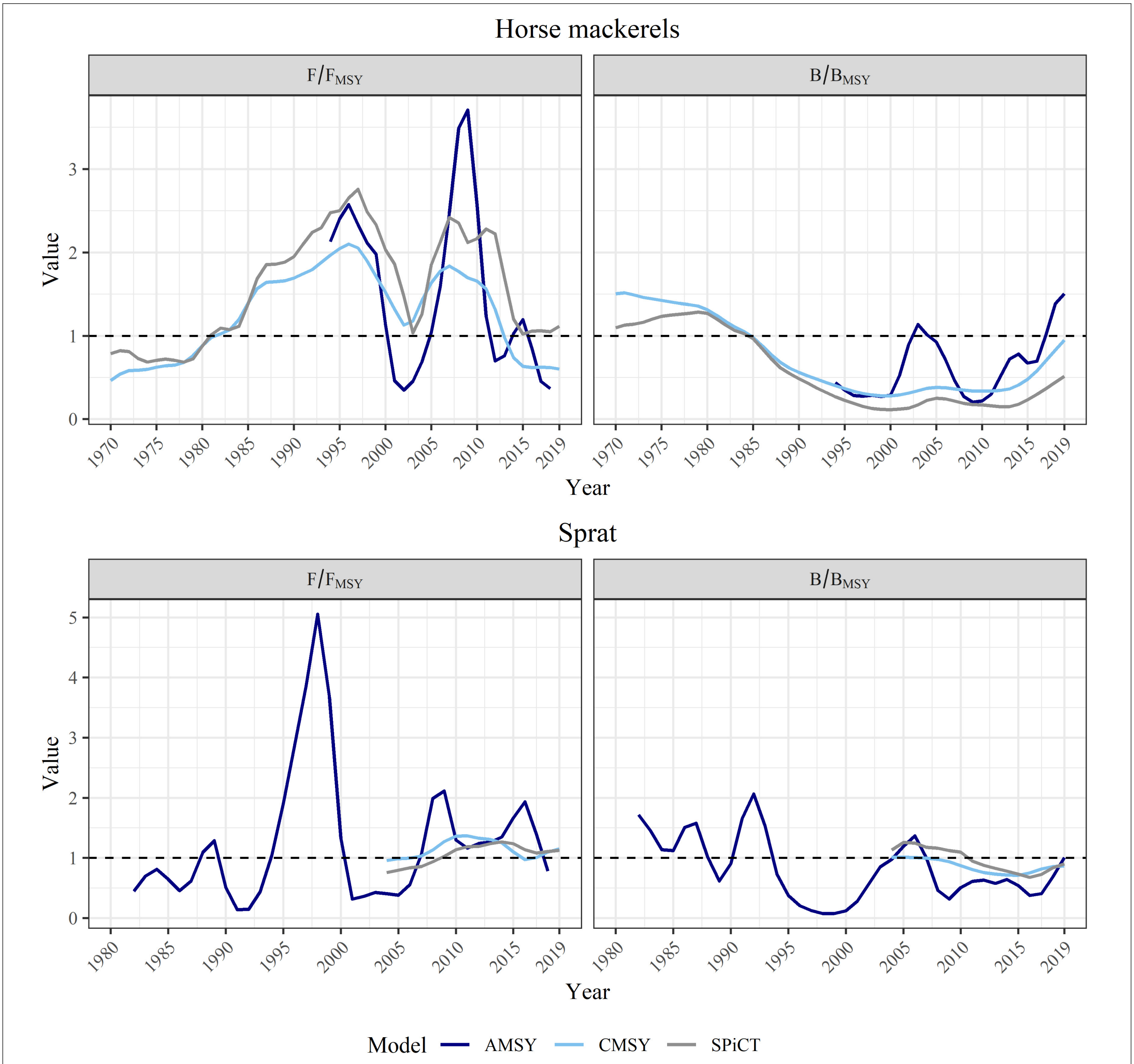


FIGURE 5 | B/B_{MSY} (right panels) and F/F_{MSY} (left panels) trends for the horse mackerel species (top panels) and European sprat (bottom panels) for the three SPMs (AMSY—blue line, CMSY—light blue line, SPiCT—gray line). The dashed line corresponds to the reference values.

compared to those presented by the Italian acoustic survey (**Figure 3**, bottom right panel), the consequent estimated biomass is lower than the one estimated by CMSY. This fact is also reflected in the resulting *K*, which is lower for the SPiCT model compared to the one estimated by CMSY (**Table 3**). Notwithstanding, the numerical estimations are different, the trends of B/B_{MSY} and F/F_{MSY} are comparable, thus describing a very similar status of this stock (**Figure 6**, top panel). More generally, the three selected SPMs present variations among the estimated parameters (**Table 3**) that can be retained reasonably since they were developed considering different settings. Lastly, AMSY results are the most appropriate model for evaluating this stock: they show the best retrospective patterns (**Supplementary Figures 4A, 6A, 9A**), while also avoiding the uncertainty related to landing data. Moreover, AMSY considers only the Italian acoustic survey, which represents the best available and longest source of information for this stock, thus supporting the integrity of this approach.

Horse Mackerel Species

Horse mackerel species, *Trachurus trachurus*, and *Trachurus mediterraneus*, are diffused around the entire north and central

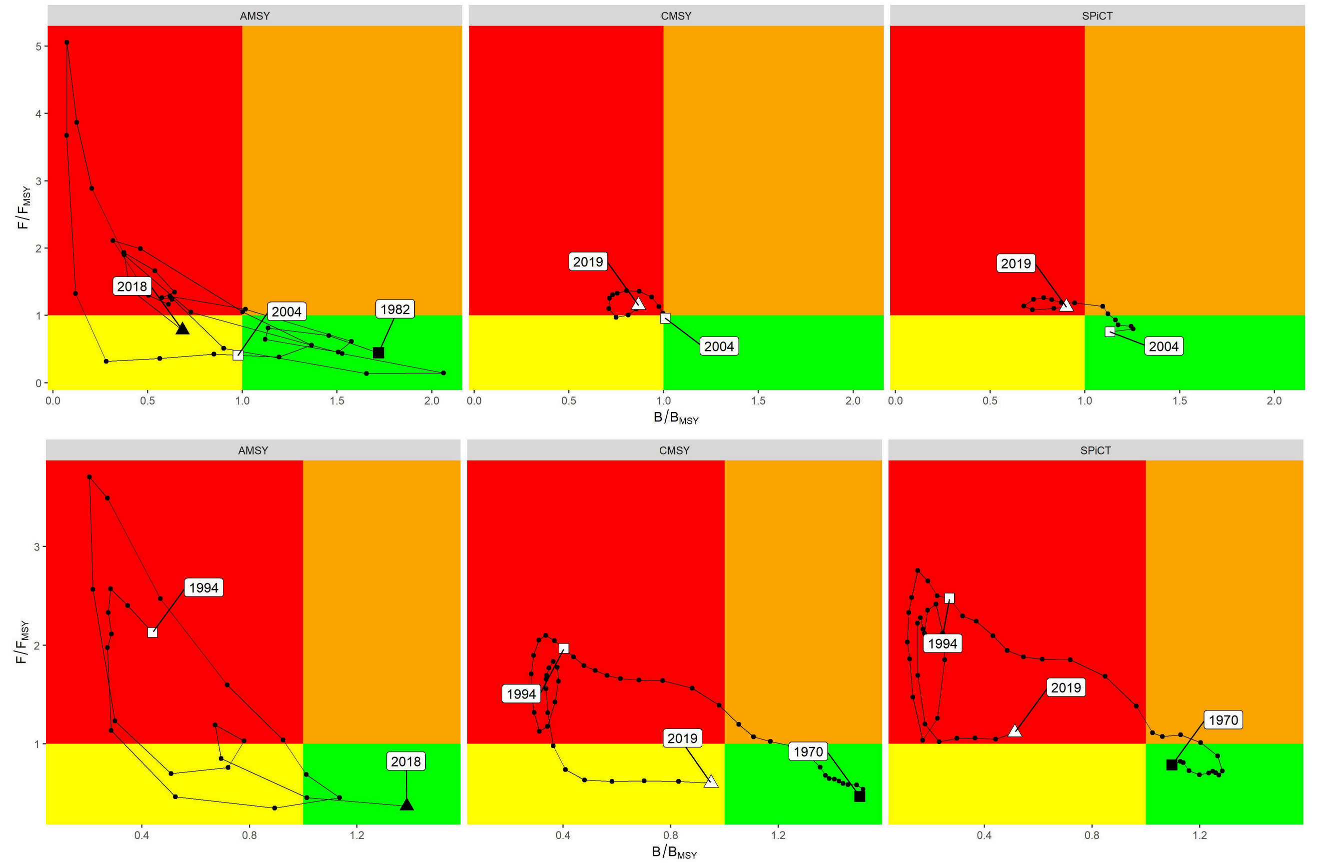


FIGURE 6 | Kobe plots for each of the tested SPMs divided by species: European sprat (top panel) and horse mackerels (bottom panel).

Adriatic Sea, as shown by the maps obtained by the MEDITS data (**Figure 4**). This figure presents the species' distribution for the years 2014, 2018, and 2019, for which georeferenced data were made available.

The situation depicted for Adriatic horse mackerel species differs among the three models. The models, i.e., CMSY and SPiCT, that take into account both landing and survey data, are developed considering a longer time series compared to the AMSY model and present a quite similar trend in terms of biomass and fishing mortality (**Figure 5** top panels, **Figure 6** bottom panel). Stock biomass results are above the reference value until the year 1985, and then decrease up to 2000; after this year biomass follows a quite stable trend before increasing continuously from 2015 up until present, reaching the value of B/B_{MSY} equal to 0.950 and 0.513 for, respectively, CMSY and SPiCT (**Figure 5** top right panel and **Table 4**). Fishing mortality describes an opposite trend: at the beginning of the time series, F/F_{MSY} describes a continuous increase up to F/F_{MSY} equal to 2.099 in 1996 and 2.757 in 1997, respectively, for CMSY and SPiCT, which then decreases rapidly until it reaches the value of 1.128 in 2002 for CMSY and 1.043 in 2003 for SPiCT (**Figure 5** top left panel). In the following years, a new increase followed by a stable period is registered, which then decreases again in recent years, reaching a value of F/F_{MSY} equal to 0.600 for CMSY and 1.115 for SPiCT in 2019 (**Figure 5** top left panel and **Table 4**).

In agreement with data availability, AMSY was developed for a shorter time series. The general trend described by this model appears similar to those depicted by the other two models; however, AMSY, which describes a general increasing biomass trend from 1994 up until present (B/B_{MSY} in 2019 equal to 1.503), also reveals a peak in 2003 (B/B_{MSY} = 1.135) not shown in the other two approaches (**Figure 5** top right panel). This peak is probably due to the survey index that shows a peak in 2004. The trend of F/F_{MSY} is similar to those described by CMSY and SPiCT; however, it accounts for the highest drop in the early 2000s (F/F_{MSY} = 0.349 in 2002), as well as the highest peak in 2009 (F/F_{MSY} = 3.707 in 2009), to then decrease accounting for the value of F/F_{MSY} = 0.368 in 2018 (**Figure 5** top left panel and **Table 4**).

Diagnostics (**Supplementary Figures 10A–18A**) present a good fitting for all the models. Estimated parameters are summarized in **Table 4**: r and K (this is not estimated for the AMSY model) values are very similar among the models; this is probably influenced by the fact that the three models use very similar input data. Considering the availability of a long time series of landing data and their important amount, particularly at the beginning of the time series, the use of a

TABLE 4 | Horse mackerel species—estimated parameters from the three SPMs.

Estimated parameters	CMSY	SPiCT	AMSY
F_{2019}	0.157	0.329	0.109*
$B_{2019\,(tons)}$	11,521.009	5,650.753	4,865.06
F_{MSY}	0.262	0.295	0.297
$B_{MSY\,(tons)}$	12,133.270	11,019	3,236
B/B_{MSY}	0.950	0.513	1.503
F/F_{MSY}	0.600	1.115	0.368*
r	0.525	0.503	0.593
K	24266.539	23566	

**This value refers to F 2018.*

model able to include both landing and survey information can facilitate the understanding of the status of this stock. Thus, CMSY or SPiCT results are the candidate models for describing the situation of horse mackerel species in the Adriatic Sea.

DISCUSSION

This study presents the comparison of three SPMs developed for evaluating the status of European sprat and horse mackerel species (Atlantic horse mackerel and Mediterranean horse mackerel) living in the Adriatic Sea. The focus on these species represents an opportunity to increase knowledge about the status of the pelagic domain in this basin since, at present, only anchovy (*Engraulis encrasicolus*) and sardine (*Sardina pilchardus*) are regularly assessed (General Fisheries Commission for the Mediterranean (GFCM), 2020) and a management plan has been in place for almost a decade (FAO, 2013). However, an increase in the number of assessed species, even if they have a low economic value, is of fundamental consequence, taking into account the increasing worldwide importance of adopting an ecosystem-centric approach, focusing both on the impacts of fisheries on the environment, and the environment on the fishes in it. In the Adriatic Sea framework, the evaluation of other small pelagic stocks rather than anchovy and sardine is going to favor the development of this approach, since ecosystem models, based on outputs available also from the present study, can be used as fisheries management tools in the context of a holistic approach and proposing plans of action (Dimarchopoulou et al., 2019; Dimarchopoulou, 2020).

Sprat is a migratory species with local importance. Considering the seasonal information from acoustic surveys and literature (Tičina and Giovanardi, 1997; Tičina et al., 2000; Azzali et al., 2002; Leonori et al., 2011), its distribution is not constant, but it is dependent on migration between the more productive shallow western Adriatic (feeding grounds) and deeper areas (spawning grounds) in the eastern Adriatic (Tičina, 2000, 2003). However, it seems concentrated mainly in the north-western side of the Adriatic Sea, as also demonstrated by the acoustic survey. This supports the use of only the Italian survey data when SPMs, i.e., CMSY and AMSY, are not able to include more than one survey index. Sprat represents a traditional food with low commercial value, as confirmed by limited landing values compared to other commercial species (EU-DCF database 2019; European Commission (EC), 2017). For this reason, sprat is considered an accessory species for the small pelagic fishery, often discarded if caught in an area where there is no market or, mostly in the eastern Adriatic, landed but reported as a mix of species (Sinovčić, 2001). This confirms the possibility that the use of landing data can be misleading for the evaluation of this stock, whereas the use of survey data, annually collected using a defined systematic scheme, seems the best source of information for estimating the status of this stock. However, it has to be mentioned that acoustic surveys underwent some modifications over the years (Leonori et al., 2021), e.g., the use of different vessels, different sampling times between the eastern and western sides, and a shift in the survey period of the western acoustic survey. The presence of these variables does not allow for easily combining the different surveys, suggesting the need for a standardization protocol to derive a single survey index to be used in stock assessment models. Consequently, in this work, since the main differences are between the eastern and western surveys, these two investigations were kept separated and, in the case of the SPiCT model, the differences in the survey period were accounted for. Finally, AMSY allows the use of a longer time series of information; this is of relevant importance in the context of SPMs in which only a limited number of information is included, thus the use of a longer time series can help in obtaining a more precise picture. A further argument for evaluating the models' reliability are the values estimated for current B and B_{MSY} (**Table 3**): the estimates provided by CMSY and SPiCT, which are based on the landing time-series, are far lower than those from AMSY, which are based on the MEDIAS biomass time-series. The pessimistic situation revealed by CMSY and SPiCT are probably due to the fluctuating landings paired with a general decreasing trend of the survey index, which reveals an important peak only at the beginning of the considered time series. In the future, improvements to these models can be obtained by the inclusion of a longer time series of catches with more reliable data, that can be obtained by the organization of a specific data collection in the main harbors which historically land sprat. Considering the uncertainty in the landing values, MEDIAS total biomass results being the best proxy of the stock biomass in a given year, this makes the CMSY and SPiCT estimates unrealistic. All these observations support the use of the AMSY model as the most appropriate approach to evaluate the status of this stock; this is also sustained by Cook (2013) who promotes the use of survey-based assessment when catch data are unreliable or unavailable while survey data have an adequate temporal and spatial coverage. However, in this case, the extreme fluctuations observed in the survey required a very wide r prior range to accommodate for the Schaefer dynamic. An unrealistically high value of r may theoretically lead to overestimating the ability of the stock to recover from low biomass status. However, the possibility that extreme values of r cause biased or unlikely stock productivity is lowered by the filtering process of the AMSY algorithm, which excluded r-Kq pairs giving unreasonable results when combined with CPUE data (Froese et al., 2020). Nevertheless, the wide uncertainty in the *r* prior is an undesirable condition, which may be better tackled if detailed uncertainty estimation is available and used for data weighting. For instance, yearly estimation of survey uncertainty may be used to model the observation error in the state-space formulation of the AMSY model. At present, very few species have been formally assessed using the AMSY model, and, based on our knowledge, the present study was the first application on a pelagic stock based on acoustic data. Instead, different examples of demersal stocks are presented in literature: Tsikliras et al. (2021) developed an AMSY model for 74 species never assessed in the Aegean Sea, Falsone et al. (2021) built AMSY and CMSY models for the *Lepidopus caudatus* in the Strait of Sicily. The limited diffusion of this model is also due to the fact that it was developed only recently. Regardless, in the upcoming future, considering the availability of survey data further developments of this model can be envisaged.

The three models used to assess the sprat stock present different outcomes; this is probably due to the fact that input data are used differently. CMSY and SPiCT were developed considering both landing and survey data, resulting in much more similar results compared to those revealed by AMSY. Also, SPiCT presents the advantages of using both the Italian and the Croatian acoustic indexes, whereas AMSY and CMSY allow the inclusion of only one survey. Notwithstanding that the Italian and the Croatian acoustic survey follow the same sampling scheme (MEDIAS Handbook, 2019), they present important differences, and thus it was preferred to keep them separated. Specifically, the two surveys are carried out by two different research vessels equipped with a different acoustic range of frequencies for acoustic data collection, even if the leading frequency (38 kHz) is the same (MEDIAS Handbook, 2019); moreover, since 2015 surveys at sea are performed in a different period (June-July for the Italian acoustic survey, September for the Croatian one). Considering the migrations of sprat, different acoustic estimates in the two survey areas (eastern and western Adriatic Sea) may occur due to different sampling seasons, even if the survey period was the same until 2014. These differences have to be treated appropriately, e.g., using a standardization protocol, if the survey information is to be used together. The choice of using different survey indexes for the West and East side of the Adriatic Sea was also the preferred solution for the anchovy and sardine assessments (General Fisheries Commission for the Mediterranean (GFCM), 2020).

Atlantic horse mackerel and Mediterranean horse mackerel have a similar distribution in the Mediterranean basin, however, the first species inhabits deeper areas and it is more common in northern Europe (source: AquaMaps, 2019a,b). In recent years another species of *Trachurus*, *Trachurus picturatus*, was reported in Mediterranean and Adriatic landings, however, it is not considered in this study since few records are available. The biology of *Trachurus* is poorly reported, while genetic studies are much more diffuse. These reveal the existence of 14 species belonging to the *Trachurus genus,* possibly lumped into three historical groups *trachurus*, *picturatus*, and *mediterraneus* (Shaboneyev, 1981) with some uncertainties about the relationship among them: some authors report a closer connection between *T. mediterraneus* and *T. picturatus* (Karaiskou et al., 2003), others describe these species as different clades (Cárdenas et al., 2005). Considering the need of clarifying the phylogeographic aspects of these species, as well as their biology and the need for reporting landing by species, we can retain the assumption of assessing *T. trachurus* and *T. mediterraneus* together as a valid option, specifically in a study like this one in which the main aim is testing different stock assessment models and not addressing management aspects. Additionally, these species are mainly captured by bottom trawlers; this type of gear represents a multispecies fishing technique (Caddy, 1993; Sánchez et al., 2007), thus the management of this fishing gear is based on the results of the stock assessments of different species.

Horse mackerel species have been also assessed comparing the three SPMs. In this case, considering the availability of a longer time series of landing data and their significant amount, particularly at the beginning of the time series, the use of a model able to include both landing and survey information can facilitate the understanding of the status of this stock. Thus, CMSY or SPiCT are as a result the favorite models to evaluate the status of these species. Only the SPiCT models describe these species in overexploitation, e.g., fishing mortality exceeds the reference point, while both models depict biomass below the reference value, though describe an improving trend for the most recent years. This positive trend is probably due to the reduction of fishing effort undergone in the last decade, for which a drop in the number of fishing days, as well as a decrease in the number of fishing boats, occurred (FAO, 2002, 2006, 2019). B and B_{MSY} estimates given by CMSY and SPiCT, based on the landing time-series, are comparable to the AMSY estimates, based on the survey index, thus supporting the reliability of these different sources of information and the coherence between them. However, the B_{MSY} value estimated by AMSY represents just 28% of the averaged value between CMSY and SPiCT; this is probably due to the shorter duration of survey data, which is not able to describe the higher biomass estimated by the other two models at the beginning of the time-series. This evidence implies that for these species the use of the AMSY model is not suggested; since the use of only the MEDITS survey data for a shorter time series might result in a misleading representation of the status of horse mackerels in the Adriatic Sea. Nevertheless, such exploration permitted to highlight how the use of different time-series (the shorter 24 years and the longer 50 years) caused an abrupt decrease of the value used as a reference point for the stock biomass, a dynamic that perfectly fits "shifting baseline syndrome" (Pauly, 1995).

In this study, different SPMs have been tested in different situations; similar comparisons are not common in literature, for which few examples are available (e.g., Bouch et al., 2020; Falsone et al., 2021). In particular, Bouch et al. (2020) tested the differences between CMSY and SPiCT and compared these results with the ICES assessments developed using age-based models. This study highlighted the fact that SPiCT generally describes a more optimistic status compared to CMSY, but both models present different results compared to the more structured approaches approved within the ICES framework. For the Adriatic case study, the performances of SPMs vs. age-based models could not be evaluated since no other assessments, other than those developed in this study, are available for these species. Also, in this study, only two stocks have been examined and for only one, the sprat, does SPiCT describe a more positive situation compared to CMSY. However, these results do not invalidate the previous study since here only a limited number of species were considered, rather they suggest developing further studies to clarify the performances between SPMs and age-based models also in the Mediterranean area. Also, since for the species considered in this study no other formal stock assessments are available, the fact remains that testing different model results is a good practice to select the most appropriate model to describe the status of these resources. In addition, the quality of the input data, together with the validity of the selected assumptions, as well as the strengthens and limitations of each approach have to be considered before selecting the best model. Moreover, instead of comparing outputs and selecting a single final model, future approaches can lead to the development of ensemble methods, which are promising approaches when a decision has to be made despite multiple and potentially conflicting estimates of stock status being present (Anderson et al., 2017). In addition, due to increasing calls in accounting for structural and parameter uncertainty (Punt et al., 2017), ensemble stacking procedure can be tested to represent variability in life-history parameters and fundamental determinants of stock status estimates in data-limited situations (Rudd et al., 2019).

Notwithstanding age-structured assessments remaining the favored models for evaluating the status of resources (Maunder, 2003; Punt and Szuwalski, 2012; Wang et al., 2014), in the last two decades, SPMs improved considerably such that they have been used for assessing important species, such as Atlantic bigeye tuna (*Thunnus obesus*; ICCAT, 2018), Mediterranean albacore tuna (*Thunnus alalonga*; ICCAT, 2017), and Indian Ocean blue shark (*Prionace glauca*; IOTC, 2017). Several examples are also developed in Mediterranean waters, where SPiCT was used for a variety of species and areas, e.g., *Mullus barbatus* in Greek waters (GSAs 20 and 22), and anchovy and sardine in the Thyrrenian sea (GSA 9) (General Fisheries Commission for the Mediterranean (GFCM), 2019a,b), whereas different stock assessments were developed using CMSY in the Adriatic basin, e.g., *Sepia officinalis* in GSA 17, and *Squilla mantis* in GSA 18 (General Fisheries Commission for the Mediterranean (GFCM), 2019a). CMSY was also attempted in a multispecies context and to test the effect of different harvest control rules (Armelloni et al., 2021). SPMs based on survey information only are less common, whereas these data are mainly used within a survey-based model, i.e., SURBA (Beare et al., 2005) or SURBAR (Needle, 2015), or used alone as trends, e.g., anchovy and sardine in GSA 7 are evaluated using survey trends only (General Fisheries Commission for the Mediterranean (GFCM), 2019b).

CONCLUSION

In this manuscript, SPMs have been tested and compared for three species, European sprat, and Mediterranean and Atlantic horse mackerel living in the Adriatic Sea, which were never previously assessed, with the aim of extending the number of the stocks' evaluations and thus investigate the impact of fishing activity on non-routinely assessed pelagic species and, more generally, on the pelagic ecosystem. Depending on the data availability a different model was suggested for describing the status of these resources: a survey-based model in the case of sprat, for which survey data were more accurate and available for a long time series, and a model based on landing and survey information when commercial landings were relevant, i.e., horse mackerel species. All these approaches were based on SPMs since age/length-structure data were not available or very scarce for these species. Notwithstanding, the use of age-based assessments is generally suggested, the use of this type of model can help in situations in which little information is available and for this reason, can have further applications in the near future.

DATA AVAILABILITY STATEMENT

The landing data that support the findings of this study are available in **Supplementary Material**, whereas data referring to DCF research surveys at sea are available upon official DCF data request. A dedicated template for data requests is available on the DCF website [Guidelines—European Commission (europa.eu)]. Requests to access the datasets should be directed to DCF website, https://datacollection.jrc.ec.europa.eu/guidelines/data-request-template.

AUTHOR CONTRIBUTIONS

IL, CM, II, VT, IC, and SA provided data and biological information. SA and EA developed stock assessment analysis. SA and EA wrote the manuscript with contributions from all authors. All authors discussed the results.

FUNDING

This study was supported by the Direzione Generale della Pesca Marittima e dell'Acquacoltura of the Italian Ministry of Agricultural, Food and Forestry Policies (MIPAAF) and by the Croatian Ministry of Agriculture within the EU Data Collection Framework (DCF—MEDITS and MEDIAS), and the Ministry of

Science and Education of the Republic of Croatia (Grant No. 001-0013077-0532).

ACKNOWLEDGMENTS

We thank Martina Scanu for her help in setting the stock assessment models and Giampaolo Coro for his useful comments. The research leading to these results has been conceived under the International Ph.D. Program "Innovative Technologies and Sustainable Use of Mediterranean Sea Fishery and Biological Resources (www.fishmed-phd.org)". This study represents a partial fulfillment of the requirements for the Ph.D. thesis of ENA.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2021.728948/full#supplementary-material

REFERENCES

Aalto, E. A., Dick, E. J., and McCall, A. D. (2015). Separating recruitment and mortality time lags for a delay-difference production model. *Can. J. Fish. Aquat. Sci.* 165, 161–165. doi: 10.1139/cjfas-2013-0415

Amoroso, R. O., Pitcher, C. R., Rijnsdorp, A. D., McConnaughey, R. A., Parma, A. M., Suuronen, P., et al. (2018). Bottom trawl fishing footprints on the world's continental shelves. *Proc. Natl. Acad. Sci. U.S.A.* 115, E10275–E10282. doi: 10.1073/pnas.1802379115

Anderson, S. C., Cooper, A. B., Jensen, O. P., Minto, C., Thorson, J. T., Walsh, J. C., et al. (2017). Improving estimates of population status and trend with superensemble models. *Fish Fish.* 18, 732–741. doi: 10.1111/faf.12200

Anonymous (2017). *MEDITS Handbook, Version No. 9. MEDITS Working Group*. 106. Avaliable online at: http://www.sibm.it/MEDITS%202011/principaledownload.htm

AquaMaps (2019a). *Computer Generated Distribution Maps for Trachurus Mediterraneus (Mediterranean horse mackerel), with modelled year 2050 native range map based on IPCC RCP8.5 emissions scenario*. Available online at: https://www.aquamaps.org (accessed March 2021).

AquaMaps (2019b). *Computer Generated Distribution Maps for Trachurus Trachurus (Atlantic horse mackerel), with modelled year 2050 native range map based on IPCC RCP8.5 emissions scenario*. Available online at: https://www.aquamaps.org (accessed March 2021).

Armelloni, E. N., Scanu, M., Masnadi, F., Coro, G., Angelini, S., and Scarcella, G. (2021). Data poor approach for the assessment of the main target species of rapido trawl fishery in Adriatic Sea. *Front. Mar. Sci.* 8:552076. doi: 10.3389/fmars.2021.552076

Azzali, M., De Felice, A., Luna, M., Cosimi, G., and Parmiggiani, F. (2002). The state of the Adriatic Sea centered on the small pelagic fish populations. PSZN. *Mar. Ecol.* 23, 78–91. doi: 10.1111/j.1439-0485.2002.tb00009.x

Barausse, A., Duci, A., Mazzoldi, C., Artioli, Y., and Palmeri, L. (2009). Trophic network model of the Northern Adriatic Sea: analysis of an exploited and eutrophic ecosystem. *Estuarine Coast. Shelf Sci.* 83, 577–590. doi: 10.1016/j.ecss.2009.05.003

Beare, D. J., Needle, C. L., Burns, F., and Reid, D. G. (2005). Using survey data independently from commercial data in stock assessment: an example using haddock in ICES division VIa. *ICES J. Mar. Sci.* 62, 996–1005. doi: 10.1016/j.icesjms.2005.03.003

Berg, C. W., Nielsen, A., and Kristensen, K. (2014). Evaluation of alternative age-based methods for estimating relative abundance from survey data in relation to assessment models. *Fish. Res.* 151, 91–99. doi: 10.1016/j.fishres.2013.10.005

Bertrand, J. A., Gil de Sola, L., Papaconstantinou, C., Relini, G., and Souplet, A. (2002a). The general specifications of the MEDITS surveys. *Sci. Mar.* 66, 9–17.

Bertrand, J. A., Leonori, I., Dremière, P. Y., and Cosimi, G. (2002b). Depth trajectory and performance of a trawl used for an international bottom trawl survey in the Mediterranean. *Sci. Mar.* 66(Suppl. 2), 169–182. doi: 10.3989/scimar.2002.66s2169

Bouch, P., Minto, C., and Reid, D. G. (2020). Comparative performance of data-poor CMSY and data-moderate SPiCT stock assessment methods when applied to data-rich, real-world stocks. *ICES J. Mar. Sci.* 78, 264–276. doi: 10.1093/icesjms/fsaa220

Branch, T. A., Jensen, O. P., Ricard, D., Ye, Y., and Hilborn, R. (2011). Contrasting global trends in marine fishery status obtained from catches and from stock assessments. *Conserv. Biol.* 25, 777–786. doi: 10.1111/j.1523-1739.2011.01687.x

Caddy, J. F. (1993). Some future perspectives for assessment and management of Mediterranean fisheries. *Sci. Mar.* 57, 121–130.

Cárdenas, L., Hernández, C. E., Poulin, E., Magoulas, A., Kornfield, I., and Ojeda, F. P. (2005). Origin, diversification, and historical biogeography of the genus *Trachurus* (Perciformes: Carangidae). *Mol. Phylogenet. Evol.* 35, 496–507. doi: 10.1016/j.ympev.2005.01.011

Colloca, F., Cardinale, M., Maynou, F., Giannoulaki, M., Scarcella, G., Jenko, K., et al. (2013). Rebuilding Mediterranean fisheries: a new paradigm for ecological sustainability. *Fish Fish.* 14, 89–109. doi: 10.1111/j.1467-2979.2011.00453.x

Cook, R. M. (2013). A fish stock assessment model using survey data when estimates of catch are unreliable. *Fish. Res.* 143, 1–11. doi: 10.1016/j.fishres.2013.01.003

Dimarchopoulou, D. (2020). *Ecosystem Approach to Fisheries Management in the Aegean Sea.* Doctorate Thesis. Thessaloniki: Aristotle University of Thessaloniki.

Dimarchopoulou, D., Tsagarakis, K., Keramidas, I., and Tsikliras, A. C. (2019). Ecosystem models and effort simulations of an untrawled gulf in the central Aegean Sea. *Front. Mar. Sci.* 6:648. doi: 10.3389/fmars.2019.00648

Dremière, P. Y., Fiorentini, L., Cosimi, G., Leonori, I., Sala, A., and Spagnolo, A. (1999). Escapement from the main body of the bottom trawl used for the Mediterranean International Trawl Survey (MEDITS). *Aquat. Living Resour.* 12, 207–217. doi: 10.1016/S0990-7440(00)88471-5

Eigaard, O. R., Bastardie, F., Hintzen, N. T., Buhl-Mortensen, L., Buhl-Mortensen, P., Catarino, R., et al. (2017). The footprint of bottom trawling in European waters: distribution, intensity, and seabed integrity. *ICES J. Mar. Sci.* 74, 847–865. doi: 10.1093/icesjms/fsw194

European Commission (EC) (2017). *Regulation (EU) 2017/1004 on the Establishment of a Union Framework for the Collection, Management and Use of Data in the Fisheries Sector and Support for Scientific Advice Regarding the Common Fisheries Policy and Repealing Council Regulation (EC) No 199/2008*. Brussels: European Commission.

European Environment Agency (EEA), (2019). *The European Environment – State and Outlook 2020. Knowledge for Transition to a Sustainable Europe.* Copenhagen: European Environment Agency.

Eurostat (2021). *Catches – Mediterranean and Black Sea (From 2000 Onwards)*. Available online at: https://ec.europa.eu/eurostat/databrowser/view/fish_ca_atl37/default/table?lang=en (accessed October 2020).

Falsone, F., Scannella, D., Geraci, M. L., Gancitano, V., Vitale, S., and Fiorentino, F. (2021). How fishery collapses: the case of *Lepidopus caudatus* (Pisces: Trichiuridae) in the Strait of Sicily (Central Mediterranean). *Front. Mar. Sci.* 7:584601. doi: 10.3389/fmars.2020.584601

FAO (2002). *Council Regulation (EC) No 2371/2002 of 20 December 2002 on the Conservation and Sustainable Exploitation of Fisheries Resources under the Common Fisheries Policy*. Rome: FAO.

FAO (2006). *Council Regulation (EC) No 1198/2006 of 27 July 2006 on the European Fisheries Fund*. Rome: FAO.

FAO (2013). *Recommendation GFCM/37/2013/1 on a Multiannual Management Plan for Fisheries Exploiting Small Pelagic Stocks in Geographical Subarea 17 (Northern Adriatic Sea) and on Transitional Conservation Measures for Fisheries*

Exploiting Small Pelagic Stocks in Geographical Subarea 18 (Southern Adriatic Sea). Rome: FAO.

FAO (2019). *Recommendation GFCM/43/2019/5 on a Multiannual Management Plan for Sustainable Demersal Fisheries in the Adriatic Sea (Geographical Subareas 17 and 18)*. Rome: FAO.

FAO (2020). *The State of Mediterranean and Black Sea Fisheries 2020. General Fisheries Commission for the Mediterranean*. Rome: FAO.

FAO-GFCM (2019). *Fishery and Aquaculture Statistics. GFCM Capture Production 1970-2017 (FishstatJ)*. Rome: FAO Fisheries and Aquaculture Department.

Fiorentini, L., Dremière, P. Y., Leonori, I., Sala, A., and Palumbo, V. (1999). Efficiency of the bottom trawl used for the Mediterranean international trawl survey (MEDITS). *Aquat. Living Resour.* 12, 187–205. doi: 10.1016/S0990-7440(00)88470-3

Fortibuoni, T., Libralato, S., Arneri, E., Giovanardi, O., Solidoro, C., and Raicevich, S. (2018). Erratum: fish and fishery historical data since the 19th century in the Adriatic Sea, Mediterranean. *Sci. Data* 5:180144. doi: 10.1038/sdata.2018.144

Free, C. M., Jensen, O. P., Anderson, S. C., Gutierrez, N. L., Kleisner, K. M., Longo, C., et al. (2020). Blood from a stone: performance of catch-only methods in estimating stock biomass status. *Fish. Res.* 223:105452. doi: 10.1016/j.fishres.2019.105452

Froese, R., and Pauly, D. (2019). *FishBase, Version 05/2019. World Wide Web Electronic Publication*. Available online at: www.fishbase.org (accessed November 7, 2019)

Froese, R., Demirel, N., Gianpaolo, C., Kleisner, K. M., and Winker, H. (2017). Estimating fisheries reference points from catch and resilience. *Fish Fish.* 18, 506–526. doi: 10.1111/faf.12190

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2020). Estimating stock status from relative abundance and resilience. *ICES J. Mar. Sci.* 77, 527–538. doi: 10.1093/icesjms/fsz230

Gabriel, W. L., and Mace, P. M. (1999). "A review of biological reference points in the context of the precautionary approach," in *Proceedings of the Fifth National NMFS Stock Assessment Workshop: Providing Scientific Advice to Implement the Precautionary Approach under the Magnuson-Stevens Fishery Conservation and Management Act, NOAA Technical Memorandum NMFS-F/SPO-40*, ed. V. R. Restrepo (Silver Spring, MD: National Marine Fisheries Service), 34–45.

General Fisheries Commission for the Mediterranean (GFCM) (2009). *Resolution GFCM/33/2009/2 on the Establishment of Geographical Subareas in the GFCM Area of Application, Amending Resolution GFCM/31/2007/2*. Rome: General Fisheries Commission for the Mediterranean.

General Fisheries Commission for the Mediterranean (GFCM) (2019a). *Scientific Advisory Committee on Fisheries (SAC). Working Group on Stock Assessment of Demersal Species (WGSAD)*. Rome: FAO.

General Fisheries Commission for the Mediterranean (GFCM) (2019b). *Scientific Advisory Committee on Fisheries (SAC). Working Group on Stock Assessment of Small Pelagic Species (WGSASP)*. Rome: FAO.

General Fisheries Commission for the Mediterranean (GFCM) (2020). *Scientific Advisory Committee on Fisheries (SAC). Report of the Benchmark Session for the Assessment of Sardine and Anchovy in GSAs 17-18. Working Group on Stock Assessment of Small Pelagic Species (WGSASP)*. Rome: FAO.

ICCAT (2017). Report of the 2017 ICCAT albacore species group intersessional meeting (including assessment of Mediterranean albacore). *Collect. Vol. Sci. Pap. ICCAT* 74, 508–583.

ICCAT (2018). *Report of the 2018 ICCAT Bigeye Tuna Stock Assessment Meeting, ICCATSCRS*. Pasaia: ICCAT.

IOTC (2017). *Report of the 13th Session of the IOTC Working Party on Ecosystems and Bycatch, IOTC–2017–WPEB13*. San Sebastian: IOTC.

Jackson, J. B. C., Kirby, M. X., Berger, W. H., Bjorndal, K. A., Botsford, L. W., Bourque, B. J., et al. (2001). Historical overfishing and the recent collapse of coastal ecosystems. *Science* 293, 629–638. doi: 10.1126/science.1059199

Karaiskou, N., Apostolidis, A., Triantafyllidis, A., Kouvatsi, A., and Triantafyllidis, C. (2003). Genetic identification and phylogeny of three species of the genus *Trachurus* based on mitochondrial DNA analysis. *Mar. Biotechnol.* 5, 493–504. doi: 10.1007/s10126-002-0099-5

Kristensen, K., Nielsen, A., Berg, C. W., Skaug, H. J., and Bell, B. (2015). TMB: automatic differentiation and Laplace approximation. *J. Stat. Softw.* 70, 1–21. doi: 10.18637/jss.v070.i05

Leonori, I., De Felice, A., Biagiotti, I., Canduci, G., Costantini, I., and Malavolti, S. (2017). "La valutazione degli stock dei piccoli pelagici in Adriatico: l'approccio acustico," in *Il mare Adriatico e le sue risorse*, eds M. Marini, G. Bombace, and G. Iacobone (Palermo: Carlo Saladino Editore), 61–79.

Leonori, I., De Felice, A., Campanella, F., Biagiotti, I., and Canduci, G. (2011). Assessment of small pelagic fish biomass in the Western Adriatic Sea by means of acoustic methodology. *Fish. Sea Resour. Mar. Res. CNR* DTA/06-2011, 2019–2029.

Leonori, I., Tičina, V., De Felice, A., Vidjak, O., Grubišić, L., and Pallaoro, A. (2012). Comparisons of two research vessels' properties in the acoustic surveys of small pelagic fish. *Acta Adriat.* 53, 389–398.

Leonori, I., Tičina, V., Giannoulaki, M., Hattab, T., Iglesias, M., Bonanno, A., et al. (2021). History of hydroacoustic surveys of small pelagic fish species in the European Mediterranean Sea. *Mediterr. Mar. Sci.* In press. doi: 10.12681/mms.26001

Lleonart, J., and Maynou, F. (2003). Fish stock assessment in the Mediterranean: state of the art. *Sci. Mar.* 67, 37–49. doi: 10.3989/scimar.2003.67s137

Marini, M., Bombace, G., and Iacobone, G. (2017). *Il mare Adriatico e le sue risorse*. Palermo: Carlo Saladino Editore, 267.

Maunder, M. N. (2003). Is it time to discard the Schaefer model from the stock assessment scientist's toolbox? *Fish. Res.* 61, 145–149. doi: 10.1016/S0165-7836(02)00273-4

Maunder, M. N., and Piner, K. R. (2015). Contemporary fisheries stock assessment: many issues still remain. *ICES J. Mar. Sci.* 72, 7–18. doi: 10.1093/icesjms/fsu015

McAllister, M. K. (2014). A generalized Bayesian surplus production stock assessment software (BSP2). *Collect. Vol. Sci. Pap. ICCAT* 70, 1725–1757.

MEDIAS Handbook (2019). *Common Protocol for the Pan-MEditerranean Acoustic Survey (MEDIAS), Version Athens, Greece*. 24. Available online at: http://www.mediasproject.eu/medias/website/handbooks-menu/handbooks/MEDIAS-Handbook-April-2019.pdf/

Methot, R. D., and Wetzel, C. R. (2013). Stock synthesis: a biological and statistical framework for fish stock assessment and fishery management. *Fish. Res.* 142, 86–99. doi: 10.1016/j.fishres.2012.10.012

Meyer, R., and Millar, R. B. (1999). BUGS in Bayesian stock assessments. *Can. J. Fish. Aquat. Sci.* 56, 1078–1086. doi: 10.1139/cjfas-56-6-1078

Mildenberger, T. K., Kokkalis, A., and Berg, C. W. (2021). *Guidelines for the Stochastic Production Model in Continuos Time (SPiCT)*. Available online at: https://raw.githubusercontent.com

Needle, C. (2015). Using self-testing to validate the SURBAR survey-based assessment model. *Fish. Res.* 171, 78–86. doi: 10.1016/j.fishres.2015.03.001

Ono, K., Punt, A. E., and Rivot, E. (2012). Model performance analysis for Bayesian biomass dynamics models using bias, precision and reliability metrics. *Fish. Res.* 125-126, 173–183. doi: 10.1016/j.fishres.2012.02.022

Osio, G. C. (2012). The historical fisheries in the Mediterranean Sea: a reconstruction of trawl gear, effort and trends in demersal fish stocks. *Diss. Abstr. Int.* 74 Suppl. B:329.

Pauly, D. (1995). Anecdotes and the shifting baseline syndrome of fisheries. *Trends Ecol. Evol.* 10:430. doi: 10.1016/S0169-5347(00)89171-5

Pedersen, M. W., and Berg, C. W. (2017). A stochastic surplus production model in continuous time. *Fish Fish.* 18, 226–243. doi: 10.1111/faf.12174

Pella, J. J., and Tomlinson, P. K. (1969). A generalized stock production model. *Bull. Inter Am. Trop. Tuna Comm.* 13, 421–458.

Piccinetti, C., Vrgoć, N., Marćeta, B., and Manfredi, C. (2012). Recent State of demersal resources in the Adriatic Sea. *Acta Adriat.* 5, 1–220.

Piroddi, C., Gristina, M., Zylich, K., Greer, K., Ulman, A., Zeller, D., et al. (2015). Reconstruction of Italy's marine fisheries removals and fishing capacity, 1950-2010. *Fish. Res.* 172, 137–147. doi: 10.1016/j.fishres.2015.06.028

Punt, A. E. (2003). Extending production models to include process error in the population dynamics. *Can. J. Fish. Aquat. Sci.* 60, 1217–1228. doi: 10.1139/f03-105

Punt, A. E., Akselrud, C. A., and Cronin-Fine, L. (2017). The effects of applying mis-specified age- and size-structured models. *Fish. Res.* 188, 58–73. doi: 10.1016/j.fishres.2016.11.017

Punt, A. E., and Szuwalski, C. (2012). How well can FMSY and BMSY be estimated using empirical measures of surplus production? *Fish. Res.* 134–136, 113–124. doi: 10.1016/j.fishres.2012.08.014

Ragonese, S., Fiorentino, F., Garofalo, G., Gristina, M., Levi, D., Gancitano, S., et al. (2004). Distribution, abundance and biological features of picarel (*Spicara flexuosa*), Mediterranean (*Trachurus mediterraneus*) and Atlantic

(*T. trachurus*) horse mackerel based on experimental bottom-trawl data (MEDITS, 1994–2002) in the Strait of Sicily. *MedSudMed Tech. Doc.* 5, 110–114.

Rudd, M. B., Thorson, J. T., and Sagarese, S. R. (2019). Ensemble models for data-poor assessment: accounting for uncertainty in life-history information. *ICES J. Mar. Sci.* 76, 870–883. doi: 10.1093/icesjms/fsz012

Sánchez, P., Sartor, P., Recanses, L., Ligas, A., Martin, J., De Ranieri, S., et al. (2007). Trawl catch composition during different fishing intensity periods in two Mediterranean demersal fishing grounds. *Sci. Mar.* 71, 765–773. doi: 10.3989/scimar.2007.71n4765

Šantić, M., Jardas, I., and Pallaoro, A. (2002). Age, growth and mortality rates of horse mackerel, *Trachurus trachurus* (L.), living in the eastern central Adriatic. *Period. Biol.* 104, 165–173.

Šantić, M., Jardas, I., and Pallaoro, A. (2003). Biological parameters of Mediterranean horse mackerel, *Trachurus mediterraneus* (Steind.) in the eastern Adriatic. *Period. Biol.* 105, 393–399.

Shaboneyev, I. Y. (1981). Systematics, morpho-ecological characteristics and origin of Carangids of the genus *Trachurus*. *J. Ichthyol.* 20, 15–24.

Shepherd, J. G. (1999). Extended survivors analysis: an improved method for the analysis of catch-at-age data and abundance indices. *ICES J. Mar. Sci.* 56, 584–591. doi: 10.1006/jmsc.1999.0498

Sinovčić, G. (2001). *Small Pelagic Fish from the Croatian Fishing Grounds. (Split, Croatia 12th-13th October 2000). Annex of GCP/RER/010/ITA/TD-03; AdriaMed Technical Documents No 3*. Available online at: https://www.faoadriamed.org/pdf/publications/

Souplet, A. (1996). "Calculation of abundance indices and length frequencies in the MEDITS survey," in *Campagne internationale de chalutage demersal en Mediterranee (MEDITS). Campagne 1995. Rapport final Vol. 11I. Rapport de contract CEEIFREMER-IEO-SIBM-NCMR (MED/93/020, 018, 006, 004)*, eds J. Bertrand et al. 5–9.

Sparre, P., and Venema, S. C. (1998). *Introduction to Tropical Fish Stock Assessment. Part 1. Manual. FAO Fish. Tech. Pap. No. 306.1, Rev. 2.* Rome: FAO, 407.

Spedicato, M. T., Massutí, E., Mérigot, B., Tserpes, G., Jadaud, A., and Relini, G. (2019). The MEDITS trawl survey specifications in an ecosystem approach to fishery management. *Sci. Mar.* 83S1, 9–20. doi: 10.3989/scimar.04915.11X

Thorson, J. T., Cope, J. M., Branch, T. A., and Jensen, O. P. (2012). Spawning biomass reference points for exploited marine fishes, incorporating taxonomic and body size information. *Can. J. Fish. Aquat. Sci.* 69, 1556–1568. doi: 10.1139/f2012-077

Tičina, V. (2000). *Biology and Commercial Importance of Sprat (Sprattus sprattus* phalericus L.) in the Adriatic Sea. (in Croatian) Ph.D. Thesis. Zagreb: Faculty of natural sciences, University of Zagreb, 133.

Tičina, V. (2003). Pelagic resources of the Adriatic Sea. *Croat. Int. Relat. Rev.* IX, 33–35.

Tičina, V., and Giovanardi, O. (1997). "Osservazioni sulla pesca del "pesce azzurro"," in *Alto Adriatico Pesca e Ambiente nella laguna di Venezia e nell'Alto Adriatico*, eds O. Giovanardi and F. Pranovi (Chioggia: ICRAM-Fondazione della pesca di Chioggia), 91–97.

Tičina, V., Katavić, I., Dadić, V., Marasović, I., Kršinić, F., Grbec, B., et al. (2006). Acoustic estimates of small pelagic fish stocks in the eastern part of Adriatic Sea. *Biol. Mar. Mediterr.* 13 Part 2, 124–136.

Tičina, V., Vidjak, O., and Kačić, I. (2000). Feeding of adult sprat, *Sprattus sprattus*, during spawning season in the Adriatic Sea. *Ital. J. Zool.* 67, 307–311. doi: 10.1080/11250000009356329

Tsikliras, A. C., Touloumis, K., Pardalou, A., Adamidou, A., Keramidas, I., Orfanidis, G. A., et al. (2021). Status and exploitation of 74 un-assessed demersal fish and invertebrate stocks in the Aegean Sea (Greece) using abundance and resilience. *Front. Mar. Sci.* 7:578601. doi: 10.3389/fmars.2020.578601

Wang, S. P., Maunder, M. N., and Aires-da-Silva, A. (2014). Selectivity's distortion of the production function and its influence on management advice from surplus production models. *Fish. Res.* 158, 181–193. doi: 10.1016/j.fishres.2014.01.017

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 25 November 2021
doi: 10.3389/fmars.2021.584657

Assessing Cephalopods Fisheries in the Strait of Sicily by Using Poor Data Modeling

Michele L. Geraci[1,2], Fabio Falsone[2], Vita Gancitano[2], Danilo Scannella[2], Fabio Fiorentino[2] and Sergio Vitale[2]*

[1] Geological and Environmental Sciences (BiGeA) – Marine Biology and Fisheries Laboratory of Fano (PU), Department of Biological, University of Bologna, Bologna, Italy, [2] Institute for Marine Biological Resources and Biotechnology (IRBIM), National Research Council – CNR, Mazara del Vallo, Italy

Cephalopods, including octopuses, squids, and cuttlefishes, are exploited by both bottom trawl and small-scale fisheries (SSF) in most of the Mediterranean areas. Bottom trawl fisheries regard cephalopods as a valuable bycatch, whereas for SSF, they are among the main target species. Cephalopods account for a relatively small proportion of the total landings in the Mediterranean. However, from an economic point of view, four cephalopods, *Eledone cirrhosa, Eledone moschata, Octopus vulgaris,* and *Sepia officinalis*, account for approximately 15% of the total landing value. Despite their economic importance, there are very few stock assessments of cephalopods in the Mediterranean because it is difficult to assess them by classical age-based methods, given their short life-cycles, and highly variable growth and recruitment. The production of *E. cirrhosa*, *E. moschata*, *Illex coindettii*, *Loligo vulgaris*, *O. vulgaris*, *S. officinalis*, and *Todaropsis eblanae* in the waters off the south of Sicily accounts for approximately 8% of the total Mediterranean yield of cephalopods. This study presents the first attempt to assess the state of these cephalopods in the Strait of Sicily by using surplus production models. Since species-wise landing statistics may be unreliable because of their morphological similarity, some octopuses (*E. cirrhosa* and *E. moschata*) and ommastrephid squids (*I. coindetii* and *T. eblanae)* were assessed combined. Landing data and abundance indices from trawl surveys were used to describe cephalopod stock dynamics through the Bayesian State Space Schaefer model (BSM) and Surplus Production model in Continuous Time (SPiCT) models. As survey data were not considered reliable indicators of their abundance, *O. vulgaris*, *S. officinalis,* and *L. vulgaris* stocks were assessed using the Catch-Maximum Sustainable Yield (CMSY) model. Overall, squid and cuttlefish stocks were observed to be in healthy conditions. However, assessments of octopus stocks indicated that their condition was critical or recovering. Here, we discuss the different stock statuses in the light of evolving fisheries and environmental factors in the area over time. Although cephalopods are not a priority in the current management system of Mediterranean fisheries, the importance of these species in the food web and their relevance for SSF underline their importance and their exploitation status should be periodically evaluated.

Keywords: stock assessment, surplus production models (SPM), maximum sustainable yield (MSY), fisheries management, catch-maximum sustainable yield (CMSY), Bayesian surplus production model (BSM), surplus production in continuous time (SPiCT)

Edited by:
Simone Libralato, Istituto Nazionale di Oceanografia e di Geofisica Sperimentale, Italy

Reviewed by:
Francesco Tiralongo, University of Catania, Italy
Natalie Anne Dowling, Oceans and Atmosphere (CSIRO), Australia

***Correspondence:**
Fabio Falsone
fabio.falsone@irbim.cnr.it

Specialty section:
This article was submitted to Marine Ecosystem Ecology, a section of the journal Frontiers in Marine Science

Received: *17 July 2020*
Accepted: *02 November 2021*
Published: *25 November 2021*

Citation:
Geraci ML, Falsone F, Gancitano V, Scannella D, Fiorentino F and Vitale S (2021) Assessing Cephalopods Fisheries in the Strait of Sicily by Using Poor Data Modeling. Front. Mar. Sci. 8:584657. doi: 10.3389/fmars.2021.584657

INTRODUCTION

Cephalopods, both as predators and prey, are key components of marine ecosystems (Boyle and Rodhouse, 2005). Furthermore, commercially important cephalopods are relatively few in number but they support several fisheries, both inshore and offshore, in many oceanic regions (Pierce and Portela, 2014; Rodhouse et al., 2014; Lishchenko et al., 2021). Most cephalopods important to fisheries are semelparous, fast-growing, short-lived, and early maturing species with several cohorts overlapping in the year and their life cycle phenologies are strongly affected by environmental factors (Jackson and O'Dor, 2001; Rodhouse et al., 2014; Jereb et al., 2015; Lishchenko et al., 2021).

In the last few decades, an increasing trend in cephalopod catch from commercial fisheries has been observed in some oceanic regions of the world, together with a progressive decline in groundfish stocks (Rodhouse et al., 2014; Arkhipkin et al., 2015, 2021; Hilborn et al., 2021). This trend has been attributed to several factors: increased biomass in response to global warming (Sauer et al., 2019), reduced competition for prey, and predation by depleted groundfish (Caddy and Rodhouse, 1998; Rodhouse et al., 2014; Doubleday et al., 2016). There is no consensus on the impact of fisheries on cephalopod stocks, with some authors highlighting their vulnerability (e.g., Rosenberg et al., 1990) and others suggesting that their "life-strategy" may be advantageous under heavy fishing pressures relative to long-lived and late-maturing fish (e.g., Caddy, 1983). On the other hand, there is a general agreement on the impact of environmental factors on cephalopod growth and recruitment, and that these affect significant population dynamics and stock assessment parameters (e.g., Rodhouse et al., 2014).

In the Mediterranean Sea, cephalopod fisheries date back to ancient times and can be traced to the Bronze Age, as depicted by Minoic potteries. In this area, cephalopods are fished by both bottom trawl and small-scale fisheries (SSF), where the latter employ gears such as trammel nets, pots, and hand-lines (Quetglas et al., 2015; Falsone et al., 2020). However, most commercial landings are currently attributed to bottom trawling (Sartor et al., 1998; Jereb et al., 2015). The waters south of Sicily [Geographical Sub Area (GSA) 16, according to the FAO General Fishery Commission for the Mediterranean (GFCM)], corresponding to the northernmost sector of the Strait of Sicily, are among the most productive areas for demersal fisheries in the Mediterranean (Milisenda et al., 2017; Di Lorenzo et al., 2018; Falsone et al., 2020). The landings of the following seven species accounted for approximately 8% of the total Mediterranean landings for cephalopods (FAO Fisheries and aquaculture software, 2021): horned octopus *Eledone cirrhosa* (Lamarck, 1798), Musky octopus *Eledone moschata* (Lamarck, 1798), broadtail shortfin squid *Illex coindettii* (Verany, 1839), European squid *Loligo vulgaris* (Lamarck, 1798), common octopus, *Octopus vulgaris* (Cuvier, 1797), common cuttlefish *Sepia officinalis* (Linnaeus, 1758), and lesser flying squid *Todaropsis eblanae* (Ball, 1841).

Despite their economic importance, studies assessing cephalopod fisheries and stock status in the Mediterranean are rather scarce. In this region, some cephalopods are caught by SSF, which are intrinsically difficult to monitor, whereas in bottom trawling, these species are generally regarded as bycatch. Moreover, although cephalopod landings are recorded in most Mediterranean countries, they are registered at the family or the genus levels due to difficulties in species identification. Another factor hampering the stock assessment of cephalopods is their life history traits (short lifespans, semelparous reproduction, high natural mortality rates, rapid and often non-asymptotic growth, complex population structures, and weak stock-recruitment relationships). These factors, together with the resource intensive work needed for direct age estimation, make the use of traditional age-based models impractical (Arkhipkin et al., 2021).

The difficulties in undertaking stock assessment are reflected in the poor management of fisheries that exploit cephalopods in the Mediterranean. To the best of the authors' knowledge, technical measures to regulate cephalopod fisheries have been adopted for common octopus only in Tunisia. According to Ezzeddine and El Abed (2004), between 16 May to 15 October of each year, it is forbidden to fish individuals weighing less than 1 kg. In this context, data-poor methods prove to be useful tools for assessing the stock status of these fishery resources. In this study, a Bayesian State Space Schaefer model (BSM), a Catch Maximum Sustainable Yield (CMSY) model (Froese et al., 2017), and a stochastic Surplus Production model in Continuous Time (SPiCT) (Pedersen and Berg, 2017), widely used within the International Council for the Exploration of the Sea (ICES) and GFCM framework, were used to assess the stock status of *E. cirrhosa, E. moschata, I. coindettii, L. vulgaris, O. vulgaris, S. officinalis,* and *T. eblanae* in the South of Sicily (GSA 16, **Figure 1**).

MATERIALS AND METHODS

Data Sources

Data were gathered through the European Data Collection Framework. In particular, two main data sources were used: (i) official landing data of SSF and bottom trawl, and (ii) survey data from the International bottom trawl survey in the Mediterranean (MEDITS) (Bertrand et al., 2002; Spedicato et al., 2019). Species-wise landing data could be affected by several factors, including species misidentification and the joint selling of different species. In this study, to cope with these difficulties, some species were assessed as combined species: (i) *E. cirrhosa* and *E. moschata* were assessed as *Eledone* spp. (hereinafter referred to as *Eledone*), and (ii) *I. coindetii* and *T. eblanae* were assessed together (hereinafter referred to as *Todill*). For the purpose of this study, the analyzed dataset spanned 2004 to 2018 for both landings and MEDITS data. The MEDITS surveys were carried out mainly in spring–summer, except for 2013 (carried out in summer–autumn), 2014, and 2017 (carried out in autumn). Accordingly, in the analysis, the biomass indices were standardized to account for the time variability of the trawl surveys. In particular, for each species, the BioIndex (Zupa et al., 2021) and BioStand (Zupa et al., 2020) routines were used to fit General Additive Models (GAMs) with Gaussian distribution (identity link), including years, months, depth, latitude, and longitude as predictive

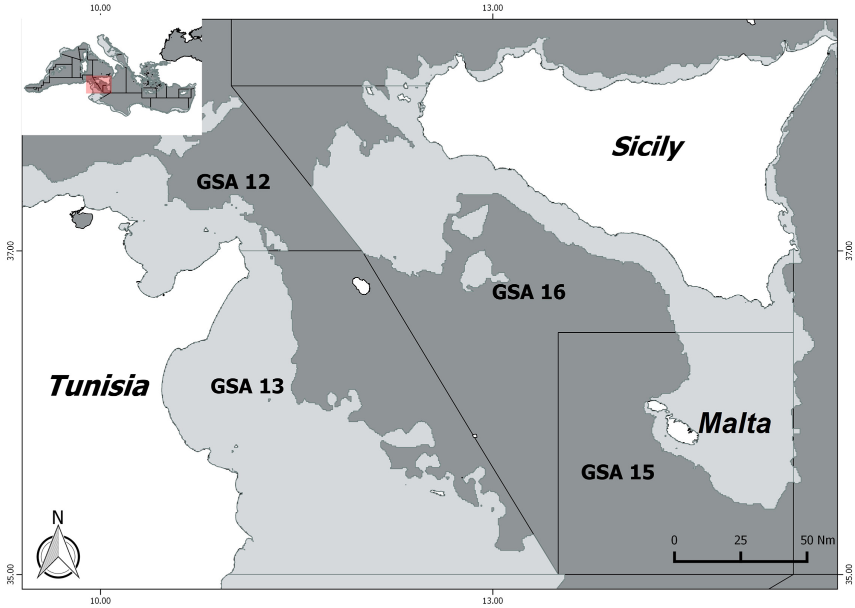


FIGURE 1 | Geographical Sub-Area 16, south of Sicily, where the data of the considered cephalopods were collected.

TABLE 1 | Prior ranges for parameter r used by CMSY and SPiCT models.

Species	**CMSY**				**SPiCT**
	Prior *r* range	**Prior *B/K***			**Prior *r***
Eledone	0.36–0.82	B: 0.2–0.6	I: 0.1–0.4	E: 0.1–0.4	0.5
Loligo vulgaris	0.22–0.51	B: 0.2–0.6	I: 0.4–0.8	E: 0.4–0.8	NA
Octopus vulgaris	0.53–1.21	B: 0.2–0.6	I: 0.01–0.4	E: 0.2–0.6	NA
Sepia officinalis	0.37–0.84	B: 0.2–0.6	I: 0.4–0.8	E: 0.4–0.8	NA
Todill	0.34–1.21	B: 0.2–06	I: 0.4–0.8	E: 0.4–0.8	0.7

In addition, biomass ranges B/K used by CMSY. In prior ranges B/K, B stands for Beginning; I, for intermediate; E, for End of the time series; NA, not available.

variables. The variables that contributed to improving the model fitting were selected through a stepwise approach, with the most parsimonious model selected through Akaike Information Criterion (AIC), Generalized Cross Validation (GCV), and the percentage of deviance explained (Zuur et al., 2009).

Selection of Models

Depletion models are considered the most comprehensive and versatile tools for assessing cephalopods (Arkhipkin et al., 2021). However, these models require high-frequency (daily, weekly, monthly) catch and effort data that may not be available for all types of cephalopod fisheries. Therefore, some alternative data-limited approaches have been suggested to assess cephalopod stock status, including catch-only models and Surplus Production Models (SPMs) (Arkhipkin et al., 2021). Many authors have applied these kinds of models for stock assessment of cephalopods worldwide; for example: (i) CMSY and BSM by Froese et al. (2018) and Wang et al. (2020), (ii) AMSY by Froese et al. (2020) and Tsikliras et al. (2021), (iii) SPiCT by ICES (2020), (iv) ASPIC by Mohsin et al. (2020), and (v) Biomass Dynamic Model with environmental effects by ICES (2017).

In the present study, cephalopod stock status was assessed using SPMs, i.e., CMSY, BSM, and SPiCT. The choice to apply SPMs was mainly dictated by the availability of annual landings and surveys of biomass indices data only. These models might seem unsuitable for cephalopods, given that they assume a constant carrying capacity, which is unlikely for a species whose recruitment and growth can vary widely according to environmental conditions (Rodhouse et al., 2014; Arkhipkin et al., 2021). However, it is worth noting that if input data have enough contrast to allow the model fitting, and main environmental drivers, such as sea surface temperature (SST) or primary production, fluctuate throughout time without any clear trend, the assumption of a carrying capacity as the mean size of an unexploited population could be considered reasonable. Nonetheless, these considerations do not exclude the assumption that a constant carrying capacity cannot be violated. Moreover, CMSY, BSM, and SPiCT require less data than other catch-only data-poor assessment methods (Dowling et al., 2018; Falsone et al., 2021) making them suitable for assessing cephalopod species. For example, the Depletion-Corrected Average Catch (DCAC) method (MacCall, 2009)

TABLE 2 | Selected GAM models with the predictive variables used for the standardization of the surveys indices.

Species	Model	R^2	Dev.expl.%	GCV
Eledone cirrhosa	BI ∼ year + s(X, Y) + s(depth) + month + 0	0.445	60.1	1.65
Eledone moschata	BI ∼ year + s(X, Y) + s(depth) + 0	0.556	73.4	2.46
Illex coindettii	BI ∼ year + s(X, Y) + s(depth) + 0	0.580	74.5	1.99
Todaropsis eblanae	BI ∼ year + s(X, Y) + s(depth) + 0	0.519	64.7	1.86

BI, Biomass Index; X, longitude; Y, latitude; s, smooth function; Dev. expl. %, deviance explained as percentage; GCV, Generalized Cross Validation.

requires information on catch, relative depletion, natural mortality (M), and F_{MSY}/M as inputs, while the Stock Synthesis Data-Limited (SS-DL) method (Cope, 2013) in the catch data configuration requires several additional basic biological and selectivity assumptions. On the other hand, the Catch-Only-Model with Sampling Importance Resampling (COM–SIR) (Vasconcellos and Cochrane, 2005) and State-Space Catch-Only Model (SSCOM) methods (Thorson et al., 2013) require catch, and priors for resilience (r) and carrying capacity (K) as inputs. Also, they are generally based on the same population dynamics assumptions (e.g., constant carrying capacity) as assumed by CMSY, BSM, and SPiCT.

Catch-Maximum Sustainable Yield Model

The CMSY model allows the computation of stock descriptors and parameters given the population's resilience and catches. Species resilience is defined as the "measure of a species ability to adapt to changes in variable states, driving influences and parameters, and still persist" (Holling, 1973). The CMSY approach derives from the Catch–MSY method by Martell and Froese (2012) but addresses several shortcomings of its predecessor by including biased estimation of unexploited stock size and productivity, adding estimation of biomass and exploitation rates, and optimization of the underlying Monte Carlo algorithm. One of the recent improvements of CMSY is the implementation of a Bayesian state–space Schaefer surplus production model (BSM) as a routine tool within the CMSY package (Froese et al., 2017). Unlike CMSY, BSM also requires catch-per-unit-effort or other relative abundance indices (Froese et al., 2017) to perform the assessment. Both models are based on the dynamic formula of the Schaefer model (Equation 1):

$$B_{t+1} = B_t + r\left(1 - \frac{B_t}{K}\right) B_t - C_t \tag{1}$$

where B_{t+1} is the exploited biomass in year $t+1$, B_t is the biomass in year t, r is the intrinsic rate of population increase, K is the carrying capacity (i.e., the mean unexploited stock size), and C_t is the catch in year t. Both models account for depensation or reduced recruitment at severely depleted stock sizes, incorporating a linear decline of surplus production (Myers et al., 1995; Schnute and Richards, 2002) (Equation 2):

$$B_{t+1} = B_t + 4\frac{B_t}{K} r\left(1 - \frac{B_t}{K}\right) B_t - C_t \; \frac{B_t}{K} < 0.25 \tag{2}$$

Specifically, a hockey-stick function is combined with the production model by introducing a multiplier which decreases linearly from 1 to zero at biomass below 0.25 K (Beverton and Holt, 1957; Ricker, 1975; Barrowman and Myers, 2000). This multiplier provides more realistic estimates of r and K in stocks with extended periods of severely depleted biomass. It also removes the bias in the CMSY estimates of final biomass in severely depleted stocks (Froese et al., 2017). Among the five cephalopod stocks, *Eledone* and *Todill* were assessed using both fishery dependent and independent data (i.e., BSM). In the case of *L. vulgaris, O. vulgaris,* and *S. officinalis*, only landing data (i.e., CMSY) was used because of the poor trawl survey performance in sampling the population at sea. The different levels of exploitation in terms of F/F_{MSY} and B/B_{MSY} were classified by using the threshold reported by Demirel et al. (2020): severely depleted ($B \leq 0.2B_{MSY}$), critical condition ($B \leq 0.5B_{MSY}$, $F > F_{MSY}$), exploited outside safe biological limits ($B \leq 0.5B_{MSY}$), subject to overfishing ($F > F_{MSY}$), recovering ($B < B_{MSY}$, $F \leq F_{MSY}$), and healthy ($B > B_{MSY}$, $F \leq F_{MSY}$).

Prior Selection

Priors for r were derived from SeaLifeBase[1] (Palomares and Pauly, 2019) for invertebrates. The prior ranges for k were based on Equations (3) and (4) for stocks with low and high prior biomass at the end of the time series, respectively.

$$K_{low} = \frac{\max(C)}{r_{high}};\ K_{high} = \frac{4\max(C)}{r_{low}} \tag{3}$$

$$K_{low} = \frac{2\max(C)}{r_{high}};\ K_{high} = \frac{12\max(C)}{r_{low}} \tag{4}$$

where K_{low} and K_{high} are the lower and upper bounds of the prior range of K, *max(C)* is the maximum catch in the time series, and r_{low} and r_{high} are the lower and upper bounds of the r range to be explored by the Monte Carlo algorithm of the CMSY. Both BSM and CMSY models require prior estimates of relative biomass (B/K) at the beginning and end of the time series, and optionally also in the middle. The rules for setting prior biomass ranges are mostly derived from patterns in catch, that is, the timing and ratio of minimum catch to maximum catch, following the approach of Froese et al. (2017; **Table 1**). Priors were calculated by applying to the catch data a 3-year moving average in order to reduce the influence of extremes.

Surplus Production Model in Continuous Time Model

The SPiCT model (Pedersen and Berg, 2017) is a fully stochastic version of the traditional Pella–Tomlinson biomass

[1] www.sealifebase.org

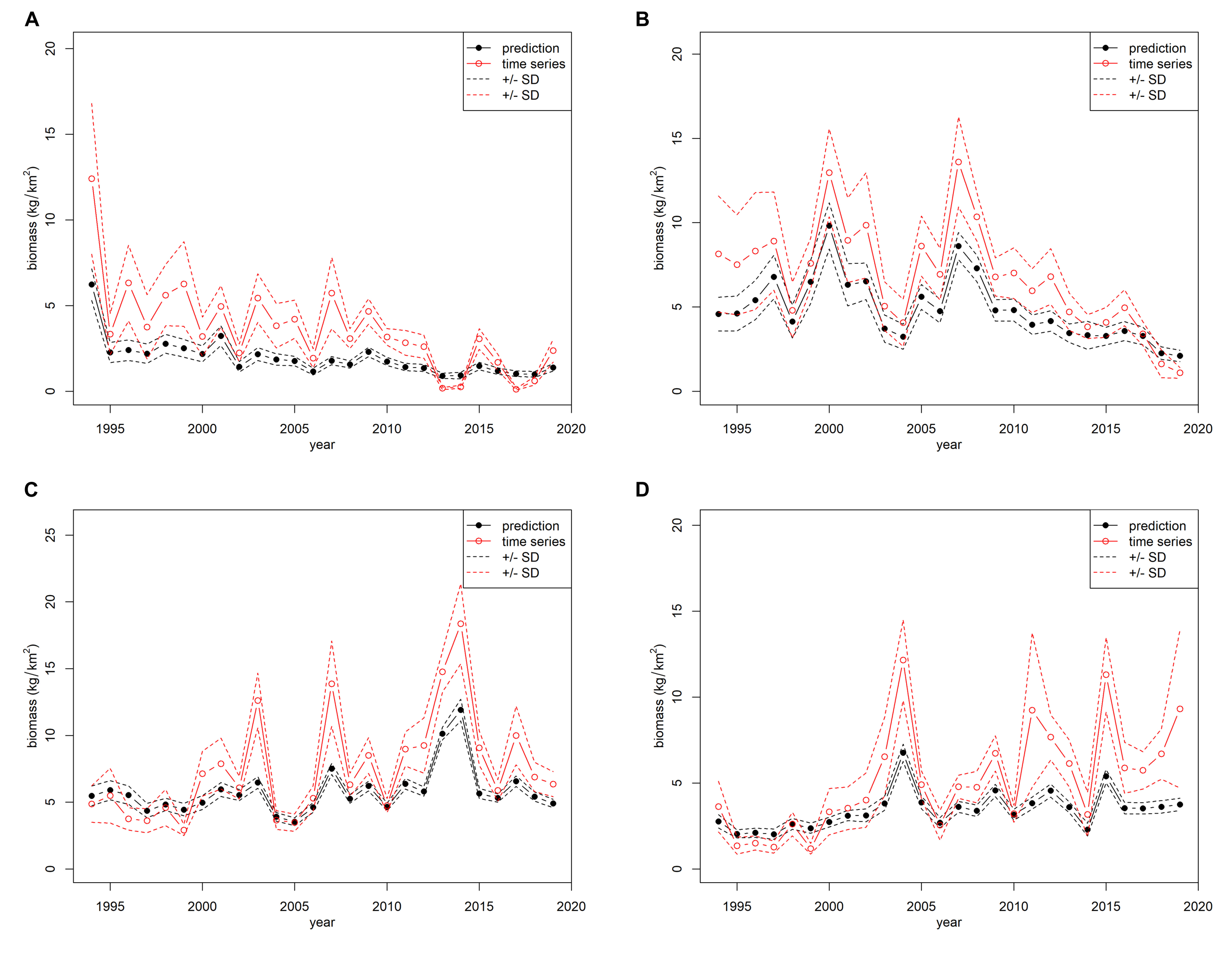


FIGURE 2 | Comparison between the observed (red lines) and standardized (black lines) biomass indices (kg/km^2) of the MEDITS survey from the south of Sicily (GSA16): **(A)** *Eledone cirrhosa;* **(B)** *Eledone moschata;* **(C)** *Illex coindetii;* **(D)** *Todaropsis eblanae.*

dynamic model (Pella and Tomlinson, 1969). It uses the re-parameterization of Fletcher (1978) and is formulated as a stochastic differential equation (SDE) that includes process noise:

$$dB_t = \left(ym\frac{B_t}{K} - ym\left[\frac{B_t}{K}\right] - F_tB_t \right) dt + \sigma_B B_t \, dWt \quad (5)$$

where y = $n^{n/(n-1)}$/(n-1), B_t is the exploitable biomass at time t, K is the carrying capacity, m is the productivity parameter, and represents the maximum attainable surplus production (MSY), n determines the shape of the production curve, σ_B is the standard deviation of the process noise, and dW_t is the Brownian motion. The SPiCT model allows the implementation of the Pella–Tomlinson biomass dynamic model for skewed production curves and includes the Schaefer (n = 2; Schaefer, 1954) and Fox (n = 1; Fox, 1970) models as special cases. For the purpose of the present study, the n parameter was set equal to 2, that is, the Schaefer production curve. The SPiCT assumptions are: (i) the analyzed stock is not subject to migration (i.e., closed population), (ii) B_t is the exploitable stock biomass, (iii) there are no lagged effects in the dynamics of B_t, (iv) the catchability in the survey and fishery are constant over the years, and (v) there is no particular pattern of recruitment. For other technical details (see Pedersen and Berg, 2017; Mildenberger et al., 2020). The same priors for r used for the CMSY and BSM approaches were used for the SPiCT model (**Table 1**). In particular, the SPiCT model was fitted to the *Eledone* and the *Todill* stocks. As with CMSY and BSM, the different levels of exploitation in terms of F/F_{MSY} and B/B_{MSY} were classified using the thresholds reported by Demirel et al. (2020).

RESULTS

Biomass Standardization

The models and predictive variables used to standardize survey indices are shown in **Table 2**. In particular, all models considered

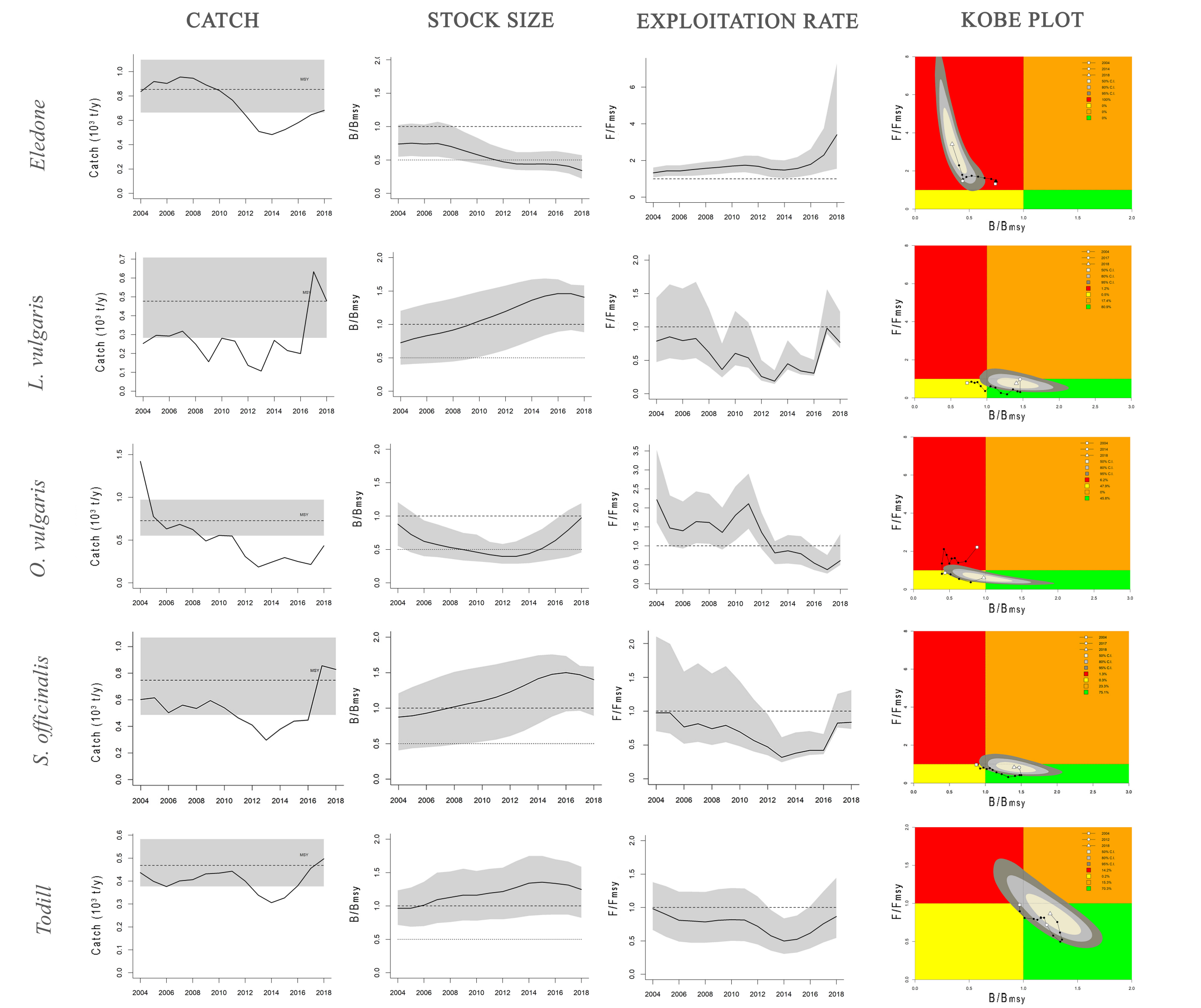


FIGURE 3 | Dynamics of cephalopod stocks in the GSA16 estimated by CMSY and BSM models. Catch panel: black solid line shows the estimated catches, black dashed line the mean value of MSY, gray shaded area the 95% confidence interval of MSY. Stock size and exploitation rate panels: trend of B/B_{MSY} and F/F_{MSY} with gray shaded area showing the 95% confidence interval. Kobe plot panel: B/B_{MSY} against F/F_{MSY} for the years 2004–2018. Quadrants are color-coded, i.e., red area: stocks that are both overfished (low relative biomass) and in overfishing (high exploitation rate) ($B \leq B_{MSY}$; $F \geq F_{MSY}$); orange area: relative biomass is quite high but exploitation rate is high ($B \geq B_{MSY}$; $F \geq F_{MSY}$); yellow area: recovering stocks ($B \leq B_{MSY}$, $F \leq F_{MSY}$); green area: stocks subject to sustainable exploitation rate and with healthy stock biomass that can produce high yields close to MSY ($B \geq B_{MSY}$, $F \leq F_{MSY}$). Shaded areas indicate the confidence interval at 50% (light gray), 80% (gray), and 95% (dark gray) of the reference points during the last year.

year, geographical coordinates (X: longitude, Y: latitude), and depth as predictive variables, except for *E. cirrhosa* for which month was also included as a predictor. The standardized and observed trawl survey indices are shown in **Figure 2**.

Stock Dynamics

Stock dynamics have been described in terms of species-wise catch (10^3 tons), relative stock size (B/B_{MSY}), and exploitation rate (F/F_{MSY}). The main aspects of the stock status by species have been synthetically shown as a Kobe plot (F/F_{MSY} against B/B_{MSY}, **Figure 3**). The main outputs of the BSM, CMSY, and SPiCT models are listed in **Table 3**. **Table 4** shows a comparison of the results obtained in this study with the cephalopod stock assessments carried out in other Mediterranean areas.

The general results seem to highlight that octopus stocks were in a critical and/or recovering condition, whereas squid stocks were in a healthy condition. Detailed results regarding the stock status of each taxon are provided below.

Eledone

BSM and SPiCT yielded similar estimates of *Eledone* stock status. In particular, BSM estimated a B/B_{MSY} ratio equal to 0.3 [confidence interval (CI) = 0.2–0.6] and F/F_{MSY} of 3.4 (1.5–7.3). SPiCT estimates were 0.5 (0.2–1.7) and 1.5 (0.6–3.6) for

TABLE 3 | Main outcomes of the CMSY model applied to five cephalopods stocks of the GSA16.

Species	MSY (BSM)	r (BSM)	K (BSM)	MSY (CMSY)	r (CMSY)	K (CMSY)	MSY (SPiCT)	r (SPiCT)	K (SPiCT)	B/B_{MSY} (CMSY/BSM)	F/F_{MSY} (CMSY/BSM)	B/B_{MSY} (SPiCT)	F/F_{MSY} (SPiCT)
Eledone	0.8 (0.7–1.1)	0.5 (0.4–0.7)	6.8 (4.7–9.8)	0.8 (0.6–1.0)	0.6 (0.4–0.7)	5.6 (4.1–7.7)	0.7 (0.5–1.0)	0.5 (0.4–0.6)	6.5 (5.4–7.9)	0.3 (0.2–0.6)	3.4 (1.5–7.3)	0.5 (0.2–1.7)	1.5 (0.6–3.6)
Loligo vulgaris	NA	NA	NA	0.4 (0.3–0.7)	0.4 (0.3–0.5)	4.6 (2.6–8.5)	NA	NA	NA	1.4 (0.9–1.6)	0.8 (0.7–1.2)	NA	NA
Octopus vulgaris	NA	NA	NA	0.7	0.7 (0.5–1.0)	3.9 (2.8–5.5)	NA	NA	NA	1.0 (0.4–1.2)	0.6 (0.5–1.3)	NA	NA
Sepia officinalis	NA	NA	NA	0.7 (0.5–1.0)	0.6 (0.5–0.9)	4.4 (2.7–7.2)	NA	NA	NA	1.4 (0.9–1.6)	0.8 (0.7–1.3)	NA	NA
Todill	0.5 (0.4–0.6)	0.7 (0.4–1.3)	2.5 (1.6–4.2)	0.5 (0.4–0.8)	0.8 (0.5–1.3)	2.4 (1.5–4.1)	0.4 (0.6–0.6)	0.7 (0.6–0.9)	2.4 (1.8–3.2)	1.2 (0.8–1.6)	0.9 (0.5–1.4)	1.3 (0.9–1.8)	0.8 (0.4–1.9)

In particular, MSY, r, k of BSM and CMSY as well as the relative to MSY levels (F/F_{MSY}, B/B_{MSY}) are shown. NA stands for Not Available. In parentheses 95% confidence interval are given in parentheses.

B/B_{MSY} and F/F_{MSY}, respectively. In addition, the estimated values for K, MSY and *r* were very similar between models (BSM: K = 6.8 × 10^3 tons, CI: 4.7–9.8; MSY = 0.8 × 10^3 tons, CI: 0.7–1.1; *r* = 0.5, CI = 0.4–0.7. SPiCT: K = 6.5 × 10^3 tons, CI: 5.4–7.9; MSY = 0.7 × 10^3 tons, CI: 0.5–1.0; *r* = 0.5, CI = 0.4–0.6). Both models indicated a decrease in stock size (B/B_{MSY}) over the years and an increase in the fishing mortality (F/F_{MSY}) in recent years, although this was more markedly observed in BSM. However, the perception of the stock during the first years of the time series is different, with SPiCT showing an increase, while BSM shows a decrease in stock size. Lastly, even though there was high uncertainty in stock status, especially for SPiCT, this was in critical condition for *Eledone* according to both models ($B \leq 0.5B_{MSY}$, $F > F_{MSY}$; **Figures 3**, **4** and **Tables 3**, **4**).

European Squid

Assessment results indicated that European squid have been in a recovering condition since the beginning of the time series ($B < B_{MSY}$, $F \leq F_{MSY}$). In the last 2 years, the F/F_{MSY} ratio increased and the B/B_{MSY} slightly decreased; however, the stocks could be considered in good condition (healthy state, $B > B_{MSY}$, $F \leq F_{MSY}$). It is worth highlighting that the CMSY estimates are characterized by low uncertainty i.e., B/B_{MSY} = 1.4 with CI = 0.9–1.6 and F/F_{MSY} = 0.8 with CI = 0.7–1.2 (**Figure 3** and **Tables 3**, **4**).

Common Octopus

The stock of common octopus showed the same trend as that of the European squid, with an overall improvement through the time series from an initial critical condition ($F > F_{MSY}$ and $B \leq 0.5\ B_{MSY}$) to a recovering state ($B < B_{MSY}$ and $F \leq F_{MSY}$) during the last year, very close to that of the healthy condition ($B > B_{MSY}$ and $F \leq F_{MSY}$). The CMSY estimated a B/B_{MSY} = 1.0 with CI = 0.4–1.2 and F/F_{MSY} = 0.6 with CI = 0.5–1.3 (**Figure 3** and **Tables 3**, **4**).

Common Cuttlefish

The common cuttlefish stock was initially in a recovering status ($B < B_{MSY}$, $F \leq F_{MSY}$). In the last few years (2017–2018), the relative fishing mortality increased and the relative biomass slightly decreased, even though the species was still in a healthy status at the end of the time series ($B > B_{MSY}$, $F \leq F_{MSY}$). The uncertainty of the CMSY model was very low, i.e., B/B_{MSY} = 1.4 with CI = 0.9–1.6 and F/FMSY = 0.8 with CI = 0.7–1.3 (**Figure 3** and **Tables 3**, **4**).

Todill

BSM estimated a B/B_{MSY} ratio equal to 1.2 (CI = 0.8–1.6) and F/F_{MSY} of 0.9 (0.5–1.4). SPiCT estimated 1.3 (0.9–1.8) and 0.8 (0.4–1.9) for B/B_{MSY} and F/F_{MSY}, respectively. In addition, the estimated carrying capacity, MSY, and *r* were very similar between models (BSM: K = 2.5 × 10^3 tons, CI: 1.6–4.2; MSY = 0.5 × 10^3 tons, CI: 0.4–0.6; *r* = 0.7, CI = 0.4–1.3; SPiCT: K = 2.4 × 10^3 tons, CI: 1.8–3.2; MSY = 0.4 × 10^3 tons, CI: 0.3–0.6; *r* = 0.7, CI = 0.6–0.9). However, in the first 2

TABLE 4 | Synopsis of the cephalopod assessments carried out in Mediterranean stocks.

Species	Area	r	K	B/B$_{MSY}$	F/F$_{MSY}$	Status	Model	Authors
Eledone cirrhosa	Ligurian Sea	1.3	0.3	0.7 (0.5–0.9)	1.0 (0.8–1.3)	R	ASPIC	Abella et al., 2010
	Ligurian Sea	NA	NA	NA	NA	H*	Y/R	Orsi Relini et al., 2006
	southern Tyrrhenian Sea	NA	NA	NA	NA	O**	Y/R	Giordano et al., 2010
	central Tyrrhenian Sea	NA	NA	NA	NA	H*	Y/R	Agnesi et al., 1998
	Aegean Sea	NA	NA	0.1	0.9	R	AMSY	Tsikliras et al., 2021
	Ionian Sea	NA	NA	0.4	4.5	C	CMSY	Froese et al., 2018
Eledone moschata	Aegean Sea	NA	NA	0.7	0.9	R	CMSY	Froese et al., 2018
	Aegean Sea	NA	NA	0.7	1.3	O	AMSY	Tsikliras et al., 2021
Eledone	Strait of Sicily	0.5	6.8	0.3 (0.2–0.6)	3.4 (1.5–7.3)	C	BSM	Present study
	Strait of Sicily	0.5	6.5	0.5 (0.2–1.7)	1.5 (0.6–3.6)	C	SPiCT	Present study
Illex coindettii	Ionian Sea	NA	NA	0.6	0.6	O	CMSY	Froese et al., 2018
	Adriatic Sea	NA	NA	0.3	1.1	C	CMSY	Froese et al., 2018
	Sardinia	NA	NA	0.6	1.1	O	CMSY	Froese et al., 2018
	Aegean Sea	NA	NA	0.8	1.3	O	CMSY	Froese et al., 2018
	Adriatic Sea	NA	NA	1.1 (0.6–2.0)	0.7 (0.1–1.7)	H	AMSY	Froese et al., 2020
Loligo vulgaris	Strait of Sicily	0.4	4.6	1.4 (0.9–1.6)	0.8 (0.7–1.2)	H	CMSY	Present study
	Balearic Island	NA	NA	NA	NA	NA	DM	Keller et al., 2015
	Adriatic Sea	NA	NA	0.2	0.9	D	CMSY	Froese et al., 2018
	Aegean Sea	NA	NA	0.6	1.3	O	CMSY	Froese et al., 2018
	Balearic Islands	NA	NA	0.4	1.1	C	CMSY	Froese et al., 2018
	Gulf of Lions	NA	NA	0.3	3.1	C	CMSY	Froese et al., 2018
	Sardinia	NA	NA	0.3	2.8	C	CMSY	Froese et al., 2018
Octopus vulgaris	Strait of Sicily	0.7	3.9	1.0 (0.4–1.2)	0.6 (0.5–1.3)	H–R	CMSY	Present study
	Adriatic Sea	NA	NA	1.0 (0.6–1.8)	0.9 (0.3–1.7)	H–R	AMSY	Froese et al., 2020
	Balearic Island	0.6	0.7	0.4 (0.3–0.6)	1.2 (0.9–1.5)	C	SPM	Quetglas et al., 2015
	Aegean Sea	NA	NA	0.5	1.1	C	CMSY	Froese et al., 2018
	Ionian Sea	NA	NA	0.3	1.2	C	CMSY	Froese et al., 2018
	Gulf of Lions	NA	NA	0.8	1.3	O	CMSY	Froese et al., 2018
	Levantine Sea	NA	NA	0.1	0.9	D	CMSY	Demirel et al., 2020
Sepia officinalis	Strait of Sicily	0.6	4.4	1.4 (0.9–1.6)	0.8 (0.7–1.3)	H	CMSY	Present study
	Adriatic Sea	NA	NA	0.5	2.1	C	CMSY	Froese et al., 2018
	Aegean Sea	NA	NA	0.6	0.9	R	CMSY	Froese et al., 2018
	Balearic Islands	NA	NA	0.3	2.7	C	CMSY	Froese et al., 2018
	Ionian Sea	NA	NA	0.8	1.4	O	CMSY	Froese et al., 2018
	Gulf of Lions	NA	NA	0.3	1.8	C	CMSY	Froese et al., 2018
	Sardinia	NA	NA	0.8	1.2	O	CMSY	Froese et al., 2018
	Adriatic Sea	NA	NA	0.6 (0.3–0.9)	0.8 (0.6–1.6)	R	BSM	Armelloni et al., 2018
	Balearic Sea	NA	NA	NA	NA	NA	DM	Maynou, 2015
	Balearic Sea	NA	NA	NA	NA	NA	DM	Keller et al., 2015
	Balearic Sea	0.8	0.2	0.6 (0.4–0.8)	1.1 (0.9–1.4)	O	SPM	Quetglas et al., 2015
	Cyprus	NA	NA	1.3 (0.7–2.3)	0.6 (0.0–1.6)	H	AMSY	Froese et al., 2020
	Egypt	NA	NA	NA	NA	O	Y/R	Mehanna and Haggag, 2011
	Levantine Sea	NA	NA	0.6	1.4	O	CMSY	Demirel et al., 2020
	Ligurian Sea	0.98	0.5	0.5 (0.4–0.7)	1.5 (1.3–1.7)	C	SPM	Abella et al., 2010
Todaropsis eblanae	Aegean Sea	NA	NA	1.7	0.2	H	AMSY	Tsikliras et al., 2021
Todill	Strait of Sicily	0.7	2.5	1.2 (0.8–1.6)	0.9 (0.5–1.4)	H	BSM	Present study
	Strait of Sicily	0.7	2.4	1.3 (0.9–1.9)	0.8 (0.4–1.9)	H	SPiCT	Present study

H, healthy, $B > B_{MSY}$, $F \leq F_{MSY}$; R, recovering, $B < B_{MSY}$ and $F \leq F_{MSY}$; O, subject to overfishing, $F > F_{MSY}$; E, exploited outside safe biological limits $B \leq 0.5\ B_{MSY}$; C, critical condition, $B \leq 0.5\ B_{MSY}$, $F > F_{MSY}$; D, severely depleted, $B \leq 0.2\ B_{MSY}$.
**Scenario codend mesh size 40 mm; **scenario codend mesh size 20 mm.*

years, BSM estimated the stock to be in a recovering condition ($B < B_{MSY}$ and $F \leq F_{MSY}$), whereas SPiCT always estimated a healthy condition over the time series ($B > B_{MSY}$, $F \leq F_{MSY}$; **Figures 3**, **4** and **Table 3**). The uncertainty of both models was higher about the estimated exploitation rates than the stock sizes (**Tables 3**, **4**).

FIGURE 4 | Dynamics of *Eledone* and *Todill* stocks estimated by SPiCT model. Catch panel: blue solid line shows the estimated catches, blue dashed lines the 95% confidence interval of the estimated catches, black solid line the mean value of MSY and gray shaded area the 95% confidence interval of MSY. Stock size and exploitation rate panels: trend of B/B_{MSY} and F/F_{MSY}, with the light blue area showing the 95% confidence interval. Kobe plot panel: B/B_{MSY} against F/F_{MSY} ratios for the years with available data (2004–2018). Quadrants are color-coded, i.e., red area: stocks that are both overfished (low relative biomass) and in overfishing (high exploitation rate) ($B \leq B_{MSY}$; $F \geq F_{MSY}$); orange area: relative biomass is quite high but exploitation rate is high ($B \geq B_{MSY}$; $F \geq F_{MSY}$); yellow area: recovering stocks ($B \leq B_{MSY}$, $F \leq F_{MSY}$); green area: stocks subject to sustainable exploitation rate and with healthy stock biomass that can produce high yields close to MSY ($B \geq B_{MSY}$, $F \leq F_{MSY}$). Gray area represents the uncertainty, expressed as 95% confidence interval, of the reference points.

DISCUSSION

The lack of contrast in the time series of catch and effort data, the short life cycle and cohort overlapping, and the resource intensive direct age estimation have been the main reasons for the limited cephalopod stock assessments to date (Pierce et al., 2010; Arkhipkin et al., 2021). In their very recent review of stock assessment methods for cephalopods, Arkhipkin et al. (2021) suggested that depletion models are the best tool for modeling the dynamics of cephalopod fisheries. However, the relative lack of interest in cephalopod fisheries in the Mediterranean makes it challenging to gather all the fine temporal scale data needed to run depletion models. Arkhipkin et al. (2021) suggested that in data-limited conditions, the recent developments in SPMs provide a means to investigate the stock status of cephalopods and to provide valid information to support management actions.

In the Strait of Sicily, cephalopods represent a significant fraction of the commercial catch, contributing highly to the profitability of fishers; nevertheless, their stock and fisheries remain largely unassessed and unregulated. In this context, the present study is the first attempt to assess the stock status of commercial cephalopods exploited in the GSA16 through surplus production models.

The assessments undertaken of these cephalopod species available in the Mediterranean showed very diverse stock statuses (**Table 4**). The critical state of *Eledone* found in the Strait of Sicily was similar to that reported for its stocks in the Aegean (Tsikliras et al., 2021), Ligurian, and Tyrrhenian Seas (Abella et al., 2010; Giordano et al., 2010; Froese et al., 2018). On the other hand, Agnesi et al. (1998) reported a healthy stock status of *E. cirrhosa* in the Tyrrhenian Sea and Orsi Relini et al. (2006) for the Ligurian Sea. The stock status of *O. vulgaris* in the Strait of Sicily was healthy/recovering, which is in agreement with that reported by Froese et al. (2020) in the Adriatic Sea. Conversely, in other Mediterranean areas, its status ranged from overfishing in the Gulf of Lions (Froese et al., 2018) to severely depleted in the Levantine Sea (Demirel et al., 2020), or critical in the Balearic Islands (Quetglas et al., 2015) and in the Ionian/Adriatic Sea (Froese et al., 2018). As for ommastrephids, the healthy state of *Todill* found in the Strait of Sicily was similar to that reported for its stocks in the Aegean (Tsikliras et al., 2021) and the Adriatic Seas (Froese et al., 2020). Conversely, Froese et al. (2018) found that the state of the ommastrephid squids varied from "overfished" in the Ionian/Aegean Sea and Sardinia to "critical" in the Adriatic Sea.

The healthy state of *L. vulgaris* estimated in the present study was in contrast with Froese et al. (2018), who reported an overfished stock status in the Aegean Sea, a critical state in the Balearic/Sardinia Islands and the Gulf of Lions, and a severely depleted state in the Adriatic Sea. Concerning *S. officinalis*, only Froese et al. (2020) indicated a healthy condition of the stock in waters around Cyprus, in agreement with the findings of the present study. In other areas of the Mediterranean, the stock status ranged from recovering in the Adriatic (Armelloni et al., 2018) and the Aegean Seas (Froese et al., 2018) to critical condition in the Adriatic Sea, Balearic Islands, Gulf of Lions

(Froese et al., 2018), and the Ligurian Sea (Abella et al., 2010); and being in overfishing off the Egyptian coasts (Mehanna and Haggag, 2011), the Balearic Islands (Quetglas et al., 2015), in the Levantine Sea (Demirel et al., 2020), the Ionian Sea, and Sardinia (Froese et al., 2018).

The CMSY and BSM models assume that recruitment is constant above the threshold of 0.25 of the carrying capacity. This condition could not be met for the species considered in this study, potentially affecting the results of the assessment. However, the convergence of results obtained by the BSM and SPiCT models, which do not assume any constraint on recruitment, suggests that the BSM assessments may be robust enough to properly assess species such as cephalopods. However, it should be noted that SPiCT provided more optimistic results than BSM during the initial years of the time series. The stock statuses of the octopods in GSA16 were worse than those of the squids and cuttlefish. These different statuses might be related to differences in biology, behavior, vulnerability to fishing gear, or reaction to abiotic factors. According to Russo et al. (2019), the nominal fishing effort of Italian bottom trawlers in the Strait of Sicily decreased from 2009 to 2016. This reduced fishing pressure on the fishing grounds could have disadvantaged octopuses in competition with demersal fishes. On the other hand, the different responses to the environmental factors could explain the different dynamics between squids, cuttlefish, and octopuses; based on habitat suitability modeling, Lauria et al. (2016) reported that in the Strait of Sicily, *I. coindetii* prefers warmer and less salty waters, whereas *T. eblanae* prefers saltier waters. Conversely, both species of *Eledone* do not seem to be definitively affected by sea water temperature, whereas *E. cirrhosa* prefers waters characterized by higher salinity. Working at the Mediterranean level, Keller et al. (2017) reported that areas of high sea surface temperature showed higher densities of *I. coindetii*, while warmer years were coincident with lower *O. vulgaris* abundance.

SPMs, like most stock assessment models, assume uniform productivity but due to climate change, this assumption may be violated (Bundy et al., 2012; Szuwalski and Hollowed, 2016). Although non-stationary population processes can introduce bias into assessments of target biomass and fishing mortality, few accepted frameworks are available for including the influence of the changing environment on the management strategies of exploited stocks (Szuwalski and Hollowed, 2016).

The present study provides insights into the dynamics of stocks of commercially important cephalopods that are not the main target species of multiannual management plans for fisheries in the Mediterranean. Although it is difficult to provide advice for the management of cephalopod exploitation, especially in the case of multi-species and low-selectivity fisheries, the role of these species in the food web and their relevance for SSF calls for attention to the importance of periodic assessment of their stock dynamics. Moreover, considering that some cephalopods are target species of specific SSFs in the area, the results suggest the need for adopting specific measures for controlling exploitation and enhancing stock status. This is the case for *S. officinalis* in the Strait of Sicily (Falsone et al., 2020), for which technical measures based on seasonal closure during critical stages, such as the spawning period, could be adopted.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

Ethical review and approval was not required for the animal study because the current methodology not required ethical review and approval.

AUTHOR CONTRIBUTIONS

SV and FFi: conceptualization and validation. FFa and MG: formal analysis. MG, FFa, DS, and VG: data curation and data collection and figures. MG: writing—original draft. MG, VG, FFa, DS, FFi, and SV: writing—review and editing. All authors contributed to the article and approved the submitted version.

FUNDING

This work was conducted thanks to the European Data Collection Framework (DCF)—Transversal Variables and MEDITS Survey Modules —funded by the European Union and the Italian Ministry for Agricultural, Food and Forestry Policies.

ACKNOWLEDGMENTS

The research leading to these results has been conceived under the International Ph.D. Program "Innovative Technologies and Sustainable Use of Mediterranean Sea Fishery and Biological Resources (www.FishMed-PhD.org)." This study represents partial fulfillment of the requirements for the Ph.D. thesis of MG. We would like to thank Editage (www.editage.com) and Dr. Martina Castelli for English language editing. Finally, we would also like to thanks the reviewers and Dr. Luca Ceriola for their significant improvement of the manuscript.

REFERENCES

Abella, A., Ria, M., and Mancusi, C. (2010). Assessment of the status of the coastal groundfish assemblage exploited by the Viareggio fleet (Southern Ligurian Sea). *Sci. Mar.* 74, 793–805. doi: 10.3989/scimar.2010.74n4793

Agnesi, S., Belluscio, A., and Ardizzone, G. D. (1998). Biologia e dinamica di popolazione di *Eledone cirrhosa* (Cephalopoda: octopoda) nel Tirreno Centrale. *Biol. Mar. Med.* 5, 336–348.

Arkhipkin, A. I., Hendrickson, L. C., Payá, I., Pierce, G. J., Roa-Ureta, R. H., Robin, J. P., et al. (2021). Stock assessment and management of cephalopods: advances and challenges for short-lived fishery resources. *ICES J. Mar. Sci.* 78, 714–730. doi: 10.1093/icesjms/fsaa038

Arkhipkin, A. I., Rodhouse, P. G. K., Pierce, G. J., Sauer, W., Sakai, M., Allcock, L., et al. (2015). World Squid Fisheries. *Rev. Fish. Sci. Aquac.* 23, 92–252. doi: 10.1080/23308249.2015.1026226

Armelloni, E. N., Masnadi, F., Scanu, M., Grati, F., Bolognini, L., Polidori, P., et al. (2018). *GFCM-WGSAD Scientific Advisory Committee on Fisheries (SAC) WorkingGroup on Stock Assessment of Demersal Species (WGSAD)*. Rome: FAO

Barrowman, N. J., and Myers, R. A. (2000). Still more spawner–recruitment curves: the hockey stick and its generalizations. *Can. J. Fish. Aquat. Sci.* 57, 665–676. doi: 10.1139/f99-282

Bertrand, J. A., Gil de Sola, L., Papaconstantinou, C., Relini, G., and Souplet, A. (2002). The general specifications of the MEDITS surveys. *Sci. Mar.* 66:9. doi: 10.3989/scimar.2002.66s29

Beverton, R. J. H., and Holt, S. J. (1957). *On the Dynamics of Exploited Fish Populations*. London: Great Britain Ministry of Agriculture, Fisheries and Food.

Boyle, P., and Rodhouse, P(ed.) (2005). "Cephalopods as predators," in *Cephalopods-Ecology and Fisheries*, (Oxford: Blackwell Publishing), 222–233. doi: 10.1002/9780470995310.ch14

Bundy, A., Bohaboy, E. C., Hjermann, D. O., Mueter, F. J., Fu, C., and Link, J. S. (2012). Common patterns, common drivers: comparative analysis of aggregate surplus production across ecosystems. *Mar. Ecol. Prog. Ser.* 459, 203–218.

Caddy, J., and Rodhouse, P. (1998). Cephalopod and groundfish landings: evidence for ecological change in global fisheries? *Rev. Fish Biol. Fish.* 8, 431–444. doi: 10.1023/A:1008807129366

Caddy, J. F. (1983). "The cephalopods: factors relevant to their population dynamics and to the assessment and management of stocks," in *Advances in Assessment of World Cephalopod Resources. Fish. Tech. Pap. 231*, ed. J. F. Caddy (Rome: FAO), 416–449.

Cope, J. M. (2013). Implementing a statistical catch-at-age model (Stock Synthesis) as a tool for deriving overfishing limits in data-limited situations. *Fish. Res.* 142, 3–14. doi: 10.1016/j.fishres.2012.03.006

Demirel, N., Zengin, M., and Ulman, A. (2020). First large-scale eastern Mediterranean and Black Sea stock assessment reveals a dramatic decline. *Front. Mar. Sci.* 7:103. doi: 10.3389/fmars.2020.00103

Di Lorenzo, M., Sinerchia, M., and Colloca, F. (2018). The north sector of the strait of sicily: a priority area for conservation in the Mediterranean Sea. *Hydrobiologia* 821, 235–253. doi: 10.1007/s10750-017-3389-7

Doubleday, Z. A., Prowse, T. A. A., Arkhipkin, A., Pierce, G. J., Semmens, J., Steer, M., et al. (2016). Global proliferation of cephalopods. *Curr. Biol.* 26, R406–R407. doi: 10.1016/j.cub.2016.04.002

Dowling, N. A., Smith, A. D. M., Smith, D. C., Parma, A. M., Dichmont, C. M., Sainsbury, K., et al. (2018). Generic solutions for data-limited fishery assessments are not so simple. *Fish Fish.* 20, 174–188. doi: 10.1111/faf.12329

Ezzeddine, S., and El Abed, A. (2004). Potential Biological and Environmental Influences on the Octopus vulgaris Population of the Gulf of Gabès (South-Eastern Tunisian Coast). MedSudMed Technical Documents, 2. 42–49.

Falsone, F., Scannella, D., Geraci, M. L., Gancitano, V., Vitale, S., and Fiorentino, F. (2021). How fishery collapses: the Case of *Lepidopus caudatus* (Pisces: Trichiuridae) in the Strait of Sicily (Central Mediterranean). *Front. Mar. Sci.* 7:1188. doi: 10.3389/fmars.2020.584601

Falsone, F., Scannella, D., Geraci, M. L., Vitale, S., Colloca, F., Di Maio, F., et al. (2020). Identification and characterization of trammel net métiers: a case study from the southwestern Sicily (Central Mediterranean). *Reg. Stud. Mar. Sci.* 39:101419. doi: 10.1016/j.rsma.2020.101419

FAO Fisheries and aquaculture software (2021). *FishStatJ - Software for Fishery and Aquaculture Statistical Time Series. In: FAO Fisheries and Aquaculture Department [online]*. Rome: FAO.

Fletcher, R. I. (1978). On the restructuring of the Pella–Tomlinson system. *U.S. Fish. Bull.* 76, 515–534.

Fox, W. W. (1970). An exponential surplus-yield model for optimizing exploited fish populations. *Trans. Am. Fish. Soc.* 99, 80–88.

Froese, R., Demirel, N., Coro, G., Kleisner, K. M., and Winker, H. (2017). Estimating fisheries reference points from catch and resilience. *Fish Fish.* 18, 506–526. doi: 10.1111/faf.12190

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A., Dimarchopoulou, D., et al. (2018). Status and rebuilding European Fisheries. *Mar. Policy* 93, 159–170. doi: 10.1016/j.marpol.2018.04.018

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2020). Estimating stock status from relative abundance and resilience. *ICES J. Mar. Sci.* 77, 527–538. doi: 10.1093/icesjms/fsz230

Giordano, D., Busalacchi, B., Bottari, T., Perdichizzi, F., Profeta, A., Perdichizzi, A., et al. (2010). Population dynamics and distribution of *Eledone cirrhosa* (Lamarck, 1798) in the Southern Tyrrhenian Sea (Central Mediterranean). *Cah. Biol. Mar.* 51, 213.

Hilborn, R., Hively, D. J., Loke, N. B., Moor, C. L., Kurota, H., Kathena, J. N., et al. (2021). Global status of groundfish stocks. *Fish and Fish.* 22, 911–928. doi: 10.1111/faf.12560

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annu. Rev. Ecol. Syst.* 4, 1–23. doi: 10.1146/annurev.es.04.110173.000245

ICES (2017). *Report of the Working Group on Cephalopod Fisheries and Life History (WGCEPH), 14–17 June 2016, ICES Headquarters, Copenhagen, Denmark. ICES Document CM 2016/SSGEPD: 03*. Copenhagen: ICES, 111.

ICES (2020). *Working Group on Cephalopod Fisheries and Life History (WGCEPH; outputs from 2019 meeting). ICES Scientific Reports. 2:46*. Copenhagen: ICES, 121. doi: 10.17895/ices.pub.6032

Jackson, G. D., and O'Dor, R. K. (2001). Time, space and the ecophysiology of squid growth, life in the fast lane. *Vie. Milieu.* 51, 205–215.

Jereb, P., Allcock, A. L., Lefkaditou, E., Piatkowski, U., Hastie, L. C., and Pierce, G. J. (eds) (2015). *Cephalopod Biology and Fisheries in Europe: II. Species Accounts. ICES Cooperative Research Report No. 325*. Copenhagen: ICES.

Keller, S., Quetglas, A., Puerta, P., Bitetto, I., Casciaro, L., Cuccu, D., et al. (2017). Environmentally driven synchronies of Mediterranean cephalopod populations. *Prog. Oceanogr.* 152, 1–14. doi: 10.1016/j.pocean.2016.12.010

Keller, S., Robin, J.-P., Valls, M., Gras, M., Cabanellas-Reboredo, M., and Quetglas, A. (2015). The use of Depletion Methods to assess Mediterranean cephalopod stocks under the current EU Data Collection Framework. *Med. Mar. Sci.* 16:513. doi: 10.12681/mms.1127

Lauria, V., Garofalo, G., Gristina, M., and Fiorentino, F. (2016). Contrasting habitat selection amongst cephalopods in the Mediterranean Sea: when the environment makes the difference. *Mar. Env. Res.* 119, 252–266. doi: 10.1016/j.marenvres.2016.06.011

Lishchenko, F., Perales-Raya, C., Barrett, C., Oesterwind, D., Power, A. M., Larivain, A., et al. (2021). A review of recent studies on the life history and ecology of European cephalopods with emphasis on species with the greatest commercial fishery and culture potential. *Fish. Res.* 236:105847. doi: 10.1016/j.fishres.2020.105847

MacCall, A. D. (2009). Depletion-corrected average catch: a simple formula for estimating sustainable yields in data-poor situations. *ICES J. Mar. Sci.* 66, 2267–2271. doi: 10.1093/icesjms/fsp209

Martell, S., and Froese, R. (2012). A simple method for estimating MSY from catch and resilience. *Fish Fish.* 14, 504–514. doi: 10.1111/j.1467-2979.2012.00485.x

Maynou, F. (2015). Application of a multi-annual generalized depletion model to the assessment of a data-limited coastal fishery in the western Mediterranean. *Sci. Mar.* 79, 157–168. doi: 10.3989/scimar.04173.28a

Mehanna, S. F., and Haggag, H. M. (2011). "Stock assessment of the common cuttlefish, Sepia officinalis in the Southeastern Mediterranean, Egypt," in *Proceedings of the 4th Global Fisheries and Aquaculture Research Conference, the Egyptian International Center for Agriculture, Giza, Egypt, 3-5 October 2011 Massive Conferences and Trade Fairs*, (Giza), 277–284.

Mildenberger, T. K., Berg, C. W., Pedersen, M. W., Kokkalis, A., and Nielsen, J. R. (2020). Time-variant productivity in biomass dynamic models on seasonal and long-term scales. *ICES J. Mar. Sci.* 77, 174–187. doi: 10.1093/icesjms/fsz154

Milisenda, G., Vitale, S., Massi, D., Enea, M., Gancitano, V., Giusto, G. B., et al. (2017). Spatio-temporal composition of discard associated with the deep water rose shrimp fisheries (*Parapenaeus longirostris*, Lucas 1846) in the south-central Mediterranean Sea. *Med. Mar. Sci.* 18, 53–63. doi: 10.12681/mms.1787

Mohsin, M., Hengbin, Y., Zhuo, C., and Mehak, A. (2020). An assessment of overexploitation risk faced by cephalopod fisheries in China: a non-equilibrium surplus production model approach. *Indian J. Geo Mar. Sci.* 49, 318–325.

Myers, R. A., Barrowman, N. J., Hutchings, J. A., and Rosenberg, A. A. (1995). Population dynamics of exploited fish stocks at low population levels. *Science* 269, 1106–1108. doi: 10.1126/science.269.5227.1106

Orsi Relini, L., Mannini, A., Fiorentino, F., Palandri, G., and Relini, G. (2006). Biology and fishery of *Eledone cirrhosa* in the Ligurian Sea. *Fish. Res.* 78, 72–88. doi: 10.1016/j.fishres.2005.12.008

Palomares, M. L. D., and Pauly, D (ed). (2019). *SeaLifeBase. World Wide Web Electronic Publication*. Available online at: www.sealifebase.org, version (12/2019) (accessed March 15, 2020).

Pedersen, M. W., and Berg, C. W. (2017). A stochastic surplus production model in continuous time. *Fish Fish.* 18, 226–243. doi: 10.1111/faf.12174

Pella, J. J., and Tomlinson, P. K. (1969). A generalized stock production model. *Bull. Int. Am. Trop. Tuna Commission* 13, 421–458.

Pierce, G. J., Allcock, A. L., Bruno, I., Bustamante, P., González, Á, Guerra, A., et al. (2010). *Cephalopod Biology and Fisheries in Europe. ICES Cooperative Research Report 303*. Copenhagen: ICES.

Pierce, G. J., and Portela, J. (2014). "Fisheries production and market demand," in *Cephalopod Culture*, eds J. Iglesias, L. Fuentes, and R. Villanueva (Berlin: Springer), 41–58. doi: 10.1007/978-94-017-8648-5_3

Quetglas, A., Keller, S., and Massutí, E. (2015). Can Mediterranean cephalopod stocks be managed at MSY by 2020? The Balearic Islands as a case study. *Fish. Manag. Ecol.* 22, 349–358. doi: 10.1111/fme.12131

Ricker, W. E. (1975). *Computation and Interpretation of Biological Statistics of fish Populations. Bulletin of the Fisheries Research Board of Canada 191, Ottawa, Canada*. Ontario, OT: Bulletin of the Fisheries Research, 382.

Rodhouse, P. G. K., Pierce, G. J., Nichols, O. C., Sauer, W. H. H., Arkhipkin, A. I., Laptikhovsky, V. V., et al. (2014). Environmental effects on cephalopod population dynamics. *Adv. Mar. Biol.* 67, 99–233. doi: 10.1016/b978-0-12-800287-2.00002-0

Rosenberg, A. A., Kirkwood, G. P., Crombie, J. A., and Beddington, J. R. (1990). The assessment of stocks of annual squid species. *Fish. Res.* 8, 335–350. doi: 10.1016/0165-7836(90)90003-e

Russo, T., Carpentieri, P., D'Andrea, L., De Angelis, P., Fiorentino, F., Franceschini, S., et al. (2019). Trends in effort and yield of trawl fisheries: a case study from the Mediterranean Sea. *Front. Mar. Sci.* 6:153. doi: 10.3389/fmars.2019.00153

Sartor, P., Belcari, P., Carboell, A., Gonzalez, M., Quetglas, A., and Sánchez, P. (1998). The importance of cephalopods to trawl fisheries in the western Mediterranean. *South Afr. J. Mar. Sci.* 20, 67–72. doi: 10.2989/025776198784126313

Sauer, W. H. H., Gleadall, I. G., Downey-Breedt, N., Doubleday, Z., Gillespie, G., Haimovici, M., et al. (2019). World Octopus Fisheries. *Rev. Fish. Sci. Aquac*. 29, 279–429. doi: 10.1080/23308249.2019.1680603

Schaefer, M. B. (1954). Some aspects of the dynamics of populations important to the management of the commercial marine fisheries. *Int. Am. Trop. Tuna Commission Bull.* 1, 25–56.

Schnute, J. T., and Richards, L. J. (2002). "Surplus production models," in *Handbook of Fish Biology and Fisheries*, Vol. 2, eds P. J. B. Hart and J. D. Reynolds (Oxford: Blackwell Publishing), 105–126.

Spedicato, M. T., Massutí, E., Mérigot, B., Tserpes, G., Jadaud, A., and Relini, G. (2019). The MEDITS trawl survey specifications in an ecosystem approach to fishery management. *Sci. Mar.* 83:9. doi: 10.3989/scimar.04915.11x

Szuwalski, C. S., and Hollowed, A. B. (2016). Climate change and non-stationary population processes in fisheries management. *ICES J. Mar. Sci.* 73, 1297–1305.

Thorson, J. T., Minto, C., Minte-Vera, C. V., Kleisner, K. M., and Longo, C. (2013). A new role for effort dynamics in the theory of harvested populations and data-poor stock assessment. *Can. J. Fish. Aquat. Sci.* 70, 1829–1844. doi: 10.1139/cjfas-2013-0280

Tsikliras, A. C., Touloumis, K., Pardalou, A., Adamidou, A., Keramidas, I., Orfanidis, G. A., et al. (2021). Status and exploitation of 74 un-assessed demersal fish and invertebrate stocks in the Aegean Sea (Greece) using abundance and resilience. *Front. Mar. Sci.* 7:578601. doi: 10.3389/fmars.2020.578601

Vasconcellos, M., and Cochrane, K. (2005). "Overview of world status of data limited fisheries: inferences from landing statistics," in *Fisheries Assessment and Management in Data-limited Situations Alaska Sea Grant Programme*, eds G. H. Kruse, V. F. Gallucci, D. E. Hay, R. I. Perry, R. M. Peterman, T. C. Shirley, et al. (Fairbanks, AK: University of Alaska Fairbanks), 1–20. doi: 10.4027/famdls.2005.01

Wang, Y., Liang, C., Wang, Y., Xian, W., and Palomares, M. L. (2020). Stock Status Assessments for 12 Exploited Fishery Species in the Tsushima Warm Current Region, Southwest Japan and East China, Using the CMSY and BSM Methods. *Front. Mar. Sci.* 7:640. doi: 10.3389/fmars.2020.00640

Zupa, W., Bitetto, I., and Spedicato, M. T. (2020). *BioStand v.2.1.3*. Torre a Mare: Coispa Tecnologia & Ricerca - Stazione sperimentale per lo Studio delle Risorse del Mare.

Zupa, W., Casciaro, L., Bitetto, I., and Spedicato, M. T. (2021). *BioIndex v.3.0*. Torre a Mare: Coispa Tecnologia & Ricerca - Stazione sperimentale per lo Studio delle Risorse del Mare.

Zuur, A. F., Ieno, E. N., Walker, N., Saveliev, A. A., and Smith, G. M. (2009). *Mixed Effects Models and Extensions in Ecology with R. Statistics for Biology and Health, XXII*. New York, NY: Springer-Verlag.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 30 November 2021
doi: 10.3389/fmars.2021.652293

Stock Assessment of Small Yellow Croaker (*Larimichthys polyactis*) Off the Coast of China Using Per-Recruit Analysis Based on Bayesian Inference

Lixin Zhu[1], Changzi Ge[1], Zhaoyang Jiang[1], Chunli Liu[1], Gang Hou[2] and Zhenlin Liang[1]*

[1] Marine College, Shandong University, Weihai, China, [2] Fisheries College, Guangdong Ocean University, Zhanjiang, China

OPEN ACCESS

Edited by:
Natalie Anne Dowling,
Oceans and Atmosphere (CSIRO),
Australia

Reviewed by:
Binbin Shan,
Key Laboratory of South China Sea Fishery Resources Exploitation and Utilization, South China Sea Fisheries Research Institute (CAFS), China
Enrico Nicola Armelloni,
National Research Council , Consiglio Nazionale delle Ricerche (CNR), Italy

***Correspondence:**
Zhenlin Liang
liangzhenlin@sdu.edu.cn

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: 12 January 2021
Accepted: 08 November 2021
Published: 30 November 2021

Citation:
Zhu L, Ge C, Jiang Z, Liu C, Hou G and Liang Z (2021) Stock Assessment of Small Yellow Croaker (Larimichthys polyactis) Off the Coast of China Using Per-Recruit Analysis Based on Bayesian Inference. Front. Mar. Sci. 8:652293. doi: 10.3389/fmars.2021.652293

This paper presents a framework for quantifying uncertainty in per-recruit analysis for small yellow croaker (*Larimichthys polyactis*) fisheries in China, in which credible estimates of life history parameters from Bayesian inference were used to generate the distribution for a quantity of interest. Small yellow croakers were divided into five spatial groups. The status of each group was examined using a yield-per-recruit (YPR) model and a spawning stock biomass-per-recruit (SSBPR) model. The optimal length at first capture (L_{copt}) was proposed to recover the biomass. The maximum observed age in the current stocks (3 years) and the maximum recorded age (≥20 years) were adopted in per-recruit analysis. Our results suggest that the framework can quantify uncertainty well in the output of per-recruit analysis for small yellow croaker. It is suited to other fish species. The SSBPR at F_{MSY} ($SSBPR_{MSY}$) is a better benchmark than the spawning potential ratio (SPR) at F_{MSY} because $SSBPR_{MSY}$ had a unimodal distribution. The SSBPR analysis can lead to a more conservative L_{copt} than the YPR analysis. The key factor influencing the assessment conclusions may be the growth parameters rather than the natural mortality rate for a stock with a younger maximum age. Overfishing likely occurred for all groups and recruitment overfishing may not occur if the maximum age is maintained at 3 years. Increasing lengths at first capture to the recommended values can help this population recover. However, F_{cur} is too high for small yellow croakers to attain the maximum recorded age. Both reducing fishing mortality rate and increasing length at first capture are needed to attain the maximum recorded age.

Keywords: yield-per-recruit model, spawning stock biomass-per-recruit model, uncertainty, Bayesian inference, small yellow croaker

INTRODUCTION

Per-recruit models such as the yield-per-recruit (YPR) model and the spawning stock biomass-per-recruit (SSBPR) model are commonly used in fish stock assessments. These models can produce YPR and SSBPR at a fishing mortality rate (F), and biological reference points. Per-recruit models are defined mainly by fish life history parameters, such as the parameters on growth, length–weight relationship (LWR), and natural mortality. Thus, the output of a per-recruit model is primarily dependent on a combination of different types of life history parameters (Restrepo and Fox, 1988). The inherent uncertainty surrounding life history parameters can lead to uncertainty in per-recruit analysis (Chang et al., 2009). Incorrect estimates of biological reference points may be derived if uncertainty in parameters is ignored. Consequently, conclusions about the status of fish stock will be inaccurate (Helser et al., 2001; Chen and Wilson, 2002; Lin et al., 2015). Quantifying uncertainty in assessment results can enhance decision making for fishery resource management and help determine the best harvest strategies (Gavaris, 1993; Doll et al., 2017).

Random values from the distributions of input parameters must be generated to quantify uncertainty in the outcome of per-recruit analysis. Conventionally, these random values are produced by introducing random errors into each subset model with a set of particular estimates. A coefficient of variation (CV) or standard deviation (SD) is often specified for a subset model according to the available knowledge of parameter uncertainty (e.g., Chen and Wilson, 2002; Grabowski and Chen, 2004; Jiao et al., 2005; Chang et al., 2009). The estimated SDs from the observed data can also be used to introduce random errors (Lin et al., 2015). For correlated parameters, random errors can be introduced using the estimated standard errors and the correlation (Hart, 2013), and the covariance matrix constructed by the estimated SDs and the correlation (Lin et al., 2010). For instance, Hart (2013) took the standard error of 0.004 for K and 0.4 for L_∞, and the correlation of −0.6 to simulate the negatively correlated parameters K and L_∞ in the von Bertalanffy growth model (von Bertalanffy, 1938). Recent advances in Bayesian estimation provide a new method to obtain random values for life history parameters. Bayesian analysis can incorporate multiple sources of information to reduce uncertainty in life history parameter estimates and obtain more realistic estimates of uncertainty (Pulkkinen et al., 2011; Froese et al., 2014; Romakkaniemi, 2015; Zhu et al., 2020). Possible parameter estimates derived from Bayesian inference are given as samples drawn from its posterior distribution using the Markov chain Monte Carlo (MCMC) technique. MCMC samples are a number of estimates for an independent parameter or pairs of estimates for the correlated parameters. MCMC samples can generate distributions for the output of a per-recruit model. Doll et al. (2017) demonstrated that uncertainty in YPR estimates could be measured using the posterior distributions of growth parameters, LWR parameters, and natural mortality rate (M) when a combination of exploitation rate and minimum length limit was given.

Small yellow croaker (*Larimichthys polyactis*) is a warm-temperate demersal fish species that is distributed throughout the northwest Pacific Ocean (Ma et al., 2017). It is a commercially valuable species in China and inhabits the Bohai Sea, Yellow Sea, and East China Sea (**Figure 1**). Biological characteristics of the stocks have significantly changed; average body size is smaller and individuals become mature at an earlier age (Jin, 1996; Li et al., 2011; Lin et al., 2011). The maximum age decreased from 21–23 years in the 1960s (Mao et al., 1987; Guo et al., 2006) to 5–7 years in the early and mid-1980s (Mao et al., 1987; Liu et al., 1999; Shui, 2003; Lin et al., 2004; Guo et al., 2006), to

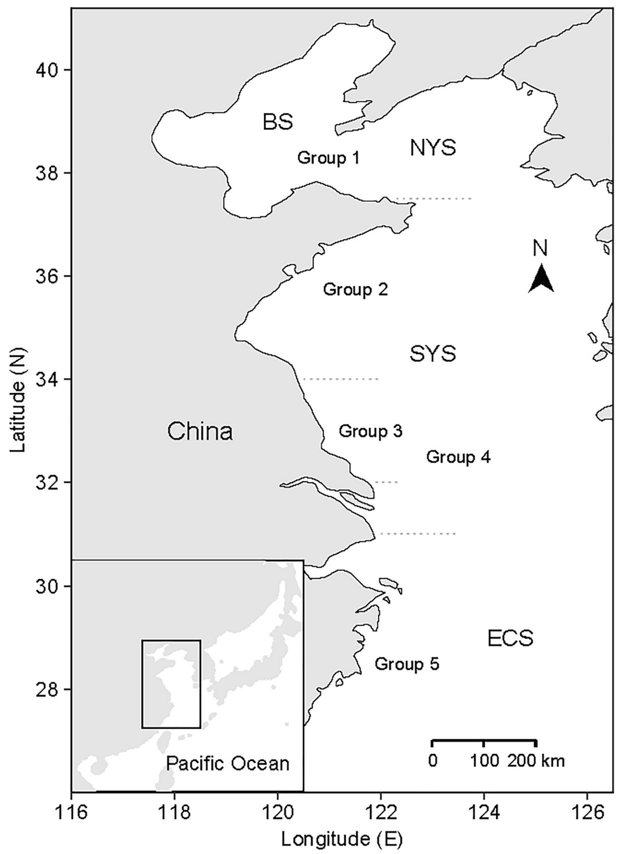


FIGURE 1 | Map of the Bohai Sea (BS), Yellow Sea, and a part of East China Sea (ECS), and the division of groups for small yellow croakers. Yellow Sea consists of North Yellow Sea (NYS) and South Yellow Sea (SYS). The figure was adapted from Zhu et al. (2020).

2–4 years in the 1990s and mid-2000s (Liu et al., 1999; Shui, 2003; Lin et al., 2004; Guo et al., 2006; Yan et al., 2006; Chen et al., 2010; Shan et al., 2017). Changes in life history traits of small yellow croaker have been attributed to increased fishing effort (Shan et al., 2013). The population has been at high risk of being overfished in recent years (Ma et al., 2020). Fishing effort needs to be reduced to recover the population to biomass level that supports maximum sustainable yield (MSY) (Ma et al., 2020). However, it is difficult to control fishing effort in China (Shen and Heino, 2014). The fishing effort of small yellow croaker increased each year from 1968 to 2015, with the exception of 1991 (Ma et al., 2020). Measures are urgently needed to reduce fishing pressure on this population. In addition, it is unclear if recruitment overfishing has occurred.

Trawl selectivity experiments demonstrated that enlarging mesh size could reduce fishing pressure on small yellow croaker, especially for juveniles (Chen et al., 2018). Thus, increasing length at first capture (L_c) may be an efficient measure to recover the population of small yellow croaker. Researchers have recommended the optimal age (t_{copt}) or length (L_{copt}) at first capture for small yellow croaker in different regions based on the results from the YPR model (Jin, 1996; Liu et al., 1999;

Lin et al., 2006; Zhang et al., 2010a; Gao et al., 2019). However, uncertainty in input parameters was not considered. The derived L_{copt} varied among these studies. In addition, Zhou et al. (2020) suggested the fishing mortality rate to achieve MSY (F_{MSY}) or the spawning potential ratio (SPR) at F_{MSY} (SPR_{MSY}) as the benchmark because the surplus production model takes into account population dynamics from one generation to the next. Thus, there may be a gap between L_{copt} derived from the YPR analysis and the SSBPR analysis.

In a previous study, the probability distributions of life history parameters were estimated using the Bayesian hierarchical approach for five groups of small yellow croakers (Zhu et al., 2020). Based on this work, a framework was presented that quantified uncertainty in per-recruit analysis for small yellow croaker and examined the status of each group of small yellow croakers using the YPR model and the SSBPR model by incorporating uncertainty in parameters. L_{copt} was estimated when SSBPR at F_{MSY} ($SSBPR_{MSY}$) was regarded as the management goal. The objective of this study was: (1) to establish a procedure for quantifying uncertainty in per-recruit analysis for small yellow croaker based on Bayesian inference and (2) to further check the status of small yellow croaker and to recommend management measures by considering both the yield and the spawning stock biomass.

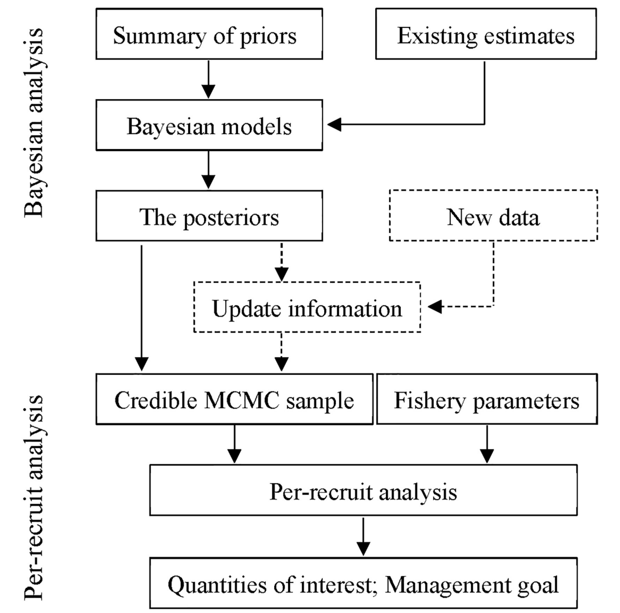


FIGURE 2 | Flowchart quantifying uncertainty for outputs of per-recruit analysis based on Bayesian inference.

MATERIALS AND METHODS

Methods and Data Sources

Previous studies have recommended to consider spatial heterogeneity in the studies for small yellow croaker due to the existence of geographic subpopulations for this species (Ying et al., 2011; Ma et al., 2020). However, division of the subpopulation for small yellow croakers is a controversial issue (Liu et al., 2013). Lin et al. (1965) divided small yellow croakers into three subpopulations based on body morphometrics in which the boundaries were 32.0 and 34.0°N (**Figure 1**). Based on this division, Liu (1990) proposed a fourth subpopulation in the central Yellow Sea (between 34.0 and 37.5°N) according to sex gland, which was supported by Wang et al. (2016) based on analysis of stable isotopic composition of otoliths. However, Xu and Chen (2010) argued that only two subpopulations exist according to their migration trajectory, and they defined a boundary of 34.0°N. Zhang et al. (2014) proposed another division of four subpopulations according to otolith features and the boundaries were about 35.5, 30.0, and 27.0°N.

In response to the controversy, small yellow croakers were divided into five groups according to the intensive investigation regions (Zhu et al., 2020), in which Group 3 was included in Group 4 (**Figure 1**). Some researchers studied small yellow croaker in the region between 32.0 and 34.0°N (e.g., Zhang et al., 2010a; Liu et al., 2013) according to the subpopulation divisions proposed by Lin et al. (1965), whereas some investigated the population in the area between 31.0 and 34.0°N (e.g., Lin et al., 2004; Yan et al., 2006). Thus, Groups 3 and 4 were regarded as two independent groups since it is unclear whether they belong to the same subpopulation (Zhu et al., 2020). Zhu et al. (2020) used the Bayesian hierarchical models to estimate life history parameters and their uncertainty for each group based on 25 growth curves, 41 LWRs, and 16 natural mortality rates collected from the literature (**Supplementary Table 1**). The resulting estimates of each type of life history parameter were 30,0000 sets of MCMC samples for each of the five groups. Growth parameters, LWR parameters, and natural mortality rate were summarized and are shown in **Supplementary Tables 2–4**, in which highest density interval (HDI) that gave the span of the most credible values (Kruschke, 2014) was used to summarize the uncertainty of a parameter.

Based on this work, we developed a procedure for quantifying uncertainty in per-recruit analysis for small yellow croakers (**Figure 2**). It consisted of two steps: estimating the posterior probability distributions for life history parameters and conducting per-recruit analysis. In the first step, already developed and undertaken by Zhu et al. (2020), the posterior distributions of life history parameters are first obtained using Bayesian approaches by combining the priors and the existing estimates, which were used to conduct per-recruit analysis when newly observed data were not collected. Otherwise, the resulting posteriors served as the priors to update the parameters by combining with new data. Then, the latest knowledge about life history parameters was used to carry out per-recruit analysis. For the second, novel step, the credible MCMC samples of each parameter generated from the first step were used to conduct per-recruit analysis and to calculate the quantities of interest by combining with fishery parameters, such as F and L_c.

We used the parameter values that had been obtained from the first step to undertake the second step. New data for estimating the growth parameters, LWR parameters, and natural mortality

TABLE 1 | Number of the total parameter sets in per-recruit analysis and number of the parameter sets failing to define $F_{\max}$ and $F_{20\%}$.

Group	Total	$F_{\max}$				$F_{20\%}$			
		$t_{\max}$ = 3	$t_{\max}$ = 5	$t_{\max}$ = 7	$t_{\max}$ = 20–23	$t_{\max}$ = 3	$t_{\max}$ = 5	$t_{\max}$ = 7	$t_{\max}$ = 20–23
Group 1	258, 955	0	0	0	0	28, 432	69	0	0
Group 2	258, 591	0	0	0	0	54, 428	230	106	38
Group 3	258, 120	166	158	158	158	70, 685	11, 801	5, 594	4, 253
Group 4	258, 637	13	13	13	13	49, 523	1, 979	487	241
Group 5	258, 793	22	22	22	22	50, 166	14, 794	7, 773	6, 162

t_{max} = 21 years for Groups 1 and 2; t_{max} = 23 years for Groups 3 and 4; t_{max} = 20 years for Group 5.

rate were not collected because almost all the recent estimates have been incorporated in Bayesian analysis in our previous work (Zhu et al., 2020). The MCMC samples inside the 95% HDI were taken as credible estimates to avoid the impact of extremely high or low values on per-recruit analysis. For the correlated parameters, a pair of estimates were taken together if the estimate of each parameter was located in its 95% HDI. The number of credible MCMC samples was different for different types of parameters. The same number of MCMC samples was taken according to the minimum number of credible MCMC samples among three types of parameters for a group. The number of parameter sets was enough to obtain the possible distributions for the output of a per-recruit model (**Table 1**).

Per-Recruit Model

Considering implementation of summer-fishing-closed-season policy in China, a discrete YPR model and a discrete SSBPR model were constructed for small yellow croaker fisheries based on the work of Govender et al. (2006). YPR (expressed in mass g) was expressed as

$$Y/\mathrm{R} = \sum_{t=1}^{t_{\max}} \frac{a_w (L_t)^{b_w} FS_{L_t} A_t}{FS_{L_t} A_t + M} (1 - \mathrm{e}^{-FS_{L_t} A_t - M}) \mathrm{e}^{-\sum_{j=1(j<t)}^{t-1} FS_{L_j} A_j + M} \quad (1)$$

where Y is the attained yield, R is the number of the recruit, and $t_{\max}$ is the maximum age in the fishery in months a_w and b_w are LWR parameters ($W = a_w L^{b_w}$). L_t is the predicted length at age t, which was calculated using von Bertalanffy growth model (von Bertalanffy, 1938). j is used to produce the cumulative sum of fishing mortality rate and natural mortality rate at each stage, and this term exists when $t \geq 2$. Here, R was assumed to be the number at 1 month old and set to 1. S_{L_t} is the gear selectivity at length L_t and was assumed to be knife-edged.

$$S_{L_t} = \begin{cases} 0, \text{if } L_t < L_c \\ 1, \text{if } L_t \geq L_c \end{cases} \quad (2)$$

A_t indicated whether a particular month corresponding to age t was open to fishing or not (Govender et al., 2006). It was 1 when the month was open to fishing. Otherwise, it was 0.

Spawning stock biomass-per-recruit (expressed in mass g) was expressed as

$$\mathrm{S}/R = \sum_{t=1}^{t_{\max}} G_t a_w (L_t)^{b_w} e^{-\sum_{j=1(j<t)}^{t-1} FS_{L_j} A_j + M} \quad (3)$$

where G_t was the fraction of mature fish at age t and was also assumed to be knife-edged (Govender et al., 2006).

$$G_t = \begin{cases} 0, \text{if } t < t_m \\ 1, \text{if } t \geq t_m \end{cases} \quad (4)$$

where t_{m} was the age at 50% maturity.

Spawning potential ratio is the ratio of SSBPR at a fishing mortality rate to the maximum SSBPR under unfished conditions (Goodyear, 1993). It was expressed as

$$\mathrm{SPR} = \frac{\mathrm{SSBPR_{fished}}}{\mathrm{SSBPR_{unfished}}} \quad (5)$$

Spawning potential ratio has a maximum value of unity and declines toward zero with an increase in fishing mortality rate (Goodyear, 1993). Similarly, $\mathrm{SPR_{MSY}}$ was expressed as (Zhou et al., 2020)

$$\mathrm{SPR_{MSY}} = \frac{\mathrm{SSBPR}_{F=F_{\mathrm{MSY}}}}{\mathrm{SSBPR_{unfished}}} \quad (6)$$

Biological Reference Points

Biological reference points derived from per-recruit models are expressed as fishing mortality rates, which are metrics of stock status (Gabriel and Mace, 1999). $F_{\max}$ and $F_{0.1}$ are reference points derived from the YPR model. $F_{\max}$ is the fishing mortality rate maximizing YPR and $F_{0.1}$ is where the slope of the YPR curve is 10% of the maximum slope (Grabowski and Chen, 2004). The reference point from the SSBPR model is expressed as $F_{\mathrm{x}\%}$ representing the fishing mortality rate that reduces SSBPR to x% of the maximum SSBPR in an unexploited state (Gabriel and Mace, 1999). $F_{\mathrm{x}\%}$ is exactly the value of SPR at a fishing mortality rate according to Eq. 5. Mace and Sissenwine (1993) advocated $F_{20\%}$ as a recruitment overfishing threshold for species with high and medium resilience and $F_{30\%}$ as a recruitment overfishing threshold for species with low resilience. Generally, small yellow croaker grows slowly, matures at an older age (2–3 years), and has low resilience (Ye, 1991; Jin and Deng, 2000). However, its resilience may increase when it matures earlier. At present, FishBase[1] gives the resilience of small yellow croaker as medium. Thus, we took $F_{20\%}$ as a recruitment overfishing threshold for small yellow croaker. We calculated $F_{\max}$, $F_{0.1}$, and $F_{20\%}$ to examine stock status and check the impact of uncertainty in life history parameters on per-recruit analysis.

[1] www.fishbase.org

Impact of Uncertainty in Parameters on Biological Reference Points

To examine the impact of a type of history life parameter on uncertainty in per-recruit analysis, reference points were calculated under four scenarios. We used credible MCMC samples of all types of life history parameters to calculate reference points in Scenario 1. Credible MCMC samples of the growth parameters, LWR parameters, and natural mortality rate were adopted in Scenarios 2, 3, and 4, respectively, and point estimates were taken for other types of parameters. The variation in biological reference points in Scenarios 2, 3, and 4 was caused by the uncertainty of a type of life history parameter.

Effect of Maximum Age

The maximum age may have not exceeded 3 years for each group of small yellow croakers since the mid-2000s (Lin et al., 2004; Guo et al., 2006; Chen et al., 2010; Yan et al., 2014; Hu et al., 2015; Shan et al., 2017). It was 2 years in some years (Lin et al., 2004; Guo et al., 2006; Yan et al., 2014; Hu et al., 2015). In this study, a maximum age of 3 years was used in per-recruit analysis for all groups. The maximum age influences YPR and SSBPR for a given F according to Eqs 1, 3, and may further affect the derived reference points. We set t_{max} = 3, 5, and 7 years to test the effect of maximum age. At present, it is unclear if small yellow croaker would reach an age of 21–23 years in the absence of fishing. The optimal maximum age (t_{optmax}) was 21 years for Groups 1 and 2, 23 years for Groups 3 and 4, and 20 years for Group 5 (Gao et al., 2019). We calculated reference points and derived L_{copt} when $t_{max} = t_{optmax}$ to further check the status of small yellow croaker and to explore management measures.

Optimal Length at First Capture

In past studies, the YPR contour was often used to determine t_{copt}, which was transformed to L_{copt}. In the YPR isopleth, age at first capture (t_c) was the vertical axis and F the horizontal axis. One line representing maximum YPR for a given F and the other line representing maximum YPR for a given t_c were plotted in the contour (Caddy, 1984). At the current fishing mortality rate, any t_c located between these two lines can be chosen as t_{copt}. Thus, t_{copt} has a range and one value is usually chosen subjectively. In this study, we chose SPR_{MSY} and $SSBPR_{MSY}$ as the target reference points to which to aim to recover the biomass of small yellow croakers and calculated their distributions. As shown in **Figure 2**, L_{copt} was found to achieve these distributions.

Fishing Mortality Rate and Other Parameters

Fishing mortality rate has an increasing trend for small yellow croaker fisheries which is in accordance with increasing fishing effort (**Supplementary Table 5**). Considering that fishing effort has consistently increased and fishing mortality rate also has a level of uncertainty, current fishing mortality rates (F_{cur}) were assigned the mean of the latest two estimates for Group 1 (1.73 year^{-1}) and Group 5 (2.73 year^{-1}). F_{cur} took the latest estimate for Group 2 (1.56 year^{-1}), Group 3 (2.38 year^{-1}), and Group 4 (2.38 year^{-1}) because other values were estimated four or more years ago for those groups. Groups 3, 4, and 5 had much higher fishing mortality rates than Groups 1 and 2, which is consistent with fishing activities (Ma et al., 2020). F_{MSY} was time-varying and ranged from 0.15 to 1.07 year^{-1} for Groups 1 and 2, and from 0.15 to 1.32 year^{-1} for Groups 3, 4, and 5 between 1968 and 2015 (Ma et al., 2020). We took the values in 1968 and 2015 for small yellow croakers with the optimal maximum age and the current maximum age, respectively.

We assumed that small yellow croakers grew up to 1 month older in May for Group 5 and in June for other groups according to the spawning time of each group (Jin, 1996; Cheng et al., 2004; Zhang et al., 2010b). L_c was set to 12 cm for all groups, which is the length at 50% retention for the trawl net and the canvas stow net with the minimum allowable mesh size of 54.0 mm (You et al., 2017; Chen et al., 2018; Xu et al., 2019). Heavy fishing pressures have resulted in earlier maturity for small yellow croaker. The proportion of the population that matures at age 1 has been over 90% since 2011 (Yan et al., 2014). The fractions of mature fish at spawning time were assumed to be 1 for all age classes of each group. Currently, the areas where small yellow croakers are distributed are closed to fishing in the summer. The seas to the north of 35.0°N are closed to fishing from May 1 to August 31 and those to the south of 35.0°N are closed from May 1 to September 16.

RESULTS

Biological Reference Points

Generally, biological reference points F_{max}, $F_{0.1}$, and $F_{20\%}$ were well defined by credible MCMC samples. $F_{0.1}$ existed for all set of credible MCMC samples of each group. However, some sets of MCMC samples could not produce F_{max} and $F_{20\%}$ (**Table 1**). Some extremely high values were also derived for $F_{20\%}$ from some sets of parameter estimates (**Figure 3**). F_{cur} was significantly higher than F_{MSY} for each group because it was greater than the upper limit of 95% credible interval (**Table 2**). It was also significantly higher than $F_{0.1}$ for Groups 1, 3, 4, and 5 when t_{max} = 3 years. But F_{cur} was not significantly greater than F_{max} and $F_{20\%}$ for each group. It even had a high probability of being lower than F_{max} and $F_{20\%}$ for Group 2 (**Figure 4**). The probability of F_{cur} being greater than $F_{0.1}$, $P(F_{cur} > F_{0.1})$, approximated 1 for all groups except Group 2 (92%). In contrast, $P(F_{cur} > F_{max})$ and $P(F_{cur} > F_{20\%})$ were relatively low and not greater than 74%. However, F_{cur} was greater than $F_{0.1}$, F_{max}, and $F_{20\%}$ with a high probability for all groups (85–97%) when $t_{max} = t_{optmax}$.

Impact of Uncertainty in Parameters on Biological Reference Points

Figure 3 shows the distributions of F_{max}, $F_{0.1}$, and $F_{20\%}$ for Group 1 in four scenarios when t_{max} = 3, 5, and 7 years. Reference points of the other four groups had a similar distribution pattern. Uncertainty about each reference point was largest for Scenario 1 at a given maximum age, in which all three types of parameters varied. For Scenarios 2, 3, and 4, the variation in the growth parameters (Scenario 2) led to the largest uncertainty in the estimates of each reference point when t_{max} = 3 years. This indicated that the uncertainty of these

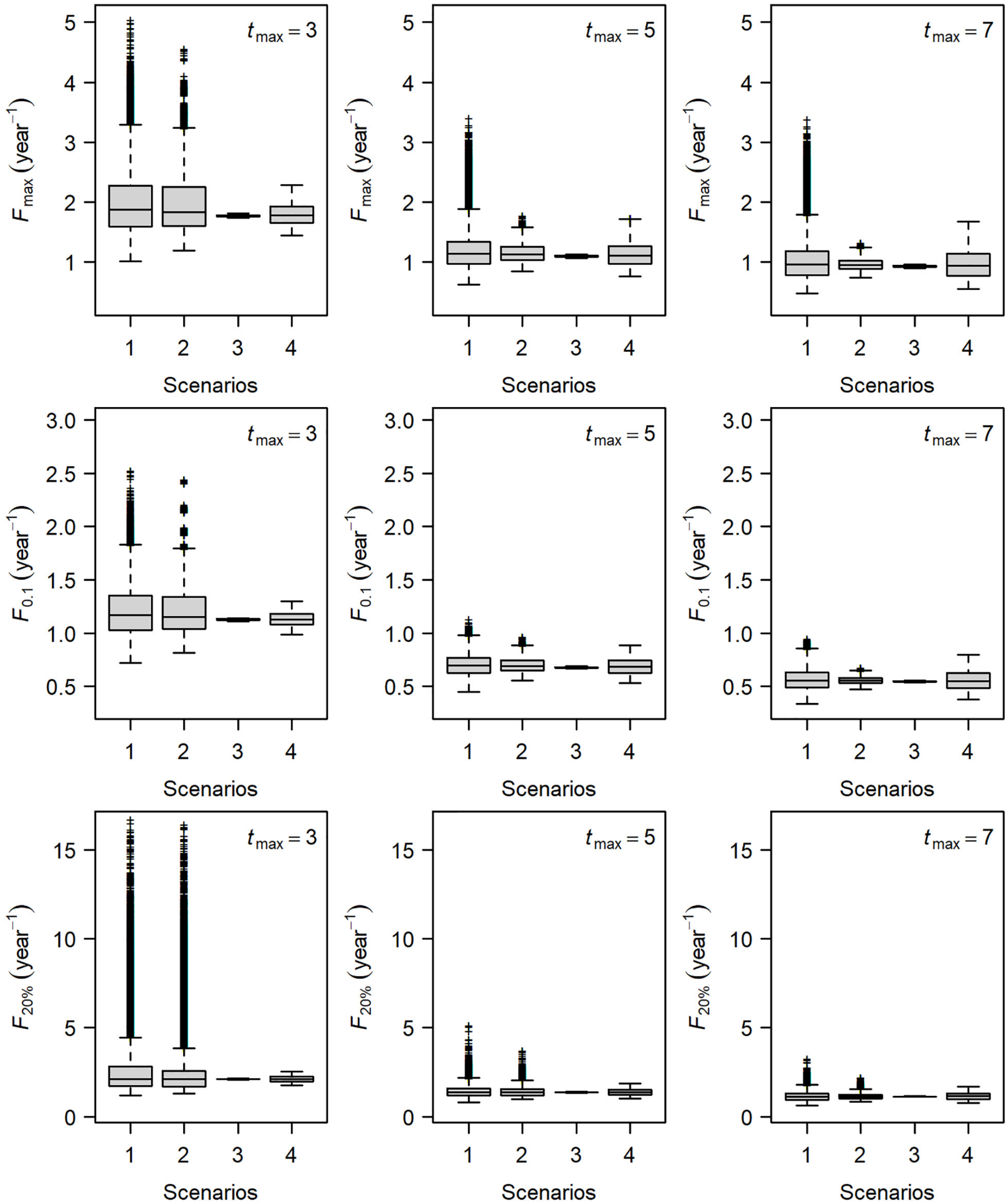


FIGURE 3 | Boxplot of biological reference points F_{max}, $F_{0.1}$, and $F_{20\%}$ in four scenarios for Group 1 of small yellow croakers. Scenario 1 denoted the variation in all types of life history parameters. Scenarios 2, 3, and 4 denoted the variation in growth parameters, length–weight relationship parameters, and natural mortality rate, respectively.

reference points was caused mainly by uncertainty surrounding the growth parameters.

Effect of Maximum Age

The number of the parameter sets that could not define $F_{20\%}$ decreased with an increase in t_{max} (**Table 1**). Relative importance of life history parameters also changed as t_{max} increased (**Figure 3**). The effect of natural mortality rate (Scenario 4) on the uncertainty of reference points became stronger than growth parameters when t_{max} = 5 years. Uncertainty in the natural mortality rate dominated the variation in each reference point when t_{max} = 7 years. The LWR parameters had less influence on the uncertainty of the reference points in all cases.

Yield-Per-Recruit and Spawning Potential Ratio

Both the YPR curve and the SPR curve were variable for each group due to uncertainty in the life history parameters

TABLE 2 | Biological reference points and current fishing mortality rates for each group of small yellow croakers.

Group	t_{max}	F_{max} (year^{-1})				$F_{0.1}$ (year^{-1})				$F_{20\%}$ (year^{-1})				F_{MSY} (year^{-1})		F_{cur} (year^{-1})
		Mean	SD	Median	95% HDI	Mean	SD	Median	95% HDI	Mean	SD	Median	95% HDI	Median	95% credible interval	
Group 1	3	1.97	0.49	1.88	1.18–2.94	1.19	0.20	1.17	0.84–1.56	2.49	1.22	2.11	1.21–4.83	1.01	0.53–1.45	1.73
Group 2	3	2.27	0.56	2.25	1.35–3.19	1.32	0.23	1.34	0.89–1.63	3.31	2.11	2.66	1.28–6.90			1.56
Group 3	3	2.70	0.93	2.48	1.42–4.41	1.43	0.28	1.41	0.97–1.88	2.77	1.71	2.33	1.39–5.30	1.20	0.74–1.48	2.38
Group 4	3	2.32	0.74	2.14	1.31–3.68	1.33	0.28	1.28	0.90–1.77	2.66	1.91	2.15	1.33–5.34			2.38
Group 5	3	2.47	0.78	2.27	1.46–4.03	1.32	0.22	1.28	0.98–1.77	2.69	1.09	2.35	1.56–5.10			2.73
Group 1	21	0.95	0.36	0.91	0.31–1.61	0.47	0.14	0.47	0.21–0.71	1.02	0.37	0.97	0.39–1.70	0.26	0.16–0.40	1.73
Group 2	21	1.09	0.31	1.05	0.57–1.69	0.53	0.10	0.52	0.33–0.71	1.19	0.33	1.13	0.65–1.83			1.56
Group 3	23	1.77	0.81	1.57	0.73–3.28	0.73	0.16	0.71	0.43–1.03	1.73	0.89	1.49	0.77–3.28	0.29	0.17–0.46	2.38
Group 4	23	1.30	0.49	1.21	0.54–2.23	0.61	0.14	0.60	0.33–0.87	1.34	0.55	1.22	0.61–2.31			2.38
Group 5	20	1.91	0.75	1.74	0.94–3.26	0.83	0.13	0.82	0.58–1.08	1.94	0.96	1.65	0.96–3.70			2.73

F_{MSY} was quoted from Ma et al. (2020).

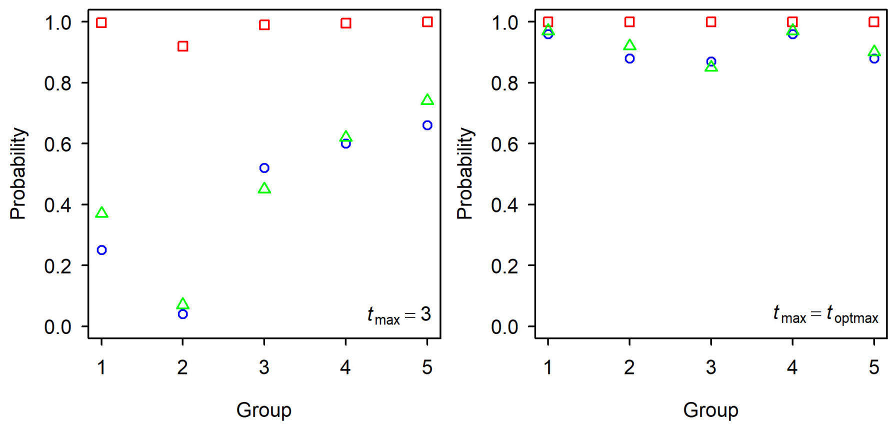


FIGURE 4 | The probability of F_{cur} being greater than the biological reference points F_{max} (green triangle), $F_{0.1}$ (red square), and $F_{20\%}$ (blue circle) for each group of small yellow croakers.

(**Figures 5**, **6**). They also varied among groups, depending on parameter estimates of each group and the level of their uncertainty. Maximum YPR ranged from 25.54 g (median value) to 34.20 g when L_c = 12.0 cm for small yellow croakers and was significantly different among groups when the exploitation pattern was similar ($p < 0.001$, **Figure 7**). The median of maximum YPR was greatest for Group 1, followed by that of Groups 4, 2, 5, and 3. However, the SPR curve of Group 1 was the lowest, whereas the SPR curves of Groups 2, 3, and 5 were relatively high (**Figure 6**). Median SPR at F_{cur} (SPR_{cur}) was lower than median SPR_{MSY} for each group. The upper limit of 95% HDI was even lower than 40% for Groups 3, 4, and 5. The distribution of SPR at a fishing mortality rate was different at two maximum ages (**Figure 8**). SPR_{cur} and SPR_{MSY} had a bimodal distribution or a multimodal distribution when t_{max} = 3 years, whereas they had a unimodal distribution for each group when $t_{max} = t_{optmax}$. But the pattern of the SSBPR at a fishing mortality was not affected by the maximum age (**Figure 9**). Median SPR_{cur} was very low (10–15%) for small yellow croakers with the optimal maximum age due to the high fishing mortality rate. A high SPR_{MSY} (55–66%, median value) was needed to attain MSY. Conversely, SPR_{cur} was relatively high when t_{max} = 3 years and a relatively low SPR_{MSY} was needed.

Optimal Length at First Capture

SPR_{MSY} was not suitable to be used as the benchmark to derive L_{copt} when t_{max} = 3 years because its distribution had two or more modes (**Figure 8**). We derived L_{copt} according to the distribution of $SSBPR_{MSY}$, which ranged from 14.80 to 15.55 cm when t_{max} = 3 years and from 22.19 to 23.30 cm when $t_{max} = t_{optmax}$ (**Figure 9**). SSBPR at F_{cur} ($SSBPR_{cur}$) and $SSBPR_{MSY}$ had a similar distribution when L_{copt} was used for each group. But uncertainty in the SSBPR increased when L_c increased to the value of L_{copt} as this increased the distribution of the SSBPR for each group. L_{copt} could also lead to a higher yield when t_{max} = 3 years (**Table 3**). Median YPR would increase 14, 6, 11, 17, and 16% for Groups 1–5, respectively.

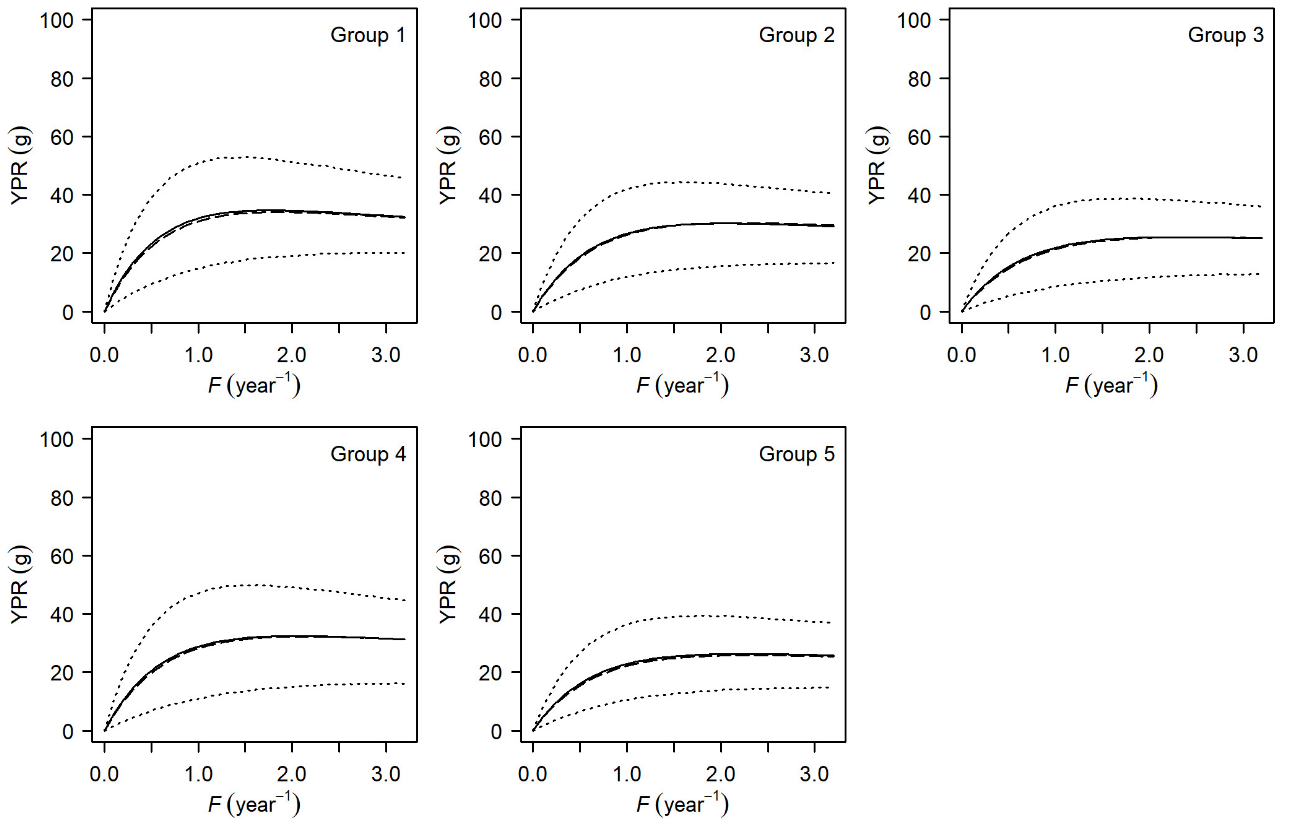


FIGURE 5 | Mean (solid line), median (long-dashed line), and the 95% HDI (dotted line) of yield-per-recruit curves for each group of small yellow croakers when t_{max} = 3 years.

DISCUSSION

This study presented a framework for measuring uncertainty in the outputs of per-recruit analysis for small yellow croaker fisheries. In this framework, the Bayesian approach was used to estimate probability distributions for life history parameters. Credible MCMC samples from Bayesian analysis were used to generate the distributions for a quantity of interest from a YPR model and an SSBPR model. Based on previous work, we checked the status of five groups of small yellow croakers and derived optimal lengths at first capture when $SSBPR_{MSY}$ was used as the benchmark. The results showed that uncertainty in a quantity of interest from per-recruit analysis, such as YPR and SSBPR at a fishing mortality rate, could be well quantified using credible MCMC samples and expressed as a probability distribution (**Figures 7**, **9**). The credible range of a quantity could be further expressed as the 95% HDI (**Tables 2**, **3**). Uncertainty in growth parameters, LWR parameters, and natural mortality rate created variation in the reference points (**Figure 3**), YPR curve (**Figure 5**), and SPR curve (**Figure 6**).

In theory, $F_{0.1}$ always exists, but F_{max} is poorly defined in some cases, and even cannot be defined (Rivard and Maguire, 1993). When the natural mortality rate is high relative to growth, the combination of life history paramters will lead to the asymptotic YPR curve, in which F_{max} cannot be found (Jensen, 2000). That $F_{20\%}$ could not be defined was also due to the low growth and a relatively high natural mortality rate. SPR is positively correlated with natural mortality and negatively correlated with various indices of size (Caddy and Mahon, 1995). The SPR curve will be too high to intersect the horizontal line passing through 20% when growth is low relative to the natural mortality rate. Although some estimates of $F_{20\%}$ were extremely high when t_{max} = 3 years (**Figure 3**), the 95% HDI could exclude them and provide the range of acceptable values (**Table 2**).

Overfishing likely occurred for all groups of small yellow croaker because F_{cur} was significantly higher than F_{MSY} for each group (**Table 2**). This is consistent with the conclusions made by Ma et al. (2020). A similar conclusion could be drawn if $F_{0.1}$ was taken as the benchmark because $P(F_{cur} > F_{0.1})$ was high for each group when t_{max} = 3 years (**Figure 4**), indicating that $F_{0.1}$ can index the status for small yellow croaker at present. F_{max} is not suited for judging the status of small yellow croaker when t_{max} = 3 years because $P(F_{cur} > F_{max})$ was not high, especially for groups 1, 2, and 3. Generally, F_{max} is not a useful conservation standard because it may be extremely high to maximize yield, which will reduce the spawning potential of the stock to near zero (Goodyear, 1993). Recruitment overfishing may not occur for the current stocks (t_{max} = 3 years) because $P(F_{cur} > F_{20\%})$ was also not high (**Figure 4**). But F_{cur} was higher than both F_{max} and $F_{20\%}$ with a high probability for

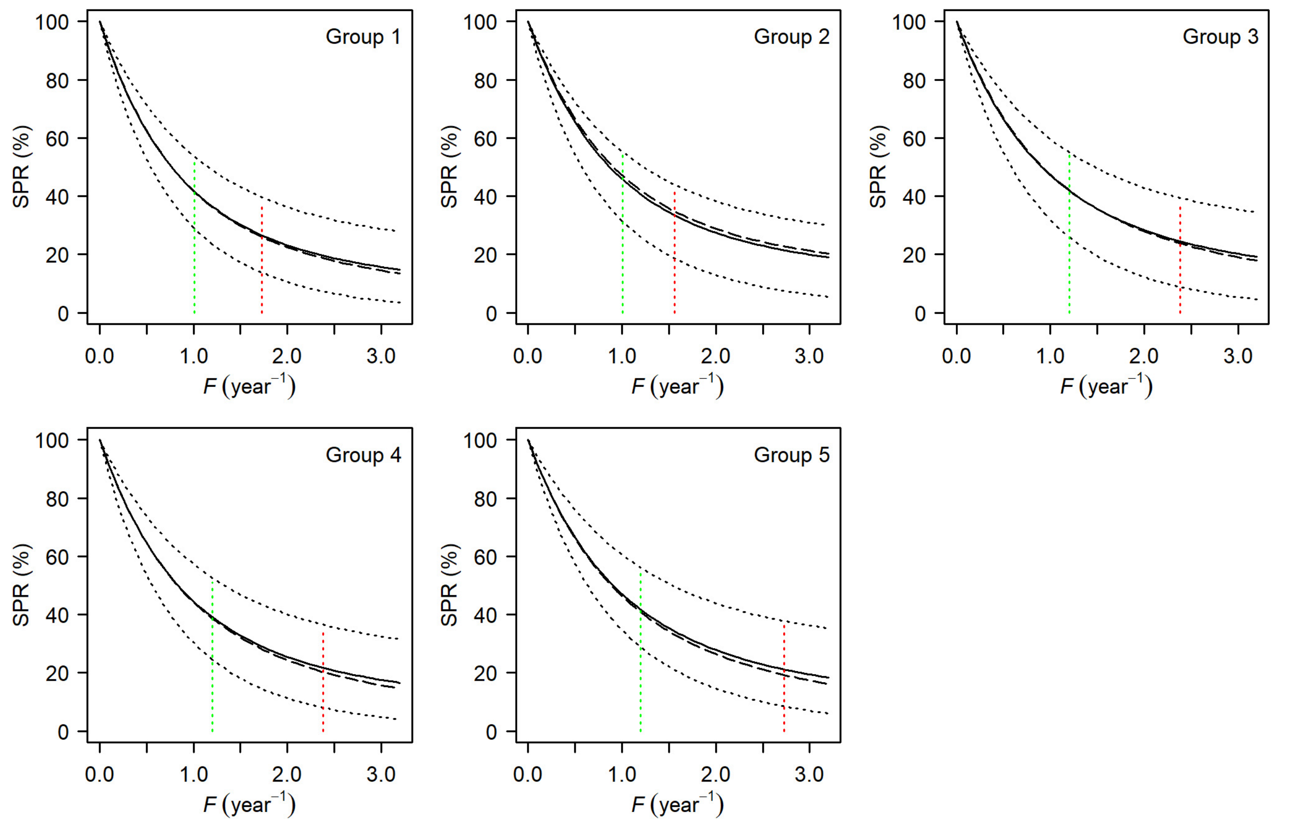


FIGURE 6 | Mean (solid line), median (long-dashed line), and the 95% HDI (dotted line) of spawning potential ratio curves for each group of small yellow croakers when t_{max} = 3 years. Green and red dotted lines show the position of F_{MSY} and F_{cur}, respectively.

each group when $t_{max} = t_{optmax}$, indicating that the current fishing mortality rate was too high for small yellow croakers with the optimal maximum age. Recruitment overfishing might have occurred in the past, but the stocks recovered by changing the life history traits. For instance, small yellow croakers now grow faster and mature earlier.

The level of uncertainty in reference points was jointly determined by uncertainty in three types of life history parameters. However, the contribution of each type of parameter was different, depending on its level of uncertainty. Generally, the LWR parameters have a low level of uncertainty for most fished species because length–weight data are easy to collect and can be measured accurately, whereas uncertainty in growth parameters and natural mortality rate is relatively high. For each group of small yellow croaker, the estimated LWR parameter was almost normally distributed and had the lowest uncertainty among the three types of life history parameters (Zhu et al., 2020). Thus, the LWR parameter had limited influence on all reference points in this study (**Figure 3**). Natural mortality rate is more difficult to estimate accurately in comparison to growth parameters. Estimates of the natural mortality rate have a high degree of uncertainty (Hamel, 2015). Thus, natural mortality rate has been commonly identified as a key factor influencing the stock assessment for a variety of species (e.g., Grabowski and Chen, 2004; Jiao et al., 2005; Chang et al., 2009). However, uncertainty surrounding growth parameters was the main contributor to the uncertainty in all reference points for small yellow croaker stocks when t_{max} = 3 years (**Figure 3**). But the relative importance of uncertainty in growth parameters and natural mortality rate changed with the assumed maximum age. The impact of uncertainty in natural mortality rate on per-recruit analysis became stronger as the maximum age increased. Natural mortality rate became the key source of uncertainty in stock assessments when t_{max} = 7 years. These results implied that growth parameters may be a key factor influencing the assessment conclusions for a stock with a younger maximum age, unless uncertainty in growth parameters is lower than that of the natural mortality rate.

Maximum age affected the per-recruit analysis. The number of parameter sets that could not generate $F_{20\%}$ reduced with an increase in maximum age (**Table 1**). Larger maximum age values resulted in more SSBPR terms according to Eq. 3. Correspondingly, the SPR curve may have a shape that can define $F_{20\%}$. The estimates of all reference points decreased with an increase in maximum age (**Figure 3**). That is, fishing mortality rate must be further reduced to let small yellow croakers grow older. A very low fishing mortality rate is needed to maintain the optimal maximum age for small yellow croakers (**Table 2**). An appropriate choice of the maximum age is particularly important for SSBPR analysis because the maximum age determines the

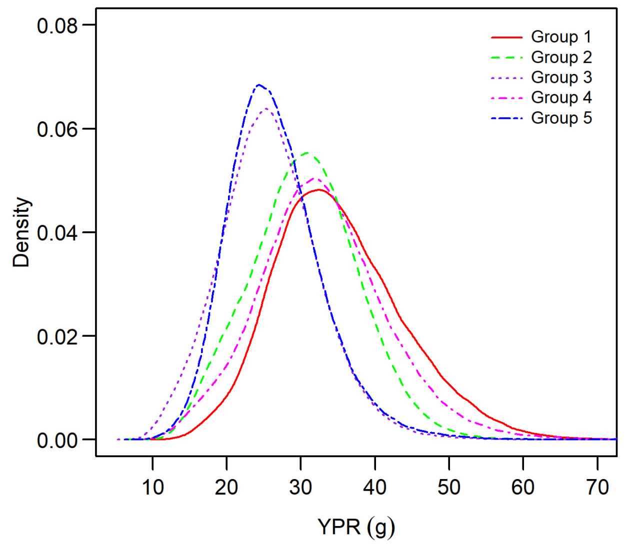


FIGURE 7 | Distribution of maximum yield-per-recruit for each group of small yellow croakers when t_{max} = 3 years.

magnitude of maximum SSBPR and further influences SPR. For instance, $SSBPR_{cur}$ was very close for the two maximum ages (**Figure 9**), but different SPR_{cur} was produced (**Figure 8**) due to the effect of maximum SSBPR. Normally, a maximum age exists for an unexploited fish stock. A younger maximum age may be observed from a sample after this stock is exploited. If this younger maximum age is employed in the SSBPR model, maximum SSBPR will be underestimated (Mace and Sissenwine, 1993). As a result, a positive bias will be introduced into the estimate of SPR (Goodyear, 1993). In this situation, the maximum age of unexploited stock must be used in the SSBPR analysis. It is worth discussing the choice of maximum age for an overexploited stock that has a much younger maximum age for many years due to long-term heavy fishing. For example, the reported oldest age for small yellow croaker is 21 years in the Bohai Sea (Guo et al., 2006) and 23 years in the southern Yellow Sea (Mao et al., 1987), but the maximum age of small yellow croakers in each region may have not exceeded 3 years for about 15 years. Therefore, it is not realistic to adopt t_{max} = 21 or 23 years to calculate the YPR and the SSBPR for current stocks. But these optimal maximum ages can be used to calculate management quantities, such as the reference points in **Table 2**.

There was a significant difference in maximum YPR among groups (**Figure 7**). YPR at a fishing mortality rate is positively correlated with growth indices and negatively correlated with natural mortality rate according to Eq. 1. Therefore, maximum YPR of Group 1 was greatest mainly because of its highest asymptotic average body size and lowest natural mortality rate among the five groups (**Supplementary Tables 2, 4**). The lowest SPR curve in Group 1 was also caused by its high growth indices and lowest natural mortality rate, which can be attributed to a negative correlation between SPR and growth, and a positive correlation between SPR and natural mortality.

Median SPR_{MSY} was higher than 40% for all groups of small yellow croaker except Group 4 when t_{max} = 3 years (**Figure 6**). Each group required a higher SPR_{MSY} when t_{max} = t_{optmax} (**Figure 8**). At present, spawning stock may drop below the level for supporting MSY. Although seas are closed to fishing in summer every year in China, this closed season policy does not prevent overfishing for small yellow croakers; rather, it temporarily enhances the biomass of small yellow croakers (Cheng et al., 2004; Yue et al., 2016). Relative abundance of small yellow croakers increases significantly during the closed months and is the greatest at the end of the closure (Cheng et al., 2004). However, relative abundance is reduced to a low level again in late December due to high fishing pressure (Cheng et al., 2004). Additional management measures are needed to ultimately enhance stocks.

Spawning stock biomass-per-recruit is superior to SPR when deriving L_{copt}. It was easy to derive L_{copt} using $SSBPR_{MSY}$ because it had a unimodal distribution (**Figure 9**). However, a younger maximum age could cause the complex distribution for SPR_{MSY} (**Figure 8**), which limited the application of SPR. The derived L_{copt} could improve both SPR and YPR for each group when t_{max} = 3 years (**Table 3** and **Figure 8**). But L_{copt} was different among groups. Groups 1 and 2 are commonly managed by one agency, whereas Groups 3–5 are co-managed by another agency. Vessels can operate anywhere within the jurisdiction of an agency. One policy that could be implemented for Groups 1 and 2 is to use a value of 15.05 cm for L_{copt}. This policy could be easily implemented in practice. Similarly, a L_{copt} of 15.55 cm can be used for Groups 3–5. These policies would be more conservative for Groups 2–4. It is not realistic to increase L_c to 22.19–23.30 cm (**Figure 9**). Fishing mortality rate also needs to be reduced to let small yellow croakers reach the optimal maximum age.

The proposed L_c from YPR analysis is usually lower than the recommended value in this study. According to the YPR isopleth, Lin et al. (2006) proposed L_c = 17.0 cm (L_{copt} range = 15.48–17.43 cm) for Groups 3–5. Zhang et al. (2010a) suggested L_c = 14.83 cm (L_{copt} range = 11.89–15.42 cm) for Group 3. Gao et al. (2019) recommended L_c = 15.0 cm (L_{copt} range = 15.15–15.91 cm) for Group 5. Although the upper limit of the L_{copt} range estimated by Gao et al. (2019) was higher than 15.55 cm, a relatively small value was chosen. Only the recommended L_c (17.0 cm) by Lin et al. (2006) was high enough to conserve Groups 3–5. But the YPR produced by an L_c of 17.0 cm at F_{cur} was lower than that produced by an L_c of 15.55 cm for these three groups. Zhai and Pauly (2019) derived an L_{copt} of 13.5 cm from YPR analysis and 14.0 cm from utility-per-recruit analysis for Group 1 based on the parameter estimates of Liu et al. (2018). These two values were lower than our result (15.05 cm). L_{copt} might have been underestimated by Zhai and Pauly (2019) due to limited data.

The estimated parameters are often imprecise and different between independent studies because the oberved data are a subsample from the population of interest (Doll et al., 2017). Uncertainty in per-recruit analysis will be dominated by the observed data when parameter estimates and their SDs derived from these data are used to generate random parameters. Uncertainty of the parameters estimated from a subsample may

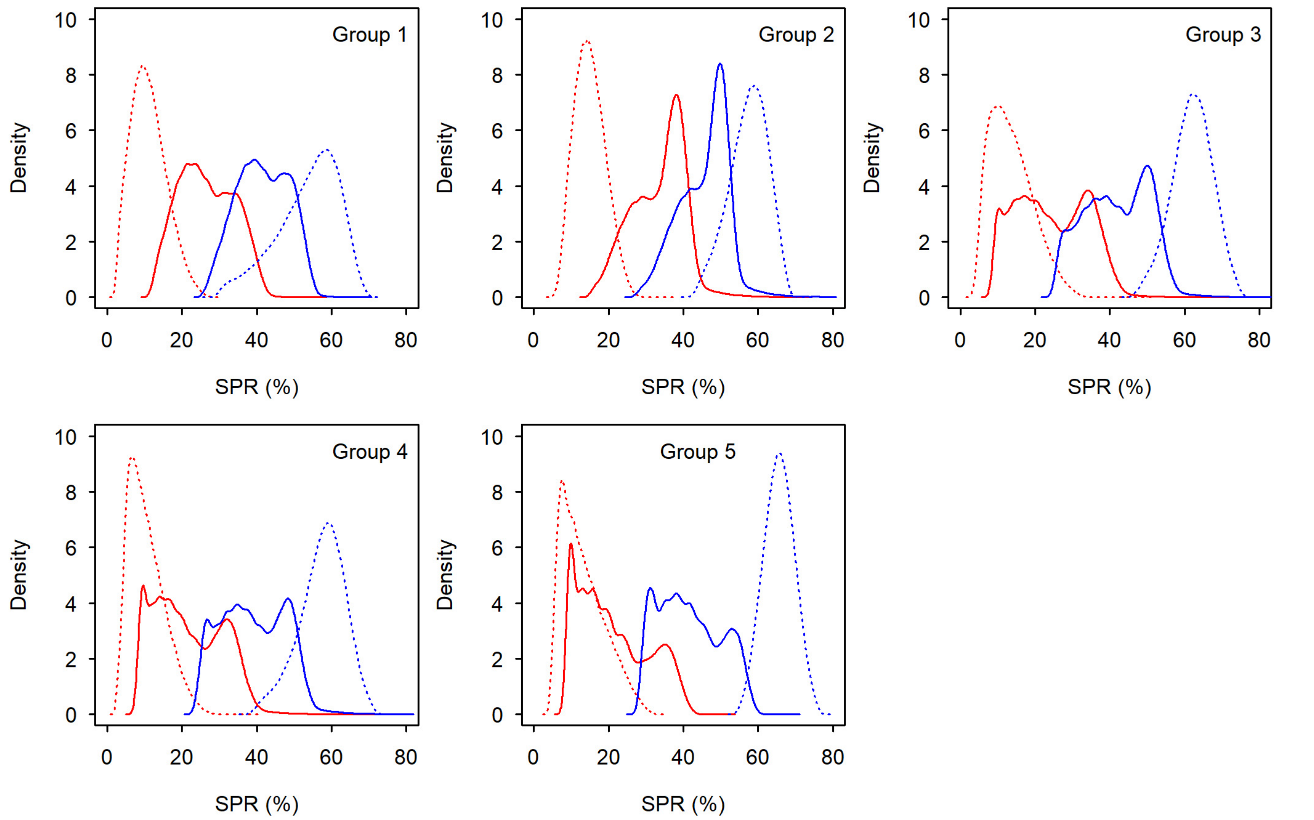


FIGURE 8 | Distribution of spawning potential ratio at F_{cur} (red lines) and at F_{MSY} (blue lines) for each group of small yellow croakers when L_c = 12.0 cm (t_{max} = 3 years: solid lines; t_{max} = t_{optmax}: dotted lines).

be narrower than when data from other years are considered (Froese et al., 2014). Thus, the resulting uncertainty in a quantity from per-recruit analysis may be underestimated. When random parameters are obtained by specifying SDs or CVs for a particular set of parameter estimates, the resulting uncertainty in the outcome of a per-recruit model will be influenced by both the specified estimates and SDs or CVs. In contrast, existing information regarding a parameter can be introduced to Bayesian analysis and the resulting uncertainty of this parameter may be more realistic. Therefore, parameter estimates from Bayesian inference may lead to more realistic uncertainty for a quantity of interest from per-recruit analysis. In addition, the correlated parameters from different types of life history can also be easily incorporated into a Bayesian model to estimate the parameter of interest using their correlation (Pulkkinen et al., 2011; Zhu et al., 2020). Moreover, uncertainty in a parameter with less information can be reduced through their correlation. Thus, estimating parameters using Bayesian inference is suited for quantifying uncertainty in per-recruit analysis.

Generating extremely low or high values from Bayesian inference is unavoidable when sampling in the posterior distribution of a parameter using the MCMC technique. The extreme values may have no biological meaning or exceed the reasonable range. We used MCMC samples inside 95% HDI to avoid the impact of extreme values. The total probability of MCMC samples in the 95% HDI is 95% and these samples are the 95% most credible values (Kruschke, 2014). These MCMC samples can generate uncertainty for a quantity for per-recruit analysis. The median of a quantity was similar when all MCMC samples were used. The mean had an increase of 2–5% for F_{max}, 1–4% for $F_{0.1}$, and 1–3% for $F_{20\%}$ when t = 3 years. The 95% HDI became wider due to the increase in the range of MCMC samples; 95% HDI of F_{max} had a largest change among these three reference points. Its lower limit decreased by 3–11% and upper limit increased by 5–10%. The variation in the mean and the median of L_{copt} was no more than 1% and was less than 2% in the limits of 95% HDI.

Markov chain Monte Carlo samples used in per-recruit analysis were derived from the existing estimates of life history parameters. Growth parameters and natural mortality rate were slightly skewed for most groups of small yellow croakers due to variation in parameter estimates and the relatively small size of the dataset (Zhu et al., 2020). As a result, the distribution of a quantity from per-recruit analysis was also not exactly normal (**Figures 7, 9**). New data are needed to reduce uncertainty in the output of per-recruit analysis by improving parameter estimates. According to the framework shown in **Figure 2**, when new data are collected for a group of small yellow croakers in the future, the distributions of parameters estimated by Zhu et al. (2020) will serve as the prior values to derive the newest distributions

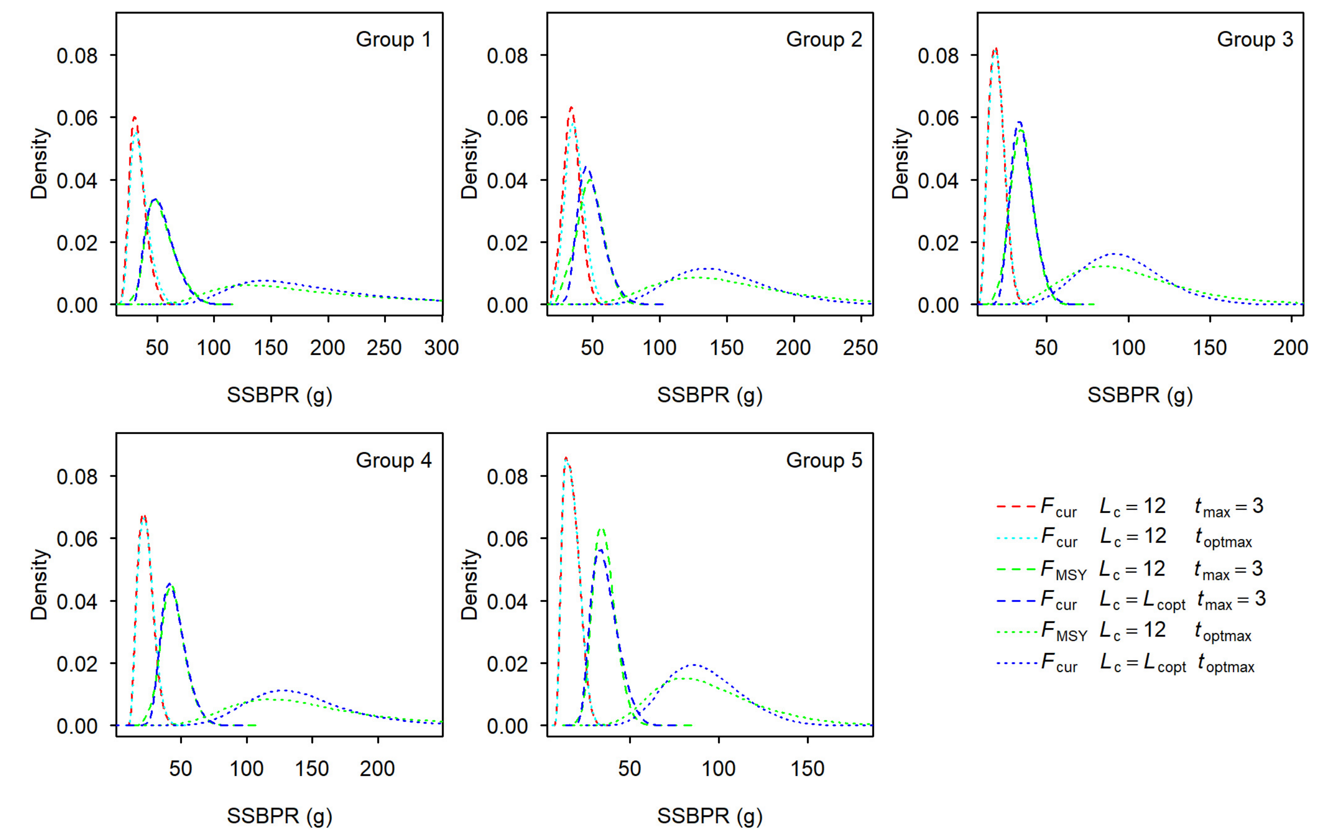


FIGURE 9 | Distribution of spawning stock biomass-per-recruit at F_{cur} and at F_{MSY} for each group of small yellow croakers when L_c = 12.0 cm and $L_c = L_{cop}$. L_{copt} was 15.05, 14.80, 15.15, 15.20, and 15.55 cm for Groups 1–5 when t_{max} = 3, and 23.30, 22.67, 22.19, 22.76, and 22.35 cm when $t_{max} = t_{optmax}$.

TABLE 3 | Summary of yield-per-recruit at the current fishing mortality rate for each group of small yellow croakers when t_{max} = 3 years (unit: g).

Statistic	Group 1		Group 2		Group 3		Group 4		Group 5	
	L_c = 12.0	L_c = 15.05	L_c = 12.0	L_c = 15.05	L_c = 12.0	L_c = 15.55	L_c = 12.0	L_c = 15.55	L_c = 12.0	L_c = 15.55
Mean	34.67	40.24	29.66	32.01	25.48	28.78	32.27	38.53	26.13	30.66
SD	8.68	13.12	7.72	10.72	6.58	10.28	8.14	13.42	6.03	9.27
Median	34.02	38.77	29.63	31.46	25.44	28.16	32.16	37.73	25.70	29.85
Left 95% HDI	18.63	16.11	14.57	11.83	12.28	9.32	15.72	13.14	14.59	13.66
Right 95% HDI	52.46	66.71	44.42	53.12	37.91	49.11	47.88	65.52	37.92	49.52

for life history parameters. Then the resulting credible MCMC samples are used to conduct per-recruit analysis to update our knowledge on a quantity of interest from per-recruit analysis. This procedure for measuring uncertainty in per-recruit analysis is general and suitable for other species. In this framework, other Bayesian approaches can also be adapted to obtain MCMC samples of life history parameters for quantifying uncertainty in the outcomes of per-recruit analysis. The conclusion regarding the status assessment and the recommended L_c in this study were also influenced by the estimates of F_{cur} and F_{MSY}. When new knowledge on F_{cur} and F_{MSY} is available, per-recruit analysis needs to be carried out again to update our understanding of the status of each group. In addition, the derived L_{copt} for small yellow croakers with the optimal maximum age was influenced by parameter values and F_{MSY}. Current parameter values may be different from those when small yellow croakers attained the optimal maximum age. Similarly, F_{MSY} in 1968 may also be biased. The groups of small yellow croakers were divided in terms of conventional investigation region. It is still unclear whether or not Groups 3 and 4 belong to the same subpopulation. Although Group 3 is the main part of Group 4 in this study, their maximum YPRs were significantly different (**Figure 7**). Group 3 had larger median values of F_{max}, $F_{0.1}$, and $F_{20\%}$ than Group 4 (**Table 2**), whereas Group 4 had higher YPR and SSBPR (**Table 3** and **Figure 9**). There is a need to discuss the division of groups for small yellow croakers to conduct better resource surveys and stock assessment for this species.

CONCLUSION

Overfishing likely occurred for all groups of small yellow croakers in China, but recruitment overfishing may not occur if the maximum age is maintained at 3 years. High fishing mortality and small length at first capture might cause SPR_{cur} to be lower than SPR_{MSY}. The current closed season policy coupled with the recommended lengths at first capture could recover the biomass to support MSY when t_{max} = 3 years. The required fishing mortality rate was very low for small yellow croakers with the optimal maximum age. Besides increasing length at first capture, the fishing mortality rate needs to be reduced to attain the optimal maximum age for each group.

The combination of the SSBPR model and F_{MSY} from the surplus production model can lead to a more conservative length at first capture than the YPR model. $SSBPR_{MSY}$ is more suitable to derive the optimal length at first capture than SPR_{MSY}.

The credible parameter values from Bayesian inference could quantify uncertainty well in the output of per-recruit analysis. The presented framework for measuring uncertainty in the outcome of per-recruit models is suited for other fish species, and the Bayesian approach to parameter estimation in this framework is not limited to that utilized in our previous work: other Bayesian methods can also be used to derive input parameters for per-recruit models.

DATA AVAILABILITY STATEMENT

The data analyzed in this study are subject to the following licenses/restrictions: The MCMC samples from Bayesian inference will be shared on reasonable request to the corresponding author. All other datasets generated for this study are included in the article/**Supplementary Material**. Requests to access these datasets should be directed to ZL, liangzhenlin@sdu.edu.cn.

ETHICS STATEMENT

Ethical review and approval was not required for the animal study because our manuscript was based on data from literatures and no live vertebrates or higher invertebrates were involved.

AUTHOR CONTRIBUTIONS

LZ performed the computing work and wrote the manuscript. CG analyzed the data. ZJ and CL drafted the figures. GH collected the data. ZL designed this study and provided financial support. All authors contributed to the article and approved the submitted version.

FUNDING

This work was funded by the Natural Science Foundation of Shandong Province, China (No. ZR2010DQ019) and China Postdoctoral Science Foundation (No. 2017M622180).

ACKNOWLEDGMENTS

The authors thank Qiuyun Ma from Shanghai Ocean University for providing values of F_{MSY} in small yellow croaker fisheries. We are grateful to the two reviewers for providing valuable comments, which improved the manuscript. The authors would like to particularly thank the Associate Editor, ND, for providing constructive comments and making corrections.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2021.652293/full#supplementary-material

REFERENCES

Caddy, J. F. (1984). Indirect approaches to regulation of fishing effort. *FAO Fish. Rep.* 289, 63–75.

Caddy, J. F., and Mahon, R. (1995). "Reference points for fisheries management" *FAO Fisheries Technical Paper* (Rome: Food and Agriculture Organization of the United Nations), 347:83.

Chang, Y. J., Sun, C. L., Chen, Y., Yeh, S. Z., and Chiang, W. C. (2009). Incorporating uncertainty into the estimation of biological reference points for a spiny lobster (Panulirus penicillatus) fishery. *New Zeal. J. Mar. Fresh* 43, 429–442. doi: 10.1080/00288330909510012

Chen, M., Lu, Z., Du, J., and Yang, S. (2010). Changes in Ecological Parameters of Small Yellow Croaker, Pseudosciaena polyactis, in Eastern Fujian Fishing Ground. *J. Xiamen. Univ.* 49, 260–265.

Chen, R., Li, X., Fan, G., Zhao, X., and Zhang, G. (2018). Minimal cod-end mesh of a pair trawl in the Yellow Sea. *J. Dalian. Ocean Univ.* 33, 258–264.

Chen, Y., and Wilson, C. (2002). A simulation study to evaluate impacts of uncertainty on the assessment of American lobster fishery in the Gulf of Maine. *Can. J. Fish. Aquat. Sci.* 59, 1394–1403. doi: 10.1139/f02-102

Cheng, J., Lin, L., Ling, J., Li, J., and Ding, F. (2004). Effects of summer close season and rational utilization on redlip croaker (Larimichthys polyactis Bleeker) resource in the East China Sea Region. *J. Fish. Sci. China* 11, 554–560.

Doll, J. C., Lauer, T. E., and Clark-Kolaks, S. (2017). Yield-per-recruit modeling of two piscivores in a Midwestern reservoir: a Bayesian approach. *Fish. Res.* 191, 200–210. doi: 10.1016/j.fishres.2017.03.012

Froese, R., Thorson, J. T., and Reyes, R. Jr. (2014). A Bayesian approach for estimating length−weight relationships in fishes. *J. Appl. Ichthyol.* 30, 78–85. doi: 10.1111/jai.12299

Gabriel, W. L., and Mace, P. M. (1999). "A review of biological reference points in the context of the precautionary approach" in *Proceedings of the Fifth National NMFS Stock Assessment Workshop: Providing Scientific Advice to Implement the Precautionary Approach Under the Magnuson-Stevens Fishery Conservation and Management Act*, ed. V. R. Restrepo (Key Largo: U.S. Department of Commerce), 34–45.

Gao, C., Ma, Q., Tian, S., Dai, X., Kindong, R., Gou, X., et al. (2019). Growth, mortality and yield per recruitment of small yellow croaker in offshore waters of southern Zhejiang. *J. Fish. Sci. China* 26, 925–937. doi: 10.3724/SP.J.1118.2019.19004

Gavaris, S. (1993). "Analytical estimates of reliability for the projected yield from commercial fisheries" in *Risk Evaluation and Biological Reference Points for*

Fisheries Management. eds S. J. Smith, J. J. Hunt, and D. Rivard (Ottawa: National Research Council of Canada). 185–191.

Goodyear, C. P. (1993). "Spawning stock biomass per recruit in fisheries management: foundation and current use" in *Risk Evaluation and Biological Reference Points for Fisheries Management*, eds S. J. Smith, J. J. Hunt, and D. Rivard (Ottawa: National Research Council of Canada). 67–81.

Govender, A., Al-Oufi, H., Mcilwain, J., and Claereboudt, M. (2006). A per-recruit assessment of the kingfish (Scomberomorus commerson) resource of Oman with an evaluation of the effectiveness of some management regulations. *Fish. Res.* 77, 239–247. doi: 10.1016/j.fishres.2005.08.010

Grabowski, R., and Chen, Y. (2004). Incorporating uncertainty into the estimation of the biological reference points F0.1 and Fmax for the Maine green sea urchin (Strongylocentrotus droebachiensis) fishery. *Fish. Res.* 68, 367–371. doi: 10.1016/j.fishres.2003.12.005

Guo, X., Jin, X., and Dai, F. (2006). Growth variations of small yellow croaker (Pseudosciaena polyactis Bleeker) in the Bohai Sea. *J. Fish. Sci. China* 13, 243–249.

Hamel, O. S. (2015). A method for calculating a meta-analytical prior for the natural mortality rate using multiple life history correlates. *ICES J. Mar. Sci.* 72, 62–69. doi: 10.1093/icesjms/fsu131

Hart, D. R. (2013). Quantifying the tradeoff between precaution and yield in fishery reference points. *ICES J. Mar. Sci.* 70, 591–603. doi: 10.1093/icesjms/fss204

Helser, T. E., Sharov, T., and Kahn, D. M. (2001). "A stochastic decision-based spproach to assessing the Delaware Bay blue crab (Callinectes sapidus) stock" in *Incorporating Uncertainty into Fishery Models*, eds J. M. Berkson, L. L. Kline, and D. J. Orth (Bethesday: American Fisheries Society Publication). 63–82.

Hu, H., Ye, Z., Li, Z., Wang, M., Wen, Q., and Yu, H. (2015). A preliminary study on the biology of the spawning stock of small yellow croaker (Pseudosciaena ployactis) inhabiting the near shore of southern Yellow Sea. *Period. Ocean Univ. China* 45, 43–45. doi: 10.16441/j.cnki.hdxb.20140325

Jensen, A. (2000). Harvest reference points for the Beverton and Holt dynamic pool model. *Fish. Res.* 47, 93–96. doi: 10.1016/s0165-7836(99)00126-5

Jiao, Y., Chen, Y., and Wroblewski, J. (2005). An application of the composite risk assessment method in assessing fisheries stock status. *Fish. Res.* 72, 173–183. doi: 10.1016/j.fishres.2004.11.003

Jin, X. (1996). Ecology and population dynamics of small yellow croaker (Pseudosciaena ployactis Bleeker) in the Yellow Sea. *J. Fish. Sci. China* 3, 32–46.

Jin, X., and Deng, J. (2000). Variations in community structure of fishery resources and biodiversity in the Laizhou Bay. *Shandong. Chin. Biodivers.* 8, 65–72.

Kruschke, J. N. (2014). *Doing Bayesian Data Analysis: a Tutorial With R, JAGS, and Stan*. Boston: Academic Press.

Li, Z., Shan, X., Jin, X., and Dai, F. (2011). Long-term variations in body length and age at maturity of the small yellow croaker (Larimichthys polyactis Bleeker, 1877) in the Bohai Sea and the Yellow Sea, China. *Fish. Res.* 110, 67–74. doi: 10.1016/j.fishres.2011.03.013

Lin, L., Cheng, J., Ling, J., and Zhang, H. (2006). First capture sizes of major commercial fishes in the East China Sea Region. *J. Fish. Sci. China* 13, 250–256.

Lin, L., Cheng, J., Ren, Y., and Ling, J. (2004). Analysis of population biology of small yellow croaker Pseudosciaena polyactis in the East China Sea region. *J. Fish. Sci. China* 11, 333–338.

Lin, L., Liu, Z., Jiang, Y., Huang, W., and Gao, T. (2011). Current status of small yellow croaker resources in the southern Yellow Sea and the East China Sea. *Chin. J. Oceanol. Limn.* 29, 547–555. doi: 10.1007/s00343-011-0182-8

Lin, X., Deng, S., Huang, Z., and Wang, Q. (1965). "Study of population on biometrics of small yellow croaker (Pseudosciaena polyactis Bleeker)" in *Collections of Marine Fishery Resource*, eds Y. Zhu and S. Zhu (Beijing: China Agriculture Press). 84–108.

Lin, Y. J., Chang, Y. J., Sun, C. L., and Tzeng, W. N. (2010). Evaluation of the Japanese eel fishery in the lower reaches of the Kao-Ping River, southwestern Taiwan using a per-recruit analysis. *Fish. Res.* 106, 329–336. doi: 10.1016/j.fishres.2010.08.015

Lin, Y. J., Sun, C. L., Chang, Y. J., and Tzeng, W. N. (2015). Sensitivity of yield-per-recruit and spawning-biomass-per-recruit models to bias and imprecision in life history parameters: an example based on life history parameters of Japanese eel (Anguilla japonica). *Fish. Bull.* 113, 302–312. doi: 10.7755/FB.113.3.6

Liu, W., Guo, Z., and Zhan, B. (1999). Analysis on the current exploitation of Pseudosciaena ployactis in the East China Sea. *J. Shanghai Fish. Univ.* 8, 105–111.

Liu, X. (1990). *Small Yellow Croaker (Pseudosciaena Ployactis)* (China: Fishery Bureau of Ministry of Agriculture), 191–200.

Liu, X., Guo, D., Wang, A., Dong, J., Wang, X., Duan, Y., et al. (2018). Growth characteristics of small yellow croaker Larimichthys polyactis in the Liaodong Bay. *Mar. Fish.* 40, 139–146. doi: 10.13233/j.cnki.mar.fish.2018.02.002

Liu, Z., Xie, H., Yan, L., Yuan, X., Yang, L., Li, Y., et al. (2013). Comparative population dynamics of small yellow croaker Larimichthys polyactis in Southern Yellow Sea and East China Sea. *J. Dalian. Ocean Univ.* 28, 627–632. doi: 10.16535/j.cnki.dlhyxb.2013.06.019

Ma, Q., Jiao, Y., and Ren, Y. (2017). Linear mixed-effects models to describe length-weight relationships for yellow croaker (Larimichthys Polyactis) along the north coast of China. *PLoS One* 12:e0171811. doi: 10.1371/journal.pone.0171811

Ma, Q., Jiao, Y., Ren, Y., and Xue, Y. (2020). Population dynamics modelling with spatial heterogeneity for yellow croaker (Larimichthys polyactis) along the coast of China. *Acta Oceanol. Sin.* 39, 107–119. doi: 10.1007/s13131-020-1602-4

Mace, P. M., and Sissenwine, M. P. (1993). "How much spawning per recruit is enough?" in *Risk Evaluation and Biological Reference Points for Fisheries Management*, eds S. J. Smith, J. J. Hunt, and D. Rivard (Ottawa: National Research Council of Canada). 101–118.

Mao, X., Yu, J., and Qin, Y. (1987). *Small Yellow Croaker*. Shanghai: East China Normal University Press). 339–356.

Pulkkinen, H., Mäntyniemi, S., Kuikka, S., and Levontin, P. (2011). More knowledge with the same amount of data: advantage of accounting for parameter correlations in hierarchical meta-analyses. *Mar. Ecol. Prog. Ser.* 443, 29–37. doi: 10.3354/meps09368

Restrepo, V. R., and Fox, W. W. Jr. (1988). Parameter Uncertainty and Simple Yield−per−Recruit Analysis. *Trans. Am. Fish. Soc.* 117, 282–289. doi: 10.1577/1548-8659(1988)117<0282:puasya>2.3.co;2

Rivard, D., and Maguire, J. J. (1993). "Reference points for fisheries management: the eastern Canadian experience" in *Risk Evaluation and Biological Reference Points for Fisheries Management*, eds S. J. Smith, J. J. Hunt, and D. Rivard (Ottawa: National Research Council of Canada). 31–57.

Romakkaniemi, A. (2015). *Best Practices for the Provision of Prior Information for Bayesian Stock Assessment*. Copenhagen: International Council for the Exploration of the Sea.

Shan, X., Li, X., Yang, T., Sharifuzzaman, S., Zhang, G., Jin, X., et al. (2017). Biological responses of small yellow croaker (Larimichthys polyactis) to multiple stressors: a case study in the Yellow Sea, China. *Acta Oceanol. Sin.* 36, 39–47. doi: 10.1007/s13131-017-1091-2

Shan, X., Sun, P., Jin, X., Li, X., and Dai, F. (2013). Long-term changes in fish assemblage structure in the Yellow River Estuary ecosystem. China. *Mar. Coast. Fish.* 5, 65–78. doi: 10.1080/19425120.2013.768571

Shen, G., and Heino, M. (2014). An overview of marine fisheries management in China. *Mar. Policy* 44, 265–272. doi: 10.1016/j.marpol.2013.09.012

Shui, B. (2003). Study on the age and growth of Pseudosciaena polyactis in the south of the Yellow Sea and the north of the East China Sea. *J. Zhejiang Ocean Univ.* 22, 16–20.

von Bertalanffy, L. (1938). A quantitative theory of organic growth (inquiries on growth laws. II). *Hum. Biol.* 10, 181–213.

Wang, Y., Huang, J., Tang, X., Jin, X., and Sun, Y. (2016). Stable isotopic composition of otoliths in identification of stock structure of small yellow croaker (Larimichthys polyactis) in China. *Acta Oceanol. Sin.* 35, 29–33. doi: 10.1007/s13131-016-0868-z

Xu, Q., Li, X., Sun, S., Fan, G., Pang, Z., and You, Z. (2019). On catch composition and selectivity of pair-trawling in the Yellow Sea. *Mar. Fish.* 41, 676–683. doi: 10.13233/j.cnki.mar.fish.2019.06.003

Xu, Z., and Chen, J. (2010). Population division of Larimichthys polyactis in China Sea. *Chin. J. Appl. Ecol.* 21, 2856–2864.

Yan, L., Hu, F., Ling, J., and Li, S. (2006). Study on age and growth of Larimichthys polyactis in the East China Sea. *Period. Ocean Univ. China* 36, 95–100.

Yan, L., Liu, Z., Zhang, H., Ling, J., Yuan, X., and Li, S. (2014). On the evolution of biological characteristics and resources of small yellow croaker. *Mar. Fish.* 36, 481–488. doi: 10.13233/j.cnki.mar.fish.2014.06.001

Ye, C. (1991). "Small yellow croaker (Pseudosciaena ployactis)" in *Marine Fisheries Biology*, eds J. Deng and C. Zhao (Beijing: China Agriculture Press), 164–200.

Ying, Y., Chen, Y., Lin, L., and Gao, T. (2011). Risks of ignoring fish population spatial structure in fisheries management. *Can. J. Fish. Aquat. Sci.* 68, 2101–2120. doi: 10.1139/F2011-116

You, Z., Zhao, X., Li, X., Sun, S., Zhu, J., Pang, Z., et al. (2017). Selectivity of cod-end mesh of pair-trawlers in the Yellow Sea. *Fish. Sci.* 36, 436–442. doi: 10.16378/j.cnki.1003-1111.2017.04.006

Yue, D., Wang, L., Xiong, S., Xiao, L., and Zhang, H. (2016). Improving the marine summer closed fishing season system: a case study of the practise of Zhejiang province and the East China Sea. *Res. Agric. Mod.* 37, 337–344. doi: 10.13872/j.1000-0275.2015.0190

Zhai, L., and Pauly, D. (2019). Yield-per-recruit, utility-per-recruit, and relative biomass of 21 exploited fish species in China's coastal seas. *Front. Mar. Sci.* 6:724. doi: 10.3389/fmars.2019.00724

Zhang, C., Ye, Z., Wan, R., Ma, Q., and Li, Z. (2014). Investigating the population structure of small yellow croaker (Larimichthys polyactis) using internal and external features of otoliths. *Fish. Res.* 153, 41–47. doi: 10.1016/j.fishres.2013.12.012

Zhang, G., Li, X., Jin, X., Zhu, J., and Dai, F. (2010a). Growth, mortality and optimum catchable size of small yellow croaker (Larimichthys polyactis Bleeker) in the Southern Yellow Sea. *J. Fish. Sci. China* 17, 839–846.

Zhang, G., Li, X., Zhu, J., Dai, F., and Jin, X. (2010b). The growth characteristics of small yellow croaker Larimichthys polyactis (Bleeker, 1987) underyearling in the central and southern Yellow Sea. *Prog. Fish. Sci.* 31, 15–22.

Zhou, S., Punt, A. E., Lei, Y., Deng, R. A., and Hoyle, S. D. (2020). Identifying spawner biomass per-recruit reference points from life-history parameters. *Fish. Fish.* 21, 760–773. doi: 10.1111/faf.12459

Zhu, L., Liang, Z., Ge, C., and Liu, C. (2020). An application of the Bayesian hierarchical approach to refining the information on main life history parameters for small yellow croaker, Larimichthys polyactis, off the coast of China. *Ocean Sci. J.* 55, 143–155. doi: 10.1007/s12601-020-0010-1

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 08 December 2021
doi: 10.3389/fmars.2021.757877

Multi-Indicator Harvest Strategies for Data-Limited Fisheries: A Practitioner Guide to Learning and Design

William J. Harford[1]*, Ricardo Amoroso[2], Richard J. Bell[3], Matias Caillaux[4], Jason Marc Cope[5], Dawn Dougherty[6], Natalie Anne Dowling[7], Frank Hurd[8], Serena Lomonico[8], Josh Nowlis[5], Dan Ovando[2], Ana M. Parma[9], Jeremy D. Prince[10,11] and Jono R. Wilson[8,12]

[1] Nature Analytics, Mississauga, ON, Canada, [2] School of Aquatic and Fishery Sciences, University of Washington, Seattle, WA, United States, [3] The Nature Conservancy, URI Bay Campus, Narragansett, RI, United States, [4] The Nature Conservancy, Arlington, VA, United States, [5] Northwest Fisheries Science Center, U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Marine Fisheries Service, Seattle, WA, United States, [6] The Nature Conservancy, Corvallis, OR, United States, [7] CSIRO Oceans and Atmosphere, Hobart, TAS, Australia, [8] The Nature Conservancy, Sacramento, CA, United States, [9] Centro Para el Estudio de Sistemas Marinos, Consejo Nacional de Investigaciones Científicas y Técnicas, Puerto Madryn, Argentina, [10] Biospherics Pty., Ltd., South Fremantle, WA, Australia, [11] Environmental and Conservation Science, Murdoch University, Perth, WA, Australia, [12] Bren School of Environmental Science and Management, University of California, Santa Barbara, Santa Barbara, CA, United States

Edited by:
Çetin Keskin,
Istanbul University, Turkey

Reviewed by:
Davide Agnetta,
Istituto Nazionale di Oceanografia e di Geofisica Sperimentale, Italy
Matthew Baker,
North Pacific Research Board, United States
Fabio Fiorentino,
Institute for Biological Resources and Marine Biotechnology, National Research Council (CNR), Italy

***Correspondence:**
William J. Harford
bill@natureanalytics.ca

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: 13 August 2021
Accepted: 12 November 2021
Published: 08 December 2021

Citation:
Harford WJ, Amoroso R, Bell RJ, Caillaux M, Cope JM, Dougherty D, Dowling NA, Hurd F, Lomonico S, Nowlis J, Ovando D, Parma AM, Prince JD and Wilson JR (2021) Multi-Indicator Harvest Strategies for Data-Limited Fisheries: A Practitioner Guide to Learning and Design. Front. Mar. Sci. 8:757877. doi: 10.3389/fmars.2021.757877

As the world population grows, fisheries practitioners will be under increased pressure to address global challenges in data-limited fisheries management. With a focus on addressing localized and case-specific management needs, we provide a practical guide to the design and development of multi-indicator frameworks for fishery management. In a data-limited context, indicators are observations or estimates of the state of the fishery resource that are typically proxies for variables of interest, rather than quantities such as stock biomass estimated from data-rich stock assessments. Indicator frameworks structure the integration and interpretation of indicators to guide tactical fishery decision-making, often when the application of more formal analytical assessments is not feasible, yet where indicators in combination provide insight into stock status. With a focus on multi-indicator frameworks, we describe a pragmatic approach for their development *via* a set of organizational steps, considering a wide spectrum of types and severity of information limitations. We highlight where multi-indicator frameworks can be insightful and informative in relation to single indicator approaches but also point to potential pitfalls, with emphasis on critical evaluation and detection of performance flaws during the design phase using methods such as management strategy evaluation.

Keywords: fishery management, indicator, management strategy, framework, stock assessment

INTRODUCTION

Fisheries provide food and jobs for hundreds of millions of people across the globe. Yet between one third to one half of fisheries are likely to be unsustainably fished, limiting their potential to achieve conservation and food provisioning objectives (Costello et al., 2012, 2016; FAO, 2020b). Fisheries with well-developed management systems, including clearly defined procedures for data collection, stock assessment and regulation (i.e., harvest strategies) tend to meet management objectives better than those fisheries without such systems (Costello and Ovando, 2019; Hilborn et al., 2020). As the world population grows to more than nine billion people by 2050, there is a need to improve the capacity of wild capture fisheries to provide food and nutrients to people (United Nations, 2019). Bringing effective management to fisheries that lack quality data (e.g., data gaps, bias, and imprecision) requires a renewed focus on the process of designing data-limited fishery management strategies (Dowling et al., 2015b, 2019; McDonald et al., 2017). There is a need for practitioners to be prepared to address global challenges in data-limited fisheries management, recognizing that solutions to these challenges will likely require focus on localized and case-specific issues (Caddy, 2004; Dowling et al., 2019).

In striving to improve data-limited fisheries management, severity of information limitations is likely to differentiate the structures of proposed solutions. A fishery must confront their currently available information with respect to management objectives, funding, capability to obtain alternate additional information, and research capacity. For fisheries with fledgling or even established monitoring programs, interim solutions may be sought along the pathway to achieving conventional stock assessment. Alternately, quality empirical indicators may be sufficient to bypass integrated stock assessment models. For fisheries with no pre-existing data or limited capacity for conventional stock assessment approaches, initial emphasis may be placed on introducing some form of "data-less" management (e.g., Prince and Hordyk, 2019) and on trying out simple monitoring schemes that can form the foundation for management (Prince et al., 2018, 2020; Plagányi et al., 2020). Fisheries management across this wide spectrum of severity in information limitation shares a necessity for cost-effective harvest strategies, built from the ground-up or from existing monitoring programs, and based on indicators that can effectively guide decision-making toward achieving fishery management objectives. It is in this context that indicator-based frameworks are helpful.

Indicators derived from observations of a fishery system can provide information about prevailing conditions and can form the basis of structured approaches to fishery decision-making (Bentley, 2015; Miethe et al., 2016). Indicators tend to be proxies for variables of interest, such as observations of fishery catch per unit effort (CPUE), or carcasses washed up on beaches, as proxies of abundance, or the observation of increasing distance traveled offshore by fishers as a proxy for localized depletion. While indicators can be obtained from a conventional stock assessment (e.g., Hordyk et al., 2019), indicator-based frameworks can provide suitable guidance for data-limited fisheries where it is infeasible to conduct a conventional, fully integrated stock assessment (e.g., stock assessments involving age or length-structured models or biomass dynamic models). Indicators can either be model-free (derived more-or-less directly from raw data) or model-based (typically estimated from simpler demographic models or analytical approaches). Indicators that do not conform to typical model-based stock assessment requirements include those that are qualitative (e.g., "good" or "poor"), time series that are too short or lack adequate contrast to inform conventional stock assessment, and those that do not support model assumptions (e.g., catch rates from opportunistic (non-targeting) multispecies fisheries often do not reflect the underlying biomass of any of the individual species). Such indicators, can, however, still support decision-making within an indicator-based framework. Multi-indicator frameworks can also be designed to complement local and customary practices, typically because they can incorporate indicators based on local expert knowledge, and are easily understood by fishers (Plagányi et al., 2020).

Indicators can be used within a pre-agreed decision rule for adjusting harvest controls as a function of resource status known as a harvest strategy. A harvest strategy consists of three parts: a monitoring scheme for data collection, a method of analysis yielding values of indicators (e.g., *via* data-limited assessment or from direct empirical observation), and a decision rule or harvest control rule (HCR; Sainsbury et al., 2000; Butterworth, 2007). An HCR guides the adjustment to a management measure, such as a total allowable catch (TAC), total allowable effort, or fishing season length (e.g., Cadrin, 2016). Thus, an HCR determines the degree of management responsiveness to measures of prevailing conditions. Harvest strategies, especially those based on a single indicator to drive adjustments in harvest controls, are increasingly common, and their design and evaluation using simulation tools is wide-spread, including entire scientific journal issues devoted to these topics (Garcia and Staples, 2000; Cury and Christensen, 2005; Carruthers et al., 2015; Geromont and Butterworth, 2015).

As a form of harvest strategy, multi-indicator frameworks have received less attention than single-indicator approaches, potentially because indicator frameworks are less formally and not prescriptively constructed, and their performance is more challenging to formally evaluate. Multi-indicator frameworks structure the integration and interpretation of information from two or more disparate sources to guide fishery decision-making. They can be structured to use different indicators simultaneously (Caddy, 1999, 2002) or sequentially (Wilson et al., 2010; Prince et al., 2011). Multiple indicators are used to address limitations where a primary indicator does not provide complete information about resource state, where interpretation of a single indicator is ambiguous, or both.

Here, our aim is to foster a more practical understanding of the applicability and design of flexible indicator frameworks for fishery management, with an emphasis on multi-indicator frameworks. We provide guidance for the design and development of multi-indicator frameworks by crafting a set of organizational steps (**Figure 1**). Like related studies that describe frameworks for harvest strategy design (Rice and Rochet, 2005; Dowling et al., 2016; McDonald et al., 2017; Hill et al., 2018), we recognize the need for a fluid approach that in practice is unlikely to proceed in a strictly stepwise manner. Supported by a synthesis of the literature, the guidance we provide is motivated by a desire to encourage practitioners to identify their own pathway to overcoming challenges in the design of multi-indicator frameworks.

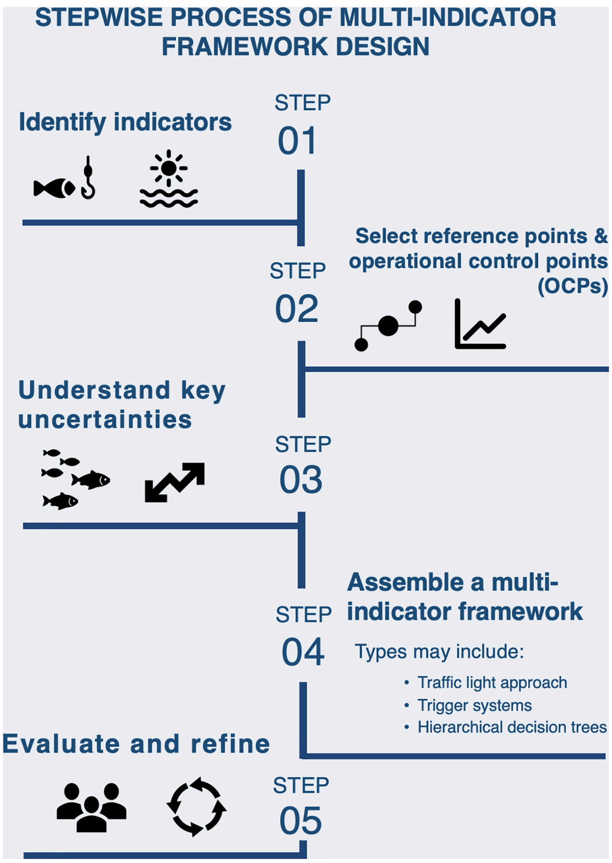


FIGURE 1 | Stepwise process of multi-indicator framework design.

WHEN TO CONSIDER A MULTI-INDICATOR FRAMEWORK?

Multi-indicator frameworks become a strong consideration when multiple data sets cannot be statistically integrated but can measure different aspects of stock status germane to management objectives and can help inform management decisions. Multi-indicator frameworks have the potential to enrich single indicator approaches such that they are more insightful and informative. For fisheries with established monitoring programs, the design of a multi-indicator framework involves screening the strengths and shortcomings of indicators and resolving the manner in which available indicators can be combined to inform decision-making (Caddy et al., 2005; Wilson et al., 2010; Harford et al., 2016). The integration of data sources used in multi-indicator frameworks is similar in concept to the use of multiple data sources in conventional stock assessment, where both approaches emphasize assimilation of information (e.g., Prince et al., 2011). For example, a standardized catch per unit effort (CPUE) time series may be the primary indicator, but secondary indicators, such as size information, spatial distribution of fishing effort, or species composition of the catch, may each provide additional information that influences how the primary indicator is interpreted. Likewise, multiple indicators are appealing when interpretation of a single indicator is ambiguous. An increase in CPUE, for example, may indicate increased abundance or an unnoticed increase in fishing power. A decrease in the mean length in the catch by itself may indicate an increase in fishing mortality or a strong recruitment pulse. But CPUE and size composition interpreted together could help to resolve such ambiguity. Moving beyond a single indicator is often essential to avoid inconclusive inferences about stock status that can arise from use of a single, but weakly informative or limited in scope, indicator. Coping with severe data limitations requires more pragmatism, exemplified by the use of simple indicators that, for example, track changes in a fishery through changes in species composition of the catch or through changes in spatial patterns of fishing (Dowling et al., 2008).

Multi-indicator frameworks are also fraught with challenges and not intended to supplant conventional stock assessments. Indicator-based approaches tend to rely on proxies for variables of interest, which should be met with adequate scrutiny about their representativeness and responsiveness in detecting changes in resource state. Where feasible, conventional stock assessments have the advantage of using a formal statistical procedure to integrate and interpret information from multiple data sources (e.g., Methot and Wetzel, 2013), allowing the estimation of stock biomass and other important management quantities instead of relying on proxies. These estimates can be used directly in combination with an HCR to drive decisions or, alternatively, assessments can inform specification of operating models used for testing simpler harvest strategies.

STEPS TO DESIGNING A MULTI-INDICATOR FRAMEWORK

Step 1: Identifying Indicators

Getting Organized

Halliday et al. (2001) provide a useful construct for organizing indicators according to elements of a fishery system such as the fish stock, the fishery, and related socio-economic factors. Ideally, estimates of biomass, fishing mortality or recruitment would be available from model-based stock assessments, or from direct surveys. However, in data-limited fisheries, such indicators are by definition not available, so alternative proxies must be sought. These can include species composition of the catch, size compositions, spatial effort distributions, or local expert knowledge. As almost any routinely observed information for fishery management can be considered as an indicator, organizing indicators according to variables of interest clarifies assumed linkages and relation to management objectives. Importantly, organization invites debate about the potential for errors in indicator interpretation and promotes discussion about whether some indicators are more directly related to a given variable of interest – and, thereby, management objectives – than others (Halliday et al., 2001; Caddy, 2004). Where additional environment and ecosystem indicators have well-defined linkages to fish populations, fishery-centric decision-making systems tend to be sufficiently flexible to integrate environment and ecosystem indicators in order to consider potential climate effects (Kelly et al., 2015; Karnauskas et al., 2021). In developing a multi-indicator framework, while acknowledging resource and capacity limitations, a wide net should be cast to identify options for indicators and to limit value judgments that may be associated with over-emphasizing any particular type of indicator (Gilbert et al., 2000; Seijo and Caddy, 2000; Dowling et al., 2019). Assessing the representativeness and responsiveness of proxy indicators may carry some subjectivity, and thus, it is important to embrace judgments from a variety of experts in delineating sets of indicators.

It is useful to classify indicators as "empirical" or "model-based" indicators (Dowling et al., 2015a; Miethe et al., 2016). Indicators derived more-or-less directly from raw data are known as "empirical indicators" or "model-free indicators" (e.g., CPUE, mean length in the catch; Rademeyer et al., 2007; Dowling et al., 2015a), although models may be involved in standardization of the indicators (e.g., for CPUE or aerial surveys). Indicators derived from raw data and other parameters in combination with data-limited stock assessment method are known as "estimated indicators" or "model-based indicators" (e.g., spawning potential ratio or fishing mortality rate estimated using simple population dynamics models). Classifying indicators as empirical or model-based connects indicator interpretation directly to the way in which the indicator is obtained, including field sampling protocols and method of analysis used in estimation. Such aspects are central to validation of indicators because poor sampling designs and poor modeling assumptions can result in indicators that fail to reliably measure their intended component of the fishery system (Caddy, 2004; Carruthers et al., 2014; Harford and Carruthers, 2017).

Confronting Indicator Suitability

After identifying available indicators, their suitability should be considered from two perspectives. First, practitioners should identify the extent to which the indicators can be linked to fishery management objectives. In general, indicators should, directly or indirectly, reflect the condition or state of the fishery system and be measurable and understandable (Caddy, 2004; Ye et al., 2011; Miethe et al., 2016). Interpretation of indicators may be based on theory, established usage that is connected to scientific rationale, or customary or traditional practices (Halliday et al., 2001). Measurable and understandable indicators enable key information to be accessible to a variety of resource user groups involved in policy and decision-making (Garcia and Staples, 2000). That is, can they be used to directly or indirectly inform whether the fishery is in a state that is acceptable to stakeholders? This may be determined according to whether stakeholders can identify that an indicator value is desirable or undesirable relative to a target value [see section "Step 2: Selecting Reference Points and Operational Control Points ", below].

Second, a process of validating indicator reliability and utility, to the extent possible, should take place. Ideally, indicators should be obtained from a reliable monitoring program, that should conform to guidelines for biological sampling and fisheries data collection (Cochran, 1977; Gulland and Rosenberg, 1992; NRC, 1998; Stamatopoulos, 2002). That said, much valuable information may be garnered from informal data gathering programs, and local expert knowledge, and in a data-limited context, it is important to be inclusive and creative when eliciting available information. Generally, however, indicator accuracy and precision should be sufficient to capture and track signals in the variable it represents (Punt et al., 2001; Apostolaki and Hillary, 2009; Mesnil et al., 2009; Trenkel and Rochet, 2011; Harford and Babcock, 2016). Indicators should be temporally and spatially representative of the distribution of the resource (Pennington et al., 2002; Walters, 2003; Prince et al., 2008). However, regardless of the indicators that may be available, shortcomings are likely to persist, and limitations and uncertainties need to be weighed against other components of a harvest strategy, including the degree of precaution in management measures. Being explicit about indicator shortcomings is essential, as other aspects of the harvest strategy (i.e., HCR and management measures) will need to account for these limitations.

Model-based indicators typically rely on a mathematical representation of population dynamics, which is used in estimating quantities of interest (a variety of methods are summarized in Carruthers et al., 2014; Huynh et al., 2018; Pons et al., 2020). Thus, working with model-based indicators requires an awareness of modeling assumptions to avoid pitfalls and to provide context for when these methods can be expected to deliver reliable results (Geromont and Butterworth, 2015; Sagarese et al., 2019). For example, while length-based indicators can be used to guide decision-making toward fishery sustainability through estimation of spawning potential ratio and fishing mortality rate, an awareness of the limitations and pitfalls of length-based indicators is essential (Cope and Punt, 2009; Hordyk et al., 2016; Huynh et al., 2018). Such guidance is available based on simulation testing (Punt et al., 2001; Cope and Punt, 2009; Klaer et al., 2012; Carruthers et al., 2014, 2015; Jardim et al., 2014; Hordyk et al., 2015; Rudd and Thorson, 2017; Sagarese et al., 2018).

In data-limited contexts, there is often little choice regarding available indicators. However, a process for eliciting indicators, and screening their suitability should be developed and conducted interactively with stakeholders and decision-makers (Dowling et al., 2016), which helps with achieving agreement at this stage of designing a harvest strategy. At the same time, practitioners will need to be pragmatic, both in terms of the extent to which available data can inform management objectives, and in terms of whether high-level policy objectives can be reconciled against the available information.

Rice and Rochet (2005) provide concrete guidance for validating indicator reliability and utility by translating general considerations (e.g., high precision, ease of measurement, and interpretation) into nine specific screening criteria along with guidance for scoring and ranking of indicators. Inclusion of diverse audiences in the screening process is key, as technical experts may favor indicators that connect current conditions to inferred historical states of the fishery or that are derived based on ecological theory, while non-technical audiences may favor indicators that are most clearly rooted in direct measurement of physical and biological variables (avoiding abstract concepts) and those connected to personal experiences (Rice and Rochet, 2005).

This balance of viewpoints is key to support both the technical basis of a harvest strategy and its degree of acceptance among user groups. Elicitation and decision-support tools can be used to structure the process of indicator consideration and refinement and support of transparent discussions about indicator suitability (Dowling et al., 2016). For example, the FishPath Tool[1] uses a software interface to align proposed management options, including indicators, with sets of positive and negative attributes that should be considered when evaluating indicators.

In situations where little to no useable data are available, stakeholders will need to buy in to a process of cost-effective data collection. This could include the provision of size data, or catch and effort reporting, or the formalization of local expert knowledge. The nature of the data collection will depend on the extent of buy-in from stakeholders. "Snapshot" collection of size data is often a good starting point as this is relatively simple to collect, easily understood, places little onus on fishers, and can readily be used to inform stock status (Hordyk et al., 2016; Rudd and Thorson, 2017).

Step 2: Selecting Reference Points and Operational Control Points

Reference points are commonly used to judge the status of the exploited population relative to management objectives. They are values of indicators that are chosen to represent important targets (the most desirable state), thresholds (values heralding changes that may warrant management attention), and limits (the least desirable state) in the fishery system (Mace, 1994; Caddy and McGarvey, 1996). Operational control points (OCPs; Cox et al., 2013), on the other hand, are values of the indicators that are used to invoke, or determine the extent of, adjustments to management measures *via* decision rules. For example, an imprecise indicator might provide justification for specifying an OCP that is well above a biological limit reference point to ensure that this limit is avoided with a high probability in the presence of errors in interpretation of an indicator (Cox et al., 2013). As such, the values of OCPs should be selected in such a way that the decision rule guides the fishery toward achieving management objectives (Australian Government, 2007; PFMC, 2020).

For stocks where estimates of abundance can be obtained directly or from an integrated assessment, target and limit reference points may be readily defined, for example, in terms of the traditional biomass corresponding to maximum sustainable, or maximum economic yield. For proxy indicators, the definition of such reference points becomes less theoretically defensible, with targets often being set to correspond to indicator values observed at times perceived by stakeholders to have been optimal for the fishery (Hilborn, 2002; Apostolaki and Hillary, 2009). If we consider the use of CPUE as an indicator, in the absence of additional information, simply picking a recent stable period of CPUE as our target runs the risk of trapping the fishery in a stable, but potentially overfished or under-exploited state. Conversely, aiming for high CPUE values achieved in the earliest days of the fishery, and thus assuming CPUE values below this level equate to overfishing, may lead to overly cautious management that reduces the economic potential of the stock. One would prefer to identify a period when the stock was believed to be in a productive and sustainable state, which can be identified with input from fishers and/or by considering additional indicators. Interpretation of historical fishery profitability, landings trends, snapshots of length frequency distributions, and patterns in shifts in the spatial distribution of the fishery could collectively support selection of target and limit reference points (Hilborn, 2002, 2010; ASMFC, 2020).

Step 3: Understanding Key Uncertainties

The theoretical simplicity of indicator frameworks can make it easy to overlook the critical step of identifying and addressing uncertainties in the design of a multi-indicator framework. However, these uncertainties are likely to be significant given the data limitations. Thus, knowing the sources of uncertainty and understanding their potential consequences on the performance of a multi-indicator framework is a prominent step in development and application. The following points provide guidance in examining uncertainties that lie within each framework component.

Point 1: Identify sources of uncertainty and imprecision. Some indicators are direct measures of one metric (e.g., mean length); others may include multiple metrics (e.g., CPUE indices have both catch and effort information) and thus the potential for measurement error in multiple components of the indicator (Maunder and Punt, 2004). While using the mean CPUE (for example) is a straightforward option, the variability around the central tendency is usually an important consideration in specifying how an indicator and the harvest control rule will work together in application. Incorporating uncertainty in the indicator comes in several forms, such as using a different, and possibly more precautionary, quantile instead of the median or mean value of the indicator (Jardim et al., 2015). Whatever the chosen treatment of each indicator, considering all aspects of indicator uncertainty (to the extent possible) is of primary concern when constructing how the components of a multi-indicator framework functions collectively. This can mean that uncertainty is addressed through the addition of secondary indicators that provide a safety-check and/or precautionary OCPs or reductions in the harvest (buffers) as a function of uncertainty estimates (Fulton et al., 2016; Dichmont et al., 2017; Dowling et al., 2019).

Point 2: Evaluate indicator assumptions and possible sources of bias. The capacity of each indicator to meaningfully measure the state or condition of a process of interest (e.g., stock status, sustainable catch levels, environmental conditions, etc.) rests on assumptions about both the sampling design and indicator representativeness of underlying processes. The violation of those assumptions (e.g., sampling bias or hyperstability of fishery-dependent CPUE) may have a large influence on the ability of an indicator-based framework to meet management objectives (Carruthers et al., 2014; Wilson et al., 2014). Assessing the assumptions of an indicator and understanding the sensitivity of different indicators to their critical assumptions is a key component in the design of an indicator-based framework.

[1] https://www.fishpath.org/

Point 3: Choosing reference points that can be related to management objectives. Reference points relate the value of an indicator to some value that is meaningful in terms of management objectives. An entrée to developing reference points can be discussion of core goals of conservation, sustainability, and fishery priorities (Keeney, 1992; Costanza et al., 1998; Ye et al., 2013; Anderson et al., 2015; Asche et al., 2018; United Nations, 2018). Another common starting point for developing reference point options is to explore their biological basis (Clark, 1991; Caddy, 2004; Zhou et al., 2012, 2020; Prince et al., 2015; Thorson et al., 2017; Harford et al., 2019). Depending on the indicator, some generic reference points may be calculated based on life-history parameters or may borrowed from similar species or from meta-analyses (Thorson et al., 2012; Zhou et al., 2012). Other indicators, for example those that reflect biomass trends, are more difficult to pair with generic reference points (e.g., biomass for maximum yields) in data-limited situations. For example, what level of the historical CPUE would correspond to a desirable state according to management objectives to compare the current CPUE? What would constitute desirable and undesirable species compositions, or average offshore distance fished, or proportions of large-sized fish in the catch? Caddy (2004) points out that specifying reference points may require some expert judgment in relating reference points to historical, current, or plausible future events occurring in the fishery.

Step 4: Assembling a Multi-Indicator Framework

The next step is to assimilate the various identified indicators into a framework that enables greater insight into the status of the stock than would any of the indicators in isolation (for example, changes in mean size data might be interpreted quite differently if fishers are also suddenly fishing further offshore, or if the target species have changed) (see **Box 1**). This step also involves determining the type of management measure(s) that could be used, along with the magnitudes of adjustments to management measures under various states of the resource. Below, we summarize approaches used to integrate indicators into decision rules, which range from simple aggregation of indicators to achieve an overall performance (e.g., traffic light approaches), to those that have unique interpretations based on combinations of indicator values (e.g., trigger systems), to those that use certain primary indicators to inform a control rule, and supplementary indicators to augment their interpretation and further adjust the management measure (hierarchical decision trees; **Table 1**). There is a wider variety of multi-indicator decision rules than we can outline herein (reviewed in Dowling et al., 2015a). Additional examples from the data-rich realm are also worth exploring as they provide useful insights into the collective use of indicators for delineating stock status and for supporting fishery decision-making (e.g., CCSBT, 2020).

Types of Multi-Indicator Decision Rules

The Traffic Light Approach

The traffic light approach utilizes multiple indicators, each being scored using color categories of red, yellow, or green, with red reflecting a dangerous condition and green reflecting satisfactory conditions, and each indicator contributing to an overall description of the condition of the fish stock (Caddy, 1999, 2002). In its most straight forward formulation, the proportion of indicators in the red category could determine the management response (Caddy, 2004). For each indicator, two OCPs are used to score it as red or green if it occurs on one side or the other of the OCP bookends (Caddy, 2004, 2015). When the indicator falls between the OCP end points, it is scored as yellow to reflect unsatisfactory conditions, occurring during transition from red to green or vice versa (Halliday et al., 2001; Caddy, 2004). The traffic light approach presents each indicator in relation to its OCPs in an understandable form and embraces uncertainty through the use of multiple indicators (Mangel and Levin, 2005; Caddy, 2015). Caddy et al. (2005) examines a comprehensive set of challenges faced in proposing a traffic light approach for the Gulf of St. Lawrence snow crab (*Chionoecetes opilio*) fishery. Challenges that will need to be confronted in developing traffic light approaches will likely include selecting a weighting method for combining multiple indicators that are proxies for the same variable and determining how to combine multiple indicators across disparate fishery elements into an effective HCR. These challenges are discussed in detail within Halliday et al. (2001) and Caddy (2004, 2015).

Trigger Systems

A trigger system invokes management responses that are determined by comparing current values of indicators against associated OCP(s). Multi-indicator trigger systems represent a diverse suite of HCRs, including those structured as conditional statements, visualized as decision trees, stated as decision matrices, or written as equations determining the strength of management response (Trenkel et al., 2007; Prince et al., 2008; Brandao and Butterworth, 2009; Harford et al., 2016; Harford, 2020). A trigger system embraces not only target and limit reference points, but also the need to capture states of a fishery system that require attention. For example, a developing fishery may start to expand, or activate latent effort, which may not correspond to a target or limit value of an effort-based indicator but may nonetheless trigger a review to determine the drivers of the fleet behavior. As such trigger systems are especially useful in fisheries that experience shifts in fisher behavior that may be unrelated to the status of the stock – e.g., new and expanding fisheries, opportunistic fisheries that switch targeting behaviors, and multispecies fisheries. A wide variety of single-indicator trigger systems have been proposed and evaluated, with guidance that is also germane to multi-indicator alternatives (Hilborn et al., 2002; De Oliveira and Butterworth, 2004; Pomarede et al., 2010; Babcock and MacCall, 2011; Little et al., 2011; McGilliard et al., 2011; Cook, 2013; Carruthers et al., 2014; Geromont and Butterworth, 2015). Dowling et al. (2008) provide examples of multi-indicator frameworks for Australian Commonwealth fisheries.

Hierarchical Decision Trees

Hierarchical decision trees contain elements of trigger systems, but have an added hierarchy that allows a management response to be reached through a sequence of intermediate decisions

BOX 1 | A thought exercise for combining multiple indicators.

A hypothetical fishery

For an artisanal single-species fishery, catch-per-unit-effort (CPUE), mean length of fish in the catch, distance traveled by the fleet, and sea surface temperature serve as primary indicators. For CPUE to be used as a proportional indicator of vulnerable fish biomass, a regression technique was employed to standardize CPUE because gear characteristics and fishing power have changed through technological advances. Mean length in the catch reveals changes in size of specimens in the fish population. Distance traveled and sea surface temperature are thought to be reliably recorded in vessel logbooks. Distance traveled by the fleet provides information about vessels having to travel further to new areas to catch fish, possibly due to local depletion. Ecological research suggests that higher temperature could be linked to reduced recruitment success, although this purported relationship remains a point of contention as thresholds for an effect are unclear, as is the form of mechanistic linkage to recruitment variability. Thus, for some combinations of indicator states, a secondary evaluation of length-frequency distributions is introduced to determine if a recruitment pulse is evident, through consideration of whether abrupt year-to-year changes have occurred in the smaller size classes of the length-frequency and whether strong cohorts can be tracked through time in length-frequencies. The presence of a recruitment pulse is determined subjectively as a qualitative indicator. See N/A in table for combinations of primary indicators that do not trigger use of secondary indicators.

What do combinations of indicator states reveal?

The fishery is carried out using fish traps, with a pre-agreed total number of traps–per-fisher. Total traps-per-fisher will be modified based on prevailing indicator values using a two-tiered decision process. Primary indicators are calculated as three-year moving averages to minimize the effect of inter-annual variability on management responsiveness and the state of the fishery is determined by comparison with indicator states from the previous year. The simple objective of this harvest strategy is to maintain stable fish biomass into the foreseeable future. Consider the following for interpreting combinations of indicator states and corresponding directionality of adjustment to fishing effort. For example, where fishing is occurring close to the port and CPUE and mean length are high, the stock could be increasing in abundance. However, if water temperature is also increasing, future recruitment success could be of concern, and a wait and see approach could be taken with no change made to fishing effort. Alternatively, warmer water conditions could also be responsible for spatially shifting the local fish population further from the port. Despite increases in CPUE and mean length, fishing farther from shore and increased water temperature trigger a precautionary management decision to decrease fishing effort This multi–indicator framework is not without its flaws. What improvements could be made?

Primary indicators				Secondary indicator		
CPUE	**Mean length**	**Distance traveled**	**Sea temp**	**Recruit pulse**	**Effort change**	**Rationale**
High	High	Near	High	N/A	Watch and wait	Indicators encouraging, but warm water which could result in poor recruitment.
High	High	Near	Low	N/A	Increase	All indicators are encouraging.
High	High	Far	High	N/A	Decrease	Increase in CPUE and size could be from new fishing areas, concern about local depletion.
High	High	Far	Low	N/A	Decrease	Increase in CPUE and size could be from new fishing areas, concern about local depletion.
High	Low	Near	High	Yes	Watch and wait	Maintain status quo because of warmer temperatures.
				No	Decrease	Decrease because of loss of larger fish and warmer temperatures.
High	Low	Near	Low	Yes	Increase	Increase because of encouraging indicator states and recruitment pulse.
				No	Decrease	Decrease because of loss of larger fish.
High	Low	Far	High	Yes	Watch and wait	Temperatures and distance traveled by the fleet concerning, but recruitment pulse.
				No	Decrease	Decrease because of loss of larger fish, warmer water and distance fleet is traveling.
High	Low	Far	Low	Yes	Watch and wait	Maintain status quo because of distance traveled, despite recruitment pulse.
				No	Decrease	Decrease because of loss of larger fish, and distance traveled.
Low	Low	Near	High	N/A	Decrease	Decrease because of low CPUE and warmer waters.
Low	Low	Near	Low	Yes	Watch and wait	Watch and wait, potential for large cohort entering fishery.
				No	Decrease	Decrease because of low CPUE, loss of larger fish.
Low	Low	Far	High	N/A	Decrease	Decrease because of drop in CPUE, mean length, warmer water and distance traveled.
Low	Low	Far	Low	N/A	Decrease	Decrease because of drop in CPUE and mean length, and distance fleet traveled.
Low	High	Near	High	N/A	Watch and wait	Maintain status quo because CPUE is low and warmer waters, while larger fish available.
Low	High	Near	Low	N/A	Watch and wait	Maintain status quo because of increase in fish size even with the decline in CPUE, also fishing on their normal fishing grounds.
Low	High	Far	High	N/A	Decrease	Decrease because CPUE is low, distance traveled, and warmer waters.
Low	High	Far	Low	N/A	Decrease	Reduce fishing because CPUE is down, and fleet is fishing outside of typical fishing grounds.

(Dowling et al., 2015a). Using a hierarchy of indicators allows for different responses to follow in different circumstances, as with trigger systems, but allows critical (the most reliable, or broadest-scale) indicators to be applied first, and to invoke the strongest adjustment to a management measure, supplemented with additional indicators as appropriate (Dowling et al., 2015a). Plagányi et al. (2020) applied such an approach to a multi-species sea cucumber fishery (family: *Holothuriidae*), imposing a precautionary initial tier with a fishery open/close trigger that functions under severe data limitations. As new data are collected, decision-making proceeds to additional tiers that offer the possibility of increasing TACs where indicators support this response. This hierarchy incentivizes data collection to the benefit of the fishery (Plagányi et al., 2020). Davies et al. (2007) and Prince et al. (2011) use indicators of relative abundance and the impact of fishing on the size composition of a stock within a hierarchical framework. These authors assimilate and interpret multiple data streams in a manner that is akin to the analytical integration that takes place in a conventional stock assessment. Wilson et al. (2010) extended the approach

TABLE 1 | Examples of multi-indicator frameworks.

Fishery	Indicators	Type	References
Australia abalone (*Haliotis spp.*)	Qualitative morphology	Trigger system	Prince et al. (2008)
Australia western deepwater trawl fishery (finfish >50 species)	Catch	Trigger system	Dowling et al. (2008)
Australian Coral Sea fishery, line, trawl and trap sub-fishery (finfish, multispecies)	Species composition of the catch, changes in spatial fishing pattern, CPUE, catch	Trigger system	Dowling et al. (2008)
Belize spiny lobster (*Panulirus argus*) and queen conch (*Strombus gigas*)	Catch, CPUE, average length in catch, pre-season abundance survey	Trigger system	Harford et al. (2016)
California red abalone (*Haliotis rufescens*)	Density survey, SPR	Trigger system	Harford (2020)
South Africa toothfish (*Dissostichus eleginoides*)	CPUE, mean length of catches	Trigger system	Brandao and Butterworth (2009)
Australian eastern tuna and billfish (*Xiphias gladius, Thunnus obesus, Thunnus albacares*)	Size-based catch rates and proportion of old fish in the catch	Hierarchical decision tree	Davies et al. (2007); Prince et al. (2011)
Australia sea cucumber fishery (Family: Holothuriidae)	Catch, CPUE, area, average length in catch, catch composition, abundance survey	Custom approach; hierarchical decision tree	Plagányi et al. (2020)
California rockfish (family: Sebastidae)	CPUE, length composition, recruitment index	Hierarchical decision tree	Wilson et al. (2010)
Gulf of St. Lawrence snow crab (*Chionoecetes opilio*)	Multiple	Traffic light approach	Caddy et al. (2005)

of Davies et al. (2007) to incorporate comparisons of fished and non-fished areas into the decision-making hierarchy as a means to account for environmental variability in indicators.

Confronting Challenges in Specifying a Decision Rule

A major component of establishing an indicator-based framework is the often-challenging process of identifying and interpreting each combination of indicators states [i.e., values relative to their OCP(s)] and specifying the corresponding adjustment to a management measure. In considering where to begin in assimilating indicators into a framework, it can be valuable to specify all combinations of indicators states. This could mean specifying the factorial combinations of states of each indicator (where chosen indicators have discrete states). For each combination, practitioners should determine what conclusions would be drawn about the status of the stock and the directionality and magnitude of adjustment to a management measure that would accordingly be made, if any. This exercise can be directly informed by stakeholders and visualized using a decision tree or table (**Box 1**). For example, an increase in mean length of the catch could be interpreted as a systematic decrease in fishing mortality over several years but might be interpreted differently if fishers have exhausted shallow-water components and have shifted further offshore where larger specimens can be found. In considering the magnitude of adjustment to a management measure, strength of response could be specified in relation to the condition of the resource. For instance, falling below a lower limit of fish abundance may trigger a cessation of fishing or substantial reduction in fishing effort, while closer proximity to an acceptable range of fish abundance may trigger small, gradual adjustments.

In conducting this exercise, instances will be encountered where combinations of indicator states will provide a clear signal about stock status, but in other instances, combinations of states will appear (or be) implausible or result in ambiguity about stock status. The latter may reflect the inability of the indicators to characterize stock status, perhaps reflecting an incorrect assumption about an underlying biological variable that the indicator represents or an indicator having low precision. The results of this exercise may help to highlight or identify indicators that work best at disentangling ambiguous or conflicting information or may help to identify alternative indicators that could create a more robust indicator framework. This exercise is also useful for exploring the relative strength of adjustment between indicator combinations, especially as it pertains to increases or decreases that are recommended by opposite signals about stock status. Such contrasts prompt consideration about the rationale for balance or disparity in strength of adjustment in response to opposite signals about stock status.

Step 5: Evaluation and Refinement

Due to the uncertainties associated with the indicators, reference points, and form of the indicator-based framework, alternative configurations (e.g., alternative indicators, alternative weightings of indicators, OCPs, and HCRs) are encouraged in designing a multi-indicator framework. The process known as Management Strategy Evaluation (MSE), facilitates rigorous examination of the effect of uncertainties on the performance of a multi-indicator framework. MSE can also be used to compare the relative degree of robustness to uncertainty among alternative configurations of a multi-indicator framework. Additional uncertainties are likely to arise in the status and dynamics of the harvested fish population, as are unpredictable ecological events (e.g., a recruitment failure or a persistent change in productivity), as well as inconsistency in implementation of management controls (e.g., due to weak enforcement).

Management Strategy Evaluation is used to simulate the interactions between data collection, data analysis, and an HCR in a way that highlights how well these interacting parts can be expected to result in the achievement of management objectives (Punt et al., 2016). MSE can also support the development of a monitoring scheme where none existed before, including considerations related to data gathering capacity and precision, cost effectiveness, and immediacy of impact on fishery management. The results of an MSE are used to determine whether application of any harvest strategy can be expected to have satisfactory performance over a time horizon of interest (De la Mare, 1986; Cooke, 1999; Peterman, 2004; Punt et al., 2016). The technical steps required to conduct MSE are provided elsewhere (Sainsbury et al., 2000; Butterworth, 2007; Butterworth et al., 2010; Punt et al., 2016).

Here, we consider ways in which MSE can complement the process of designing a multi-indicator framework. First, MSE can be used to guide the specification of OCPs. Because simulation includes a representation of fish stock dynamics, at any point in simulating the performance of a multi-indicator framework the underlying state of the fish stock is "known." This allows performance of an indicator-based framework to be reconciled against biological reference points (*sensu* Mace, 1994; Caddy and Mahon, 1995) that are retrieved from the "known" state of the fish population. Second, MSE can be used to evaluate whether a multi-indicator framework is likely to provide satisfactory performance against plausible levels of indicator measurement or estimation errors, violation in assumptions, as well as error in implementation of management measures (see Principles 1 and 2 in the Uncertainty section). Because MSE simulates data collection and data analysis, these processes can be specified to occur with varying degrees of imprecision and bias to evaluate how they affect performance. Third, MSE can be used to support a scientific and transparent process of stakeholder engagement. Not all multi-indicator frameworks will achieve the same balance between performance metrics, and thus, trade-offs between achievement of management objectives are inevitable. MSE provides a platform for discovering whether management options are palatable to stakeholders and can also promote dialogue collaboration between scientists, decision-makers, and stakeholder in designing and iteratively refining the details of multi-indicator framework (Cooke, 1999; Cox et al., 2013; Pilling et al., 2016; Punt, 2017).

While MSE has become a standard evaluation approach, there are other qualitative approaches, such as retrospective analysis, or a Delphic approach. The latter is a polling technique employed for the systematic solicitation of expert opinion (Bernstein and Cetron, 1969). Retrospective analysis involves determining what decisions would have been made in the past when applying a proposed harvest strategy given the data and assessments available at the time. While unable to consider longer-term outcomes, retrospective analysis allows practitioners to consider whether the decisions arising from the retrospective application are sensible with regard to the subsequent history of the fishery (Dowling et al., 2015b). In the absence of research funding or capacity, or for frameworks where the indicators are largely qualitative, such alternatives may be utilized to evaluate the likely performance of the indicator-based framework.

Post-implementation review of any harvest strategy should be conducted at reasonable intervals (e.g., 5–10 years, though dependent of species life history) to ensure that the appropriate indicators are in use and that the strategy is producing useful management advice in line with the objectives of the fishery. Expedited review of the harvest strategy may be necessary when simulated performance (*via* MSE) does not align with post-implementation reality (Carruthers and Hordyk, 2018). Review could also provide opportunities to mitigate additional threats to fishery resilience, including climate change (Cheung et al., 2010; FAO, 2018). While management measures that regulate location, timing, and quantity of harvest are fundamental in fishery management, additional management planning to mitigate anticipated effects of climate change may be advantageous (Pecl et al., 2014; Pinsky and Mantua, 2014; Johnson et al., 2016; Bell et al., 2020).

POSSIBLE PITFALLS OF MULTI-INDICATOR FRAMEWORKS

When initiating development of a multi-indicator framework, it is crucial to acknowledge that this is a challenging process, not least because of the lack of a prescription for the design process, the common use of indirect proxy indicators, and, possibly, a lack of understanding as to how multiple indicators interact. As such, it is also crucial to develop an awareness of the potential for complications (Davies et al., 2007; Fulton et al., 2016; Harford, 2020), that can contribute to the failure of a well-intended design to perform as expected. The reasons for unexpected performance are many and nuanced (Sagarese et al., 2019). Firstly, indicator-based frameworks typically classify discrete resource states as triggers for adjustments to management measures. When the indicators are borderline between states, stakeholder disputes as to the "true" state, and indicator oscillation around (above and below) thresholds can occur, resulting in too frequent and unnecessary adjustments to management measures. This problem can be exacerbated by the imprecision of indicators, consequently affecting the frequency and magnitude of adjustments to management measures, raising concerns about whether management responses are tracking signals or chasing noise. At its worst, this oscillation behavior can result in decision-making that bounces between extremes of resource states, such as overfished (low biomass) or under-utilized (high biomass), rather than gently adjusting fishing effort or catches to achieve long-term stability. Problematic choices of reference points for indicators can sometimes lead to continual increases or decreases of catches, regardless of resource state, known as a ratchet effect (Klaer et al., 2012). Likewise, time lags between changes to resource states and their subsequent detection by a "lag" indicator (one that detects a change long after it has taken place) can result in indicator frameworks that incorrectly delay necessary adjustments. Thus, while the pre-specification of a harvest strategy is intended to avoid *ad hoc* negotiation of management measures (Butterworth, 2007), a malfunctioning strategy is unlikely to meet management objectives. Again, this is where MSE can help to illuminate pitfalls in multi-indicator framework design (**Table 1**).

Confronting such issues requires the indicator-based framework to be responsive to changes in resources states, while avoiding unnecessary disruptions to the fishery. Careful examination of the results of MSE is particularly instructive to finding the correct balance. It is advisable to not only examine the long-term simulated outcomes of a harvest strategy, but to examine the temporal variability in management measures (e.g., when a TAC is undesirably variable from year-to-year, MSE can help to fine-tune the procedures to improve performance). Further, examining whether management responses (based on simulation of imperfect observation of indicators) are correctly triggered when they are truly needed can help to reveal whether achievable levels of indicator precision will lead to a sufficiently responsive harvest strategy. It is also useful to be cognizant of the interwoven nature of components of a harvest strategy. When considered as a cohesive framework, short-comings in data precision or analysis assumptions can sometimes be remediated through adjustments of other components of the harvest strategy, specifically those that specify the form and magnitude of the HCR (Dowling et al., 2019).

CONCLUSION

Multi-indicator frameworks provide a vehicle for empirical or simple model-based indicators to be used in combination to infer stock status, where conventional stock assessments may be infeasible. Multi-indicator frameworks provide a means to obtain maximum insight utilizing all available sources of information, and improve the management of unassessed fisheries (Hilborn and Ovando, 2014; Berkson and Thorson, 2015; Flood et al., 2016; FAO, 2020a), while addressing the urgency for solutions that embrace social, economic, and political contexts at a local level (Gutiérrez et al., 2011; Purcell and Pomeroy, 2015). As they involve a pre-agreed procedure for adjusting management measures, all parties need to commit to their design, as attempts to modify decision-making in an *ad hoc* manner will undermine the process (Butterworth, 2007).

That stated, pragmatism must play an overarching role in managing expectations and in reconciling the severity of data limitations with the capacity for achievement of objectives (Cadrin and Pastoors, 2008; Dowling et al., 2015b). Achieving management objectives *via* multi-indicator frameworks will often require tempering expectations, introducing precautionary HCRs that are robust in the face of considerable uncertainty, and embracing evaluation and modification or refinement of harvest strategies as possible shortcomings become apparent prior to or after implementation.

In designing a multi-indicator framework, challenges will need to be confronted. It can be helpful to engage with specialists with diverse knowledge of local fishing practices, local ecological knowledge and customary practices, statistical sampling design, fishery science and theory, management science, and economics (Rice and Rochet, 2005; Harford and Babcock, 2016; Dowling et al., 2019). For example, in capacity-limited fisheries, translating management objectives into a form that can be operationalized through an HCR is likely to be a priority task (Hill et al., 2018). In addition, specialists in facilitation, communication, and policy development can help to ensure that management options are likely to result in policies that can be implemented and achieve equitable outcomes.

Despite a variety of challenges and inherent uncertainties, multi-indicator frameworks provide a vehicle for data that are otherwise unable to be utilized in a formal assessment, and a means to obtain greater insight into stock status than may be obtained from single indicator in isolation. The guidance here is intended to optimize chances of successful design and implementation. When carefully articulated and evaluated and embedded within a harvest strategy with adequately precautionary control rules, multi-indicator frameworks can provide a way forward for the formal management of data limited fisheries that may otherwise be unable to be realized.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work, and approved it for publication.

FUNDING

This study was financially supported by The Nature Conservancy with in-kind support from CSIRO and NOAA.

ACKNOWLEDGMENTS

We thank three reviewers for their comments that led to improvements to this manuscript.

REFERENCES

Anderson, J. L., Anderson, C. M., Chu, J., Meredith, J., Asche, F., Sylvia, G., et al. (2015). The fishery performance indicators: a management tool for triple bottom line outcomes. *PLoS One* 10:e0122809. doi: 10.1371/journal.pone.0122809

Apostolaki, P., and Hillary, R. (2009). Harvest control rules in the context of fishery-independent management of fish stocks. *Aquat. Living Resour.* 22, 217–224.

Asche, F., Garlock, T. M., Anderson, J. L., Bush, S. R., Smith, M. D., Anderson, C. M., et al. (2018). Three pillars of sustainability in fisheries. *Proc. Natl. Acad. Sci. U S A.* 115, 11221–11225. doi: 10.1073/pnas.1807677115

ASMFC (2020). *2020 American Lobster Benchmark Stock Assessment and Peer Review Report*. Arlington, VA: Atlantic States Marine Fisheries Commission (ASMFC).

Australian Government (2007). *Commonwealth Fisheries Harvest Strategy Policy Guidelines*. Canberra: Australian Government Department of Agriculture.

Babcock, E. A., and MacCall, A. D. (2011). How useful is the ratio of fish density outside versus inside no-take marine reserves as a metric for fishery management control rules? *Can. J. Fish. Aquat. Sci.* 68, 343–359. doi: 10.1139/f10-146

Bell, R. J., Odell, J., Kirchner, G., and Lomonico, S. (2020). Actions to promote and achieve climate-ready fisheries: summary of current practice. *Mar. Coast. Fish.* 12, 166–190. doi: 10.1002/mcf2.10112

Bentley, N. (2015). Data and time poverty in fisheries estimation: potential approaches and solutions. *ICES J. Mar. Sci.* 72, 186–193.

Berkson, J., and Thorson, J. T. (2015). The determination of data-poor catch limits in the United States: is there a better way? *ICES J. Mar. Sci.* 72, 237–242. doi: 10.1093/icesjms/fsu085

Bernstein, G. A., and Cetron, M. J. (1969). SEER: a Delphic approach applied to information processing. *Technol. Forecast.* 1, 33–54. doi: 10.1016/0099-3964(69)90005-2

Brandao, A., and Butterworth, D. S. (2009). A proposed management procedure for thetoothfish (Dissostichus eleginoides) resource in the Prince Edward Islands vicinity. *CCAMLR Sci.* 16, 33–69.

Butterworth, D. S. (2007). Why a management procedure approach? some positives and negatives. *ICES J. Mar. Sci. J. Cons.* 64, 613–617. doi: 10.1093/icesjms/fsm003

Butterworth, D. S., Bentley, N., Oliveira, J. A. A. D., Donovan, G. P., Kell, L. T., Parma, A. M., et al. (2010). Purported flaws in management strategy evaluation: basic problems or misinterpretations? *ICES J. Mar. Sci.* 67, 567–574. doi: 10.1093/icesjms/fsq009

Caddy, J. F. (1999). Deciding on precautionary management measures for a stock based on a suite of limit reference points (LRPs) as a basis for a multi-LRP harvest law. *NAFO Sci. Couns. Studies* 32, 55–68.

Caddy, J. F. (2002). Limit reference points, traffic lights, and holistic approaches to fisheries management with minimal stock assessment input. *Fish. Res.* 56, 133–137. doi: 10.1016/s0165-7836(01)00343-5

Caddy, J. F. (2004). Current usage of fisheries indicators and reference points, and their potential application to management of fisheries for marine invertebrates. *Can. J. Fish. Aquat. Sci.* 61, 1307–1324. doi: 10.1139/f04-132

Caddy, J. F., and Mahon, R. (1995). *Reference Points for Fisheries Management*. Rome: FAO. FAO Fisheries Technical Paper. No. 347.

Caddy, J. F., and McGarvey, R. (1996). Targets or limits for management of fisheries? *North Am. J. Fish. Manag.* 16, 479–487. doi: 10.1577/1548-8675(1996)016<0479:tolfmo>2.3.co;2

Caddy, J. F., Wade, E., Surette, T., Hebert, M., and Moriyasu, M. (2005). Using an empirical traffic light procedure for monitoring and forecasting in the Gulf of St. Lawrence fishery for the snow crab, Chionoecetes opilio. *Fish. Res.* 76, 123–145. doi: 10.1016/j.fishres.2005.06.003

Caddy, J. F. (2015). The traffic light procedure for decision- making: its rapid extension from fisheries to other sectors of the economy. *Glob. J. Sci. Front. Res.* 15, 11–39.

Cadrin, S. X. (2016). "Management strategies for mixed-species commercial, recreational, and subsistence fisheries," in *Assessing and Managing Data-Limited Fish Stocks*, eds T. Quinn II, J. Armstrong, M. Baker, J. Heifetz, and D. Witherell (Alaska: University of Alaska Fairbansk).

Cadrin, S. X., and Pastoors, M. A. (2008). Precautionary harvest policies and the uncertainty paradox. *Fish Res.* 94, 367–372. doi: 10.1016/j.fishres.2008.06.004

Carruthers, T. R., and Hordyk, A. R. (2018). Using management strategy evaluation to establish indicators of changing fisheries. *Can. J. Fish. Aquat. Sci.* 76, 1653–1668. doi: 10.1139/cjfas-2018-0223

Carruthers, T. R., Kell, L. T., Butterworth, D. D. S., Maunder, M. N., Geromont, H. F., Walters, C., et al. (2015). Performance review of simple management procedures. *ICES J. Mar. Sci. J.* 73:fsv212.

Carruthers, T. R., Punt, A. E., Walters, C. J., MacCall, A., McAllister, M. K., Dick, E. J., et al. (2014). Evaluating methods for setting catch limits in data-limited fisheries. *Fish Res.* 153, 48–68. doi: 10.1016/j.fishres.2013.12.014

CCSBT (2020). *Report of the 25th Meeting fo the Scientific Commitee, 7 September 2020*. Canberra: Commission for the Conservation of Southern Bluefin Tuna.

Cheung, W. W. L., Lam, V. W. Y., Sarmiento, J. L., Kearney, K., Watson, R., Zeller, D., et al. (2010). Large-scale redistribution of maximum fisheries catch potential in the global ocean under climate change. *Glob. Change Biol.* 16, 24–35. doi: 10.1111/j.1365-2486.2009.01995.x

Clark, W. G. (1991). Groundfish exploitation rates based on life history parameters. *Can. J. Fish Aquat. Sci.* 48, 734–750. doi: 10.1139/f91-088

Cochran, W. G. (1977). *Sampling Techniques*, 3rd Edn. New York, NY: John Wiley & Sons.

Cook, R. M. (2013). A fish stock assessment model using survey data when estimates of catch are unreliable. *Fish. Res.* 143, 1–11. doi: 10.1016/j.fishres.2013.01.003

Cooke, J. G. (1999). Improvement of fishery-management advice through simulation testing of harvest algorithms. *ICES J. Mar. Sci.* 56, 797–810. doi: 10.1006/jmsc.1999.0552

Cope, J. M., and Punt, A. E. (2009). Length-based reference points for data-limited situations: applications and restrictions. *Mar. Coast. Fish.* 1, 169–186. doi: 10.1577/c08-025.1

Costanza, R., Andrade, F., Antunes, P., Belt, M., van den, Boersma, D., et al. (1998). Principles for sustainable governance of the oceans. *Science* 281, 198–199. doi: 10.1126/science.281.5374.198

Costello, C., and Ovando, D. (2019). Status, institutions, and prospects for global capture fisheries. *Annu. Rev. Environ. Resour.* 44, 177–200. doi: 10.1073/pnas.2108532118

Costello, C., Ovando, D., Clavelle, T., Strauss, C. K., Hilborn, R., Melnychuk, M. C., et al. (2016). Global fishery prospects under contrasting management regimes. *Proc. Natl. Acad. Sci. U S A.* 113, 5125–5129. doi: 10.1073/pnas.1520420113

Costello, C., Ovando, D., Hilborn, R., Gaines, S. D., Deschenes, O., and Lester, S. E. (2012). Status and solutions for the world's unassessed fisheries. *Science* 338, 517–520. doi: 10.1126/science.1223389

Cox, S. P., Kronlund, A. R., and Benson, A. J. (2013). The roles of biological reference points and operational control points in management procedures for the sablefish (Anoplopoma fimbria) fishery in British Columbia. Canada. *Environ. Conserv.* 40, 318–328. doi: 10.1017/s0376892913000271

Cury, P. M., and Christensen, V. (2005). Quantitative ecosystem indicators for fisheries management. *ICES J. Mar. Sci.* 62, 307–310.

Davies, C., Campbell, R., Prince, J., Dowling, N., Kolody, D., Basson, M., et al. (2007). *Development and Preliminary Testing of the Harvest Strategy Framework for the Eastern Tuna and Billfish Fishery. Final Report to the Australian Fisheries Management Authority*. Canberra, ACT: CSIRO, Marine and Atmospherics Research

De la Mare, W. (1986). Simulation studies on management procedures. *Report Int. Whaling Comm.* 36, 429–450.

De Oliveira, J. A. A., and Butterworth, D. S. (2004). Developing and refining a joint management procedure for the multispecies South African pelagic fishery. *ICES J. Mar. Sci. J. Cons.* 61, 1432–1442. doi: 10.1016/j.icesjms.2004.09.001

Dichmont, C. M., Fulton, E. A., Gorton, R., Sporcic, M., Little, L. R., Punt, A. E., et al. (2017). From data rich to data-limited harvest strategies—does more data mean better management? *ICES J. Mar. Sci.* 74, 670–686.

Dowling, N. A., Dichmont, C. M., Haddon, M., Smith, D. C., Smith, A. D. M., and Sainsbury, K. (2015a). Empirical harvest strategies for data-poor fisheries: a review of the literature. *Fish Res.* 171, 141–153.

Dowling, N. A., Dichmont, C. M., Haddon, M., Smith, D. C., Smith, A. D. M., and Sainsbury, K. (2015b). Guidelines for developing formal harvest strategies for data-poor species and fisheries. *Fish Res.* 171, 130–140.

Dowling, N. A., Smith, A. D. M., Smith, D. C., Parma, A. M., Dichmont, C. M., Sainsbury, K., et al. (2019). Generic solutions for data-limited fishery assessments are not so simple. *Fish Fish.* 20, 174–188.

Dowling, N. A., Smith, D. C., Knuckey, I., Smith, A. D. M., Domaschenz, P., Patterson, H. M., et al. (2008). Developing harvest strategies for low-value and data-poor fisheries: case studies from three Australian fisheries. *Fish. Res.* 94, 380–390. doi: 10.1016/j.fishres.2008.09.033

Dowling, N. A., Wilson, J. R., Rudd, M. B., Babcock, E. A., Caillaux, M., Cope, J., et al. (2016). "FishPath: a decision support system for assessing and managing data- and capacity- limited fisheries," in *Assessing and Managing Data-Limited Fish Stocks*, eds T. J. Quinn II, J. L. Armstrong, M. Baker, J. Heifetz, and D. Witherell (Alaska Sea Grant: University of Alaska Fairbanks).

FAO (2018). *Impacts of Climate Change on Fisheries and Aquaculture: Synthesis of Current Knowledge, Adaptation and Mitigation Options. United Nations' Food and Agriculture Organization*. Rome: FAO. Fisheries and Aquaculture Technical Paper 627.

FAO (2020a). *Proceedings of the International Symposium on Fisheries Sustainability: Strengthening the Science-policy Nexus. FAO Headquarters, 18-21 November 2019*. Rome: FAO. FAO Fisheries and Aquaculture Proceedings No. 65.

FAO (2020b). *The State of World Fisheries and Aquaculture 2020. Sustainability in Action*. Rome: FAO.

Flood, M. J., Stobutzki, I., Andrews, J., Ashby, C., Begg, G. A., Fletcher, R., et al. (2016). Multijurisdictional fisheries performance reporting: how Australia's nationally standardised approach to assessing stock status compares. *Fish. Res.* 183, 559–573.

Fulton, E. A., Punt, A. E., Dichmont, C. M., Gorton, R., Sporcic, M., Dowling, N., et al. (2016). Developing risk equivalent data-rich and data-limited harvest strategies. *Fish Res.* 183, 574–587. doi: 10.1016/j.fishres.2016.07.004

Garcia, S. M., and Staples, D. (2000). Sustainability indicators in marine capture fisheries: introduction to the special issue. *Mar. Freshw. Res.* 51, 381–384.

Geromont, H. F., and Butterworth, D. S. (2015). Complex assessments or simple management procedures for efficient fisheries management: a comparative study. *ICES J. Mar. Sci.* 72, 262–274. doi: 10.1093/icesjms/fsu017

Gilbert, D. J., Annala, J. H., and Johnston, K. (2000). Technical background to fish stock indicators for state-of-environment reporting in New Zealand. *Mar. Freshw. Res.* 51, 451–464. doi: 10.1071/mf99054

Gulland, J. A., and Rosenberg, A. A. (1992). *A Review of Length-based Approaches to Assessing Fish Stocks*. Rome: FAO. FAO Fisheries Technical Paper. No. 323.

Gutiérrez, N. L., Hilborn, R., and Defeo, O. (2011). Leadership, social capital and incentives promote successful fisheries. *Nature* 470, 386–389. doi: 10.1038/nature09689

Halliday, R. G., Fanning, L. P., and Mohn, R. K. (2001). *Use of the Traffic Light Method in Fishery Management Planning*. Ottawa: Canadian Science Advisory Secretariat.

Harford, W. J., and Babcock, E. A. (2016). Aligning monitoring design with fishery decision-making: examples of management strategy evaluation for reef-associated fisheries. *Aquat. Living Resour.* 29:205. doi: 10.1051/alr/2016018

Harford, W. J., and Carruthers, T. R. (2017). Interim and long-term performance of static and adaptive management procedures. *Fish. Res.* 190, 84–94. doi: 10.1016/j.fishres.2017.02.003

Harford, W. J., Gedamke, T., Babcock, E. A., Carcamo, R., McDonald, G., and Wilson, J. R. (2016). Management strategy evaluation of a multi-indicator adaptive framework for data-limited fisheries management. *Bull. Mar. Sci.* 92, 423–445.

Harford, W. J., Sagarese, S. R., and Karnauskas, M. (2019). Coping with information gaps in stock productivity for rebuilding and achieving maximum sustainable yield for grouper-snapper fisheries. *Fish Fish.* 20, 303–321. doi: 10.1111/faf.12344

Harford, W. J. (2020). *Management Strategy Evaluation: Recreational Red Abalone Management Strategy Integration*. Report prepared for California Fish and Game Commission. Miami, FL: University of Miami

Hilborn, R. (2002). The dark side of reference points. *Bull. Mar. Sci.* 70, 403–408.

Hilborn, R. (2010). Pretty good yield and exploited fisheries. *Mar. Policy* 34, 193–196. doi: 10.1016/j.marpol.2009.04.013

Hilborn, R., Amoroso, R. O., Anderson, C. M., Baum, J. K., Branch, T. A., Costello, C., et al. (2020). Effective fisheries management instrumental in improving fish stock status. *Proc. Natl. Acad. Sci. U S A.* 117, 2218–2224. doi: 10.1073/pnas.1909726116

Hilborn, R., and Ovando, D. (2014). Reflections on the success of traditional fisheries management. *ICES J. Mar. Sci.* 71, 1040–1046. doi: 10.1093/icesjms/fsu034

Hilborn, R., Parma, A., and Maunder, M. (2002). Exploitation rate reference points for west coast rockfish: are they robust and are there better alternatives? *North Am. J. Fish. Manag.* 22, 365–375. doi: 10.1577/1548-8675(2002)022<0365:errpfw>2.0.co;2

Hill, N. J., Peatman, T., Wakefield, C. B., Newman, S. J., Halafihi, T., Kinch, J., et al. (2018). Improving guidelines for implementing harvest strategies in capacity-limited fisheries - lessons from Tonga's deepwater line fishery. *Mar. Policy* 98, 85–91. doi: 10.1016/j.marpol.2018.09.015

Hordyk, A. R., Huynh, Q. C., and Carruthers, T. R. (2019). Misspecification in stock assessments: common uncertainties and asymmetric risks. *Fish Fish.* 20, 888–902.

Hordyk, A. R., Loneragan, N. R., and Prince, J. D. (2015). An evaluation of an iterative harvest strategy for data-poor fisheries using the length-based spawning potential ratio assessment methodology. *Fish Res.* 171, 20–32. doi: 10.1016/j.fishres.2014.12.018

Hordyk, A. R., Ono, K., Prince, J. D., and Walters, C. J. (2016). A simple length-structured model based on life history ratios and incorporating size-dependent selectivity: application to spawning potential ratios for data-poor stocks. *Can. J. Fish Aquat. Sci.* 73, 1787–1799. doi: 10.1139/cjfas-2015-0422

Huynh, Q. C., Beckensteiner, J., Carleton, L. M., Marcek, B. J., Kc, V. N., Peterson, C. D., et al. (2018). Comparative performance of three length-based mortality estimators. *Mar. Coast. Fish.* 10, 298–313. doi: 10.1002/mcf2.10027

Jardim, E., Azevedo, M., and Brites, N. M. (2014). Harvest control rules for data limited stocks using length-based reference points and survey biomass indices. *Fish. Res.* 171, 12–19. doi: 10.1016/j.fishres.2014.11.013

Jardim, E., Azevedo, M., and Brites, N. M. (2015). Harvest control rules for data limited stocks using length-based reference points and survey biomass indices. *Fish. Res.* 171, 12–19.

Johnson, J. E., Welch, D. J., Maynard, J. A., Bell, J. D., Pecl, G., Robins, J., et al. (2016). Assessing and reducing vulnerability to climate change: moving from theory to practical decision-support. *Mar. Policy* 74, 220–229.

Karnauskas, M., Walter, J. F., Kelble, C. R., McPherson, M., Sagarese, S. R., Craig, J. K., et al. (2021). To EBFM or not to EBFM? that is not the question. *Fish Fish.* 22, 646–651. doi: 10.1111/faf.12538

Keeney, R. L. (1992). *Value-Focused Thinking*. Cambridge: Harvard University Press.

Kelly, R. P., Erickson, A. L., Mease, L. A., Battista, W., Kittinger, J. N., and Fujita, R. (2015). Embracing thresholds for better environmental management. *Philos. Trans. R. Soc. B Biol. Sci.* 370:20130276. doi: 10.1016/j.jenvman.2010.08.024

Klaer, N. L., Wayte, S. E., and Fay, G. (2012). An evaluation of the performance of a harvest strategy that uses an average-length-based assessment method. *Fish. Res.* 13, 42–51.

Little, L. R., Wayte, S. E., Tuck, G. N., Smith, A. D. M., Klaer, N., Haddon, M., et al. (2011). Development and evaluation of a cpue-based harvest control rule for the southern and eastern scalefish and shark fishery of Australia. *ICES J. Mar. Sci. J. Cons.* 68, 1699–1705.

Mace, P. M. (1994). Relationships between common biological reference points used as thresholds and targets of fisheries management strategies. *Can. J. Fish Aquat. Sci.* 51, 110–122. doi: 10.1139/f94-013

Mangel, M., and Levin, P. S. (2005). Regime, phase and paradigm shifts: making community ecology the basic science of fisheries. *Philos. T Roy Soc. B* 360, 95–105. doi: 10.1098/rstb.2004.1571

Maunder, M. N., and Punt, A. E. (2004). Standardizing catch and effort data: a review of recent approaches. *Fish. Res.* 70, 141–159.

McDonald, G., Harford, B., Arrivillaga, A., Babcock, E. A., Carcamo, R., Foley, J., et al. (2017). An indicator-based adaptive management framework and its development for data-limited fisheries in Belize. *Mar. Policy* 76, 28–37. doi: 10.1016/j.marpol.2016.11.027

McGilliard, C. R., Hilborn, R., MacCall, A., Punt, A. E., and Field, J. C. (2011). Can information from marine protected areas be used to inform control-rule-based management of small-scale, data-poor stocks? *ICES J. Mar. Sci. J. Cons.* 68, 201–211. doi: 10.1093/icesjms/fsq151

Mesnil, B., Cotter, J., Fryer, R. J., Needle, C. L., and Trenkel, V. M. (2009). A review of fishery-independent assessment models, and initial evaluation based on simulated data. *Aquat. Living Resour.* 22, 207–216.

Methot, R. D., and Wetzel, C. R. (2013). Stock synthesis: a biological and statistical framework for fish stock assessment and fishery management. *Fish. Res.* 142, 86–99. doi: 10.1016/j.fishres.2012.10.012

Miethe, T., Dobby, H., and McLay, A. (2016). *The Use of Indicators for Shellfish Stocks and Fisheries: a Literature Review. Report Number: Scottish Marine and Freshwater Science No 16Affiliation: Marine Scotland Science*. Available online at: https://www.researchgate.net/publication/327060551_The_Use_of_Indicators_for_Shellfish_Stocks_and_Fisheries_A_Literature_Review (Accessed September 30, 2020)

NRC (1998). *Improving Fish Stock Assessments*. Washington, D.C: National Academy Press.

Pecl, G. T., Ward, T., Briceño, F., Fowler, A., Frusher, S., Gardner, C., et al. (2014). *Preparing Fisheries for Climate Change: Identifying Adaptation Options for Four Key Fisheries in South Eastern Australia*. Canberra: Fisheries Research and Development Corporation.

Pennington, M., Burmeister, L. M., and Hjellvik, V. (2002). Assessing the precision of frequency distributions estimated from trawl-survey samples. *Fish Bull.* 100, 74–80.

Peterman, R. M. (2004). Possible solutions to some challenges facing fisheries scientists and managers. *ICES J. Mar. Sci.* 61, 1331–1343.

PFMC (2020). *Pacific Coast Groundfish Fishery Management Plan: for the California, Oregon, and Washington Groundfish Fishery*. Portland, OR: Pacific Fishery Management Council (PFMC).

Pilling, G. M., Berger, A. M., Reid, C., Harley, S. J., and Hampton, J. (2016). Candidate biological and economic target reference points for the south Pacific albacore longline fishery. *Fish. Res.* 174, 167–178.

Pinsky, M. L., and Mantua, N. J. (2014). Emerging adaptation approaches for climate-ready fisheries management. *Oceanography* 27, 146–159.

Plagányi, É. E., Murphy, N., Skewes, T., Dutra, L. X. C., Dowling, N., and Fischer, M. (2020). Development of a data-poor harvest strategy for a sea cucumber fishery. *Fish. Res.* 230:105635.

Pomarede, M., Hillary, R., Ibaibarriaga, L., Bogaards, J., and Apostolaki, P. (2010). Evaluating the performance of survey-based operational management procedures. *Aquat. Living Resour.* 23, 77–94.

Pons, M., Cope, J. M., and Kell, L. T. (2020). Comparing performance of catch-based and length-based stock assessment methods in data-limited fisheries. *Can. J. Fish. Aquat. Sci.* 77, 1026–1037. doi: 10.1139/cjfas-2019-2276

Prince, J., and Hordyk, A. (2019). What to do when you have almost nothing: a simple quantitative prescription for managing extremely data-poor fisheries. *Fish Fish.* 20, 224–238. doi: 10.1111/faf.12335

Prince, J., Lalavanua, W., Tamanitoakula, J., Tamata, L., Green, S., Radway, S., et al. (2020). Spawning potential surveys in Fiji: a new song of change for small-scale fisheries in the Pacific. *Conserv. Sci. Pract.* 3:e273. doi: 10.1111/csp2.273

Prince, J. D., Dowling, N. A., Davies, C. R., Campbell, R. A., and Kolody, D. S. (2011). A simple cost-effective and scale-less empirical approach to harvest strategies. *ICES J. Mar. Sci.* 68, 947–960.

Prince, J. D., Hordyk, A., Mangubhai, S., Lalavanua, W., Tamata, I., Tamanitoakula, J., et al. (2018). Developing a system of sustainable minimum size limits for Fiji. *South. Pac. Bull.* 155, 51–60.

Prince, J. D., Hordyk, A., Valencia, S. R., Loneragan, N., and Sainsbury, K. (2015). Revisiting the concept of Beverton– – –Holt life-history invariants with the aim of informing data-poor fisheries assessment. *ICES J. Mar. Sci.* 72, 194–203.

Prince, J. D., Peeters, H., Gorfine, H., and Day, R. W. (2008). The novel use of harvest policies and rapid visual assessment to manage spatially complex abalone resources (Genus Haliotis). *Fish Res.* 94, 330–338. doi: 10.1016/j.fishres.2008.07.016

Punt, A. E. (2017). Strategic management decision-making in a complex world: quantifying, understanding, and using trade-offs. *ICES J. Mar. Sci.* 74, 499–510. doi: 10.1093/icesjms/fsv193

Punt, A. E., Butterworth, D. S., de Moor, C. L., De Oliveira, J. A. A., and Haddon, M. (2016). Management strategy evaluation: best practices. *Fish Fish* 17, 303–334. doi: 10.1111/faf.12104

Punt, A. E., Campbell, R. A., and Smith, A. D. M. (2001). Evaluating empirical indicators and reference points for fisheries management: application to the broadbill swordfish fishery off eastern Australia. *Mar. Freshw. Res.* 52, 819–832. doi: 10.1071/mf00095

Purcell, S. W., and Pomeroy, R. S. (2015). Driving small-scale fisheries in developing countries. *Front. Mar. Sci.* 2:44. doi: 10.3389/fmars.2015.00044

Rademeyer, R. A., Plagányi, É. E., and Butterworth, D. S. (2007). Tips and tricks in designing management procedures. *ICES J. Mar. Sci.* 64, 618–625. doi: 10.1093/icesjms/fsm050

Rice, J. C., and Rochet, M.-J. (2005). A framework for selecting a suite of indicators for fisheries management. *ICES J. Mar. Sci.* 62, 516–527. doi: 10.1016/j.icesjms.2005.01.003

Rudd, M. B., and Thorson, J. T. (2017). Accounting for variable recruitment and fishing mortality in length-based stock assessments for data-limited fisheries. *Can. J. Fish Aquat. Sci.* 75, 1019–1035. doi: 10.1139/cjfas-2017-2143

Sagarese, S. R., Harford, W. J., Walter, J. F., Bryan, M. D., Isely, J. J., Smith, M. W., et al. (2019). Lessons learned from data-limited evaluations of data-rich reef fish species in the Gulf of Mexico: implications for providing fisheries management advice for data-poor stocks. *Can. J. Fish. Aquat. Sci.* 76, 1624–1639. doi: 10.1139/cjfas-2017-2482

Sagarese, S. R., Rios, A. B., Cass-Calay, S., McCarthy, K. J., Matter, M. V., Bryan, M. D., et al. (2018). Working towards a framework for stock evaluations in data-limited fisheries. *N. Am. J. Fish Man.* 38, 507–537.

Sainsbury, K., Punt, A. E., and Smith, A. D. M. (2000). Design of operational management strategies for achieving fishery ecosystem objectives. *ICES J. Mar. Sci.* 57, 731–741.

Seijo, J. C., and Caddy, J. F. (2000). Uncertainty in bio-economic reference points and indicators of marine fisheries. *Mar. Freshw. Res.* 51, 477–483. doi: 10.1071/mf99087

Stamatopoulos, C. (2002). *Sample-based Fishery Surveys: a Technical Handbook*. Rome: FAO. FAO Fisheries Technical Paper. No. 425.

Thorson, J. T., Cope, J. M., Branch, T. A., and Jensen, O. P. (2012). Spawning biomass reference points for exploited marine fishes, incorporating taxonomic and body size information. *Can. J. Fish. Aquat. Sci.* 69, 1556–1568. doi: 10.1139/f2012-077

Thorson, J. T., Munch, S. B., Cope, J. M., and Gao, J. (2017). Predicting life history parameters for all fishes worldwide. *Ecol. Appl.* 27, 2262–2276. doi: 10.1002/eap.1606

Trenkel, V. M., and Rochet, M.-J. (2011). Performance of indicators derived from abundance estimates for detecting the impact of fishing on a fish community. *Can. J. Fish. Aquat. Sci.* 60, 67–85.

Trenkel, V. M., Rochet, M.-J., and Mesnil, B. (2007). From model-based prescriptive advice to indicator-based interactive advice. *ICES J. Mar. Sci.* 64, 768–774. doi: 10.1093/icesjms/fsm006

United Nations (2018). *Sustainable Development Goals. Goal 14: Life Below Water*. New York, NY: United Nations.

United Nations (2019). *United Nations (UN), Department of Economic and Social Affairs, Population Division (2019). World Population Prospects 2019: Highlights (ST/ESA/SER.A/423)*. New York, NY: United Nations.

Walters, C. J. (2003). Folly and fantasy in the analysis of spatial catch rate data. *Can. J. Fish. Aquat. Sci.* 60, 1433–1436.

Wilson, J. R., Prince, J. D., and Lenihan, H. S. (2010). A management strategy for sedentary nearshore species that uses marine protected areas as a reference. *Mar. Coast Fish* 2, 14–27. doi: 10.1577/C08-026.1

Wilson, J. R., Valencia, S. R., Kay, M. C., and Lenihan, H. S. (2014). Integration of no-take marine reserves in the assessment of data-limited fisheries. *Conserv. Lett.* 7, 451–458. doi: 10.1111/conl.12073

Ye, Y., Cochrane, K., Bianchi, G., Willmann, R., Majkowski, J., Tandstad, M., et al. (2013). Rebuilding global fisheries: the world summit goal, costs and benefits. *Fish Fish* 14, 174–185. doi: 10.1111/j.1467-2979.2012.00460.x

Ye, Y., Cochrane, K., and Qiu, Y. (2011). Using ecological indicators in the context of an ecosystem approach to fisheries for data-limited fisheries. *Fish. Res.* 112, 108–116. doi: 10.1016/j.fishres.2011.06.004

Zhou, S., Punt, A. E., Lei, Y., Deng, R. A., and Hoyle, S. D. (2020). Identifying spawner biomass per-recruit reference points from life-history parameters. *Fish Fish.* 21, 760–773. doi: 10.1111/faf.12459

Zhou, S., Yin, S., Thorson, J. T., Smith, A. D. M., Fuller, M., and Walters, C. J. (2012). Linking fishing mortality reference points to life history traits: an empirical study. *Can. J. Fish Aquat. Sci.* 69, 1292–1301. doi: 10.1139/f2012-060

Conflict of Interest: WH is employed by the Nature Analytics. JP is employed by the Biospherics Pty., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 03 February 2022
doi: 10.3389/fmars.2021.757503

Fishery Dynamics, Status, and Rebuilding Based on Catch-Only Data in Coastal Waters of China

Linlong Wang[1], Li Lin[1], Yang Liu[1], Lu Zhai[2] and Shen Ye[3,4]*

[1] Fisheries College, Ocean University of China, Qingdao, China, [2] The Key Laboratory of Sustainable Exploitation of Oceanic Fisheries Resources, National Engineering Research Center for Oceanic Fisheries, College of Marine Science, Shanghai Ocean University, Shanghai, China, [3] Zhejiang Mariculture Research Institute, Wenzhou, China, [4] Zhejiang Key Laboratory of Exploitation and Preservation of Coastal Bio-Resource, Wenzhou, China

OPEN ACCESS

Edited by:
Giuseppe Scarcella, National Research Council (CNR), Italy

Reviewed by:
Maria Rita Pegado, Marine and Environmental Sciences Centre (MARE), Portugal
Shanshan Zhang, Quanzhou Normal University, China

***Correspondence:**
Shen Ye
leafdeep@163.com

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture, and Living Resources, a section of the journal Frontiers in Marine Science

Received: *12 August 2021*
Accepted: *20 December 2021*
Published: *03 February 2022*

Citation:
Wang L, Lin L, Liu Y, Zhai L and Ye S (2022) Fishery Dynamics, Status, and Rebuilding Based on Catch-Only Data in Coastal Waters of China. Front. Mar. Sci. 8:757503. doi: 10.3389/fmars.2021.757503

China has become the largest contributor to marine fisheries in the world with its fishing fleets explosively increasing their fishing effort and resulting catch, but its fishery composition and sustainability have deteriorated. Limited information on fishery exploitation status encumbers effective resource management. In this study, a data-poor Monte Carlo method, the Catch-Maximum Sustainable Yield (CMSY) method, was used to estimate the historical exploited dynamics and current stock status of ten Chinese economic marine fish stocks, including *Trichiurus lepturus*, *Larimichthys crocea*, *Larimichthys polyactis*, *Thamnaconus modestus*, *Scomberomorus niphonius*, *Ilisha elongate*, *Decapterus maruadsi*, *Scomber japonicus*, *Engraulis japonicus*, and *Clupea pallasii*, which accounted for about 50% of total fish catches in the coastal waters of China and covered five functional groups (i.e., large, medium benthopelagic, large, medium, and small pelagic). Species *L. crocea* and *L. polyactis* had been subjected to overfishing since the 1950s. The others showed a decreasing trend in biomass along with the explosively increasing fishing efforts since the 1990s. Benthopelagic fish experienced overfishing pressure about a decade earlier than pelagic species. All the fish stocks investigated in this study were depleted (current biomass lower than the biomass capable of producing maximum sustainable yields, i.e., $B < B_{msy}$) in 2019, and most species were still facing high-fishing pressure (current fishing mortality higher than the mortality capable of producing maximum sustainable yields, i.e., $F > F_{msy}$). Also, a Schaefer model was used to assess stocks rebuilding status until 2030 under four exploitation scenarios, i.e., fishing mortality equals 0.5, 0.6, 0.8, or 0.95 times F_{msy}. Most species stocks will likely recover to the B_{msy}, which indicates that reduction of fishing pressure is probably the most effective way for fishery recovery.

Keywords: data-poor method, CMSY, stock assessment, Chinese coastal fisheries, fishery rebuilding, fishery protection

INTRODUCTION

Overfishing has altered structures of fish population (Zhang W. et al., 2019) and caused the continual decline of global fisheries (Link and Watson, 2019). The total fishing vessel power in China had incredibly increased from 0.02×10^6 kilowatts (kW) in 1951 to 140×10^6 kW in 2017 (Ministry of agriculture of China, 2017), which contributed to the highest marine fishery catches in the world (Cao et al., 2015; FAO, 2016). However, the aggravating fishing pressure has imposed a significant impact on fish stocks (Shan et al., 2011, 2013; Zhang W. et al., 2019) and changed fishery composition (Li et al., 2011; Shan et al., 2013). For example, the catch per unit effort (CPUE) in the Bohai Sea in 2011 (3.62 $kg \cdot haul^{-1} \cdot h^{-1}$) has dropped to 0.86% of that in 1959 (421.66 $kg \cdot haul^{-1} \cdot h^{-1}$) (Shan et al., 2013; Zhang W. et al., 2019), and the dominant species had been altered from the high-valued and large-sized species, e.g., largehead hairtail *Trichiurus lepturus*, to the species in lower trophic level, such as Scaly hairfin anchovy *Setipinna taty* and Japanese anchovy *Engraulis japonicus*. In the Yellow Sea and the East China Sea, CPUE has reduced 46.7% from 1991 (73.54 $kg \cdot haul^{-1} \cdot h^{-1}$) to 2000 (39.19 $kg \cdot haul^{-1} \cdot h^{-1}$), accompanied by miniaturization and early maturing of catch species (Cheng and Yu, 2004; Li et al., 2011). In the South China Sea, overfishing was the main driver that led to the biomass declination of fishery resources (Zhang W. et al., 2019) and even to the extinction of some coral reef fishes (Arai, 2015).

Fisheries can be managed effectively when understanding the population exploited status through the stock assessment (Demirel et al., 2020). Comprehensive stock assessments based on biological characteristics (e.g., life history and age) have been implemented in some developed countries for many fishes, and specific requirements for rebuilding fisheries have been proposed (Ricard et al., 2012; Free et al., 2020). For example, the Common Fisheries Policy (CFP) of the European Union has become a basic legally binding regulation (Froese et al., 2018), which explicitly required that the biomass (B_{2020}) of all commercially developed fish stocks should be rebuilt above the level at which the biomass is capable of producing the best maximum sustainable yields (B_{msy}) by 2020. Even so, the majority of fish stocks in other parts of the world remain unassessed (Costello et al., 2012), which hindered the development of species-specific management. For example, the Mediterranean and Black Seas were generally classified as "fishery data-poor regions" due to unavailable landing yields, insufficient biological data, and lack of stock assessment (Demirel et al., 2020). Similarly in China, fishery resources are still poorly managed due to a lack of effective data accumulation.

The Monte Carlo Catch-Maximum Sustainable Yield (CMSY) method is a data-poor and low-cost assessment approach that relies on less input, including time-series data of catch, maximum intrinsic rate of population increase (r), and the ratio of biomass to carrying capacity (B/k) at the beginning and the end of the time series. The current biomass status (B_{end}/B_{msy}) and remaining level of exploitation (F_{end}/F_{msy}) obtained from CMSY provide references to promote effective management toward fishery sustainability and useful information for the recovery of the overexploited stocks (Martell and Froese, 2013; Froese et al., 2017). In Europe, CMSY indicated that 69% of the stocks were suffering from overfishing when evaluating the current status and exploitation patterns of fisheries based on catch data since 2000. However, by reducing 40–50% fishing efforts, nearly 80% of stocks could rebuild in 10 years with higher catches than currently obtained (Froese et al., 2018). Demirel et al. (2020) examined the exploitation levels of 34 species utilizing CMSY analyses in the Black Sea and the Mediterranean Sea and proposed that 85% of them were overfished. They also estimated the stock rebuilding time under four varying scenarios and suggested more than 60% of the populations could recovery by 2032 under the scenario of fishing mortality (F) equals 0.5 F_{msy} (the fishing mortality capable of producing maximum sustainable yields).

In this study, based on the time-serial catch data extracted from China Fishery Statistical Yearbook, ten coastal economic fish species, accounting for approximate 50% of Chinese total domestic landing catch (Ministry of agriculture of China, 2019), were selected to estimate their historical dynamics using the CMSY model, including *T. lepturus*, large yellow croaker *Larimichthys crocea*, small yellow croaker *Larimichthys polyactis*, black scraper *Thamnaconus modestus*, Japanese Spanish mackerel *Scomberomorus niphonius*, Elongate ilisha *Ilisha elongate*, Japanese scad *Decapterus maruadsi*, Pacific chub mackerel *Scomber japonicus*, *E. japonicus*, and Pacific herring *Clupea pallasii*. These species included top predators, middle carnivores, omnivores, and plankton feeders, which covered the large benthopelagic, medium benthopelagic, large pelagic, medium pelagic, and small pelagic groups of species. Then, the reference points for management such as *MSY*, current exploited status (B_{2019}/B_{msy}), and remaining level of exploitation (F_{2019}/F_{msy}) of these species were modeled. Finally, the fishery rebuilding trajectories under different exploitation scenarios, i.e., fishing mortality equals 0.5, 0.6, 0.8, or 0.95 times mortality capable of producing maximum sustainable yields (0.5 F_{msy}, 0.6 F_{msy}, 0.8 F_{msy}, or 0.95 F_{msy}), were projected. We hope this work could help giving recovery opinions to sustainable fishery management.

MATERIALS AND METHODS

Data Sets

All the data for the analysis were extracted from China Fishery Statistical Yearbooks (Ministry of Agriculture of China, 1956–2019) and were shown in **Supplementary Table 1**. More than 30-year catch data were selected to improve the model performance (**Table 1**).

Catch-Maximum Sustainable Yield Modeling

Using the maximum intrinsic rate of population increase (r), catch data, and stock status (B/k) at the beginning year and the

TABLE 1 | The prior range for *r* and *B/k* and other information of the investigated stocks in China.

Species	Feeding habit	Functional group	Time series	Resilience	Prior *r* range	*B/k* at start year	*B/k* at end year
Trichiurus lepturus	Top predator	Large benthopelagics	1956–2019	Medium	0.53–1.20[1]	0.8–1.0	0.01–0.4[6]
Larimichthys crocea	Middle carnivores	Medium benthopelagics	1956–2019	Medium	0.20–0.45[1]	0.4–0.8 [3,4]	0.01–0.4 [4,8]
Larimichthys polyactis	Middle carnivores	Medium benthopelagics	1956–2019	Medium	0.37–0.85[1]	0.01–0.4 [5]	0.2–0.6[6]
Thamnaconus modestus	Plankton feeder	Medium benthopelagics	1977–2019	Medium	0.60–1.50[2]	0.8–1.0	0.01–0.4[9]
Scomberomorus niphonius	Top predator	Large pelagics	1978–2019	Medium	0.37–0.85[1]	0.8–1.0	0.01–0.4[6]
Ilisha elongata	Omnivores	Medium pelagics	1980–2019	Medium	0.58–1.32[1]	0.8–1.0	0.01–0.4[10,11]
Decapterus maruadsi	Middle carnivores	Small pelagics	1980–2019	High	0.60–1.50[2]	0.8–1.0	0.2–0.6[6,7]
Scomber japonicus	Middle carnivores	Medium pelagics	1980–2019	Medium	0.32–0.73[1]	0.8–1.0	0.2–0.6[6,7]
Engraulis japonicus	Plankton feeder	Small pelagics	1989–2019	High	0.78–1.76[1]	0.8–1.0	0.01–0.4[6,7]
Clupea pallasii	Plankton feeder	Medium pelagics	1989–2019	Medium	0.37–0.84[1]	0.8–1.0	0.01–0.4[12]

[1] Referred from FishBase (www.fishbase.org); [2] Froese et al., 2017; [3] Cheng and Fan, 2001; [4] Liu and De Mitcheson, 2008; [5] Zhuang, 2006; [6] Zhai and Pauly, 2019; [7] Liang and Pauly, 2017; [8] Ling et al., 2006; [9] Cheng and Yu, 2004; [10] Wang et al., 2016; [11] Wang et al., 2004; and [12] Shan et al., 2013.

end year as a prior input, CMSY based on the Monte Carlo approach estimates fishery reference indices, including viable *r-k* (maximum intrinsic rate of population increase and carrying capacity) and fishery reference points for management (e.g., *MSY*, B_{2019}/B_{msy}, and F_{2019}/F_{msy}). Values of *r* (**Table 1**) were obtained from FishBase[1] or estimated by the empirical equation (Froese et al., 2017):

$$r \approx 2M \approx 2F_{\text{msy}} \approx 3K \approx 3.3/t_{\text{gen}} \approx 9/t_{\max} \tag{1}$$

where, *r* is maximum intrinsic rate of population increase, *M* is natural mortality, F_{msy} is fishing mortality at the maximum sustainable yields, *K* is von-Bertalanffy somatic growth rate, t_{gen} is generation time, and $t_{\max}$ is the maximum age. CMSY requires "expert" prior information of biomass consumption (i.e., very low, low, medium, strong, and very strong depletion) specified at the beginning and end of the time series and also the relative biomass range suggested by Froese et al. (2017) and CMSY User Guide[2]. In this study, given the low total power of fishing boats before the mid-1980s (**Supplementary Table 1**), the depletion status of each species at the start year was defined as "very low depletion" (prior *B/k* range: 0.8–1.0), except values of *L. crocea* and *L. polyactis* directly from relevant studies (Cheng and Fan, 2001; Zhuang, 2006; Liu and De Mitcheson, 2008). The prior ranges of *B/k* at the end year of the time series of all the species were cited from previous stock assessments in Chinese coastal waters (Cheng and Yu, 2004; Wang et al., 2004, 2016; Ling et al., 2006; Liu and De Mitcheson, 2008; Shan et al., 2013; Liang and Pauly, 2017; Zhai and Pauly, 2019).

The Catch-Maximum Sustainable Yield method determines the prior range of *k* by Equation (2) for lower relative biomass or Equation (3) with higher biomass in the end year (Froese et al., 2017):

$$k_{\text{low}} = {}^{\max(C)}/_{r_{\text{high}}} \text{ and } k_{\text{high}} = {}^{4\max(C)}/_{r_{\text{low}}} \tag{2}$$

$$k_{\text{low}} = {}^{2\max(C)}/_{r_{\text{high}}} \text{ and } k_{\text{high}} = {}^{12\max(C)}/_{r_{\text{low}}} \tag{3}$$

where, k_{low} and k_{high} are the lower and upper bounds for *k* respectively, max (*C*) is the recorded maximum catch, and r_{low} and r_{high} are the bounds for prior *r* values.

The *r-k* pairs from the prior input were randomly selected in the first year to predict biomass in subsequent years along the time series using Equation (4) (Schaefer, 1954):

$$B_{t+1} = B_t + r(1 - {}^{B_t}/_k)B_t - C_t \tag{4}$$

where, B_t is biomass in year t, *r* is the maximum intrinsic rate of population increase, *k* is carrying capacity, and C_t is a catch in year t. When B_{t+1} is not smaller than 0.01 *k* and the predicted value of final biomass falls into the prior range, the corresponding *r-k* pair is feasible and can be retained. CMSY will subsequently calculate the *MSY*, B_{msy}, F_t, and F_{msy} using Equations (5–8) (Schaefer, 1954; Ricker, 1975):

$$MSY = r \times k/4 \tag{5}$$

$$B_{\text{msy}} = k/2 \tag{6}$$

$$F_t = {}^{C_t}/_{B_t} \tag{7}$$

$$F_{\text{msy}} = -\ln(1 - {}^{MSY}/_{B_{\text{msy}}}) = r/2 \tag{8}$$

Fisheries Rebuilding

Based on the estimates of B_{2019}, B_{msy}, F_{2019}, and F_{msy} by CMSY, a Schaefer model was used to assess stock rebuilding status until 2030. The time needed for rebuilding fisheries to the level of B_{msy} was calculated by Equation (9) (Quinn and Deriso, 1999):

$$\Delta t = {}^{1}/_{(2F_{\text{msy}} - F)}\, ln\left(\frac{{}^{B_{\text{msy}}}/_{B}\, 2\left(1 - {}^{F}/_{2F_{\text{msy}}}\right) - 1}{2\left(1 - {}^{F}/_{2F_{\text{msy}}}\right) - 1}\right) \tag{9}$$

where, Δt is the time consumption, B_{msy} and F_{msy} are the biomass and fishing pressure that could produce *MSY*, *B*, and *F* as the biomass and fishing pressure at the last year.

[1] www.fishbase.org
[2] http://oceanrep.geomar.de/34476/

The biomass in the next year (B_{t+1}) was calculated by Equations (10, 11) from the Schaefer model (Schaefer, 1954):

$$^{B_{t+1}}/_{B_{msy}} = {}^{B_t}/_{B_{msy}} + 2F_{msy}\,{}^{B_t}/_{B_{msy}}\left(1 - {}^{B_t}/_{2B_{msy}}\right) - {}^{B_t}/_{B_{msy}}F_t;\ {}^{B_t}/_{B_{msy}} \geq 0.5 \tag{10}$$

$$^{B_{t+1}}/_{B_{msy}} = {}^{B_t}/_{B_{msy}} + 2F_{msy}2F_{msy}{}^{B_t}/_{B_{msy}}\left(1 - {}^{B_t}/_{2B_{msy}}\right) - {}^{B_t}/_{B_{msy}}F_t;\ {}^{B_t}/_{B_{msy}} < 0.5 \tag{11}$$

Four future exploitation scenarios were used to predict the stock rebuilding status until 2030: (1) 0.5 F_{msy}, i.e., no fishing when biomass was lower than 0.5 B_{msy} ($B < 0.5$); otherwise, the fishing mortality (F) equaled 0.5 F_{msy} ($F = 0.5\ F_{msy}$). (2) 0.6 F_{msy}, i.e., $F = 0.6\ F_{msy}$ when $B \geq 0.5B_{msy}$; otherwise, F was linearly reduced to 0 along with the decrease in biomass when $B < 0.5\ B_{msy}$. The reduction in the fishing mortality ($F_{reduced}$) was calculated in Equation (12) (Froese et al., 2018):

$$F_{reduced} = 2^{B}/_{B_{msy}}\,F \tag{12}$$

(3) 0.8 F_{msy} exploitation scenario, $F = 0.8\ F_{msy}$ when $B \geq 0.5\ B_{msy}$; otherwise, F was also linearly reduced. (4) 0.95 F_{msy} exploitation scenario, $F = 0.95\ F_{msy}$ in any cases.

The change of stock biomasses and fishing catches along with rebuilding times under four exploitation scenarios was projected and presented. The catch in 2019 served as the starting year of the prediction trajectory, and the fishing pressure in 2019 was used to calculate the biomass and catches for 2020–2021. Then, resource recovery times until 2030 were predicted under these four exploitation scenarios.

All the analyses were executed in R (R Development Core Team, 2020). CMSY R codes were downloaded from http://oceanrep.geomar.de/34476/ and revised accordingly.

RESULTS

Model Diagnostics and Prior-Posterior Variance Ratio

The model diagnostics and prior-posterior variance ratios for *T. lepturus*, *L. crocea*, *I. elongate*, and *E. japonicus* were selected as the surrogates of top predators, middle carnivores, omnivores, and plankton feeders, respectively, and shown in **Supplementary Figures 1, 2**. Diagnostics present a good fitting for all species, with the relative lower prior-posterior variance ratio (PPVR) of key parameters, indicating that the posterior knowledge is more improved relative to prior knowledge.

Historical Exploitation Dynamics

The historical exploitation dynamics of the ten species were presented as catches, relative biomass to the biomass capable of producing maximum sustainable yields (B/B_{msy}), and relative fishing mortality to the mortality capable of producing maximum sustainable yields (F/F_{msy}) (**Figure 1**). The F/F_{msy} of two benthopelagic species, i.e., *T. lepturus* and *T. modestus*, increased sharply since the mid-1980s, with drastic changes in catches, and then B/B_{msy} began to decline rapidly, with the catches reaching *MSY* in 1998 and 1985, respectively. Six pelagic species *S. niphonius*, *I. elongata*, *D. maruadsi*, *S. japonicus*, *E. japonicus*, and *C. pallasii* showed similar patterns with *T. lepturus* and *T. modestus*, but the timeline has been pushed back by the mid-1990s. The historical exploitation records documented that *L. crocea* had been overfished ($F > F_{msy}$) since the beginning of records and showed no signs of recovery so far. Species *L. polyactis* sustained three stages, namely, overexploited at the beginning with biomass depletion ($B < B_{msy}$), a contemporary recovery to some extent, and a continuously decline as a result of re-enhanced fishing pressure (**Figure 1**).

Fisheries Reference Points for Management and Current Status

The maximum intrinsic rate of population increase (r) ranged from 0.24 of *L. crocea* to 1.29 of *E. japonicus*. Environmental carrying capacity (k) ranged from 203 × 10^3 metric tons of *C. pallasii* to 5,151 × 10^3 metric tons of *T. lepturus*. All species had fewer catches in 2019 than *MSY* (**Table 2**). *Clupea pallasii* had the lowest B_{2019}/B_{msy} (0.19) value, while *D. maruadsi* had the highest (0.95). The F_{2019}/F_{msy} ranged from 0.79 of *D. maruadsi* to 5.64 of *C. pallasii*, with the fishing mortalities for seven species of the ten were higher than F_{msy}. The Kobe plot (**Figure 2**) based on the relationship between current exploited status (B_{2019}/B_{msy}), and the remaining level of exploitation (F_{2019}/F_{msy}) showed that seven fish species, i.e., *T. lepturus*, *T. modestus*, *S. niphonius*, *I. elongata*, *S. japonicus*, *E. japonicus*, and *C. pallasii*, were in the red area ($B_{2019} < B_{msy}$ and $F_{2019} > F_{msy}$), indicating overexploited stocks that were suffering overfishing. *C. pallasii* was in the worst condition, followed by *T. modestus*. *D. maruadsi*, *L. crocea*, and *L. polyactis* were in the yellow area, indicating the recovering of overexploited stocks from reduced fishing pressure (**Figure 2**).

Fisheries Rebuilding and Catch Changes

Under the four future predictive exploitation scenarios, most Chinese coastal fisheries show more or less recovery of biomass by 2030, and the catches are rising to similar or even higher than they were in 2019 (**Table 3** and **Supplementary Figure 1**). Two species, *T. lepturus* and *I. elongata* were selected as the surrogates of carnivores and omnivores, respectively, to show the fishery rebuilding trajectories and catch changes (**Figure 3A**, other species were shown in **Supplementary Figure 1**). The fastest biomass recovery rate was found under the scenario of 0.5 F_{msy}. Nine of the species would likely rebuild the optimum status ($B_{2030} > B_{msy}$) by 2030. Under the 0.95 F_{msy} scenario, the biomasses of only four species would likely reach the B_{msy}. The recovery of stock biomasses under both 0.6 F_{msy} and 0.8 F_{msy} scenarios was intermediate, among which 0.6 scenario was faster. For catch changes, species *T. lepturus*, *S. niphonius*, and *I. elongata* would increase the most under the scenario of 0.8 F_{msy} by 2030, while *L. crocea*, *L. polyactis*, *D. maruadsi*, *S. japonicus*, and *E. japonicus* increase the most under the scenario of 0.95 F_{msy} (**Table 3**). The fishery rebuilding trajectories and catch changes of

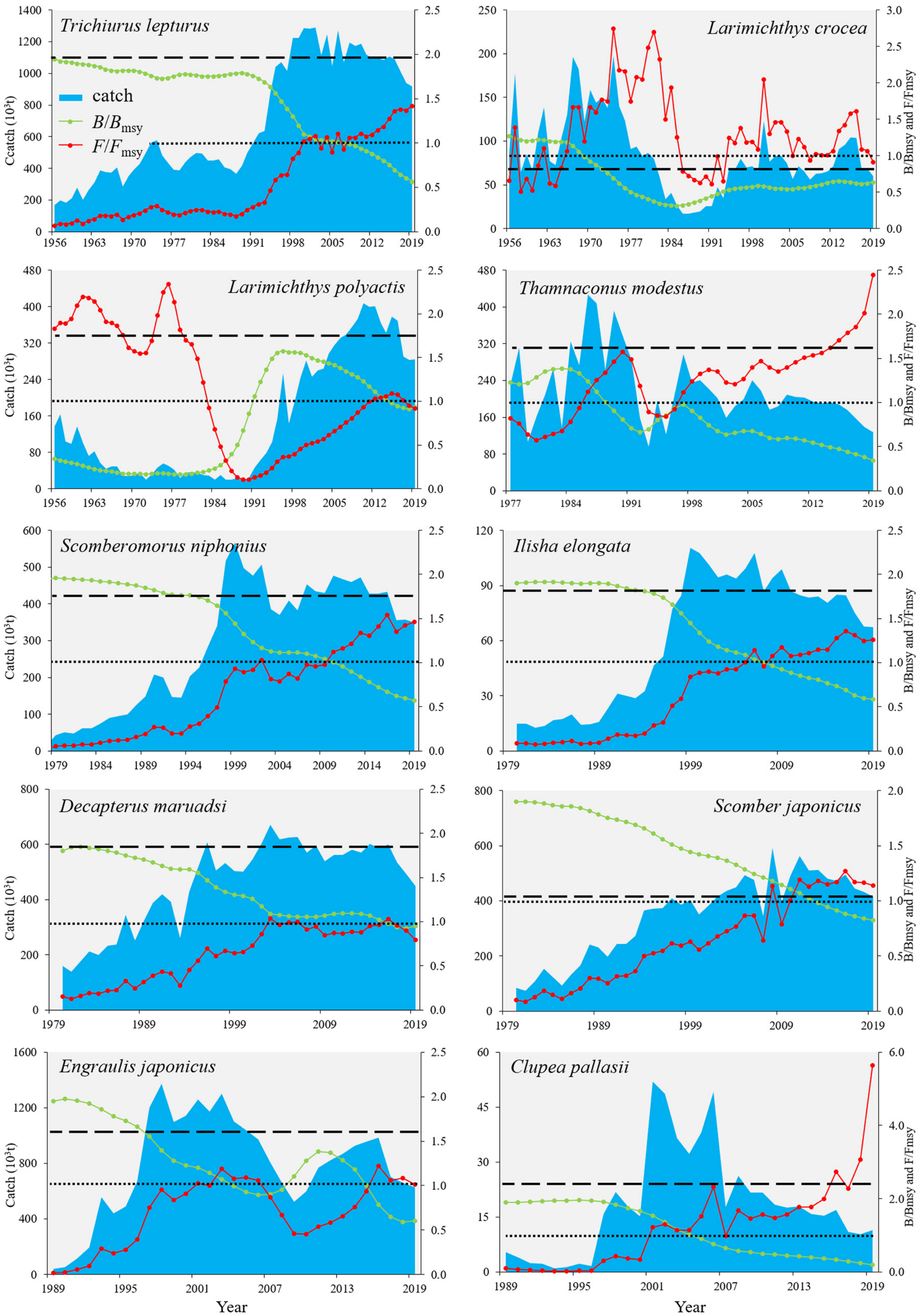


FIGURE 1 | Time-serial stock exploitation dynamics of ten Chinese commercial fishes extracted from Catch-Maximum Sustainable Yield (CMSY) method. Dashed line indicated the maximum sustainable yield (*MSY*), the dotted line signified that the biomass/fishing mortality is capable of producing the best maximum sustainable yields (i.e., B/B_{msy} = 1 or F/F_{msy} = 1), the green line signified the relative biomass to the biomass capable of producing maximum sustainable yields (B/B_{msy}), and the red line indicated the relative fishing mortality to the mortality capable of producing maximum sustainable yields (F/F_{msy}).

TABLE 2 | Model outputs of reference points for fish management.

Species	r	K (10^3t)	C_{2019} (10^3t)	MSY (10^3t)	B_{2019} (10^3t)	B_{2019}/k	B_{msy} (10^3t)	B_{2019}/B_{msy}	F_{2019} (year^{-1})	F_{msy} (year^{-1})	F_{2019}/F_{msy}	Status in 2019[1]
Trichiurus lepturus	0.88	5151	916	1122	1466	0.29	2575	0.57	0.63	0.44	1.42	Over-fished
Larimichthys crocea	0.24	1682	60	102	536	0.32	841	0.64	0.11	0.12	0.92	Over-fished
Larimichthys polyactis	0.64	2109	284	346	1295	0.46	1397	0.93	0.22	0.25	0.92	Slightly over-fished
Thamnaconus modestus	0.65	1463	128	239	249	0.17	732	0.34	0.55	0.33	2.45	Grossly over-fished
Scomberomorus niphonius	0.64	2646	349	417	752	0.28	1323	0.57	0.46	0.32	1.46	Over-fished
Ilisha elongata	0.95	382	67	91	112	0.29	191	0.59	0.60	0.48	1.26	Over-fished
Decapterus maruadsi	1.11	2139	448	587	1017	0.48	1070	0.95	0.44	0.56	0.79	Slightly over-fished
Scomber japonicus	0.55	3208	415	438	1325	0.41	1604	0.83	0.31	0.28	1.14	Slightly over-fished
Engraulis japonicus	1.29	3177	625	1011	954	0.30	1589	0.60	0.66	0.65	1.01	Over-fished
Clupea pallasii	0.54	203	11	27	19	0.10	101	0.19	0.59	0.27	5.64	Collapsed

r, maximum intrinsic rate of population increase; k, the environmental carrying capacity; t, metric tons; C_{2019}, catch in 2019; MSY, maximum sustainable yield; B_{2019}, biomass in 2019; B_{msy}, the biomass capable of producing maximum sustainable yield; F_{2019}, fishing mortality in 2019; F_{msy}, the mortality capable of producing maximum sustainable yield;[1] referred from Palomares et al. (2018); slightly overfished, 0.8 < B_{2019}/B_{msy} < 1.0; overfished, 0.5 < B_{2019}/B_{msy} < 0.8; grossly overfished, 0.2 < B_{2019}/B_{msy} < 0.5; collapsed, B_{2019}/B_{msy} < 0.2.

two plankton feeders *T. modestus* and *C. pallasii* were different from other species. Under the scenario of 0.95 F_{msy} by 2030, the biomass of both species will likely be degenerating instead of recovering (**Table 3** and **Figure 3B**).

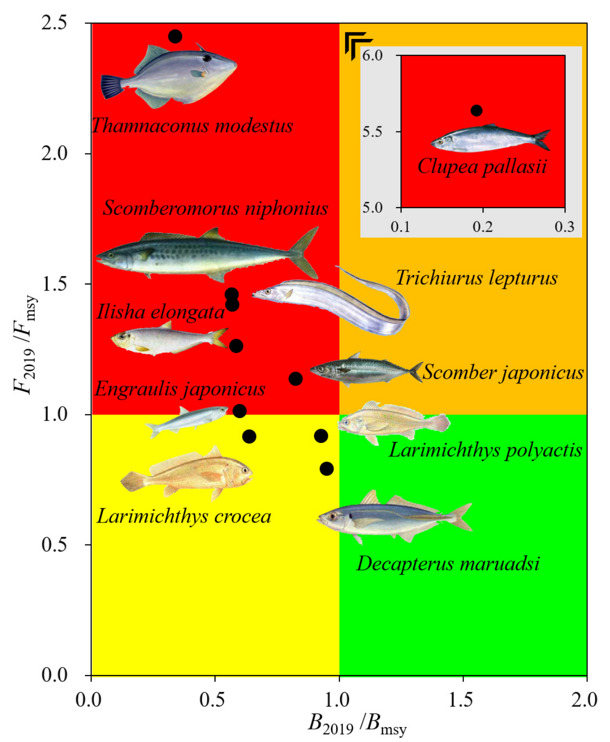


FIGURE 2 | Fishing pressure Kobe plot for the fishes in 2019 based on current exploitation status (B_{2019}/B_{msy}) and remaining level of exploitation (F_{2019}/F_{msy}). The red area indicates the worst conditions of overexploited stocks under overfishing; the yellow area indicates recovering of overexploited stocks from reduced fishing pressure; the green area indicates a healthy stock size with sustainable fishing pressure; and the brown area indicates healthy stock sizes but facing overfishing.

DISCUSSION

Model Fitting

The China Fishery Statistical Yearbook serves as a record of the overall capture of the national fishery but contains only catch data that can be used for resource assessment. As an assessment approach relies on less input, CMSY has been proved to have a good evaluation effect, and its estimated parameters can match well with Schaefer, Fox, and BSM models (Ji et al., 2019; Angelini et al., 2021). In this study, the *r-k* pairs predicted by CMSY were found to be compatible with the catches and the prior information, with the most likely *r-k* pair and confidence limits in the range of the priors. The equilibrium curve predicted by CMSY also showed good fitting with the Schaefer equilibrium curve (**Supplementary Figure 1**). In addition, a common misconception of Bayesian analyses is that the priors determine the results. The comparison of prior and posterior densities showed the PPVR were very low (**Supplementary Figure 2**); the lower the PPVR, the more the posterior knowledge is improved relative to prior knowledge, indicating the good performance of CMSY constructed in this study.

Historical Exploitation Dynamics of Species

Except *L. crocea* and *L. polyactis*, the fisheries of the other eight fish species were all good, and the catches were low before the 1990s. Then, the catches increased rapidly, and the stocks continued to decline. The total power of domestic marine fishing vessels had increased by 2 × 10^6 kW from the 1950s to 1980s and continued to increase rapidly by about 12 × 10^6 kW in the following 20 years, which led to the continuous increase in the total catch but decline in CPUE (Ministry of Agriculture of China, 1956–2019). This was the key factor accounting for most fisheries declination since the 1990s in Chinese coastal waters. CMSY indicated that although these eight species showed similar dynamic changes in biomass and catches, benthopelagic species *T. lepturus* and *T. modestus* experienced a sharp increase

TABLE 3 | The predicted fishery biomasses and catch recoveries in 2030 under four exploitation scenarios (i.e., F = 0.5, F_{msy}, 0.6 F_{msy}, 0.8 F_{msy}, and 0.95 F_{msy}).

Species	Scenarios							
	B_{2030}/B_{msy}				C_{2030}/MSY			
	0.5	0.6	0.8	0.95	0.5	0.6	0.8	0.95
Trichiurus lepturus	1.48	1.33	1.11	0.76	0.76	0.82	0.92	0.76
Larimichthys crocea	1.18	1.09	0.96	0.85	0.60	0.67	0.79	0.82
Larimichthys polyactis	1.50	1.40	1.20	1.06	0.77	0.86	0.99	1.02
Thamnaconus modestus	1.23	0.94	0.76	0.24	0.64	0.59	0.63	0.25
Scomberomorus niphonius	1.40	1.23	1.03	0.73	0.72	0.76	0.85	0.73
Ilisha elongata	1.49	1.37	1.16	0.85	0.75	0.83	0.94	0.82
Decapterus maruadsi	1.52	1.42	1.22	1.07	0.78	0.87	1.00	1.04
Scomber japonicus	1.47	1.38	1.18	1.04	0.75	0.85	0.97	1.02
Engraulis japonicus	1.50	1.40	1.20	1.05	0.77	0.86	0.98	1.02
Clupea pallasii	0.79	0.52	0.42	0.06	0.39	0.30	0.30	0.06

B_{2030}, biomass in 2030; B_{msy}, biomass capable of producing maximum sustainable yield; C_{2030}, catch in 2030; MSY, the maximum sustainable yield.

in fishing pressure about 10 years earlier than pelagic species *S. niphonius*, *I. elongata*, *D. maruadsi*, *S. japonicus*, *E. japonicus*, and *C. pallasii*. This was most possibly correlated with when bottom trawling, gill netting, and seine netting were widely used in coastal waters of China. Bottom trawling catches demersal organisms, while seine nets and gill nets mainly catch pelagic fish. In 1985, the domestic catch of trawls was only 1.39×10^6 metric tons, but it had increased 2.86 times to 5.36×10^6 metric tons by 1995. During the same period, the catches of seine nets and gill nets only increased from 0.96×10^6 to 1.82×10^6 metric tons (Ministry of Agriculture of China, 1985–1995). The wide use of bottom trawls seriously damaged seabed habitats and diminished benthic fish populations such as *T. lepturus* and *T. modestus* (McConnaughey et al., 2019). Then, from 1995 to 2005, the total catch of seine nets and gill nets increased continuously from 1.82×10^6 to 3.35×10^6 metric tons (Ministry of Agriculture of China, 1995–2005), and the spreading use of seine nets and gill nets correlated with the decline of the pelagic fish stocks.

Traditional economic species, large yellow croaker *L. crocea* and small yellow croaker *L. polyactis*, were caught by non-mechanical boats before the 1950s (Zhuang, 2006). For example, the relative biomass *L. polyactis* in the first documented year (B_{1956}/B_{msy} = 0.34) had already exceeded the safe biological limit (B/B_{msy} = 0.5, Demirel et al., 2020; Froese et al., 2018). This status lasted until the implementation of summer fishing banning in the 1990s. *L. polyactis* spawns from February to April (Lin, 2009). Summer fishing banning (May to August) ensures the survival of juveniles from commercial catches, which effectively support population supplement and stock restoration. In the East China Sea, yields of this fish increased significantly after the 1990s and peaking at 160×10^3 metric tons in 2000 (Zhuang, 2006). However, its population structure did not improve in the short term. According to the field survey data, the minimum length of maturity (L_{50}) of this species changed from 152.8 mm in 1960 to 105.3 mm in 2003 in the Bohai Sea and 184.4 mm in 1960 to 110.1 mm in 2010 in the Yellow Sea (Li et al., 2011). With increasing fishing pressure in recent years, the biomass of *L. polyactis* has gradually declined again due to its fragile population structure. For *L. crocea*, large-scale fishing operations such as a knock on the boats (by knocking the bamboo pole on the wooden boats, to send out a huge sound wave into the sea, causing otolith resonance of *L. crocea*, and resulting in its coma and death) were carried out in their spawning grounds and feeding grounds before the mid-1960s, which diminished its stocks in Zhoushan fishing ground, Zhenan fishing ground, and Mindong fishing ground (Zhang Q. et al., 2017). Then, in the mid-1970s, a large number of *L. crocea* were captured in the overwintering grounds such as Jiangwai fishing ground and Zhouwai fishing ground, and the catch reached the highest record in history, which also caused the serious depletion of its population (Zheng et al., 2013). As an important measure to restore its fishery, Fujian Province carried out the first artificial propagation and releasing with an average total length of 93.1 mm in 1987 combined with the implementation of the fishing banning in the 1990s, which facilitated its gradual stock recovery (Zhang et al., 2010). However, the age structure of the *L. crocea* population is complex, and the maximum age is up to 30 years. In addition, the slow growth and weak stock renewal ability are the main reasons for its slow fishery recovery (Zhuang, 2006; Zheng et al., 2013).

Fisheries Current Exploitation Status

In 2019, all the species were strongly depleted in biomass ($B_{2019} < B_{msy}$) due to overfishing. Except for *L. crocea*, *L. polyactis*, and *D. maruadsi*, the others were still under higher fishing mortality ($F_{2019} > F_{msy}$), which possibly lead to a further decline in stocks. This corroborates the results proposed in other regional stock assessments or fishery surveys in coastal waters of China (Zhang K. et al., 2017; Zhang C. et al., 2019; Liang and Pauly, 2020). For example, Zhai and Pauly (2019) and Zhai et al. (2020) proposed that *S. niphonius* was grossly overfished (B_{2013}/B_{msy} = 0.48) in the East China Sea in 2013, and *L. polyactis* and *E. japonicus* were grossly overfished (B_{2018}/B_{msy} = 0.42) and overfished (B_{2018}/B_{msy} = 0.71) in 2018, respectively. In the coastal waters of China, the status for the *D. maruadsi* and *S. japonicus* was evaluated as slightly overfished (B_{2014}/B_{msy} = 0.83) and overfished (B_{2017}/B_{msy} = 0.70) in 2014 and 2017, respectively (Liang et al., 2020). While it may be due to differences in the conducted time and sea area that cause B/B_{msy} and F/F_{msy} in these studies to differ slightly from our results, it does not change the indisputable fact that overfishing has contributed to the

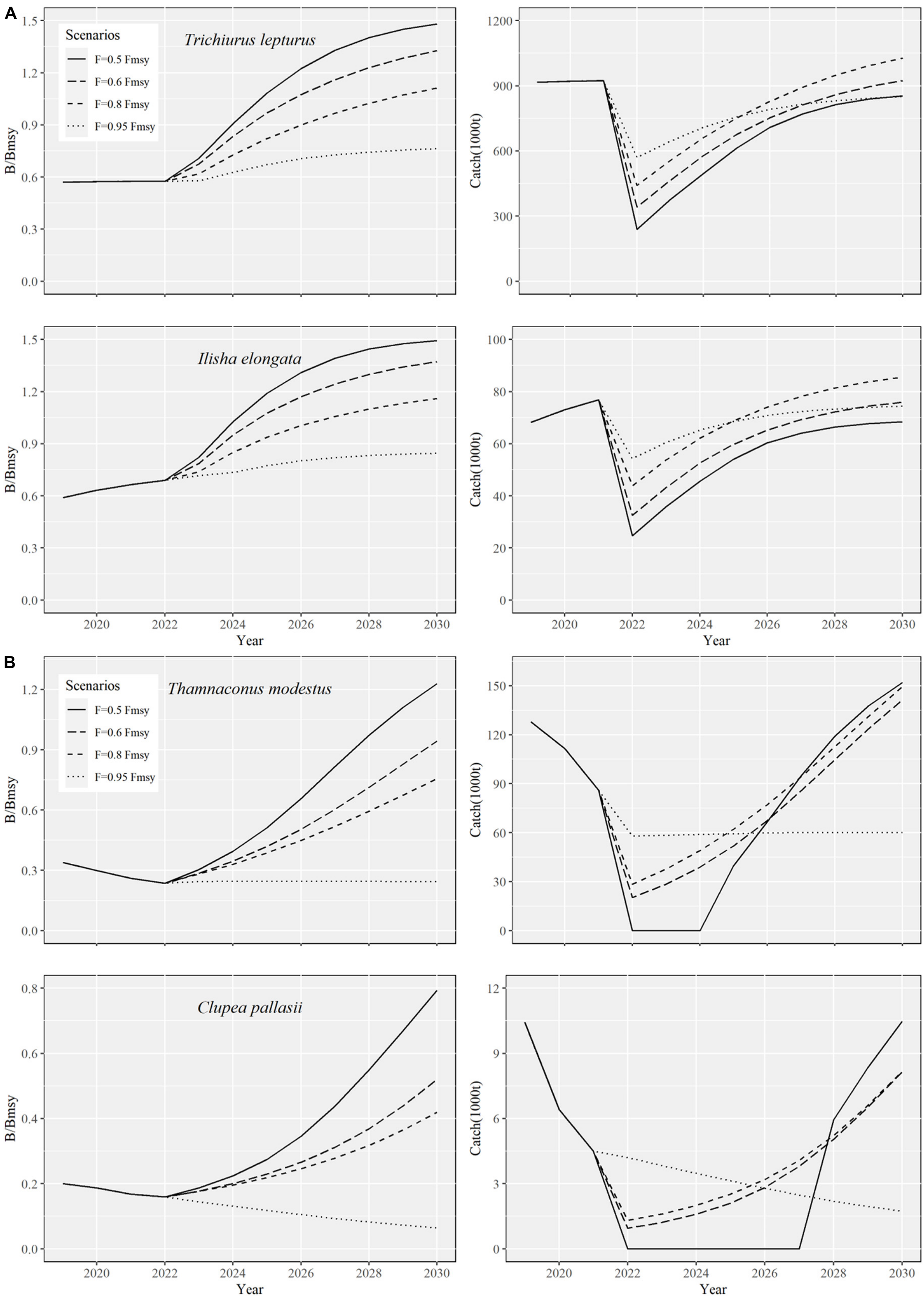


FIGURE 3 | The predicted stock recoveries under four exploitation scenarios (2020–2030), i.e., fishing mortality equals 0.5, 0.6, 0.8, or 0.95 times mortality capable of producing maximum sustainable yields (0.5 F_{msy}, 0.6 F_{msy}, 0.8 F_{msy}, or 0.95 F_{msy}). The left panels show the recovery trends of the relative biomasses, i.e., ratios of biomass to the biomass capable of producing maximum sustainable yields (B/B_{msy}); the right panels show the predicted catch trajectories under the different scenarios. **(A)** *T. lepturus* and *I. elongata* were selected to show the fishery rebuilding trajectories and catch changes; **(B)** *T. modestus* and *C. pallasii* will likely be degenerating under the scenario of 0.95.

decline of fishery resources in the coastal waters of China. In addition, in the Bohai Sea, *T. lepturus*, *C. pallasii,* and *I. elongate* had been locally extinct in 2011 (Shan et al., 2013). At the same time, the high-trophic species *T. modestus* exhibited an obvious decreasing trend in the northern East China Sea and suffered a significant resources decline since 2000 (Cheng and Yu, 2004). Based on fishery survey in Fujian Province in 2011, the dominant body length of *L. crocea* was 110–150 mm (L_{∞} = 385 mm), and the exploitation rate was 0.8, suggested the obvious individual miniaturized and serious resource decline (Ye et al., 2012).

Fisheries Rebuilding and Managements

Excessive exploitation had resulted in both declinations of marine catches and economic values simultaneously of Chinese coastal fisheries (Zhai and Pauly, 2019). Therefore, not only could the rebuilding of fishery stocks improve the structures and functions of the ecosystems but also help to increase catches and fishery profitability. Under the four future exploitation scenarios (F = 0.5 F_{msy}, 0.6 F_{msy}, 0.8 F_{msy}, and 0.95 F_{msy}), scenario 0.5 F_{msy} was the fastest way. All fish species except *C. pallasii* had likely reached B_{msy} in 2030 ($B_{2030} > B_{\text{msy}}$). On the other hand, scenario 0.95 F_{msy} was the slowest way, and only four fish species, including *L. polyactis*, *D. maruadsi*, *S. japonicus,* and *E. japonicus*, could likely recover to the B_{msy} by 2030. Although the species recovery on biomass at 0.8 F_{msy} and 0.95 F_{msy} was slower, it would increase the catches compared with 0.5 F_{msy} and 0.6 F_{msy} (**Supplementary Figure 5**). The fishery rebuilding can be adjusted flexibly according to management objectives. For example, if 2030 is taken as the cut-off year for fish stocks to be rebuilt above that can produce the maximum sustainable yield ($B > B_{\text{msy}}$), *T. lepturus*, *S. niphonius*, and *I. elongate* can choose 0.8 F_{msy} exploitation scenario; *L. polyactis*, *D. maruadsi*, and *E. japonicus* can be 0.95 F_{msy}; *L. crocea* can be 0.6 F_{msy}; *T. modestus* and *C. pallasii* can be 0.5 F_{msy}.

The time needed for rebuilding their fisheries to the level of B_{msy} is different. According to Equations (10, 11), the fisheries biomass in the next year (B_{t+1}) is mainly related to the current biomass (B_t), the fishing pressure that could produce *MSY* (F_{msy}), and the current fishing pressure (F_t). Under future exploitation scenarios, F_t has a linear relationship with F_{msy} (i.e., F_t = 0.5 F_{msy}, 0.6 F_{msy}, 0.8 F_{msy}, and 0.95 F_{msy}), so B_{t+1}/B_{msy} is only related with B_t/B_{msy} and F_{msy}. As Equation (8) shows, F_{msy} is twice as much as the maximum intrinsic rate of population increase (r); thus, the different recovery rates among ten stocks are related to the biomass status in the initial year (B_{2019}) and species-specific r. For example, the less damage to the B_{2019}, the better the recovery of the B_{2030} (as illustrated by *L. polyactis* vs. *S. niphonius*), and the bigger the r, the faster the stock's recovery (as illustrated by *T. lepturus* vs. *S. niphonius*). According to Equation (1), many factors affect r, such as von-Bertalanffy somatic growth rate (K), reproductive strategy (r-k selection), generation time (t_{gen}), and maximum age ($t_{\max}$). Species with higher r such as *D. maruadsi* (r = 1.11) and *E. japonicus* (r = 1.29) both mature early and have a short generation time ($t_{\text{gen}} < 1.25$ year) to double population size (FishBase, see text footnote 1), while the stock of *L. crocea* with the smallest r has a more complex population structure and bigger $t_{\max}$ ($t_{\max}$ = 30 years, Zheng et al., 2013; Zhuang, 2006).

The cases of *T. modestus* and *C. pallasii* deserved cautious attention and alert vigilance. Our fisheries rebuilding results implied that fish with severe biomass depletion might recover more slowly. Moreover, these stocks even further declined under 0.95 F_{msy} scenario. Many managers take $F = F_{\text{msy}}$ as the best fishing pressure for fisheries exploitation and rebuilding (Demirel et al., 2020), but our results demonstrated that this fishing level did not have any positive effect on fisheries rebuilding for *T. modestus* and *C. pallasii*. The relative biomass of *T. modestus* and *C. pallasii* in 2019 (B_{2019}/B_{msy}) both exceeded the safe biological limits (B/B_{msy} = 0.5), suggesting the stocks were on the edge of collapse (B/k = 0.17 and 0.10, respectively, Palomares et al., 2018). Fish species with serious biomass depletion were also deficient in population recruitment capacity (Myers et al., 1994). In addition, the lower population r of *T. modestus* (0.65) and *C. pallasii* (0.54) would further degrade the fisheries recovery rate.

To ease the decline of fishery resources, China has introduced several fishery policies, such as the "Dual Control" policy proposed in 1987 to control the number and power of fishing vessels, the "Proliferation and Release" of commercial fishes proposed in 1989, the "Summer Fishing Banning" proposed in 1995, the "Zero-Growth" in fishery catches proposed in 2000, the construction of "Marine Conservation Areas" in 2011, and the development of "Marine Ranching" in 2015 (Han, 2018). Some of these policies have shown good results, such as the policy of "Proliferation and Release" (Zhang et al., 2010) and "Summer Fishing Banning" (Cheng et al., 2004; Jiang et al., 2009; He et al., 2019), which have played an active role in the resource conservation of the *L. crocea* and *L. polyactis*, respectively, and the relevant events were also reflected in the results of this article. Thus, this feasible measure should be continued. In addition, policies such as "Total Resource Management" and "Quota Catch Management" were also proposed in 2017 (Han, 2018); the fishery reference points such as MSY estimated in this study could provide a reference for them. However, the results of this article showed that China's fishery resources were declined ($B < B_{\text{msy}}$), and most of them were still facing high fishing pressure ($F > F_{\text{msy}}$), which was mainly caused by the current high fishing intensity (**Supplementary Table 1**). Our results indicated that cutting fishing efforts down (e.g., strict implementation of policies such as "Dual Control" and "Zero-Growth") was probably the most effective way for fishery sustainability. We have to admit that this measure would probably be a hard decision as a trade-off between economics and conservation, but the fisheries structure will benefit from this, and finally, the catches will be enhanced. Moreover, gears selection must be taken into serious considerations to avoid the capture of juvenile fishes before sexual maturity (Wang et al., 2020).

CONCLUSION

General pictures of the basic situation of these economic fishes in China's coastal waters provide reference information to fisheries management. CMSY indicates a decreasing trend in biomass along with the explosively increasing fishing efforts since the 1980s–1990s for most species. All the fish stocks have seriously depleted in 2019 ($B_{2019} < B_{msy}$), and most were still facing high-fishing pressure ($F_{2019} > F_{msy}$). Corresponding protection measures should be taken into immediate action to rebuild the fisheries. Otherwise, the fish stocks would further decline and their recoveries would be much more difficult. Most species stocks would likely rebuild to B_{msy} level, and the more the fishing pressure is reduced, the faster the fisheries will be recovered. Although there would be several years of reduction in catches during the rebuilding process, the recovered fisheries would bring more production and economic and social benefits.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author.

ETHICS STATEMENT

The animal study was reviewed and approved by Animal Care and Ethics Committee of the Ocean University of China.

AUTHOR CONTRIBUTIONS

LW contributed to conceptualization, methodology, investigation, resources, writing – original draft, and writing – review and editing. LL, YL, and LZ contributed to data curation and investigation. SY contributed to supervision, project administration, conceptualization, methodology, resources, and writing – review and editing. All authors contributed to the article and approved the submitted version.

FUNDING

This study was supported by the National Natural Science Foundation of China (Grant No. 41976091) and Fundamental Research Funds for the Central Universities (Grant No. 202012023). National Key Research and Development Program of China (Grant No. 2020YFD0900805) and Investigation of Fishery Resources Program of Zhejiang (Grant No.158053).

ACKNOWLEDGMENTS

The authors thank Rainer Froese for his help with R code regarding fishery rebuilding.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2021.757503/full#supplementary-material

REFERENCES

Angelini, S., Armelloni, E. N., Costantini, I., De Felice, A., Isajlović, I., Leonori, I., et al. (2021). Understanding the Dynamics of Ancillary Pelagic Species in the Adriatic Sea. *Front. Mar. Sci.* 8:728948. doi: 10.3389/fmars.2021.728948

Arai, T. (2015). Diversity and conservation of coral reef fishes in the Malaysian South China Sea. *Rev. Fish. Biol. Fisher.* 25, 85–101. doi: 10.1007/s11160-014-9371-9

Cao, L., Naylor, R., Henriksson, P., Leadbitter, D., Metian, M., Troell, M., et al. (2015). China's aquaculture and the world's wild fisheries. *Science* 347, 133–135. doi: 10.1126/science.1260149

Cheng, J. H., Lin, L. S., Ling, J. Z., Li, J. S., and Ding, F. Y. (2004). Effects of summer close season and rational utilization on redlip croaker (*Larimichthys polyactis* Bleeker) resource in the East China Sea Region. *J. Fish. Sci. China* 11, 554–560.

Cheng, J. S., and Yu, L. F. (2004). The change of structure and diversity of demersal fish communities in the Yellow Sea and East China Sea in winter. *J. Fish. China* 1, 29–35.

Cheng, Y. H., and Fan, W. (2001). Study of time-serial analysis of marine capture yield in the East China Sea region. *J. Fish. Sci. China* 8, 31–34.

Costello, C., Ovando, D., Hilborn, R., Gaines, S. D., Deschenes, O., and Lester, S. E. (2012). Status and solutions for the world's unassessed fisheries. *Science* 338, 517–520. doi: 10.1126/science.1223389

Demirel, N., Zengin, M., and Ulman, A. (2020). First large-scale Eastern Mediterranean and Black Sea stock assessment reveals a dramatic decline. *Front. Mar. Sci.* 7:103. doi: 10.3389/fmars.2020.00103

FAO (2016). *Fishery and Aquaculture Statistics*. Rome: Food and Agriculture Organization of the United Nation.

Free, C. M., Jensen, O. P., Anderson, S. C., Gutierrez, N. L., Kleisner, K. M., Longo, C., et al. (2020). Blood from a stone: performance of catch-only methods in estimating stock biomass status. *Fish. Res.* 223:105452. doi: 10.1016/j.fishres.2019.105452

Froese, R., Demirel, N., Coro, G., Kleisner, K. M., and Winker, H. (2017). Estimating fisheries reference points from catch and resilience. *Fish Fish.* 18, 506–526. doi: 10.1111/faf.12190

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2018). Status and rebuilding of European fisheries. *Mar. Policy* 93, 159–170. doi: 10.1016/j.marpol.2018.04.018

Han, Y. (2018). Marine Fishery Resources Management and Policy Adjustment in China Since 1949. *Chin. Rural Econ.* 9, 14–28.

He, X., Li, J., Shen, C., Shi, Y., Feng, C., Guo, J., et al. (2019). Length-weight relationship and population dynamics of Bombay duck (*Harpadon nehereus*) in the Min River Estuary, East China Sea. *Thalassas* 35, 253–261. doi: 10.1007/s41208-018-0117-7

Ji, Y. P., Liu, Q., Liao, B. C., Zhang, Q. Q., and Han, Y. N. (2019). Estimating biological reference points for largehead hairtail (*Trichiurus lepturus*) fishery in the Yellow Sea and Bohai Sea. *Acta Oceanol. Sin.* 38, 20–26. doi: 10.1016/j.fishres.2011.05.007

Jiang, Y. Z., Cheng, J. H., and Li, S. F. (2009). Temporal changes in the fish community resulting from a summer fishing moratorium in the northern East China Sea. *Mar. Ecol. Prog. Ser.* 387, 265–273. doi: 10.3354/meps08078

Li, Z., Shan, X., Jin, X., and Dai, F. (2011). Long-term variations in body length and age at maturity of the small yellow croaker (*Larimichthys polyactis* Bleeker, 1877) in the Bohai Sea and the Yellow Sea. *China. Fish. Res.* 110, 67–74. doi: 10.1016/j.fishres.2011.03.013

Liang, C., and Pauly, D. (2017). Growth and mortality of exploited fishes in China's coastal seas and their uses for yield-per-recruit analyses. *J. Appl. Ichthyol.* 33, 746–756. doi: 10.1111/jai.13379

Liang, C., and Pauly, D. (2020). Masking and unmasking fishing down effects: the Bohai Sea (China) as a case study. *Ocean Coast. Manag.* 184:105033. doi: 10.1016/j.ocecoaman.2019.105033

Liang, C., Xian, W., and Pauly, D. (2020). Assessments of 15 Exploited Fish Stocks in Chinese, South Korean and Japanese Waters Using the CMSY and BSM Methods. *Front. Mar. Sci.* 7:623. doi: 10.3389/fmars.2020.00623

Lin, L. S. (2009). *Study on the Fishery Biology and Management Strategy of Larimichthys polyactis in the Southern Yellow Sea and the East China Sea*. Ph.D thesis, Qingdao: Ocean University of China.

Ling, J. Z., Li, S. F., and Yan, L. P. (2006). Analysis on the utilization of main fishery resources in the East China Sea. *Mar. Fish* 28, 111–116.

Link, J. S., and Watson, R. A. (2019). Global ecosystem overfishing: clear delineation within real limits to production. *Sci. Adv.* 5:eaav0474. doi: 10.1126/sciadv.aav0474

Liu, M., and De Mitcheson, Y. S. (2008). Profile of a fishery collapse: why mariculture failed to save the large yellow croaker. *Fish Fish.* 9, 219–242. doi: 10.1111/j.1467-2979.2008.00278.x

Martell, S., and Froese, R. (2013). A simple method for estimating MSY from catch and resilience. *Fish Fish.* 14, 504–514. doi: 10.1111/j.1467-2979.2012.00485.x

McConnaughey, R. A., Hiddink, J. G., Jennings, S., Pitcher, C. R., Kaiser, M. J., Suuronen, P., et al. (2019). Choosing best practices for managing impacts of trawl fishing on seabed habitats and biota. *Fish Fish.* 21, 319–337. doi: 10.1111/faf.12431

Ministry of Agriculture of China (1956–2019). *China Fishery Statistical Yearbook*. Beijing: China Agriculture Press.

Myers, R. A., Rosenberg, A. A., Mace, P. M., Barrowman, N., and Restrepo, V. R. (1994). In search of thresholds for recruitment overfishing. *ICES. J. Mar. Sci.* 51, 191–205. doi: 10.1006/jmsc.1994.1020

Palomares, M. L. D., Froese, R., Derrick, B., Noel, S. L., Tsui, G., Woroniak, J., et al. (2018). *A Preliminary Global Assessment of the Status of Exploited Marine Fish and Invertebrate Populations*. Vancouver: Sea Around Us.

Quinn, T. J., and Deriso, R. B. (1999). *Quantitative Fish Dynamics*. New York, NY: Oxford University Press.

R Development Core Team (2020). *R: A Language and Environment for Statistical Computing*. Austria: R Development Core Team.

Ricard, D., Minto, C., Jensen, O. P., and Baum, J. K. (2012). Examining the knowledge base and status of commercially exploited marine species with the RAM Legacy Stock Assessment Database. *Fish Fish.* 13, 380–398. doi: 10.1111/j.1467-2979.2011.00435.x

Ricker, W. E. (1975). Computation and Interpretation of Biological Statistics of fish Populations. *Bull. Fish. Res. Bd Can.* 191:382.

Schaefer, M. B. (1954). Some aspects of the dynamics of populations important to the management of the commercial marine fisheries. *Inter. Am. Trop. Tuna Commission Bull.* 1, 27–56.

Shan, X., Jin, X., Zhou, Z., and Dai, F. (2011). Fish community diversity in the middle continental shelf of the East China Sea. *Chin. J. Oceanol. Limn.* 29, 1199–1208. doi: 10.1007/s00343-011-0321-2

Shan, X., Sun, P., Jin, X., Li, X., and Dai, F. (2013). Long-term changes in fish assemblage structure in the Yellow River Estuary ecosystem. *China. Mar. Coast. Fish.* 5, 65–78. doi: 10.1080/19425120.2013.768571

Wang, L., Lin, L., Li, Y., Xing, Y., and Kang, B. (2020). Sustainable exploitation of dominant fishes in the largest estuary in Southeastern China. *Water* 12:3390. doi: 10.3390/w12123390

Wang, Q., Zhang, J., Matsumoto, H., Kim, J., and Li, C. (2016). Population structure of elongate ilisha Ilisha elongata along the Northwestern Pacific Coast revealed by mitochondrial control region sequences. *Fish. Sci.* 82, 771–785. doi: 10.1007/s12562-016-1018-4

Wang, X. H., Qiu, Y. S., and Du, F. Y. (2004). Estimation of growth and mortality parrameters of Chinese herring (*Ilisha elongata*) in Zhujiang River estuary. *J. Trop. Oceanogr.* 23, 42–48.

Ye, J. Q., Xu, Z. L., Chen, J. J., and Kang, W. (2012). Resources status analysis of large yellow croaker in Guanjinyang using von Bertalanffy growth equation and fishing mortality parameters. *J. Fish. China* 36, 238–246. doi: 10.3724/SP.J.1231.2012.27640

Zhai, L., Liang, C., and Pauly, D. (2020). Assessments of 16 Exploited Fish Stocks in Chinese Waters Using the CMSY and BSM Methods. *Front. Mar. Sci.* 7:483993. doi: 10.3389/fmars.2020.483993

Zhai, L., and Pauly, D. (2019). Yield-per-recruit, utility-per-recruit, and relative biomass of 21 exploited fish species in China's coastal seas. *Front. Mar. Sci.* 6:724. doi: 10.3389/fmars.2019.00724

Zhang, C., Seo, Y., Kang, H., and Lim, J. (2019). Exploitable carrying capacity and potential biomass yield of sectors in the East China Sea, Yellow Sea, and East Sea/Sea of Japan large marine ecosystems. *Deep Sea Res. Part II.* 163, 16–28. doi: 10.1016/j.dsr2.2018.11.016

Zhang, K., Liao, B. C., Xu, Y. W., Zhang, J., Sun, M. S., Qiu, Y. S., et al. (2017). Assessment for allowable catch of fishery resources in the South China Sea based on statistical data. *Acta Oceanol. Sin.* 39, 25–33. doi: 10.3969/j.issn.0253-4193

Zhang, Q., Hong, W., and Chen, S. (2017). Stock changes and resource protection of the large yellow croaker (*Larimichthys crocea*) and ribbon fish (*Trichiurus Japonicus*) in coastal waters of China. *J. Appl. Oceanogr.* 36, 438–445.

Zhang, Q., Hong, W., Yang, S., and Liu, M. (2010). Review and prospects in the restocking of the large yellow croaker (*Larimichthys crocea*). *Mod. Fish. Inf.* 25, 3–5.

Zhang, W., Liu, M., De Mitcheson, S. Y., Cao, L., Leadbitter, D., Newton, R., et al. (2019). Fishing for feed in China: facts, impacts and implications. *Fish Fish.* 21, 47–62. doi: 10.1111/faf.12414

Zheng, Y., Hong, W., and Zhang, Q. (2013). Review and prospects for resource biology of main marine demersal food fishes along the coastal waters of China. *J. Fish. China* 37, 151–160. doi: 10.3724/SP.J.1231

Zhuang, P. (2006). *Fish in the Yangtze River Estuary*. Shanghai: Shanghai Scientific & Technical Publishers.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 08 February 2022
doi: 10.3389/fmars.2022.759591

Assessing the Distribution and Sustainable Exploitation of *Lophius litulon* in Marine Areas Off Shandong, China

Zhaopeng Zhang[1,2,3†], *Yuanchao Wang*[1,2,3†], *Shude Liu*[4], *Cui Liang*[1,2,5,6*] and *Weiwei Xian*[1,2,3,5,6*]

[1] Key Laboratory of Marine Ecology and Environmental Sciences, Institute of Oceanology, Chinese Academy of Sciences, Qingdao, China, [2] Laboratory for Marine Ecology and Environmental Science, Qingdao National Laboratory for Marine Science and Technology, Qingdao, China, [3] University of Chinese Academy of Sciences, Beijing, China, [4] Shandong Fisheries Development and Resources Conservation Center, Yantai, China, [5] Center for Ocean Mega-Science, Chinese Academy of Sciences, Qingdao, China, [6] CAS Engineering Laboratory for Marine Ranching, Institute of Oceanology, Chinese Academy of Sciences, Qingdao, China

OPEN ACCESS

Edited by:
Giuseppe Scarcella,
National Research Council (CNR), Italy

Reviewed by:
Fabio Fiorentino,
Institute for Biological Resources and Marine Biotechnology, National Research Council (CNR), Italy
Bin Xia,
Qingdao Agricultural University, China

***Correspondence:**
Cui Liang
liangc@qdio.ac.cn
Weiwei Xian
wwxian@qdio.ac.cn

† These authors have contributed equally to this work and share first authorship

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: 16 August 2021
Accepted: 03 January 2022
Published: 08 February 2022

Citation:
Zhang Z, Wang Y, Liu S, Liang C and Xian W (2022) Assessing the Distribution and Sustainable Exploitation of Lophius litulon in Marine Areas Off Shandong, China. Front. Mar. Sci. 9:759591. doi: 10.3389/fmars.2022.759591

In recent years, the proportion and economic value of *Lophius litulon* (family Lophiidae) in the coastal fishery off Shandong Province, China has increased. In this study, we mapped the distribution of *L. litulon* abundance [catch per unit effort (CPUE)] and applied a generalized additive model (GAM) to explore the relationship between CPUE and environmental factors. Two data-limited methods (the BSM related to the CMSY method and the AMSY method) were used to evaluate the stock status and relevant fishery reference points of *L. litulon*. The results showed that the *L. litulon* stock was concentrated in the central Yellow Sea, at 34.0°–37.0° N and 121.0°–124.0° E, and the highest average CPUE of *L. litulon* in this area occurred in winter. The three most significant environmental factors affecting species abundance were bottom temperature, bottom salinity, and depth. *L. litulon* was most abundant when bottom temperature ranged from 5.8 to 10.6°C, depth was > 18 m, and bottom salinity varied from 31.0 to 33.2‰. The BSM and AMSY models indicated that the *L. litulon* stock was unhealthy and had been overfished in recent years, as its biomass remained below the level that can support maximum sustainable yield. The relative exploitation ratios were also high. These results provide the basic data for improving sustainability of the exploitation of *L. litulon* in the Yellow and Bohai Seas.

Keywords: ***Lophius litulon*, spatial-temporal distribution, stock assessment, data-limited methods, BSM, AMSY**

INTRODUCTION

Marine fishery resources face a variety of threats globally, which has roused international concern (Ricard et al., 2012). Multiple stresses, such as overfishing, global warming, and pollution have changed the structure of fishery resources and caused a decline in catch quantity and quality (Watson et al., 2013; Costello et al., 2016). Currently, approximately 34.2% of fish stocks are caught at unsustainable levels (FAO, 2020). China has been one of the largest national fisheries in the world since 1989 and has witnessed a decline in its coastal fishery resources (Wang et al., 2006; Zhang and Qiu, 2019).

Shandong Province, adjacent to the Yellow Sea and Bohai Sea, is one of the major fishing provinces in China. Shandong coastal waters are the most productive areas for fishing, as they are spawning and feeding grounds for a variety of commercial fish. The fishing boats in Shandong coastal waters are mainly from Shandong province, but also from Liaoning, Jiangsu, Hebei Province, and Tianjin city. According to the *2010–2020 China Fishery Statistical Yearbook*, the number of domestic offshore fishing vessels in Shandong Province in 2020 decreased by 8.4% compared with 2019, and by 23.8% compared with 2010, indicating a continuous decline (Fisheries and Fisheries Administration, 2010, 2019, 2020). The marine fishery yield of Shandong Province mainly comes from the Yellow Sea and Bohai Sea, which provides more than 80% of the total catch, with the remainder mainly from the East China Sea. In the past few decades, Shandong Province has benefited substantially from marine fishery development, at the cost of resources and environmental deterioration (Chen, 1991). Pollution in coastal waters, excessive fishing intensity, and a decline in food resources have reduced catches of high value species, such as *Trichiurus lepturus* (Zou et al., 2019). Species with traditionally less economic value comprise as much as 60%–70% of the current catch, thus lowering the overall fishing benefit (Huang, 2012). In this context, changes in the distribution and resource status of marine organisms require urgent study to ensure current exploitation are sustainable.

Lophius litulon (family Lophiidae) is a demersal marine fish that is distributed in the northwestern Pacific constituting an important part of the catches of neighboring countries. Ji et al. (2007) showed that there was no significant difference in genetic structure between two geographical populations of *L. litulon* in the Yellow Sea and the Sea of Japan. Li X. et al. (2021) showed that *L. litulon* was the dominant species among 134 captured fish in the Shandong coastal waters. Furthermore, in waters off southwestern Korea, *L. litulon* was the dominant species, accounting for more than 60% of the total catch, together with *Pampus echinogaster*, *Trichiurus lepturus*, *Engraulis japonicus*, and *Larimichthys polyactis* (Kim et al., 2007). With the decline of traditional commercial fish resources, *L. litulon*, whose economic value has increased in recent years, has become a common species in China's domestic fish market and one of the main fish products exported abroad in recent years. Most previous studies on *L. litulon* have focused on its biological characteristics (Xu et al., 2010; Zhang et al., 2011), feeding habits (Xue et al., 2007), and migratory distribution (Michiol et al., 2002). Assessments of resource status and the influence of environmental factors are scarce. Although China has adopted a series of policies to protect coastal fisheries, the *L. litulon* population in the Yellow Sea is thought to have a simpler age structure and smaller body size (Li et al., 2012). Sustainable exploitation of *L. litulon* is required.

The assessment of fishery resources can be used as a scientific basis for fishery management, but few assessments of the *L. litulon* stock in the Yellow Sea have been conducted due to the lack of data (Wang et al., 2020). In recent years, three computer-intensive methods, the Monte Carlo method CMSY (catch-maximum sustainable yield), the related Bayesian Schaefer model (BSM), and the abundance maximum sustainable yield (AMSY) have been proposed to evaluate stocks and related reference points of fishery resources in data-poor situations (Froese et al., 2017, 2020). In particular, CMSY uses only a time series of catches and ancillary qualitative information to quantify the stock status and related fisheries reference points. In cases where relative abundance data [i.e., catch per unit effort; CPUE] are available in addition to catch data, the BSM method can be used to combine information from both datasets. AMSY is the most recent method for assessing fish populations based on abundance (CPUE) time series (Froese et al., 2020). Froese et al. (2018) and Palomares et al. (2018) showed that the fish stock status could be defined based on the B/B_{MSY} and F/F_{MSY} in the final year of the time series. When $B/B_{\text{MSY}} \geq 1$ and $F/F_{\text{MSY}} \leq 1$, the assessed stock is in a healthy state; when $B/B_{\text{MSY}} < 1$ and $F/F_{\text{MSY}} > 1$, the stock is overfished, with higher F/F_{MSY} and lower B/B_{MSY} indicating more severe overfishing.

A complex functional relationship exists between CPUE and related influential factors. This relationship can be modeled using species distribution models, such as the generalized additive model (GAM) (Hastie and Tibshirani, 1990; Xiao et al., 2004). In recent years, the GAM has been widely used to study the association between the temporal and spatial distribution of fishery resources, environmental factors, and fish stocks (Li Y. et al., 2021; Ma et al., 2021). For example, Ma et al. (2021) used GAM to analyze the relationship between nominal and standardized CPUE and environmental factors for *L. litulon* in the Yellow Sea and Bohai Sea. Li et al. (2012) showed that the relationship between the spatial and temporal distribution of CPUE and environmental factors (such as year, position, water depth, and sea surface temperature) for *L. litulon* in the southern Yellow Sea was better explained by a GAM than a generalized linear model.

This study illustrated the temporal and spatial distribution of *L. litulon* CPUE in the Yellow Sea and Bohai Sea based on the production statistics from fishing vessels in Shandong Province from 2012 to 2019 and bottom trawl survey data in Shandong Province from 2016 to 2017. We evaluated the stock status and related fishery reference points using BSM and AMSY methods, and analyzed the relationship between CPUE and marine environmental factors such as surface temperature, salinity, and depth. The results can inform the Maritime Shandong Strategy put forward by Shandong Province and help fisheries advance into the era of farming the sea, herding, and fishing. These methods also provide theoretical baseline information for the management and development of *L. litulon* resources in the Yellow Sea and Bohai Sea and promote the sustainable exploitation of marine fishery resources.

MATERIALS AND METHODS

Study Area

The Shandong Peninsula protrudes into the Bohai Sea and Yellow Sea, with numerous rivers flowing into both. The coastal waters of Shandong provide breeding, feeding, and nursery habitats for many fishery resources in the Yellow Sea and Bohai Sea, and support rich fishery resources for neighboring countries

(Li F. et al., 2015). The distribution of fishing areas for *L. litulon* in this study is shown in **Figure 1**.

Datasets

The *L. litulon* datasets used for the BSM and AMSY models were derived from the fishing logs of offshore fishing vessels in Shandong Province from 2012 to 2019, which included fishing power, mode of operation, fishing area, operating time, catch species, and yield. However, no records of fishing areas were available in the logbooks for 2017. Therefore, after standardizing the annual mean nominal CPUE for the other years, interpolation was used to obtain the mean nominal CPUE for 2017. The spatial resolution of each fishing area was 0.5° × 0.5°, and its location was represented by the latitude and longitude of the center point.

Commercial fishery monitoring and trawl surveys were combined to obtain the catch rate of *L. litulon* for each fishing area (Pecquerie et al., 2004; Gonzalez et al., 2021). The datasets used to draw monthly spatial distribution maps of *L. litulon* CPUE and to fit the GAM were obtained from (i) fishing logs of commercial fleets from 2014 to 2016, and (ii) bottom trawl survey data for the Shandong inshore fishery resources in October 2016 and January, May, and August 2017. The fishing data of *L. litulon* from 2014 to 2016 were used, as they were complete and more representative. The monthly mean nominal CPUE was calculated using both sources of data. Mean values represented nine months of the year, namely January-May and September-December, as data were not available from June to August due to the closed fishing season.

Environmental data from dataset "ii" (the bottom trawl resource survey) were used to fit the relationship between *L. litulon* and environmental factors. Environmental factors used in this study included surface temperature (ST), bottom temperature (BT), surface salinity (SS), bottom salinity (BS), water depth (D), and surface chlorophyll *a* concentration (SChl_A). Missing SChl_A data were supplemented by the MODIS_Aqua model on the NASA Ocean Color website[1], and the SS and ST data were supplemented by the AQUA_MODIS model on the Physical Oceanography Distributed Active Archive Center website[2]. The spatial resolution of the environmental data was higher than that of the fishery data, so this study used the average value of the environmental data in each fishing area to match the spatial-temporal resolution of the *L. litulon* fishery datasets.

Calculation of Nominal Catch Per Unit Effort

In this study, the nominal CPUE [$CPUE_j$, kg/(kW*d)] was calculated as follows (Maunder and Langley, 2004):

$$CPUE_j = \frac{\sum_{i=1}^{n_j} C_{ij}}{\sum_{i=1}^{n_j} P_i \times d_{ij}}$$

where, C_{ij} (kg) is the total monthly catch of fishing vessel i in fishing area j, P_i (kW) is the power of operating fishing vessel i, d_{ij} is the number of days of fishing vessel i operating in fishing area j in a month, and n_j is the number of all fishing vessels operating in fishing area j in a month. The resulting nominal CPUE (and catch) datasets for commercial vessel logs and trawl survey are detailed in **Supplementary Tables 1, 2**.

Distribution Maps

Spatial distribution contour maps of *L. litulon* abundance were drawn by the ordinary kriging method using Surfer16

[1] https://oceancolor.gsfc.nasa.gov/l3

[2] https://coastwatch.pfeg.noaa.gov/erddap/griddap/index.html?page=1&itemsPerPage=1000

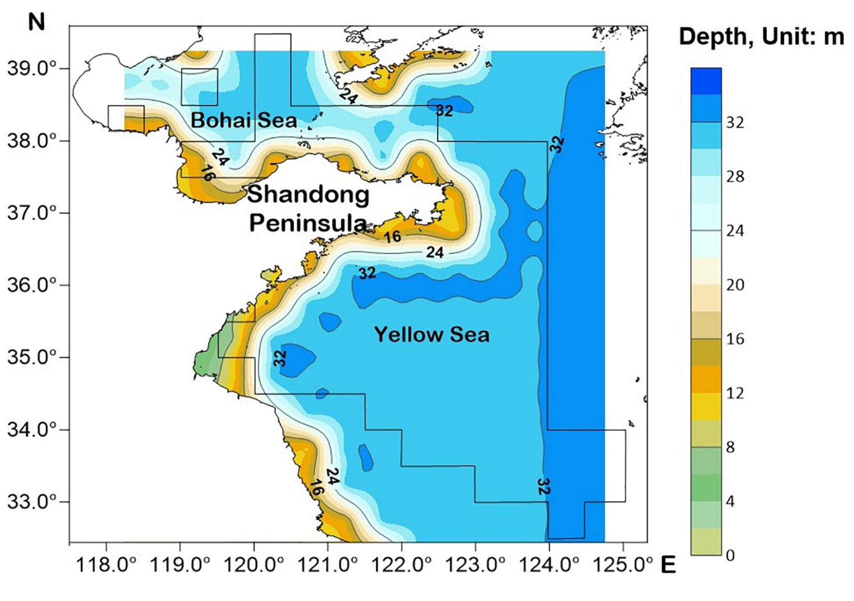


FIGURE 1 | Scope of the Shandong coastal waters and fishing areas where *Lophius litulon* occur.

(Golden Software, Colorado). The data used to map the species distribution are presented in **Supplementary Tables 2, 3**, and the annual/monthly mean nominal CPUE is given in **Supplementary Tables 4, 5**.

Generalized Additive Model Method

A generalized additive model (GAM) was used to express the nonlinear relationship between the relative abundance of *L. litulon* and various environmental factors. GAM is presented as follows (Hastie and Tibshirani, 1990; R Core Team, 2018):

$$g(Y) = \beta + f_1(x_1) + f_2(x_2) + \ldots + f_n(x_n) + \varepsilon$$

where, g() is the connection function, Y is the abundance of *L. litulon*, β is the intercept term (as the response variable), $f_n(x_n)$ is the nonparametric function used to describe the relationship between g(Y) and the nth explanatory variable, which is estimated by the spline smoothing function, n is the number of selected environmental variables, and ε is the random error term (Xiao et al., 2004).

The connection function varies according to the actual distribution of response variable Y. In this study, the connection function g(Y) = log(CPUE+1) was used as the response variable, and month, ST, BT, SS, BS, D, SChl_A, Lon, and Lat were used as explanatory variables. Month was classified as a discrete variable, and all other variables were classed as continuous. The error distribution of the model was assumed to have a Gaussian distribution. Model construction was conducted using the RStudio software.

Bayesian Schaefer Model Method

In addition to the time series of catch and abundance data, BSM also requires ancillary qualitative information, that is, priors for relative biomass, intrinsic rate of population increase (r), and carrying capacity (k). According to Froese et al. (2017), the default prior for relative biomass, B/k was set to 0.2–0.6 (medium) for the start year (B_{start}/k). From FishBase (Froese and Pauly, 2019), the resilience of *L. litulon* is "Low," corresponding to a prior r range of 0.05–0.5 (Froese et al., 2017). The prior range for an unexploited population size or carrying capacity (k) was calculated as:

$$k_{low} = \frac{\max(C)}{r_{high}} \text{ and } k_{high} = \frac{4\max(C)}{r_{low}} \quad (1)$$

$$k_{low} = \frac{2\max(C)}{r_{high}} \text{ and } k_{high} = \frac{12\max(C)}{r_{low}} \quad (2)$$

where, k_{low} and k_{high} are the lower and upper boundary priors for k for low and high levels of biomass at the end of the time series, respectively, max(C) is the maximum catch value of the time series of catch data, and r_{low} and r_{high} are the lower and upper boundary priors of the r value.

Applying the values of r and k, and the relative biomass for the first year of the time-series of catch data (B_{start}), the Monte Carlo method was used to filter out suitable r–k pairs. Basic biomass dynamics are described by the following formula:

$$B_{t+1} = B_t + r\left(1 - \frac{B_t}{k}\right)B_t - C_t \quad (3)$$

where, B_{t+1} is the exploited biomass in the subsequent year t+1, B_t is the current biomass, and C_t is the catch in year t.

If $\frac{B_t}{k}$ is < 0.25, Eq. (3) is replaced by the following:

$$B_{t+1} = B_t + 4\frac{B_t}{k}r\left(1 - \frac{B_t}{k}\right)B_t - C_t \quad (4)$$

where, the term $4\frac{B_t}{k}$ assumes a linear decline in recruitment below half of the biomass capable of producing MSY. More detailed equations and concepts can be found in Froese et al. (2017).

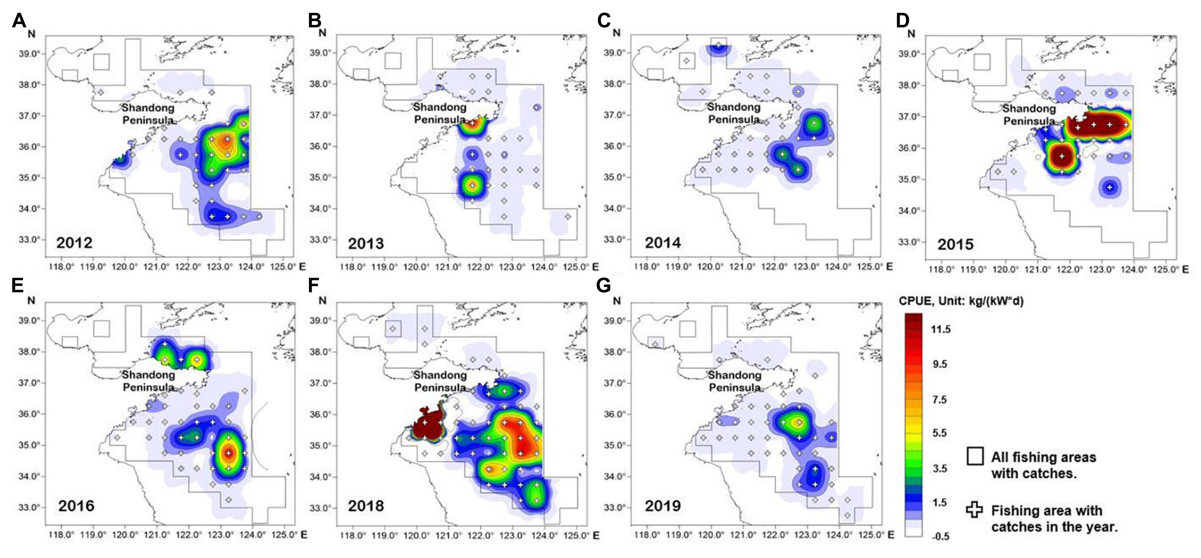


FIGURE 2 | Spatial distribution map of *Lophius litulon* abundance by fishing area and year (except 2017). **(A)** 2012; **(B)** 2013; **(C)** 2014; **(D)** 2015; **(E)** 2016; **(F)** 2018; **(G)** 2019.

Given that the assessment was based on just 8 years of catch and effort data, sensitivity analyses were also conducted to investigate the potential effect of the relative biomass prior (B_{start}/k; 0.2–0.6) on estimates of B/B_{MSY} and F/F_{MSY}, compared with a higher prior (0.4–0.8) and a lower prior (0.1–0.4).

The time series of catch and CPUE are displayed in **Supplementary Table 4**, and the R code for the BSM method, as well as **Supplementary Materials** describing the method in detail, can be downloaded from R Core Team (2018).

Abundance Maximum Sustainable Yield Method

The AMSY model was used to determine the maximum sustainable yield from the abundance data. The advantage of this method is that it uses only CPUE or other relative abundance time series to evaluate the exploitation pattern and stock status without catch data (Froese et al., 2020). The required input data for the AMSY method included a time-series of CPUE and prior ranges for r and relative stock size $\frac{B_t}{k}$ in a given year. The time-series of CPUE data are given in **Supplementary Table 4**, and the method of obtaining the prior range of r was the same as described above (Froese et al., 2020). Priors for $\frac{B}{k}$ together with population dynamics and the proportional factor of upper and lower limits were used to put the observed CPUE into a preliminary MSY framework, which was then refined by Monte Carlo filtering. The AMSY method estimates the relative catch based on several transformations of the Schaefer model, which requires biomass data for two consecutive years (Froese et al., 2020); hence, the relative catch (Catch/MSY), fishing pressure (F), and exploitation level (F/F_{MSY}) were estimated up to the second-to-last year in the time series. Froese et al. (2020) provide a detailed description of the theory and equations behind AMSY. In our contribution, sensitivity analyses similar to the BSM method were also conducted for AMSY.

RESULTS

Resource Distribution

The spatial distribution of *L. litulon* abundance in Shandong coastal waters from 2012 to 2019 (except for 2017) is shown in **Figure 2**. *Lophius litulon* was caught in 70 fishing areas. The distribution features of this stock in the coastal waters of Shandong in recent years were as follows: (1) the species was widely distributed in the Yellow Sea, but was less common in the Bohai Sea; (2) the resource was concentrated in the central area of the Yellow Sea (34.0°–37.0° N, 121.0°–124.0° E); (3) *L. litulon* appeared in most fishing areas in 2018 and showed the highest abundance; (4) although *L. litulon* still showed a wide distribution in 2019, the reported stock abundance was low.

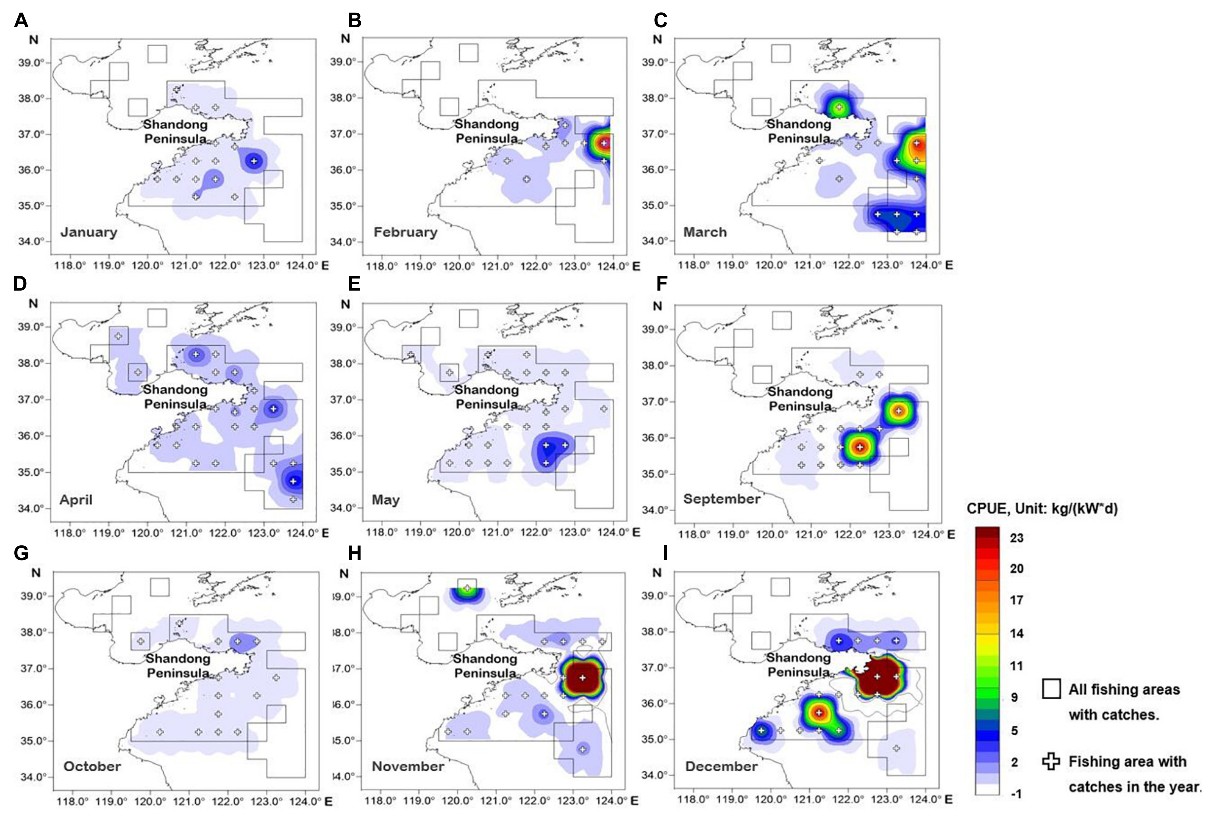


FIGURE 3 | Spatial distribution map of *Lophius litulon* abundance by fishing area and month (except from June to August due to fishing closure). **(A)** January; **(B)** February; **(C)** March; **(D)** April; **(E)** May; **(F)** September; **(G)** October; **(H)** November; **(I)** December.

TABLE 1 | Approximate significance of smooth terms.

Factors	edf	Ref.df	F	p-value
				<0.001***
s(D)	1	1	4.113	0.044279*
s(Lat)	4.594	5.55	4.116	0.001065**
s(BT)	6.977	8.029	3.575	0.000728***
s(BS)	2.944	3.663	3.042	0.018747*
s(Lon)	1.254	1.454	7.009	0.010169*
s(ST)	3.047	3.779	2.083	0.094287
s(SChl_A)	1.652	2.062	2.711	0.067607

D, water depth; Lat, latitude; BT, bottom temperature; BS, bottom salinity; Lon, longitude; ST, surface temperature; and SChl_A, surface chlorophyll a concentration.

**** Indicates extremely significant differences ($P < 0.001$); ** indicates a significant correlation at the level of 0.01 ($P < 0.01$); * indicates a significant correlation at the level of 0.05 ($P < 0.05$).*

Figure 3 shows the monthly distribution of *L. litulon*, which was caught in 43 fishing areas. The species appeared more concentrated offshore from January to September and moved west toward the coast from October to December. The highest CPUE was usually in the central and southern coastal areas of Shandong, peaking in November and December. In January, April, May, and October, the CPUE values were low over the entire study area, with the lowest value occurring in October.

Effects of Environmental Factors

A GAM was used to fit the relationship between the relative abundance of *L. litulon* and environmental factors. To obtain the optimal model, impact factors were screened according to the minimum Akaike Information Criterion (AIC). The full screening process is presented in **Supplementary Table 6**. The final expression of the model is as follows:

$$\mathrm{Log(CPUE + 1) = Month + s(D) + s(Lat) + s(BT) + s(BS) + s(Lon) + \varepsilon}$$

Deviation analysis indicated that the cumulative deviation of the selected modeling factors was 51.70% ($R = 0.446$, $P < 0.05$). In addition to the influence of month (time factor), the *F*-tests showed that the environmental factor with the greatest influence was depth (D), followed by latitude (Lat), BT, BS, and longitude (Lon, **Table 1**). There was an extremely significant correlation between BT and the relative abundance of *L. litulon* ($P = 0.000728$).

Figure 4 shows the effect of environmental factors, as simulated by the GAM, on the abundance of *L. litulon*. **Figure 4** indicates that: (1) when D was > 18 m, the abundance of *L. litulon* increased with D; (2) the abundance of *L. litulon* was higher between 35.25° and 36.00° N, and decreased north of 38.00°

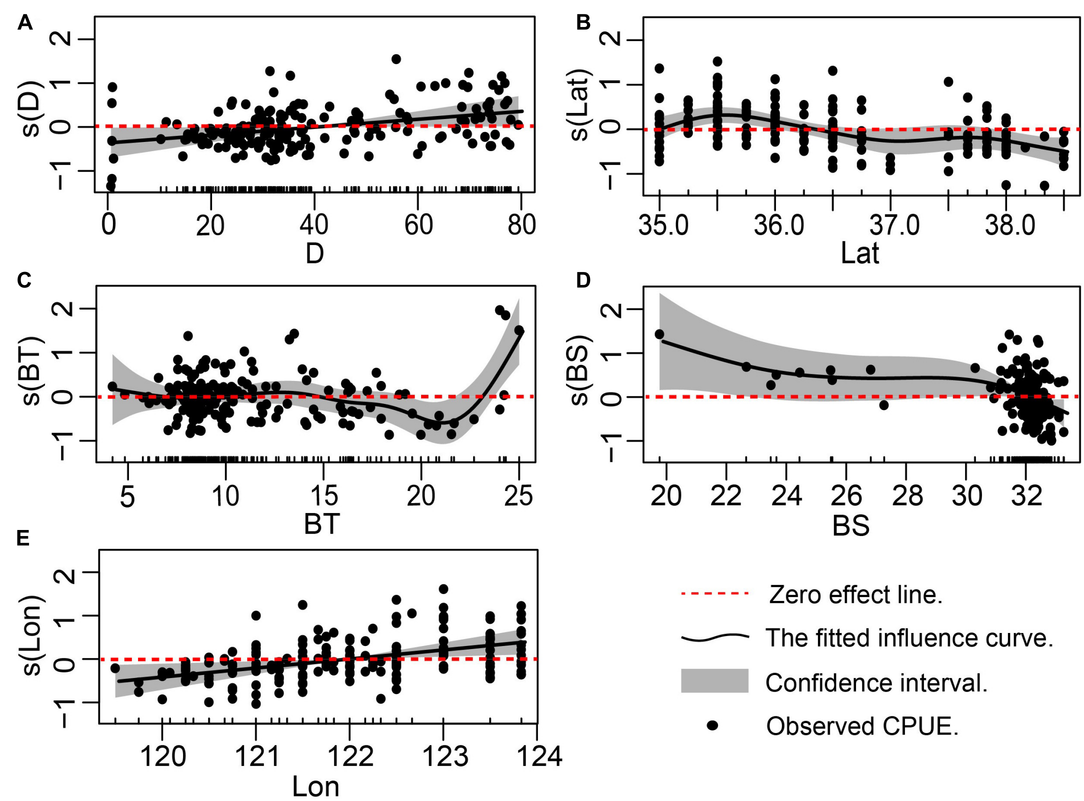


FIGURE 4 | Effects of environmental factors on the CPUE of *Lophius litulon* in Shandong coastal waters. **(A)** Depth; **(B)** Latitude; **(C)** Bottom temperature; **(D)** Bottom salinity; **(E)** Longitude.

TABLE 2 | Results of the BSM and AMSY analyses.

Items	BSM	AMSY
r-k pairs	19027	5003
r (95% CL)	0.20 (0.07–0.57)	0.25 (0.11–0.64)
k (95% CL, tons)	2558 (1554–4212)	/
MSY (95% CL, tons)	129 (62.1–267)	/
Median *k* (95% CL)	/	2.49 (2.08–2.89)
Median MSY (95% CL)	/	0.156 (0.07–0.368)
B/B_{MSY} in last year (97.5% CL)	0.538 (0.353–1.12)	0.801 (0.436–1.42)
F/F_{MSY} (97.5% CL)	2.41 (0.677–8.63)	1.47 (-0.197–4.26)

N; (3) *L. litulon* was densely distributed in the waters with BT varying between 5.8 °C and 10.6 °C; (4) as BS increased, *L. litulon* abundance decreased, especially in the range from 31 to 33.2‰; (5) there was a positive association between *L. litulon* abundance and Lon.

Resource Evaluation

The results and confidence intervals for *r*, *k*, and MSY evaluated using the BSM and AMSY methods were similar (**Table 2**). The exploitation rate (F/F_{MSY}) was consistently estimated to be > 1.0, and the relative biomass (B/B_{MSY}) in the last year was predicted to be < 1.0, which implied an unhealthy *L. litulon* stock status in Shandong coastal waters.

Figure 5A shows 19,027 feasible *r-k* pairs screened by BSM (black dots; gray dots for CMSY), and the darker gray cross was the best *r-k* pair with a 95% confidence interval (CI) (the light gray cross for CMSY). **Figure 5B** depicts 5003 feasible *r-k* pairs identified by AMSY (black dots), and the cross represents the best pair with its 95% CI. **Figure 5C** (estimated by the BSM method), indicates that *L. litulon* catches fluctuated greatly over time, with the lowest value occurring in 2013 and the highest in 2018. **Figure 5D** shows the time-series of CPUE data overlaid with the estimated biomass that would achieve MSY (gray line). The CPUE predicted by AMSY also exhibited significant fluctuations between 2012 and 2019, with the lowest value in 2017 and the highest in 2018.

The relative biomass trajectory (B/B_{MSY}) produced by BSM is depicted in **Figure 6A**, and the gray area represents its 97.5% CI. B/B_{MSY} has been declining since 2015, and the B/B_{MSY} value in the last year of the time series was 0.538 (< 1). **Figure 6B** shows that the AMSY model estimated that the relative biomass trajectory (B/B_{MSY}) decreased gradually before 2014, stabilized between 2014 and 2016, and increased gradually after 2016, but the end point of B/B_{MSY} was 0.801 (< 1), which was closer to the level MSY. **Figure 6C** shows that the exploitation rate (F/F_{MSY}) curve predicted by BSM, increased gradually after 2013, and the terminal F/F_{MSY} value was 2.41 (> 1). **Figure 6D** shows that the exploitation rate estimated by AMSY gradually decreased after 2014, and the F/F_{MSY} in the second to last year was 1.47 (> 1).

The results of the sensitivity analyses are shown in **Figure 7** and **Supplementary Table 7**, which indicate that the change in priors had a high impact on the outcome of the BSM, being very low in the AMSY model. Herein, selecting the appropriate prior values is crucial to avoid bias in the BSM estimates.

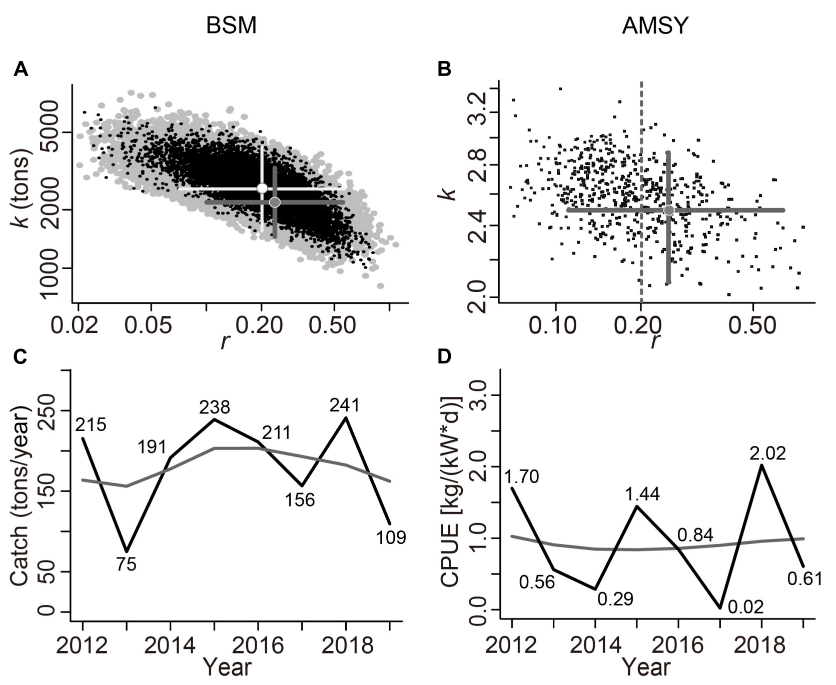


FIGURE 5 | Analysis of viable *r-k* pairs and stock size (Catch for BSM related to CMSY, CPUE for AMSY) by BSM and AMSY. Notice the match between the left and right panels. **(A)** Feasible *r-k* pairs identified by BSM (in black) related to CMSY (in gray) **(B)** feasible *r-k* pairs identified by AMSY; **(C)** Catch (in black) relative to the MSY (in gray) estimated by BSM; **(D)** CPUE (in black) relative to MSY (in gray) predicted by AMSY.

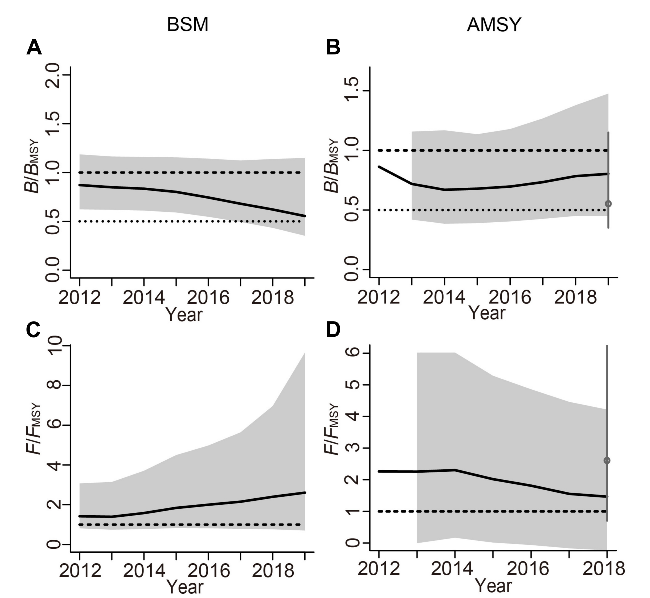


FIGURE 6 | Comparison of relative biomass (B/BMSY) and exploitation level (F/FMSY) trajectories estimated by BSM and AMSY methods, with the gray areas representing the 97.5% CIs. **(A)** Relative biomass (B/BMSY) trend estimated by BSM; **(B)** relative biomass (B/BMSY) trend estimated by AMSY; **(C)** relative exploitation level (F/FMSY) trajectory predicted by BSM; **(D)** relative exploitation level (F/FMSY) trajectory predicted by AMSY.

DISCUSSION

Spatial-Temporal Dynamics and Environmental Influences

In this study, the marine area with the highest frequency of *L. litulon* occurrence from 2012 to 2019 was the central Yellow Sea (34.5°–37° N, 121°–124° E). Li Z. et al. (2015) investigated the relative resource density and distribution of *L. litulon* from 1985 to 2009 and found that the area with the highest density of *L. litulon* in the Yellow Sea was between 34°–35° N and 122°–123° E. In this study, although the mean CPUE in some years (e.g., 2014 and 2019) was lower than that in adjacent years, *L. litulon* was more widely distributed than in the 1985–2009 period.

During the 9 months of this study, *L. litulon* was widely distributed over the entire marine area from February to April, but the CPUE was low. This was possibly because spring is the spawning season for *L. litulon*, and either the catches comprise mostly recruits with light individual weights or the individuals are too small to be caught by nets. Conversely, the high CPUE in autumn (from September to November) might be attributed to biomass accumulated during the summer fishing moratorium.

Li et al. (2012) found that ST had a significant effect on *L. litulon* CPUE in the southern Yellow Sea in spring. Li Z. et al. (2015) also pointed out that the catch yield of *L. litulon* in the central and southern parts of the Yellow Sea was significantly correlated with the ST. This study showed that BT was the main environmental factor significantly affecting the abundance of *L. litulon* in the Yellow Sea. Furthermore, *L. litulon* was concentrated in areas of the Yellow Sea and Bohai Sea with low temperatures, high salinities, and depths >18 m. Wang et al. (2013) showed that *L. litulon* in Haizhou Bay and its adjacent sea areas (within the scope of this study) had a strong negative correlation with temperature, salinity, and depth in winter, but was positively related to surface pH. Herein, we suggest that further studies should consider more environmental factors to improve the accuracy of the correlation estimates. In addition, different resource-modeling approaches should be developed and adopted.

Stock Status and Suggestions for Sustainable Development

In many developing countries, including China, most of the species caught on a large scale have not yet been assessed, nor do they have an adaptive management plan to guarantee their sustainable use and protection (Costello et al., 2012). Stock assessments are generally lacking for fish that gradually become a dominant part of the catch and progressively increase their economic value, as is the case for *L. litulon*.

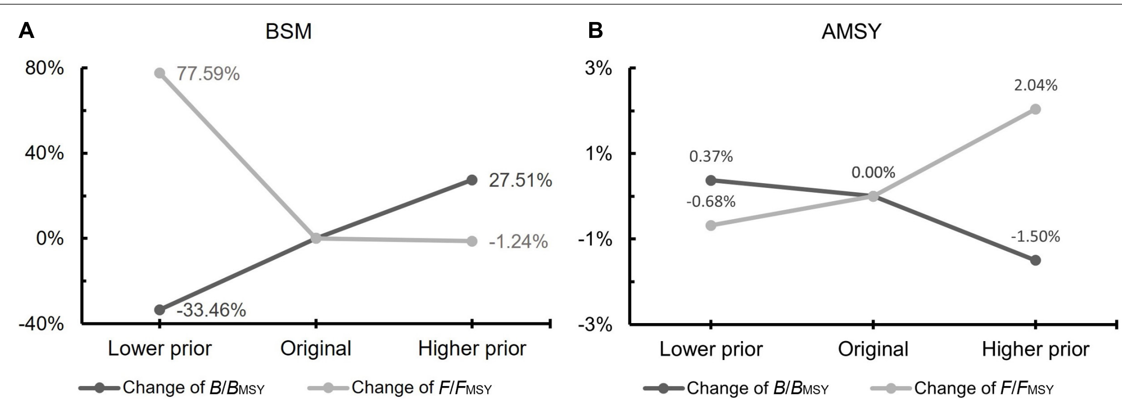


FIGURE 7 | Sensitivity of B/B_{MSY} and F/F_{MSY} to changes of the priors. **(A)** BSM; **(B)** AMSY.

In 2002, the total annual catch of *L. litulon* in the East China Sea was ranked ninth of 153 species, accounting for 1.14% of the total catch, and its existing stock size was estimated to exceed 2,000 tons (Lin and Zheng, 2004). The frequency and relative resource density of *L. litulon* in the central and southern Yellow Sea showed an increase from 1985 to 2009 (Li Z. et al., 2015). However, owing to the strong fishing pressure in the south of the Yellow Sea, the caught individuals of *L. litulon* became smaller and the population structure became younger (Li Z. et al., 2015).

In this study, the results of the BSM and AMSY approaches showed that, although there were some differences in precision and biomass trajectories between different methods, the same conclusions were evident. That is, the population of *L. litulon* is now in an unhealthy and overfished state, and the biomass remains below the level that can produce MSY. Our results are consistent with the findings of Wang et al. (2020), indicating that the resource status of *L. litulon* is unacceptable in the coastal waters off Shandong.

Interestingly, the BSM showed that the status of *L. litulon* stock is worsening, while the AMSY model suggested it is improving. Although AMSY uses the surplus yield model of the filtered *r-k* pairs to predict catches that conform to the CPUE time series and the priors, its estimates of the exploitation index (F/F_{MSY}) are normally given with wide margins of uncertainty (Froese et al., 2020). The accuracy and applicability of AMSY will be affected by how closely the stock abundance and catch follow the assumptions of the surplus yield model, so it may be less suitable than BSM for management purposes. Nevertheless, AMSY should be well suited for estimating the productivity index (r) and relative stock size (B/B_{MSY}), so it may be useful in the management of data-poor stocks. Furthermore, sensitivity analysis demonstrated that the BSM was more sensitive to the initial relative biomass prior than AMSY. In other words, B/B_{MSY} and F/F_{MSY} estimates generated by the BSM model were greatly affected by the selection of priors, which might be attributed to the short time series of catch and CPUE used in this study. In such cases, reasonable prior ranges are important for obtaining reliable estimates.

Since the early 1990s, China has adopted a series of fisheries management systems to develop and protect its marine resources, including fishing moratoria, fishing permits, fishing effort controls, quota systems, and resource allocation. However, declines in marine fishery resources continue to occur. Therefore, cautious management of *L. litulon* resources in coastal waters of China is required.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding authors.

ETHICS STATEMENT

Ethical review and approval was not required for the animal study because our data are sourced from existing fisheries data.

AUTHOR CONTRIBUTIONS

ZZ completed the data collection and analysis and wrote the first draft. YW provided guidance on research methods and writing ideas and participated in data processing. YW, CL, and WX conceived and designed the study, and revised the first draft. SL provided the data. All authors contributed to the manuscript and approved the submitted version.

FUNDING

This research was funded by grants from the National Natural Science Foundation of China (31872568 and 41976094), the Natural Science Foundation of China-Shandong Joint Fund for Marine Ecology and Environmental Sciences (U1606404), and Open Fund of CAS Key Laboratory of Marine Ecology and Environmental Sciences, Institute of Oceanology, Chinese Academy of Sciences (KLMEES202004).

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2022.759591/full#supplementary-material

REFERENCES

Chen, D. G. (1991). *Fisheries Ecology of Yellow Sea and Bohai Sea*. Beijing: Chian Ocean Press.

Costello, C., Ovando, D., Clavelle, T., Strauss, C., Hilborn, R., Melnychuck, M., et al. (2016). Global fishery prospects under contrasting management regimes. *Proc. Natl. Acad. Sci. U.S.A.* 113, 5125–5129. doi: 10.1073/pnas.1520420113

Costello, C., Ovando, D., Hilborn, R., Gaines, S. D., Deschenes, O., and Leater, S. E. (2012). Status and solutions for the world's unassessed fisheries. *Science* 338, 517–520. doi: 10.1126/science.1223389

FAO (2020). *The State of World Fisheries and Aquaculture (SOFIA)*. Rome: Sustainability in action.

Fisheries and Fisheries Administration (2010). *China Fishery Statistical Yearbook 2010*. Beijing: China Agriculture Press.

Fisheries and Fisheries Administration (2019). *China Fishery Statistical Yearbook 2019*. Beijing: China Agriculture Press.

Fisheries and Fisheries Administration (2020). *China Fishery Statistical Yearbook 2020*. Beijing: China Agriculture Press.

Froese, R., Demirel, N., Coro, G., Kleisner, K. M., and Winker, H. (2017). Estimating fisheries reference points from catch and resilience. *Fish Fish.* 18, 506–526. doi: 10.1111/faf.12190

Froese, R., and Pauly, D. (eds) (2019). *FishBase. World Wide Web Electronic* Publication. Available online at: www.fishbase.org

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2018). Status and rebuilding of European fisheries. *Mar. Policy* 93, 159–170. doi: 10.1016/j.marpol.2018.04.018

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2020). Estimating stock status from relative abundance and resilience. *ICES J. Mar. Sci.* 77, 527–538. doi: 10.1093/icesjms/fsz230

Gonzalez, G. M., Wiff, R., Marshall, C. T., and Cornulier, T. (2021). Estimating spatio-temporal distribution of fish and gear selectivity functions from pooled scientific survey and commercial fishing data. *Fish. Res.* 243:106054. doi: 10.1016/j.fishres.2021.106054

Hastie, T. J., and Tibshirani, R. J. (1990). *Generalized Additive Models*. London: Chapman & Hall .

Huang, S. (2012). Analysis on the development of marine fisheries in Shandong Province. *Chin. Fish. Econ.* 30, 98–103.

Ji, G., Gao, T., and Takashi, Y. (2007). Morphological difference sand isozyme variations between *Lophius litulon* of Yellow Sea and Japan Sea. *Mar. Fish. Res.* 28, 73–79.

Kim, J., Choi, I., Kim, J., Choi, S., and Chun, Y. (2007). Factors affecting the wintering habitat of major fishery resources in southwestern Korean waters. *Ocean Sci. J.* 42, 41–48. doi: 10.1007/BF03020909

Li, F., Zhou, X., Zhang, L., Ren, Z. H., and Lü, Z. B. (2015). Taxonomic diversity of fish assemblages in coastal waters off Shandong. *Acta Ecol. Sin.* 35, 2322–2330. doi: 10.5846/stxb201306101579

Li, X., Wang, K., Xu, B., Xue, Y., Yiping, R., and Zhang, C. (2021). Annual variation of species composition and spatial structure of fish community in Shandong coastal waters. *J. Fish. Sci. China* 45, 552–562. doi: 10.11964/jfc.20200312206

Li, Y., Zhang, C., Ji, Y., Xue, Y., Xu, B., and Ren, Y. (2021). Spatio-temporal distribution of *Larimichthys polyactis* in southern waters off the Shandong Peninsula and its relationship with environ mental factors. *J. Fish. Sci. China* 28, 442–450. doi: 10.12264/JFSC2020-0288

Li, Z., Shan, X., Jin, X., Dai, F., and Lu, H. (2015). Interannual variations in the biological characteristics, distribution and stock density of anglerfish *Lophius litulon* in the central and southern Yellow Sea Interannual variations in the biological characteristics, distribution and stock density of anglerfish *Lophius litulon* in the central and southern Yellow Sea. *Acta Ecol. Sin.* 35, 4007–4015. doi: 10.5846/stxb201310262585

Li, Z., Ye, Z., Zhang, C., and Zhuang, L. (2012). Effects of environmental factors on catch distribution of stow net *Pseudosciaena polyactis* and *Lophius litulon* in southern Yellow Sea in spring. *J. Appl. Ecol.* 23, 2887–2892. doi: 10.13287/j.1001-9332.2012.0394

Lin, L. S., and Zheng, Y. J. (2004). Preliminary research on stock of *Lophius litulon* in the East China Sea region. *Mar. Fish.* 26, 176–183.

Ma, Y., Xu, B., Zhang, C., Yu, H., Xue, Y., and Ren, Y. (2021). Spatio-temporal distribution and standardization of CPUE for *Scomberomorus niphonius* pair trawler fishery in the Yellow and Bohai Seas. *J. Fish. Sci. China* 28, 493–502. doi: 10.12264/JFSC2020-0257

Maunder, M. N., and Langley, A. D. (2004). Integrating the standardization of catch-per-unit-of-effort into stock assessment models: testing a population dynamics model and using multiple data types. *Fish. Res.* 70, 389–395. doi: 10.1016/j.fishres.2004.08.015

Michiol, Y., Muneharu, T., Hiroshi, H., Keisuke, Y., Michiya, M., and Shuhei, M. (2002). Spawning migration of the anglerfish *Lophius litulon* in the East China and Yellow seas. *Fish. Sci.* 68, 310–313. doi: 10.2331/fishsci.68.sup1_310

Palomares, M. L., Froese, R., Derrick, B., Nöel, S., Tsui, G., Woroniak, J., et al. (2018). *A Preliminary Global Assessment of the Status of Exploited Marine Fish and Invertebrate Populations*. A Report Prepared by the Sea Around Us for OCEANA. Vancouver, BC: The University of British Columbia.

Pecquerie, L., Drapeau, L., Fréon, P., Coetzee, J. C., Leslie, R. W., and Griffiths, M. H. (2004). Distribution patterns of key fish species of the southern Benguela ecosystem: an approach combining fishery-dependent and fishery-independent data. *Afr. J. Mar. Sci.* 26, 115–139. doi: 10.2989/18142320409504053

R Core Team (2018). *A Language and Environment for Statistical Computing*. Vienna: R Foundation for Statistical Computing.

Ricard, D., Minto, C., Jensen, O. P., and Baum, J. K. (2012). Examining the knowledge base and status of commercially exploited marine species with the RAM legacy stock assessment database. *Fish Fish.* 13, 380–398. doi: 10.1111/j.1467-2979.2011.00435

Wang, S. B., Song, Y., and Li, P. (2006). Current situation of China fishery resources and countermeasures for the sustainable development. *Chin. Fish. Econ.* 1, 24–27.

Wang, X., Xu, B., Yupeng, J., and Ren, Y. (2013). Fish community structure and its relationships with environmental factors in Haizhou Bay and adjacent waters of East China in winter. *Chin. J. Appl. Ecol.* 24, 1707–1714. doi: 10.13287/j.1001-9332.2013.0350

Wang, Y., Wang, Y., Liu, S., Liang, C., Zhang, H., and Xian, W. (2020). Stock assessment using LBB method for eight fish species from the Bohai and Yellow Seas. *Front. Mar. Sci.* 7:164. doi: 10.3389/fmars.2020.00164

Watson, R., Cheung, W., Anticamara, J., Sumaila, U., Zeller, D., and Pauly, D. (2013). Global marine yield halved as fishing intensity redoubles. *Fish Fish.* 14, 493–503. doi: 10.1111/j.1467-2979.2012.00483

Xiao, Y., Punt, A. E., Millar, R. B., and Quinn, T. J. (2004). Models in fisheries research: GLMs, GAMs and GLMMs. *Fish. Res.* 70, 137–139. doi: 10.1016/j.fishres.2004.08.001

Xu, K., He, Z., Zhu, W., Li, P., and Zhang, S. (2010). Distribution pattern of *Lophius litulon* and its' relationship with environmental factors in the south Yellow Sea and north East China Sea. *Mar. Fish.* 32, 59–65. doi: 10.13233/j.cnki.mar.fish.2010.01.010

Xue, Y., Jin, X., Zhao, X., Liang, Z., and Li, X. (2007). Food consumption by the fish community in the central and southern Yellow Sea in autumn. *J. Ocean Univ. China* 37, 75–82. doi: 10.16441/j.cnki.hdxb.2007.01.014

Zhang, X., Cheng, J., Shen, W., Liu, Z., and Yuan, X. (2011). Reproductive biology of yellow goosefish *Lophius litulon*. *J. Fish. Sci. China* 18, 290–298. doi: 10.3724/SP.J.1118.2011.00290

Zhang, Y., and Qiu, S. (2019). A preliminary study on current situation of fishery resources in Shandong offshore. *Nat. Sci. Eng. Ed.* 32, 61–67. doi: 10.13951/j.cnki.37-1213/n.2019.01.011

Zou, Y., Liu, T., Wang, Y., Wu, Y., Liu, C., and Song, A. (2019). Analysis on changes of major marine fishing economic fish resources offshore in Shandong Province. *J. Guangxi Acad. Sci.* 35, 301–307. doi: 10.13657/j.cnki.gxkxyxb.20191210.006

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 16 February 2022
doi: 10.3389/fmars.2022.775180

Stock Assessment Using Length-Based Bayesian Evaluation Method for Three Small Pelagic Species in the Northwest Pacific Ocean

*Yongchuang Shi[1,2], Xiaomin Zhang[3], Yuru He[4], Wei Fan[1,2] and Fenghua Tang[1,2]**

[1] Key Laboratory of East China Sea and Oceanic Fishery Resources Exploitation and Utilization, Ministry of Agriculture, East China Sea Fisheries Research Institute, Chinese Academy of Fishery Sciences, Shanghai, China, [2] Key and Open Laboratory of Oceanic Laboratory of Remote Sensing Information Technology in Fishing Resource, East China Sea Fisheries Research Institute, Chinese Academy of Fishery Sciences. Shanghai, China, [3] Shandong Provincial Key Laboratory of Restoration for Marine Ecology, Shandong Marine and Fishery Research Institute, Yantai, China, [4] College of Marine Culture and Law, Shanghai Ocean University, Shanghai, China

OPEN ACCESS

Edited by:
Simone Libralato,
Istituto Nazionale di Oceanografia e di Geofisica Sperimentale, Italy

Reviewed by:
Vita Gancitano,
Institute for Biological Resources and Marine Biotechnology, National Research Council (CNR), Italy
Jin Gao,
Memorial University of Newfoundland, Canada

Correspondence:
Fenghua Tang
f-h-tang@163.com

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: *13 September 2021*
Accepted: *20 January 2022*
Published: *16 February 2022*

Citation:
Shi Y, Zhang X, He Y, Fan W and Tang F (2022) Stock Assessment Using Length-Based Bayesian Evaluation Method for Three Small Pelagic Species in the Northwest Pacific Ocean. Front. Mar. Sci. 9:775180. doi: 10.3389/fmars.2022.775180

Chub mackerel (*Scomber japonicus*), Pacific saury (*Cololabis saira*), and Pacific sardine (*Sardinops sagax*) are key economic and ecological species in the Northwest Pacific Ocean (NPO). In recent years, there have been some interannual changes in their catches due to the increasing number of fishing vessels and climate change. With the establishment of the North Pacific Fisheries Commission (NPFC) to better manage these three species, it is particularly important to develop an accurate understanding of the stock status of those fisheries resources. According to the production statistics of Chub mackerel, Pacific saury, and Pacific sardine in the NPO, the length-based Bayesian evaluation (LBB) method was adopted to conduct a stock assessment on the three fisheries in this study. Research results show that the asymptotic length of Chub mackerel in the NPO L_{inf} is 37.54 cm, with the parameter ratios of L_c/L_{c_opt} = 1.10, F/M = 0.57, B/B_0 = 0.65, and B/B_{MSY} = 1.10. The asymptotic length of Pacific saury in the NPO L_{inf} is 33.24 cm, with the ratios of L_c/L_{c_opt} = 1.10, F/M = 0.14, B/B_0 = 0.82, and B/B_{MSY} = 2.10. While the asymptotic length of Pacific sardine L_{inf} is 39.33 cm, with the ratios of L_c/L_{c_opt} = 1.20, F/M = 0.20, B/B_0 = 0.77, and B/B_{MSY} = 2.20. At present, the three species in the NPO are in a healthy state and have not yet been overfished. Body length bin may affect the estimation of some parameters without compromising the estimation of stock status. Our study indicates that the LBB model serves as an efficient method to evaluate the fisheries resources in the NPO, especially when length frequencies are the only available data. Hopefully, the results in this study can provide technical support for the conservation and management of Chub mackerel, Pacific saury, and Pacific sardine in the NPO.

Keywords: small pelagic species, length-frequency data, LBB method, stock assessment, Northwest Pacific Ocean

INTRODUCTION

Chub mackerel (*S. japonicus*), Pacific saury (*C. saira*), and Pacific sardine (*S. sagax*) are the ecologically and commercially important species inhabiting the Northwest Pacific Ocean (NPO) (Tian et al., 2004; Yukami et al., 2009). Japanese fishermen were pioneers to exploit these species, and in recent years, the major countries and island constituencies harvesting these three species include Japan, China, Chinese Taipei, Russia, and Korea (Kawai et al., 2002; Ueno et al., 2017). The annual catches of Chub mackerel, Pacific saury, and Pacific sardine recorded in 2019 were about 64,364, 51,400, and 24,773 tons in China, which accounted for 14.00, 12.26, and 11.08% of the global production, respectively (FAO, 2019). Influenced by an increasing number of fishing vessels under the global development of these fisheries, coupled with marine climate and environmental change, these resources fluctuated, and their harvest has gone through interannual changes (Shi et al., 2020). Since 2015, Chub mackerel and Pacific saury have been listed among the priority fish species by the North Pacific Fisheries Commission (NPFC), and the Pacific sardine is also considered as one of the species to be managed in the future (North Pacific Fisheries Commission [NPFC], 2017). Due to their increasing commercial and ecological values, the research and management of these three small pelagic species in the NPO have gained much interest and concern in the field of fishery science (Arnold and Heppell, 2014).

According to the report of FAO (2016, 2019), only about 11% of fisheries in the world are assessed by sophisticated models or have been properly managed. A precise stock assessment will contribute to the stock management, sustainable development, and oceanic ecosystem studies of target fisheries (Jiao et al., 2011; Punt, 2011; Guan et al., 2016). However, the scarcity of long series of age structure data and stock abundance indices is unavailable in data-limited fisheries, which makes it incredibly tough to assess the stock status using conventional models (Magnusson and Hilborn, 2007; Wang et al., 2016). Chub mackerel, Pacific saury, and Pacific sardine fisheries are typical data-limited fisheries in the NPO. They have the biological characteristics of a short life cycle and a long migration route, and their populations are extremely sensitive to large-scale climatic events and regional environmental changes in the NPO (Watanabe and Yatsu, 2004; Yatsu et al., 2005; Iwahashi et al., 2006). At present, there are some stock assessment studies on these three species. For instance, Shi et al. (2018) carried out the stock assessment and risk analyses of different management strategies for the Pacific saury using a Bayesian Schaefer surplus production model, wherein they identified the stock status as "good" and immune to overfishing or overfished. North Pacific Fisheries Commission [NPFC] (2017) used the Bayesian state-space model to assess the stock dynamics of the Pacific saury in the NPO. Guan et al. (2014) simulated two subpopulations of Chub mackerel based on the meta-population concept by setting up 12 scenarios. Although certain research results have been obtained, there are still some uncertainties in the estimation of parameters and biological reference points (Wetzel and Punt, 2011). For example, these studies are based on the surplus production model, in which the population growth, mortality, and recruitment converge are in one equation. Therefore, errors in individual growth are inevitably ignored in the stock assessment. Besides, the effects of environmental factors and process errors are not considered, which may bring uncertainty to the model results. Hence, it is essential to conduct effective stock assessments, and scholarly attention needs to be devoted to the sustainable use and fishery management (Ma et al., 2021). As attaining high-quality fisheries statistics within a short period of time can be a challenging task, the data-poor approach has attracted more and more attention from RFMOs. In recent years, in order to meet the increasing demand for scientific management of data-limited fisheries, various data-limited methods have been developed to perform the stock assessment for these fisheries, which are also the hot spot of current fisheries stock assessment (MacCall, 2009; Dick and MacCall, 2011; Martell and Froese, 2013; Hordyk et al., 2015; Froese et al., 2018; Rudd and Thorson, 2018). The length-based data-limited methods, such as Length-Based Spawning Potential Ratio (LBSPR) model, Length-Based Integrated Mixed Effects (LIME) model, and Length-Based Bayesian (LBB) model, have become popular due to their easy availability of the length-frequency (LF) data (Klaer et al., 2012; Chong et al., 2020). Among them, the LBB method can be applied to estimate the related parameters and biological reference points by Bayesian Monte Carlo Markov Chain (MCMC) approach based on the size composition data from commercial catches (Froese et al., 2018). Its main assumption is that recruitment, growth, and mortality are constant, and the LF data can be representative of that exploited stock (Froese et al., 2018). The LBB model has been used to evaluate the sock status of some data-limited stocks. For example, Wang et al. (2020) assessed eight common and commercially important marine fishes using the LBB method. Liang et al. (2020) applied this model to 14 fish and invertebrate stocks in the coastal waters of China to estimate their growth, lengths at first capture, and current relative biomass from the LF data. Those researches indicated that the LBB model can provide reliable results for the stock status estimation of data-limited fisheries.

In this study, the LBB approach was used to analyze the three populations of small pelagic species captured by the Chinese commercial fishing vessels operating in the NPO. The objectives of this research were to: (1) identify life history parameters and explore the biomass depletion levels of these three species populations caused by fishing, (2) investigate the impact of different length bins on the estimated results of the LBB model, and (3) compare the stock assessment results of these three species between LBB model and previous researches. Results of this study could provide technical support for the sustainable use and scientific management of these three fisheries.

MATERIALS AND METHODS

Data Resources

The study area was distributed between 35–50°N and 145–170°E covering the main fishing ground of these three species in the NPO. According to the existing data, the LF data of Chub mackerel were obtained from commercial fishing in the NPO from 2016 to 2018. The LF data of Pacific saury and Pacific sardine were derived from commercial fishing in the NPO in 2017. The length and weight were measured for each specimen, and the number of measured specimens for all three species ranged from 872 to 6,091, with sizes including both small- and large-sized individuals, representing a wide size range. In this study, the LF data of three species were obtained from commercial fishing in China, and each fishery had only one kind of fishing gear instead of multiple kinds of fishing gears, which meet the requirements of the LBB model. The basic information of three small pelagic species used in this study is shown in **Table 1**.

Length-Based Bayesian Evaluation Model

The LBB model is a fast and simple approach for assessing stock status using the LF databases on the MCMC approach (Froese et al., 2018). The species that are suitable for the LBB method are those that continue to grow throughout their lives, for instance, invertebrates and commercial fishes (Pons et al., 2020). In the LBB model, only the LF data of a fishery representing the true population structure are required as input since these use prespecified priors on parameters. While, sometimes, required prior parameters including the asymptotic length ($L_{\inf}$), mean length at first capture (L_c), and relative natural mortality (M/K) may be input manually by users if they have good estimates of these parameters from independent studies (Carruthers et al., 2016). LBB estimates several parameters of target species, including L_c, $L_{\inf}$, relative fishing mortality (F/M), and M/K. In this study, we just listed the basic information and formulas [refer to Froese et al. (2018) for more details].

The growth function of von Bertalanffy (1938) was used in the LBB model for describing the growth in size (Pauly, 1998).

$$L_t = L_{inf}\left[1 - e^{-K(t-t_0)}\right] \tag{1}$$

where L_t is the length when the age is t, K is the rate by which L_{inf} is approached (year^{-1}), and t_0 is the theoretical age when the length is zero (Froese et al., 2018).

If there were no mortality, most species would approach L_{inf}, which is expressed as follows:

$$N_{t2} = N_{t1} \cdot exp-(Z(t_2 - t_1)) \tag{2}$$

where N_{t1} represents the population number at t_1, and N_{t2} is the population number at t_2. Z indicates the instantaneous rate of total mortality, including fishing and natural mortality (Pauly, 1998). For each species, the lengths affected by partial selection are given by the ogive function expressed as follows:

$$S_L = \frac{1}{1 + e^{-\alpha(L-L_c)}} \tag{3}$$

where S_L means the fraction of individuals that are retained by the gear at length L, and α describes the steepness of the ogive (Quinn and Deriso, 1999; Froese et al., 2018).

The combination and rearrangement of Eqs 1–3 lead to the following equations:

$$N_{L_i} = N_{L_{i-1}}\left(\frac{L_{inf} - L_i}{L_{inf} - L_{i-1}}\right)^{\frac{M}{K} + \frac{F}{K}S_{L_i}} \tag{4}$$

$$C_{L_i} = N_{L_i}S_{L_i} \tag{5}$$

where N_{L_i} is the individual number when the length is L_i, $N_{L_{i-1}}$ represents the number of individuals at length L_{i-1}, and C_{L_i} is the number of individuals vulnerable to the gear when the length is L_i. In the LBB model, the ratios F/M and M/K are output, i.e., $F/M = (F/K)/(M/K)$, which can be deduced by fitting Eq. 4 to the LF data.

Relative yield-per-recruit (Y'/R) can be computed by the following equation (Froese et al., 2018):

$$\frac{Y'}{R} = \frac{F/M}{1 + F/M}\left(1 - \frac{L_c}{L_{\inf}}\right)^{\frac{M}{K}} \left(1 - \frac{3(1 - L_c/L_{\inf})}{1 + \frac{1}{M/K + F/K}} + \frac{3(1 - L_c/L_{\inf})^2}{1 + \frac{2}{M/K + F/K}} - \frac{(1 - L_c/L_{\inf})^3}{1 + \frac{3}{M/K + F/K}}\right) \tag{6}$$

Assuming catch per unit effort (CPUE) proportional to biomass, Eq. 6 divided by F/M gives the following equation:

$$\frac{CPUE'}{R} = \left(\frac{Y'}{R}\right)/\left(\frac{F}{M}\right) = \left(\frac{1}{1 + \frac{F}{M}}\right)\left(1 - \frac{L_c}{L_{\inf}}\right)^{\frac{M}{K}} \left(1 - \frac{3(1 - L_c/L_{\inf})}{1 + \frac{1}{M/K + F/K}} + \frac{3(1 - L_C/L_{\inf})^2}{1 + \frac{2}{M/K + F/K}} - \frac{(1 - L_c/L_{\inf})^3}{1 + \frac{3}{M/K + F/K}}\right) \tag{7}$$

The relative biomass in the potentially exploited phase of the population is expressed as follows when the stock is unexploited:

$$\frac{B'_0 > L_c}{R} = (1 - L_c/L_{\inf})^{\frac{M}{K}} \left(1 - \frac{3(1 - L_c/L_{\inf})}{1 + \frac{1}{M/K}} + \frac{3(1 - L_c/L_{\inf})^2}{1 + \frac{2}{M/K}} - \frac{(1 - L_c/L_{\inf})^3}{1 + \frac{3}{M/K}}\right) \tag{8}$$

where B_0 is the unexploited biomass, and the ratio B/B_0 is obtained from Eqs 7, 8 as follows:

$$B/B_0 = \left(\frac{CPUE'}{R}\right)/\left(\frac{B'_0 > L_c}{R}\right) \tag{9}$$

Meanwhile, we have the following equation:

$$L_{opt} = L_{\inf} * 3/(3 + M/K) \tag{10}$$

TABLE 1 | Summary of year, the size range, and the number of individuals measured of three species collected in the Northwest Pacific Ocean (NPO).

Species	Year	Catch numbers	Length range/mm
Chub mackerel (*Scomber japonicus*)	2016	1,050	115–367
Chub mackerel (*Scomber japonicus*)	2017	1,339	114–324
Chub mackerel (*Scomber japonicus*)	2018	872	175–352
Pacific saury (*Cololabis saira*)	2017	6,091	159–322
Pacific sardine (*Sardinops sagax*)	2017	1,268	105–337

where L_{opt} is the length when a cohort of fish has its peak biomass (Holt, 1958). The optimal length at first capture L_{c_opt} is obtained from the following equation:

$$L_{c\_opt} = \frac{L_{inf}\left(2 + 3\frac{F}{M}\right)}{\left(1 + \frac{F}{M}\right)\left(3 + \frac{M}{K}\right)} \quad (11)$$

A proxy for relative biomass maximum sustainable yield (MSY; B_{MSY}/B_0) can be obtained by means of rerunning Eqs 6–9 with $F/M = 1$ and $L_c = L_{c\_opt}$. Based on these parameters, the current relative stock size (B/B_{MSY}) was estimated, which was converted into qualifiers of fisheries status (Palomares et al., 2018). According to the values of estimated B/B_0 and B/B_{MSY}, we can classify the stocks as described by Palomares et al. (2018). The results of the LBB model can directly be used in the provisional management of data-limited fisheries populations based on the two basic and simple rules: if the relative stock size $B/B_0 < B_{MSY}/B_0$, catches of this species should be reduced; and if $L_c < L_{c\_opt}$, fishing would better start from larger sizes.

In this study, the LF data obtained for each species were sampled for at least 1 year, with a wide range of sample sizes representing the population structure. In addition, to reduce uncertainty in LBB results, apart from LF data, species having asymptotic lengths obtained from prior studies were also included in the input information database (Suyama et al., 1992; Watanabe et al., 1995; Shiraishi et al., 2008). Data analyses in this study were performed using the LBB software, which is installed in the R-core environment.

Sensitivity Analysis

To fully consider the influence of length bin on the evaluation results of the LBB model, the body length of three species was grouped by the length bins of 5, 10, and 15 mm, respectively, and the results of three scenarios were then compared. The scenario of length bin equal to 10 mm was used for the base case, and the other scenarios were sensitive analysis scenarios. The goodness-of-fit coefficient (R^2) was used to evaluate the fitting goodness as follows.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i-1}^{n}\left(y_i - \bar{y}_i\right)^2} \quad (12)$$

where y is the relative frequency, $\hat{y}$ is the predicted relative frequency, $\bar{y}$ is the mean of y, and i is the number of the relative frequency data. The length bin and the prior value of LBB parameters of the three species are shown in **Table 2**.

RESULTS

Stock Status of Chub Mackerel

Figure 1 shows the estimated results of the LBB model under different length bins. According to the goodness-of-fit measurements, the R^2 values of three length bins were 0.698, 0.732, and 0.683, respectively, which means that the length bin of 10 mm made the analysis fit better. Chub mackerel, which reaches a maximum length of 37.54 cm under the base case (**Figure 1B**), is widely distributed in the NPO. The estimate of $F/M = 0.57$ indicates that Chub mackerel fishery was not subject to increasing fishing pressure; meanwhile, the estimate parameters of $B/B_0 = 0.65$, and $B/B_{MSY} = 1.10$ confirm that the stock of Chub mackerel is in a good state in the NPO. The estimate of $L_c/L_{c\_opt} = 1.10$ implies that large fishes are still present (**Figure 1** and **Table 3**).

Stock Status of Pacific Saury

Figure 2 shows the stock assessment results for Pacific saury using the LBB method. The R^2 values of three length bins were 0.779, 0.796, and 0.700, respectively. Therefore, the scenario of length bin equal to 10 mm can be used for the stock status estimation of Pacific saury. Pacific saury is wildly distributed in the international waters of the NPO ranging from subarctic to subtropical region. This species reaches a maximum length of 33.24 cm under the base case (**Figure 2B**), and in this study, the parameter $F/M = 0.14$ indicates that the current fishing pressure will not damage the stock of Pacific saury. The ratios $B/B_0 = 0.82$ and $B/B_{MSY} = 2.10$ suggest that its biomass is at a high level. According to the result of ratio L_c/L_{c_opt} in this study, the value is above unity, implying the presence of large specimens (**Figure 2** and **Table 4**).

Stock Status of Pacific Sardine

The scenario of length bin equal to 10 mm was chosen to evaluate the stock status of Pacific sardine according to the R^2 value (R^2 of length bin 5 mm is 0.892, R^2 of length bin 10 mm is 0.910, and R^2 of length bin 15 mm is 0.865). The stock of Pacific sardine, which reaches a maximum length of 39.33 cm under the base case, is in

TABLE 2 | Scenarios and priors of three species used in this study.

Species	Year	Class bin (mm)	L_{inf} prior	*Z/K* prior	*M/K* prior	*F/K* prior	L_c prior	*Alpha* prior
Chub mackerel	2016–2018	5	37.49	2.30	1.50	0.82	19.53	15.99
Chub mackerel	2016–2018	10	36.53	1.90	1.50	0.45	19.79	10.17
Chub mackerel	2016–2018	15	36.14	0.62	1.50	0.30	20.04	7.50
Pacific saury	2017	5	38.62	1.80	1.50	0.32	16.58	42.25
Pacific saury	2017	10	36.96	1.30	1.50	0.30	16.83	48.21
Pacific saury	2017	15	43.20	2.00	1.50	0.50	16.07	33.70
Pacific sardine	2017	5	36.80	1.70	1.50	0.16	18.36	16.61
Pacific sardine	2017	10	39.00	1.30	1.50	0.30	18.36	15.88
Pacific sardine	2017	15	39.60	1.40	1.50	0.30	17.60	14.76

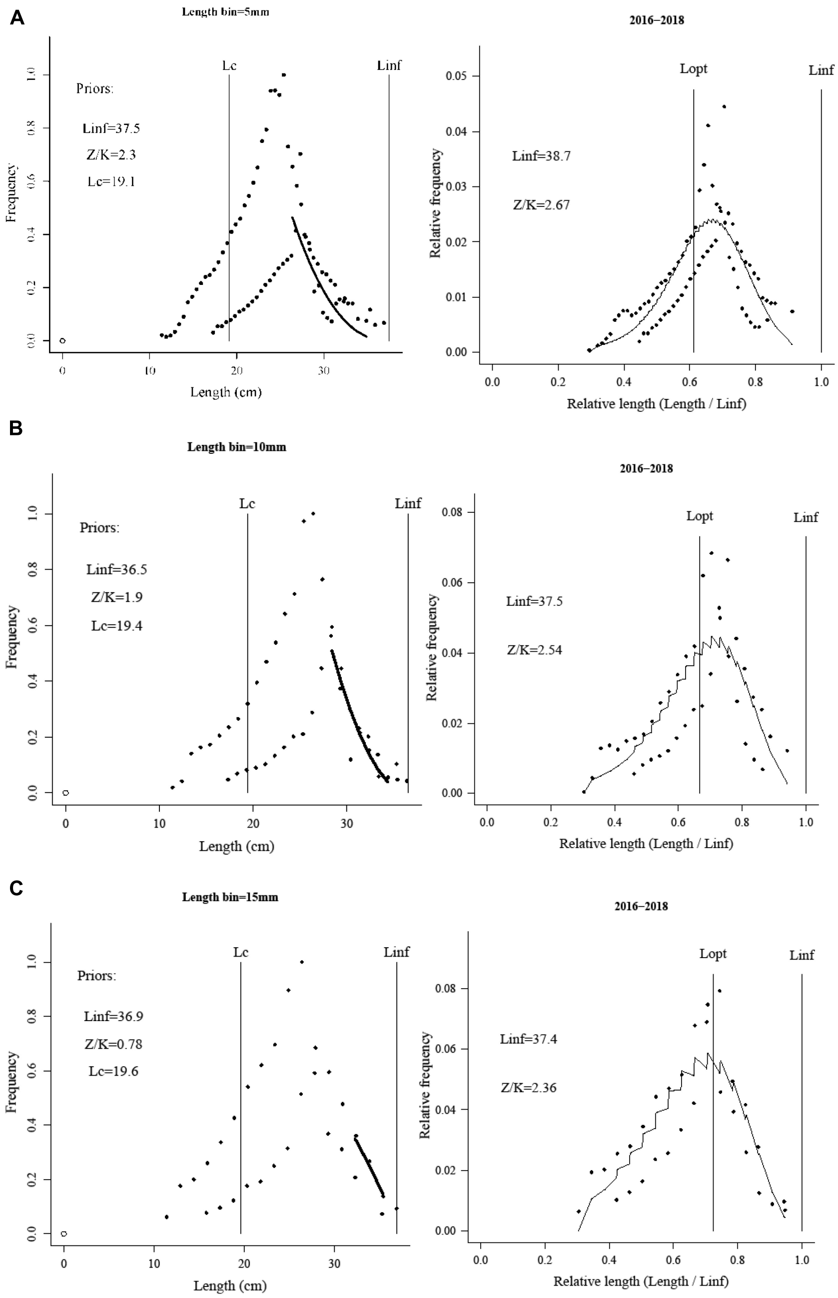


FIGURE 1 | Assessment results of the length-based Bayesian (LBB) method to Chub mackerel in the Northwest Pacific Ocean (NPO).

TABLE 3 | Summary of the length-based Bayesian (LBB) results for Chub mackerel.

Species	Year	Class bin (mm)	R^2	L_{inf}	L_c/L_{c_opt}	F/M	B/B_0	B/B_{MSY}	Stock status
Chub mackerel	2016–2018	5	0.698	38.72 (37.92–39.26)	1.20	0.68 (0.43–0.87)	0.63 (0.37–1.22)	1.20 (0.87–1.90)	Healthy
Chub mackerel	2016–2018	10	0.732	37.54 (36.83–38.66)	1.10	0.57 (0.32–0.78)	0.65 (0.34–1.27)	1.10 (0.29–1.70)	Healthy
Chub mackerel	2016–2018	15	0.683	37.41 (36.15–38.83)	1.40	0.18 (0.08–0.33)	0.81 (0.16–1.70)	1.80 (0.45–3.70)	Healthy

a good state in the NPO (**Figure 3B**). The parameters $F/M = 0.20$, $B/B_0 = 0.77$, and $B/B_{MSY} = 2.20$ indicate that the stock status of Pacific sardine is healthy and the fishing pressure may not be the major cause for the fluctuation in the biomass of this species. In addition, there are still a large number of big specimens in the stock of Pacific sardine ($L_c/L_{c\_opt} > 1$) (**Figure 3** and **Table 5**).

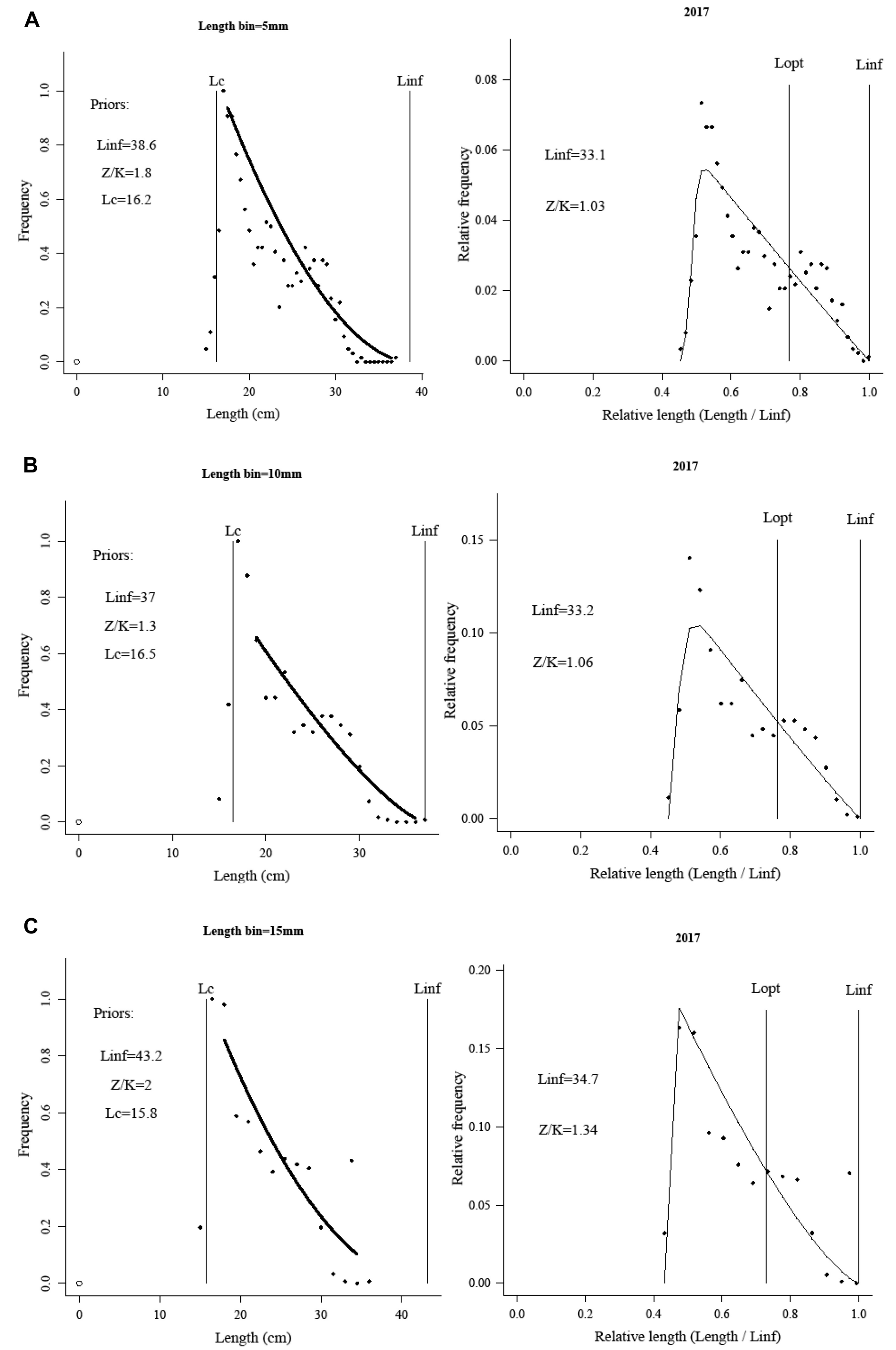


FIGURE 2 | Assessment results of length-based Bayesian (LBB) method to Pacific saury in the Northwest Pacific Ocean (NPO).

TABLE 4 | Summary of length-based Bayesian (LBB) results for Pacific saury.

Species	Year	Class bin (mm)	R^2	L_{inf}	L_c/L_{c_opt}	F/M	B/B_0	B/B_{MSY}	Stock status
Pacific saury	2017	5	0.779	33.06 (33.02–33.17)	1.10	0.19 (0.09–0.41)	0.80 (0.15–1.98)	2.20 (0.62–3.50)	Healthy
Pacific saury	2017	10	0.796	33.24 (33.12–33.45)	1.10	0.14 (0.06–0.37)	0.82 (0.24–2.02)	2.10 (0.40–3.20)	Healthy
Pacific saury	2017	15	0.700	34.73 (34.59–34.85)	1.20	0.20 (0.09–0.47)	0.74 (0.14–1.84)	1.90 (0.41–3.11)	Healthy

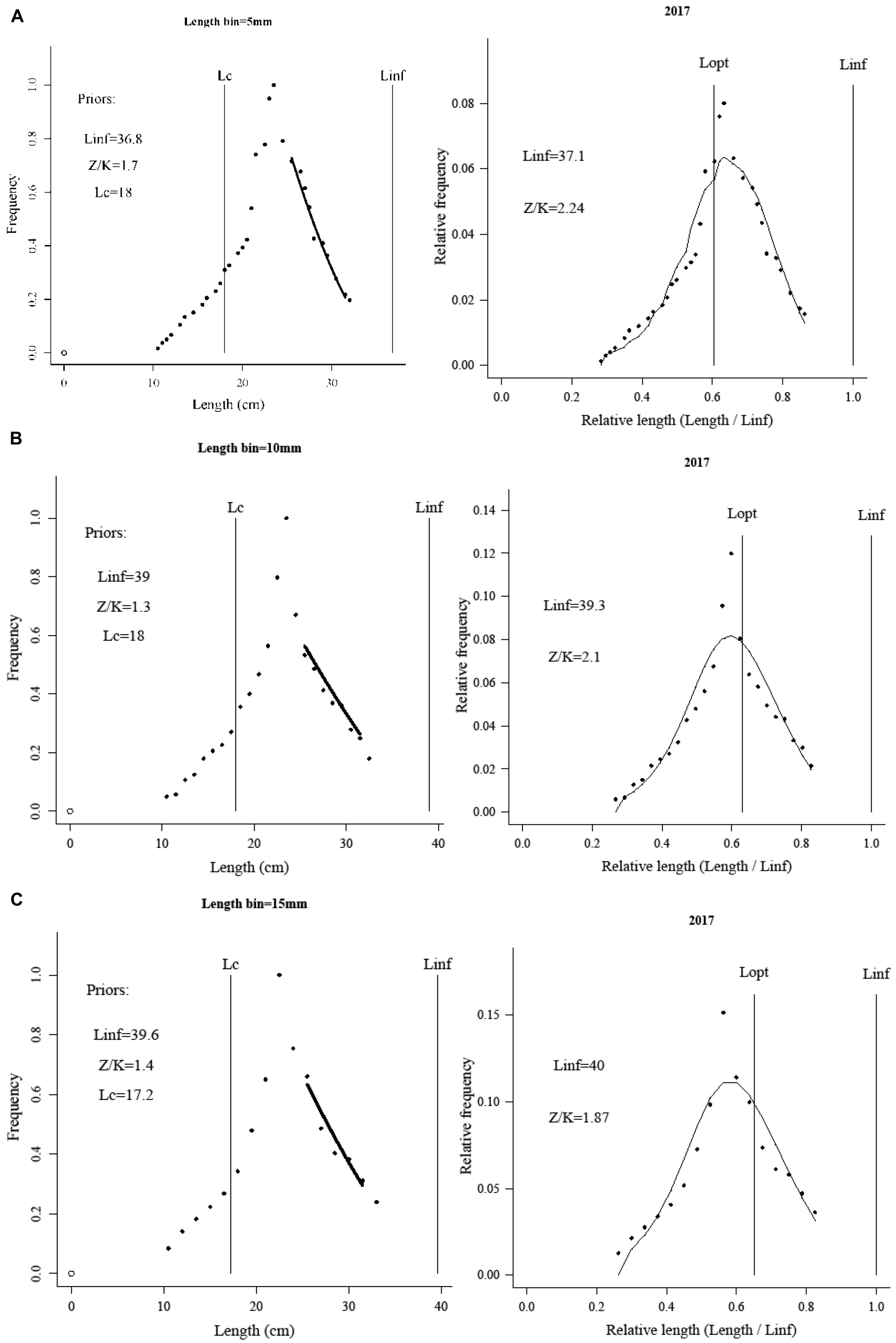


FIGURE 3 | Assessment results of length-based Bayesian (LBB) method to Pacific sardine in the Northwest Pacific Ocean (NPO).

TABLE 5 | Summary of length-based Bayesian (LBB) results for Pacific sardine.

Species	Year	Class bin (mm)	R^2	L_{inf}	L_c/L_{c_opt}	F/M	B/B_0	B/B_{MSY}	Stock status
Pacific sardine	2017	5	0.892	37.11 (36.59–37.76)	1.40	0.14 (0.04–0.36)	0.82 (0.14–1.8)	2.20 (0.23–3.80)	Healthy
Pacific sardine	2017	10	0.910	39.33 (38.48–40.03)	1.20	0.20 (0.07–0.36)	0.77 (0.09–1.60)	2.20 (0.16–4.60)	Healthy
Pacific sardine	2017	15	0.865	40.01 (39.43–40.82)	1.10	0.16 (0.07–0.30)	0.80 (0.16–1.70)	1.9 (0.56–4.70)	Healthy

Sensitivity Analysis

Three levels of length bins were applied to analyze the influence of the length bin on the evaluated results of the LBB model. **Figure 4** shows the estimated key parameters based on different length bins. For Chub mackerel, the estimated L_c/L_{c_opt} ratios varied from 1.10 to 1.40 with the length bin, and the F/M ratios ranged from 0.68 to 0.18. When the length bin varied from 5 to 15 mm, the B/B_0 ratios varied from 0.63 to 0.81, with their B/B_{MSY} ratios varying from 1.2 to 1.8 (**Figure 4A**). For Pacific saury, L_c/L_{c_opt} ratios ranged from 1.1 to 1.2 with the changes of length bin, and the F/M ratios ranged from 0.14 to 0.20. The B/B_0 ratios ranged from 0.74 to 0.82, with their B/B_{MSY} ratios varying from 1.9 to 2.2 (**Figure 4B**). For Pacific sardine, the estimated L_c/L_{c_opt} ratios ranged from 1.10 to 1.40, and the F/M ratios ranged from 0.14 to 0.20. The B/B_0 ratios ranged from 0.77 to 0.82, with their B/B_{MSY} ratios varying from 1.9 to 2.2 (**Figure 4C**). On comparing the effects of different length bins on the estimated key parameters, it was discovered that although the parameter values had a certain change, the change range was not noticeable.

DISCUSSION

The LBB model was recommended as a new supplement to the stock assessment approach for the data-limited stocks that have very limited or unreliable catch data (Kindong et al., 2020). Compared with similar length-based models (e.g., LBSPR and LIME), the LBB model does not need any information on age, mortality, growth, and recruitment, which only requires the LF data that can represent the stock from commercial fisheries (Froese et al., 2016). Froese et al. (2018) indicated that the LBB method will perform poorly if the LF data cannot represent the length structure of the exploited stock. Chub mackerel, Pacific saury, and Pacific sardine that have a short life span tend to exhibit marked population fluctuations (Sakurai et al., 2000). Previous studies have stated that the fishing grounds and biomass of short-lived species are affected by oceanographic factors, such as sea surface temperature (SST) and sea surface height (SSH) (Watanabe et al., 2006; Kuroda and Yokouchi, 2017). Due to insufficient long-term series of age-structured data and fisheries-independent data, the application of a full stock assessment model in data-limited circumstances might be challenging and questionable (Guan et al., 2013; Wang et al., 2016; Geng et al., 2021). The LBB model has been well applied in several data-limited fisheries (Kindong et al., 2020; Liang et al., 2020; Wang et al., 2020). In this study, the LF data of three species were derived from commercial gear for at least 1 year and represented the length composition of the target species, therefore meeting all the demands of the LBB model (Froese et al., 2018). In addition, the results of the LF data for three populations fit presented asymmetric patterns, which mean that the LF data were appropriate to be analyzed by this model (Froese et al., 2018). Therefore, it is reasonable and feasible to assess the stock status for the three small pelagic species in the NPO using the LBB model.

The length bin of 10 mm was chosen to estimate the stock status for three species based on the goodness-of-fit measurements. According to the estimation of the LBB model, the ratio L_c/L_{c_opt} of Chub mackerel was above unity, which means that there were still a considerably large amount of specimens in the population. The estimation of ratio B/B_{MSY} was bigger than one, suggesting that the stock of Chub mackerel is not being overfished. As few studies on the stock assessment of Chub mackerel in NPO were conducted in previous research, the study area was mainly concentrated on the coastal waters of China and Japan (Yatsu et al., 2002; Zhang et al., 2009; Yan et al., 2010). Yan et al. (2010) adopted the Virtual Population Analysis (VPA) to assess the stock of Chub mackerel. Their results suggested that the stock of Chub mackerel in the western East China Sea could remain relatively steady, which corroborates with the results presented in this study. Reports by Ichikawa and Okamura (2016) were also consistent with this study, and they applied the autoregressive state-space models to estimate the Chub mackerel stock status. For Pacific saury, the estimated ratios L_c/L_{c_opt} and B/B_{MSY} were above unity, which suggests that a great quantity of large individuals were still present and the stock status of Pacific saury was healthy. Shi et al. (2018, 2020) indicated that the stock of Pacific saury was at a high level, which was corroborated by our findings to show that the population is immune to overfishing or overfished of this stock in the NPO. Reports of North Pacific Fisheries Commission [NPFC] (2017) agreed with the results in this study as well. Although few models have been applied to assess the stock of Pacific sardine, Demer and Zwolinski (2014) still reported that current catches would not damage the stock of Pacific sardine. These authors insisted that new data should be collected in advance for the future assessment of Pacific sardine, which will facilitate the scientific management of this fishery.

The development and utilization of the three kinds of fisheries resources have been paid attention to by the RFMOs. At present, Chub mackerel and Pacific sardine are listed among the priority fish species by NPFC, and the Pacific sardine is also among one of the species to be managed in the future (Hua et al., 2020). China, Japan, and Russia have conducted a preliminary stock assessment for Chub mackerel in the NPO based on the Age-Structured Assessment Program (ASAP), VPA, and State-space Assessment Model (SAM), respectively. However, they indicated that the stock assessment results and model

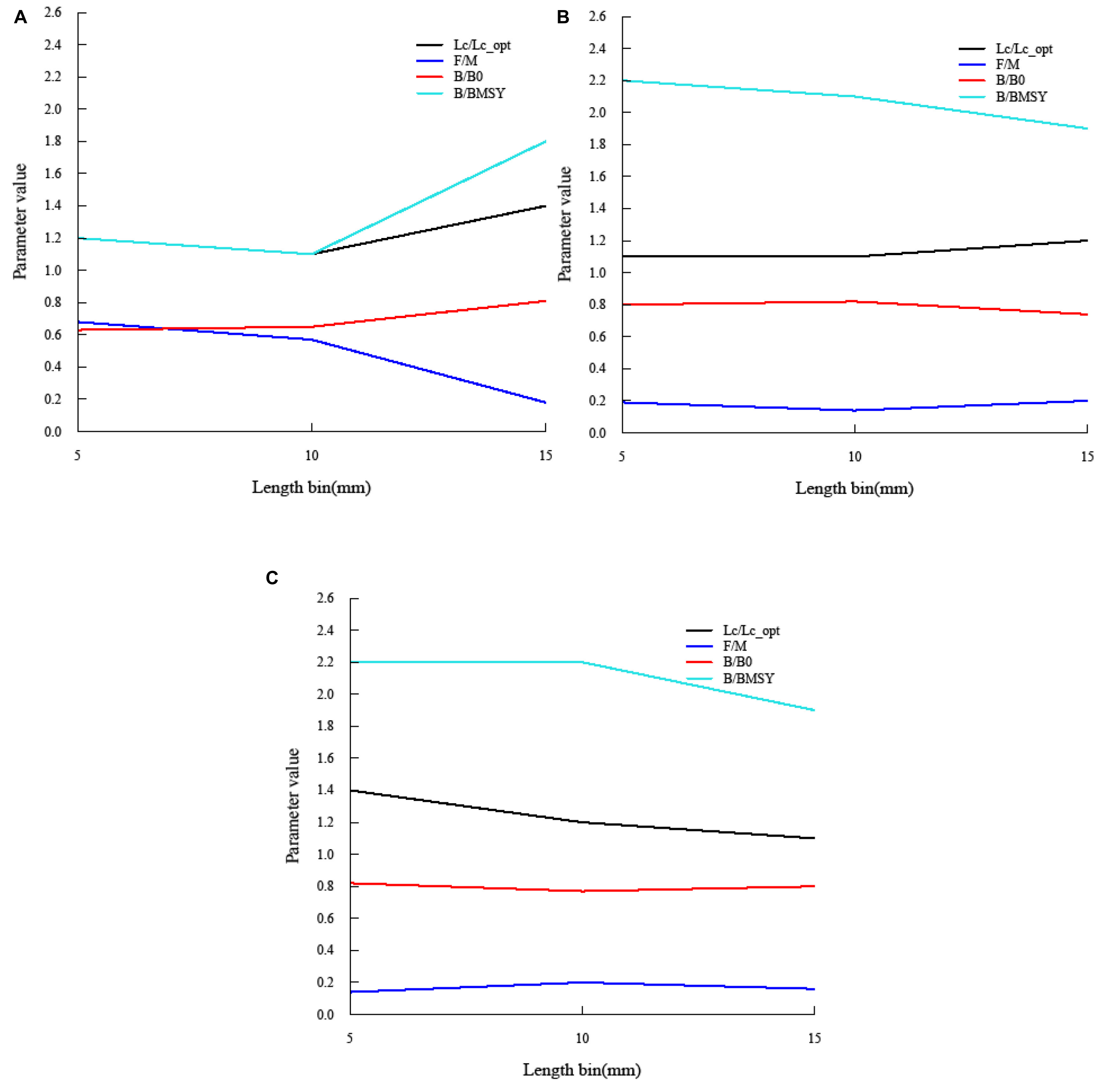


FIGURE 4 | Estimated key parameters based on different length bins.

performance were highly influenced by the availability and quality of data for Chub mackerel and suggested that more basic biological research and scientific resource investigation should be carried out. The stock of Pacific saury was assessed using the Bayesian state-space biomass dynamic model (BSSPM) by the members of NPFC. Results of China pointed out that the current biomass of Pacific saury was bigger than B_{MSY} and the stock was in good condition. Chinese Taipei indicated that the stock of Pacific saury did not appear to be overfished and overfishing. The stock assessment results of Japan concluded that the biomass level is currently above the level of MSY for any scenarios (North Pacific Fisheries Commission [NPFC], 2017). In addition, the fundamental fisheries research of Pacific sardine has been carried out by NPFC for future stock assessment.

In this study, three different length bin scenarios were set up to evaluate the impact of the body length bin on the estimation of the LBB model. According to the sensitivity analysis, there is a minimal fluctuation of key parameters depending on the length bin, which means that the length bin has a limited impact on the estimation of the LBB model. This conclusion was consistent with the study by Froese et al. (2018). Hordyk et al. (2018) stated that the LBB master equation is incomplete because it fails to correct for the pile-up effect due to aggregating length measurements into length bins. However, Froese et al. (2019) responded that the assumptions of the pile-up effect mentioned by Hordyk et al. (2018) are not realistic for most sampling schemes and stocks. This study indicated that although the body length bins may affect the parameter estimation of the LBB model, it will not affect the estimation result of stock status (**Tables 3–5**).

Compared with similar length-based methods [e.g., LBSPR, catch-curve stock reduction analysis(CC-SRA), and LIME], the LBB model has some advantages in assessing the stock in data-limited situations. For instance, compared with LBSPR, the LBB method does not need to include the information about length-fecundity parameters or maturation schedules. It considers the issue of knife-edge assumption and calculates M/K and L_{inf} based on the available data. The main difference between the LBB method and the CC-SRA model is that the CC-SRA model requires age-structured data, which are often scarce in the data-limited fisheries. The input data of the LIME method are similar to the LBB model, but the former still requires the life history data such as maturation, growth, and natural mortality. Froese et al. (2018) suggested that the stock estimated depletion of the LBB model was closer to independent estimates and thus recommended that it can be used as preliminary guidance and priors for the stock assessment and management of data-limited stocks. However, some uncertainties in the LBB model should be considered. LF data in this study were derived from the fishery-dependent data, which might lead to some potential bias. For instance, the LF data may not be representative if the sample sites were not widely distributed in the main fishing ground, and the selection and measurement error of the sample might have some impacts on the results of the LBB model. Therefore, basic biological research of these three fisheries should be strengthened in future research in order to provide the database for fishery stock assessment and management.

In this study, the LF data we used were derived from the main type of fishing gears in commercial fisheries, which can represent all body length groups of these stocks. Besides, the LF samples of three populations showed asymmetric plot patterns, thus meeting the requirement of the LBB model (Froese et al., 2018). Therefore, the results of this study could provide valuable information for the fisheries management of these three species. Besides, this study also indicated that the LBB model can be a good selection for the stock status estimation of data-limited fisheries. In order to make better use of and conserve these three fishery stocks, the collection of various types of data and the long-term systematic biological research need to be actively carried out. Alternative approaches (e.g., age-structured model) to assess the stock status of these species are the important area for future research.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

YS contributed to the conception and design of this study, acquisition of data, visualization, software, and writing—original draft. XZ contributed to the investigation and resources. YH and WF contributed to writing—review and editing. FT contributed to acquisition of data and writing—original draft. All authors contributed to the article and approved the submitted version.

FUNDING

This study was supported by the National Key R&D Program of China (2019YFD0901405), the Central Public-Interest Scientific Institution Basal Research Fund, ECSFR, CAFS (2021T04), and the Central Public-Interest Scientific Institution Basal Research Fund, ECSFR, CAFS (2021M06).

ACKNOWLEDGMENTS

We gratefully acknowledge the help of our colleagues in the Key and Open Laboratory of Oceanic Laboratory of Remote Sensing Information Technology in Fishing Resource. We are also grateful to the developer of the LBB method, Rainer Froese. We would like to thank all the reviewers for their valuable comments and advice.

REFERENCES

Arnold, L. M., and Heppell, S. S. (2014). Testing the robustness of data-poor assessment methods to uncertainty in catch and biology: a retrospective approach. *ICES J. Mar. Sci.* 72, 243–250. doi: 10.1093/icesjms/fsu077

Carruthers, T. R., Kell, L. T., Butterworth, D. D. S., Maunder, M. N., Geromont, H. F., Walters, C. et al. (2016). Performance review of simple management procedures. *ICES J. Mar. Sci.* 73, 464–482. doi: 10.1093/icesjms/fsv212

Chong, L., Mildenberger, T. K., Rudd, M. B., Marc, H., Taylor, M. H., Cope, J. M., et al. (2020). Performance evaluation of data-limited, length-based stock assessment methods. *ICES J. Mar. Sci.* 77, 97–108. doi: 10.1093/icesjms/fsz212

Demer, D. A., and Zwolinski, J. P. (2014). Optimizing Fishing Quotas to Meet Target Fishing Fractions of an Internationally Exploited Stock of Pacific Sardine. *North Am. J. Fish Manage* 34, 1119–1130. doi: 10.1080/02755947.2014.951802

Dick, E. J., and MacCall, A. D. (2011). Depletion-based stock reduction analysis: A catch-based method for determining sustainable yields for data-poor fish stocks. *Fish Res.* 110, 331–341. doi: 10.1016/j.fishres.2011.05.007

FAO (2016). *Report of the FAO/CECAF Working Group on the Assessment of Small Pelagic Fish-Subgroup South. CECAF/ECAF SERIES 12/74*. Rome: FAO.

FAO (2019). *FAO Yearbook*. Rome: Fishery and Aquaculture Statistics, 2017.

Froese, R., Winker, H., Gascuel, D., Sumaila, U. R., and Pauly, D. (2016). Minimizing the impact of fishing. *Fish Fish* 17:785802. 12146 doi: 10.1111/faf

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2018). A new approach for estimating stock status from length frequency data. *ICES J. Mar. Sci.* 75, 2004–2015. doi: 10.1016/j.eururo.2011.1 1.040

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2019). On the pile-up effect and priors for L_{inf} and M/K: response to a comment by hordyk et al. on "A new approach for estimating stock status from length-frequency data. *ICES J. Mar. Sci.* 76, 461–465. doi: 10.1093/icesjms/fsy199

Geng, Z., Wang, Y., Richard, K., Zhu, J. F., and Dai, X. J. (2021). Demographic and harvest analysis for blue shark (*Prionace glauca*) in the Indian Ocean. *Reg. Stud. Mar. Sci.* 41:101453. doi: 10.1016/j.rsma.2020.101583

Guan, W. J., Gao, F., Li, G., and Chen, X. J. (2014). Risk evaluation for meta-population management:a case study using chub mackerel. *Acta Ecologica Sinica* 34, 3682–3692.

Guan, W. J., Tang, L., Zhu, J. F., Tian, S. Q., and Xu, L. X. (2016). Application of a Bayesian method to data-poor stock assessment by using Indian Ocean albacore (*Thunnus alalunga*) stock assessment as an example. *Acta Oceanol. Sin.* 35, 117–125. doi: 10.1007/s13131-016-0814-0

Guan, W. J., Tian, S. Q., Zhu, J. F., and Chen, X. J. (2013). A review of fisheries stock assessment models. *J. Fish. Sci. China.* 20, 1112–1120. doi: 10.3724/sp.j.1118.2013.01112

Hua, C. X., Li, F., Zhu, Q. C., and Meng, L. W. (2020). Habitat suitability of Pacific saury (*Cololabis saira*) based on a yield-density model and weighted analysis. *Fish Res.* 221:105408. doi: 10.1016/j.fishres.2019.105408

Holt, S. J. (1958). *"The evaluation of fisheries resources by the dynamic analysis of stocks, and notes on the time factors involved," in International Commission for the Northwest Atlantic Fisheries*. Vancouver: ICNAF Special Publication, 77–95.

Hordyk, A. R., Prince, J. D., Carruthers, T. R., and Walters, C. J. (2018). Comment on "A newapproach for estimating stock status from length frequency data" by Froese *et al.* (2018). *ICES J. Mar. Sci.* 76, 457–460. doi: 10.1093/icesjms/fsy168

Hordyk, A., Ono, K., Valencia, S. R., Loneragan, N., and Prince, J. (2015). A novel length-based empirical estimation method of spawning potential ratio (SPR), and tests of its performance, for small-scale, data-poor fisheries. *ICES J. Mar. Sci.* 72, 217–231. doi: 10.1093/icesjms/fsu004

Ichikawa, M., and Okamura, H. (2016). Modeling of fishery with autoregressive state-space models for quantifying management effectiveness in the Pacific Chub Mackerel fishery. *Proc. Inst. Stat. Math.* 64, 59–75. doi: 10.1890/14-1216.1

Iwahashi, M., Isoda, Y., Ito, S., Oozeki, Y., and Suyama, S. (2006). Estimation of seasonal spawning ground locations and ambient sea surface temperatures for eggs and larvae of Pacific saury (*Cololabis saira*) in the western North Pacific. *Fish Oceanogr.* 15, 125–138. doi: 10.1111/j.1365-2419.2005.00384.x

Jiao, Y., Cortés, E., Andrews, K., and Guo, F. (2011). Poor-data and data-poor species stock assessment using a Bayesian hierarchical approach. *J. Appl. Ecol.* 21, 2691–2708. doi: 10.1890/10-0526.1

Kawai, H., Yatsu, A., Watanabe, C., Mitani, T., Katsukawa, T., and Matsuda, H. (2002). Recovery policy for chub mackerel stock using recruitment-per-Spawning. *Fish. Sci.* 68, 963–971. doi: 10.1046/j.1444-2906.2002.00520.x

Kindong, R., Gao, C. X., Pandong, N. A., Ma, Q. Y., Tian, S. Q., Wu, F., et al. (2020). Stock status assessments of five small pelagic species in the Atlantic and Pacific Oceans using the Length-Based Bayesian estimation (LBB) method. *Front. Mar. Sci.* 7:592082. doi: 10.3389/fmars.2020.592082

Klaer, N. L., Wayte, S. E., and Fay, G. (2012). Anevaluation of the performance of a harvest strategy that uses an average-length-based assessment method. *Fish Res.* 134-136, 42–51. doi: 10.1016/j.fishres.2012.08.010

Kuroda, H., and Yokouchi, K. (2017). Interdecadal decrease in potential fishing areas for Pacific saury off the southeastern coast of Hokkaido, Japan. *Fish. Oceanogr.* 26, 439–454. doi: 10.1111/fog.12207

Liang, C., Xian, W., Liu, S., and Pauly, D. (2020). Assessments of 14 exploited fish and invertebrate stocks in Chinese waters using the LBB method. *Front. Mar. Sci.* 7:314. doi: 10.3389/fmars.2020.00314

Ma, Q. Y., Tian, S. Q., Han, D. Y., Richard, K., Gao, C. X., and Liu, W. C. (2021). Growth and maturity heterogeneity of three croaker species in the East China Sea. *Reg. Stud. Mar. Sci.* 41:101483. doi: 10.1016/j.rsma.2020.101483

MacCall, A. D. (2009). Depletion-corrected average catch: A simple formula for estimating sustainable yields in data-poor situations. *ICES J. Mar. Sci.* 66, 2267–2271. doi: 10.1093/icesjms/fsp209

Magnusson, A., and Hilborn, R. (2007). What makes fisheries data informative? *Fish. Fish.* 8, 337–358. doi: 10.1111/j.1467-2979.2007.00258.x

Martell, S., and Froese, R. (2013). A simple method for estimating MSY from catch and resilience. *Fish. Fish.* 14, 504–514. doi: 10.1111/j.1467-2979.2012.00485.x

North Pacific Fisheries Commission [NPFC] (2017). *NPFC Yearbook 2017*. Vancouver, BC: North Pacific Fisheries Commission, 385.

Palomares, M. L. D., Froese, R., Derrick, B., Nöel, S. L., Tsui, G., and Woroniak, J. (2018). *"A preliminary global assessment of the status of exploited marine fish and invertebrate populations," in A Report Prepared by the Sea Around Us for OCEANA*. Washington, DC: OCEANA, 64.

Pauly, D. (1998). Beyond our original horizons: the tropicalization of Beverton and Holt. *Rev. Fish Biol. Fish.* 8, 307–334.

Pons, M., Cope, J. M., and Kell, L. T. (2020). Comparing performance of catch-based and length-based stock assessment methods in data-limited fisheries. *Can. J. Fish. Aquat. Sci.* 77, 1026–1037. doi: 10.1139/cjfas-2019-0276

Punt, A. E. (2011). Extending production models to include process error in the population dynamics. *Can. J. Fish. Aquat. Sci.* 60, 1217–1228.

Quinn, T. J., and Deriso, R. B. (1999). *Quantitative Fish Dynamics*. New York, NY: Oxford University Press.

Rudd, M. B., and Thorson, J. T. (2018). Accounting for variable recruitment and fishing mortality in length-based stock assessments for data-limited fisheries. *Can. J. Fish. Aquat. Sci.* 75, 1019–1035. doi: 10.1139/cjfas-2017-0143

Sakurai, Y., Kiyofuji, H., Saitoh, S., Goto, T., and Hiyama, Y. (2000). Changes in inferred spawning areas of *Todarodes pacificus* (*Cephalopoda: Ommastrephidae*) due to changing environmental conditions. *ICES J. Mar. Sci.* 57, 24–30. doi: 10.1006/jmsc.2000.0667

Shi, Y. C., Hua, C. X., Zhu, Q. C., Huang, S. L., and Feng, H. L. (2020). Applying the Catch-MSY model to the stock assessment of the northwest Pacific saury *Cololabis Saira*. *J. Oceanol. Limnol.* 38, 1945–1955. doi: 10.1007/s00343-019-9156-z

Shi, Y. C., Zhu, Q. C., Huang, S. L., and Hua, C. X. (2018). Stock Assessment of Pacific Suary (*Cololabis Saira*) in the Northwest Pacific Using a Bayesian Schaefer Model. *Prog. Fish. Sci.* 40, 1–10.

Shiraishi, T., Okamoto, K., Yoneda, M., Sakai, T., Ohshimo, S., Onoe, S., et al. (2008). Age validation, growth and annual reproductive cycle of chub mackerel Scomber japonicus, off che waters of northern Kyushu and in the East China Sea. *Fish. Sci.* 74, 947–954. doi: 10.1111/j.1444-2906.2008.01612.x

Suyama, S., Sakurai, Y., Meguro, T., and Shimazaki, K. (1992). Estimation of the age and growth of Pacific saury *Cololabis saira* in thr central North Pacific Ocean determined by otolith daily growth increments. *Nippon Suisan Gakkaishi*. 58, 1607–1614. doi: 10.2331/suisan.58.1607

Tian, Y. J., Akamine, T., and Suda, M. (2004). Modeling the influence of oceanic-climatic changes on the dynamics of Pacific saury in the northwestern Pacific using a life cycle model. *Fish. Oceanogr.* 13, 125–137. doi: 10.1111/j.1365-2419.2004.00314.x

Ueno, Y., Suyama, S., Nakagami, M., Naya, M., Sakai, M., and Kurita, Y. (2017). Direct estimation of stock abundance of Pacific saury Cololabis saira in the northwestern Pacific Ocean using a mid-water trawl. *Fish. Sci.* 83, 23–33.

von Bertalanffy, L. (1938). A quantitative theory of organic growth (inquiries on growth laws. II.). *Hum. Biol.* 10, 181–213.

Wang, J. T., Yu, W., Chen, X., and Chen, Y. (2016). Stock assessment for the western winter-spring cohort of neon flying squid (*Ommastrephes bartramii*) using environmentally dependent surplus production models. *Sci. Mar.* 80, 69–78.

Wang, Y., Wang, Y., Liu, S., Liang, C., Zhang, H., and Xian, W. (2020). Stock Assessment Using LBB Method for Eight Fish Species from the Bohai and Yellow Seas. *Front. Mar. Sci.* 7:164. doi: 10.3389/fmars.2020

Watanabe, C., and Yatsu, A. (2004). Effects of density-dependence and sea surface temperature on interannual variation in length-at-age of chub mackerel (*Scomber japonicus*) in the Kuroshio-Oyashio area during 1970-1997. *Fish. Bull.* 102, 196–206.

Watanabe, K., Tanaka, E., Yamada, S., and Kitakado, T. (2006). Spatial and temporal migration modeling for stock of Pacific saury *Cololabis saira* (Brevoort), incorporating effect of sea surface temperature. *Fish. Sci.* 72, 1153–1165. doi: 10.1111/j.1444-2906.2006.01272.x

Watanabe, Y., Zenitani, H., and Kimura, R. (1995). Population decline of the Japanese sardine Sardinops melanostictus owing to recruitment failures. *J. Can. Sci. Halieutiques Aquat.* 52, 973–983.

Wetzel, C. R., and Punt, A. E. (2011). Model performance for the determination of appropriate harvest levels in the case of data-poor stocks. *Fish Res.* 110, 342–355. doi: 10.1016/j.fishres.2011.04.024

Yan, L. P., Li, J. S., Ling, J. Z., Ye, S. Z., and Zhang, H. L. (2010). Assessment on the biomass of *Scomber japonicas* resources in the western East China Sea by length-structure VPA. *Prog. Fish. Sci.* 31, 16–22.

Yatsu, A., Mitani, T., Watanabe, C., Nishida, H., Kawabata, A., and Matsuda, H. (2002). Current stock status and management of chub mackerel, Scomber japonicas, along the Pacific coast of Japan an example of allowable biological catch determination. *Fish. Sci.* 68, 93–96. doi: 10.2331/fishsci.68.sup1_93

Yatsu, A., Watanabe, T., Ishida, M., Sugisaki, H., and Jacobson, L. D. (2005). Environmental effects on recruitment and productivity of Japanese sardine *Sardinops melanostictus*, and chub mackerel *Scomber japonicus*, with recommendations for management. *Fish Oceanogr.* 14, 263–278. doi: 10.1111/j.1365-2419.2005.00335.x

Yukami, R., Ohshimo, S., Yoda, M., and Hiyama, Y. (2009). Estimation of the spawning grounds of chub mackerel *Scomber japonicus* and spotted mackerel *Scomber australasicus* in the East China Sea based on catch statistics and biometric data. *Fish. Sci.* 75, 167–174. doi: 10.1007/s12562-008-0015-7

Zhang, G. W., Chen, X. J., and Li, G. (2009). Bio-economic model and its application of Chub mackerel in the East China Sea and Yellow Sea. *J. Shanghai Ocean Univ.* 18, 447–452.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers in Marine Science

ORIGINAL RESEARCH
published: 16 February 2022
doi: 10.3389/fmars.2021.759465

Using Data-Limited Methods to Assess the Status of Bartail Flathead *Platycephalus indicus* Stocks in the Bohai and Yellow Seas

Lei Zheng[1,2,3†], Yuanchao Wang[1,2,3†], Shude Liu[4], Cui Liang[1,2,5,6*] and Weiwei Xian[1,2,3,5,6*]

[1] Key Laboratory of Marine Ecology and Environmental Sciences, Institute of Oceanology, Chinese Academy of Sciences, Qingdao, China, [2] Laboratory for Marine Ecology and Environmental Science, Qingdao National Laboratory for Marine Science and Technology, Qingdao, China, [3] University of Chinese Academy of Sciences, Beijing, China, [4] Shandong Fisheries Development and Resources Conservation Center, Yantai, China, [5] Center for Ocean Mega-Science, Chinese Academy of Sciences, Qingdao, China, [6] CAS Engineering Laboratory for Marine Ranching, Institute of Oceanology, Chinese Academy of Sciences, Qingdao, China

OPEN ACCESS

Edited by:
Yngvar Olsen,
Norwegian University of Science and Technology, Norway

Reviewed by:
Jason Marc Cope,
National Marine Fisheries Service (NOAA), United States
Myriam Khalfallah,
University of British Columbia, Canada
Chiara Manfredi,
University of Bologna, Italy

***Correspondence:**
Cui Liang
liangc@qdio.ac.cn
Weiwei Xian
wwxian@qdio.ac.cn

†These authors have contributed equally to this work and share first authorship

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: 16 August 2021
Accepted: 30 December 2021
Published: 16 February 2022

Citation:
Zheng L, Wang Y, Liu S, Liang C and Xian W (2022) Using Data-Limited Methods to Assess the Status of Bartail Flathead Platycephalus indicus Stocks in the Bohai and Yellow Seas. Front. Mar. Sci. 8:759465. doi: 10.3389/fmars.2021.759465

We applied Catch and Maximum Sustainable Yield (CMSY), Bayesian Schaefer model (BSM), and Abundance Maximum Sustainable Yield (AMSY) methods to estimate the status of *Platycephalus indicus* stocks in the Bohai and Yellow Seas, assessed model performance, and determined the impact of priors derived from expert knowledge on the performance of each model. Results showed that *P. indicus* stock in the Bohai Sea had collapsed, while that in the Yellow Sea stock was recovering. With the input of an expert prior derived from the length-based Bayesian biomass (LBB) estimation method, the CIs of each model narrowed, but the changes in biomass trajectory were not significant, and the estimates of B/B_{MSY} were differed compared with model results using default rules. These three models can be used to evaluate data-limited stocks to reflect stock dynamics when reliable inputs are available. However, the ranges of priors, which are preferably obtained from other stock assessment tools, should be carefully established.

Keywords: stock assessment, fishery, *Platycephalus indicus*, Bohai Sea, Yellow Sea, data-limited methods

INTRODUCTION

Marine fisheries are important for the economy and wellbeing of coastal communities, because they provide food and livelihood security, and traditional cultural identity (FAO, 2005). According to FAO statistics, world fishery yield experienced a period of rapid growth after World War II, and then, it has declined since the 1980s and nowadays can only maintain at around 100 million tons each year (FAO, 2020). As the largest fishing country in the world, China accounts for about 15% of the total global fishery production and exceeds the total catch of the next two ranking countries (FAO, 2020). The increase of Chinese fishery production by one order of magnitude from 1950 to 2010 could be regarded as a success story (Srinivasan et al., 2012), but the cost is the depletion of its coastal marine fishery resources. One-third of globally assessed fish populations are overexploited (FAO, 2018), and in China, the situation might be worse. At the same time, comparatively less information about Chinese fishery status is actually available, due to the lack of data and experts, which precludes the possibility of fishery resources recovery. Therefore, it is necessary to evaluate the status of the coastal fishery resources of China.

The bartail flathead *Platycephalus indicus* is commercially fished off the coast of China. In recent years, surveys have reported general declines in the resources of commercially harvested fish species in the Yellow and Bohai Seas. With the decline of traditional fishery resources, the stock of *P. indicus* has become one of the few commercial species with a certain yield along the coast of Liaoning, and its yield is becoming more and more valuable (Li et al., 2018). Studies on *P. indicus* focused mainly on the characteristics of its morphology, age, growth, and sexual maturity. Although many studies have examined the biology and ecology of *P. indicus*, few have assessed its stocks. Only Qin and Gao (2012) studied the seasonal variation of *P. indicus* stock resource abundance in Dongying coastal waters, and additional research is required to assess its resources and time-series trends in the coastal waters of China. Such studies will guide the more sustainable management of the coastal fishery resources of China.

The lack of relevant fishery data (i.e., population structure data, abundance data, and body-length data) and data-limitation models restricts the options for research. However, the Catch and Maximum Sustainable Yield (CMSY) and Bayesian Schaefer model (BSM) proposed by Froese et al. (2017) provide relatively new potential solutions to the data deficiency problem. By using the time series of catch data (and catch-per-unit-effort (CPUE) data) and ancillary qualitative information, CMSY (and BSM) methods can quantify biomass, exploitation rate, maximum sustainable yield (MSY), and related fisheries reference points for a given stock. The exploitation level and stock status are unknown for most of the fish stocks of China because the data required for full stock assessments are missing. To resolve this, a new method, i.e., the Abundance Maximum Sustainable Yield (AMSY), was proposed by Froese et al. (2020), to estimate relative stock size when no catch data are available. This method uses the time series of CPUE data or other relative abundance indices as main inputs. AMSY estimates for relative stock size do not differ significantly from "true" values when conducted with simulated data (Froese et al., 2020). CMSY, BSM, and AMSY models are well suited to estimate productivity and relative stock size and may, therefore, aid the management of data-poor stocks, such as that for *P. indicus*.

In this contribution, we applied CMSY, BSM, and AMSY models to assess the resource status and fishery reference points of *P. indicus* in the Bohai and Yellow Seas, China, and set up two groups (a default group and an expert group) for each model to explore the influence of the use of an expert prior on the model results. Finally, based on the biology and fishery knowledge of *P. indicus*, we discussed a sustainable fishery management scheme and the potential applications for the three models. This contribution can serve as a baseline for more sustainable fisheries management in the future.

MATERIALS AND METHODS

Data Sources

The catch data for *P. indicus* were collected from the fishing logs of offshore fishing vessels in Shandong Province from 2012 to 2019. Fishing areas are shown in **Figure 1**. We obtained CPUE data by dividing the total catch by the multiplication of fishing time and fishing power (**Supplementary Table 1**). Since there were no other factors that could be included in the CPUE standardization, the abundance index that we used here was a raw CPUE.

Catch and Maximum Sustainable Yield and Bayesian Schaefer Model Methods

The CMSY model, a Monte Carlo method, enables the estimation of biomass to provide MSY (B_{MSY}) and related fishery reference points such as relative stock size (B/B_{MSY}) and exploitation (F/F_{MSY}) (Martell and Froese, 2013; Froese et al., 2017). When further relative abundance data, such as CPUE or biomass, are also available, a Bayesian state-space implementation of the Schaefer production model (BSM; based on Millar and Meyer, 1999) could be used for these assessments together with CMSY. Both CMSY and BSM methods are based on the logic of the surplus production model of Schaefer (1954, 1957). By inputting a time series of catch (and abundance data) and qualitative stock status information (or set as NA for default), the usable ranges of parameters, such as r and k, are filtered with a Monte Carlo algorithm. In this contribution, CMSY was based on the catch time series recorded in the fishing logs of Shandong Province from 2012 to 2019, which were standardized according to the number of fishing vessels. BSM was based on the same catch time-series data as CMSY, and the CPUE data were calculated according to catch data, working hours, and fishing vessel power. Since the CPUE data for the Yellow Sea in 2018 were missing, the data for this year were replaced by the average of the previous (2017) and following (2019) years.

Abundance Maximum Sustainable Yield Method

The AMSY is a new data-limited method that estimates fishery reference points when no catch data are available, using time series of CPUE data or other relative abundance indices as the main input (Froese et al., 2020). In addition to these data, AMSY also needs a prior for relative stock size (B/k, ranging from 0 to 1) in a certain year of the time series. AMSY uses this information and tests a high number of combinations of r and k for their compatibility with these inputs. A detailed explanation of the theory and equations behind AMSY is provided by Froese et al. (2020).

Setting Prior Parameters Ranges

In addition to catch and CPUE data, each model needs to input a prior on relative biomass (B/k) and r range or to set these inputs as "NA" to use default settings (Froese et al., 2017). To explore the influence of prior inputs, we divided each of the Bohai and Yellow Sea stocks into a default group and an expert group, respectively.

In the default group, except for the input of catch and CPUE data, other settings were set to default values. It should be noted that Froese et al. (2017) have given the setting rules for the default starting relative biomass (in order to avoid the confusion of relative biomass in different years, in this study, we used B_{start}/k to represent the starting relative biomass and B_{inter}/k for the intermediate relative biomass) range of CMSY and BSM: if the time series of catch data starts before 1960, high initial biomass (0.5–0.9) is estimated, given that most fisheries were either still

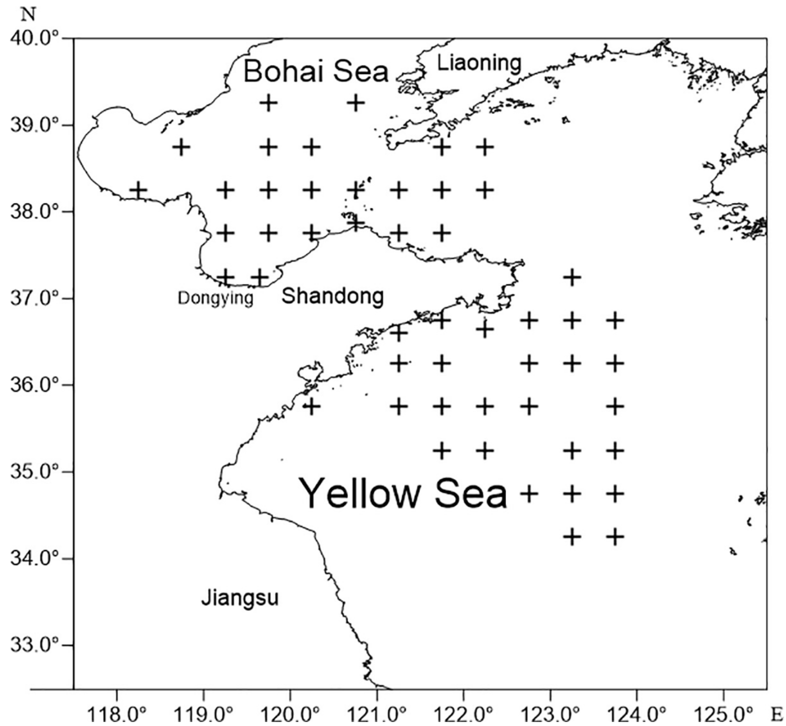


FIGURE 1 | Fishing areas, Bohai and Yellow Seas, China.

recovering or starting anew after World War II; in all other cases, medium initial relative biomass (0.2–0.6) is estimated. Meanwhile, the rules for setting intermediate biomass (B_{inter}/k) are provided as supplementary materials by Froese et al. (2017). As for the AMSY method, the model provides four options of initial relative biomass (B_{start}/k) ranges for selection when there is no reliable starting relative biomass data for use. In this study, we chose the setting of "very low (0.01–0.15)." This did not conflict with our expert data, because it included the range of our expert data and was specified by the model. More details can be found in the *Preliminary User Guide for AMSY*, available from http://oceanrep.geomar.de/47135/. It is fine to use a different starting relative biomass between AMSY and CMSY/BSM, because the main aim of this study was to explore the difference between the default group and the expert group for each model (i.e., AMSY and CMSY), instead of observing the difference between models, and each model has its own application situation. Moreover, we tried to avoid using too much information in the default group to affect the judgment of the model itself, so we used the settings provided by the model.

In the expert group, prior ranges for the start year and intermediate year relative biomass of the time series of catch and/or abundance data were obtained from the length-based Bayesian biomass (LBB) estimation model (Froese et al., 2018). The body length-frequency data required for the LBB analysis were collected from published studies (**Table 1**). The value of B_{start}/k was obtained from the LBB model with the data provided by Qin and Gao (2012), and B_{inter}/k was also obtained from the LBB model with the data of 2015 fishing logs of Shandong Province. The prior ranges of r and B for three models can be found in **Table 2**.

Prior ranges for the intrinsic rate of population increase (r), referred to as "resilience" by Musick (1999), were obtained from FishBase (Froese and Pauly, 2021). The prior range for the unexploited population size or carrying capacity (k) is calculated as follows:

$$k_{low} = \frac{\max(C)}{r_{high}} \text{ and } k_{high} = \frac{4\max(C)}{r_{low}} \tag{1}$$

$$k_{low} = \frac{2\max(C)}{r_{high}} \text{ and } k_{high} = \frac{12\max(C)}{r_{low}} \tag{2}$$

where k_{low} and k_{high} are the lower and upper boundary priors for k, respectively; max(C) is the maximum catch value of the time series of catch data; r_{low} and r_{high} are the lower and upper boundary priors of the r value, respectively.

RESULTS

Bohai Sea Stock

For the Bohai Sea stock, both groups (default and expert) were identified to be seriously overfished by all models. The exploitation rate (F/F_{MSY}) was estimated to be >1.0 in each scenario, with stock size (B/B_{MSY}) ranging from 0.149 to 0.693, and the stock size of the expert group was lower than that of the default group (**Figure 2** and **Table 3**). The Kobe plots based on all scenarios indicated a probability of 40.9–74.3% that the Bohai Sea

TABLE 1 | Main outputs of length-based Bayesian biomass (LBB) model for different periods.

Sea area	Number of samples	Time	Body length		Output											Source
			Min	Max	B/k	lcl	ucl	B/B_{MSY}	lcl	ucl	F/M	lcl	ucl	L_{mean}/L_{opt}	L_{95th}/L_{inf}	
Yellow Sea	742	1966	167	500	0.76	0.24	2.4	1.9	0.6	6	0.18	0.0971	0.523	0.87	0.96	Chen and Zhao, 1986
Bohai Sea	Unknown	2010	62	327	0.1	0.061	0.15	0.28	0.17	0.42	1.7	1.21	2.47	0.42	0.63	Qin and Gao, 2012
Bohai Sea	165	2015	43	520	0.32	0.21	0.5	0.86	0.56	1.4	0.96	0.72	1.45	0.8	0.89	2015 fish log of Shandong

TABLE 2 | Prior ranges of *r* and *B* for Catch and Maximum Sustainable Yield (CMSY), Bayesian Schaefer model (BSM), and Abundance Maximum Sustainable Yield (AMSY).

	Bohai Sea stock						Yellow Sea stock					
	CMSY		BSM		AMSY		CMSY		BSM		AMSY	
	Default	Expert	Default	Expert	Default	Expert	Default	Expert	Default	Expert	Default	Expert
r	0.2–0.8	0.42–0.96	0.2–0.8	0.42–0.96	0.2–0.8	0.42–0.96	0.2–0.8	0.42–0.96	0.2–0.8	0.42–0.96	0.2–0.8	0.42–0.96
B_{start}	0.2–0.6	0.061–0.15	0.2–0.6	0.061–0.15	0.01–0.2	0.061–0.15	0.2–0.6	0.061–0.15	0.2–0.6	0.061–0.15	0.01–0.2	0.061–0.15
B_{inter}	0.5–0.9	0.21–0.5	0.5–0.9	0.21–0.5	/	/	0.5–0.9	0.21–0.5	0.5–0.9	0.21–0.5	/	/

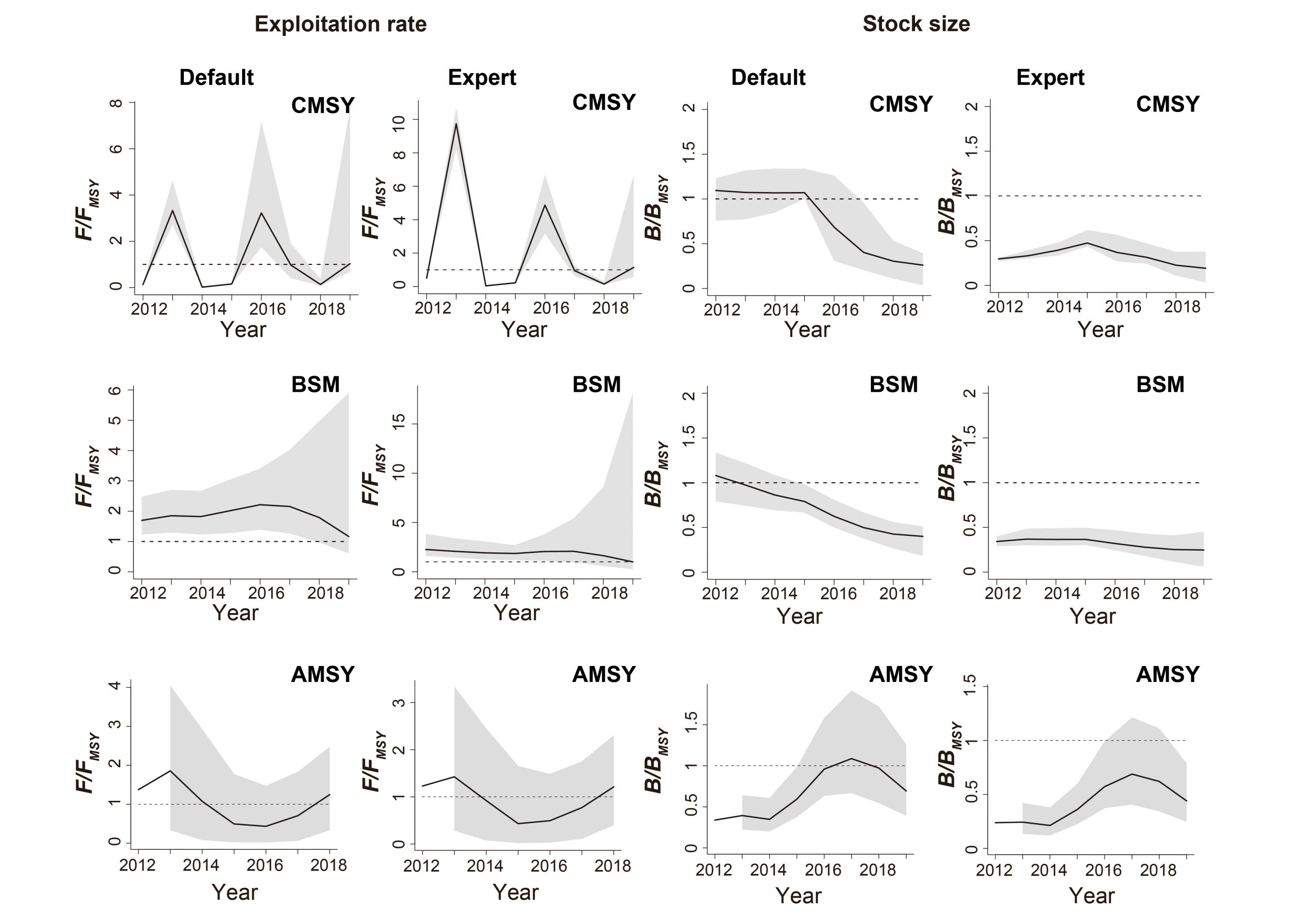


FIGURE 2 | Estimated relative biomass (B/B_{MSY}) and fishing mortality (F/F_{MSY}) trajectories for the Bohai Sea stock, with the gray areas indicating the CIs.

TABLE 3 | The main outputs of CMSY, BSM, and AMSY.

	Bohai Sea stock						Yellow Sea stock					
	CMSY		BSM		AMSY		CMSY		BSM		AMSY	
	Default	Expert	Default	Expert	Default	Expert	Default	Expert	Default	Expert	Default	Expert
F/F_{MSY}	1.09	1.93	1.17	1.14	1.25	1.21	0.92	1.33	0.789	0.682	0.236	0.295
B/B_{MSY}	0.254	0.149	0.4	0.191	0.693	0.441	1.37	0.767	1.33	0.884	1.48	1.24

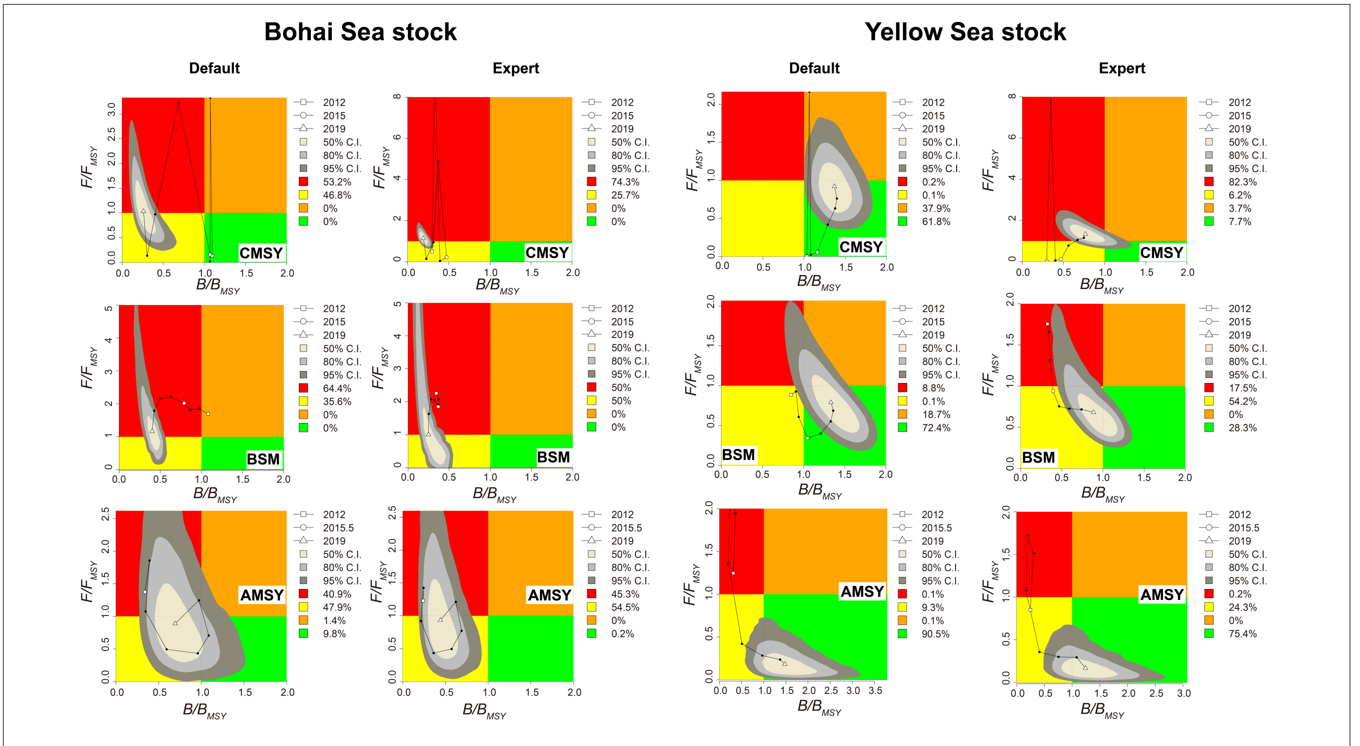


FIGURE 3 | Kobe plots showing B/B_{MSY} against F/F_{MSY} ratios estimated by three models for Bohai Sea and Yellow Sea stocks.

stock experienced ongoing overfishing (red part), and the stock size was very small to produce MSY (**Figure 3**).

The CMSY results suggested that the Bohai Sea stock was seriously overfished in 2013 and 2016 (**Figure 2**). F/F_{MSY} of the default group in 2013 was not much different from that in 2016, while for the expert group, the F/F_{MSY} estimate in 2013 was particularly high, and it was almost two times that in 2016. The estimation of B/B_{MSY} at the start year was also quite different between the two groups. B/B_{MSY} estimate in 2012 for the default group was >1.0, while the expert group indicated that the population was already unhealthy at the start year ($B/B_{MSY} < 1.0$). According to the Kobe plots, the probabilities of the Bohai Sea stock collapse were 53.2% for the default group and 74.3% for the expert group (**Figure 3**).

The BSM results revealed that F/F_{MSY} of the Bohai Sea stock always exceeded 1.0, and the B/B_{MSY} estimates were low (**Figure 2**). The results of the default group indicated that F/F_{MSY} of the Bohai Sea stock increased first and then decreased back to near 1.0, and F/F_{MSY} of the expert group experienced a constant decrease. For the estimation of B/B_{MSY}, the default group gave a B/B_{MSY} trajectory implying that the stock shifted from healthy to gradually collapsed, while the expert group suggested that the stock was overfished ($B/B_{MSY} < 1.0$) throughout the time series. The Kobe plots revealed 50% (expert group) and 64.4% (default group) probabilities of stock collapse (**Figure 3**).

The trajectories of F/F_{MSY} and B/B_{MSY} estimated by AMSY for default and expert groups were consistent (**Figure 2**). F/F_{MSY} estimates increased from 2012 to 2013 (the highest point) and then declined and fell to their lowest value in 2015. As for B/B_{MSY}, a low period was experienced between 2012 and 2014, after which it peaked in 2017 and then decreased again. The Kobe plots results of AMSY revealed the probabilities of 40.9% (default group) and 45.3% (expert group) of Bohai Sea stock collapse (**Figure 3**).

Yellow Sea Stock

The Yellow Sea stock was suggested to have a relatively optimistic status (**Figure 4**). Only the expert group estimated by the CMSY method was supposed to have $F/F_{MSY} > 1.0$ and $B/B_{MSY} < 1.0$. Other scenarios predicted F/F_{MSY} ranging from 0.236 to 0.92 and B/B_{MSY} ranging from 0.884 to 1.48. All Kobe plots, except for

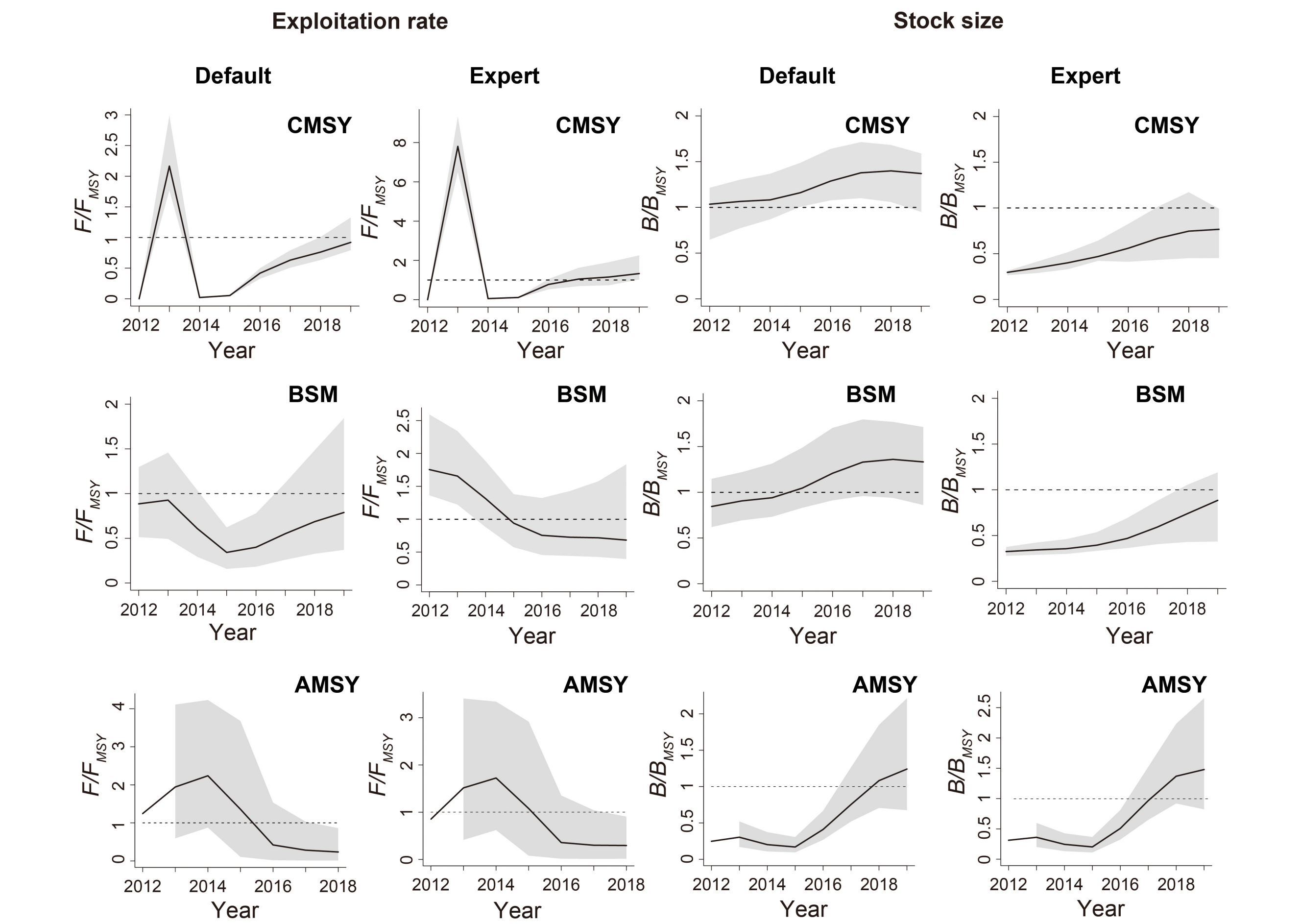


FIGURE 4 | Estimated relative biomass (B/B_{MSY}) and fishing mortality (F/F_{MSY}) trajectories for the Yellow Sea stock, with the gray areas indicating the CIs.

the CMSY plot for the expert group, had a probability of 28.3–90.5% that the stock was being sustainably fished and capable of producing high yields close to MSY (**Figure 3**).

The CMSY results indicated that the Yellow Sea stock had a high F/F_{MSY} value in 2013, and in other years, F/F_{MSY} was low (**Figure 4**). For the estimated B/B_{MSY} in the Yellow Sea, the default and expert groups noticeably differed, mainly reflected in the relative biomass at the beginning of the time series. Although relative biomass trended upward in both groups, due to the influence of the initial relative biomass, the B/B_{MSY} of the default group exceeded 1.0 in 2019, while that of the expert group was <1.0. This also made the Kobe plots results different, with the default group indicating that 61.8% of the stock was healthy in 2019, while the expert group suggested that the stock had an 82.3% probability of collapse (**Figure 3**). Besides, the input of an expert prior shrank the CIs of the fishery reference points (**Figures 4**).

As for the results of BSM, the overall F/F_{MSY} of the default group was <1.0, and the highest value occurred in 2013 (**Figure 4**). The expert group suggested that the stock was overfished already in 2012, and then, the F/F_{MSY} value decreased year by year, until 2019, when it was <1.0. The B/B_{MSY} estimates indicated that the stock was slowly recovering, similar to that of CMSY results. According to the CIs of the Kobe plots, the probabilities of the stock being healthy were 72.4% (for the default group) and 28.3% (for the expert group) (**Figure 3**). Similar to CMSY, the fishery reference points of the expert group had narrower CIs than that of the default group (**Figure 4**).

The F/F_{MSY} and B/B_{MSY} trajectories of both default and expert groups produced by the AMSY method were surprisingly consistent (**Figure 4**). F/F_{MSY} peaked in 2014, then decreased consistently, and remained at a lower level from 2016 to 2019. The B/B_{MSY} trajectory indicated that after a period of low relative biomass from 2012 to 2015, it rapidly increased and exceeded 1.0 by 2019. According to the Kobe plots for AMSY, the probability of this stock being healthy in 2019 was 75.4–90.5% (**Figure 3**).

DISCUSSION

The marine fishing industry of China has expanded dramatically over the past 70 years and is currently at the forefront of the world (Aksnes and Browman, 2016; FAO, 2018; Fu et al., 2018). The total marine catch in China has increased by more than two times, from 1.48×10^6 t in 1961 to 3.87×10^6 t in 1985, and then tripled to reach a peak of 12.03×10^6 t in 1999. Catch was subsequently stabilized at a higher level, with small fluctuations, and in 2018, it was about 10.44×10^6 t (Ding et al., 2021). The total biological allowable catch of China is estimated to be around 9×10^6 t (Yang et al., 2016; Yue et al., 2017; Han, 2018), but since the mid-1990s, the domestic marine catches have exceeded these limits. Fishery resources are now under great pressure from intensive fishing activities, and fishing practices in China are largely indiscriminate. Bottom trawling contributes to 47% of the total domestic marine catch, which inevitably has a negative impact on fishery resources (Hiddink et al., 2011; Szuwalski et al., 2017). The accelerated fishing activities and inadequate fishery management have led to reductions in the biomass of traditionally high-value species and the structural changes of marine ecosystems (Jin, 2004; He et al., 2014; Liang and Pauly, 2017; Liu, 2019). Since 1979, the fisheries administrative department of China has formulated a series of measures to improve the management of marine resources (Shen et al., 2014; Su et al., 2020). China also seeks new ways to effectively manage and restore its inshore fisheries.

Effective measures require stock assessments to provide the baseline data. In this study, we applied three data-limited stock assessment models, namely, CMSY, BSM, and AMSY methods, to assess the stock status of *P. indicus* in the Bohai and Yellow Seas. BSM and CMSY results indicated that the Bohai Sea stock had collapsed or was grossly overfished, according to the classification of stock status based on the B/B_{MSY} in the final year (2019) of the time-series data (Palomares et al., 2018). The AMSY model suggested that these stocks were slightly overfished. The exploitation rate (F/F_{MSY}) for all three models exceeded 1.0. Our results are confirmed by Qin and Gao (2012), who suggested that the biomass of *P. indicus* in the Bohai Sea had decreased significantly, with an average catch rate at a lower level. Fisheries management should delimit the protection scope centered on the spawning ground and sustainably exploit the species by strengthening management and policy implementation.

For the Yellow Sea stock, each model suggested that the stock was slightly overfished or healthy (**Table 3**). Except for the expert group estimated by the CMSY method, the predictions of F/F_{MSY} in 2019 for the Yellow Sea stock were suggested to be <1.0, which indicated that the stock in the Yellow Sea was recovering. In a study of Yellow Sea fishery resources, Lv (2018) reported resource levels to be low in 2010 and 2011, before recovering. In 2016, China strengthened the supervision measures for fishing vessels during the closed season, and resources quickly recovered to 2014 levels. According to the Kobe plots for each model, there was a high probability that, by 2019, the Yellow Sea stock had recovered to a healthy level.

To determine the effect of an expert prior on model results, we ran an additional control group for each model using priors derived from expert knowledge for relative biomass and *r*. For both stocks, the AMSY model was less affected by expert inputs. Obviously, the expert *r* and *B/k* inputs significantly narrowed the prior range of *r*–*k* pairs, resulting in a reduction of *r*–*k* pairs (**Supplementary Figures 1**, **2**). There were no changes in trends of other parameters, but CIs shrank, and the overall value of the expert group was slightly lower than that of the default group, such as for Catch/MSY, B/B_{MSY}, and F/F_{MSY}.

We maintained that when reliable expert priors are available, they should be used, because an expert prior improves model performance, narrows CIs, and provides better biomass trajectories and estimates. If continuous catch time-series data and abundance data are available, it would be more appropriate to use the BSM model, as BSM combines information from both datasets. Should only catch or abundance data be available, CMSY or AMSY method can be used, and it still provides valuable information for managing data-limited stocks (Froese et al., 2017, 2020).

To obtain the expert relative biomass (B_{start}/k) prior, we used the LBB model based on the body length-frequency data collected from published studies. It should be noted that when there are other data more than catch time series, such as body-length data, stock synthesis (SS), which can flexibly incorporate multiple data sources, may provide a more robust solution for stock assessment. In addition, the BSM model used in this study is a full Bayesian implementation of a surplus production estimation model, which expands the application of CMSY, and makes it easier to compare estimates from both models. But BSM is a special case of the Bayesian model and is considered here for this restricted testing. More flexible Bayesian stock assessment approaches, such as the Just Another Bayesian Biomass Assessment (JABBA) (Winker et al., 2018), should be used under normal circumstances.

Fishing logs used in this contribution do not provide the CPUE data, but they do record vessel power and working hours, enabling us to calculate CPUE. However, because some data are missing for working hours in 2012, we used 24 h instead, which might decrease the real CPUE. Also, in 2018, there are no CPUE data for the Yellow Sea stock, and AMSY requires continuous time-series CPUE data. To accommodate this, we averaged the data for 2017 and 2019 to replace these missing data. This may explain why the results of AMSY differed from those of the other two models, but its forecast trend was otherwise generally consistent with them. If all three methods are to be used widely, then reliable, long-term catch time-series data are required, which are generally lacking for fisheries in the waters of China. Because the official fishery statistics of China only lists the catches of several major commercial species, these statistics must be improved on a large scale to enable improved assessment and monitoring of management efforts (Liang et al., 2020).

China loses millions of tons of potential catch annually due to overfishing (Mallory, 2016) and has now taken measures to control this excess fishing effort. We used three models to evaluate the present status of *P. indicus* stocks in the Bohai and Yellow Seas and reported each to provide valuable information regarding these data-poor stocks. We concluded that each model has merit in these circumstances, with a selection of the most appropriate model to use determined by the type and amount of data.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding authors.

ETHICS STATEMENT

Ethical review and approval were not required in this study because our data were sourced from existing fisheries data.

AUTHOR CONTRIBUTIONS

LZ performed data collection and analysis and wrote the first draft of the manuscript. YW gave guidance on research methods and writing ideas and participated in the data processing. SL provided the data. YW, WX, and CL conceived and designed the study. All authors contributed to the manuscript and approved the submitted version.

FUNDING

This study was financially supported by grants from the National Natural Science Foundation of China (31872568 and 41976094) and the Natural Science Foundation of China-Shandong Joint Fund for Marine Ecology and Environmental Sciences (U1606404).

ACKNOWLEDGMENTS

We acknowledge Steve O'Shea, from Liwen Bianji (Edanz) (www.liwenbianji.cn/), for editing the English text of a draft of this manuscript.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2021.759465/full#supplementary-material

REFERENCES

Aksnes, D. W., and Browman, H. I. (2016). An overview of global research effort in fisheries science. *ICES J. Mar. Sci.* 73, 1004–1011. doi: 10.1093/icesjms/fsv248

Chen, W., and Zhao, W. (1986). Age and growth of flathead fish (*Platycephalus indicus* Linnaeus) in Yellow Sea. *J. Fish. China* 10, 289–304.

Ding, Q., Shan, X., Jin, X., and Gorfine, H. (2021). A multidimensional analysis of marine capture fisheries in China's coastal provinces. *Fish. Sci.* 87, 297–309. doi: 10.1007/s12562-021-01514-9

FAO (2005). Review of the state of world marine fishery resources. *FAO Fish. Tech. Pap.* 457, 73–79.

FAO (2018). *FAO Yearbook. Fishery and Aquaculture Statistics 2016*. Rome: FAO.

FAO (2020). *FAO Yearbook. Fishery and Aquaculture Statistics 2018*. Rome: FAO, doi: 10.4060/cb1213t

Froese, R., Demirel, N., Coro, G., Kleisner, K. M., and Winker, H. (2017). Estimating fisheries reference points from catch and resilience. *Fish Fish.* 18, 506–526. doi: 10.1111/faf.12190

Froese, R., and Pauly, D. (2021). *FishBase. World Wide Web electronic publication*. Philippines: Fishbase

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2018). A new approach for estimating stock status from length frequency data. *ICES J. Mar. Sci.* 75, 2004–2015. doi: 10.1093/icesjms/fsy078

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2020). Estimating stock status from relative abundance and resilience. *ICES J. Mar. Sci.* 77, 527–538. doi: 10.1093/icesjms/fsz230

Fu, X. M., Zhang, M. Q., Liu, Y., Shao, C. L., Hu, Y., Wang, X. Y., et al. (2018). Protective exploitation of marine bioresources in China. *Ocean Coast. Manag.* 163, 192–204. doi: 10.1016/j.ocecoaman.2018.06.018

Han, Y. (2018). Marine Fishery Resources Management and Policy Adjustment in China Since 1949. *Chin. Rural Econ.* 09, 14–28.

He, Q., Bertness, M. D., Bruno, J. F., Li, B., Chen, G., Coverdale, T. C., et al. (2014). Economic development and coastal ecosystem change in China. *Sci. Rep.* 4:5995. doi: 10.1038/srep05995

Hiddink, J. G., Johnson, A. F., Kingham, R., and Hinz, H. (2011). Could our fisheries be more productive? Indirect negative effects of bottom trawl fisheries on fish condition. *J. Appl. Ecol.* 48, 1441–1449. doi: 10.1111/j.1365-2664.2011.02036.x

Jin, X. S. (2004). Long-term changes in fish community structure in the Bohai Sea, China. *Estuar. Coast. Shelf Sci.* 59, 163–171. doi: 10.1016/j.ecss.2003.08.005

Li, Y., Liu, X., Guang, J. I., Xuguang, Y. U., Yiping, L. I., and Jie, F. U. (2018). Structure and genetic diversity of mtdna d-loop sequences of sand gurnard *Platycephalus indus* inhabiting liaoning coast. *Fish. Sci.* 37, 818–824.

Liang, C., and Pauly, D. (2017). Growth and mortality of exploited fishes in China's coastal seas and their uses for yield-per-recruit analyses. *J. Appl. Ichthyol.* 33, 746–756. doi: 10.1111/jai.13379

Liang, C., Xian, W., and Pauly, D. (2020). Assessments of 15 exploited fish stocks in Chinese, South Korean and Japanese waters using the CMSY and BSM methods. *Front. Mar. Sci.* 7:623. doi: 10.3389/fmars.2020.00623

Liu, Z. (2019). Research on the status, causes and governance of marine fishing ground desertification. *Issues Agric. Econ.* 06, 105–116.

Lv, T. (2018). *Assessment of Important Fishery Resources in the South Offshore of Shandong From 2010 to 2017*. Master thesis. YanTai: YanTai University.

Mallory, T. G. (2016). Fisheries subsidies in China: quantitative and qualitative assessment of policy coherence and effectiveness. *Mar. Policy* 68, 74–82.

Martell, S., and Froese, R. (2013). A simple method for estimating MSY from catch and resilience. *Fish Fish.* 14, 504–514. doi: 10.1111/j.1467-2979.2012.00485.x

Millar, R. B., and Meyer, R. (1999). *Nonlinear state-space modeling of fisheries biomass dynamics using the Gibbs sampler. Technical Report STAT9901, Department of Statistics*. Auckland, New Zealand: The University of Auckland, 33.

Musick, J. A. (1999). Criteria to define extinction risk in marine fishes - The American Fisheries Society initiative. *Fisheries* 24, 6–14. doi: 10.1577/1548-8446(1999)024<0006:ctderi>2.0.co;2

Palomares, M. L. D., Froese, R., Derrick, B., Nöel, S.-L., Tsui, G., Woroniak, J., et al. (2018). *A preliminary global assessment of the status of exploited marine fish and invertebrate populations. A report prepared by the Sea Around Us for OCEANA*. Vancouver: The University of British Columbia, 64.

Qin, Y., and Gao, T. (2012). Fishery biology and resource abundance of *Platycephalus indicus* in coastal water of Dongying. *J. Ocean Univ. China* 42, 106–111.

Schaefer, M. B. (1954). Some aspects of the dynamics of populations important to the management of the commercial marine fisheries. *Inter-Am. Trop. Tuna Comm. Bull.* 1, 23–56.

Schaefer, M. B. (1957). A study of the dynamics of the fishery for yellowfin tuna in the eastern tropical Pacific Ocean. *Inter-Am. Trop. Tuna Comm. Bull.* 2, 243–285.

Shen, G., Heino, M., and Brown, E. (2014). An overview of marine fisheries management in China. *Mar. Policy* 44, 265–272. doi: 10.1016/j.marpol.2013.09.012

Srinivasan, U. T., Watson, R., and Sumaila, U. R. (2012). Global fisheries losses at the exclusive economic zone level, 1950 to present. *Mar. Policy* 36, 544–549.

Su, S., Tang, Y., Chang, B., Zhu, W., and Chen, Y. (2020). Evolution of marine fisheries management in China from 1949 to 2019: how did China get here and where does china go next? *Fish Fish.* 21, 435–452.

Szuwalski, C. S., Burgess, M. G., Costello, C., and Gaines, S. D. (2017). High fishery catches through trophic cascades in China. *Proc. Natl. Acad. Sci. U. S. A.* 114, 717–721. doi: 10.1073/pnas.1612722114

Winker, H., Carvalho, F., and Kapur, M. (2018). JABBA: just another bayesian biomass assessment. *Fish. Res.* 204, 275–288.

Yang, H., Xing, L., and Zhang, L. (2016). Promoting systematic design and innovation-driven development for modern fishery. *Bull. Chin. Acad. Sci.* 31, 1339–1346.

Yue, D., Wang, L., Zhu, X., Geng, R., Fang, H., Xiong, M., et al. (2017). Problems and countermeasures in the supply side of marine capture fishery in China. *J. Agric. Sci. Technol.* 19, 17–26.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

ORIGINAL RESEARCH
published: 20 July 2022
doi: 10.3389/fmars.2022.762203

OPEN ACCESS

Edited by:
*Jie Cao,
North Carolina State University,
United States*

Reviewed by:
*Kui Zhang,
South China Sea Fisheries Research Institute, Chinese Academy of Fishery Sciences (CAFS), China
Athanassios C. Tsikliras,
Aristotle University of Thessaloniki, Greece
Ruben Hernan Roa-Ureta,
King Fahd University of Petroleum and Minerals, Saudi Arabia
Beyah Meissa,
Institut Mauritanien de Recherches Océanographiques et des Pêches, Mauritania*

***Correspondence:**
*Laurence T. Kell
laurie@seaplusplus.co.uk*

Specialty section:
This article was submitted to Marine Fisheries, Aquaculture and Living Resources, a section of the journal Frontiers in Marine Science

Received: 21 August 2021
Accepted: 11 May 2022
Published: 20 July 2022

Citation:
Kell LT, Sharma R and Winker H (2022) Artefact and Artifice: Evaluation of the Skill of Catch-Only Methods for Classifying Stock Status. Front. Mar. Sci. 9:762203. doi: 10.3389/fmars.2022.762203

Artefact and Artifice: Evaluation of the Skill of Catch-Only Methods for Classifying Stock Status

Laurence T. Kell[1*], Rishi Sharma[2] and Henning Winker[3]

[1] Centre for Environmental Policy, Imperial College London, London, United Kingdom, [2] Fisheries and Aquaculture Division, Food and Agriculture Organization of the United Nations, Rome, Italy, [3] Joint Research Centre (JRC), European Commission, Ispra, Italy

In data and capacity limited situations, catch-only models are increasingly being used to provide summaries of the state of regional and global fisheries. Due to the lack of information on stock trends, heuristics are required for initial and final depletion priors. The lack of data for calibration means that results are sensitive to the choice of heuristics. We, therefore, evaluate the value of obtaining additional information for classifying stock status. We found that heuristics alone performed nearly as well as the catch-only model. This highlights that catch-only models cannot be used as part of management control, where data updates are used to monitor the effectiveness of interventions. To implement management for data-poor stocks, additional data and knowledge are therefore required. The value of obtaining additional information for reducing risk due to loss of yield through adopting a risk equivalence approach should be evaluated. This will help identify the value-of-information and prioritise the development of scientific management frameworks that protect marine ecosystems and the well-being of people who have a stake in the resources at regional and local levels.

Keywords: biomass dynamic, data or capacity limited, evaluation, receiver operator characteristics, stock assessment, value of information

1 INTRODUCTION

Fisheries are important economically and socially, but are also a source of conflict since stocks can straddle Exclusive Economic Zones and be conducted in areas beyond national jurisdiction (Palacios-Abrantes et al., 2020). They may also impact endangered, threatened and protected species or vulnerable marine ecosystems (Brown and Hermes, 2019). Therefore, strategic planning and the implementation of Ecosystem-Based Fisheries Management requires assessments of fish stocks on both regional and global scales (Hilborn et al., 2020).

There is an increasing expectation for decision makers to use robust scientific advice on the status of exploited fish stocks (Smith et al., 2009). For example, the International Council for the Exploration of the Sea (ICES) classifies stocks depending on the quality and type of data, ranging from full analytical assessments to those where catch or landings only are available (see Fischer et al., 2020). Therefore, many data-limited approaches have been developed where data and resources are limited (e.g. Dowling et al., 2015b; Wetzel and Punt, 2015; Rosenberg et al., 2018).

A problem when assessing fish stocks is that they can rarely be observed directly, so estimates of status rely on models and a range of fishery-dependent and independent datasets. Many small-scale fisheries, however, lack the datasets required to conduct traditional stock assessments. These are commonly known as data-poor, or data or capacity limited fisheries (e.g. Dowling et al., 2015a). For example, although the Food and Agriculture Organization (FAO) of the United Nations' landings database includes over 20,000 individual catch histories by FAO region, country, and taxon, the RAM Legacy Stock Assessment Database (www.ramlegacy.org), which includes most of the publicly available stock assessments contains only 1,200 assessments (Ovando et al., 2021a).

Various approaches, based on catch-only or length data, have been developed to assess stocks in such situations (e.g. Pons et al., 2018). For example, catch-only models can be used to make general statements about global and regional stock status (Worm et al., 2006), identify stocks of most concern as part of a risk assessment, or provide advice on a stock-specific basis (Bouch et al., 2020). Catch-only models reconstruct historical abundance relative to reference points by making assumptions about productivity and final biomass relative to the unfished state (e.g. Thorson et al., 2012; Froese et al., 2017; Zhou et al., 2018). Simulation has shown, however, that catch-only models are highly sensitive to the choice of priors about such known unknowns (Wetzel and Punt, 2015).

There is a need, therefore, for the validation of catch-only models, particularly as there are potentially many stakeholders with conflicting objectives and divergent views, which may mean that uncertainties are used to support polarised positions (Fromentin et al., 2014). Validation is required to ensure that a model can explain the data and that predictions made for the consequences of management actions, and should be done using observations (Kell et al., 2021). However, this is difficult for catch-only models, where the only observations are catch, and so techniques such as cross-validation cannot be used.

A key step is to identify what information, data and knowledge, are required to permit current catch-only methods to classify stock status relative to overfishing. We, therefore, evaluate the robustness of the assumptions used in catch-only models and the benefit of obtaining better priors and additional information, such as an unbiased estimate of abundance. To achieve this, we use the Bayesian biomass dynamic state-space model JABBA (Winker et al., 2018), which can be configured either as a data-poor or data-moderate assessment. This allows stock status to be estimated relative to maximum sustainable yield (*MSY*) reference points for catch-only models and compared to data-moderate methods that use an index of abundance. To achieve this, we used a reference set of data-rich assessments obtained from the RAM legacy database[1].

2 MATERIAL AND METHODS

Formal model validation requires estimates to be compared to known values (i.e. observations) or well estimated historical values (Kell et al., 2021). However, the only observations used in catch-only models are the catches themselves, and if these observations are removed, then the models cannot be run. There are, therefore, two ways to validate catch-only models, either to use simulation (e.g. Rosenberg et al., 2014a), or to compare with data-rich assessments (Sharma et al., 2021). We chose the latter approach, as this also allows us to better identify the value of obtaining better information, and requires fewer assumptions to be made than in a synthetic simulation study. To accomplish this, a reference set of data-rich stocks were extracted from the RAM database. The database collates stock assessment time series from various regions, species, and fisheries. It, therefore, allows evaluation across a range of fishery types and regions of the benefits of obtaining indices of relative abundance, and improved information on initial and final relative biomass, growth rate (r), and the shape of the production function.

To estimate the skill of alternative models to classifying stock status relative to *MSY* reference points, we use Receiver Operating Characteristic (ROC Green et al., 1966) curves.

2.1 Material

The RAM Legacy database contains stock datasets and estimates derived from a variety of assessment models. Assessments may be based on integrated statistical models using length and age data which estimate reference points as part of the fitting process, virtual population analysis where reference points are estimated in post-processing or biomass dynamic models where assumptions related to density dependence (i.e. growth, mortality and recruitment) are modelled by a production function the maximum of which provides the *MSY* reference points. We selected those assessment datasets that provide estimates of biomass, spawning stock biomass (SSB) or exploitable biomass, and instantaneous fishing mortality or harvest rate relative to *MSY* reference points. This allowed the extraction of dimensionless trends in F/F_{MSY}, B/B_{MSY}, and *Catch/MSY* for a total of 85 stock assessments.

Stock trends, relative to *MSY* benchmarks, are summarised in **Figure 1**. Catches (**Figure 1A**) gradually increased, peaking around 1990 after which they showed a slight decline. Fishing mortality (**Figure 1B**) also increased, but the initial increase was more gradual until 1980. Fishing mortality, like catch, also peaked in 1990 and has stayed around F_{MSY} subsequently. This behaviour is probably due to the adoption of management frameworks based on target and limit reference points by

[1]RAM Legacy Stock Assessment Database. 2018. Version 4.44-assessment-only. Released 2018-12-22. Accessed [Date accessed 2020-10-30]. Retrieved from DOI:10.5281/zenodo.2542919

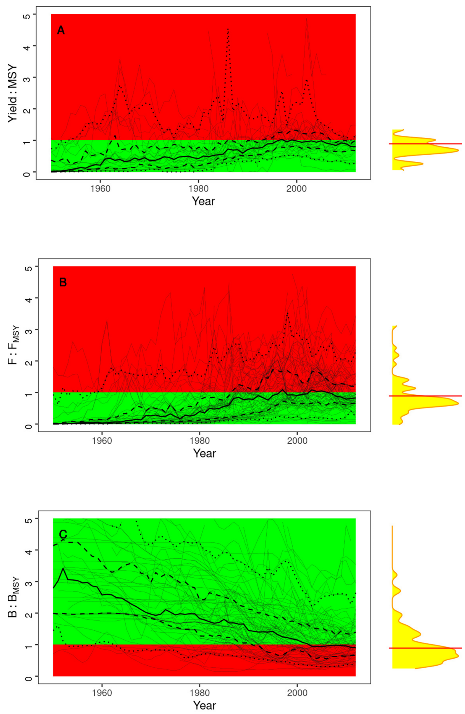


FIGURE 1 | Time series relative to MSY benchmarks for the RAM Legacy database assessments; the faint lines represent individual stocks, the thick line the median trend, the thick dashed lines the interquartile range, and the thin dashed lines the 90 th percentiles. States relative to the MSY benchmarks in the nal year are shown as marginal densities; for **(A)** Yield/ MSY **(B)** F/FMSY **(C)** SSB/BMSY .

many bodies to implement a Precautionary Approach (PA, Garcia, 1996). Biomass (**Figure 1C**) declined from the start of the series in the 1950s until 2000, after which the stocks stabilised. A noticeable feature is that some stock shows high inter-annual variability, while others show smooth trends. Currently, catches are mostly below *MSY*, and yields follow the general trends in biomass and fishing mortality. Fishing mortality is the most variable of the three quantities, reflecting that management is generally based on catch and biomass is influenced by environmental variability. In summary, stocks were lightly exploited in the 1950s, exploitation then increased until the adoption of the precautionary approach, after which exploitation stopped increasing but was still highly variable, and large variations are seen by stock.

2.2 Methods

2.2.1 Assessment Methods

A variety of catch-only methods have been developed to assess data-limited fisheries, these include Catch-MSY, (Martell and Froese, 2013), CMSY (Froese et al., 2017), catch-only model (Zhou et al., 2018), and stock reduction analysis (Dick and MacCall, 2011). The methods are all mainly variations on a theme, as they are based on a surpus production function, and developers have implemented heuristics to provide values for parameters for which there is insufficient information in the data to estimate. These heuristics are based on meta-analysis, and their appropriateness depend on the management frameworks used to manage the stocks. There has therefore been a growing interest in comparing performance across catch-only methods (Rosenberg et al., 2014a; Free et al., 2020). Model comparisons are typically performed using default settings and the inbuilt heuristics, e.g. to derive relative biomass priors specific to each software. However, there has been less attention paid to the value-of-information, i.e. evaluating the benefits of actually obtaining data for informing priors for productivity (r) and relative initial and terminal biomass levels.

We used the JABBA biomass dynamic model (Winker et al., 2018) as this provides a unifying, flexible framework based on a production function that can be used to estimate stock status and reference points under various prior assumptions and data scenarios. JABBA is predominantly used to conduct data-moderate stock assessment by fitting catch and one or multiple relative abundances or catch-per-unit-effort indices with priors for population growth rate (r), initial depletion (K), the shape parameter (m) of the production function and associated variance parameters for process and measurement error. At the data-poor end of the stock assessment spectrum, JABBA can be set up to approximate the behaviour of CMSY (Froese et al., 2017), sampling from prior distributions to obtain parameter values that given a catch history that does not crash the population and satisfy priors for initial and final depletion. This allows the value of improving information in the form of both data (e.g., obtaining abundance trends) and priors to be evaluated within the same, flexible framework.

A generalized production function (Pella and Tomlinson, 1969) was assumed, which allows the shape, the ratio between the biomass at MSY (B_{MSY}) and virgin biomass (K), to be varied to represent alternative assumptions about productivity and reference points. Scenarios considered were for population growth rate (r) and the shape of the production function (m). The shape m is determined by the assumed form of density dependence. Which in aged-based assessments is mainly determined by the form of the stock recruitment relationship and steepness (h), defined as the fraction of recruitment from an unfished population obtained when the spawning stock biomass is 20% of its unfished level, and depends on the maximum per capita productivity, natural mortality and schedules of size and maturity at age (Mangel et al., 2010).

The shape of the production function was assumed to be either logistic (Schaefer, m=2) or Gompertz (Fox, m=1.001). In the latter case, production is maintained at lower stock sizes, as MSY is found at $B_{MSY}/K = 0.37$ compared to at $B_{MSY}/K = 0.5$ for the former.

The population growth rate at low stock size r and shape m can be derived from life-history parameters such as natural mortality (M) and the stock-recruitment relationship (Winker et al., 2020). However, these parameters are difficult to estimate (e.g. Lee et al., 2011; Jiao et al., 2012; Lee et al., 2012; Simon et al., 2012), and so in many data-rich assessments are either fixed, or uncertainty grids are used where M and h are varied independently. However, h and M are related as h describes density-dependent mortality of recruits (Simon et al., 2012). Therefore, two scenarios based on low and high M and h were employed to develop the r prior (see **Supplementary Material**).

The choice of the final biomass depletion prior has been shown to be particularly influential on the performance of catch-only models (Rosenberg et al., 2014b; Sharma et al., 2021). Rosenberg et al. (2014b) found that the generic heuristics for the initial, intermediate and final depletion priors as described in Froese et al. (2017) performed the best of the approaches tested. These are based on simple rules derived from patterns in the catch (Froese and Kesner-Reyes, 2002). Lacking expert priors, the catch heuristic of Froese et al. (2017) was used to assign ranges for initial and final biomass depletion.

To reduce the influence of extreme values, a 3-years simple moving average (SMA) was applied to the catch data. If the data-points are p_1,p_2,…,p_n, then the mean over the last k data-points is calculated as:

$$\begin{aligned} SMA_k &= \frac{p_{n-k+1}+p_{n-k+2}\cdots+p_n}{k} \\ &= \frac{1}{k}\sum_{i=n-k+1}^{n} p_i \end{aligned} \tag{1}$$

The final year's catch is then divided by the maximum catch C_{max} and the ratio used to set the final depletion based on the following catch heuristic:

$$range\left(B_{final}/K\right) = \begin{cases} 0.4-0.8 & \text{if } C_{final} \div C_{max} > 0.8 \\ 0.2-0.6 & \text{if } 0.5 < C_{final} \div C_{max} \le 0.8 \\ 0.01-0.4 & \text{if } 0.35 > C_{final} \div C_{max} \le 0.5 \\ 0.01-0.3 & \text{if } 0.15 < C_{final} \div C_{max} \le 0.35 \\ 0.01-0.2 & \text{if } 0.05 < C_{final} \div C_{max} \le 0.15 \\ 0.01-0.1 & \text{if } C_{final} \div C_{max} \le 0.05 \end{cases} \tag{2}$$

Log-normal priors were formulated based on the mean of the assigned depletion range and assuming a CV of 0.3.

Scenarios were set up to evaluate the impact of the priors and assumption on the ability to estimate depletion in the final year (**Table 1**). As a benchmark, against which the catch-only models can be compared, a biomass dynamic assessment was conducted with an unbiased index, based on the biomass predicted by data-rich stock assessments in the RAM legacy database for the recent half of the time series.

All modelling was performed in R using the FLR simulation framework (Kell et al., 2007).

2.2.2 Receiver Operator Characteristics

In binary classification, e.g. identifying whether a stock above or below a reference point, where outcomes are labelled as either positive (P) or negative (N), there are four possible outcomes. If a prediction is positive (P) and the actual value is also positive then it is termed a true positive (TP); however, if the actual value is negative (N), then it is said to be a false positive (FP). A true negative (TN) occurs when the prediction and the actual value are both N, and a false negative (FN) is when although the prediction is negative, the actual value is P. To have classification skill, an indicator must have both high true positive rate [TPR=TP/(TP+FN)] and a low false positive rate [FPR=FP/(FP+TN)].

Receiver operating characteristics (ROC) graphs are useful for comparing classifiers and visualising their performance. ROC graphs are commonly used in medical decision-making, and recently have been increasingly used in machine learning and data mining research (Fawcett, 2006). ROC curves were constructed by sorting the B/B_{MSY} and F/F_{MSY} values from the catch-only methods by their predicted scores, with the highest scores first. Plotting TPR against FPR at the different threshold settings provides a tool to select the best candidate assessment methods. The cumulative TPR and True Negative Rate (TNR) were then calculated for the ordered observed outcomes from the data-rich assessments. The curve is then generated by plotting the area under the probability distribution (i.e. the cumulative distribution function) of the detection probability (TPR) on the y-axis versus the cumulative distribution function of the false-alarm probability (FPR) on the x-axis. Sensitivity ($\frac{TP}{TP+FN}$) measures the ability of a test to identify positive cases, i.e. the proportion of positives that are correctly identified, while specificity ($\frac{TN}{TN+FP}$) measures the proportion of negatives that are correctly identified.

The ROC curve is a probability curve, and the area under the curve (AUC) is a metric for measuring performance. A coin toss would produce a curve that fell along the $y = x$ line and the area under the curve would be equal to 0.5. While a perfect classifier would have a value of 1. Therefore, the area under the curve measures how well an index can distinguish between states, since the closer the area under the curve is to 1, the better the model is

TABLE 1 | Catch-only model settings, for shape of the production function, and the derivation of population growth rate (r) from natural mortality and the steepness of the stock recruitment relationship, see **Supplementary Material** for details of derivation.

	Levels (N)	Π N	Values
Shape	2	2	Schaeffer; Fox
Prior for r	2	4	Low M & steepness; High M & Steepness
Prior for K	2	8	RAM with 20% CV; Catch Heuristic
Prior for intial depletion	2	16	Heuristic; Actual
Prior for final depletion	2	32	Heuristic; Actual

Depletion priors were either based on the heuristic or the actual value from the data rich assessment was used. N is the number of factors levels.

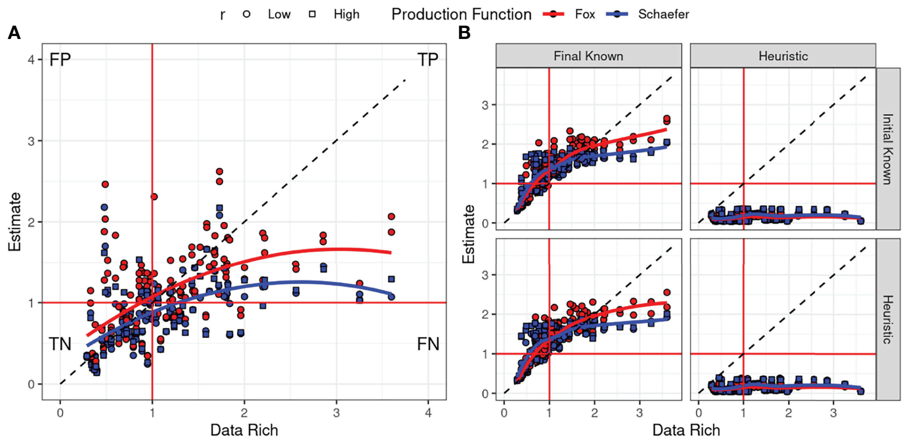


FIGURE 2 | Comparisons of estimates of $B{:}B_{MSY}$ in the final year with the data-rich (i.e. RAM legacy DB) values. The biomass dynamic assessment model with the index of abundance estimates are shown in panel **(A)**, and the catch-only model values in panel **(B)** If the biomass assessment with index was unbiased y = x. True positive (TP) is when a prediction and the actual value are both positive; false positive (FP) is when a prediction is positive the actual value is negative; true negative (TN) is when where the prediction and actual value are both negative; and false negative (FN) is when the prediction is negative and the actual value is P.

at ranking. The best performing discrimination threshold values are those closest to the top left-hand corner (TPR=1, FPR=0), and so Receiver Operator Characteristics can be used to identify the bias in the reference point used for classification. For example, how far is the point B/B_{MSY} = 1 on the curve from the point closest to (TPR=1, FPR=0)?

3 RESULTS

Estimates of B/B_{MSY} in the final year are compared to the data-rich (i.e. RAM legacy) reference set in **Figure 2**. The estimates from the biomass dynamic assessment calibrated with an index of abundance based on the RAM Legacy DB estimates are shown in panel A, and those from the catch-only model values in panel B. The red and blue points and smoothers correspond to the Fox and Schaefer production functions respectively, and the cross-hairs indicate B/B_{MSY} = 1. If there were no error in the model estimates, the points would all fall along the dashed $y = x$ line. A negative bias is evident at higher stock size, as shown by the smoother, due to the wider range of production function shapes seen in the data-rich assessments. For the catch-only models, there is no difference whether the initial depletion is known or the heuristic is used (row), this because the time series of catches were generally long, and so initial conditions had little effect on final depletion. While, if the heuristic is used for final depletion (column) all stocks are classified as overfished.

In the reference set, the positive condition (P) is defined when $B \geq B_{MSY}$ and the negative condition (N) when $B < B_{MSY}$. The number of positive cases correctly classified as true positive (TP) fall in the top right-hand quadrant. Those correctly identified as negative, i.e. true negative (TN), fall in the bottom left-hand quadrant. The false positive (FP) cases are equivalent to a false alarm or Type I error; while false negative (FN) cases are equivalent to a Type II error.

The corresponding Receiver Operator Characteristics curves are shown in **Figure 3**. The area under the curve is high for the model fits and varies between 0.76 and 0.8 (panel A). The points corresponding to the discriminated threshold (B/B_{MSY} = 1) for the Fox model show that 80% of cases are correctly classified as positive and only 25% are incorrectly classified. However, in the case of the Schaefer model although nearly 100% of cases are classified as positive, 70% of cases are incorrectly classified as positive. Therefore, a model based on Schaefer could be used for ranking but not classification. The results are insensitive to the choice of r prior, since the dashed and solid lines coincide.

For the catch-only model (panel B), if the heuristic is used for final depletion (right column panel B) then the area under the curve is around 65% and the same as when the heuristic alone is used (purple line), and so is little better than a coin toss ($y = x$ line). Again the Fox model out performs the Schaefer and the choice of r prior has an effect for the Schaefer model.

Classification skill for F/F_{MSY} is summarised in **Figure 4**, since the heuristic alone cannot be used to estimate $F/F{+}MSY$ no purple line is shown. This shows that a catch-only model cannot be used to assess exploitation level.

4 DISCUSSION

The FAO performs a systematic assessment for 445 stocks on a biannual basis, covering approximately 70% of global landing records (Sharma et al., 2021). Catch-only models are a main tool for assessing the state of regional and global fisheries that lack the data required to run traditional assessment models. However, the limited quantity and quality of data along with methodological

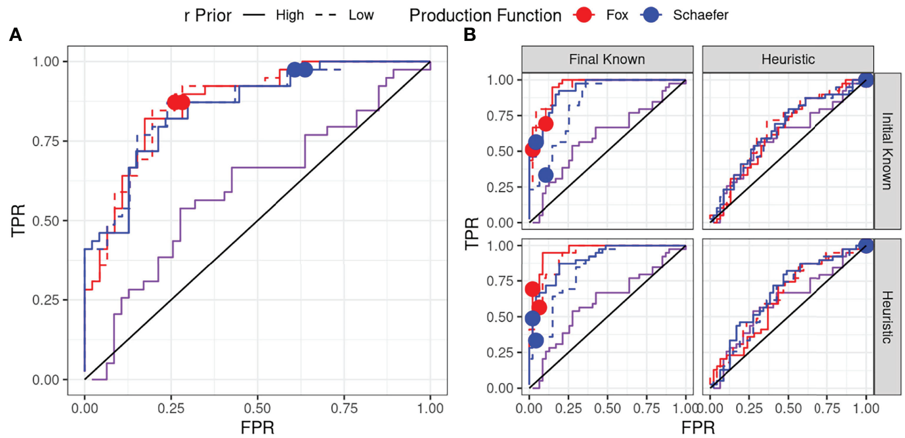


FIGURE 3 | Receiver Operator Characteristics curves for $B{:}B_{MSY}$, The biomass dynamic assessment model with the index of abundance estimates are shown in panel **(A)**, and the catch-only model values in panel **(B)** The true positive rate (TPR) is the proportion of positive cases correctly identified and false positive rate (FPR) is the proportion of negative cases incorrectly identified as being positive. The points are for when the estimates of $B{:}B_{MSY} = 1$. The black line ($y = x$) is equivalent to a coin toss, and the purple corresponds to the reference case where the heuristic for final depletion alone was used, i.e. running the catch-only model without data. The blue and red lines are the estimates for the two production functions, and the dashed/solid lines are for the choice of *r* prior. The dots correspond to a discrimination threshold of $B/B_{MSY} = 1$, i.e. is the estimate unbiased. If the biomass assessment with index was unbiased then points will fall along y=x.

differences often produce counter-intuitive and conflicting results (Ovando et al., 2021b). Therefore, the debate about the status and productivity of global fisheries continues (e.g. Anderson et al., 2017; Rousseau et al., 2019; Costello et al., 2020; Palomares et al., 2020). For example, two views have been put forward about how much inference can be made based on catch data alone. The first is based on the premises that total annual catch data contains signals about stock status and as it is often the only data publicly available should be used, i.e. "*While fisheries researchers continue the important debate about which fisheries are declining, why and to what degree, most fishermen worldwide are finding fewer fish in their hauls than their predecessors did. Knowing what tonnage is pulled out of the oceans each year is crucial to knowing how to reverse this trend*" (Pauly, 2013). The second view expresses concern that inferring stock status from catch-only methods can be misleading and overly pessimistic, and instead encourages "*... researchers to use all the available data in addition to the FAO database, and to validate their results by consulting local experts or other data sources*" (Hilborn and Branch, 2013).

While (Pauly, 2013) makes a case for doing something with the available information, it is important that models should be

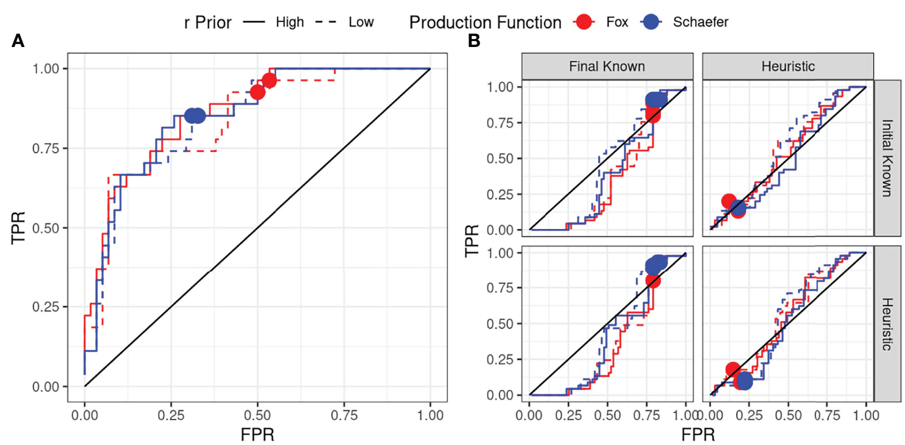


FIGURE 4 | Receiver Operator Characteristics curves for $F{:}F_{MSY}$, The biomass dynamic assessment model with the index of abundance estimates are shown in panel **(A)**, and the catch-only model values in panel **(B)** The points are for when the estimates of $F{:}F_{MSY} = 1$. The black line ($y = x$) is equivalent to a coin toss, and the purple corresponds to the reference case where the heuristic for final depletion alone was used, i.e. running the catch-only model without data. The blue and red lines are the estimatesfor the two production functions, and the dashed/solid lines are for the choice of *r* prior. The dots correspond to a discrimination threshold of $B/B_{MSY} = 1$, i.e. is the estimate unbiased.

consistent with prior knowledge and corroborated with multiple sources of information (Connell and Keane, 2006). Furthermore models should ideally be validated if they are to provide robust and credible advice (Saltelli et al., 2020). For a model to be valid it must be plausible that a system equivalent to the model generated the data (Thygesen et al., 2017). However, catch-only models cannot be validated with observations. We found that estimates were entirely driven by expert judgement codified as heuristics, as the ROC curves showed that catch-only models perform little better than a coin toss. Our results therefore support (Hilborn and Branch, 2013) call to use all the available data and to incorporate alternative data sources.

Catch-only methods are an attempt to incorporate available biological information and expert knowledge about initial and final depletion. The main catch-only models implement the same basic algorithms but vary in their default ways for setting priors, heuristics for depletion, and the assumed form of the production function (Froese et al., 2017; Zhou et al., 2018; FAO, 2019). Empirical, rule-based heuristics are only recommended for cautious use when expert information or alternative depletion estimates are lacking (Froese et al., 2017). However, the reliance on expert knowledge to formulate informative priors makes traditional simulation testing to evaluate catch-only models challenging (Cope et al., 2015; Free et al., 2020), and therefore simulation testing has been limited to specific default rules (e.g. Rosenberg et al., 2014b; Froese et al., 2017; Pons et al., 2018). Others have tested default rules for harvest control rules as part of a Management Procedure (e.g. Carruthers et al., 2014; Wetzel and Punt, 2015). In our study, we focused on heuristics and compare those to unbiased expert priors, as representative expert elicitation methods can be challenging to replicate in simulations (Chrysafi et al., 2019). We found that the heuristics rather than the data determined the estimates of current stock status, and that they performed little better than a coin toss. Therefore, if advice was to be based on such methods, there would be a high risk of both over- and under-fishing. It would also be impossible to monitor the effect of management.

There are various motivations for applying data-poor methods; as well as classifying stock status to provide synoptic views of world fisheries, these include conducting single stock assessments, and ranking stocks as part of a risk assessment. A main problem is how to validate the different implementations across stocks, species, regions, and fisheries. Particularly since diagnostics such as goodness of fit based on residuals are not applicable. Validation requires that the system be observable and measurable (Hodges et al., 1992). However, the only observations in a catch-only model are catches, and if an observation is omitted from the model the observation cannot be estimated. Therefore, we compared estimates to those from data-rich assessments based on the RAM Legacy database, as these provide a range of stock, fishery and species characteristics.

The Receiver Operator Characteristics analysis showed that correct classification of biomass relative to B_{MSY} relies on setting final biomass depletion priors correctly. The generic heuristic alone performed poorly for ranking and classification, and including catch data made little if any improvement. Sharma et al. (2021) conducted a similar exercise comparing SRA+ and CMSY for stocks assessed by ICES, and again, poor performance was reported for inbuilt default heuristics, but as the quality of the biomass prior information increased, classification improved regarding FAO's 3-tier classification of biomass levels relative to B_{MSY}. In addition, we found that there was no classification skill for distinguishing between sustainable fishing ($F<FMSY$) and overfishing ($F>FMSY$) for the catch-model, irrespective of whether final biomass depletion was correctly specified. Additional data is therefore required to quantify sustainable fishing levels.

Our results showed that using catch-only methods with generic default settings to classify stock status is inappropriate in most cases, and should not be used in classification. Walters et al. (2006) and Martell and Froese (2013) showed how catch-only methods could be used to estimate MSY. However, the original intention was not classify stock status with respect to biomass and fishing mortality targets. Our study further strengthens this argument and demonstrates that using catch-only models based on heuristics provide biased and imprecise results.

The lack of classification skill may be partially attributed to the use of data-rich stocks for the analysis, whose catch dynamics are likely to systematically differ from many unregulated data-poor fisheries as a result of active catch quota management. Therefore, estimates of F_{MSY} from catch-only model may be similarly susceptible to violations of steady-state assumption of fishing effort as per-recruit approaches (Hordyk et al., 2014; Pons et al., 2018; Haupt et al., 2020). Ovando et al. (2021a) pointed out the paradox that catch-only models possible work better for unregulated data limited fisheries, but testing of these methods relies on data rich stocks, where the relationships between catch and biomass is likely to be the weakest due to active management and strong market drivers. An alternative is to obtain alternative data sources, such as effort (Ovando et al., 2021b) and size composition (LBB, Froese et al., 2018), that can be incorporated into biomass dynamic models as information about fishing pressure or relative depletion, and then validate the model based on prediction skill (Kell et al., 2021).

Many stocks exploited by data-poor fisheries are for stocks with high r, like cephalopods, or endangered species that have low r. Also, the variability of time series and the level of process error will have an impact, particularly as catch-only methodswere shown to only be able to assess state and not exploitation level, so even if a catch-only model can assess status relative to B_{MSY} it may not be able to explain whether it was due to the environment or fishing.

Validation is required to increase confidence in the outputs of a model, and is essential to increase trust among the public, stake and asset-holders and policymakers (Saltelli et al., 2020). Validation can also identify model limitations that should be addressed in future research. (Ovando et al., 2021b) concluded that improvements to estimates of the state of the world's exploited fish populations depend more on efficient use of existing data and expanding the collection of new information, rather than the development of new models. Bayesian biomass dynamic models, such as JABBA, can be fitted to as little as two observations of annual abundance indices, thus enabling a continuous transition from a catch-only to a data moderate assessment. Additional data sources include length data, which can be used as a proxy for fishing mortality (e.g. Miethe et al., 2019) or relative depletion (Froese et al., 2018; LBB), and economic data as a proxy for fishing effort. Length data are potentially available for many fisheries, and even data from a single year could be used in an assessment model to provide an estimate of exploitation level. While port collection schemes could be established to monitor trend in size composition and catch-per-unit and hence exploitation and abundance indices. This way an initial catch-only model can be adapted and updated with new data as those become available and eventually be validated.

The next step after assessment is management, and if a stock is declining due to overfishing, then a reduction in catch should be implemented. Catch-only methods, however, have clear limitations in monitoring rebuilding if there are no data other than catch (Wetzel and Punt, 2015). Since monitoring a stock's response to management requires new observations to update the assessment. However, as the data used to set catch are the same as the management regulation, it is unlikely that catch-only models can provide robust estimates and be able to update advice. Lacking observations, neither can they be validated. Therefore, rebuilding plans should be accompanied by data collection programmes designed to monitor progress and provide feedback control. Potential datasets for improving information are indices of trends e.g. in catch rate, size composition, tag recovery rate, survey estimates of abundance or species composition.

Reframing stock assessment as risk management would help in the development of scientific management frameworks. A definition of risk, is an uncertain event or set of circumstances that, should it occur, will affect the achievement of objectives (Bartlett, 2004). In fisheries management, the level of risk is a choice made by managers and stakeholders, e.g. a given probability of stock collapse or forgone yield relative to *MSY*. Uncertainty is generally quantified as part of the stock assessment process, when considering alternative scenarios in an ensemble of models or deriving probabilistic estimates of model outputs, or when conditioning Operating Models as part of Management Strategy Evaluation. For a given level of risk when information is low, there will be great uncertainty over stock size, and so catches should be set low, and vice versa. For a given level of risk there should therefore be a positive relationship between information and use so their is a positive value of information to and control (Cooke, 1999). In contrast, in non-precautionary management, catches are not reduced until there is sufficient information to demonstrate the necessity for limits: under such regimes, information and control has a negative value to the fishery in the short term.

A consideration of risk equivalence could assist in adapting existing practice and systematically explore management options using the available information to condition management advice to ensure objectives are still met (Roux et al., 2021). Risk equivalence is defined as the probability of a stock being depleted below a limit reference point or not being maintained at a target reference point, irrespective of the stock assessment method used to provide management advice and the amount of data available (Fulton et al., 2016). Therefore, in capacity or data limited situations, risk equivalence can help provide, robust and accountable management decision-making in the absence of perfect knowledge and provide an incentive to evaluate the value-of-information and the development of robust feedback control.

The catch-only method, in this study, was implemented in the Bayesian state-space biomass dynamic model JABBA, which has been widely applied to conduct data moderate assessments to provide advice on stock status relative to target and limit reference points, and can be validated (Kell et al., 2021). The use of JABBA will allow the evaluation of the value of different sources of information in the form of different data types, assumptions, knowledge and priors, and models to be evaluated. JABBA is also callable from FLR (Kell et al., 2007) allowing Management Strategy Evaluation to be conducted to evaluate robust control rules in data-limited situations (e.g. Fischer et al., 2020).

5 CONCLUSIONS

An artefact is "something observed in a scientific investigation or experiment that is not naturally present but occurs as a result of the preparative or investigative procedure", while artifice is "something contrived or made up to achieve an end". We need to protect against both artefact and artifice when developing models for advice. Therefore, the objective of this study was to evaluate the validity of catch-only methods used to classify stock status. A motivation was that Sharma et al. (2021) found that catch-only models can show notable bias when run with their inbuilt default heuristics, and that as the quality of prior information increased, classification improved. We therefore agree with Ovando et al. (2021b) that the improvement of catch-only models depends on developing robust biomass, fishing effort or mortality priors. To do this requires an objective way to evaluate classification skill. Therefore, we configured a data-moderate stock assessment method as a catch-only model to compare the value-of-information, then used Receiver Operator Characteristics to compare estimates to data-rich assessments. A main finding was that in the catch-only models the data have no effect. Although catch-only methods have been used to provide a "Snapshot", this requires that factors that affect depletion are known, which precludes adaptive management. A major problem is that catch-only methods cannot be validated using observations nor be used in Management Strategy Evaluation as a feedback controller. The solution therefore is to collect better data and to develop robust management strategies. The value of obtaining additional information for reducing risk due to loss of yield through adopting a risk equivalence approach should also be evaluated. This will help identify the value-of-information and prioritise the development of scientific management frameworks that protect marine ecosystems and the well-being of people who have a stake in the resources at regional and local levels.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

LK was the main author responsible for the hypotheses, modelling, and synthesis; RS provided the rational and overview; HW was responsible for implementing JABBA as a catch-only model. All authors contributed to the writing of the manuscript.

FUNDING

FAO Sofia improvement funds provided support for LK.

ACKNOWLEDGMENTS

This is a short text to acknowledge the contributions of specific colleagues, institutions, or agencies that aided the efforts of the authors.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2022.762203/full#supplementary-material

REFERENCES

Anderson, S. C., Cooper, A. B., Jensen, O. P., Minto, C., Thorson, J. T., Walsh, J. C., et al. (2017). Improving Estimates of Population Status and Trend With Superensemble Models. *Fish. Fish.* 18, 732–741. doi: 10.1111/faf.12200

Bartlett, J. (2004). *Project Risk Analysis and Management Guide* (High Wycombe, UK: APM publishing limited).

Bouch, P., Minto, C., and Reid, D. G. (2020). Comparative Performance of Data-Poor CMSY and Data-Moderate SPiCT Stock Assessment Methods When Applied to Data-Rich, Real-World Stocks. *ICES J. Mar. Sci* 78, 264–276. doi: 10.1093/icesjms/fsaa220

Brown, D., and Hermes, R. (2019). The Food and Agriculture Organization of the Un and Asian Lmes: A Commentary. *Deep. Sea. Res. Part II.: Top. Stud. Oceanogr.* 163, 124–126. doi: 10.1016/j.dsr2.2019.03.002

Carruthers, T., Punt, A., Walters, C., MacCall, A., McAllister, M., Dick, E., et al. (2014). Evaluating Methods for Setting Catch Limits in Data-Limited Fisheries. *Fish. Res.* 153, 8–68. doi: 10.1016/j.fishres.2013.12.014

Chrysafi, A., Cope, J. M., and Kuparinen, A. (2019). Eliciting Expert Knowledge to Inform Stock Status for Data-Limited Stock Assessments. *Mar. Policy* 101, 167–176. doi: 10.1016/j.marpol.2017.11.012

Connell, L., and Keane, M. T. (2006). A Model of Plausibility. *Cogn. Sci.* 30, 95–120. doi: 10.1207/s15516709cog0000_53

Cooke, J. (1999). Improvement of Fishery-Management Advice Through Simulation Testing of Harvest Algorithms. *ICES J. Mar. Sci.* 56, 797. doi: 10.1006/jmsc.1999.0552

Cope, J., Thorson, J., Wetzel, C., and DeVore, J. (2015). Evaluating a Prior on Relative Stock Status Using Simplified Age-Structured Models. *Fish. Res.* 171, 101–109. doi: 10.1016/j.fishres.2014.07.018

Costello, C., Cao, L., Gelcich, S., Cisneros-Mata, M.Á., Free, C. M., Froehlich, H. E., et al. (2020). Enthe Future of Food From the Sea. *Nature* 588 (7836), 95–100. doi: 10.1038/s41586-020-2616-y

Dick, E., and MacCall, A. D. (2011). Depletion-Based Stock Reduction Analysis: A Catch-Based Method for Determining Sustainable Yields for Data-Poor Fish Stocks. *Fish. Res.* 110, 331–341. doi: 10.1016/j.fishres.2011.05.007

Dowling, N., Dichmont, C., Haddon, M., Smith, D., Smith, A., and Sainsbury, K. (2015a). Empirical Harvest Strategies for Data-Poor Fisheries: A Review of the Literature. *Fish. Res.* 171, 141–153. doi: 10.1016/j.fishres.2014.11.005

Dowling, N. A., Dichmont, C. M., Haddon, M., Smith, D. C., Smith, A. D. M., and Sainsbury, K. (2015b). Guidelines for Developing Formal Harvest Strategies for Data-Poor Species and Fisheries. *Fish. Res.* 171, 130–140. doi: 10.1016/j.fishres.2014.09.013

FAO (2019). EnglishReport of the Fao Expert Consultation Workshop on the "Development of Methodologies for the Global Assessment of Fish Stock Status, Rome, Italy. *FAO Fish. Aquacult. Rep. 1262* 2019, 4–6.

Fawcett, T. (2006). An Introduction to Roc Analysis. Pattern Recognition Letters. *ROC Anal. Pattern Recog.* 27, 861–874. doi: 10.1016/j.patrec.2005.10.010

Fischer, S. H., De Oliveira, J. A., and Kell, L. T. (2020). Linking the Performance of a Data-Limited Empirical Catch Rule to Life-History Traits. *ICES J. Mar. Sci.* 77, 1914–1926. doi: 10.1093/icesjms/fsaa054

Free, C. M., Jensen, O. P., Anderson, S. C., Gutierrez, N. L., Kleisner, K. M., Longo, C., et al. (2020). Blood From a Stone: Performance of Catch-Only Methods in Estimating Stock Biomass Status. *Fish. Res.* 223, 105452. doi: 10.1016/j.fishres.2019.105452

Froese, R., Demirel, N., Coro, G., Kleisner, K. M., and Winker, H. (2017). Estimating Fisheries Reference Points From Catch and Resilience. *Fish. Fish.* 18, 506–526. doi: 10.1111/faf.12190

Froese, R., and Kesner-Reyes, K. (2002). Impact of Fishing on the Abundance of Marine Species. *ICES CM.* 50, 12.

Froese, R., Winker, H., Coro, G., Demirel, N., Tsikliras, A. C., Dimarchopoulou, D., et al. (2018). A New Approach for Estimating Stock Status From Length Frequency Data. *ICES J. Mar. Sci.* 75, 2004–2015. doi: 10.1093/icesjms/fsy078

Fromentin, J.-M., Bonhommeau, S., Arrizabalaga, H., and XXXL. Kell, L. (2014). The Spectre of Uncertainty in Management of Exploited Fish Stocks: The Illustrative Case of Atlantic Bluefin Tuna. *Mar. Policy* 47, 8–14. doi: 10.1016/j.marpol.2014.01.018

Fulton, E. A., Punt, A. E., Dichmont, C. M., Gorton, R., Sporcic, M., Dowling, N., et al. (2016). Developing Risk Equivalent Data-Rich and Data-Limited Harvest Strategies. *Fish. Res.* 183, 574–587. doi: 10.1016/j.fishres.2016.07.004

Garcia, S. (1996). The Precautionary Approach to Fisheries and its Implications for Fishery Research, Technology and Management: An Updated Review. *FAO Fish. Tech. Pap.*, 1–76.

Green, D. M., Swets, J. A., et al. (1966). *Signal Detection Theory and Psychophysics.* (Wiley New York: Wiley) Vol. 1, 1969–2012.

Haupt, M., Winker, H., Parker, D., and Kerwath, S. (2020). Are South African Linefishes Recovering and What Makes Them Prone to Overexploitation? *Afr. J. Mar. Sci.* 42, 361–373.

Hilborn, R., Amoroso, R. O., Anderson, C. M., Baum, J. K., Branch, T. A., Costello, C., et al. (2020). Effective Fisheries Management Instrumental in Improving Fish Stock Status. *Proc. Natl. Acad. Sci.* 117, 2218–2224. doi: 10.1073/pnas.1909726116

Hilborn, R., and Branch, T. A. (2013). Fisheries: Does Catch Reflect Abundance? Counterpoint No, it is Misleading. *Nature* 494, 303–306. doi: 10.1038/494303a

Hodges, J. S., Dewar, J. A., and Center, A. (1992). *Is it You or Your Model Talking?: A Framework for Model Validation* (Santa Monica, CA: Rand).

Hordyk, A., Ono, K., Valencia, S., Loneragan, N., and Prince, J. (2014). A Novel Length-Based Empirical Estimation Method of Spawning Potential Ratio (Spr), and Tests of its Performance, for Small-Scale, Data-Poor Fisheries. *ICES J. Mar. Sci.* 72, 217–231. doi: 10.1093/icesjms/fsu004

Jiao, Y., Smith, E. P., O'Reilly, R., and Orth, D. J. (2012). Modelling non-Stationary Natural Mortality in Catch-at-Age Models. *ICES J. Mar. Sci.* 69, 105–118. doi: 10.1093/icesjms/fsr184

Kell, L., Mosqueira, I., Grosjean, P., Fromentin, J., Garcia, D., Hillary, R., et al. (2007). FLR: An Open-Source Framework for the Evaluation and Development of Management Strategies. *ICES J. Mar. Sci.* 64, 640. doi: 10.1093/icesjms/fsm012

Kell, L. T., Sharma, R., Kitakado, T., Winker, H., Mosqueira, I., Cardinale, M., et al. (2021). Validation of Stock Assessment Methods: Is it Me or My Model Talking? *ICES J. Mar. Sci.*, Fsab104. doi: 10.1093/icesjms/fsab104

Lee, H.-H., Maunder, M. N., Piner, K. R., and Methot, R. D. (2011). Estimating Natural Mortality Within a Fisheries Stock Assessment Model: An Evaluation Using Simulation Analysis Based on Twelve Stock Assessments. *Fish. Res.* 109, 89–94. doi: 10.1016/j.fishres.2011.01.021

Lee, H.-H., Maunder, M. N., Piner, K. R., and Methot, R. D. (2012). Can Steepness of the Stock–Recruitment Relationship be Estimated in Fishery Stock Assessment Models? *Fish. Res.* 125, 254–261. doi: 10.1016/j.shres.2012.03.001

Mangel, M., Brodziak, J., and DiNardo, G. (2010). Reproductive Ecology and Scientific Inference of Steepness: A Fundamental Metric of Population Dynamics and Strategic Fisheries Management. *Fish. Fish.* 11, 89–104. doi: 10.1111/j.1467-2979.2009.00345.x

Martell, S., and Froese, R. (2013). A Simple Method for Estimating Msy From Catch and Resilience. *Fish. Fish.* 14, 504–514. doi: 10.1111/j.1467-2979.2012.00485.x

Miethe, T., Reecht, Y., and Dobby, H. (2019). Reference Points for the Length-Based Indicator L_Max5 for Use in the Assessment of Data-Limited Stocks. *ICES J. Mar. Sci.* 76, 2125–2139. doi: 10.1093/icesjms/fsz158

Ovando, D., Free, C. M., Jensen, O. P., and Hilborn, R. (2021a). A History and Evaluation of Catch-Only Stock Assessment Models. *Fish. Fish.* 23 (3), 616–630. doi: 10.1111/faf.12637

Ovando, D., Hilborn, R., Monnahan, C., Rudd, M., Sharma, R., Thorson, J. T., et al. (2021b). Improving Estimates of the State of Global Fisheries Depends on Better Data. *Fish. Fish.* 22, 1377–1391. doi: 10.1111/faf.12593

Palacios-Abrantes, J., Reygondeau, G., Wabnitz, C. C., and Cheung, W. W. (2020). The Transboundary Nature of the World's Exploited Marine Species. *Sci. Rep.* 10, 1–12. doi: 10.1038/s41598-020-74644-2

Palomares, M. L. D., Froese, R., Derrick, B., Meeuwig, J. J., Nöel, S. L., Tsui, G., et al. (2020). Enfishery Biomass Trends of Exploited Fish Populations in Marine Ecoregions, Climatic Zones and Ocean Basins. *Estuar. Coast. Shelf. Sci.*, 106896. doi: 10.1016/j.ecss.2020.106896

Pauly, D. (2013). Fisheries: Does Catch Reflect Abundance? Point: Yes, it is a Crucial Signal. *Nature* 494, 303–306. doi: 10.1038/494303a

Pella, J., and Tomlinson, P. (1969). *A Generalized Stock Production Model* (San Diego, USA: Inter-American Tropical Tuna Commission).

Pons, M., Cope, J., and Kell, L. (2018). *Performance of Catch-Based and Length-Based Methods in Data-Limited Fisheries*. 1–17.

Rosenberg, A. A., Fogarty, M. J., Cooper, A. B., Dickey-Collas, M., Fulton, E. A., Gutierrez, N. L., et al. (2014a). *Developing New Approaches To Global Stock Status*, Vol. 1086, 01.

Rosenberg, A. A., Fogarty, M. J., Cooper, A. B., Dickey-Collas, M., Fulton, E. A., Gutiérrez, N. L., et al. (2014b). Developing New Approaches to Global Stock Status Assessment and Fishery Production Potential of the Seas. *FAO Fish. Aquacult. Circul. 0_1*.

Rosenberg, A. A., Kleisner, K. M., Afflerbach, J., Anderson, S. C., Dickey-Collas, M., Cooper, A. B., et al. (2018). Enapplying a New Ensemble Approach to Estimating Stock Status of Marine Fisheries Around the World. *Conserv. Lett.* 11, e12363. doi: 10.1111/conl.12363

Rousseau, Y., Watson, R., Blanchard, J., and Fulton, E. (2019). Evolution of Global Marine Fishing Fleets and the Response of Fished Resources. *Proc. Natl. Acad. Sci.*, 201820344. doi: 10.1073/pnas.1820344116

Roux, M.-J., Duplisea, D., Hunter, K., and Rice, J. (2021). Consistent Risk Management in a Changing World: Risk Equivalence in Fisheries and Other Human Activities Affecting Marine Resources and Ecosystems. doi: 10.31219/osf.io/6d8h7

Saltelli, A., Bammer, G., Bruno, I., Charters, E., Di Fiore, M., Didier, E., et al. (2020). Five Ways to Ensure That Models Serve Society: A Manifesto. doi: 10.1038/d41586-020-01812-9

Sharma, R., Winker, H., Levontin, P., Kell, L., Ovando, D., Palomares, M. L. D., et al. (2021). Assessing the Potential of Catch-Only Models to Inform on the State of Global Fisheries and the UN's SDGs. *Sustainability* 13, 6101. doi: 10.3390/su13116101

Simon, M., Fromentin, J.-M., Bonhommeau, S., Gaertner, D., Brodziak, J., and Etienne, M.-P. (2012). Effects of Stochasticity in Early Life History on Steepness and Population Growth Rate Estimates: An Illustration on Atlantic Bluefin Tuna. *PloS One* 7, e48583. doi: 10.1371/journal.pone.0048583

Smith, D., Punt, A., Dowling, N., Smith, A., Tuck, G., and Knuckey, I. (2009). Reconciling Approaches to the Assessment and Management of Data-Poor Species and Fisheries With Australia's Harvest Strategy Policy. *Manage. Mar. Coast. Fish.: Dyn. Ecosyst. Sci.* 1, 244–254. doi: 10.1577/C08-041.1

Thorson, J. T., Branch, T. A., Jensen, O. P., and Quinn, T. (2012). Using Model-Based Inference to Evaluate Global Fisheries Status From Landings, Location, and Life History Data. *Can. J. Fish. Aquat. Sci.* 69, 645–655. doi: 10.1139/f2012-016

Thygesen, U. H., Albertsen, C. M., Berg, C. W., Kristensen, K., and Nielsen, A. (2017). Validation of Ecological State Space Models Using the Laplace Approximation. *Environ. Ecol. Stat* 24, 317–339. doi: 10.1007/s10651-017-0372-4

Walters, C. J., Martell, S. J., and Korman, J. (2006). A Stochastic Approach to Stock Reduction Analysis. *Can. J. Fish. Aquat. Sci.* 63, 212–223. doi: 10.1139/f05-213

Wetzel, C. R., and Punt, A. E. (2015). Evaluating the Performance of Data-Moderate and Catch-Only Assessment Methods for Us West Coast Groundfish. *Fish. Res.* 171, 170–187. doi: 10.1016/j.fishres.2015.06.005

Winker, H., Carvalho, F., and Kapur, M. (2018). Jabba: Just Another Bayesian Biomass Assessment. *Fish. Res.* 204, 275–288. doi: 10.1016/j.fishres.2018.03.010

Winker, H., Carvalho, F., Thorson, J., Kell, L., Parker, D., Kapur, M., et al. (2020). Jabba-Select: Incorporating Life History and Fisheries' Selectivity Into Surplus Production Models. *Fish. Res.* 222, 105355. doi: 10.1016/j.fishres.2019.105355

Worm, B., Barbier, E. B., Beaumont, N., Duffy, J. E., Folke, C., Halpern, B. S., et al. (2006). Impacts of Biodiversity Loss on Ocean Ecosystem Services. *Science* 314, 787–790. doi: 10.1126/science.1132294

Zhou, S., Punt, A. E., Smith, A. D. M., Ye, Y., Haddon, M., Dichmont, C. M., et al. (2018). An Optimised Catch-Only Assessment Method for Data Poor Fisheries Shijie Zhou. *ICES J. Mar. Sci.* 75, 964–976. doi: 10.1093/icesjms/fsx226

Conflict of Interest: The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

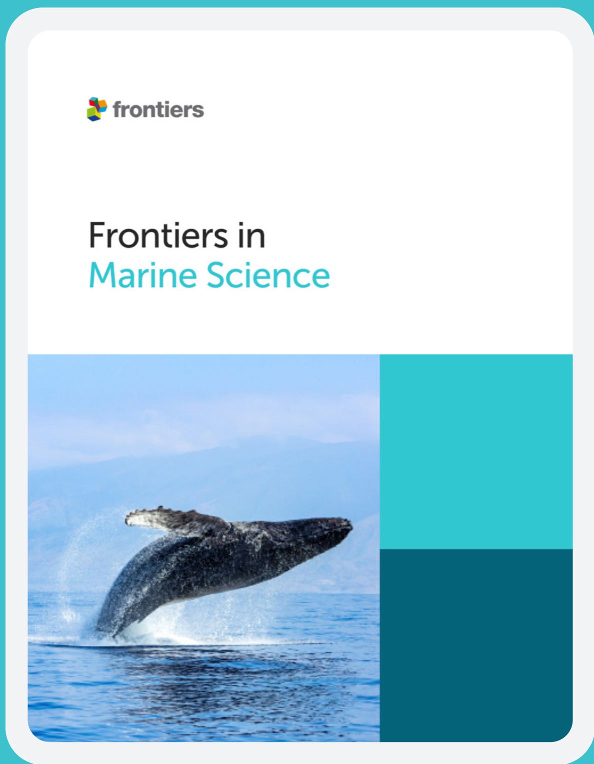
Frontiers in Marine Science

Explores ocean-based solutions for emerging global challenges

The third most-cited marine and freshwater biology journal, advancing our understanding of marine systems and addressing global challenges including overfishing, pollution, and climate change.

Discover the latest Research Topics

See more →



Frontiers

Avenue du Tribunal-Fédéral 34
1005 Lausanne, Switzerland
frontiersin.org

Contact us

+41 (0)21 510 17 00
frontiersin.org/about/contact