SEASONAL TO DECADAL PREDICTION OF MARINE ECOSYSTEMS: OPPORTUNITIES, APPROACHES, AND APPLICATIONS

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SEASONAL TO DECADAL PREDICTION OF MARINE ECOSYSTEMS: OPPORTUNITIES, APPROACHES, AND APPLICATIONS

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Waking to a new day on the North Sea onboard R/V Dana.
Image: Mark R. Payne.

Tremendous advances in oceanographic observing and modeling systems over the last decade have led to unprecedented developments in the nature of information available to marine science. While improvements in observational technologies and networks have garnered much attention, remarkable developments in forecasting the ocean have received much less focus. Exploiting this new predictive skill to improve scientific understanding, generate advice and aid in the management of marine resources, is emerging as one of the new challenges of marine science.

Translating predictions of the physical environment into biological outcomes, however, is not straightforward. Fisheries scientists, for example, have been trying to understand the links between physics and biology, and generate predictions of variables such as recruitment, for close to a century, with limited success. Nevertheless, spatial distributions and the timing of key events, which have received less focus, are often tightly linked to the physical environment and may have management-relevant applications. The first-such forecasts based on this skill are now starting to emerge.

This *Frontiers in Marine Science* Research Topic provides a snapshot of the state-of-the-art in Marine Ecological Prediction. It covers the opportunities for developing such forecasts, technical approaches that could be employed, and examples where the technology is already being applied. This body of work therefore marks an important milestone on the route to developing this new and exciting field of marine science.

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frontiers in Marine Science

EDITORIAL
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Editorial: Seasonal-to-Decadal Prediction of Marine Ecosystems: Opportunities, Approaches, and Applications

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Editorial on the Research Topic

Seasonal-to-Decadal Prediction of Marine Ecosystems: Opportunities, Approaches, and Applications

A quiet revolution is taking place in marine science. Like a caterpillar entering its chrysalis, marine biology is metamorphosing into something new. Leaving its empirical origins behind, the first signs of the predictive skill that characterizes sciences such as physics and chemistry are now also emerging in biology. Climate scientists and oceanographers, taking advantage of the tremendous advances in observational technology, scientific understanding, and computing power in recent years, can now make skilful forecasts of the state of the ocean seasons, years, and in some cases up to a decade into the future (Doblas-Reyes et al., 2013; Meehl et al., 2014). Such forecasts are an exciting opportunity for marine ecologists and fisheries scientists, who finally may be able to realize the dream of predictive skill present at the very birth of their field (e.g., Helland-Hansen and Nansen, 1909). The first such pioneering products have already been operational for some years now (e.g., Hobday et al., 2011; Eveson et al., 2015), and a second wave of products, inspired by the successes of the first, is now building. A revolution is indeed, underway.

The manuscripts collated here sample the state-of-the art in seasonal-to-decadal forecasting of marine ecosystems. Starting with the ocean itself, we look at developments in forecasting the physical and biogeochemical environment. Case studies examine both operational marine ecological forecast products and other instances where products could be developed. We then look more generally at the way that forecasts can be used and evaluated and at their relationship to climate-scale projections. Finally, we synthesize the lessons learned from this first generation of forecasts.

Ocean predictability forms the basis for ecological predictability, and advances in this field are providing exciting new opportunities to develop ecological forecasts from seasonal to multi-annual to even decadal scales. For example, while the open ocean has been the main focus of forecast development, economically important coastal regions have received less attention. Tommasi et al. assess the ability of an earth system model to make predictions of such regions on the multi-annual timescale. They find surprisingly good results, showing useful skill for most regions, allowing potential development of forecasts directly relevant to fisheries, aquaculture, and coastal assets such as coral reefs. Rousseaux et al. highlight another new front by demonstrating the ability of a fully-coupled biogeochemical model to forecast chlorophyll. They suggest that it may be possible to move beyond temperature-driven ecological forecasts and potentially incorporate other biologically relevant variables, such as productivity.

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We present several case studies of systems where there are already operational forecast products, or where they could be developed in the future. NOAA's Monthly Bleaching Outlook, detailed by Liu et al. is one of the longest running high profile marine ecological forecast products. This system was key in foreseeing and responding to the third global bleaching event (2014–2016), where it motivated adaptation responses (e.g., closing reefs to tourism) even before the event started. Mills et al. describe the development of a forecast system for the timing of American lobster landings in the Gulf of Maine, inspired by the needs of the local fishing industry. The work serves as an excellent example of the full development cycle of a forecast product, starting from end-user needs, applying science, and communicating the results in an easily understood manner. Hátún et al. proposes a causal link between the breeding success of kittiwakes on the Faroe Islands and the abundance of zooplankton on the feeding grounds that can potentially drive a predictive system. Strand et al. present an investigation of the advection of cod larvae along the Norwegian coast, showing that wind driven events can hinder larvae reaching their nursery grounds and potentially inform a recruitment forecast.

The ultimate test of model performance comes when it is applied in the real world. Turner et al. test a bycatch forecast model using a designed experiment with commercial fishing vessels but find that, in the real world, their model has little predictive skill. While this may be disappointing, there have nevertheless been clear benefits arising from close collaborative research with the industry.

Seasonal and decadal forecasting systems are also intimately linked to climate projection systems: indeed, in most cases they are actually the same model being used in slightly different ways. Hobday et al. show how to combine predictions and projections to develop a full picture of the evolution of the ocean system. Their framework can be used by marine managers and businesses to improve their decision making and profitability, but also to prepare coping strategies during adverse times. Silber et al. also examine this relationship via a discussion about the challenges of modeling marine mammal distributions in a changing climate. The authors provide a useful scheme for prioritizing the organisms to focus on, with the best candidates being vulnerable species where there is a high management need and plentiful data.

The final paper, Payne et al. reviews the current state of marine ecological forecasting, with a view to summarizing the lessons learned. They find that the majority of operational marine ecological forecast products are of species' spatial distributions, rather than their abundance. As abundance prediction is critical for fisheries management and quota setting, improving ecological abundance forecasts will expand the set of users. The lesson common to all of the forecast products they examine is the importance of a close collaboration between scientists, who can inform about what is feasible, and end-users, who can define what is useful.

In conclusion, the papers here show that marine ecological forecasting is a rapidly evolving field with great potential to support the decision-making of end-users. However, what ultimately emerges from the chrysalis remains to be seen. Will the field break into the scientific and management mainstream, or will it remain limited to niche applications? Will multi-year forecasting be possible in all regions of the worlds ocean? Maintaining the existing momentum and increasing the portfolio of ecological forecast products will be challenging, particularly once the "low-hanging fruit" have all been "picked." Nevertheless, based on the products available to-date, it is clear that seasonal-to-decadal prediction of marine ecosystems is both a viable scientific discipline and one that will make a significant contribution to the management and performance of marine industries now and in the years to come.

AUTHOR CONTRIBUTIONS

MP prepared a first draft of the manuscript. All authors contributed to further editing and refinements. All authors have approved the final version of the manuscript.

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ORIGINAL RESEARCH
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Multi-Annual Climate Predictions for Fisheries: An Assessment of Skill of Sea Surface Temperature Forecasts for Large Marine Ecosystems

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Decisions made by fishers and fisheries managers are informed by climate and fisheries observations that now often span more than 50 years. Multi-annual climate forecasts could further inform such decisions if they were skillful in predicting future conditions relative to the 50-year scope of past variability. We demonstrate that an existing multi-annual prediction system skillfully forecasts the probability of next year, the next 1–3 years, and the next 1–10 years being warmer or cooler than the 50-year average at the surface in coastal ecosystems. Probabilistic forecasts of upper and lower seas surface temperature (SST) terciles over the next 3 or 10 years from the GFDL CM 2.1 10-member ensemble global prediction system showed significant improvements in skill over the use of a 50-year climatology for most Large Marine Ecosystems (LMEs) in the North Atlantic, the western Pacific, and Indian oceans. Through a comparison of the forecast skill of initialized and uninitialized hindcasts, we demonstrate that this skill is largely due to the predictable signature of radiative forcing changes over the 50-year timescale rather than prediction of evolving modes of climate variability. North Atlantic LMEs stood out as the only coastal regions where initialization significantly contributed to SST prediction skill at the 1 to 10 year scale.

Keywords: decadal predictions, multi-annual predictions, climate forecasts, large marine ecosystems, fisheries, probabilistic forecasts, sea-surface temperature predictions

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INTRODUCTION

Living marine resources (LMRs) and the marine ecosystems within which they exist are critical to human health and coastal economies, providing services worth US$21 trillion each year (Costanza et al., 1997). LMRs are strongly influenced by climate variability (Cushing and Dickson, 1976; Sharp, 1987; Lehodey et al., 2006; Brander, 2007, 2010; Drinkwater et al., 2010; Ottersen et al., 2010), creating a challenge for marine resource managers and fishers. Temperature fluctuations, serving as proxies of important climate-driven ocean or ecosystem processes, are often associated with variation in the productivity and spatial distribution of LMRs (e.g., Ellertsen et al., 1989; Dorn, 1992; Peterman et al., 1998; Mueter et al., 2002, 2011; Beaugrand et al., 2003; Perry et al., 2005; Sullivan et al., 2005; Nye et al., 2009; Hunt et al., 2011; Kristiansen et al., 2011; Lindegren and Checkley, 2013; Pinsky et al., 2013; Pershing et al., 2015).

Century-scale temperature projections have been used to show the impact of climate change on LMRs (Stock et al., 2011). More recently, seasonal SST forecasts have started to improve management and industry decisions at shorter time-scales (Hobday et al., 2016; Tommasi et al., 2017a). Many decisions, however, would benefit from climate forecasts over multi-annual scales, in which both climate change and internal climate variability can act to provide predictability (Tommasi et al., 2017b). For instance, catch advice is dependent on a forecast of fish abundance 1–3 years into the future (Brander, 2003). To set rebuilding targets for overfished stocks, such forecasts need to be extended 10 years into the future (NRC, 2014). Currently, these stock status projections are developed using historical observations that often span 30–50 years (RAM Legacy Stock Assessment Database, www.ramlegacy.org). Fisheries managers are therefore interested in assessing if temperature over the next years to decade will be high or low relative to the past 30–50 years used to develop their management frameworks. Such forecasts can inform managers on the need to develop reference points more reflective of future conditions and climate-informed stock status projections (Tommasi et al., 2017b). Multi-annual climate predictions can also benefit long-term spatial planning decisions regarding changes to closed areas, the setting of future closures, preparation for emerging fisheries, adjustment of quotas for internationally shared fish stock, and industry capital investment decisions (Tommasi et al., 2017b). However, while the skill of seasonal SST forecasts has been assessed at an LMRs-relevant spatial scale (i.e. the coastal shelf) (Stock et al., 2015), multi-annual SST predictability in coastal ecosystems has not been quantified, limiting their use in LMRs management decisions.

How SST will evolve across inter-annual to decadal time scales is a function of both internal climate variability (e.g., El-Niño Southern Oscillation, ENSO; the Pacific Decadal Oscillation, PDO; Atlantic Multidecadal Variability, AMV) and forced climatic changes from greenhouse gases and aerosol emissions, as well as natural forcings like volcanoes and solar variations (Meehl et al., 2009, 2014; Doblas-Reyes et al., 2013). Thus, multi-annual predictive skill is dependent on initializing a climate model in the correct state of internal climate variations (i.e., an initial-value problem), imposing accurate external forcing (i.e., a boundary-value problem), and correctly simulating the evolution of the predictable climate system components arising from the initial state and external forcing. Each of these is challenging on its own. Several studies, however, have now shown that in the North Atlantic Ocean, the Southern Ocean, and, more weakly, the western North Pacific Ocean, initialization of the present climate state can significantly contribute to forecast skill over many years (van Oldenborgh et al., 2012; Doblas-Reyes et al., 2013; Yang et al., 2013; Meehl et al., 2014; Msadek et al., 2014; Corti et al., 2015). Further studies suggest that, over most of the globe, the main source of 2–10 year SST prediction skill is the externally forced signal due to greenhouse gases and aerosols (van Oldenborgh et al., 2012; Corti et al., 2015). That is, greenhouse gases, ozone and aerosol conditions today and their future evolution allow one to make meaningful predictions about the next decade relative to the range of conditions over the past half-century.

By exploiting both sources of predictability, skillful multi-annual SST predictions are possible (Smith et al., 2007; Keenlyside et al., 2008; van Oldenborgh et al., 2012; Doblas-Reyes et al., 2013; Yang et al., 2013; Corti et al., 2015), with the North Atlantic, Indian Ocean, and western Pacific being regions of significant skill even at the longer lead times of 6–10 years (Meehl et al., 2014). Interpretation of these results must be tempered by the limited effective sample size for assessing decadal predictions (Meehl et al., 2014) but they provide reason for cautious optimism concerning the use of multi-annual to decadal predictions for marine resource applications. It remains to be assessed if the observed multi-annual prediction skill over large ocean regions results in useful multi-annual prediction skill at the coastal scales relevant to most marine resource decisions. Furthermore, it is unclear whether the forced signal, which becomes prominent across century scales, is also sufficient to produce significant skill relative to the 30–50 year reference data sets common in fisheries management. That is, will the next 1–10 years be warmer or cooler than the past 30–50 years upon which decisions are being made?

In this paper, multi-annual SST forecasts are evaluated through this fisheries lens. More specifically, we assess the ability of the forecast system to predict if conditions over the next year, 1–3 or 1–10 years will be warmer or colder than the last 50. This is also the first time that these multi-annual SST predictions are evaluated over Large Marine Ecosystems (LMEs) (**Figure 1**), a coastal scale relevant to managed fisheries stock. LMEs are coastal areas of 200,000 km^2 or greater, whose extent is determined by similarities in ecologically relevant variables including bathymetry, hydrography, productivity, and trophic relationships (Sherman, 2014). These coastal ecosystems serve as a particularly relevant scale for LMRs decisions as, while only making up ∼1/10th of the world's oceans, they provide 95% of the world's total fish catch (Stock et al., 2017). We focus on assessing the probabilistic skill of the upper and lower terciles of SST, as these events are of greatest concern to LMRs managers and industry stakeholders (e.g., Spillman et al., 2015). While forecast users are largely concerned with the overall forecast skill, to improve multi-annual prediction systems it is also important to identify sources of prediction skill. Thus, to determine the sources of multi-annual SST predictability in LMEs we verify forecasts with both initialization and external forcing via greenhouse gases and aerosols ("initialized") and those that include just the external forcing ("uninitialized").

METHODS

Multi-Annual Climate Predictions

We enlist a set of initialized and uninitialized climate forecasts to accomplish our objectives. The uninitialized forecasts isolate the contribution of the "forced" signal (i.e., that due to greenhouse gases and aerosols), while the initialized forecasts include skill arising from both the forcing and the initialization. The combination thus allows us to determine the source of prediction skill, at least between these two broad categories.

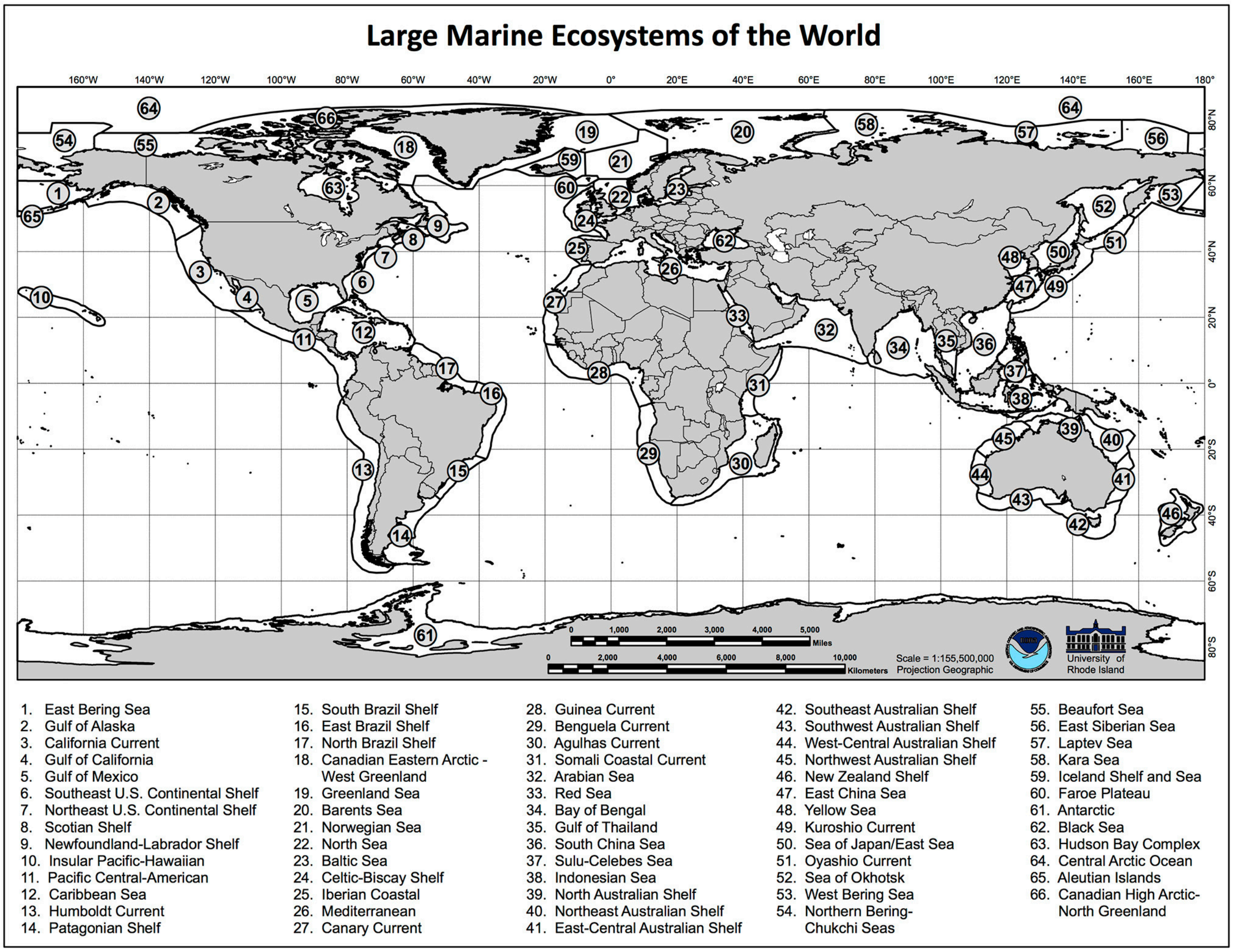

FIGURE 1 | Global map of Large Marine Ecosystems (LMEs). Image Credit: NOAA Large Marine Ecosystem Program. No permission was required from the copyright holder for the preproduction of this image.

Both initialized and uninitialized climate forecasts are produced with the Geophysical Fluid Dynamics (GFDL) CM 2.1 global climate model (Delworth et al., 2006). CM 2.1 has an atmospheric resolution of 2° and an ocean resolution of 1° (see Table A1 in the Supplement for a specification of how many ocean model grid points are in each LME). In initialized predictions, the model is constrained by the observed climate state using the Ensemble Coupled Data Assimilation system (ECDA, Zhang et al., 2007; Zhang and Rosati, 2010, ECDA output is available at https://www.gfdl.noaa.gov/ocean-data-assimilation-model-output/). The atmosphere assimilates the NCEP atmospheric reanalysis (Kalnay et al., 1996), while the ocean is constrained by SST observations from satellite and profiles of temperature and salinity from the World Ocean Database (Boyer et al., 2009). All simulations use observed volcanic forcing.

The chaotic nature of the climate system, uncertain and limited observations used to initialize prediction systems, imperfections in climate model formulations, and uncertainty in future radiative forcing lead to climate predictions being inherently uncertain. The first three sources of uncertainty are the most dominant for multi-annual climate forecasts. To quantify some of this uncertainty, climate prediction centers produce a set of predictions called a forecast ensemble. Each ensemble member is a prediction produced using slightly different initial conditions. These ensemble forecasts are also essential to communicate to users the likelihood of future climate outcomes through probabilistic forecasts. Here, a 10-member ensemble of retrospective predictions of 1–10-year lead time was developed by first initializing the model on January 1 of every year from 1965-2011 and then making predictions of annual SST conditions 1–10 years into the future (Yang et al., 2013; Msadek et al., 2014). For instance, a 1-year lead SST forecast initialized in 1995 corresponds to the average SST from January to December 1995, while a 10-year lead SST forecast initialized in 1995 corresponds to the average SST from January to December 2004. Hence the hindcast period varies with lead time, spanning the period of 1965–2011 for a lead 1 forecast and the period of 1974–2020 for a 10-year lead prediction. The 47 initialization years, 10 lead times, and 10 ensemble members resulted in a total of 4,700 predictions. Using these predictions, we developed SST forecasts for management timeframes of interest to LMR users: over the next year, over the next 3 years, and over the next 10 years. A 1-year lead time prediction provided the forecast of next year SST conditions. Forecasts of annual SST conditions over the next 3 or 10 years were developed by averaging predictions of 1–3-year or 1 to 10-year lead times, respectively.

The model was forced with prescribed temporally varying anthropogenic (e.g., greenhouse gases) and natural (e.g., volcanic aerosols) radiative forcing following the CMIP5 historical and RCP4.5 scenarios (Meinshausen et al., 2011). The uninitialized 10-member ensemble predictions were computed in the same manner except that the model was not initialized to observations. Its initial state is consistent with the greenhouse gas and aerosol conditions for each year, but the internal modes of climate variability (e.g., ENSO) overlying this mean climate state are random. Thus, skill of the uninitialized predictions is only dependent on the forced signal (greenhouse gases and aerosols). The predictions were retrieved from the GFDL archive, but are also available on the GFDL data portal (data1.gfdl.noaa.gov). SST predictions for each LME were extracted from the global dataset and spatially averaged over each LME.

Forecast Verification

Forecast skill was evaluated against the Hadley Centre Sea Ice and Sea Surface Temperature (HadlSST1.1) observational dataset at 1° resolution. The monthly data for 1965–2015 was downloaded from the U.K. Met Office (www.metoffice.gov.uk/hadobs/hadisst/) and annual averages were computed for each LME. Note that because of ice coverage and other issues, the Antarctic and Arctic LMEs had sparse annual observational SST data going back to the 1960s and hence were removed from the analysis.

Due to imperfections in the climate model formulation, after initialization, the model drifts to its preferred climate state. Hence, there is a systematic difference between the model and the observed climatologies. This systematic bias in the mean was removed by subtracting a lead-dependent model climatology from the prediction and computing forecast anomalies (CLIVAR, 2011). The climatology spanned the length of the hindcasts and was produced using cross-validation, that is without the year being forecasted. Note that as observations were available up to 2015, the length of hindcasts that could be verified for lead times 6–10 years ranged from 46 to 42 years, respectively, instead of the 47 years used for lead times 1–5 years.

Once the forecast anomalies were produced, the upper and lower terciles of SST for each LME were calculated. Following Becker and van den Dool (2016), for each lead time, a normal distribution was fit over all available hindcasts (minus the year being forecasted) across all ensemble members, and the standard deviation (std. dev.) was calculated. Forecast anomalies above +0.43*std. dev. were considered above normal (upper tercile) and forecast anomalies below −0.43*std. dev. were considered below normal (lower tercile). Using the standard deviation fit to the forecast data to define the forecast terciles corrects for systematic biases in forecast spread (Becker and van den Dool, 2016).

Performance of the retrospective forecasts was assessed by calculating forecast accuracy and the Brier Score (BrS). Accuracy measures the proportion correct of a yes/no forecast of an event (Wilks, 2011) and is defined as:

$$\text{Accuracy} = (\text{hits} + \text{correctnegatives})/\text{totalnumberofhindcasts}$$

Here the event was SST being in the upper (or lower) tercile. Upper and lower tercile events were assessed separately, and the prediction for each ensemble member, initiation year, and lead time was assigned a 1 (event happened) or a 0 (event did not happen). The event was forecast to occur if more than half of the ensemble members predicted the event. Hits were the number of times that both the forecast and observations were in the upper (or lower) tercile and correct negatives were the number of times that both the forecast and observations were not in the upper (or lower) tercile. Forecast accuracy ranges between 0 and 1 (perfect skill), with, for terciles, accuracy greater than 0.56 being better than chance (Spillman and Hobday, 2014).

Forecast accuracy is a relatively easy to understand skill metric, but all the ensemble predictions are reduced to a single yes/no forecast. Hence, we also produced a probability forecast for each category as the fraction of ensemble members being in the upper (or lower) tercile for each initiation year and lead time. The quality of the probabilistic forecast was assessed using the Brier Score (BrS). The BrS is an estimate of the mean square error of the probabilistic forecast (Wilks, 2011) and is defined as:

$$\text{BrS(t)} = \frac{1}{N}\sum\nolimits_{\alpha=1}^{N} (f_{\propto}(t) - o_{\propto}(t))^2$$

Where t is the lead time, f is the forecasted probability of an event determined by the fraction of forecast ensemble members within the upper (lower) tercile, o is the observed probability of an event (either 0 or 1), and N is the length of the hindcast period. The BrS ranges from 0 (perfect score) to 1.

Currently, fisheries decisions assume that future environmental conditions impacting fish productivity (i.e., recruitment, mortality, growth), will be like the past. Future productivity is determined by drawing random samples from the full range of past environmental conditions. Thus, it is of interest to evaluate forecast skill relative to climatology (i.e., assume that upper and lower tercile events will always have a 0.33 probability of occurrence). Probabilistic forecast skill was hence also assessed relative to climatology using the Brier Skill Score (BSS), which compares the BrS or the forecast to that of a reference forecast (Wilks, 2011):

$$\text{BSS(t)} = 1 - \text{BrS(t)}/\text{BrS}_{\text{ref}}\text{(t)}$$

The BrS_{ref} was computed using the climatological frequencies (0.33 in the case of tercile events).

Finally, to assess if most of the forecast skill was derived from correctly forecasting the internal variability of the climate system (i.e., ENSO or PDO events) or from the warming trend, the skill of the initialized forecast was compared to that of an uninitialized forecast by computing a BSS where the BrS_{ref} was the probability forecast of the uninitialized forecasts, post-processed in the same manner as the initialized forecasts. The BSS ranges from 1 (perfect score) to negative infinity (no skill). Negative scores indicate no additional skill as compared to the reference forecast.

Sampling uncertainty was assessed by computing confidence intervals for each of the skill metrics described above using a bootstrap procedure (Mason, 2008; Wilks, 2011). Forecast-observation pairs were randomly resampled with replacement to generate 1,000 new forecast-observation vectors of length 47. Skill metrics were computed for each of the 1,000 vectors to obtain a sampling distribution for the skill scores. The lower and upper 95% confidence intervals were defined by the 0.025 and 0.975 quantiles.

RESULTS

Forecast accuracy in predicting temperatures as being in the higher or lower tercile with a 1 year lead time exceeded 0.7 in 80% of LMEs (**Figures 2–4**). Forecast accuracy was particularly high for LME's in the North Atlantic, with LMEs from the Norwegian to the Iberian coastal shelves in the eastern Atlantic and the Newfoundland-Labrador Shelf, the Caribbean Sea, and the North Brazil Shelf on the western side exceeding 0.8 accuracy for predictions of both upper and lower tercile events (**Figures 2**, **3**). In the Indian Ocean, forecast accuracy exceeded 0.8 in the West-Central Australian Shelf. While accuracy was generally lower for Pacific Ocean LMEs, upper and lower tercile events in the East China Sea, South China Sea and Sulu-Celeb Sea, were predicted with over 0.8 accuracy (**Figures 2**, **3**). By contrast, forecast accuracy in southern and eastern Pacific Ocean LMEs, namely the Indonesian Sea, the Northeast and Southeast Australian shelves, New Zealand, the Humboldt Current, the Central-American shelf, the Gulf of California, and, for the lower tercile, the California Current, was not significantly higher than random chance (**Figure 4**). Forecast skill was also low in the Patagonia Shelf, the Benguela Current and the Southeast US (**Figures 2–4**).

When the forecast lead time was extended to 1–3 years, forecast accuracy for both upper and lower terciles generally increased (**Figures 2–4**). At this lead time, accuracy greater than 0.8 was extended to most LMEs in the Indian and western Pacific Ocean, and to the Scotian Shelf, Northeast US, and East Brazil Shelf in the Atlantic Ocean (**Figures 2**, **3**). However, accuracy remained not significantly different than that of a random forecast in the Benguela Current, Southeast US and the southern and eastern Pacific Ocean (**Figures 2–4**).

When the forecast lead time was extended to 1–10 years, forecast accuracy for both upper and lower tercile events increased in most LMEs (**Figures 2–4**). Forecast accuracy for both upper and lower terciles was greater than 0.9 for all LMEs in the Indian Ocean except the Gulf of Thailand, all Atlantic LMEs except the Southeast US, the South Brazil Shelf, and the Patagonia Shelf, and in the western Pacific from the East-Central Australian shelf to the Sea of Japan (**Figures 2**, **3**). In the eastern Pacific, the only LME showing an increase in accuracy was the equatorial Central-American Shelf (**Figures 2**, **3**). Accuracy remained not significantly different than that of a random forecast for the Gulf of Alaska, the California Current, the Gulf of California, and the Humboldt Current (**Figure 4**). The observed increased prediction skill from 1 year to 1–10 year averages reflects the prominence of the forced signal in driving multi-annual prediction skill. This may seem counter-intuitive, as the 10-year time horizon minimizes the value of initialization. However, for a 1–10 years prediction this negative impact is surpassed by longer averaging periods, which smooth out unpredictable internal variability, and longer time horizons increasing the prominence of a predictable forced signal. When the averaging period was reduced to three years, as in the 1–3 years forecast, for a prediction of conditions 8–10 years into the future, forecast accuracy, while still significant over many LMEs owing to the prominence of the forced signal, decreased as compared to a 1–3 years forecast because of the reduced impact of initialization at this longer lead time (Compare **Figures 2**, **3–5**).

Probabilistic forecast skill of both upper and lower tercile SST anomalies, as determined by the BrS, mirrored patterns in forecast accuracy. For a 1 year lead time, forecast error was highest in the Patagonia Shelf, the Southeast Australian Shelf, the Southeast US, the Benguela Current and the Gulf of California (**Figures 2**, **3**, and Figure A1). Forecast error generally decreased with increasing forecast average, a notable exception being the eastern Pacific Ocean LMEs, the Patagonian Shelf, the South Brazil Shelf, the New Zealand Shelf, the Gulf of Thailand, and the Southeast US (**Figures 2**, **3**, and Figure A1).

The accuracy and BrS demonstrated that forecasts of upper and lower SST terciles relative to conditions over the past 50 years were skillful for most LMEs globally and across lead times of interest to fisheries decisions (**Figures 2–4**). Forecasts were generally more skillful than climatology, with the BSS being positive over most LMEs for all lead times for both upper and lower tercile events (**Figures 6**, **7**). As was the case with accuracy and BrS, BSS increased from 1, 1–3 to 1–10 years, with similar patterns of relative skill across systems. At 1 year lead times, uncertainty was sufficiently large that forecast skill was significantly better than climatology (i.e., BSS confidence interval did not cross 0) only in North Atlantic LMEs, the western equatorial Pacific Ocean LMEs, and the Western Central Australia Shelf (**Figures 6**, **7**, and Figure A2). Skill over climatology was generally better for lower tercile events, with significantly positive BSS also extending to the Agulhas Current, Somali Coastal Current, Bay of Bengal, and all LMEs in the Australian shelf in the Indian Ocean; the California Current and Gulf of Alaska in the eastern Pacific Ocean; and to the Canary Current, the Scotian shelf, the Caribbean Sea, and the East and South Brazil shelves in the Atlantic Ocean (**Figure 7** and Figure A2). As forecast skill improved with increasing forecast average for most LMEs, so did skill over climatology, except for the Southeast US, the Patagonian Shelf, the South Brazil Shelf, the New Zealand Shelf, and eastern Pacific LMEs which showed no

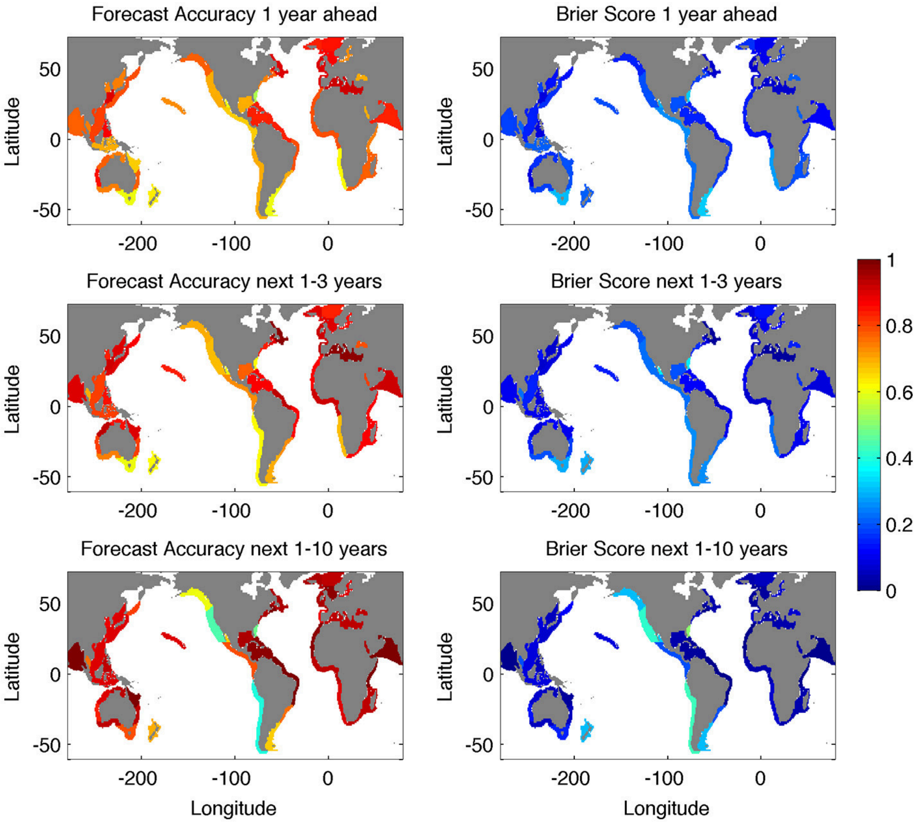

FIGURE 2 | Forecast accuracy **(left)** and Brier Score (BrS, **right**) for upper SST tercile predictions for a 1 year ahead forecast and over the next 3 and 10 years. Forecast accuracy ranges between 0 (no skill) and 1 (perfect skill). The BrS ranges from 0 (perfect score) to 1 (no skill).

improvement over climatology for a 10 years forecast average (**Figures 6**, **7**, and Figure A2).

The BSS relative to the uninitialized forecasts was positive for most LMEs for both upper and lower tercile events for a 1 year lead time forecast, suggesting that initialization contributed to forecast skill at this lead time (**Figures 6**, **7**). However, forecasts were uncertain and most lower 95% confidence intervals exceeded zero (Figure A3). Only predictions for the Celtic-Biscay Shelf, the Faroe Plateau, the Newfoundland-Labrador Shelf, the Gulf of Alaska, and the West-Central Australian Shelf LMEs showed significantly better skill than the uninitialized forecasts at a 1 year lead time (Figure A3). As forecast lead time progressed, skill relative to the uninitialized forecast decreased (**Figures 6**, **7**). The BSS relative to the uninitialized forecast was near 0 or negative in many LMEs at the 10 years forecast average as much of the forecast skill was derived from the forced signal (**Figures 6**, **7**). As for the 1 year lead time, there was largely no significant difference between initialized and uninitialized forecasts at 1–3 and 1–10 years lead times (Figure A3). Forecasts for LMEs around the Atlantic subpolar gyre, namely the Newfoundland-Labrador Shelf, Scotian Shelf, Faroes Plateau, Norwegian Sea, North Sea, Celtic-Biscay Shelf, and the Iberian Coastal, were an exception, showing significant skill over the uninitialized forecast for the 10 years forecast average for both upper and lower tercile events (**Figures 6**, **7** and Figure A3).

DISCUSSION

This work demonstrates that global climate forecasts have significant skill in predicting occurrence of above average warm or cold SST events at a multi-annual scale in coastal areas, with average being the mean SST conditions over the past 50 years. At a 1 year lead time, forecasts were more skillful than climatology in the North Atlantic, the Western Central Australia Shelf, and the western equatorial Pacific Ocean. Prediction skill increased with longer forecast averages. Predictions of upper and lower SST terciles over the next 3 or 10 years were significantly better than climatology over most LMEs in the North Atlantic, the western Pacific, and Indian oceans. This is consistent with studies showing multi-annual retrospective forecast skill over the Indian, western Pacific and North Atlantic oceans (van Oldenborgh et al., 2012; Doblas-Reyes et al., 2013; Karspeck et al., 2015).

Over large ocean regions, much of the predictive skill at a multi-annual scale is associated with the ability of multi-annual prediction systems to correctly predict the response of the climate system to increasing greenhouse gas emissions (van Oldenborgh et al., 2012; Doblas-Reyes et al., 2013; Yang et al., 2013; Müller et al., 2014; Corti et al., 2015; Karspeck et al., 2015). Here we show that this conclusion also applies to the regional shelf scale, with forecast skill of the uninitialized predictions being comparable to that of the initialized forecasts over most LMEs. Furthermore, as

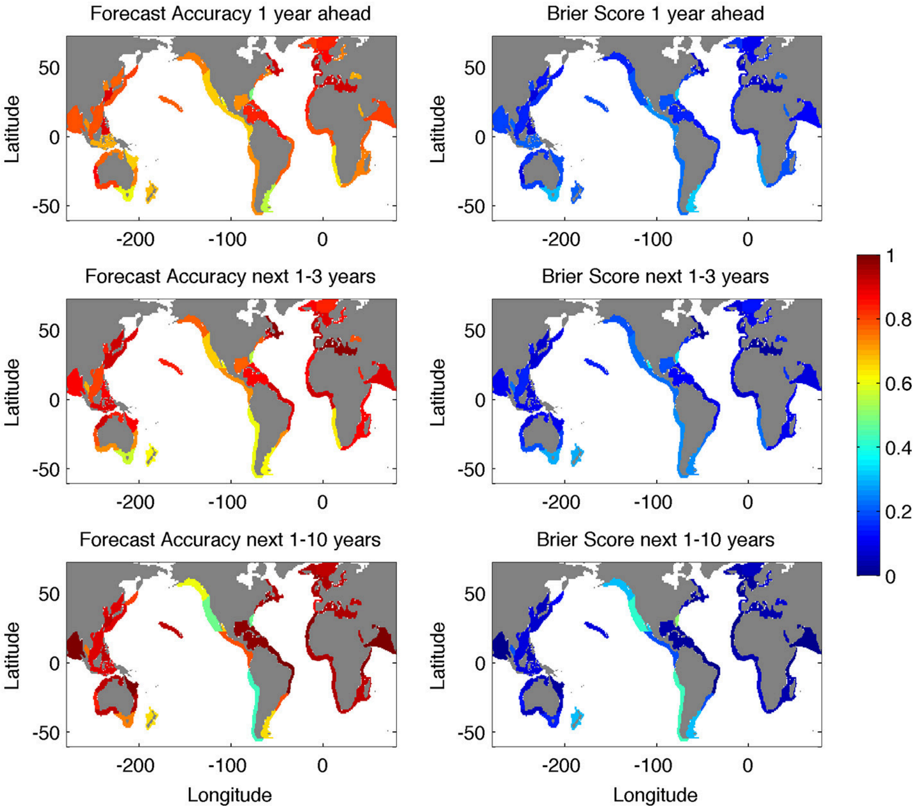

FIGURE 3 | Forecast accuracy **(left)** and Brier Score (BrS, **right**) for lower SST tercile predictions for a 1 year ahead forecast and over the next 3 and 10 years. Forecast accuracy ranges between 0 and 1 (perfect skill). The BrS ranges from 0 (perfect score) to 1 (no skill).

unpredictable internal variability is smoothed out by forecasting over a longer period (García-Serrano and Doblas-Reyes, 2012), the relative importance of the warming trend in driving SST increases for forecasts of SST conditions over the next 3 or 10 years and these forecasts were more skillful than 1 year lead time predictions. The importance of the radiatively forced signal in providing skill on a 1–10 years scale suggests the potential viability of a purely statistical forecasting system in those LMEs where the forced signal dominates. Such a comparison is outside of the scope of this paper. We note, however, that a statistical approach would be unable to capture changes in the rate of warming over time and the high multi-annual prediction skill of North Atlantic LMEs arising from initialization.

North Atlantic LME's stood out as the only ones where initialized SST forecasts for the next 10 years were significantly more skillful than the uninitialized predictions. Even when the forecast lead time was increased to 8–10 years, initialized forecast skill remained significantly higher than that of an uninitialized prediction for some North Atlantic LMEs (Figure A6). Other work has shown that initialization greatly improves multi-annual forecast skill in the subpolar gyre region of the North Atlantic (Keenlyside et al., 2008; Pohlmann et al., 2009; van Oldenborgh et al., 2012; Doblas-Reyes et al., 2013; Yang et al., 2013; Meehl et al., 2014; Corti et al., 2015; Karspeck et al., 2015). Multi-annual SST variability in this subpolar gyre region of the North Atlantic is influenced by ocean dynamics, particularly by decadal variability in the Atlantic meridional overturning circulation (Delworth et al., 1997; Matei et al., 2012; Robson et al., 2012a; Barrier et al., 2015). Hence, initialization of ocean conditions can substantially improve prediction skill (Matei et al., 2012; Robson et al., 2012b, 2014; Yeager et al., 2012; Yang et al., 2013; Msadek et al., 2014). Here we demonstrate that the higher skill derived from initialization can be extended to the coastal shelves influenced by the subpolar Atlantic gyre circulation.

Multi-annual prediction skill was limited for eastern Pacific coastal areas from the Gulf of Alaska to the Humboldt Current. Large scale SST variability in the eastern Pacific is strongly forced by the atmosphere (Chhak et al., 2009; Johnstone and Mantua, 2014), which has a short memory. Furthermore, ocean dynamics driving SST in this region, such as coastally trapped Kelvin waves and eastern boundary currents, act on a faster time scale than, for instance, the Atlantic overturning circulation. Hence, eastern Pacific SST predictability may be intrinsically more limited than in other regions, such as the North Atlantic, where slow ocean dynamics play a dominant role in determining SST fluctuations (Robson et al., 2014). For instance, Eastern Pacific SST variability is strongly influenced by ENSO and its teleconnections. This results in some of the highest seasonal SST prediction skill across global LMEs (Stock et al., 2015), but the low predictability for ENSO beyond the seasonal timescale (CLIVAR, 2001; Palmer

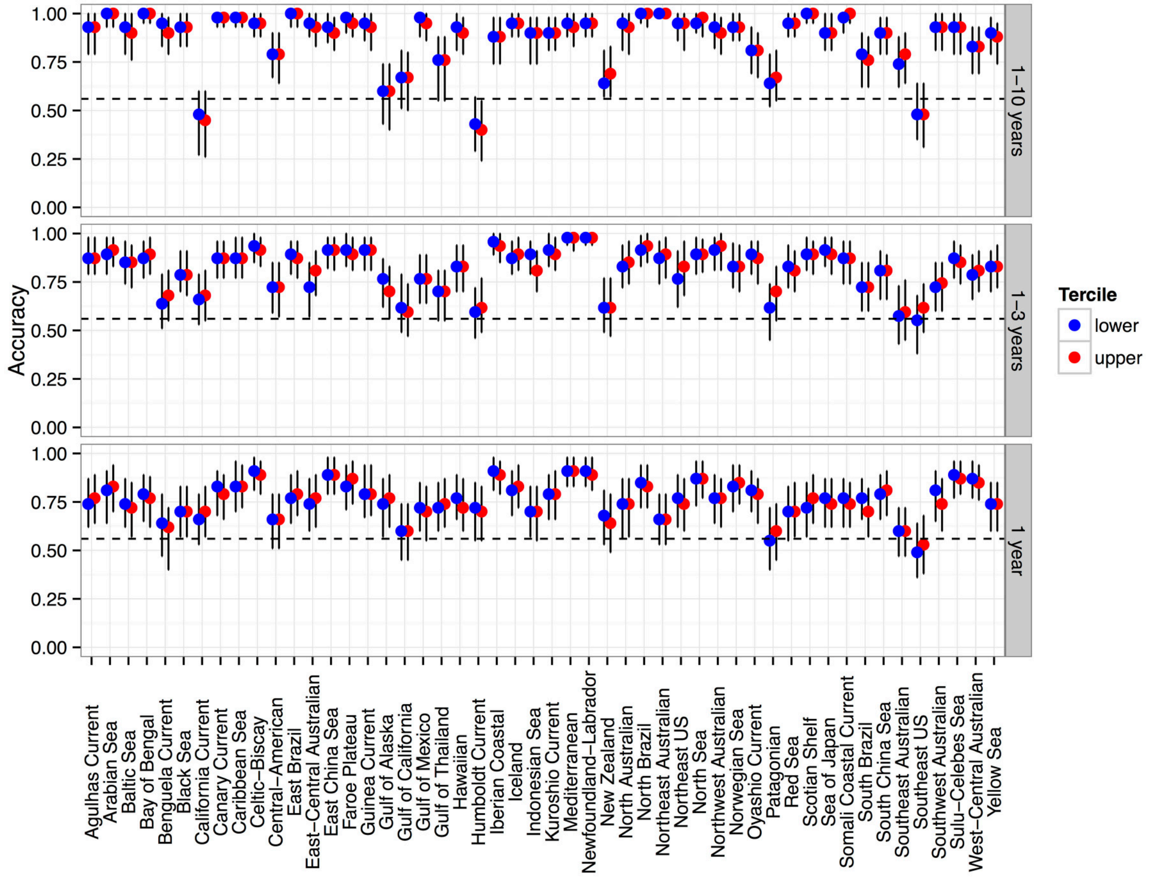

FIGURE 4 | Forecast Accuracy with 95% confidence intervals for each LME for upper and lower SST tercile predictions for a 1 year ahead forecast and over the next 3 and 10 years. Accuracy scores higher than the dotted line are better than chance.

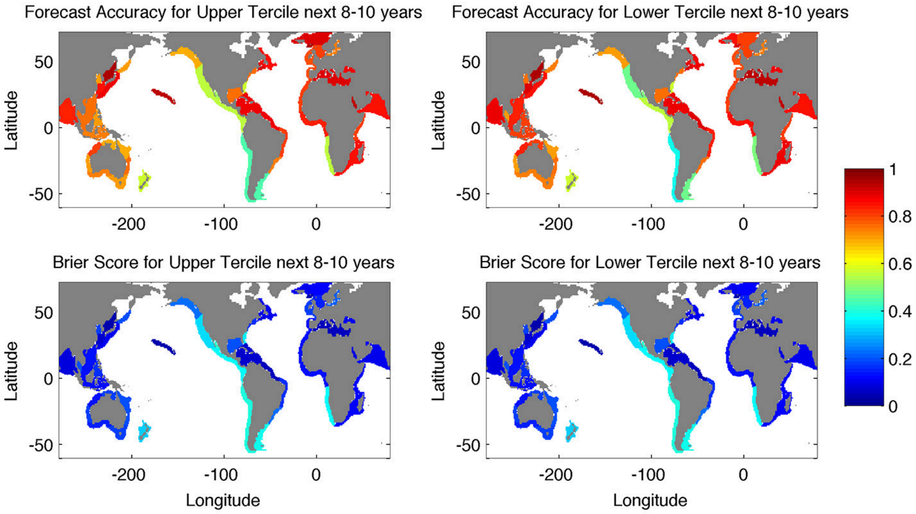

FIGURE 5 | Forecast accuracy **(top)** and Brier Score (BrS, **bottom**) for upper and lower SST tercile predictions for a 8–10 years forecast. Forecast accuracy ranges between 0 and 1 (perfect skill). The BrS ranges from 0 (perfect score) to 1 (no skill).

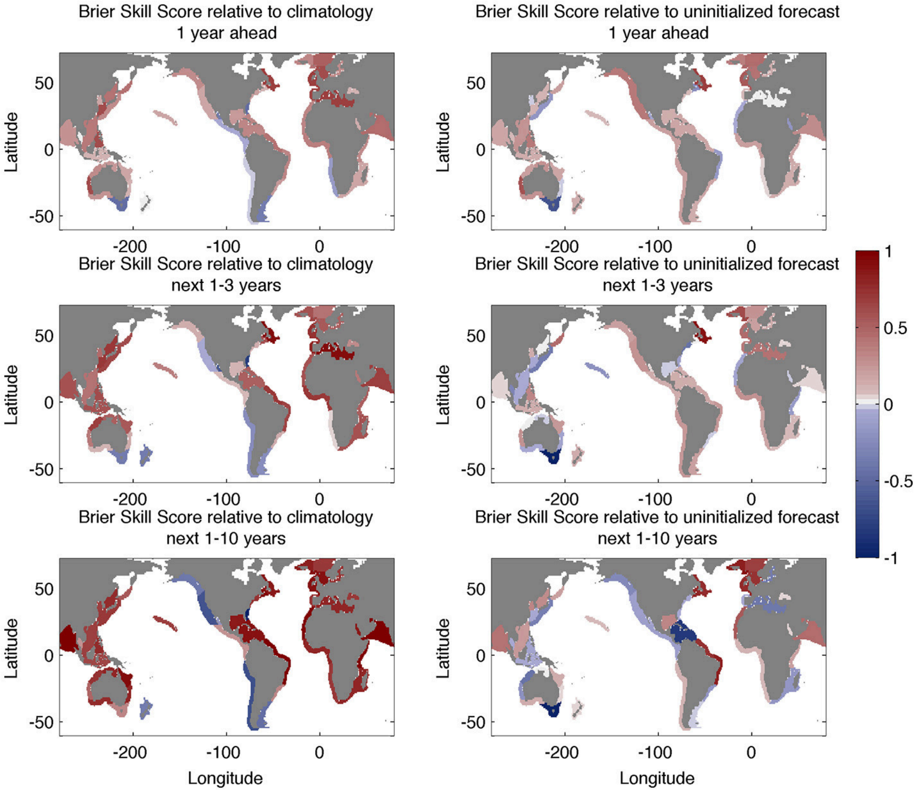

FIGURE 6 | Brier Skill Score (BSS) for upper SST tercile predictions relative to climatology **(left)** and uninitialized predictions **(right)** for a 1 year ahead forecast and over the next 3 and 10 years. The BSS ranges from 1 (perfect score) to negative infinity (no skill). Negative scores indicate no additional skill as compared to the reference forecast.

et al., 2004; Jin et al., 2008; Tippett et al., 2012; Ludescher et al., 2014) reduces multi-annual prediction skill in this region (García-Serrano and Doblas-Reyes, 2012; Karspeck et al., 2015). Eastern Pacific LMEs also stood out because, unlike most LMEs, multi-annual predictability declined with increasing forecast averages. This may stem from the lower relative importance of the linear warming trend over internal variability in determining SST variability in this region (Doblas-Reyes et al., 2013, Karspeck et al., 2015). Indeed, Eastern Pacific LMEs show some of the weakest evidence of a warming trend, with SST over the two major upwelling regions, the California and Humboldt currents, decreasing over the past thirty years (Belkin, 2009).

Multi-annual predictability is also limited by model error. SST bias of CM 2.1 is most evident in upwelling regions and in the Southern Ocean (Delworth et al., 2006). LMEs in the major upwelling centers, the California, Humboldt, and Benguela currents, and those bordering the Southern Ocean, namely the Southeast Australian Shelf, New Zealand, and the Patagonian Shelf showed some of the lowest multi-annual prediction skill. Bias in Gulf Stream position, which tends to be too northerly in CM2.1 (Saba et al., 2016), may have decreased prediction skill in the Southeast US shelf LME. Moreover, SST predictability in coastal regions remains limited by the inability of current multi-annual prediction systems to represent fine-scale shelf processes, such as upwelling and coastal wave dynamics (Jacox et al., 2015), and fine-scale bottom topography (Saba et al., 2016). Higher resolution and improved representation of ocean and shelf processes may further enhance multi-annual SST predictability in LMEs. Furthermore, it should be stressed, that these results are from one model. Their robustness should be tested across multi-annual prediction systems. Operationalization of coastal scale multi-annual forecasts will require further testing with a multi-model ensemble as was done for the first real-time global multi-annual predictions in Smith et al. (2013). A multi-model ensemble may also reduce sampling uncertainty and increase predictability, as was observed for seasonal predictions of SST in LMEs (Hervieux et al., 2017).

Our work demonstrates that current multi-annual SST predictions, when assessed as anomalies relative to conditions over the past 50 years, have significant skill in many coastal ecosystems, particularly when averaged over the next three or ten years. This presents opportunities for fisheries managers, which are required to produce multi-annual forecasts of fish stock biomass. Current management decisions are based on the scope of past variability. Integration of more precise forecasts of environmental conditions into fisheries models may reduce bias in fisheries projections, provide warning of changes in fish productivity, and produce

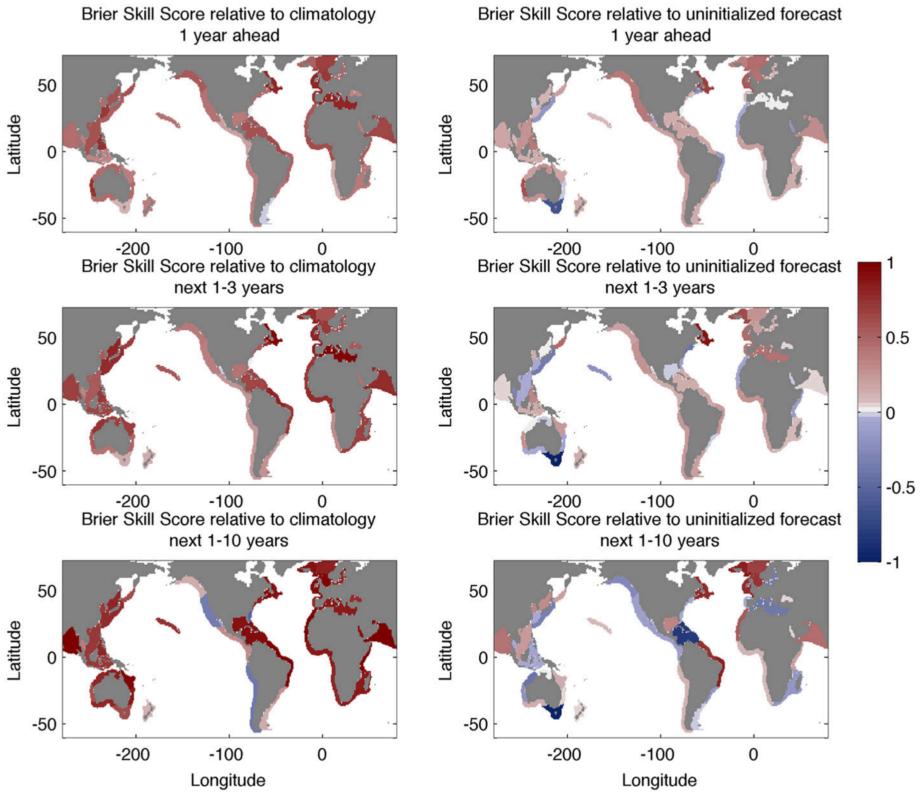

FIGURE 7 | Brier Skill Score (BSS) for lower SST tercile predictions relative to climatology **(left)** and uninitialized predictions **(right)** for a 1 year ahead forecast and over the next 3 and 10 years. The BSS ranges from 1 (perfect score) to negative infinity (no skill). Negative scores indicate no additional skill as compared to the reference forecast.

better estimates of the rebuilding potential of overfished stocks (Pershing et al., 2015; Miller et al., 2016; Tommasi et al., 2017a). Fisheries decisions would also greatly benefit from the inclusion, in addition to SST, of multi-annual predictions of other fishery-relevant variables such as bottom temperature or primary productivity (e.g. Séférian et al., 2014).

While promising, it needs to be stressed that retrospective forecast skill represents likely, not actual, future forecast skill. In particular, the hindcasts presented here included prescribed forcing from stratospheric aerosols resulting from large volcanic eruptions (such as those of El Chichón in 1982 and Pinatubo in 1991). Eruptions such as these are not presently predictable on multi-year timescales, so real-time forecasts would not be able to forecast the impact of unpredictable volcanoes. While van Oldenborgh et al. (2012), in an assessment of the relative impacts of volcanic aerosols on retrospective SST forecast skill, showed that forcing from volcanos provides only a small contribution to multi-annual SST predictability relative to the greenhouse-gas forced trend, an evaluation of real-time forecast skill (e.g., Smith et al., 2013) at an LME scale would increase condifence in the reliability of the predictive skill here presented. Development of such real-time, operational multi-annual forecast capabilities would also be required for continued use of such forecasts into fisheries decisions. Furthermore, the observed SST predictability at multi-annual scales relative to the 50-year reference stems from past and ongoing anthropogenic climate change. Thus, while there is cause for optimism regarding the utility of multi-annual predictions to the fishery sector in adapting to this warming trend, this optimism rests within the reality of strong multi-annual change.

AUTHOR CONTRIBUTIONS

DT and CS designed the research, DT analyzed the data, and DT, CS, MA, XY, AR, and GV wrote the paper.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: http://journal.frontiersin.org/article/10.3389/fmars.2017.00201/full#supplementary-material

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Forecasting Ocean Chlorophyll in the Equatorial Pacific

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Using a global ocean biogeochemical model combined with a forecast of physical oceanic and atmospheric variables from the NASA Global Modeling and Assimilation Office, we assess the skill of a chlorophyll concentrations forecast in the Equatorial Pacific for the period 2012–2015 with a focus on the forecast of the onset of the 2015 El Niño event. Using a series of retrospective 9-month hindcasts, we assess the uncertainties of the forecasted chlorophyll by comparing the monthly total chlorophyll concentration from the forecast with the corresponding monthly ocean chlorophyll data from the Suomi-National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (S-NPP VIIRS) satellite. The forecast was able to reproduce the phasing of the variability in chlorophyll concentration in the Equatorial Pacific, including the beginning of the 2015–2016 El Niño. The anomaly correlation coefficient (ACC) was significant ($p < 0.05$) for forecast at 1-month ($R = 0.33$), 8-month ($R = 0.42$) and 9-month ($R = 0.41$) lead times. The root mean square error (RMSE) increased from 0.0399 μg chl L^{-1} for the 1-month lead forecast to a maximum of 0.0472 μg chl L^{-1} for the 9-month lead forecast indicating that the forecast of the amplitude of chlorophyll concentration variability was getting worse. Forecasts with a 3-month lead time were on average the closest to the S-NPP VIIRS data (23% or 0.033 μg chl L^{-1}) while the forecast with a 9-month lead time were the furthest (31% or 0.042 μg chl L^{-1}). These results indicate the potential for forecasting chlorophyll concentration in this region but also highlights various deficiencies and suggestions for improvements to the current biogeochemical forecasting system. This system provides an initial basis for future applications including the effects of El Niño events on fisheries and other ocean resources given improvements identified in the analysis of these results.

Keywords: enso, chlorophyll, phytoplankton, forecast, biogeochemical modeling

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INTRODUCTION

Forecast models of atmospheric conditions have considerably improved over the past few decades and are routinely used to predict weather patterns including hurricanes, winds and other potentially threatening conditions. Natural processes in the atmosphere, ocean and land can each influence climate in sometimes predictable ways. Developing forecasting systems for ocean biogeochemical processes is a scientific challenge that has important implications in the management of marine ecosystems and resources. One of the challenges of improving subseasonal to seasonal forecasting skill is to identify and characterize sources of subseasonal to seasonal natural modes of variability (e.g., El Niño Southern Oscillation), slowly varying processes (e.g. ocean biogeochemistry), and external forcing (e.g., winds, radiation).

Most oceanographic forecasts emphasize physical conditions (e.g., temperature, mixing), ocean biogeochemical forecasts are less common and have mostly focused on the prediction of algal blooms and hypoxia (e.g., Wynne et al., 2005; Greene et al., 2009; Stumpf et al., 2009; Evans and Scavia, 2010). Various approaches have been developed to predict biogeochemical variables from statistical relationships with temperature, wind speed and other variables to the use of more complex numerical models. A typical application of these biogeochemical forecasts is the prediction of Harmful Algal Blooms (e.g., Stumpf et al., 2009; Raine et al., 2010). One example is the Eastern Gulf of Mexico Harmful Algal Bloom Operational Forecast System (GOMX HAB-OFS) developed by NOAA to follow the development of a toxic dinoflagellate, *Karenia brevis*, that produces Neurotoxic Shellfish Poisoning, kills fishes and marine mammals and leads to health and economical losses resulting from respiratory irritation in the waters off Florida. This forecasting system relies on satellite ocean color and transport direction data from satellite imagery combined with in situ samples. They issue semi-weekly bulletins that serve as decision support tools for coastal resource managers, federal and state agencies, public officials, and academic institutions (Kavanaugh et al., 2016). The forecast was expanded to other regions and the system is described in several papers (e.g., Stumpf et al., 2003, 2009; Tomlinson et al., 2004). Other examples of biogeochemical forecast efforts include the forecast of hypoxia zone in the Gulf of Mexico (Scavia et al., 2003), net primary production in the tropical Pacific (Séférian et al., 2014), annual salmon yields (Scheuerell and Williams, 2005), sardines distribution (Kaplan et al., 2016), seasonal distributions of southern Bluefin tuna (Hobday et al., 2011; Eveson et al., 2015) and coral bleaching (Goreau and Hayes, 2005).

While some of these forecasting systems rely on satellite ocean color data, others rely on biochemical variables that cannot be directly derived from ocean color data or that do not have statistical relationship with variables that can be derived from satellite data (e.g., nutrient, oxygen concentration). Furthermore, satellite data can have large gaps (e.g., clouds, aerosols, interorbital gaps, high solar zenith angles) that do not allow for a systematic and complete coverage of the area of interest. Here we combine an established biogeochemical model with a seasonal forecast of atmospheric and ocean conditions to provide a 9-month forecast of total chlorophyll in the Equatorial Pacific for the period 2012–2015. The assimilation of satellite ocean color to provide the initial conditions for the forecast ensures the best use of the data available, while the forecast provides a complete coverage of the chlorophyll concentration (among other variables) for a 9-month forecast. The skill of the forecasting system is assessed by comparing the total chlorophyll to those from the satellite Suomi-National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (S-NPP VIIRS).

MATERIALS AND METHODS

The NASA Ocean Biogeochemical Model (NOBM) is a three dimensional biogeochemical model of the global ocean coupled with a circulation and radiative model (Gregg et al., 2003; Gregg and Casey, 2007). NOBM has a near-global domain that spans from −84° to 72° latitude at a 1.25° resolution in water deeper than 200 m. NOBM is coupled with the Poseidon ocean general circulation model. The Poseidon model (Schopf and Loughe, 1995) is a reduced gravity ocean model with 14 layers in quasi-isopycnal coordinates forced by wind stress, sea surface temperature, and shortwave radiation (Gregg and Casey, 2007). The NOBM contains 4 explicit phytoplankton taxonomic groups (diatoms, cyanobacteria, chlorophytes and coccolithophores), 3 detritus components (silicate, nitrate/carbon and iron), 4 nutrients (nitrate, silicate, iron and ammonium) and one zooplankton group. The growth of phytoplankton is dependent on total irradiance, nitrogen (nitrate + ammonium), silicate (for diatoms only), iron and temperature (see Rousseaux and Gregg, 2015 for more details). Surface photosynthetically available radiation is derived from the Ocean-Atmosphere Spectral Irradiance Model (OASIM; Gregg and Casey, 2009).

A spin-up run of 100 years has been shown to produce stable initial conditions for biological variables (Gregg and Rousseaux, 2014). The NOBM model is then run for 14 years using ocean and atmospheric variables as forcing from the Modern-Era Retrospective analysis for Research and Applications (MERRA, Rienecker et al., 2011) and ocean chlorophyll data from Sea-Viewing Wide Field-of-View Sensor (SeaWiFS) and Moderate-resolution imaging spectroradiometer (MODIS)-Aqua in data assimilation mode (Gregg and Rousseaux, 2014). Starting in 2012, the model assimilates chlorophyll data from S-NPP VIIRS and uses transient MERRA data to force the circulation model. The assimilation of satellite chlorophyll uses a multivariate methodology where the nutrients are adjusted corresponding to the chlorophyll assimilation using nutrient-to-chlorophyll ratios embedded in the model (Rousseaux and Gregg, 2012). The difference between the chlorophyll assimilation results and the prior chlorophyll produced by the model (the analysis increments) are used to adjust the nutrient concentrations. The multivariate assimilation is applied to silica and dissolved iron, as well as nitrate. These conditions are used as initial conditions for each forecast (using the month prior to the start of the forecast). The forcing data used for the forecast include zonal and meridional wind stress, sea surface temperature and shortwave radiation. These forecast files are produced by the NASA Global Modeling and Assimilation Office (GMAO) using the GEOS-5 system (https://gmao.gsfc.nasa.gov/weather_prediction/). These forecasted atmospheric and ocean variables are currently provided to the North American Multi-Model Ensemble (NMME) prediction project, as well as to other national (International Research Institute for Climate and Society, IRI) and international (Asia-Pacific Climate Center, APCC) ensemble seasonal forecasting efforts (Borovikov et al., in review).

The bias and uncertainties in the system are assessed by (1) comparing the satellite ocean chlorophyll used for validation and data assimilation to in situ data, (2) comparing the chlorophyll concentration from a free-run model (without data assimilation) to satellite ocean color and (3) comparing the chlorophyll concentration from a run assimilating satellite chlorophyll with those from the satellite (**Figure 1**). The in situ data used to evaluate the bias and uncertainties in the S-NPP VIIRS chlorophyll include data collected from the National Oceanographic Data Center (Gregg and Conkright, 2002), NASA in situ database (Werdell and Bailey, 2002; Werdell et al., 2003), and Atlantic Meridional transect (Aiken et al., 2000) archives (Gregg et al., 2009). The quality of the biogeochemical system used is then assessed using a hindcast from 2012 to 2015 forced using MERRA data (procedure 2a, b on **Figure 1**). The uncertainties in this system are evaluated by comparing the chlorophyll concentration in the Equatorial Pacific from this run with those from S-NPP VIIRS. To evaluate the effects of the forcing data on the chlorophyll concentration estimates, we then compare a free-run model forced by transient MERRA forcing data with one forced by climatological MERRA data. Finally we compare the monthly chlorophyll concentration from the assimilation run to the monthly concentration from S-NPP VIIRS (procedure 3 on **Figure 1**). Bias is quantified by averaging the monthly percent difference between the chlorophyll concentration from the model (free-run and assimilating run) and the satellite chlorophyll concentration for the period 2012–2015 and the standard error is calculated. The uncertainty is quantified using a correlation coefficient. A statistically significant correlation coefficient is defined as one with a p-value smaller than 0.05.

The skill of the various forecasts is assessed using three metrics: (1) the percent difference between the NPP-VIIRS chlorophyll data and the forecast (bias) (procedure 4 on **Figure 1**), (2) the anomaly correlation coefficient (ACC) and (3) the root mean square error (RMSE). The anomaly correlation coefficient provides information on the linear association between forecast and observations but is insensitive to biases and error in variances. It is calculated as between the model prediction (p) and satellite observation (o) of chlorophyll over N months ($N = 38$) and computed as:

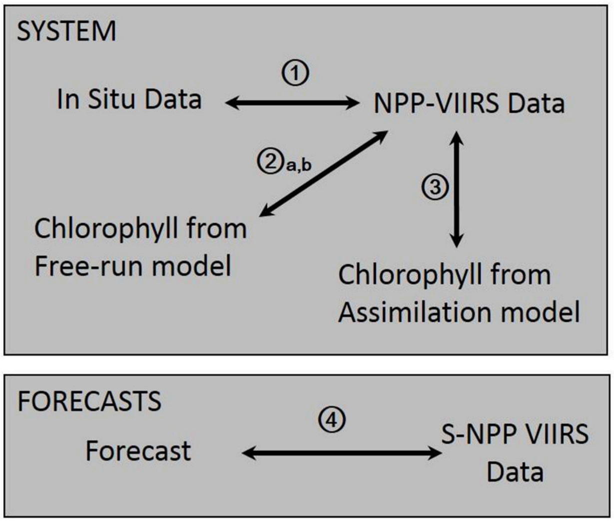

FIGURE 1 | Diagram describing the different procedures used to characterize bias and uncertainties in the system and forecasts described in this study.

$$ACC = \frac{\sum(p-\bar{p})(o-\bar{o})}{\sqrt{\sum(p-\bar{p})^2\sum(o-\bar{o})^2}}$$

The RMSE measures the magnitude of the error, is sensitive to large values but does not indicate the direction of the error. It is calculated as:

$$RMSE = \sqrt{\frac{1}{N}\sum[(p-\bar{p})(o-\bar{o})]^2}$$

where $\bar{p}$ and $\bar{o}$ are the temporal averages of chlorophyll.

A total of 38 retrospective forecasts were run, each for a 9-month period. The first forecast started in March 2012 and the last forecast started in April 2015. The percent difference between the satellite and the forecast chlorophyll quantifies the mean error in the forecast. It allows us to assess whether the forecast has on average a positive or a negative bias.

RESULTS AND DISCUSSION

Assessing the Skill of the Model System

The first source of uncertainty reflects the inherent bias of satellite-derived chlorophyll concentration and is assessed by comparing the S-NPP VIIRS chlorophyll to in situ fluorometric chlorophyll data. For the period from 2012 to 2014, the global chlorophyll from S-NPP VIIRS compared favorably to in situ chlorophyll (bias = 11.8%, semi-interquartile range = 27.9% and $R = 0.86$; **Table 1**).

The second source of uncertainty lies in how well the model simulates chlorophyll concentration. This source of uncertainty is assessed by comparing the chlorophyll concentration (Toggweiler et al., 1991) from the free-run model (no data

TABLE 1 | Summary table of bias and uncertainties of the various elements of the system used to forecast.

Type of bias/uncertainties	Bias	Uncertainties
Chlorophyll from satellite versus in situ data (Global)	11.8%	$R = 0.86$, $P < 0.05$
Chlorophyll from free-run model versus satellite chlorophyll (transient forcing data, Equatorial Pacific, 2012–2015)	27.87 ± 1.72%	$R = 0.72$, $p < 0.05$
Chlorophyll from free-run model versus satellite chlorophyll (climatological forcing data, Equatorial Pacific, 2012–2015)	85.67 ± 2.77%	$R = 0.47$, $p < 0.05$
Chlorophyll concentration from assimilating run versus satellite chlorophyll (Equatorial Pacific, 2012–2015)	12.34 ± 0.52%	$R = 0.95$, $P < 0.05$

assimilation but uses transient forcing conditions from MERRA) with the corresponding satellite ocean color data. For the period from 2012 until 2015, monthly chlorophyll concentration from the free-run model were significantly correlated to those from the satellite ocean color (S-NPP VIIRS, $R = 0.72$, $p < 0.05$; **Table 1**). The chlorophyll from the free-run model was on average within 27.87 ± 1.72% (average ± standard error) of the S-NPP VIIRS chlorophyll. Chlorophyll fields in the Equatorial Pacific showed agreement with satellite data (**Figure 2**). The model reproduces the main features observed by the satellite ocean color. The consistent positive bias in chlorophyll concentration in the Equatorial Pacific in the free-run model suggest that the upwelling in the Equatorial Pacific in the model is overestimated and therefore leads to higher chlorophyll concentration than those observed. The overprediction of the upwelling in the Equatorial Pacific in models has been suggested for some time (e.g., Toggweiler et al., 1991; Zheng et al., 2012). In some other areas, such as along the South America coastline as well as in the region of the Costa Rica Dome, the chlorophyll concentration from the free-run model was underestimated. This is most likely due to the nature of the reduced gravity circulation model. The model therefore does not include topographic effects, nor does it allow the representation of cross-shelf advection and convection.

In the Equatorial Pacific, the monthly chlorophyll concentration from a run assimilating S-NPP VIIRS chlorophyll data was significantly correlated ($R = 0.95$, $P < 0.01$; **Table 1**) and on average within 12.34 ± 0.52% of the S-NPP VIIRS chlorophyll concentration. The assimilation of satellite chlorophyll to provide the initial conditions used for the forecast is therefore an improvement over using the initial conditions provided by the free-run model without data assimilation. We therefore use this set-up to provide the initial conditions for the forecasting systems.

Finally the data used to force the model have their own inherent bias and uncertainties. While this is beyond the scope of this paper, we note that the bias in the forcing data

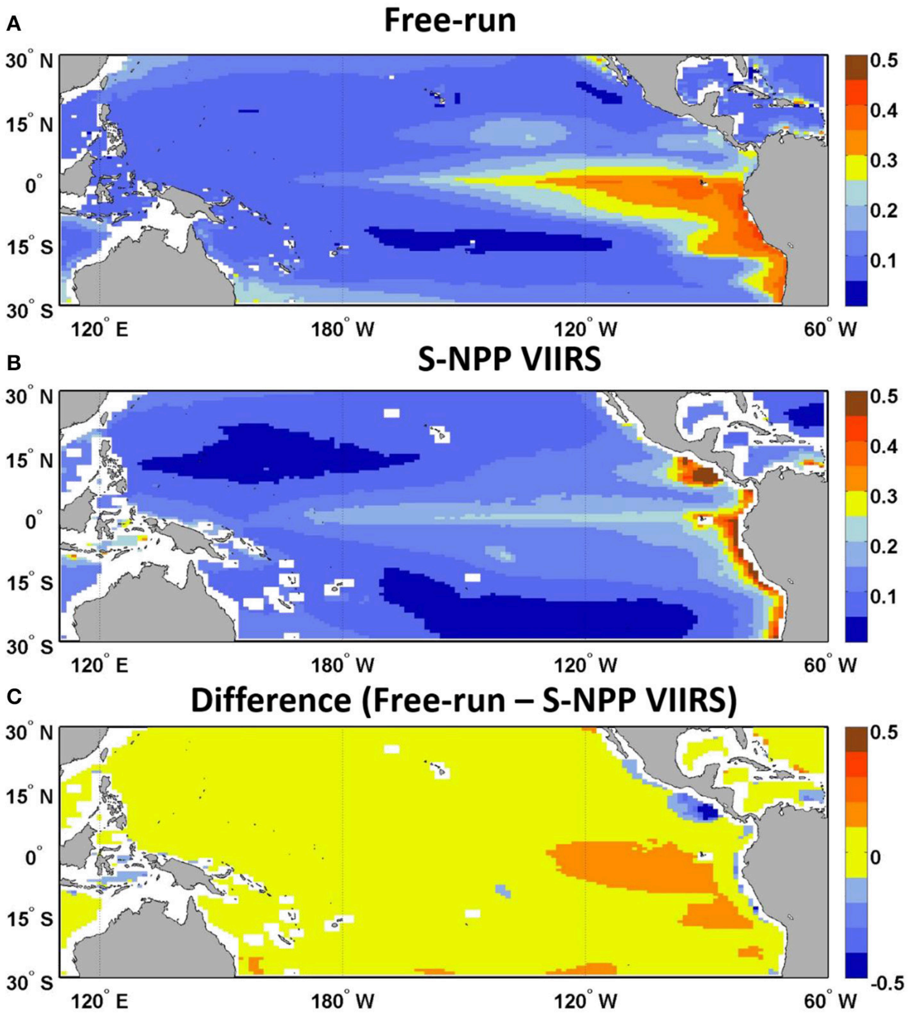

FIGURE 2 | Climatology of chlorophyll concentration (µg chl L^{-1}, 2012–2015) map of **(A)** the free-run model, **(B)** S-NPP VIIRS, and **(C)** the difference between the free-run model and S-NPP VIIRS in the Equatorial Pacific.

used here have been assessed in other papers (e.g., Rienecker et al., 2011). By comparing the chlorophyll concentration from the free-run model using climatological MERRA forcing data compared to using transient MERRA data we can assess the improvements that such transient forcing data can provide to the system. The chlorophyll concentration from the free-run model using transient MERRA forcing data were considerably closer to the chlorophyll concentration from the S-NPP VIIRS (27.87 ± 1.72%) than the free-run model using climatological MERRA data (85.67 ± 2.77%, **Figure 3**). This indicates the advantage of using transient forcing data to further improve the initial conditions used for the forecasting system.

General Skill of the Forecasts

We assess the skill of our forecast by comparing each 9-month forecast to the observed chlorophyll concentration in the Equatorial Pacific from S-NPP VIIRS for the corresponding month. There was a consistent positive bias in the chlorophyll forecasted, as in the hindcast from the free-run model compared with S-NPP VIIRS (**Figure 2**). Of the 38 forecasts, the average percent difference between the forecasted chlorophyll and the S-NPP VIIRS chlorophyll varied between 23% (3 months lead time, the equivalent of 0.033 μg chl L^{-1}) and 30.7% (9 months lead time, the equivalent of 0.042 μg chl L^{-1}, **Figures 4**, **5**). Except for the monthly chlorophyll concentration at 5 and 6-month lead time, the chlorophyll concentration from the forecasts were always significantly correlated to those from S-NPP VIIRS (data not shown). The highest correlation coefficient was observed at 8-month lead time ($R = 0.53$, $p < 0.01$).

To assess the uncertainties in our forecast, we utilize two deterministic skill metrics: ACC and RMSE. The ACC for the forecast was significant for the 1-month lead time ($R = 0.33$, $P < 0.05$) as well as for the 8- and 9-month lag forecast ($R = 0.42$ and $R = 0.41$ respectively, **Table 2**). This indicates that for these leads, the forecast chlorophyll had statistically the correct phasing when compared to those from S-NPP VIIRS. The spatial distribution of the anomaly correlation coefficient further reflects the overprediction of the upwelling in this Equatorial Pacific (**Figure 6**). While the forecasted chlorophyll concentrations at 1-month lead are significantly correlated with those from S-NPP VIIRS for the majority of the Equatorial Pacific, some areas in the upwelling tongue are not significant. The second skill metric, RMSE, increased from 0.040 μg chl L^{-1} at 1-month lead to 0.047 μg chl L^{-1} at 9-month lead forecast. These results suggest that while the phasing may have been reasonable at 8- and 9-month lag forecast, the amplitude of the signal was getting worse. Regardless, RMSE of 0.047 μg chl L^{-1} is still very acceptable for a 9-month lag forecast. These results suggest some skill in forecasting the chlorophyll variability in the Equatorial Pacific especially at 1-month lag when the ACC is significant and the RMSE is at its lowest. For all forecasts, the chlorophyll concentrations were always within 30.7% of the chlorophyll concentration from S-NPP VIIRS. This is similar to the uncertainties reported for this instrument (semi-interquartile range of S-NPP VIIRS versus in situ chlorophyll = 27.9%).

Prediction of the 2015 El Niño

In the Equatorial Pacific, the El Niño Southern Oscillation is the dominant source of interannual variability and has been shown to have a considerable impact of the biogeochemistry, including chlorophyll concentration and recruitment of higher trophic levels, in this region (e.g., Strutton and Chavez, 2000; Martinez et al., 2009). Forecasting El Niño events is the focus of many prediction centers. While the focus of assessments such as the North American Multi-Model Ensemble home has been on the skills in forecasting sea surface temperature, there has

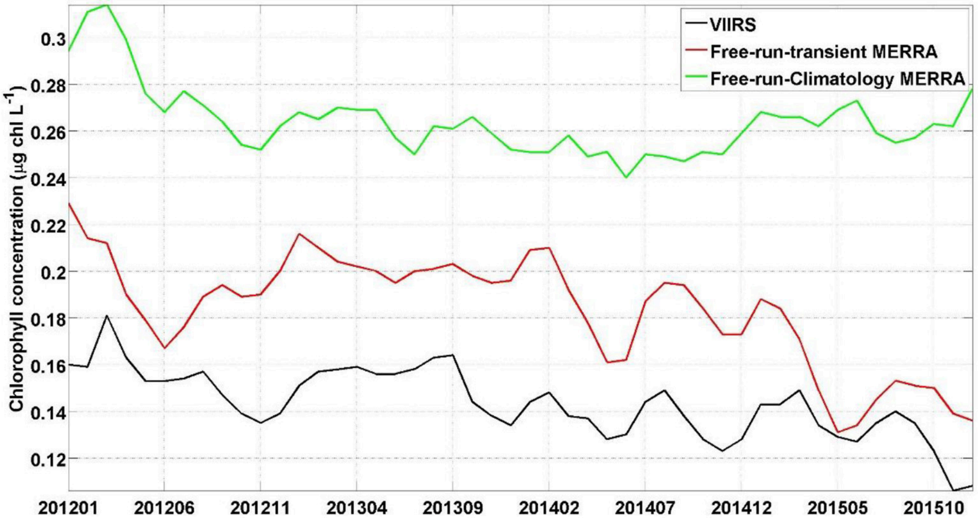

FIGURE 3 | Time series of chlorophyll concentration (μg chl L^{-1}) for NPP-VIIRS (black), free-run model with transient MERRA forcing data (red) and free-run model with a climatological MERRA forcing data (green).

been very little work on forecasting biogeochemical variables such as chlorophyll using a dynamical system. The temporal evolution of the various forecasts in this study highlights the variability between the forecasts and our skills in predicting the decline in chlorophyll concentration that was observed in the Equatorial Pacific during the 2015 El Niño event (**Figure 4**). Starting in January 2015 the forecast suggested a decline in chlorophyll concentration that would reach a minimum in May 2015 (average of the 8 forecasts available for this month of 0.13 μg chl L^{-1}). The S-NPP VIIRS data observed this minimum 1 month later in June 2015 (0.13 μg chl L^{-1}). The chlorophyll concentration from S-NPP VIIRS then increased to reach a peak in August 2015 (0.14 μg chl L^{-1}). This increase in chlorophyll was also reflected in the various forecasts although it was overestimated. After August 2015, chlorophyll concentration declined reflecting the onset of the 2015 El Niño and the suppression of the upwelling in the Equatorial Pacific. This decline was also observed in the chlorophyll concentration from S-NPP VIIRS. Of the four forecasts available for September 2015, only one had predicted this decline. The other three forecasts

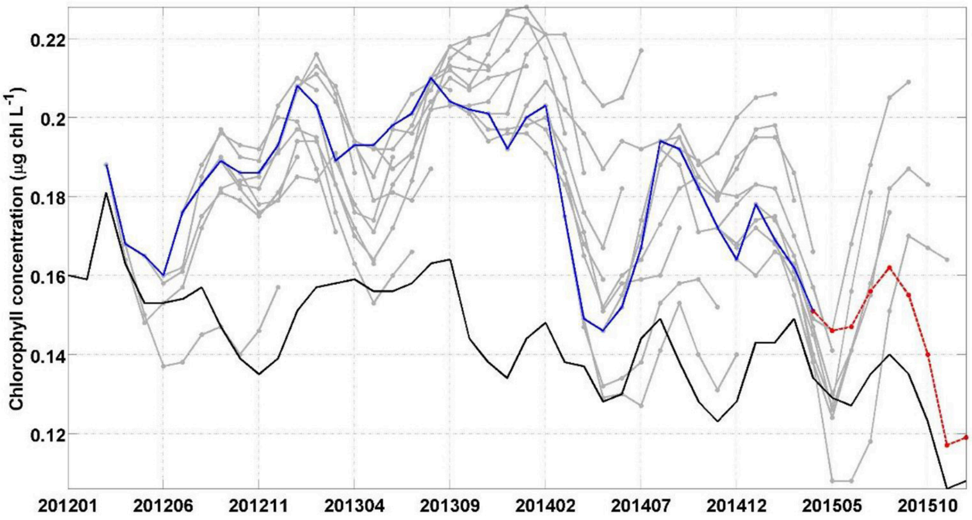

FIGURE 4 | Chlorophyll concentration in the Equatorial Pacific (10°S–10°N) for the period 2012–2015 from S-NPP VIIRS (black), individual forecasts (gray) and the 1-month lead chlorophyll concentration of every forecast (blue). The last forecast is highlighted in red.

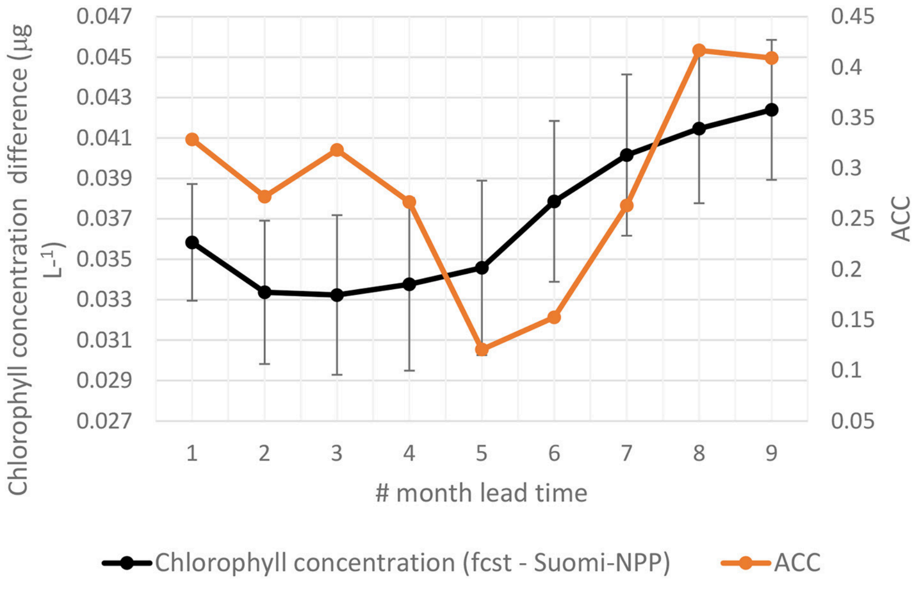

FIGURE 5 | Average difference between forecasted chlorophyll and chlorophyll from S-NPP VIIRS for corresponding month (left axis) and Anomaly Correlation Coefficient (ACC; right axis).

TABLE 2 | Anomaly Correlation Coefficient (ACC) and RMSE between the chlorophyll concentration in the Equatorial Pacific from the forecast at 1- to 9-month lead time and the corresponding monthly chlorophyll concentration from S-NPP VIIRS.

No. months lead time	ACC	RMSE
1	0.329*	0.0399
2	0.272	0.0397
3	0.318	0.0411
4	0.267	0.0427
5	0.121	0.0435
6	0.153	0.0450
7	0.263	0.0470
8	0.417*	0.0471
9	0.409*	0.0472

**indicates that the anomaly correlation coefficient was significant ($p < 0.05$).*

predicted a decline but delayed by 1 month (chlorophyll started to decline in October 2015). For the four forecasts, September 2015 was their 6- to 9-month lead forecast which we previously showed had relatively low skills compared to the 1-month lead forecasts. In the last forecast (highlighted in red in **Figure 3**), September 2015 corresponded to its 6-month lead forecast and this forecast predicted particularly well the decline in chlorophyll concentration that occurred between August and December 2015 in the Equatorial Pacific in response to the El Niño event. The spatial distribution of the chlorophyll anomaly between December 2015 and March 2015 (first month of the last forecast available) coincides well with that from S-NPP VIIRS for the corresponding month (**Figure 7**). The area of negative anomaly in chlorophyll concentration along the South American coast is distinguishable in both the forecast and the S-NPP VIIRS chlorophyll data. The overestimation of the upwelling system in the forecast is also visible on this spatial representation of the chlorophyll anomalies. The temporal evolution of these various forecasts highlights the impacts that the atmospheric forcing data have on the forecast of chlorophyll. As the forecasts get closer to the El Niño event, the forecasted atmospheric and oceanographic physical forcing data have more skills and therefore lead to a better forecast in chlorophyll concentration. The forecast of chlorophyll in this region therefore relies heavily on the existence of accurate forecast of atmospheric forcing data. The initial conditions seem to play a more minor role in the forecasting skill for predicting chlorophyll in this region.

Uncertainties of the Approach

The uncertainties in the forecast of atmospheric and oceanic variables used to force the model play a critical role in our ability to provide a successful forecast. The skill of the variables produced by the GMAO forecasting system and that are used to force the model in forecast mode can also be a source of uncertainties and have been assessed in (Borovikov et al., in review). The SST anomaly correlation coefficient from the forecast in the tropical Pacific has a high correlation coefficient ($R > 0.8$) with the Reynolds SST for lead month 1–3 and remained above 0.6 by lag month 9 indicating significant ($p < 0.05$) skill. A case study of the El Niño event of 2015/2016 in (Borovikov et al., in review) suggested an overprediction of the magnitude in SST anomalies observed during the 2015/2016 El Niño event but was overall in good agreement with the conditions that were observed.

The forecast of chlorophyll concentration presented here is based on one single set of forecasting data while the forecasting system used at GMAO provides forecasts for several ensembles. Using ensemble forecasting instead of a single forecast might further improve our skill. Initial conditions can be perturbed in various ways to account for initial condition uncertainty. The uncertainty in the forecasted forcing data provided by GMAO could be accounted for by running with the various ensembles they provide for the variables used to force the biogeochemical forecast. Finally the model uncertainty could be accounted for using some stochastic parametrization at the sub-grid level such as the one used by the European Centre for Medium Range Weather Forecasts (Buizza et al., 1999).

Another source of uncertainty in our forecast is the assimilation methodology, the Conditional Relaxation Analysis Method used for bias correction for SST products (Reynolds, 1988) and applied here for chlorophyll (Gregg, 2008). This method does not utilize ensembles which can potentially improve the initial conditions for the forecast. It would also extend the memory of the assimilation, which appears to survive <2 months here and assist in the skill of the 1-month forecast. However, there is little evidence that the 2–9 month forecasts could benefit substantially from improved initial conditions, which are quite close to the S-NPP VIIRS chlorophyll as suggested in **Table 1**.

Future Improvements and Applications

While these results suggest some skill in our ability to forecast chlorophyll concentration in the Equatorial Pacific, they also highlight potential weaknesses and avenues for improvements. The skill of the forecasting system relies as previously mentioned on the bias in the model's representation of physical and biogeochemical processes in the oceans, and the uncertainties in the forcing and assimilation data used. To further improve the forecasting system, each of these sources of bias and uncertainties needs to be assessed individually for weaknesses and possibilities for improvements. The range of applications of such a forecasting system, once properly set, can be extended for other variables. Applications include but are not limited to the prediction of Harmful Algal Blooms, fisheries, hypoxia/anoxia events, oil spills or the dispersal of pollutants. Prediction of temperature, ocean currents and velocities have for example been used for monitoring fisheries success, transport and spread of fish larvae, as well as seasonal fish migration (Johnson et al., 2005; Hobday and Hartmann, 2006; Bonhommeau et al., 2009). While the use of physical variables such as temperature, salinity and currents have been successfully used as covariates to explain

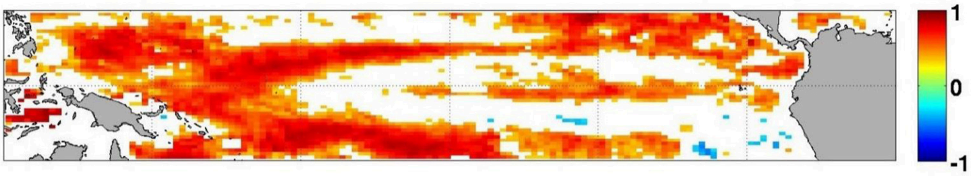

FIGURE 6 | Anomaly correlation coefficient between the forecasted chlorophyll at 1-month lead and S-NPP VIIRS chlorophyll for the period 2012–2015. White indicates that the correlation was not significant ($p > 0.05$).

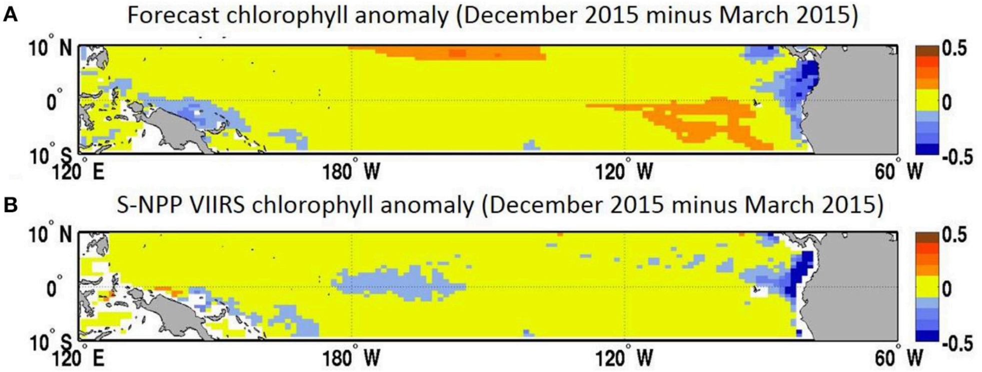

FIGURE 7 | (A) Chlorophyll concentration anomaly (December 2015 minus March 2015, μg chl L^{-1}) from the March 2015 forecast for December 2015 and **(B)** chlorophyll concentration from S-NPP VIIRS (μg chl L^{-1}).

distribution and catch rates of various species (e.g., Herron et al., 1989; Cole, 1999; Zagaglia et al., 2004; Bigelow and Maunder, 2007; Kaplan et al., 2016), these relationships can be limited since the behavior and recruitment of fish relies on changes in their prey concentration and composition. Accurate forecasts of the resources on which fish populations rely could provide the potential for strategic rather than reactive marine resource management during El Niño events for example. In the Equatorial Pacific, forecast of the effects of ENSO events on the physical conditions have been the subject of several studies starting in the 1980s (Cane et al., 1986). In the last two decades we have witnessed the development of two major El Niño events that had considerable impacts on both land and ocean conditions. The 1997-98 El Niño was particularly devastating for the ocean resources and led to the collapse of several fisheries and dramatic socio-economical repercussions for countries such as Peru. Anchovies, as well as other fisheries collapsed during both the 1982-83 and 1997-98 El Niño events. Forecasts such as the one presented here could therefore provide a framework to improve our management of resources during these events. Furthermore, the forecasting system presented here may provide a basis to expand the forecast from total chlorophyll to specific species including Harmful Algal Blooms. This could provide support for the management of many areas that need to monitor closely any development of harmful species in their waters. In the regions prone to Harmful Algal Blooms, such a forecast could also be used to improve the strategies to detect and manage most efficiently these events to minimize the repercussion on the human population and the associated economy.

AUTHOR CONTRIBUTIONS

CR: Lead the research, analysis of the data and writing of the manuscript. WG: Provided support in the analysis and writing of the paper.

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METHODS
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Predicting Heat Stress to Inform Reef Management: NOAA Coral Reef Watch's 4-Month Coral Bleaching Outlook

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The U.S. National Oceanic and Atmospheric Administration's (NOAA) Coral Reef Watch (CRW) operates a global 4-Month Coral Bleaching Outlook system for shallow-water coral reefs in collaboration with NOAA's National Centers for Environmental Prediction (NCEP). The Outlooks are generated by applying the algorithm used in CRW's operational satellite coral bleaching heat stress monitoring, with slight modifications, to the sea surface temperature (SST) predictions from NCEP's operational Climate Forecast System Version 2 (CFSv2). Once a week, the probability of heat stress capable of causing mass coral bleaching is predicted for 4-months in advance. Each day, CFSv2 generates an ensemble of 16 forecasts, with nine runs out to 45-days, three runs out to 3-months, and four runs out to 9-months. This results in 28–112 ensemble members produced each week. A composite for each predicted week is derived from daily predictions within each ensemble member. The probability of each of four heat stress ranges (Watch and higher, Warning and higher, Alert Level 1 and higher, and Alert Level 2) is determined from all the available ensemble members for the week to form the weekly probabilistic Outlook. The probabilistic 4-Month Outlook is the highest weekly probability predicted among all the weekly Outlooks during a 4-month period for each of the stress ranges. An initial qualitative skill analysis of the Outlooks for 2011–2015, compared with CRW's satellite-based coral bleaching heat stress products, indicated the Outlook has performed well with high hit rates and low miss rates for most coral reef areas. Regions identified with high false alarm rates will guide future improvements. This Outlook system, as the first and only freely available global coral bleaching prediction system, has been providing critical early warning to marine resource managers, scientists, and decision makers around the world to guide management, protection, and monitoring of coral reefs since 2012.

This has been especially valuable during the third global coral bleaching event that started in mid-2014 and extended into mid-2017. The Outlook system is an integrated component of CRW's global decision support system for coral bleaching. Recent management actions taken in light of this system are discussed.

Keywords: coral, coral bleaching, sea surface temperature, thermal stress, heat stress, outlook, prediction, Coral Reef Watch

INTRODUCTION

Mass coral bleaching due to anomalously warm water temperatures has occurred with increasing frequency and severity in recent decades (Eakin et al., 2010; Heron et al., 2016a; Hughes et al., 2018). It is now the most significant single contributor to the decline of coral reef ecosystems on a global scale (Wilkinson, 2008; Spalding and Brown, 2015). Coral bleaching occurs when the symbiotic relationship between corals and the microscopic algae (zooxanthellae) living in their tissues breaks down due to environmental stress (Jaap, 1979; Jokiel and Coles, 1990). After most zooxanthellae are expelled, the underlying white calcium carbonate coral skeleton becomes visible through the transparent coral tissue; this phenomenon is known as bleaching. Heat stress that persists for several weeks, with ambient water temperatures as little as 1–2°C above a coral's tolerance level, has been shown to cause bleaching (Glynn and D'Croz, 1990; Berkelmans and Willis, 1999). While bleached corals can die due to lack of food produced by symbiotic zooxanthellae if the stress is severe or long lasting, more frequently, death results when weakened corals are infected with subsequent disease (Miller et al., 2009; Rogers et al., 2009; Eakin et al., 2010). Extensive bleaching events have dramatic, long-term, ecological, economic, and social impacts (Baker et al., 2008; Munday et al., 2008; Doshi et al., 2012). Even under favorable conditions, it can take decades or longer for severely bleached reefs to recover, and if they do, it is usually with reduced species diversity and a loss of important reef-building species (Wilkinson, 2008).

The U.S. National Oceanic and Atmospheric Administration's (NOAA) Coral Reef Watch (CRW) program has provided critical information to coral reef managers and scientists based on near real-time satellite monitoring of the heat stress that can cause mass coral bleaching since 1997 (Liu et al., 2006, 2013). As many actions laid out in bleaching preparedness or response plans are expensive and require significant planning (Maynard et al., 2009), marine resource managers have long requested information on the likelihood of bleaching months in advance to prepare for upcoming events (e.g., Tommasi et al., 2017). In 2008, CRW partnered with NOAA's Earth System Research Laboratory to release the world's first global prediction tool for mass coral bleaching heat stress weeks-to-months in advance (Liu et al., 2009). It was based on weekly predictions from a statistical global sea surface temperature (SST) forecast system using the Linear Inverse Modeling (LIM) approach (Penland and Matrosova, 1998) and observed data (1° weekly Optimum Interpolation SST (OISST); Reynolds et al., 2002). This pioneer tool was limited to a single, deterministic forecast of the heat stress that can cause coral bleaching with a coarse spatial resolution of 2°. Subsequently, researchers at the Australian Bureau of Meteorology (BoM) developed a probabilistic bleaching forecast system focused on the Great Barrier Reef based on the Predictive Ocean Atmosphere Model for Australia (POAMA) developed by BoM and the Commonwealth Scientific and Industrial Research Organisation (CSIRO; Spillman et al., 2011, 2013).

Through partnership with the NOAA National Centers for Environmental Prediction (NCEP), in July 2012, CRW released its first probabilistic global subseasonal-to-seasonal-scale Coral Bleaching Outlook system (Eakin et al., 2012). It was based on 9-month SST predictions from NCEP's operational Climate Forecast System Version 1 (CFSv1) (Saha et al., 2006). CFSv1, implemented in August 2004, was NCEP's first quasi-global, fully coupled atmosphere–ocean–land model for seasonal prediction. CFSv1 was a dynamical modeling system that, for the first time in the history of U.S. operational seasonal prediction, demonstrated a level of skill in many predicted fields that was comparable to the skill of the statistical methods used by the NCEP (Saha et al., 2006). Saha et al. (2006) indicated that the CFS had an acceptably low bias in tropical SST prediction and a level of skill in forecasting Niño-3.4 SST better than persistence and comparable to statistical methods used operationally at NCEP and was a large improvement over the previous operational coupled model at NCEP. Barnston et al. (2012) also concluded that the current generation of dynamical seasonal forecast systems, including CFSv2, has a skill better than the statistical seasonal forecast system in predicting Niño-3.4 SST. CRW's probabilistic Bleaching Outlook Version 1 was at a spatial resolution of 1° and updated weekly. This version of the Outlook also used the 1° weekly OISST (Reynolds et al., 2002), which NCEP utilized for initial conditions and skill analysis of the CFS (Saha et al., 2006, 2010, 2014), to calculate accumulated stress at short lead-times.

After the CFS Version 2 (CFSv2) became available in March 2011 (Saha et al., 2014), CRW upgraded its Outlook system. Evaluation of the CFSv2 hindcasts by Saha et al. (2014) showed that CFSv2 significantly improved global SST forecasts over CFSv1 on the seasonal and subseasonal scales, with relatively higher skill in the tropical Pacific than the rest of the globe. CRW's probabilistic Outlook Version 2, released in December 2012, used the CFSv2 9-month SST predictions but maintained the same 1° spatial resolution. The Outlook Version 3, released in February 2015, matched the native spatial resolution of the CFSv2 (0.5°) and used the daily OISST Version 2 (dOISSTv2) at 0.25° resolution (Reynolds et al., 2007; Banzon et al., 2016) for short lead-times. The Outlook Version 4, released in May 2017, subsequently incorporated three daily runs of 90-day predictions and nine daily runs of 45-day predictions, which quadrupled the number of model runs used in the short-term ensembles.

The third, longest, and most widespread global coral bleaching event on record started in the Commonwealth of the Northern Mariana Islands (CNMI) and Guam in June 2014 (Heron et al., 2016b; Eakin et al., 2017). It continuously affected coral reefs around the world until May 2017, when it appeared the global extent of the event had ended (Eakin et al., 2017). Reported impacts to reefs worldwide have been greater than from any previously documented global bleaching event (Eakin et al., 2017; Hughes et al., 2017). CRW's Outlooks, along with its near real-time satellite monitoring, provided critical guidance to coral reef managers, scientists, and other stakeholders throughout the tropics leading up to and during this event (e.g., Eakin et al., 2017; Hughes et al., 2017; Tommasi et al., 2017).

In this article, CRW's probabilistic 4-Month Coral Bleaching Outlook Version 3 system is detailed, as are enhancements in the newest Outlook Version 4. Initial results from the Outlook skill analysis performed on Version 3 are also discussed. Finally, applications of the Outlook by users during the third global bleaching event are demonstrated.

DATA

Climate Forecast System Version 2 SST

CRW's probabilistic 4-Month Outlook Versions 3 and 4 use SST predictions from NCEP's CFSv2, a global, fully coupled atmosphere-ocean-sea ice-land, dynamical, seasonal prediction system made operational in March 2011 (Saha et al., 2010, 2014).

CFSv2's ocean component has global coverage. Its meridional resolution is 0.25° between 10°S and 10°N, gradually increasing poleward to 0.5° at 30°S and 30°N; its zonal resolution is 0.5° globally. CRW interpolates the SST predictions to a uniform 0.5° resolution before ingesting them into the Outlook system. The ocean model has 40 vertical layers, with 27 layers in the upper 400 m and a bottom depth of approximately 4.5 km. Its vertical resolution is 10 m from the surface to 240 m depth, gradually increasing to about 500 m in the bottom layer. Predicted temperatures of the top layer (top 10 m) are used as the predicted SST in CRW's Outlook system. The predicted SST represents the daily averaged value through both day and night.

The near real-time operational CFSv2 has 16 runs daily: four producing daily predictions out to 9-months; three out to one season (between about 90 and 120-days); and nine out to 45-days. All predictions are initialized using ocean, atmosphere, and land conditions from the operational Climate Data Assimilation System Version 2 (CDASv2; Saha et al., 2014). The four 9-month runs are control runs and are based on initial conditions at 0000, 0600, 1200, and 1800 UTC. The remaining 12 runs are initialized with perturbed initial conditions (X. Wu, pers. comm.), such that the three 3-month runs begin at 0000 UTC, and the nine 45-day runs begin at 0600, 1200, and 1800 UTC (three runs at each time). CRW's Outlook Version 3 used only the predictions from the four 9-month runs; the Outlook Version 4 uses all 16 runs to increase the number of ensemble members for the near-term Outlook.

The CFSv2 SST hindcasts were used to derive the Outlook's climatologies. The hindcasts contained daily predictions from four 9-month runs initialized at 0000, 0600, 1200, and 1800 UTC on every fifth day, based on the regular calendar year, starting on January 1 each year, from 1982 to 2010 (see Table B1 of Saha et al., 2014). Thus, the hindcasts were run on the same calendar dates every year; February 29 in a leap year was ignored. The initial conditions were from the Climate Forecast System Reanalysis (CFSR) (Saha et al., 2014).

Daily OISST Version 2

For each predicted day, CRW's Outlook requires daily SST values from the 12-weeks leading up to the predicted day (see the Methods section). Hence, predicting heat stress for any day within 12-weeks of the initial condition day needs historical SST values; the daily SST from the dOISSTv2 (Reynolds et al., 2007; Banzon et al., 2016) is used. This widely used dOISSTv2 dataset, an operational near real-time NOAA/National Environmental Satellite, Data, and Information Service (NESDIS) SST analysis, combines satellite and *in situ* measurements to produce a day-night blended SST analysis. CRW's Outlook utilizes the version of dOISSTv2 that is based on satellite data from only the Advanced Very High Resolution Radiometer (AVHRR) satellite sensors.

Complementing the near real-time dOISSTv2, NESDIS produces a reprocessed version in a 14-day delay mode, providing a long-term data record (1981-present). For its Outlook system, CRW used the reprocessed dOISSTv2 to develop the climatology required for deriving the historical heat stress variables for the initial condition day, and earlier days, of each near real-time CFSv2 run.

METHODS

The Outlook was developed to emulate, with minor modifications, the algorithm used in CRW's near real-time operational satellite coral bleaching heat stress monitoring (Liu et al., 2013, 2014). From the CFSv2 SST predictions, the Outlook system generates model-based versions of CRW's daily satellite Coral Bleaching HotSpot, Degree Heating Week (DHW), and Bleaching Alert Area variables.

The first two of the following four subsections (i.e., Climatology and Bleaching Heat Stress Metrics) describe how the Outlook algorithm was developed based on CRW's satellite algorithm. In each, a concise overview of the relevant satellite algorithm is given as background, followed by details on the development of the corresponding Outlook algorithm. A detailed description of CRW's satellite algorithm can be found in Liu et al. (2014). The algorithm for constructing the probabilistic Outlook and the product availability are presented in the last two subsections.

Climatology

CRW's satellite-based heat stress detection algorithm is based on positive SST anomalies and therefore requires an accurate climatology (historical reference temperature) from which the anomaly is determined. The algorithm for developing the climatology used in CRW's satellite monitoring was described by Liu et al. (2014), Liu et al. (2013), and Heron et al. (2015) and is summarized in the first subsection below. It was adapted to develop the model-based climatologies described herein.

Climatology Used in CRW's Satellite Monitoring

CRW's satellite monitoring uses the maximum of the monthly mean (MMM) SST climatology as the threshold, above which corals experience heat stress known to cause bleaching. The MMM climatology for any given grid cell is the maximum value among the 12 monthly mean SST climatologies at the grid cell. This value represents the long-term mean SST of the climatologically warmest calendar month. To avoid any potential bias, the climatology should be derived from the same SST dataset used for observations. When that is not possible, a compatible dataset with similar characteristics can be substituted.

In CRW's original satellite monitoring, the baseline time period of the climatology was 1985–1990 and 1993 (i.e., centered at 1988.3, with 1991–1992 omitted due to contamination by volcanic aerosols from Mt. Pinatubo). This was due to the limited availability of high-quality historical SST data at the time (Heron et al., 2014). The interpretation of CRW's original satellite products developed from that climatology was thus referenced to that time period (Liu et al., 2013). For climatologies used in newer, higher-resolution satellite products, CRW developed methodologies to maintain this reference time period, even when using longer datasets (Heron et al., 2014, 2015). For the Outlook, MMM climatologies were derived from 1985 to 2006 CFSv2 daily SST hindcasts, then time-centered to 1988.3 (following the original CRW satellite climatology; see section CFSv2 SST Climatology for details). The time-centered MMM is used as a threshold in the Outlook system to identify heat stress.

dOISSTv2 SST Climatology

In the Outlook Versions 3 and 4, the dOISSTv2 is used as needed to produce a consecutive 12-week time series (part observed, part predicted), for predicting daily accumulated heat stress within 12-weeks of the run date (i.e., initial condition date). Values of the reprocessed dOISSTv2 from 1985 to 2006 were used to derive the climatology for calculating dOISSTv2-based heat stress, following Heron et al. (2014). The following method was applied to develop a climatology for each grid cell independently. Firstly, the mean of each calendar month of each year was calculated as the average of all daily dOISSTv2 values within the month. The climatology for each calendar month was then derived as the average of all means for that month during 1985–2006. Each of the resulting 12 monthly mean climatologies was then re-centered from 1995.5 (the mid-point of 1985–2006) back to 1988.3 (the center of the original CRW reference time period), based on the linear SST trend determined from the means of that month from 1985 to 2006. The dOISSTv2 MMM climatology is the maximum of the re-centered 12 monthly mean climatologies. The process was repeated for each grid cell.

While the processing algorithms used in the near real-time and reprocessed dOISSTv2 datasets are identical, the daily values of the near real-time version used in CRW's Outlook may differ slightly from the reprocessed values used to derive the climatology. This has similarities with the satellite system in that the satellite climatology had to be developed from a dataset distinct from the near real-time satellite SST data, which therefore required that the difference (bias) between these be accounted for (Heron et al., 2014, 2015). An in-depth analysis to characterize systematic bias between the two versions of dOISSTv2 over a sufficient comparison period was not possible, as the near real-time data are not archived by NESDIS. However, long-term averaging of daily values applied in deriving the climatology should significantly reduce any daily difference. With this in mind, no bias adjustment was needed and the climatology was used to derive accumulated heat stress, which is needed to derive the Outlook prediction.

CFSv2 SST Climatology

The 1985–2006 CFSv2 daily SST hindcasts up to 9-months were used to derive a set of lead-time dependent MMM climatologies for Outlook Versions 3 and 4. To reduce lead-time and initialization date dependent biases usually present in model forecasts (Stockdale, 1997; Saha et al., 2006; Hudson et al., 2010; Spillman et al., 2011; Fučkar et al., 2014), an MMM climatology was constructed for each of the lead-times ranging from 1 to 270-days.

In CRW's Outlook systems, lead-time for a predicted day is defined as the number of days between the initial condition day of a forecast run and the predicted day. The prediction for the day after the initial condition day has a lead-time of 1-day.

First, a monthly mean climatology for each calendar month had to be derived, which required calculation of the mean for every month of every year from 1985 to 2006. Daily SST predictions of a model run were required for all days in a month to calculate the monthly mean of that run. For instance, for a run initialized on either the first or the last day of a calendar month, the earliest month for which a monthly mean could be derived was the following month. As each hindcast run produced daily predictions out to 9-months, this included eight entire months and one incomplete month that contained the initial condition day. Multiple runs in a day were averaged to produce daily values. The lead-time for the monthly mean for each entire month in the prediction was set as the number of days between the initial condition date and the 15th day of that month. As the hindcasts were run only every fifth day, beginning with January 1 each year, lead-times also were produced with 5-day intervals. Hence, the minimum lead-time for a monthly mean varied by month from 15 to 19-days. Similarly, the maximum possible lead-time for a monthly mean produced directly from daily hindcasts was <270-days. From 1985 to 2006, 22 means were produced for each calendar month with a distinct lead-time and initialized on a specific date each year. For example, an August mean with a lead-time of 76-days was always initialized on May 31 of each year. These 22 means were then averaged to generate the monthly mean climatology of the lead-time for the month, which is both lead-time and initialization date dependent. We calculated the linear trend of these 22 means over 1985–2006 and re-centered the climatology of the month from the center of the 22 years (i.e., 1995.5) back to the CRW reference time point (i.e., 1988.3) based on the linear trend. This process was repeated for each grid cell.

As the CFSv2 daily SST hindcasts were run every 5-days, the CFSv2 monthly mean climatologies were produced with lead-times at 5-day intervals (i.e., 4-day gaps in lead-time). Lead-time gaps were filled by applying linear interpolation between the previously produced, re-centered climatologies of the lead-times at the ends of each gap. For lead-times of 1-day to less than the minimum lead-time that was produced directly from the hindcasts (described earlier), the climatology of the minimum lead-time was used. The same methodology was applied to lead-times greater than the maximum lead-time and up to 270-days by using the maximum lead-time produced. The impact of the change in climatology in the initial and final periods cannot be evaluated but is not expected to be significant. This completed development of the set of 12 re-centered monthly mean climatologies for each lead-time (1–270-days).

Finally, the CFSv2 MMM climatology for each lead-time (1–270-days) was extracted as the maximum of the 12 re-centered CFSv2 monthly mean climatologies of that lead-time and used as a reference to predict heat stress (see details in section Model Prediction Metrics). This process preserved the lead-time and initialization date dependences of the monthly mean climatologies in the resulting MMM.

Bleaching Heat Stress Metrics

Satellite Monitoring Metrics

In CRW's satellite algorithm, the Coral Bleaching HotSpot is a positive-only anomaly registering the departure of satellite-observed SST above the corresponding MMM climatology, measuring the magnitude of daily heat stress that can lead to coral bleaching. Since both intensity and duration of heat stress contribute to the occurrence and severity of bleaching, especially mass coral bleaching, CRW's daily satellite DHW (expressed in the unit °C-weeks) accumulates all daily HotSpot values that are at least 1°C, over a 12-week period (84-days). The DHW thereby nowcasts the occurrence and potential severity of bleaching events (Glynn and D'Croz, 1990; Liu et al., 2003, 2013, 2014; Eakin et al., 2010; Heron et al., 2016a). Based on the finding that temperatures exceeding 1°C above the usual summertime maximum are sufficient to cause bleaching in corals (Glynn and D'Croz, 1990), the temperature of MMM+1°C (i.e., HotSpot = 1°C) was set as a high-pass filter threshold for accumulating the daily heat stress, measured by the HotSpot, into the DHW.

CRW's satellite Bleaching Alert Area identifies locations where bleaching heat stress reaches various risk levels based on the HotSpot and DHW values (**Table 1**). At Alert Level 1, ecologically significant bleaching is likely and at Alert Level 2, widespread bleaching with significant mortality is likely. The Bleaching Alert Area is extremely useful in management applications as it provides a single, convenient tool for describing critical levels of heat stress that can negatively impact coral health.

Model Prediction Metrics

CRW's Outlook systems (including Versions 3 and 4) first generate daily predictions of HotSpot and DHW at each lead-time ranging from 1-day (the day after the initial condition day) to 270-days, using daily CFSv2 SST predictions of each model run (ensemble member).

As in the satellite monitoring, the HotSpot prediction at a given grid cell on a particular day is calculated as the (positive) difference between the daily CFSv2 SST prediction and the Outlook MMM (re-centered MMM described in section CFSv2 SST Climatology) at the corresponding lead-time. The DHW prediction for the day accumulates 84 consecutive daily HotSpot predictions ending on the predicted date. The method of using the lead-time dependent MMM climatology to calculate HotSpots from the CFSv2 daily SST predictions of corresponding lead-times is consistent with the systematic error correction applied by Saha et al. (2014) and Zhang and van den Dool (2012) on the CFSv2 predictions.

For a daily DHW prediction with lead-times of up to 83-days, the DHW is computed as described above but using a combination of dOISSTv2-based and predicted HotSpots. The dOISSTv2-based daily HotSpot is the observed HotSpot, calculated as the anomaly between the dOISSTv2 and the dOISSTv2-based MMM (described in section dOISSTv2 SST Climatology); hence, the predicted daily DHW for lead-times <84-days accumulates both observed HotSpots and predicted HotSpots. The accumulation of dOISSTv2-based HotSpots into the DHW prediction applies CRW's satellite algorithm.

A modification from the satellite algorithm is required to account for differences between the model and satellite SSTs. Variability of the daily CFSv2 SST forecast within the top 10 m layer of the ocean was observed to be smaller than the variability in the top 1 m (X. Wu, pers. comm.), against which the satellite SST analysis is calibrated. Also, the upper meter of the ocean usually experiences significant diel variation during the low wind and clear sky conditions often present during bleaching events. The differences between the 10 and 1 m SST values can result in dampened daily SST excursion above the corresponding Outlook MMM climatologies. If the same high-pass filter (threshold) of 1°C, used in the satellite monitoring, were applied to filter daily HotSpot predictions at all lead-times, fewer predicted HotSpots at longer lead-times would be accumulated and the predicted DHW would be smaller than the observed satellite DHW. To relate the predicted DHW value to a bleaching risk level using the same classifications as in CRW's satellite algorithm (**Table 1**), while preserving the satellite HotSpot algorithm in calculating the predicted HotSpot, a HotSpot threshold that is <1°C is necessary for any predicted daily HotSpot. This is the approach applied in the previous and current versions of CRW's Outlook systems.

A lead-time dependent HotSpot threshold was originally developed for CRW's LIM-based, statistical seasonal Coral Bleaching Outlook system (Liu et al., 2009) and then adapted for the CFSv1-based Outlook Version 1 (Eakin et al., 2012). It was based on experiments that predicted spatial distributions and magnitudes of heat stress and compared those to CRW's satellite monitoring during various confirmed mass bleaching events, including the 2005 Caribbean-wide and the 2010 global bleaching events. Applying a uniform HotSpot threshold of 0°C caused overestimation in the DHW prediction for shorter lead-times, while a HotSpot threshold of 0°C was required for predicting sufficient

TABLE 1 | Bleaching heat stress levels defined for CRW's satellite Bleaching Alert Area product, based on CRW's satellite HotSpot and DHW products, and CRW's Outlook Versions 3 and 4.

Stress Level	Definition		Effect
	Satellite Monitoring	Outlook	
No Stress	HotSpot $\leq$ 0°C	HotSpot $\leq$ 0°C	No stress
Bleaching Watch	0°C < HotSpot < 1°C	0°C < HotSpot and DHW < $\mathrm{DHW}_{\mathrm{threshold}}$	Presence of low-level heat stress
Bleaching Warning	1°C $\leq$ HotSpot and 0°C-week < DHW < 4°C-weeks	$\mathrm{HotSpot}_{\mathrm{threshold}} \leq$ HotSpot and $\mathrm{DHW}_{\mathrm{threshold}} \leq$ DHW < 4°C-weeks	Possible bleaching
Alert Level 1	1°C $\leq$ HotSpot and 4°C-weeks $\leq$ DHW < 8°C-weeks	$\mathrm{HotSpot}_{\mathrm{threshold}} \leq$ HotSpot and 4°C-weeks $\leq$ DHW < 8°C-weeks	Bleaching likely
Alert Level 2	1°C $\leq$ HotSpot and 8°C-weeks $\leq$ DHW	$\mathrm{HotSpot}_{\mathrm{threshold}} \leq$ HotSpot and 8°C-weeks $\leq$ DHW	Mortality likely

heat stress for longer lead-times. The lead-time dependent HotSpot threshold used with the LIM-based outlook was hence adapted for Outlook Versions 3 and 4, with a minor adjustment.

Outlook Versions 3 and 4 apply a HotSpot threshold ($\mathrm{HotSpot}_{\mathrm{threshold}}$) that decreases linearly from 1°C at the lead-time of 0-days (i.e., the initial condition day) to 0°C at lead-times of 70-days (Day 70; i.e., the end of 10-weeks) and beyond (**Figure 1**; **Table 1**). This formula was chosen after testing various slopes with 1-week increments for a few known major bleaching events. For a predicted date, if the predicted HotSpot value reach the $\mathrm{HotSpot}_{\mathrm{threshold}}$ for the corresponding lead-time, the HotSpot value is accumulated into the DHW prediction. Such conditions initiate at least a predicted Bleaching Warning for the date in question. However, modifying the HotSpot threshold required a lead-time dependent DHW threshold for categorizing heat stress as well. As the $\mathrm{HotSpot}_{\mathrm{threshold}}$ decreases to zero by Day 70, any subsequent positive HotSpot value results in a DHW accumulation. If the satellite-based stress classification (**Table 1**) had been applied directly for those days, the Bleaching Watch level would have been skipped and the stress would have jumped directly from No Stress to Bleaching Warning. To prevent this from occurring, a linearly varying DHW threshold, $\mathrm{DHW}_{\mathrm{threshold}}$, was introduced (**Figure 1**). It started with 0°C-weeks at Day 0 and increased linearly to 2°C-weeks at Day 70 to maintain the Bleaching Watch level throughout the lead-times included in the Outlook. Note that the linear change in the HotSpot threshold over lead-times of 1–70-days was developed to allow sufficient daily predicted HotSpots to be accumulated into the DHW prediction while preventing too much DHW accumulation. This is not related to the DHW accumulation time period of 84-days. Other approaches may produce Outlook values with good or better matches with observed heat stress and will be tested for future versions.

Our most recent examinations, based on predictions made for the 2015 bleaching event in the Main Hawaiian Islands (MHI) and 2016 bleaching event in the northern Great Barrier Reef (GBR), further verified the application of lead-time dependent HotSpot and DHW thresholds. Note that published analyses of the CFSv2 (e.g., Xue et al., 2013; Saha et al., 2014) did not evaluate changes in variability of the CFSv2 SST over lead-times on daily or weekly bases.

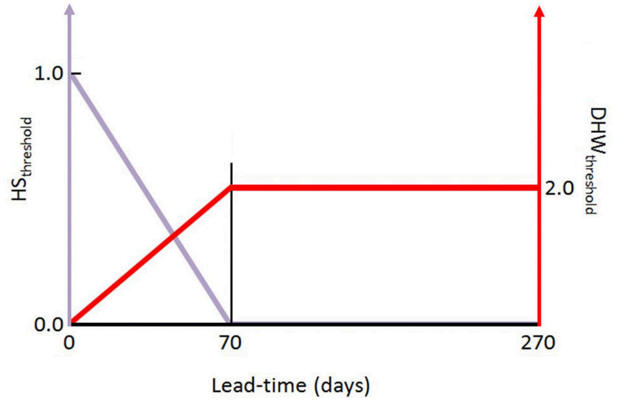

FIGURE 1 | Schematic of lead-time dependent HotSpot threshold ($\mathrm{HotSpot}_{\mathrm{threshold}}$, purple) and Degree Heating Week (DHW) threshold ($\mathrm{DHW}_{\mathrm{threshold}}$, red) used in the algorithm for Outlook Versions 3 and 4.

Mass bleaching of corals across a reef usually takes weeks of stressful conditions to develop. CRW's Outlook, updated once a week, is not designed to provide guidance on the daily development of heat stress. Therefore, weekly predictions are derived from the daily predictions before further processing. Given that the HotSpot and DHW are positive-only variables, the medians of seven daily values of the HotSpot and DHW over a calendar week are used as the predictions for that week. The weekly Bleaching Alert Area prediction of an ensemble member is then determined from the weekly HotSpot and DHW predictions of that member, based on the stress classifications provided in **Table 1**. The weekly predictions are calculated for each ensemble member separately.

In CRW's Outlook system, a weekly time period covers Monday–Sunday and is tracked by Sunday's date. A weekly prediction with a lead-time of 1-week is for the week immediately following the initial condition week (defined below); weekly predictions are produced out to approximately 4-months.

Probabilistic Bleaching Outlook

Weekly Outlook

The weekly probabilistic Outlook for a week is constructed based on the weekly Bleaching Alert Area predictions from all the available ensemble members for the week. The Outlook Version 4 has been developed and replaced Version 3 in May 2017. The difference between the two versions is the number of CFSv2 daily runs used in the probabilistic Outlook, as described below.

Weekly Outlook Version 3

The probability of predicted stress was determined from the ensemble of model runs each week. In the Outlook Version 3, the 28 Bleaching Alert Area values (i.e., four runs per day over 7-days of the initial condition week), derived from the four 9-month CFSv2 SST runs daily, were pooled for each predicted week. A probabilistic forecast was then produced for each predicted week by determining the heat stress levels reached or exceeded by 10 specified percentages of ensemble members at each grid cell. The 10 pre-set probabilistic levels range from 10 to 100%, in increments of 10%. For example, the 90% probabilistic Outlook for a predicted week at a grid cell would be the stress level (**Table 1**) that 26 of the 28 ensemble members met or exceeded. The probability of each of four bleaching heat stress ranges (Watch and higher, Warning and higher, Alert Level 1 and higher, and Alert Level 2) also was determined from all available ensemble members for the week to form a full set of weekly probabilistic Outlook products.

Weekly Outlook Version 4

In the Outlook Version 4, all 16 daily runs, including the four 9-month runs used in the Outlook Version 3, as well as the other 12 daily runs with shorter forecast ranges, are incorporated. All 45-day and one-season runs initialized over a calendar week can consistently predict for at least 5 and 12-weeks, respectively, into the future. Pooling all available members for each week, the first 5-weeks in the prediction have 112 ensemble members; weeks 6–12 have 49 members; and weeks 13–37 have 28 members. The same algorithm used in the Version 3 is used to generate Version 4 of the probabilistic weekly Outlooks. The only difference comes from the varying number of ensemble members over the course of the 4-month time period. As in Version 3, for each predicted week, heat stress levels are determined for 10 pre-set probabilistic levels (from 10 to 100%, in increments of 10%) at each grid cell, along with the probabilities for the four stress ranges.

Although the Outlook Version 4 uses more ensemble members than the Outlook Version 3, initial comparisons have revealed that they are remarkably similar (not shown). This may indicate that the four 9-month control runs capture most of the variability found in the full set of runs. Versions 3 and 4 of the weekly Outlooks are identical for Week 13 and longer lead-times.

Four-Month Outlook

CRW's probabilistic 4-Month Outlook is constructed from the weekly Outlooks described above. A period of 4-months is the approximate length of a bleaching season (warm season) on most coral reefs. The 4-month period of the Outlook starts with the second predicted week (lead-time of 2-weeks), and Sunday's date determines the first month. The Outlook period ends on the last Sunday of the fourth month. Weekly Outlooks ranging from a lead-time of 2-weeks to at least 15-weeks and up to 20-weeks (depending on the lead-time of the last Sunday in the fourth month) are used to derive the 4-Month Outlook. The weekly Outlook with 1-week lead-time is excluded, as the 4-Month Outlook is updated weekly in the middle of that week.

For each of the 10 predetermined probabilistic levels (from 10 to 100%, in increments of 10%) used in the weekly Outlooks, the maximum temporal composite over the 4-month period is created by extracting the maximum values from all of the weekly Outlooks with the corresponding probabilistic level. The resulting 10 4-month maximum composites are the probabilistic 4-Month Outlooks for the corresponding probabilistic levels. For each of the four stress ranges, the probabilistic 4-Month Outlook provides the highest weekly probability predicted among all of the weekly Outlooks during a 4-month period.

Product Availability

Global and regional maps of the most recent update of the probabilistic 4-Month Outlook at 90% and 60% probabilities (**Figures 2A,B** for Version 3, respectively) are posted on CRW's website at https://coralreefwatch.noaa.gov. These are updated weekly, along with the weekly Outlooks of the corresponding probabilities. Four probabilistic maps showing the percentage of ensemble members reaching the four heat stress ranges (Alert Level 2, Alert Level 1 and higher, Bleaching Warning and higher, and Bleaching Watch and higher) also are displayed (**Figures 2C–F** for Version 3, respectively).

Given that the daily runs need to be collected over a calendar week to form an ensemble system, the Outlook is run and products are updated weekly. This occurs every Tuesday at approximately 19:00 Z, when all of the daily CFSv2 SST predictions produced during the previous week (through Sunday) become available to CRW. The Outlooks are publicly available via CRW's website: https://coralreefwatch.noaa.gov.

The very first runs of the CFSv2 SST forecast were run using initial conditions from April 1, 2011, so the earliest week producing a complete set of 7-day CFSv2 runs was the week ending on April 10, 2011. Thus, the first predicted week ended on April 17, 2011 and the earliest 4-Month Outlook Versions 3 and 4 were for the period April-July 2011.

PERFORMANCE OF OUTLOOK VERSION 3

CFSv2 SST Skill

The skill analysis of the CFSv2 SST was discussed by Saha et al. (2014), Xue et al. (2013), and Zhang and van den Dool (2012), among others. A set of CFSv2 SST skill maps showing the correlation and Root Mean Square Error (RMSE) of the SST hindcasts, as compared with the dOISSTv2 SST (Reynolds et al., 2002), is accessible at: http://www.cpc.ncep.noaa.gov/products/people/mchen/CFSv2HCST/metrics/rmseCorl.html. A subset of the correlation maps that are relevant to CRW's Outlook is reproduced in **Figure 3** using the matching color scale. The correlation maps are for the daily SST hindcasts

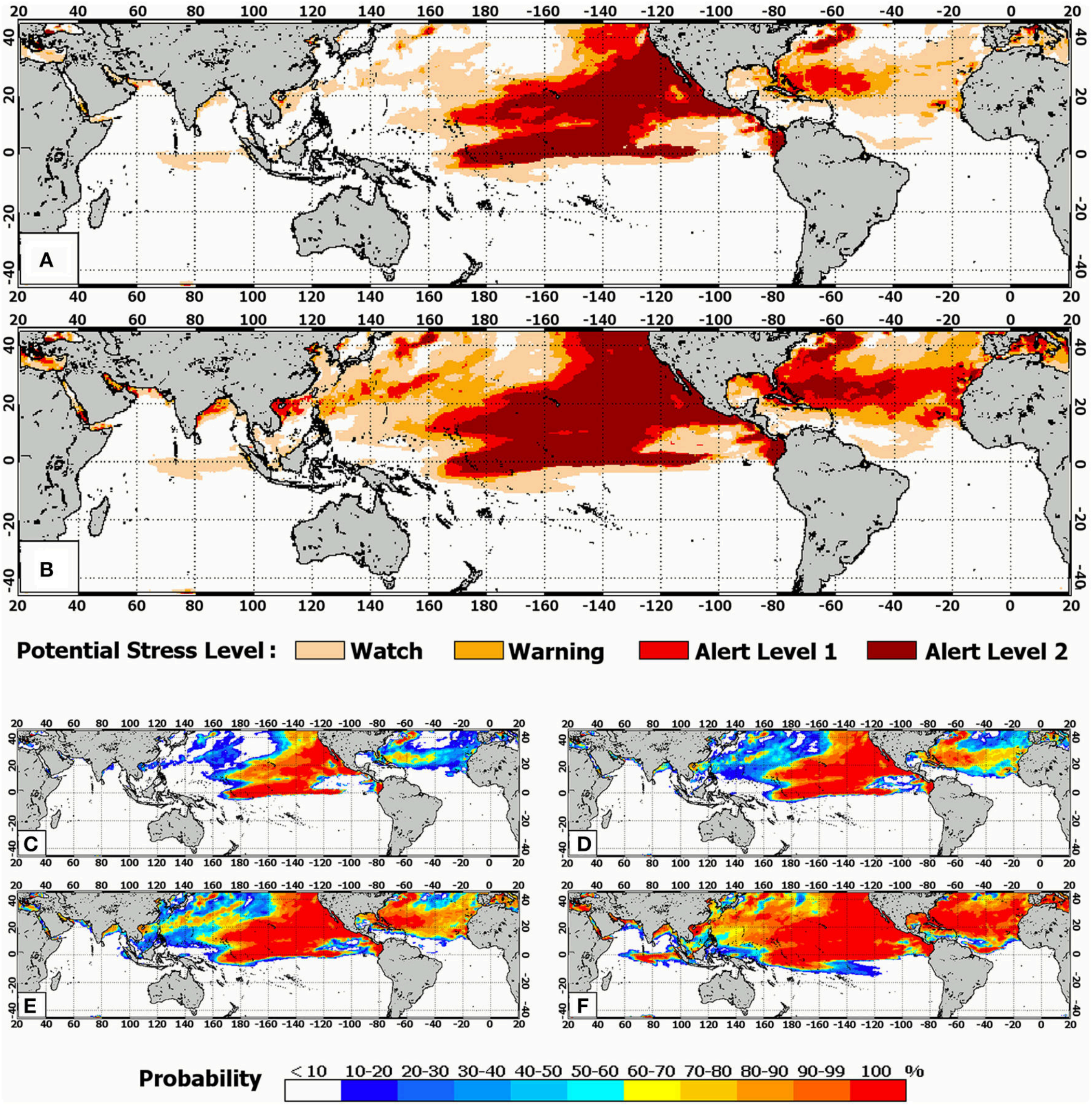

FIGURE 2 | CRW's probabilistic 4-Month Coral Bleaching Outlook Version 3 issued on July 7, 2015 for July–October 2015: stress levels with **(A)** 90% and **(B)** 60% probabilities; probabilities for **(C)** Alert Level 2, **(D)** Alert Level 1 and higher, **(E)** Warning and higher, and **(F)** Watch and higher. Note that the Outlook was derived for each grid cell in the maps regardless of the existence of shallow-water coral reefs at that specified grid cell.

of 1982–2009. The maps of 0-month lead-time are for the 3-month period immediately after the initial condition month; the maps of 1-month lead-time are for the 3-month period starting with the second month after the initial condition month. Given that CRW's Outlook covers a period of up to four months, only the lead-times of 0- and 1-month, together covering four months after the initial condition month, are relevant. The CFSv2 SST skill depends on both the month predicted and lead-time. The skill for most of the global tropical oceans, particularly areas where corals live (**Figure 4A**), was high (correlation > 0.7 and RMSE < 0.6°C; see the CFSv2 SST skill website mentioned above for RMSE) for both lead-times of 0- and 1-month. As a result, it was expected that for most of the global tropical regions, the daily CFSv2 SST predictions would produce a skillful 4-Month Coral Bleaching Outlook.

A map of global tropical coral reef locations is provided in **Figure 4A** as a reference for discussing CFSv2 SST and Outlook skills. Global coral reef locations were compiled by CRW from several data sources (Heron et al., 2016b); the multi-source compilation by the United Nations Environment Programme–World Conservation Monitoring Centre (UNEP-WCMC) and the WorldFish Centre, in collaboration with the World Resources Institute (WRI) and The Nature Conservancy (TNC) (UNEP-WCMC WorldFish Centre, 2010), includes the Millennium Coral Reef Mapping Project and the World Atlas

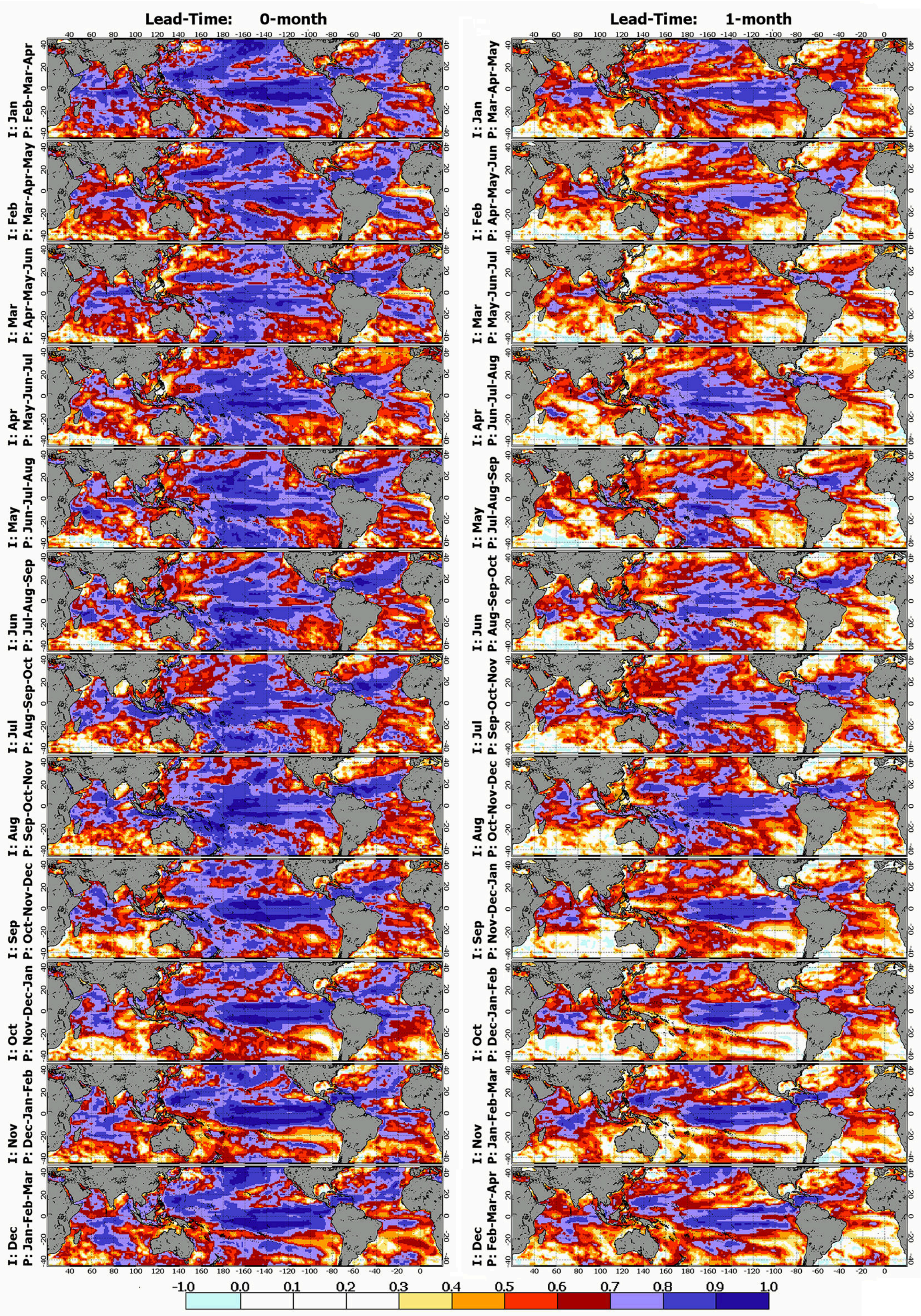

FIGURE 3 | Correlations between 1982–2009 daily CFSv2 SST hindcasts and dOISSTv2 SSTs for 12 initial condition months (**rows**, January–December) and lead-times of 0- **(left column)** and 1-month **(right column)**. I: initial condition month; P: predicted 3-month period. Images reproduced from NOAA's CFSv2 website.

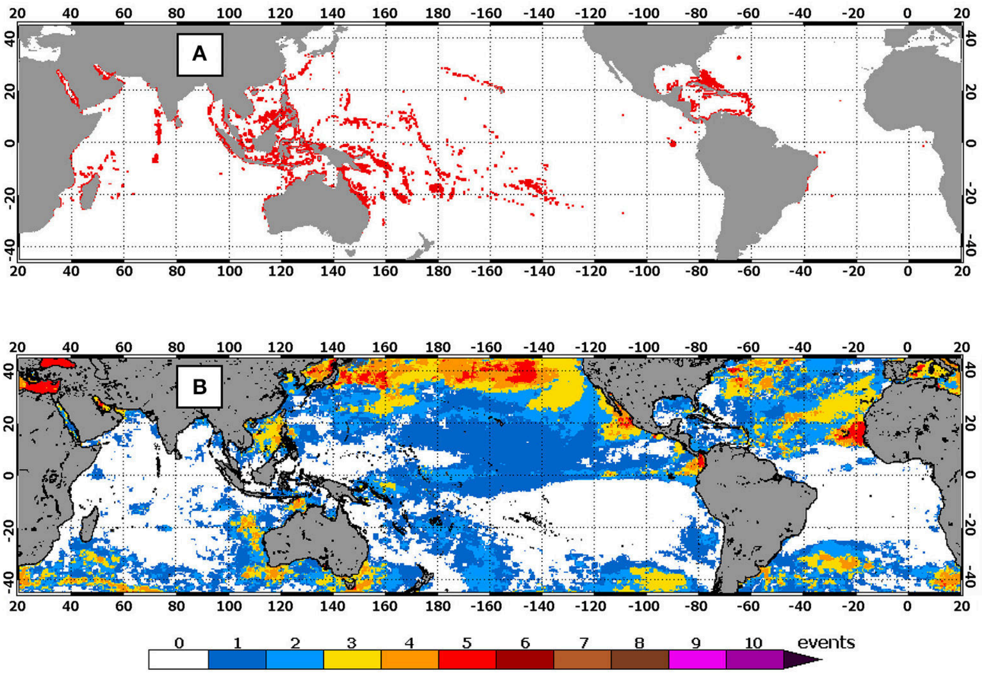

FIGURE 4 | (A) Map of tropical coral reef locations; **(B)** Numbers of observed bleaching events identified by CRW's 50 km satellite monitoring during the comparison time period of August 1, 2011–December 27, 2015.

of Coral Reefs. This was augmented using other local marine atlases (e.g., UNEP/IUCN, 1988a,b) and direct communication with researchers (i.e., where reef observation surveys had been reported).

We further examined SST skill for the bleaching season of major coral reef regions globally. For example, the SST hindcasts initialized in June were high in skill ($r > 0.7$) for predicting both the July-August-September (0-month lead-time) and August-September-October (1-month lead-time) periods for most of the tropical oceans. These months are during the bleaching season for reefs of the Hawaiian archipelago, the Marshall Islands, Japan, the Caribbean, and Florida (Heron et al., 2016a), among other regions. The SST hindcasts initialized in February, March and April were high in skill ($r > 0.7$) for predicting 1-month lead time periods of April-May-June, May-June-July, and June-July-August, respectively, which are the bleaching seasons in Indonesia, Malaysia, Thailand, Guam and the CNMI (Heron et al., 2016a), among other coral reef areas. However, the skill of SST hindcasts for the Great Barrier Reef (GBR)'s peak bleaching season (February-March-April) did not reach 0.7 for most of the region. The reason for relatively lower SST prediction skill in the GBR will require further investigation.

Outlook Skill

A limited analysis of the Outlook's performance was carried out by comparing predicted bleaching events with heat stress events identified by CRW's operational 50 km satellite bleaching heat stress monitoring (Liu et al., 2013; https://coralreefwatch.noaa.gov). The 50 km satellite products started in late 2000 (Liu et al., 2013) and continued until January 2016, when the original satellite SST analysis was discontinued and replaced (see Heron et al., 2014). Hence, the satellite data available for the evaluation were for 2001–2015. A more complete evaluation is planned using CRW's new CoralTemp 5 km dataset from 1985-present once available in 2018.

The skill analysis discussed here is for the Outlook Version 3 only. It was based on weekly Outlooks with lead-times ranging from two to at least 15-weeks and up to 20-weeks. Hence, the analyses were conducted on the weekly Outlooks for lead-times of 3, 5, 9, 13, and 17-weeks; these approximate to the beginning weeks of the half, one, two, three, and 4-months into the future. As noted above, the earliest available initial condition week for Version 3 was April 10, 2011; therefore, the first predicted weeks available for the five lead-times were May 1, May 15, June 12, July 10, and August 7, 2011, respectively. The common predicted time period by all five lead-times was chosen for the skill analysis; i.e., August 1, 2011 (the Monday of the week ending on August 7) through December 27, 2015 (the last Sunday of 2015). For each specified lead-time, all of its weekly Outlooks were extracted to form a time series. Then, in each of the five time series, predicted bleaching events (see the definition of bleaching event below) were compared with bleaching events observed by satellite monitoring over the same period to produce hit, miss, and false alarm analyses.

Although both the satellite Bleaching Alert Area and modeled Outlook had the same spatial resolution, their grid cell layouts were a half grid cell off in both zonal and meridional directions. As a result, both were resized to a 0.25° grid cell layout by dividing every original 0.5° grid cell uniformly into four 0.25° grid cells that were assigned the same value as the original grid cell; the comparison was carried out at co-located 0.25° grid cells.

Two types of events were defined for this analysis: heat stress events and bleaching events. A bleaching event was recorded as the presence of Alert Levels 1 and/or 2, both of which are associated with at least significant bleaching (**Table 1**). A heat stress event was recorded as the presence of stress at or greater than Bleaching Warning. Hence, any bleaching event was contained in a heat stress event, but a heat stress event did not necessarily contain a bleaching event. The beginning day of a heat stress event was set on the first day on which a Bleaching

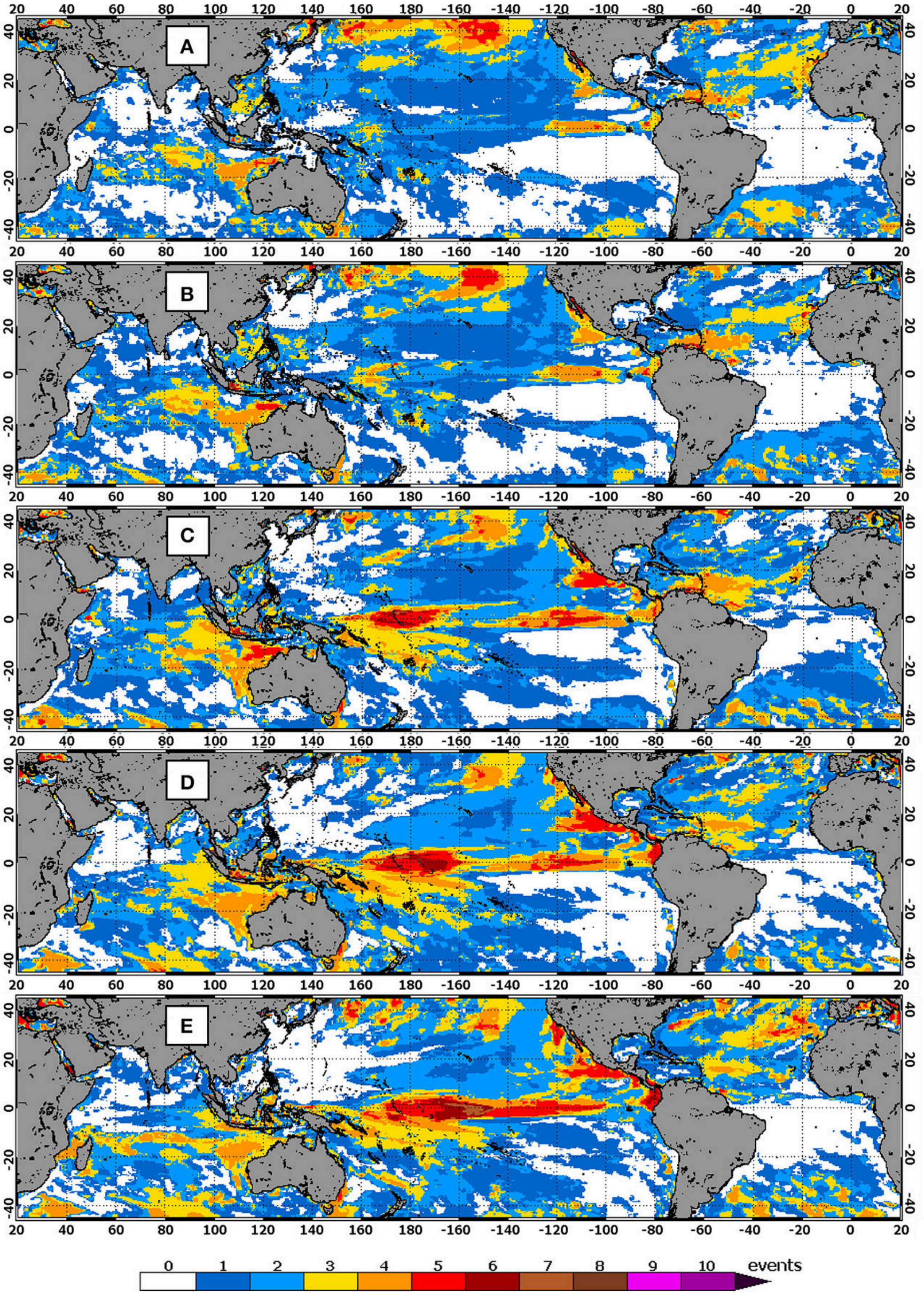

FIGURE 5 | Numbers of bleaching events identified by CRW's weekly Outlooks (Version 3) of 60% probability during the comparison time period of August 1, 2011–December 27, 2015 for lead-times of: **(A)** 3-weeks, **(B)** 5-weeks, **(C)** 9-weeks, **(D)** 13-weeks, and **(E)** 17-weeks.

Warning appeared; the beginning day of a bleaching event was set on the first day on which Alert Level 1 or 2 appeared. A heat stress event ended when the stress decreased to a level below Bleaching Warning (i.e., No Stress or Bleaching Watch) and remained there for at least 84-days. The ending day of a bleaching event was set on the last day when Alert Level 1 or 2 was experienced within a heat stress event. 84-days is the duration of the DHW accumulation. CRW's satellite data indicated that at some equatorial locations, in some years, heat stress did not decrease to a level of No Stress or did not remain at No Stress for up to 84-days before a new bleaching event started. Also, a grid cell could have a long period of time experiencing heat stress at the Bleaching Warning level with only a short burst of Alert Level 1 or 2, as short as one twice-weekly period. This still would be classified as a bleaching event. Similar situations occurred in the Outlook. In cases when a heat stress event and/or bleaching event existed on the first day of an examined time period, the corresponding event beginning date was recorded as of that day, although the event may have started well before the first predicted week. The predicted bleaching events (not heat stress events) were compared with satellite detected bleaching events. Hereafter, a bleaching event identified by the satellite monitoring is referred to as an observed bleaching event or observed event. As this is a test of the skill in predicting the heat stress that causes bleaching, the Outlook is only compared with heat stress data and not field observations of bleaching. Finally, CRW uses the Outlook of 60% probability to issue warnings of impending bleaching; therefore, the performance of the 60% probability Outlook is discussed herein.

The temporal resolution of the 50 km satellite Bleaching Alert Area was twice-a-week, based on a repeated Monday–Wednesday (3-days) and Thursday–Sunday (4-days) SST analysis cycle. The beginning and end dates of an event were the first and last date of the corresponding twice-a-week periods, respectively. The Outlook had a weekly temporal resolution (Monday–Sunday), so the beginning and end dates of a predicted event were the Monday and Sunday of the corresponding weeks, respectively. Given that the heat stress level is based on accumulated stress over 84 consecutive days, any potential offset by half a week in the event beginning and end dates between the satellite monitoring and Outlook can be ignored.

Hits, misses, and false alarms by the Outlook were counted at each grid cell, and compared with observed bleaching events (determined by their beginning and end dates), for each of the five lead-times over the same comparison time period. For each observed event, overlapping predicted events were searched for, regardless of event duration and the relative beginning and end dates. Any predicted event that overlapped an observed event was a hit. If an observed event was not overlapped by a predicted event, a miss was counted. If a predicted event did not overlap any observed event, a false alarm was registered.

The number of observed events identified for each grid cell for the comparison time period is plotted in **Figure 4B**; the corresponding numbers of predicted events for examined lead-times are plotted in **Figure 5**. Among all the grid cells, the maximum number of observed events was six, and the maximum numbers of predicted events were six, eight, seven, seven, and eight for the lead-times of 3, 5, 9, 13, and 17-weeks, respectively (**Table 2**).

Given that there were at most six observed events at a grid cell (**Table 2**) and a good percentage of grid cells did not have any observed events, calculating rates of hit, miss, and false alarm could not provide normally-distributed data to quantitatively analyze skill. A longer time series of Outlook data (beyond 2011–2015) will be needed to conduct a fully quantitative skill analysis. Hence, hit, miss, and false alarm counts, instead of their rates and other derived skill indices, are presented in **Figures 6–8**, respectively. The maximum counts of hit, miss, and false alarm among all grid cells for each of the five lead-times are provided in **Table 2**. For regions with a count of zero for hit, miss, and false alarm, the Outlook was successful in not predicting a bleaching event at the corresponding lead-times.

Figures 6 (hit), **7** (miss) show that throughout the lead-times, the Outlook performed well in predicting observed bleaching events for most coral reef regions for up to 4-months into the future. Exceptions to this were areas such as the northern Philippines, South China Sea, and Timor Sea, where miss counts were mostly up to four, especially at longer lead-times (**Figure 7**). At the 17-week lead-time, the Outlook missed some observed events in the Northwestern Hawaiian Islands (NWHI) and in the eastern Caribbean (**Figure 7E**). Numbers of misses

TABLE 2 | The maximum numbers of observed and predicted bleaching events, their shortest and longest event durations, and the maximum counts of hits, misses, and false alarms of the Outlook, among all grid cells, for lead-times of 3, 5, 9, 13, and 17-weeks, during the comparison time period of August 1, 2011–December 27, 2015.

	Maximum # of events	Shortest duration (days)	Longest duration (days)	Maximum # of hits	Maximum # of misses	Maximum # of false alarms
Observed	6	3	689	-	-	-
3-week lead-time	6	7	756	5	5	6
5-week lead-time	8	7	742	6	5	8
9-week lead-time	7	7	595	6	5	7
13-week lead-time	7	7	756	6	5	7
17-week lead-time	8	7	1,169	6	5	7

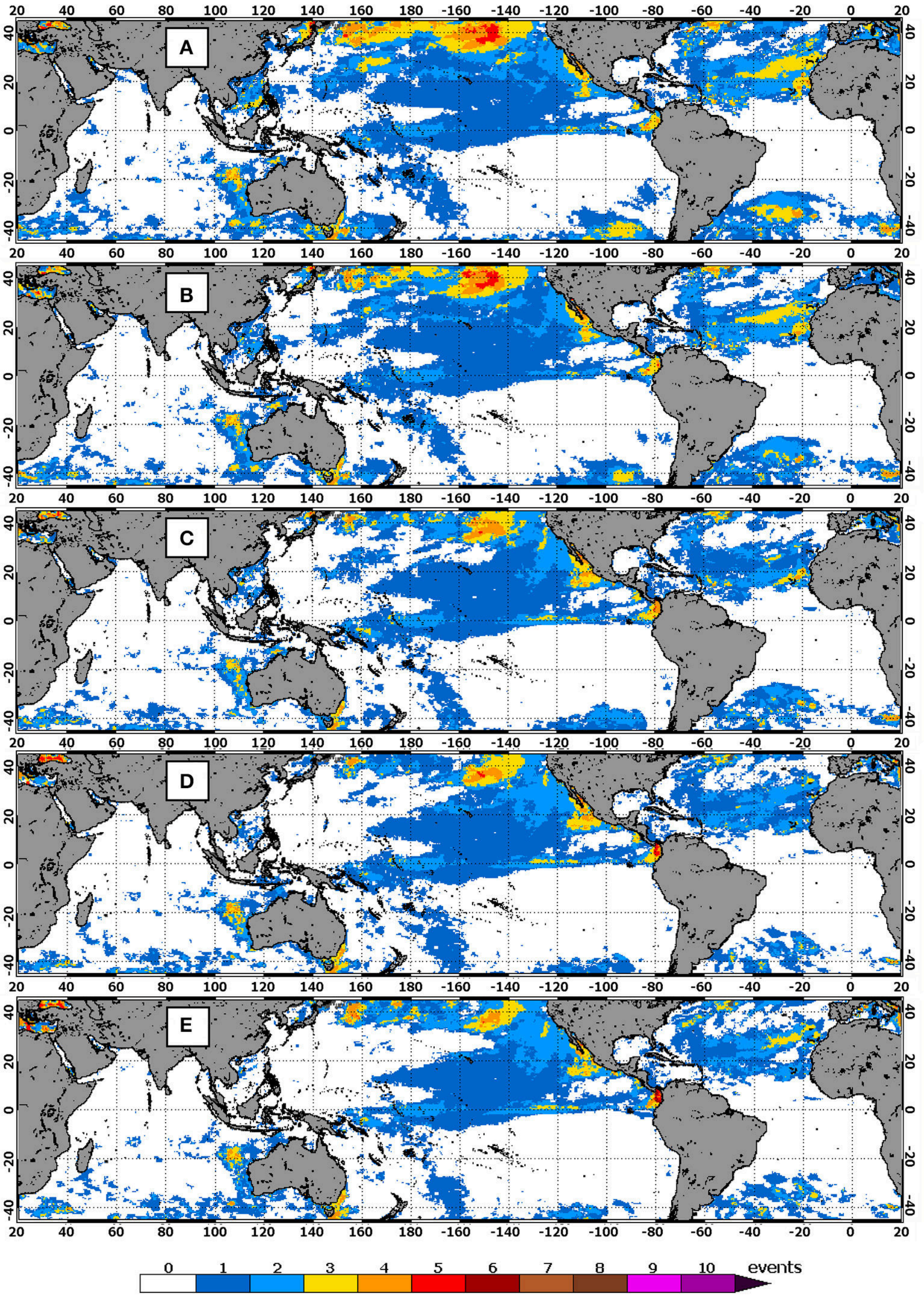

FIGURE 6 | Numbers of hits by CRW's weekly Outlooks (Version 3) of 60% probability during the comparison time period of August 1, 2011–December 27, 2015 for lead-times of: **(A)** 3-weeks, **(B)** 5-weeks, **(C)** 9-weeks, **(D)** 13-weeks, and **(E)** 17-weeks.

at each lead-time were low across most equatorial regions (**Figure 7**).

The false alarm is another critical aspect of the skill analysis. At short lead-times of 3 and 5-weeks, the false alarm count was relatively high in the eastern equatorial Pacific, southeastern Caribbean, off the Northern Territory of Australia, in parts of southern Indonesia, and in the central Indian Ocean (**Figures 8A,B**). Areas with higher false alarm counts expanded spatially at the longer lead-time of 9-weeks to include portions of the western equatorial Pacific Ocean (**Figures 8C,D**). At the lead-time of 17-weeks, the false alarm count decreased in the eastern Indian Ocean and the Caribbean

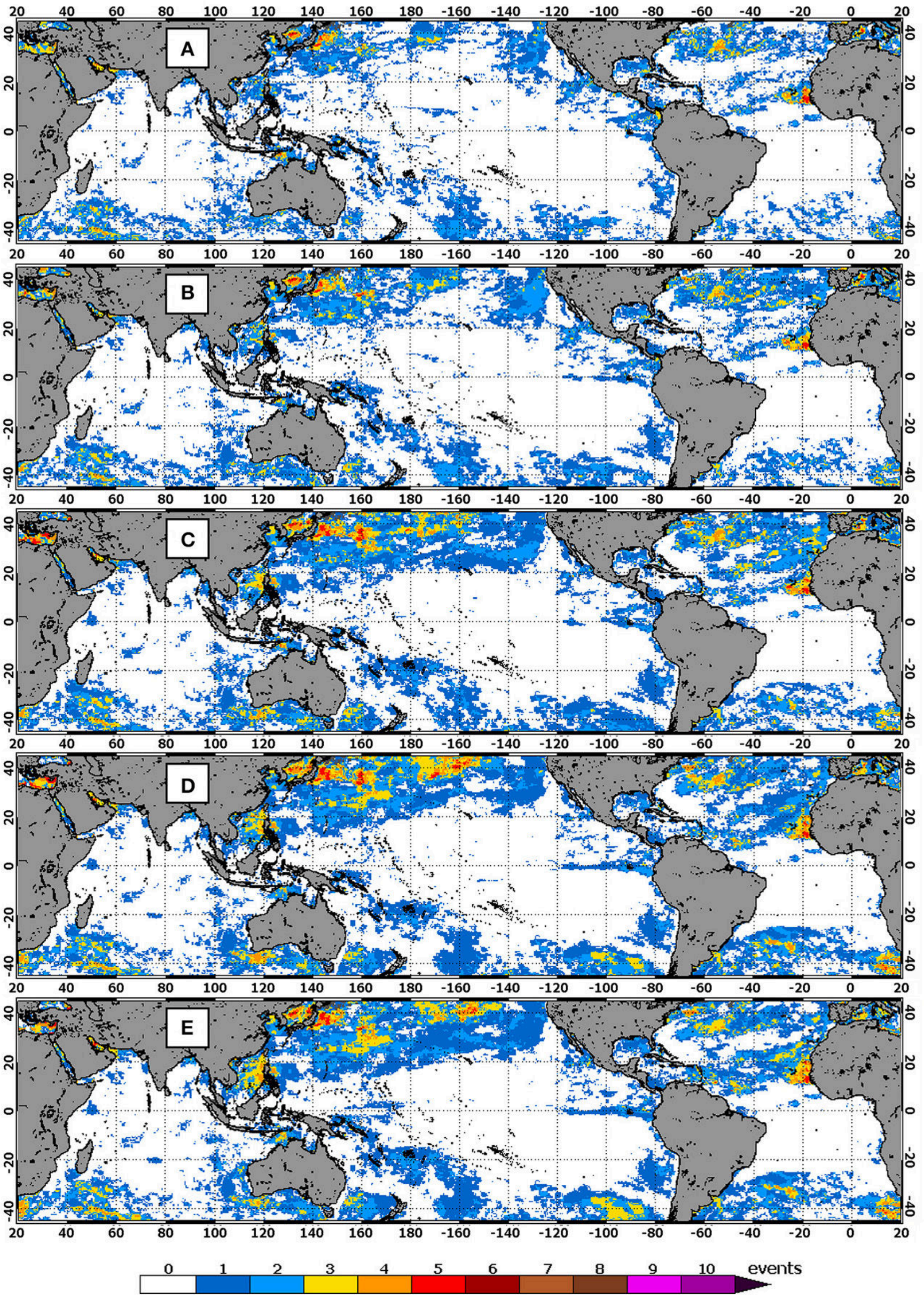

FIGURE 7 | Numbers of misses by CRW's weekly Outlooks (Version 3) of 60% probability during the comparison time period of August 1, 2011–December 27, 2015 for lead-times of: **(A)** 3-weeks, **(B)** 5-weeks, **(C)** 9-weeks, **(D)** 13-weeks, and **(E)** 17-weeks.

but increased in the central and western equatorial Pacific Ocean and western Indian Ocean (**Figure 8E**). Over-prediction may have been caused by highly variable and short-lived weather events, especially tropical storms and shifts in the monsoon, which are not predictable by seasonal-scale climate forecast systems. Tropical storms can relieve heat stress that otherwise would have caused severe bleaching (Manzello et al., 2007; Hughes et al., 2017). Detailed discussion of extreme weather event impacts is outside the scope of this paper. The decrease in the HotSpot threshold with increasing lead-time may have contributed to some false alarms. Regions identified with relatively high miss and false alarm counts will

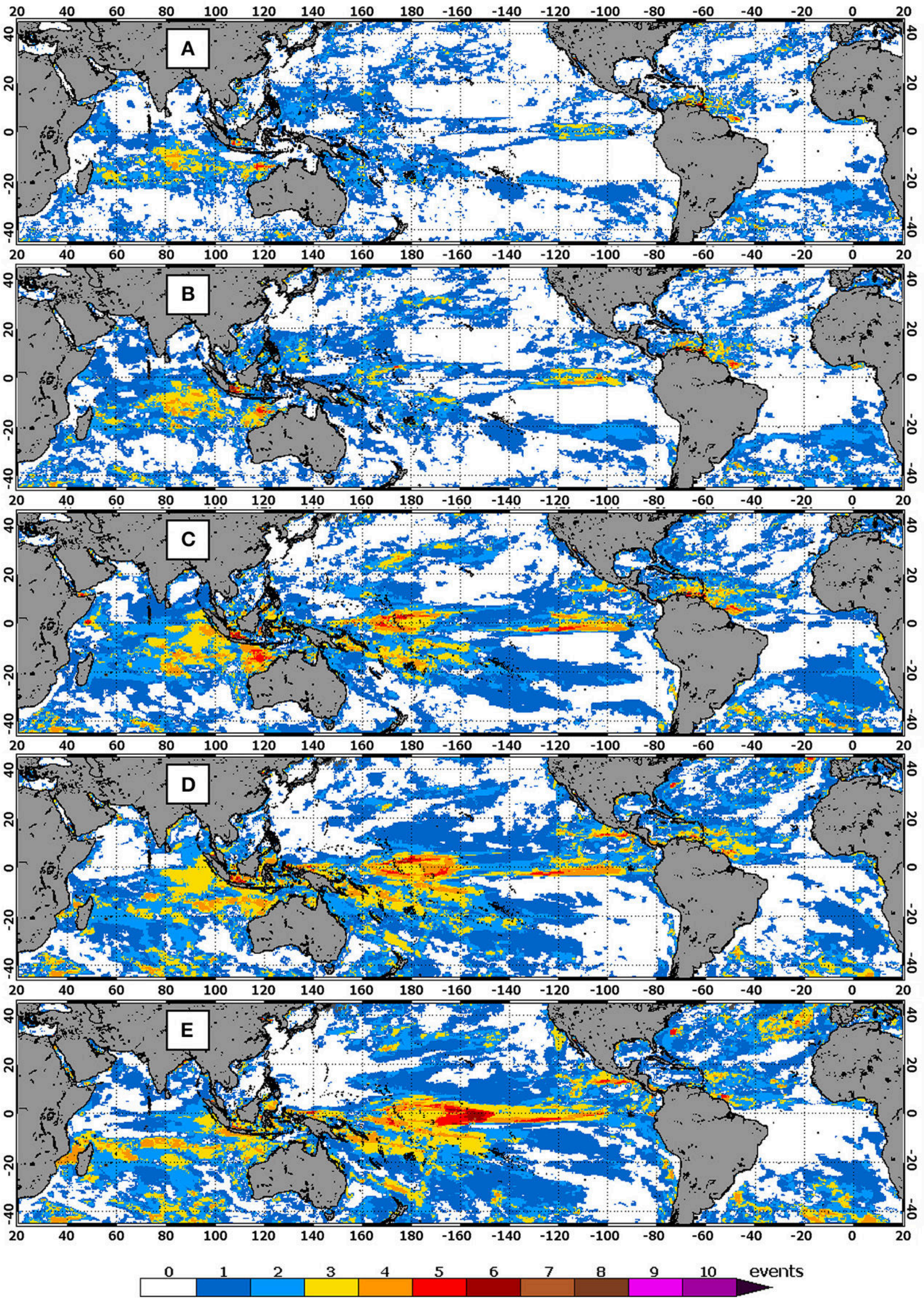

FIGURE 8 | Numbers of false alarms by CRW's weekly Outlooks (Version 3) of 60% probability during the comparison time period of August 1, 2011–December 27, 2015 for lead-times of: **(A)** 3-weeks, **(B)** 5-weeks, **(C)** 9-weeks, **(D)** 13-weeks, and **(E)** 17-weeks.

be investigated further once longer time series of satellite and modeled data are available for an appropriate comparison. For the regions with a tendency toward false alarm, prediction of upcoming bleaching events, especially at longer lead-times, should be treated cautiously in making management decisions. The predictions may be useful to guide early preparation but should be further informed by viewing CRW's near real-time satellite monitoring.

In this evaluation, counts of hit, miss, and false alarm did not take into account the duration of the bleaching event, only the presence and absence of overlaps between observed and predicted events. Multiple observed events may have overlapped one predicted event, and vice versa. Refined analyses taking into account event duration will be conducted when a longer data time series becomes available. As an example, maps of the shortest and longest durations of the predicted bleaching events for the 5-week lead-time and the corresponding observed bleaching events are provided in **Figure 9** to demonstrate that the Outlook was compatible with the satellite observations in terms of spatial distribution and range of event duration. **Table 2** also lists the ranges of event duration for the five lead-times.

As the hindcasts were run on 1-day out of every five (as described earlier) and the real-time version of the CFSv2 runs every day, the ensemble system has to be revised to accommodate the lower number of weekly ensemble members in the hindcast. Given that the focus of this manuscript is on the algorithm, we plan to analyze the Outlook hindcast results and associated skill analysis for publication in a separate article.

APPLICATION OF CRW'S OUTLOOK IN PREDICTING THE THIRD GLOBAL CORAL BLEACHING EVENT

The third global coral bleaching event started in the CNMI and Guam in June 2014 and was declared global in its extent by NOAA in October 2015 after widespread bleaching had been reported in the Pacific, Atlantic, and Indian Ocean basins (NOAA News Release, 2015; Eakin et al., 2017). The extremely strong 2015–2016 El Niño further spread and worsened the global event in 2016 (Normile, 2016; Eakin et al., 2017). By February 2016, it

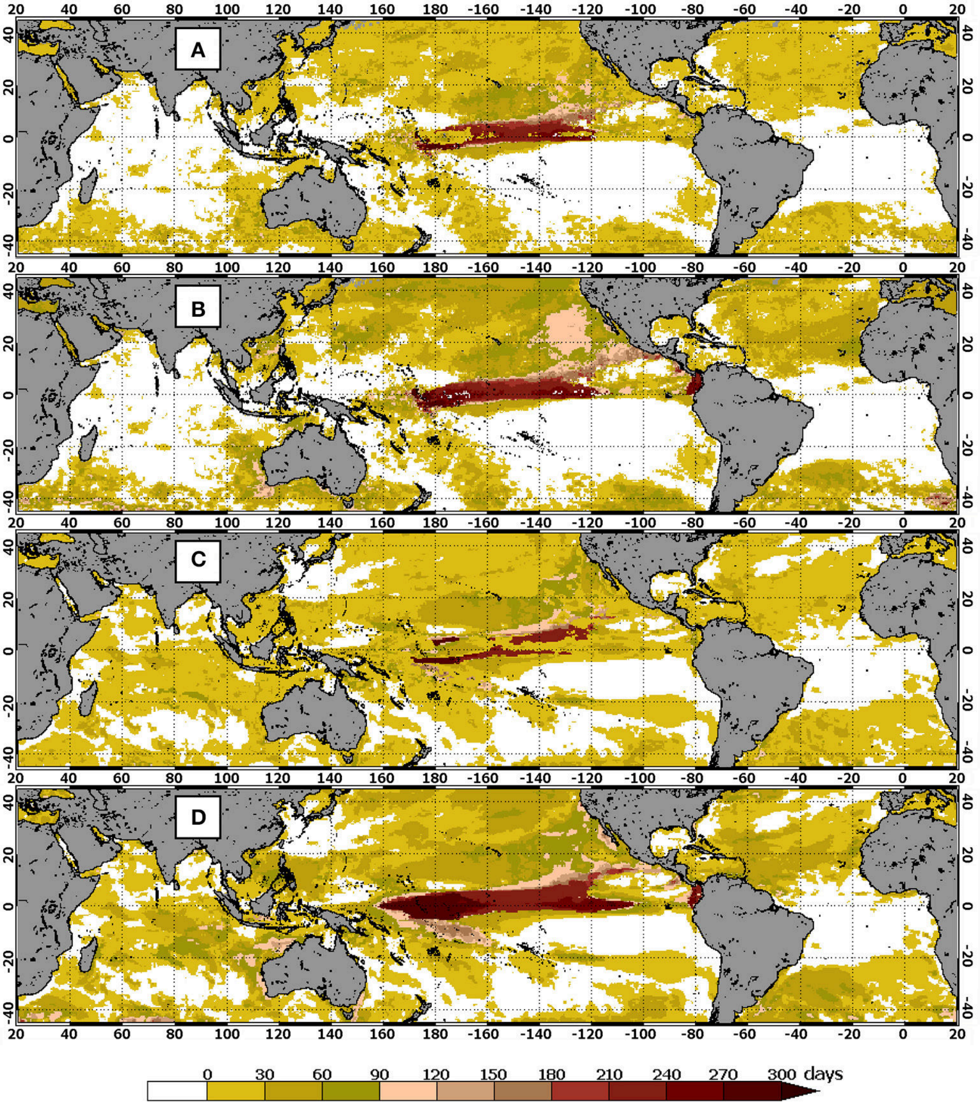

FIGURE 9 | The shortest **(A)** and longest **(B)** event durations identified by CRW's 50 km satellite monitoring and the shortest **(C)** and longest **(D)** event durations predicted by CRW's weekly Outlooks (Version 3) of 60% probability with a lead-time of 5-weeks during August 1, 2011–December 27, 2015.

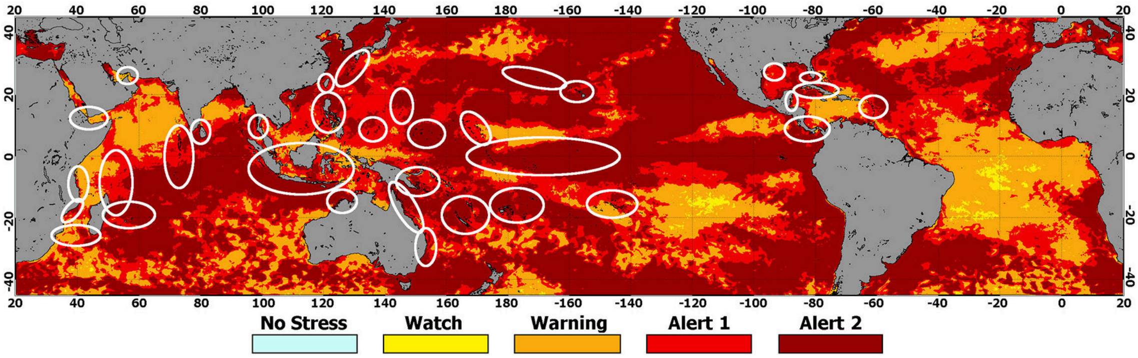

FIGURE 10 | Maximum composite of CRW's daily global 5 km satellite Bleaching Alert Area (Version 3) for June 2014–May 2017. Major bleaching has been reported to CRW by resource managers, scientists, and the public in the coral reef regions outlined by ellipses.

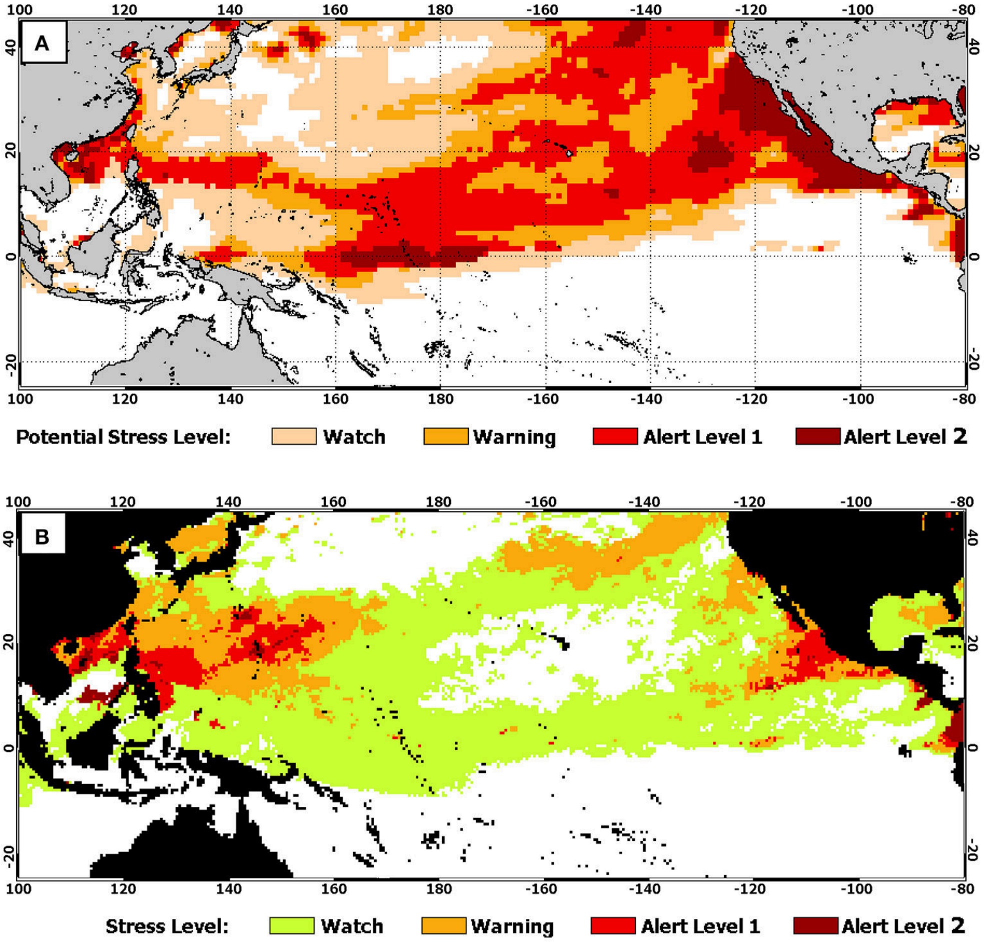

FIGURE 11 | CRW's **(A)** 4-Month Outlook (Version 3) of 60% probability issued on June 24, 2014 for July–October 2014, predicting Alert Level 1 in the Commonwealth of the Northern Mariana Islands (CNMI), Guam, and the Main Hawaiian Islands (MHI), and the **(B)** monthly maximum 50 km satellite Bleaching Alert Area for July 2014, observing Alert Levels 1 and 2 in the CNMI.

was the longest global event ever recorded (NOAA News Release, 2016a) and in June 2016 was projected to become a continuous 3-year event (NOAA News Release, 2016b). This event affected more reefs in the U.S. and worldwide than either previously documented global bleaching event (1998 and 2010; Eakin et al., 2017). It has been the worst ever in some locations [e.g., the northern GBR (Hughes et al., 2017), Kiritimati Island (The Washington Post, 2016), Jarvis Island (Brainard et al., 2018), and the NWHI (Couch et al., 2017)]. Some reefs bleached extensively for the first time on record (e.g., the northern GBR; Hughes et al., 2017), and some reefs were affected in consecutive years [e.g., Hawaii, the Florida Keys (Eakin et al., 2017), and the CNMI (Heron et al., 2016b)].

CRW's Outlook and its near real-time satellite products predicted, monitored, and tracked this multi-year global bleaching event starting well before it began. They were used for management preparedness and response: e.g., governmental closures of major dive sites in anticipation of extensive coral bleaching (e.g., The Guardian, 2016) and changes in location and resource allocation for in-water monitoring and ecological impact surveys (e.g., Heron et al., 2016b; Eakin et al., 2017). **Figure 10**, based on CRW's daily global 5 km satellite monitoring (Liu et al., 2014; https://coralreefwatch.noaa.gov), shows the highest heat stress levels reached during June 2014–May 2017. The 5 km products are CRW's next-generation satellite products; in early 2016, they replaced CRW's heritage 50 km products as the core component of CRW's decision support system for coral bleaching management (Heron et al., 2016b; Liu et al., 2017). In the figure, ellipses outline those reef regions where CRW's 5 km products indicated bleaching should be occurring and where field partners and users had reported extensive bleaching. CRW is still actively collating observations of coral bleaching and no bleaching from the field. Analysis of this global bleaching event and the performance of CRW's satellite and Outlook products during the event will be conducted and published soon.

Following the timeline of the third global bleaching event, the application of CRW's Outlook to predict some key phases of the event is described herein. The Outlook issued on June 24, 2014 (**Figure 11A**) predicted imminent bleaching in the CNMI

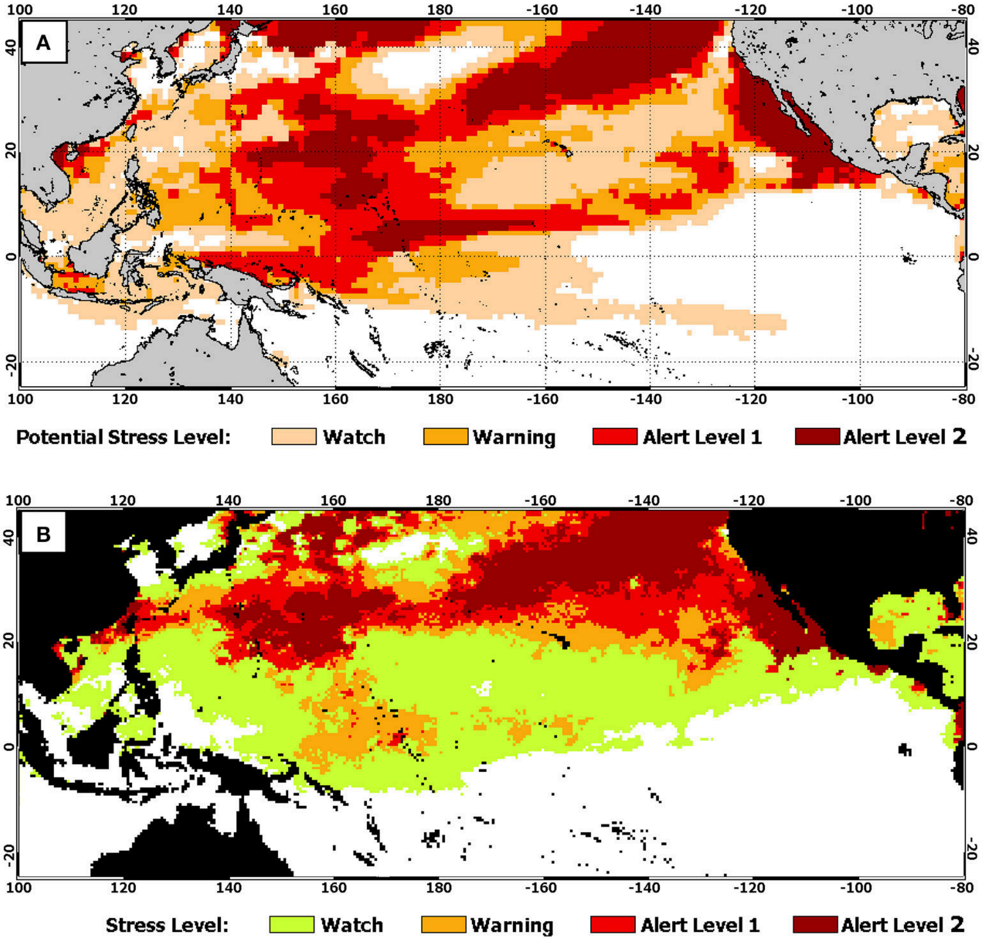

FIGURE 12 | CRW's **(A)** 4-Month Outlook (Version 3) of 60% probability issued on August 26, 2014 for September–December 2014, predicting Alert Levels 1 and 2 in the Northwestern Hawaiian Islands (NWHI), and the **(B)** monthly maximum 50 km satellite Bleaching Alert Area for September 2014, observing Alert Levels 1 and 2 in the NWHI and the CNMI.

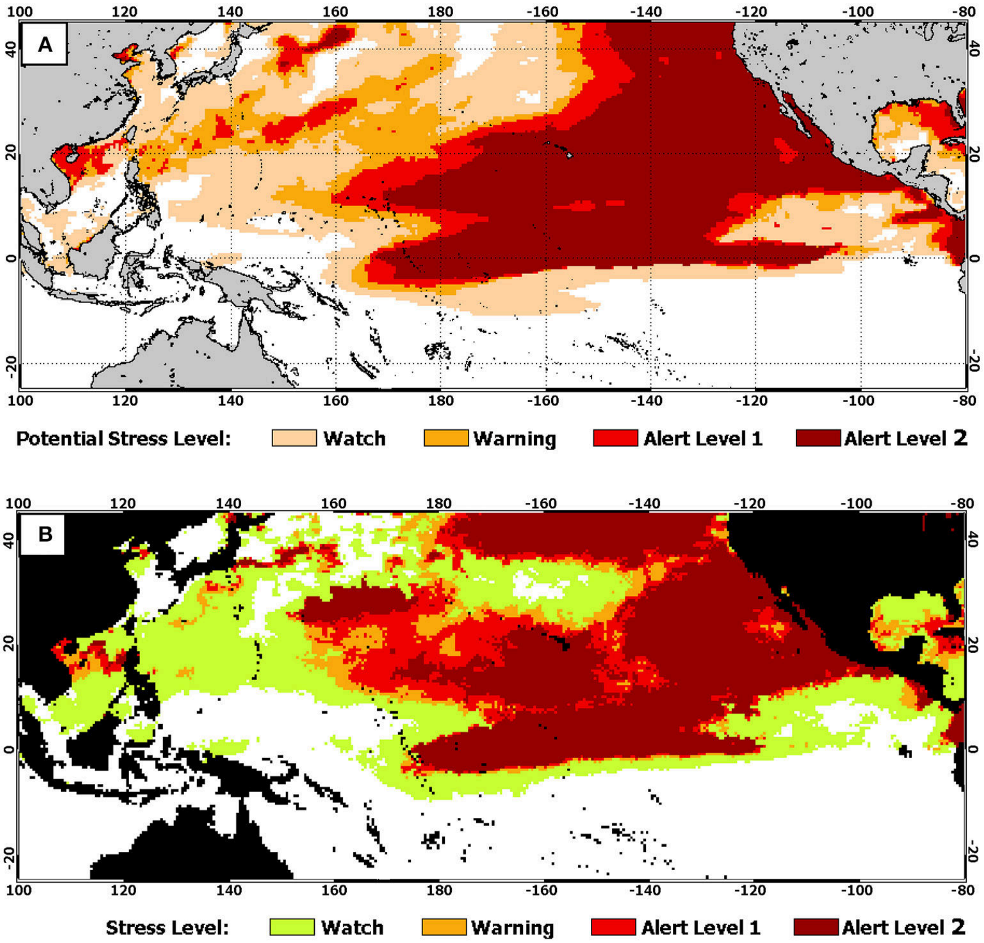

FIGURE 13 | CRW's **(A)** 4-Month Outlook (Version 3) of 60% probability issued on July 7, 2015 for July–October 2015, predicting Alert Level 2 at the southeast end of the NWHI and in the Main Hawaiian Islands (MHI) during summer/fall 2015, and the **(B)** monthly maximum 50 km satellite Bleaching Alert Area for September 2015, observing Alert Level 2 in the same region.

and Guam that would start early that month (weekly Outlooks are not shown but are accessible on the CRW website). This marked the onset of the third global bleaching event. Subsequent Outlooks (accessible on the CRW website), updated weekly, continued to predict the presence of Alert Level 1 or 2 in the region until late September 2014. This was confirmed by CRW's satellite monitoring at 50 km and 5 km resolutions. The 50 km satellite monitoring, for example, showed that Alert Levels 1 and 2 occurred in the region from early July (**Figures 11B**, **12B**) through late September 2014, as confirmed by field observations (Heron et al., 2016b).

Four-Month Outlooks issued in June (**Figure 11A**), August (**Figure 12A**), and September 2014 (not shown) indicated the potential for Alert Levels 1 and 2 across the Hawaiian archipelago, especially in the NWHI in late 2014. These were confirmed by CRW's satellite monitoring (**Figure 12B**) and field observations, indicating widespread bleaching, with the middle section of the NWHI experiencing unprecedented mass bleaching (Bahr et al., 2015; Couch et al., 2017; Eakin et al., 2017).

As early as June 23, 2015, CRW predicted potential mass bleaching (https://coralreefwatch.noaa.gov) that later occurred in the MHI in summer/fall 2015; the Outlook issued on July 7, 2015 (**Figure 13A**) showed the spatial extent of Alert Level 2 that would be realized. CRW's satellite monitoring pinpointed the bleaching event in the Hawaiian archipelago, especially in the MHI, as lasting from August through October 2015 (**Figure 13B**) – as predicted by the Outlook. Concerned over CRW's Outlooks and near real-time satellite monitoring, the "Eyes of the Reef" volunteer reporting network held its first state-wide Bleach Watch "Bleachapalooza" monitoring event on October 3, 2015 (Hawaii Department of Land and Natural Resources, 2015)[1]; this is the critical first tier of the Hawaii Department of Land and Natural Resources' Rapid Response Contingency Plan. It turned out to be an unprecedented, widespread, severe bleaching event in the MHI (Eakin et al., 2017). Based on CRW's Outlook, the Hawaii Division of Aquatic Resources collected

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[1] http://dlnr.hawaii.gov/blog/2015/09/25/nr15-148 (Accessed Nov 29, 2016).

specimens of rare corals to preserve them in onshore nurseries in case the mortality was severe. One of these species can no longer be found living on the reefs in Oahu; its genotypes are now found only in the nursery specimens (D. Gulko, pers. comm.).

In October 2015, NOAA officially declared the third global coral bleaching event (NOAA News Release, 2015), based on CRW's satellite monitoring and reported bleaching throughout the Pacific, Indian, and Atlantic Oceans. Based on CRW's Outlook of October 6, 2015 for October 2015–January 2016 (https://coralreefwatch.noaa.gov), the news release further indicated that the event would continue in the weeks and months ahead, affecting at least the Caribbean and central equatorial Pacific Ocean.

As early as December 1, 2015, CRW's Outlook predicted a mass bleaching event on the GBR during its summer season (February–April) 2016 (**Figure 14A**). That event turned out to be the worst in the GBR's history, especially in the northernmost portion of the GBR, where severe and widespread coral die-off was observed (e.g., Hughes et al., 2017). The December 1, 2015 Outlook also predicted the bimodal distribution of warm water (both in the northern GBR and New South Wales) that was eventually observed. Severe bleaching also was reported in and around Sydney Harbor (The ABC, 2016). Prior to peak bleaching, Thailand used CRW's prediction of severe heat stress to close numerous coral reefs to tourism as a way to reduce further stress to the reefs (The Guardian, 2016).

Kiritimati and Jarvis Islands, among other isolated islands and atolls in the central equatorial Pacific Ocean, were at the epicenter of the extremely strong 2015-16 El Niño. As predicted by CRW's Outlook (**Figures 13–15**) and confirmed by CRW's 5 km and 50 km satellite monitoring (**Figures 10**, **13**, **14**), Alert Level 2 bleaching heat stress lasted from May 2015 through May 2016 at some reef locations in the region. Once among the world's lushest coral reef ecosystems, the third global bleaching event killed most corals on these reefs (Associated Press, 2016a,b; NOAA Fisheries News Release, 2016; The Washington Post, 2016).

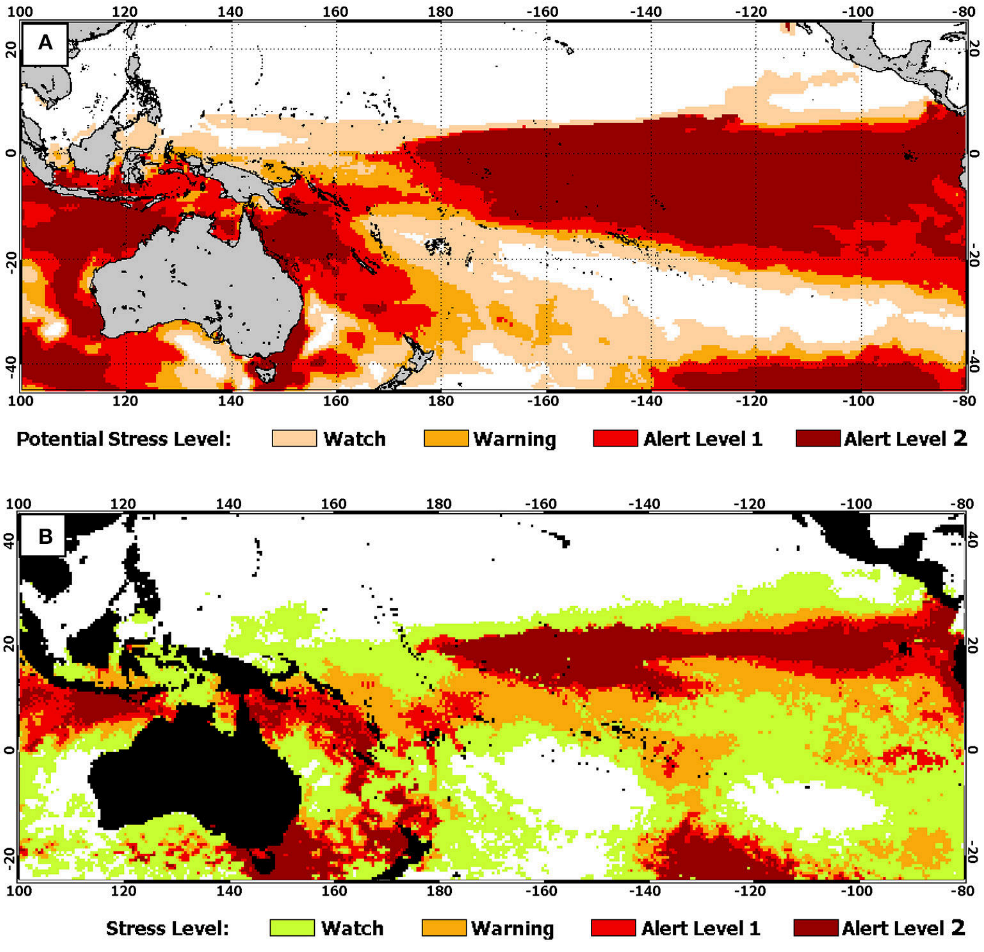

FIGURE 14 | CRW's **(A)** 4-Month Outlook (Version 3) of 60% probability issued on December 1, 2015 for December 2015–March 2016, predicting Alert Levels 1 and 2 on the Great Barrier Reef (GBR) and in the waters off southeast Australia during the region's 2016 summer, and the **(B)** monthly maximum 50 km satellite Bleaching Alert Area for March 2015, observing Alert Levels 1 and 2 in the regions.

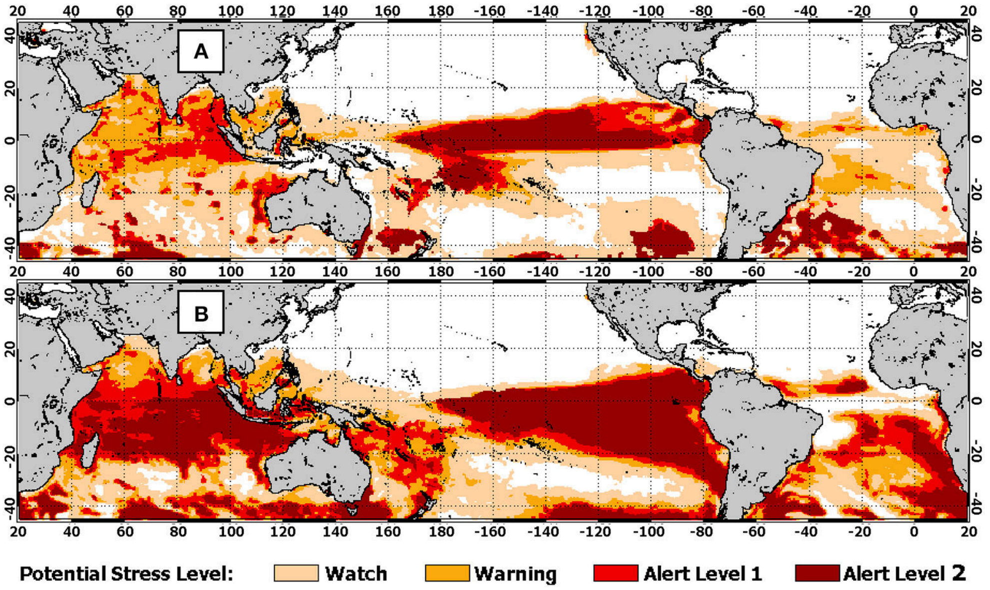

FIGURE 15 | CRW's 4-Month Outlook (Version 3) of 60% probability **(A)** issued on March 3, 2015 for March-June 2015 and **(B)** on February 2, 2016 for February–May 2016. Long-lasting, continuous Alert Level 2 heat stress was predicted over islands and atolls in the central equatorial Pacific Ocean, including Kiritimati and Jarvis Islands, located at the epicenter of the extremely strong 2015-16 El Niño.

When the third global bleaching event ended its second year in mid-2016, NOAA again used CRW's Outlook to project the third year of the global event (NOAA News Release, 2016b). The global event continued into mid-2017 with bleaching predicted by CRW's Outlook (https://coralreefwatch.noaa.gov) and observed in-water in Fiji, Niue, American Samoa, and at scattered locations along the GBR (i.e., Eakin et al., 2017; The Guardian, 2017).

CONCLUDING REMARKS

CRW's probabilistic 4-Month Coral Bleaching Outlook system (https://coralreefwatch.noaa.gov) is the first and only freely available global system for predicting the heat stress that leads to mass coral bleaching.

As with any model predictions, improving forecast skill is always a challenge and remains a focus of CRW's ongoing development efforts. While we anticipate that improved versions of NOAA's CFS will become available within the next few years to enhance CRW's Outlook system and benefit the global coral reef community, CRW also will continue to work on refining the Outlook algorithm to enhance prediction skill across the global tropical oceans. The analysis presented in this study will guide future quantitative analyses and development and improvement of the Outlook system.

The recent release of Version 3 of CRW's daily, global 5 km satellite coral bleaching heat stress monitoring product suite significantly improved near real-time monitoring accuracy (C.M. Eakin, and G. Liu, pers. comm.). This version of the daily satellite HotSpot will replace dOISSTv2-based HotSpots in the Outlook system Version 5. Any advance in the satellite monitoring algorithm also will be applied in future versions of the Outlook.

A longer time series of Outlook hindcasts will be developed from the 1982–2010 CFSv2 SST hindcast run for a more complete and in-depth skill analysis. The results will be used to improve the Outlook algorithm and for guiding regional application of the Outlook. In addition, a new, longer CRW SST dataset, CoralTemp, will be released shortly. This 1985-present 5 km dataset will be instrumental in conducting a full skill analysis of the Outlook.

The CFSv2 SST exhibits low prediction skills for longer lead-times in many regions, as shown earlier. This contributes to the significantly varying skills in the Outlook. We will evaluate the feasibility of improving Outlook performance at regional scales. Furthermore, recent research has demonstrated the potential of using multi-model ensembles (MME) to improve seasonal prediction (e.g., Kirtman et al., 2014). The use of such MMEs in the Outlook also will be explored.

The Outlook already has provided critical warning to coral reef managers, scientists, and decision makers around the world to guide the management, monitoring, and protection of coral reefs. As an integrated component of CRW's global decision support system for coral bleaching management, the Outlook, together with CRW's satellite coral bleaching heat stress monitoring, has been extremely useful in forecasting and nowcasting the progression of the third global bleaching event from June 2014–May 2017. These CRW products have been incorporated into numerous bleaching preparedness and response plans, bleaching conditions bulletins and newsletters, and other documents and outreach materials established and distributed by coral reef managers and scientists around the globe.

AUTHOR CONTRIBUTIONS

GL, CE, MC, and AK designed the study. GL and MC developed the products. GL, JD, and EG operated the products. All authors participated in the product interpretation, evaluation, improvement, and dissemination. GL, CE, JD, and SH wrote the paper with revisions, comments and suggestions from all other co-authors.

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Forecasting the Seasonal Timing of Maine's Lobster Fishery

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The fishery for American lobster is currently the highest-valued commercial fishery in the United States, worth over US$620 million in dockside value in 2015. During a marine heat wave in 2012, the fishery was disrupted by the early warming of spring ocean temperatures and subsequent influx of lobster landings. This situation resulted in a price collapse, as the supply chain was not prepared for the early and abundant landings of lobsters. Motivated by this series of events, we have developed a forecast of when the Maine (USA) lobster fishery will shift into its high volume summer landings period. The forecast uses a regression approach to relate spring ocean temperatures derived from four NERACOOS buoys along the coast of Maine to the start day of the high landings period of the fishery. Tested against conditions in past years, the forecast is able to predict the start day to within 1 week of the actual start, and the forecast can be issued 3–4 months prior to the onset of the high-landings period, providing valuable lead-time for the fishery and its associated supply chain to prepare for the upcoming season. Forecast results are conveyed in a probabilistic manner and are updated weekly over a 6-week forecasting period so that users can assess the certainty and consistency of the forecast and factor the uncertainty into their use of the information in a given year. By focusing on the timing of events, this type of seasonal forecast provides climate-relevant information to users at time scales that are meaningful for operational decisions. As climate change alters seasonal phenology and reduces the reliability of past experience as a guide for future expectations, this type of forecast can enable fishing industry participants to better adjust to and prepare for operating in the context of climate change.

Keywords: seasonal forecast, temperature, fishery landings, lobster fishery, climate variability

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INTRODUCTION

Societies have long been structured around typical seasonal and interannual cycles. The ability to anticipate the types, timing, and magnitude of variability—even in an intuitive manner—has afforded the ability to plan activities in ways that are compatible with environmental conditions. For example, farming relies on timing activities such as tilling, planting, growth, and harvesting of crops to typical annual rainfall and temperature cycles. However, this tight link between human activities and seasonal cycles can also disrupt societies when large, abrupt events or unexpected changes occur. Climate change is now pushing environments beyond conditions that have come to be intuitively expected based on personal experiences. As such, shifts in the timing of seasonal events and magnitudes of extremes (Mora et al., 2013; Poloczanska et al., 2013; Thomas et al., 2017; Alexander et al., in press) can pose substantial challenges for and require adaptation of coupled ecological and social systems (Mills et al., 2013; Alexander et al., 2017).

While climate change will require new capacities to adapt to changing environmental conditions, societies are becoming more prepared and capable of confronting these challenges. Increases in observational and computing power are greatly expanding our ability to understand and predict changes in environmental conditions as well as their effects on ecosystem features and human activities. Indeed, forecasting—in a variety of forms and at multiple time scales—has become an essential part of modern life. The ability to accurately predict weather conditions days in advance has improved daily life, generating over US$30 billion in benefits to weather forecast users in the United States alone (Lazo et al., 2009). Seasonal climate forecasts support decision-making and help avoid major disruptions across many natural resources sectors, such as agriculture (Hansen et al., 2011; Ramírez-Rodrigues et al., 2016) and water resources (Hamlet et al., 2002; Kwon et al., 2009). In addition, long-term projections enable the consideration of environmental change over a range of decisions. For example, projecting the consequences of anthropogenic carbon dioxide emissions allows communities to plan for expected impacts of warming and sea level rise and to weigh the costs and benefits of different adaptation strategies (Shepard et al., 2012).

Forecasts have long been central to the operation and management of marine fisheries. The quota-setting process at the heart of fisheries management involves projecting the expected performance of the stock and the yield that can be obtained from it. Similarly, longer-term projections of the growth of stocks that are at low biomass levels are used to determine rebuilding plans and timelines. While environmental variability has been recognized as exerting a substantial influence on the recruitment and productivity of fish stocks (Vert-pre et al., 2013; Szuwalski et al., 2014), this information has not been widely incorporated into fish population models and projections. However, recent examples have demonstrated that population projections used to set catch quotas and rebuilding plans can be more reliable for some stocks if environmental factors, particularly temperature, are considered in projections (Jacobson and McClatchie, 2013; Hill et al., 2014; Pershing et al., 2015; Tommasi et al., 2017).

These types of stock projections establish the general harvest constraints under which fisheries are prosecuted, and within this context, fishing industry participants make a variety of shorter-term operational decisions. Fishermen decide on a day-to-day basis when and where to fish, which species to target given their suite of permits and gear, and how to manage their operational costs. Dealers face decisions about which species to purchase given storage options, transportation capacity, and supply chain demand. And processors determine the type, amount, and timing of products to produce as well as how to adjust factory operations for different production activities. Forecasting efforts that are directed at industry-based operating decisions on seasonal or shorter time scales are now emerging; for example, Hobday et al. (2016) showcase several seasonal forecasts that support operations in both wild harvest fisheries and aquaculture.

Our interest in seasonal forecasting to support fisheries decision-making was motivated by the experience of the Maine lobster fishery during a marine heat wave in 2012 (Mills et al., 2013). American lobster supports the most valuable commercial fishery in the United States at present (>US$620 million in 2015; National Marine Fisheries Service, 2016), and over 80% of its landings occur in the state of Maine. The Maine lobster fishery is highly seasonal, with low landings rates during the winter and spring, followed by an abrupt shift into a high landings period in early summer. The high landings period is driven by lobsters migrating into nearshore waters where they become accessible to the large small-boat fleet, becoming more active and entering traps, and molting into a harvestable size class. These three processes are all tightly related to water temperature (Cooper and Uzmann, 1971; Aiken, 1973; Aiken and Waddy, 1975; Ennis, 1984; Crossin et al., 1998). During 2012, sea surface temperatures (SST) on the northeast U. S. continental shelf were 1–3°C warmer than the 1982–2011 average, the highest documented in 150 years of measurements (Friedland, pers. comm.) and on par with the mean SST change that climate models project for the region by the end of the century (Mills et al., 2013). The heatwave led to spring temperatures warming 3 weeks ahead of the typical schedule, and lobster landings also rose sharply 3 weeks earlier than normal. The supply chain was not prepared for the rapid uptick and high volume of landings, which outstripped holding, transportation, and processing capacity as well as market demand (Mills et al., 2013). While record high landings volume was reported in 2012 (National Marine Fisheries Service, 2016), an ensuing price collapse left many fishermen struggling to break even.

The events of 2012 highlighted the potential usefulness of seasonal forecasts to support decision-making at multiple points in the supply chain. Prior to 2012, the entire production process for American lobster—from harvest to processing to tables—was based on a historically reliable and intuitively understood seasonal cycle. Advance notice that the high landings period would begin much earlier than usual may have enabled dealers to increase storage and transportation capacity, processors to prepare equipment and hire seasonal staff, and marketers to intensify efforts to expand markets for the product. Alternatively, a forecast of an early season could have enabled harvesters or managers to adopt strategies that better aligned supply with demand, with a goal of avoiding a price collapse. While the 2012 heat wave demonstrated weaknesses of relying on past experiences, the chain of events that occurred also showcased the tight and lagged coupling between water temperature and the Maine lobster fishery.

At the request of members of Maine's lobster fishery, we set out to develop a forecast system to provide advanced warning of unusual conditions in the seasonality of the Maine lobster fishery. The forecast focuses on the timing of when the fishery shifts into its high-landings summer period, and it is based on real-time temperature measurements provided by NERACOOS (Northeastern Regional Association of Coastal and Ocean Observing Systems), the regional contribution to the U.S. Integrated Ocean Observing System. Our results demonstrate the potential for using a simple process to forecast features of the human system (i.e., fishery landings) from temperature months in advance. Similar forecasts that are targeted to inform specific decisions faced by users will become increasingly valuable as climate change inhibits reliance on familiar past patterns and as multiple actors in a range of fishing industries seek to adapt to unfamiliar extremes and new levels of variability that are associated with climate change.

METHODS

The goal of our analysis is to assess the potential to predict the phenology of the Maine lobster fishery using temperature data. Our approach involves characterizing seasonal patterns of lobster landings and then developing statistical models to explain changes in landing rates as a function of temperature. Results are conveyed through a probabilistic forecast of when the rate of landings is expected to increase. This forecast is updated weekly from early March through mid-April and is served via a public website to interested users.

Temperature Data

Temperature data are accessed from buoys B, E, F, and I of the Northeastern Regional Association of Coastal and Ocean Observing Systems (NERACOOS; www.neracoos.org, Pettigrew et al., 2011). These buoys are all located in coastal waters of the Gulf of Maine, USA. Buoy B is representative of the Western Maine Shelf; Buoy E is representative of the Central Maine Shelf; Buoy F is located at the mouth of Penobscot Bay; and Buoy I is representative of the Eastern Maine Shelf (**Figure 1**). All four buoys became active during July 2001 and record water temperature on an hourly basis at the surface (1 m), 2, 20, and 50 m. Temperatures for 2002–2016 were used for analyses presented herein.

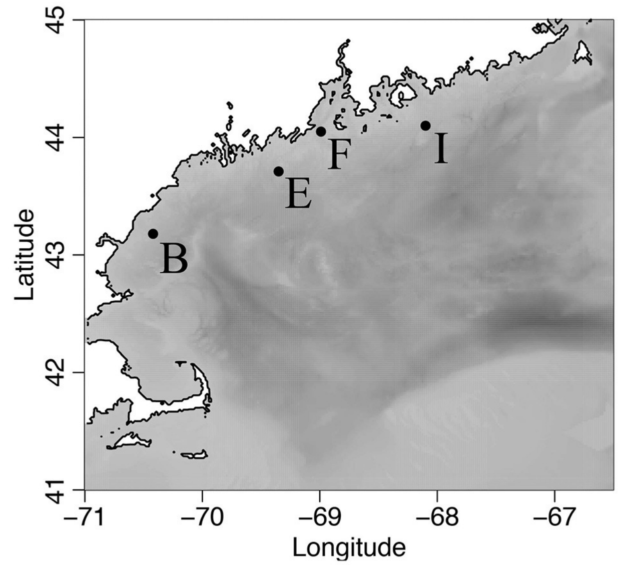


FIGURE 1 | Site map of NERACOOS buoys from which water temperatures at 50 m depth were derived. Buoys B, E, and I are representative of the Western, Central, and Eastern Maine Shelf, respectively. Buoy F, at the mouth of Penobscot Bay, is influenced by river outflow.

To process the temperature data, a daily average is first computed, and then an 8-day centered moving average is applied. When data are missing at depth (0.1–3.2% of the data points at each buoy) and available at the surface, a linear regression is used to fill the gaps in the temperature record at depth, by using the 8-day smoothed surface temperature as the independent variable. This generates smoothed time series of temperatures at 50 m for each of the four buoys.

For each buoy, a mean annual temperature cycle is generated by averaging daily temperatures between 2002 and 2011. This mean annual cycle is then subtracted from the smoothed daily temperatures (2002–2016) to produce a daily temperature anomaly time series for each buoy. These are also averaged over the four buoys to produce one time series of region-wide anomalies. For simplicity, we will only present models built using data from the 50 m sensors. This depth provides the best available approximation to bottom temperatures for Maine's coastal waters where the bulk of the lobster fishery occurs. Models built using data from other depths produce similar results.

We assess temperature persistence at the four buoys and for the 4-buoy average to understand its potential influence on the forecast. This analysis is conducted by computing the Pearson product moment correlation between temperatures at 50 m on the forecast day and daily 50 m temperatures for the remainder of the year. For this analysis, we use only direct temperature measurements, not those derived from surface-depth regressions.

Lobster Landings Phenology

Although regulations enable the Maine lobster fishery to remain open year-round, for practical purposes there is a strong seasonality to its operation. Landing rates are low during the winter but increase abruptly in the early summer as lobsters move into nearshore waters, become more active, and molt to larger sizes. The annual cumulative landings show a sharp change in slope between late June and mid-July (**Figure 2**). We define the day when this change occurs as the "start day" for the high-landings period.

Statewide landings data are provided by the Maine Department of Marine Resources. From 1990 to 2007, they are reported as monthly totals; from 2008 to 2016, they are available as daily totals. Because daily data are not available prior to 2008, we use a procedure to find the start day using only monthly data. For years in which only monthly data are available, the cumulative landings over the year are computed to obtain the total biomass of landings at the end of each month. We then linearly interpolate between months to approximate daily cumulative landings, whereby we implicitly assume that the landing rate is constant within each month. For 2008–2016, we compared the start days defined by the monthly vs. daily landings and found a tight correlation (Pearson's product moment: $r = 0.985$, $p < 0.01$). Subsequently, we apply a standard procedure across all years that uses the daily interpolation of monthly landings to determine the start day.

To define the start day for each year, piecewise linear regression is used to fit two lines to the cumulative daily landings. The first portion incorporates data from March 31 to day d; the second piece uses data from day d to October 2 (**Figure 2**). The

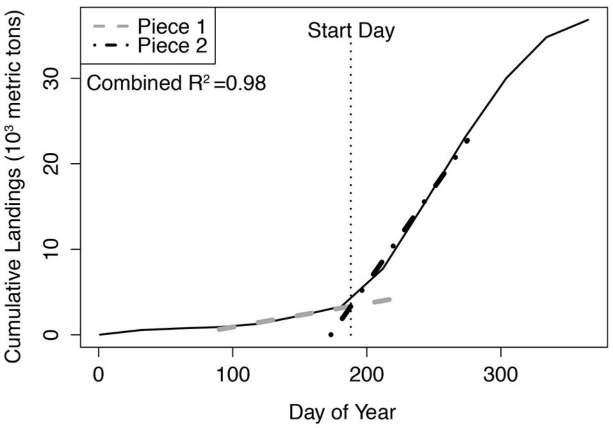


FIGURE 2 | Cumulative landings (10^3 metric tons) in 2009, demonstrating the piecewise regression method for defining start day. Landings data between day-of-year 90 and day-of-year 275 are split into two pieces. These are fitted by simple linear regression, shown by the gray and black dashed lines, and their intersection defines the start day, shown by the vertical dotted line. Landings in 2009 would indicate a start day on day-of-year 188 (July 7).

model fitting procedure is repeated for values of *d* between March 31 and October 2. We quantify the performance of the model for each break day *d* by taking the weighted average of the R^2-values of the two linear components.

$$\frac{{R_1}^2 * n_1 + {R_2}^2 * n_2}{n_1 + n_2} \tag{1}$$

where n_1 is the number of days between March 31 and d, n_2 is the number of days between d and October 2, and ${R_1}^2$ and ${R_2}^2$ are the R^2-values of the corresponding linear models. The piecewise regression model with the highest weighted average R^2 is selected, and the date on which the two lines intersect is recorded as the start day for that year. Similar methods have been employed to identify transition dates in studies of vegetation phenology (e.g., Zhang et al., 2013; Sweet et al., 2015).

Temperature-Start Day Relationships

After the annual start days are specified, their relationship to temperature can be investigated. Through this analysis, we determine if statistical relationships exist between the start day and 8-day smoothed 50 m water temperature anomalies, and if so, a time period in which these relationships are the strongest. We fit linear models relating the annual time series of temperature on a particular day (also termed the "forecast day") to the start day time series. Models were developed for temperatures from each buoy and for the region-wide average (a total of five temperature time series) for dates between January 1 and June 30. The performance of these models was compared using their R^2 statistics to identify a time window during which statistically reliable forecasts may be possible and that we would use as the forecasting period.

Paired data on NERACOOS buoy temperatures and lobster fishery start days are available for 2002 through 2016. In order to test the predictive power of the forecast, we used data from this full time series to evaluate how well the forecast may perform if future years are similar to the range of experiences in the past. Theoretical forecasts were simulated for each year using a leave-one-out approach, whereby the data from the year being predicted were excluded (i.e., a theoretical forecast for 2002 was generated using the data from 2003 to 2016). Due to the relatively small sample size and the presence of at least one "extreme" data point (2012), 95% prediction intervals were found to be too wide to be useful for communication and application. Instead, the forecast is constructed using a modified Monte Carlo (mMC) approach in order to more clearly represent the uncertainty in the forecast and the spread of the predictions based on the variance in the dataset. The mMC approach fits a series of temperature-start day linear regression models using a random sample of the available years. From the 13 years of data available to use for each forecast, the mMC simulation randomly selects 9, performs a univariate linear regression, and then uses the temperature from the forecast year to predict the start day. For each of the five temperature time series, 3,000 mMC simulations are run to ensure that repeated forecasts would be appropriately stable.

Forecast Communication

The forecast is made available to the public in the form of a graphical histogram showing the proportion of mMC simulations that falls into each of seven 1-week bins. The "normal" bin is bounded by June 30th and July 7th, and is centered on the mean start day for 2002–2011 (July 3rd), a period of years that aligns with the temperature baseline. Seven bins were required in order to keep the forecast image symmetrical while encompassing the range of observed start days. The bins are shaded according to the proportion of mMC simulations they contain, which we interpret as the likelihood of the start day being observed in that bin.

We updated the forecast weekly during the forecasting period. Results were served via a website (www.gmri.org/lobster-forecast) that delivers the forecast for the week as well as the series of forecasts produced for the season so that changes can be viewed over the forecasting period. In addition, the website provides interpretive information that (1) contextualizes temperature patterns that are shaping the forecast and (2) provides a comparison of the current forecast to comparable years in the past.

RESULTS

Between 2002 and 2016, the spring (March, April, May) temperature range spanned ∼3°C, from negative anomalies of −1.45°C in May 2004 to positive anomalies of 1.73°C in March 2012. The strength and direction of temperature anomalies in most years persisted over the spring months, with patterns in March, April, and May exhibiting tight relationships to one another. Strong negative anomalies (< −1.0°C in March, April or May) were observed in 2003 and 2004, while strong positive temperature anomalies (>1.0°C) were experienced in 2002, 2006, 2012, 2013, and 2016 (**Figure 3**). An analysis of temperature persistence at the buoys used for this analysis indicates that 50 m water temperature on April 1 serves as a good indicator of 50 m temperature through early to mid-October for Buoys B, E, and F and through the end of the year for Buoy I (**Figure 4**).

The mean start day of the fishery between 2002 and 2011, as defined by our two-part linear procedure, was July 3. Over the entire study period, the start day varied by ∼40 days, from a season that began more than 20 days earlier than the mean (negative anomaly) in 2012 to one that started 16 days later than the mean (positive anomaly) in 2003. Positive start day anomalies of more than 5 days, reflecting a late start to the season, were characteristic of 2003, 2004, 2005, and 2014. The start day defined for 2012 was the earliest in the time series, but start day anomalies in 2002, 2006, 2010, 2013, and 2016 were also more than 5 days early. A general negative association was observed between temperature anomalies and start day anomalies (**Figure 3**).

The strength of the relationship between 8-day smoothed 50 m temperature and start day increases from January 1 to early spring, becoming statistically significant ($p < 0.05$) by late January. The average coefficient of determination (R^2) over all models exceeds 0.7 from March 6 through May 3, and it exceeds 0.75 from March 8 through April 20 (**Figure 5**). Buoy F 50 m temperatures and the 4-buoy 50 m temperature average appear to have higher capacity for predicting the start day than other buoys through March and April. The predictive capacity of Buoy B, F, and the 4-buoy average 50-m temperatures remains relatively stable through March and April. The predictive capacity of temperatures at Buoy I peaks in late March and Buoy E peaks in early April (**Figure 5**). Based on these results, we defined March 6 through May 3 as the forecasting period, as temperatures during this span of time provide a strong indication of the timing of the fishery 3–4 months in the future.

We used April 1 as the forecast date for display purposes in this paper since R^2 values over all models were high through this date (**Figure 5**). We can evaluate the forecast by considering how the likelihood of predicted fishery start days compares to the "observed" start day defined by the stepwise regression analysis. Across conditions experienced in all years since 2002, the sign of the deviation of predicted start days from the center of the "normal" bin was consistent with the observed start days (**Figure 6**). Further, for conditions in most years, the actual start days would have been within or adjacent to the bin that was predicted to have the highest likelihood of containing the start day (**Figure 6**). For 10 of the 15 years, more than half of the mMC simulations predicted a start day within a 7-day window centered on the observed start day (**Figure 6**). The forecast model performed well for conditions in 2005, 2008, 2009, and 2012, with a greater than 33% likelihood of the predicted start days falling within a 3-day window centered on the observed start day. Conversely, the model performed poorly under 2006 conditions, with ∼4% likelihood of predicting the start day within a 7-day window of the date defined as the actual start. Even for 2006 conditions though, the model would have correctly forecasted the direction of deviation from the "normal" bin by predicting an early start of the high landings period. There is no obvious bias between skill in forecasting early years as opposed to late years, and the skill in an extremely early year like 2012 is similar to the skill in years with more normal temperature conditions, such as 2008 or 2009 (**Figure 6**).

Demonstrating the forecast for 2012 conditions, the 4-buoy average model built with data from 2002 to 2016 (excluding 2012) would have given advanced warning of an extremely early start to the summer season based on conditions on April 1 ($R^2 = 0.86$; **Figure 7**). The temperature-start day regression model would have predicted a start day of 166 (June 15), while the actual start occurred even a few days earlier than that, on day 163 (June 12; **Figure 7**). The forecast would have been for an extremely early start to the season (>75% likelihood), and it would have been stable as the spring progressed (**Figure 8**).

DISCUSSION

As seasonal cycles that cue ecological events and human activities change in ways that move beyond typical past experiences, decision-making under variable environmental conditions will increasingly benefit from forward-looking information about resources of interest at appropriate temporal and spatial scales. We have demonstrated the technical capacity to forecast the timing of the seasonal increase in statewide landing rates in the Maine lobster fishery from buoy-based temperature observations. Using 50 m water temperatures from four NERACOOS buoys that span the coast of Maine, we are able to forecast the start day of the fishery to within 1 week of the actual start under conditions experienced in most test years. Further, we can issue this forecast 3–4 months prior to the typical shift into the high-landings period, providing important advance notice of major shifts in the timing of the fishery. The forecast performed well under conditions experienced during an extremely warm year in which the high-landings period began very early (i.e., 2012), indicating its potential reliability as climate change progresses and pushes conditions beyond those experienced in the past.

Seasonal forecasts of marine resources based on temperature have proven useful for a variety of purposes (Hobday et al., 2016). These resource-focused forecasts typically rely on an underlying forecast of temperature, but the skill of temperature forecasts is weak in coastal waters of the Northeast U.S. (Stock et al., 2015). In this forecast for the Maine lobster fishery, our predictive capacity is likely derived in part from temperature persistence. Over the Northeast U. S. large marine ecosystem, April sea surface temperatures are strongly correlated with temperatures 2 months in the future, and weaker correlation signals are maintained for 5 months (Stock et al., 2015). An analysis of temperature persistence at the buoys used for this analysis provides similar results for temperatures at 50 m depth (**Figure 4**).

The predictive skill of the Maine lobster fishery forecast is also likely attributable to lagged biological responses to temperature and a tight biological-social link that initiates the rise in landings rates. The annual landings cycle of the fishery is driven by the migration and molting cycle of the lobster population. The small-boat fleet (∼80% of all vessels) relies on lobsters migrating into shallow nearshore waters, molting into legal size classes, and

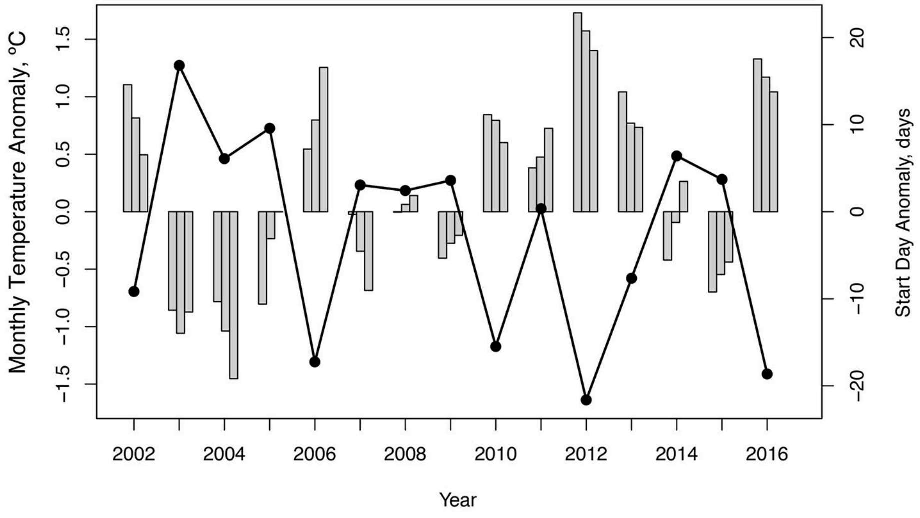


FIGURE 3 | Spring temperatures and start days, 2002–2016. Bars show the monthly temperature anomalies for March, April, and May. The black line plots the start day anomaly from the 2002–2011 mean. The start day anomaly is generally anti-correlated with the spring temperature anomaly.

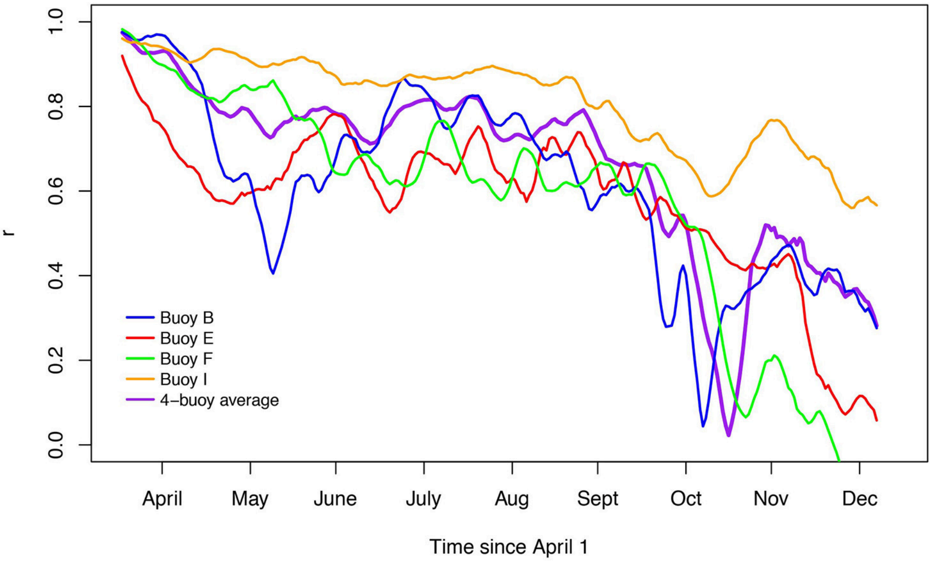


FIGURE 4 | Persistence of correlation to April 1 temperature. Correlation of 50-m temperatures at four buoys on April 1 to temperatures on subsequent days of the year. Statistically significant correlations persist through early to mid-October at Buoys B, E, and F; through mid-November for the 4-buoy average; and through the end of the year for Buoy I.

becoming more active so that they move into traps. Both seasonal migration and smaller-scale movement behaviors are cued by temperature (Cooper and Uzmann, 1971; Ennis, 1984; Crossin et al., 1998). Temperature has been shown to be an important factor in the initiation and progression of molting (Aiken, 1973; Aiken and Waddy, 1975; Kelly, 1993), a critical process that creates a tight biological-social link since 85% of landings in the fishery are of lobsters that have recently molted into a legal size class (Atlantic States Marine Fisheries Commission, 2015). It has been proposed that early stages of the molting process are triggered when a temperature of 5–6°C is reached, after which the ambient temperature determines the number of days to molting (Kelly, 1993). The fact that a temperature threshold appears to initiate the molting process provides a possible mechanism connecting April temperatures to molt timing and an uptick in fishery landings in June or July. Preliminary analyses indicate correlations between (1) the April 1 temperature anomaly and day when the 8-day smoothed 5°C temperature threshold is reached ($r = -0.85$ for 4-buoy average) and (2) the temperature threshold date and fishery start day ($r = 0.80$ for 4-buoy average). This threshold trigger for molting may also explain why the predictive skill of the forecast declines in May, rather than

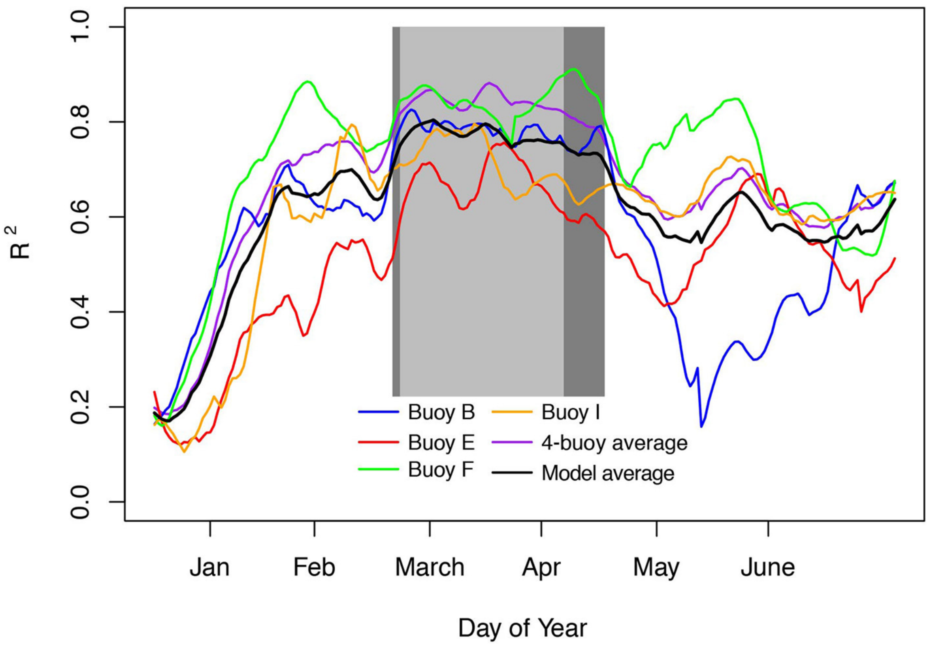


FIGURE 5 | Temperature and start day correlations. Temperatures on January 1 through June 30 at each buoy and for the 4-buoy average were used to predict the start day of the fishery. Results show the R^2-value of these regression models by day. The model average R^2-values exceeded 0.75 from March 8 through April 20 (light gray rectangle) and were above 0.7 for March 6 through May 3 (dark gray rectangle).

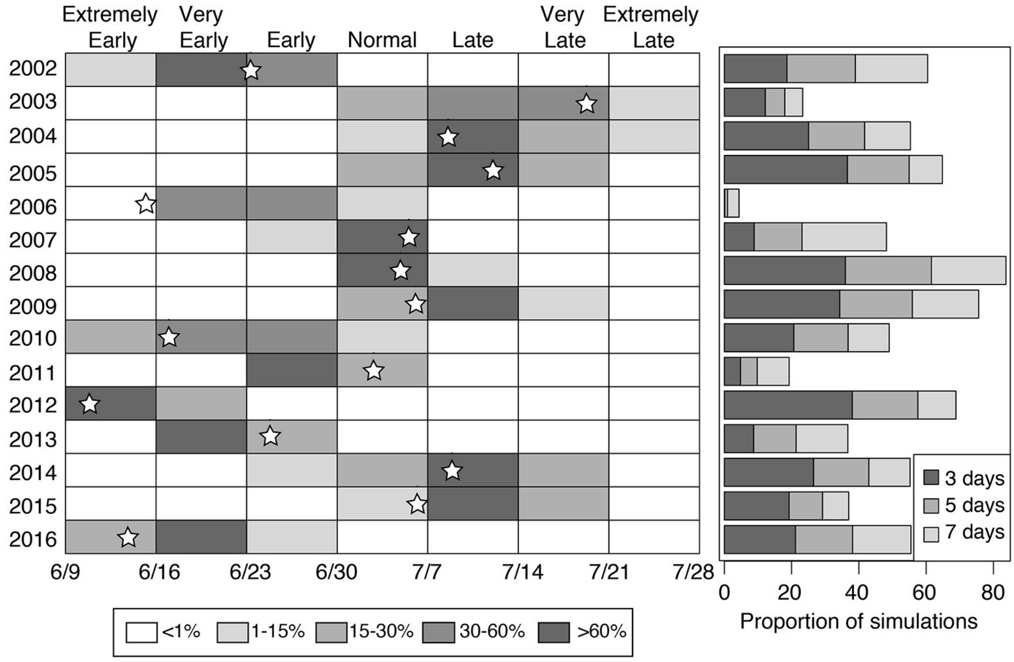


FIGURE 6 | Past performance of forecast. An April 1 forecast is run for each year 2002–2016, using all available data except the year being tested. In the left panel, the boxes represent 7-day windows, centered on a "normal" start day bin that encompasses June 30-July 7. Bins are shaded according to the percentage of simulations that predict a start day in the week represented by the bin (legend shown below panel). The observed start day is plotted as a star. In the right panel, the stacked bar plot shows the proportion of mMC simulations predicting a start day inside a 3-, 5-, and 7-day window centered on the observed start day.

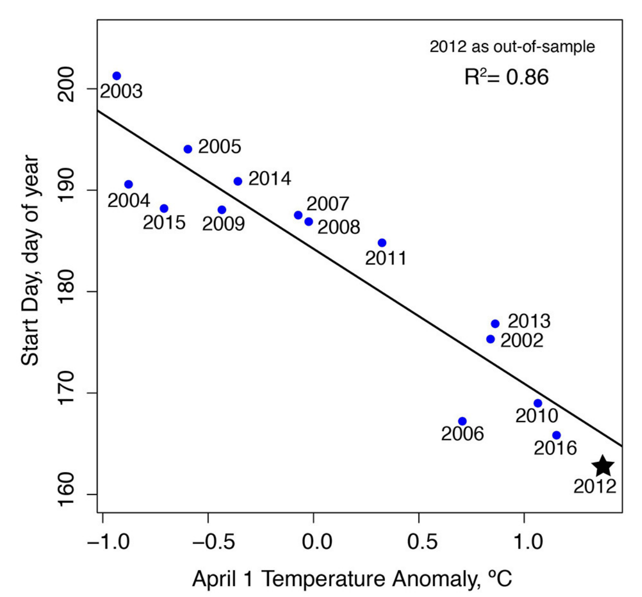
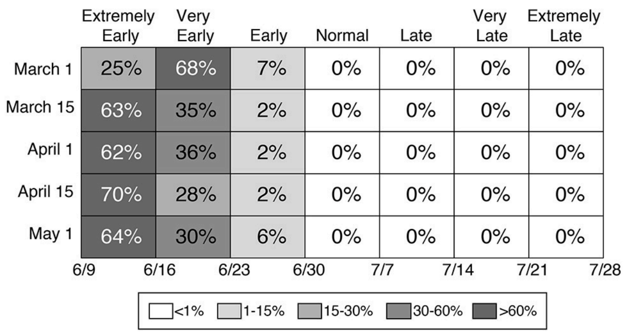


FIGURE 7 | Simple linear regression between start day and April 1 temperature anomaly. Start days from 2002 to 2016 are plotted against the April 1 (4-buoy average) temperature anomaly from the same year. Treating 2012 as an out-of-sample test, the linear regression fits well (R^2 = 0.86) and would predict a start day of 166 (June 16). The observed start day in 2012 was 163 (June 12).



	Extremely Early	Very Early	Early	Normal	Late	Very Late	Extremely Late
March 1	25%	68%	7%	0%	0%	0%	0%
March 15	63%	35%	2%	0%	0%	0%	0%
April 1	62%	36%	2%	0%	0%	0%	0%
April 15	70%	28%	2%	0%	0%	0%	0%
May 1	64%	30%	6%	0%	0%	0%	0%

FIGURE 8 | 2012 forecast series. A forecast is run on five dates in 2012, using data available from 2002 to 2016. The boxes, representing 7-day bins, are shaded according to the proportion of mMC simulations that predict a start day in that bin (legend shown below panel), and the proportion (rounded to the nearest percent) is displayed in each box. Based on spring temperatures in 2012, a high likelihood for an extremely early start to the high landings period would have been predicted by a forecast issued as early as March 15, and this prediction remained stable through May 1.

steadily improving as the start day draws closer (**Figure 5**). Further investigation is needed to fully evaluate this potential mechanism and to understand how a temperature threshold that initiates molting vs. subsequent temperatures that control the speed of that process may affect the forecast of the start day, which inherently integrates both types of temperature influences.

Grounding this forecast in a mechanistic framework is an important step in its future development. At present, the forecast model is empirical and effectively amounts to a hypothesis that temperatures in the spring trigger a chain of events that leads to inshore movement and molting of lobsters, causing the fishery to shift into its high landings summer mode. Empirical models such as this have a poor track record in fisheries (Myers, 1998) and their reliance on historical data is inherently limiting when they are applied to novel conditions. As extreme events like the 2012 heat wave are overlaid on rising mean trends, conditions will move beyond historical analogs, and forward-looking information streams that are not bounded by past conditions will be needed to provide insights that shape operational and management decisions in fisheries (Mills et al., in review). The empirical nature of the current forecast may make it less accurate in future years in which temperature patterns deviate from those encountered during the study period; this is particularly likely for years in which the temperature cycle deviates substantially from a sinusoidal shape. More importantly, the dependent variable—the timing of landings—is complex and combines influences of lobster biology with the behavior of fishermen. The latter can be strongly impacted by changes in economic conditions or regulations.

Our motivation to develop this forecast stemmed from a need expressed by leaders within the Maine lobster industry and management system following the 2012 Northwest Atlantic marine heat wave (Mills et al., 2013), and we have now demonstrated the technical capacity to issue a forecast of the seasonal timing of the lobster fishery. Since we have started providing the forecast, initial conversations with industry users indicate that they have applied the forecast information to guide decisions as diverse as scheduling seasonal maintenance and operations, setting debt payment dates, and planning for transportation needs to distribute the lobsters to processors or retail outlets. We anticipate that the forecast will enhance preparedness of the industry, supply chain, and managers for the start of the season, particularly in extremely early years in the future. This awareness should help align production capacities, marketing initiatives, and other operations to ensure a smooth flow of lobsters from the water to tables across the globe. This continuity may help optimize economic value derived from the resource during a period when lobster productivity is increasing in the state (Atlantic States Marine Fisheries Commission, 2015). In contrast to the situation in Maine, substantial temperature-related lobster population declines have decimated the fishery in more southern regions of New England USA (Atlantic States Marine Fisheries Commission, 2015). Operating the fishery and its supply chain in ways that maximize economic benefits may prove critical for buffering impacts of any future climate-related productivity declines that may occur in Maine. Given the state's high dependence on the lobster resource (i.e., 85% of the value of all fishery landings), forward-looking forecast information can improve near-term operational decisions and longer-term planning efforts to help sustain the fishery, its associated industry, and coastal communities.

While we have developed the technical capacity to issue a forecast that we anticipate will provide valuable information to users, real-world application of forecasts has proven challenging in a variety of situations (Hobday et al., 2016), and we anticipate similar challenges to uptake of the forecast information.

Although it appears that we could have provided a reliable forecast of the early start to the 2012 season, sudden provision of this forecast in 2012 may not have helped the situation on the ground at that time. End-users need time to become familiar with a forecast and develop their own sense of its reliability and how to use it before they are likely to act on the information. Issuing the forecast even in years when major impacts to the landings cycle are not expected provides potential users with opportunities to relate the information to their own operations, which may be particularly valuable if another major disruption is predicted in the future. Longer-term familiarity with and confidence in the forecast may spur forward-looking planning, which will enhance resilience of individual operators and of this integrated industry to future disruptions.

Further development of the forecast will also benefit from additional end-user engagement. Hobday et al. (2016) recommended systematic engagement of stakeholders in the forecasting process to ensure the applicability and usability of the information in real-world decision-making contexts. This three-stage process begins by assessing needs of the end users, including relevant temporal and spatial scales. A forecast can then be developed to target these information needs. Finally, the implementation stage entails delivering the forecast, supporting and educating users, applying information to a decision, and gathering feedback to improve the product (Hobday et al., 2016). Initial input from users has indicated that developing the forecast at smaller spatial scales (e.g., for coastal regions or lobster management zones) would make the information more relevant and useful. In addition, benefits may be gained by targeting communication strategies and formats to specific user groups. We view the forecast that we describe herein as a pilot stage from which we can work toward a future product that is shaped by more deliberate and focused stakeholder input so that it can support a range of applications by end users.

The impacts of climate change are being felt by fisheries in many marine ecosystems. While climate-related forecast information tends to focus on gradual environmental trends over 50- to 100-year time horizons, fishing industry participants face decisions on much more immediate time scales. These decisions may be affected not just by the magnitude of environmental conditions but also by their timing, as evidenced by the experience of the Maine lobster fishery during the 2012 ocean heat wave (Mills et al., 2013). Providing forward-looking information relevant to the scales at which decisions are made is a critical step, and seasonal forecasts offer one avenue toward achieving this alignment. As shifts in the timing of warming and cooling occur in marine ecosystems (Burrows et al., 2011; Thomas et al., 2017), the phenology of life events in organisms, operations and outcomes of fisheries targeting those species, and effectiveness of fishery management efforts may all be affected (Mundy and Evenson, 2011; Peer and Miller, 2014). Seasonal forecast information directed toward the phenology of important events can provide a longer planning horizon than weather forecasts and bring climate information to bear on fisheries at a time scale that is meaningful for operational and management decisions made throughout the fishing industry.

AUTHOR CONTRIBUTIONS

AP and KM conceived of the forecast. CH led the design of the model with guidance from AP and KM. CH implemented the models. All authors wrote the paper.

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The Dynamics of the North Atlantic Subpolar Gyre Introduces Predictability to the Breeding Success of Kittiwakes

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Since the open-ocean subpolar Atlantic is amongst the most predictable regions in the world, our results hold promise for predicting the general production to seabird populations over a large geographical region adjacent to the northern North Atlantic and the Arctic Mediterranean. Colonies of black-legged kittiwakes *Rissa tridactyla* in the North Atlantic have declined markedly since the mid-1990s, partly due to repeatedly failing breeding seasons. We show a close link between the breeding success of a kittiwake colony in the Faroe Islands and the subpolar gyre index. Successful breeding follows winters with an expanded subpolar gyre and, by inference, increased zooplankton abundances southwest of Iceland. The environmental conditions in the northwestern Atlantic during the non-breeding and pre-breeding seasons might therefore be important. Furthermore, the subpolar gyre dynamics might influence the local food abundance on the Faroe shelf during the breeding season.

Keywords: North Atlantic subpolar gyre, predictability, seabirds, breeding success, oceanic front, *Calanus finmarchicus*, sub-decadal variability

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INTRODUCTION

The populations of black-legged kittiwakes *Rissa tridactyla* (hereafter kittiwake), terns, and auks have declined markedly in the Northeastern (NE) Atlantic and adjacent shelf seas during the last 25 years. This is partly due to large declines in chick production, also referred to as the *breeding success* (Frederiksen et al., 2007a; Descamps et al., 2017, in press). There is a broad consensus that the decline must be driven by large-scale changes in the climate (Frederiksen, 2010). Climatic changes are often proxied simply as temperature changes (Frederiksen et al., 2007b), while the physical processes responsible have largely remained elusive. The advent of geolocators has revealed that many seabird species from the NE Atlantic occupy northwestern (NW) Atlantic waters during the non-breeding period, likely due to better food availability during winter (Frederiksen et al., 2012). Processes impacting the food abundance in the NW overwintering region (Bogdanova et al., 2011) could therefore have a profound impact on several seabird populations due to "carry-over effects" on the breeding success during the following summer, and also due to the high mortality during the non-breeding season (Harris et al., 2005).

The marked 1990s reduction in the size of kittiwake and Brünnich's guillemots colonies have previously been linked to the dynamics of the subpolar gyre (SPG; Descamps et al., 2013, 2017, in press; Fluhr et al., 2017), although only qualitatively. The SPG is a large body of cold and low-saline subarctic water, which circulates counterclockwise south of Greenland and Iceland (**Figure 1**). The size and circulation strength of the SPG declined abruptly after the mid-1990s, inducing rapid warming and salinification (Hátún et al., 2005) as well as a major ecosystem shift in the NE Atlantic (Hátún et al., 2009). These changes were initiated by weaker atmospheric forcing and shallower winter convection in the NW Atlantic (Häkkinen and Rhines, 2004). The variable shape and circulation strength of the SPG is intimately related to the morphology of main oceanic fronts (Thierry et al., 2008; Hátún et al., 2016). Such fronts are highly biologically productive and have been identified as feeding hotspots of migratory seabirds while occupying the high seas during the non-breeding period (Edwards et al., 2013; Scales et al., 2014).

During years when the winter mixed layer is anomalously deep in the Labrador-Irminger Sea, the subpolar gyre expands, and the productive subarctic front west of the Reykjanes Ridge (**Figure 1**) shifts toward Iceland (Hátún et al., 2016). Such years result in increased abundance of the ecologically most important zooplankton species, *Calanus finmarchicus,* both within the Irminger Sea and on the south Iceland shelf ("Z" in **Figure 1**; Hátún et al., 2016). The zooplankton concentration southwest of Iceland thus exhibits strong inter-annual variability.

In March, after the kittiwakes return from the NW Atlantic to European waters, many birds make yet another exodus westwards just prior to breeding, along strikingly similar paths (Bogdanova et al., 2011). The westward route follows the Icelandic shelf, from where Hátún et al. (2016) presented long-term on-shelf zooplankton data. In the west the birds gather in a region between 29° and 36°W (Bogdanova et al., 2011), which roughly coincides with the highly productive subarctic front west of the Reykjanes Ridge (Pedchenko, 2005; Hátún et al., 2016).

Environmental conditions both in non-breeding and breeding regions must be significant drivers of the demographic processes of the seabirds. The relative importance of such remote and regional drivers has for example been investigated for the adult kittiwake survival rates in northern Norway (Reiertsen et al., 2014). A large percentage of the variation in adult kittiwake survival rates in northern Norway was explained as a combination of zooplankton variability in the SPG region and the state of a fish stock in the Barents Sea.

The breeding success of kittiwakes on the Faroe shelf ("K" in **Figure 1**) has, so far, only been compared to the regional food abundances. Significant correlations were identified to the average length of the local O-group sandeel population ($r^2 = 0.41$), and even higher correlations were found when compared to a sandeel biomass index ($r^2 = 0.56$; Eliasen, 2013). Several key ecosystem records from the Faroe shelf are, however, characterized by "high-or-low" variability (Gaard et al., 2002) comparable the zooplankton abundance southwest of Iceland (Hátún et al., 2016). Since the geolocators reveal occupancy of these western waters immediately prior to breeding (Bogdanova et al., 2011), an additional carry-over effect is possible. Acknowledging the importance of local food abundance, we here want to test if food availability in the Icelandic feeding hotspots during the non-breeding/pre-breeding period also might impact the breeding success of the Faroe kittiwakes.

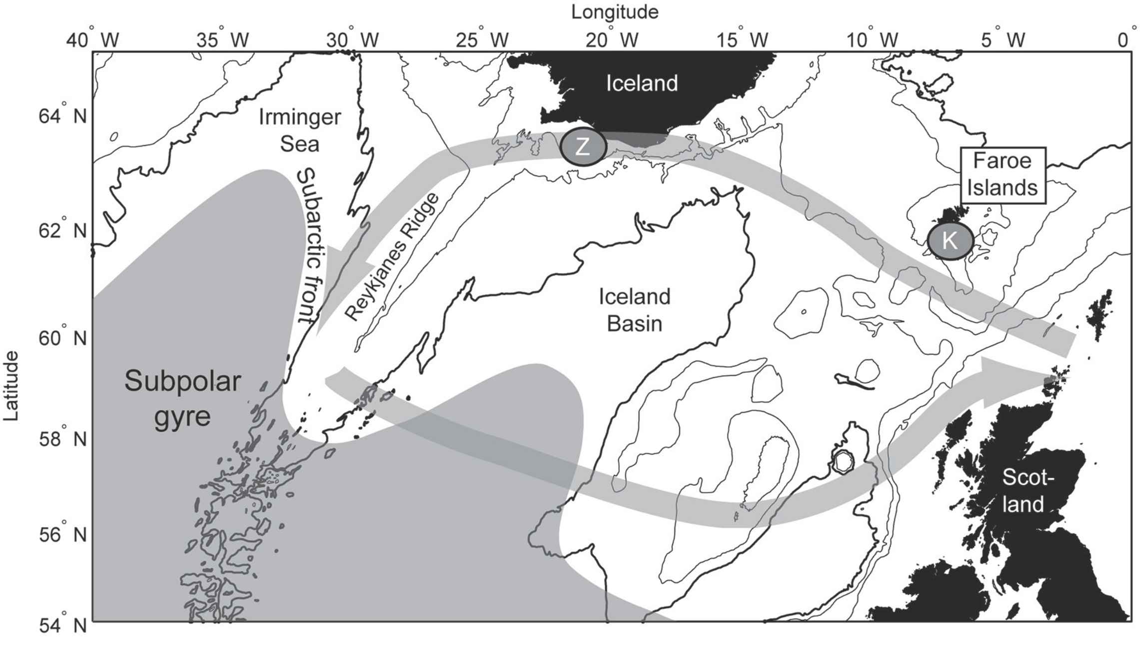

FIGURE 1 | Map of the northeastern Atlantic Ocean. The subpolar gyre is illustrated in gray, and the pre-breeding kittiwake feeding excursion is shown with the gray arrows. The Faroe kittiwake breeding success is sampled at site "K," and the Icelandic zooplankton record is sampled at site "Z."

MATERIALS AND METHODS

Food Proxy for the SPG

The gyre index is the principal component obtained from an Empirical Orthogonal Function (EOF; Preisendorfer, 1988) analysis of the sea surface height (SSH) field over the entire North Atlantic Ocean (30°–60°N; Häkkinen and Rhines, 2004; Hátún et al., 2005, 2016; Larsen et al., 2012). The high-pass filtered gyre index has previously been used as a metric for the lateral position of the subarctic front (the *Frontal position*) and the intensity of vertical winter mixing (Hátún et al., 2016). It has previously been demonstrated that the *Frontal position* (the detrended gyre index) is highly correlated with the zooplankton biomass on the south Iceland shelf ($r = 0.80$, $p < 10^{-8}$ for 1970–2011), and the abundance of *C. finmarchicus* within the SPG—abundance increases when the front shifts toward Iceland (Hátún et al., 2016).

A new version of Ssalto/DUACS altimetry products (SSH) was released in April 2014—the so-called *DUACS 2014*. This included a change of reference period (now 1993–2012 instead of 1993–1999), and a new Cartesian 1/4° resolution is used instead of the 1/3° Mercator grid, which has had a strong impact on the physical information in these data. The spatial resolution improved below 41.5°N, but the grid is now coarser north of this latitude. In order to emphasize the SPG, where the kittiwakes overwinter (Frederiksen et al., 2012), an EOF analysis was applied to the DUACS 2014 data for a more limited domain encompassing the SPG (Figure S1). The obtained new gyre index is more "linear" than the previous one from Larsen et al. (2012), and the important interannual fluctuation associated with deep winter convection (Hátún et al., 2016) have now diminished (**Figure 2**). Especially, the peak entailing the convection event during winter 1999–2000 is much less evident in the presently used DUACS 2014–based gyre index. The detrended DUACS 2014–based gyre index has been utilized as our updated *Frontal position*. The model-based *Frontal position* index from Hátún et al. (2016) is used for the pre-altimetry period (before 1993).

The Ssalto/*Duacs* altimeter products were produced and distributed by the Copernicus Marine and Environment Monitoring Service (CMEMS; http://marine.copernicus.eu/).

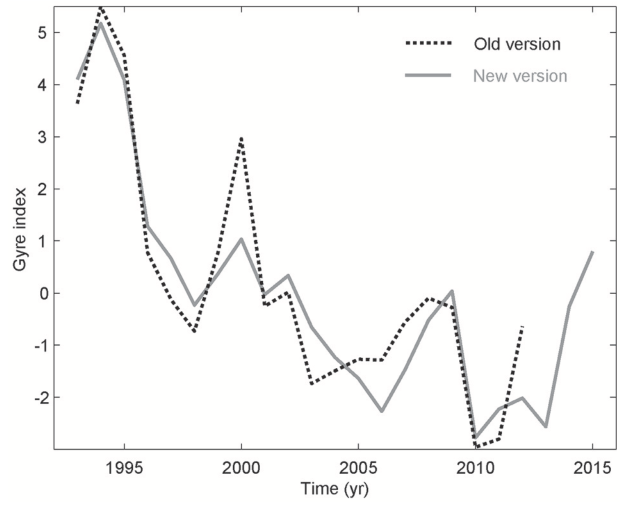

FIGURE 2 | Altimetry-based gyre indices, calculated from the new (gray) and the old AVISO data versions (dashed, Larsen et al., 2012), respectively.

Zooplankton Data on the Iceland Shelf

Zooplankton data were collected during late May and early June 1971–2013 at five stations along a transect extending from the coast and beyond the shelf edge south of Iceland (**Figure 1**). From 1970 to 1991, the samples were collected with a standard Hensen net (0.42 m^2 mouth area, 200 μm mesh size), whereas after that all the samples were collected using a WP2 net (0.25 m^2 mouth area, 200 μm mesh size). The volume of water filtered was measured with HydroBios flowmeters fitted in the mouth of the net. For the present analysis, data on zooplankton dry weight biomass standardized per m^3 averaged across all stations have been used. Until 2001, the volume of zooplankton samples was measured at sea and the dry weight calculated using a conversion factor from Matthews and Heimdal (1980). From 2002 onwards the samples were deep frozen at sea and dried and weighed on shore (Postel et al., 2000). The copepod *C. finmarchicus* usually constitutes the dominant component of mesozooplankton biomass in the samples (Astthorsson and Gislason, 1995).

Faroe Kittiwake Breeding Success

The kittiwake data are from the island Skúvoy (61°47′N and 6°51′W), which is one of the largest seabird colonies in the Faroe Islands. The west facing part of the island is a 5 km long steep seabird cliff, reaching a high of 394 m and holding ∼12,000 breeding pairs of kittiwakes in 2008 and 2009. The studied colony, Høvdin, is the northernmost colony on the island. It is about 200 m wide and 130 m high, and kittiwakes have been breeding here for generations. The number of nests fluctuates, but since 2001 the average number of nests has been 2,624 (1,149–4,525).

The counting unit is the number of chicks/nest late in the breeding season when most of the chicks are ready to fly. The start date of counting depends on when the chicks are large enough, and it is determined based on regular visits to the colony before start of the counting. The number is based on a maximum number of fledged chicks as some of the smaller chicks may not survive. Prior to 2000, subsamples at an average of 1,050 (200–1,736) nests were counted, but since 2001 all the nests and chicks have been counted. All the countings but one (in 1990), have been done by the same counter, so inter-counter differences do not impact the results.

The predation in the colony has been rather stable. There are no ground predators on the island like house mouse (*Mus musculus*), brown rat (*Rattus norvegicus*), and cat (*Felis catus*), which do populate many of the other islands. The most common predator of eggs, chicks, and adult kittiwakes is the great skua (*Stercorarius skua*), however, herring gull (*Larus argentatus*), great black-backed gull (*Larus marinus*), raven (*Corvus corax* *varius*), and crow (*Corvus corone cornix*) are also seen preying on the colony although in a lesser extent.

Therefore, the large fluctuation in chick production in the studied colony most likely reflect the adult kittiwake's ability to find food for their chicks. As these fluctuations occur simultaneously in most of the Faroese kittiwake colonies, it is a good proxy for the production in the total Faroese kittiwake population.

RESULTS

Recent Convection and Zooplankton Increase

The gyre index, and thus the *Frontal position* metric, increased markedly in 2014 and 2015 (**Figure 3A**). This reflects the increased convection in the Labrador Sea during winter 2013–2014, and an even deeper mixing during winter 2014–2015, which also involved the Irminger Sea (de Jong and de Steur, 2016; Yashayaev and Loder, 2016). The previously established link between the *Frontal position* and the zooplankton abundance on the south Iceland shelf still holds ($r = 0.70$, $p < 0.001$ for 1993–2015, c.f. **Figures 3A,B**), and the forecasted zooplankton increase during 2014 (Hátún et al., 2016) indeed did occur.

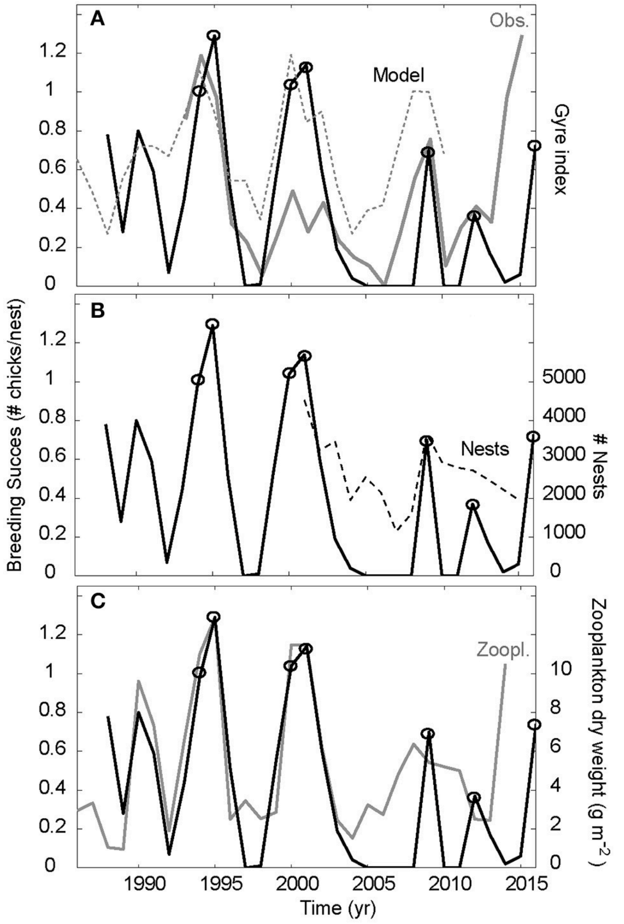

FIGURE 3 | Synchrony between east and west. The Faroe kittiwakes breeding success with full line in all three panels. This is compared to **(A)** the detrended observed (gray) and simulated (dashed) gyre index, **(B)** the number of nests in the colony (dashed) and **(C)** the south Iceland zooplankton abundances (gray). Cold periods with deep convection are associated peaks in the gyre index. The year with peaks in breeding success (1994–1995, 2000–2001, 2009, 2012, and 2016) are highlighted with open circles.

Western Food Resource and the Kittiwake Breeding Success

The breeding success of the Faroe kittiwakes is significantly correlated to the pre-breeding food abundance southwest of Iceland, proxied by the *Frontal position* ($r = 0.71$, $p < 0.001$ for 1993–2013, **Figure 3A**). The breeding success is highly variable, and the peaks in 1994–1995, 2000–2001, 2009, and 2012 are all associated with deep convection events. The intensified convection during the winters 2013–2015, and the associated increased *Frontal position* value did not, however, result in the expected increased breeding success. The reaction came in 2016, with a great increase in breeding success. A lag of 1.5 years between deep winter convection and increased chick production, like the event in 2008–2009 (**Figure 3A**), can be expected (Hátún et al., 2016), but not 2.5 years. When 2014 and 2015 are included, the *Frontal position*—breeding success correlation drops to 0.58 (which is still significant on a 0.5% level).

The co-variability between the south Iceland zooplankton record and the Faroe kittiwake breeding success was also tight until the years 2005–2008 when no fledlings were produced (**Figure 3B**). The linkage is much less clear thereafter, but despite the misfit during 2014 the overall correlation is still significant ($r = 0.75$, $p < 0.001$ for 1988–2014).

DISCUSSION

In migratory birds, environmental conditions in both breeding and non-breeding areas may affect breeding success and hence be significant drivers of demographic processes. The kittiwakes occupy the western central SPG during the mid-winter non-breeding season where food is available on the surface (Frederiksen et al., 2012). The gyre index represents the size and circulation strength of the SPG (Hátún et al., 2005), which in turn is inherently associated with the winter convection. When convection is strong, the abundance of *C. finmarchicus* increases within the SPG (Hátún et al., 2016), and here we show that these years also coincide with increased kittiwake breeding success (**Figure 3**). This supports previous suggestions that the dynamics of the SPG will impact seabirds in the NE Atlantic, although this inference is still qualitative (Descamps et al., 2013, 2017, in press; Fluhr et al., 2017).

A stronger tie between east and west appears from that fact that the kittiwakes can make a second westward exodus, after having entered the colonies along northwest European shores during spring (Bogdanova et al., 2011). Without a description of the main oceanographic structures, it could not be explained why the birds follow the south Iceland slope on their strikingly parallel westward route. The food production on the south Iceland shelf is much higher than in the adjacent Iceland Basin, which becomes a nutrient depleted "desert" during summer, avoided by e.g., the westward food migrating mackerel stock (Pacariz et al., 2016). Having circumvented the Iceland Basin, the kittiwakes settle in a region between 29° and 36°W (Bogdanova et al., 2011), which is on and just west of the Reykjanes Ridge (**Figure 1**). This is the location of the subarctic front, which is one of the most productive regions in the North Atlantic (Pedchenko, 2005; Hátún et al., 2016). The metrics presented by Hátún et al. (2016) connect the mixed layer depth and the *C. finmarchicus* abundance in the Irminger Sea, lateral shifts of the subarctic front, and the zooplankton abundance on the south Iceland shelf. Here, we show that the Faroe kittiwake breeding success co-varies closely with the south Iceland zooplankton abundance, the position of the subarctic front and the *C. finmarchicus* concentrations within the SPG (not shown, see Hátún et al., 2016). Additionally, since the pre-breeding round-trip takes place as late as March, a carry-over effect to the subsequent summer is likely.

Understanding how the marine climate in the SPG regulates the food production and availability, thus likely holds a common key to understanding the demography of several seabird populations. Furthermore, the potential predictability of the marine climate within the SPG could be utilized to project the general conditions for the seabirds in the near-future. The strongest predictability is likely associated with the highly variable depth of winter convection in the Labrador-Irminger Seas (Hátún et al., 2016). A very strong winter might boost biological production the following season ($\sim$0.5 year horizon), and might even precondition the subsequent winter's convection ($\sim$1.5 year horizon). The more gradual hydrographic changes in the subpolar Atlantic ascribed to shifts in horizontal gyre circulations (Hátún et al., 2005; Lohmann et al., 2009a) or the strength of the Atlantic Meridional Overturning Circulation (AMOC) (Lohmann et al., 2009b; Robson et al., 2012) has received more attention in the literature, than the more erratic convection-related signal. The subpolar Atlantic is suggested to hold particularly strong decadal-scale prediction potential (Matei et al., 2012a), likely associated with the gyre and/or AMOC circulation dynamics (Matei et al., 2012b). A remaining question is if the strong convection signal in the northwestern Atlantic will disrupt the decadal-scale predictability there—e.g., a strong winter will reset a large part of the "memory" in the horizontally advected water masses.

Strong winter cooling over the Labrador-Irminger Seas in winters 2013–2015 resulted in exceptional deep convection (de Jong and de Steur, 2016; Yashayaev and Loder, 2016) and induced a large "cold blob," which was widely discussed in the media during 2015. As suggested by Hátún et al. (2016), this should have led to increased production in several ecosystem components during 2014, 2015, and maybe even 2016. There was a marked increase in the south Iceland zooplankton abundance (**Figure 3B**), the breeding success of the Atlantic puffins (*Fratercula arctica*) and the Arctic terns (*Sterna paradisaea*) in Faroese colonies (Unpublished data, Bergur Olsen), as well as the kittiwake breeding success in 16 Shetland colonies during 2014 (Pers. Comm. Martin Heubeck). The poor breeding performance of the Faroe kittiwakes in 2014 and 2015 therefore at first appears as a conundrum.

One issue which could disturb predictability is that the general intensity of winter convection has weakened over the last 25 years (Hátún et al., 2016), and the nutrient concentrations over the entire subpolar North Atlantic have declined markedly during the same period (Hátún et al., Submitted). This trend is likely to impact the phytoplankton community composition and thus higher trophic levels and food quality over large spatial scales. No fledged chicks were observed in 2005–2008 at the studied Faroese colony (**Figure 3**) and a similar breeding failure was also observed in Britain between 2001 and 2008 (Coulson, 2011). One could thus speculate if the general food productivity in both the non-breeding and breeding waters has reached critically low levels for sustaining the kittiwake population. If this is correct, it may disturb the demographic processes and thus the identified predictability of the breeding succes.

Summer Feeding Conditions on the Faroe Shelf

Kittiwake chicks are fledged late in July and early August and crave food during this period. After just a few days of food shortage, chicks will starve, and die (Coulson, 2011). The local food availability is therefore also very important. The O-group from the local stock of sandeel (*Ammodytes marinus*) is a principal food item for the kittiwake chicks (Eliasen, 2013). Sandeel lay demersal eggs between November and January, and their planktonic larvae are present in the water column from late January to May (Eliasen, 2013). Sandeel prey on younger stages and eggs of zooplankton and obtain as much energy as fast as possible (refs in Eliasen, 2013), thereby becoming a favorable prey to numerous higher trophic level species.

It has previously been suggested, that variable influx of *C. finmarchicus* from core gyre regions to adjacent shelves regions around the subpolar Atlantic might regulate the on-shelf biomass of this species (Gislason and Astthorsson, 2000; Harms et al., 2000; Sundby, 2000) and intermittent northward expansions of the SPG do result in higher zooplankton abundances on the south Iceland shelf (Hátún et al., 2016). We here tentatively suggest that SPG-related processes might also regulate the influx of ecologically important zooplankton products onto the Faroe shelf. Additional work is required to investigate this suggestion.

The on-shelf primary production must, however, also be important, which is supported by the positive correlation between the Faroe shelf primary production and the abundance of sandeel (Eliasen et al., 2011). The early phase of the on-shelf spring bloom, which mainly consists of large fast-growing diatoms, becomes silicate limited during late May-early June (Eliasen et al., in press). Furthermore, winters with deep convection increase the pre-bloom silicate content in the North Atlantic Ocean (Hátún et al., submitted), and all years with a strong gyre (high *Frontal position* index, 1994–1995, 2000–2001, and 2008–2009, **Figure 3A**) coincide with elevated Faroe shelf primary production (see Eliasen et al., 2011). The strong-gyre years 2014 and 2015 also resulted in very high chlorophyll concentrations on the shelf, but the blooms were much delayed compared to the previous years (Eliasen et al., 2017). Productive years have typically been characterized by high chlorophyll concentrations in May, but the blooms in 2014 and 2015 were initiated during mid-June and early July, respectively, and such late blooms have not been observed before.

The Atlantic puffins and the Arctic terns were apparently able to adapt to this marked shift in bloom timing (phenology), and were able to produce fledlings in 2014 and 2015 (Pers. Comm. Bergur Olsen). The kittiwakes are less phenologically flexible. They build their nests and decide whether or not to start breeding during May, and collectively lay their eggs during late May (Coulson, 2011). An investigation of daily pictures of the kittiwake colony reveals increased nest building and numbers of chicks during both 2014 and 2015 (not shown), but most of the chicks suddenly died during their most food craving period these years. We interpret this as sign of good conditions during the pre-breeding phase, but that local food shortage, possibly caused by the anomalously late blooms, acted as a severe "bottle neck." The causes underlying the recent delay of the spring bloom are not well-understood and require further attention.

CONCLUSIONS

In conclusion, the dynamics of the North Atlantic subpolar gyre likely impacts the feeding conditions for the black-legged kittiwakes (*Rissa tridactyla*) in the northwest Atlantic overwintering regions during the non-breeding and pre-breeding seasons. A winter with deep convection and an intensifying gyre increases the zooplankton food availability and improves the physical condition of the birds, which in turn could have a positive carry-over effect on the breeding success the subsequent summer. Gyre-related oceanic dynamics could, furthermore, influence the Faroe shelf food availability during early summer through onto-shelf influxes of oceanic zooplankton species *Calanus finmarchicus* and their eggs nauplii, and/or nutrients which can boost the on-shelf primary production. The promising predictability of the marine climate adjacent to the subpolar gyre could thus carry over into the general production of seabird populations surrounding the northern North Atlantic Ocean. The less predictable conditions around the nesting sites of individual populations might, however, act as a "bottle-neck" for making realistic forecasts of the kittiwake breeding success. Over the next century, climate models predict global declines in nutrients and thus in primary production, due to shallower winter mixing, with a particularly strong imprint on the North Atlantic (Groeger et al., 2013). If correct, this would change seabird life in the subpolar regions from what is known today.

ETHICS STATEMENT

Authors declare that for this study no ethics approval was required as per institutional and national guidelines. Data for this study are based on visual observations of birds in their natural environment. No animal experiments were performed.

AUTHOR CONTRIBUTIONS

HH has composed the story told, worked up the altimetry data, and led the writing process. BO produced the kittiwake data. He has initiated and maintained the counting unit at Høvdin all years. BO has also helped in writing and approving of the document. SP has participated in developing the underlying idea, and in the writing process.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: http://journal.frontiersin.org/article/10.3389/fmars.2017.00123/full#supplementary-material

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frontiers in Marine Science

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The Northeast Greenland Shelf as a Potential Habitat for the Northeast Arctic Cod

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Observations (1978–1991) of distributions of pelagic juvenile Northeast Arctic cod (*Gadus morhua* L.) show that up to 1/3 of the year class are dispersed off the continental shelf and into the deep Norwegian Sea while on the way from the spring-spawning areas along the Norwegian coast to the autumn-settlement areas in the Barents Sea. The fate of this variable fraction of pelagic juveniles off-shelf has been an open question ever since Johan Hjort's (1914) seminal work. We have examined both the mechanisms causing offspring off-shelf transport, and their subsequent destiny using an individual-based biophysical model applied to quantify growth and dispersal. Our results show, consistently with the observations, that total off-shelf transport is highly variable between years and may be up to 27.4%. Offspring from spawning grounds around Lofoten have a higher chance of being displaced off the shelf. The off-shelf transport is dominated by episodic events where frequencies and dates vary between years. Northeasterly wind conditions over a 3–7-day period prior to the off-shelf events are a good proxy for dispersal of offspring off the shelf. Offspring transported into the open ocean are on average carried along three following routes: back onto the adjacent eastern shelves and into the Barents Sea (36.9%), recirculating within the Lofoten Basin (60.7%), or drifting northwest to the northeast Greenland shelf (2.4%). For the latter fraction the transport may exceed 12% depending on year. Recent investigations have discovered distributions of young cod on the northeast Greenland shelf indicating that conditions may support survival for Northeast Arctic cod offspring.

Keywords: connectivity, pelagic juvenile, cross-shelf, spawning ground, nursery ground, forecast, northeast arctic cod, recruitment

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INTRODUCTION

The Northeast Arctic (NEA) cod, the historically largest stock of Atlantic cod (*Gadus morhua* L.) (Yaragina et al., 2011), has its feeding area in the Barents Sea and undertakes spawning migration southwards along the Norwegian coast during winter, partly far outside its feeding habitat (Bergstad et al., 1987). After spawning in March and April (Ellertsen et al., 1989) from Møre (62° N) to the Finnmark coast (71° N) (Sundby and Nakken, 2008) the offspring returns to the Barents Sea by pelagic drift in the Norwegian Coastal Current (NCC) on the shelf and in part in the more offshore Norwegian Atlantic Slope Current (NASC) that runs parallel to the NCC (Vikebø et al., 2005). En route toward the Barents Sea, they drift in the upper mixed layer where shifting winds due to passing weather systems significantly affects strength and direction of the flow, making them vulnerable to the variable meteorological conditions (Vikebø et al., 2007). By October, when the pelagic juveniles have reached a typical length of more than 8 cm, they gradually migrate out of the pelagic layer (Yaragina et al., 2011) and become associated with depths closer to the bottom, which in the Barents Sea ranges from 150 to more than 350 m depth. From that stage, they are distributed over their natural habitat at the shelf region in the Barents Sea (**Figure 1**).

Similarly, cod stocks across the North Atlantic have their habitats confined to the continental shelves fringing the North Atlantic proper (Sundby, 2000). The pelagic eggs, larvae and free-drifting early juveniles that happen to become advected by variable currents out over the deep ocean have generally been considered lost for recruitment to the stock (e.g., Werner et al., 1993, 1997). This idea, i.e., that drift of pelagic offspring to unfavorable regions might cause recruitment loss, was already suggested by Hjort (1914), and later defined by Sinclair et al. (1985) as Hjort's second recruitment hypothesis.

Based on the post-larval (hereafter denoted pelagic juvenile) surveys conducted by the Institute of Marine Research (IMR) during the period 1977–1991 (sampled in June/July at an average age of ∼70 days) it became evident that a variable portion, and in some years, a quite considerable one, of the new year class of cod was, indeed, found off the shelf in the Norwegian Sea (Bjørke and Sundby, 1987; Sundby et al., 1989). In the year 1988, which had the largest number of observed larvae offshore among these years, 35% of the year class of cod as pelagic juveniles was found in the deep-sea region off the shelf to the west of the NASC (Suthers and Sundby, 1993). Moreover, analysis of length, condition factor, and age (based on counts of daily otolith rings) discovered that this "stray" portion of the 1988 year-class consisted of larger individuals in better condition than the portion of the year class than was "on the right track" toward the Barents Sea. Suthers and Sundby (1993) ascribed this to higher accumulated ambient temperature, and hypothesized that higher zooplankton food abundances in the Norwegian Sea could be a second factor causing the increased growth as the Norwegian Sea proper is the core region for abundance of the main prey species *Calanus finmarchicus* (Sundby, 2000).

Similar to the off-shelf observations from pelagic juvenile surveys, the subsequent 0-group stage, observed during August and September by IMR-surveys, have years when the 0-group is partly found to the west of the shelf edge outside the natural habitat in the Barents Sea, apparently also in high concentrations (see maps of distributions in Eriksen and Prozorkevich, 2011). However, since the 0-group survey only covers a small area outside the western fringe of the Barents Sea it is not possible to quantify how large portion of the year class that exists outside the natural habitat at this stage.

Although such considerable portions of pelagic juvenile cod have repeatedly been observed off the prevailing current paths to the Barents Sea habitat, the destinies of these individuals have never been explored in further detail, most probably because the prevailing view has been dominated by Hjort's second recruitment hypothesis which posits that they might simply be lost for recruitment. However, for the NEA cod there are alternative scenarios. Johan Hjort (1914) himself pointed to one such alternative following his recruitment hypotheses: "*During the first cruise of the "Michael Sars" in the Norwegian Sea, I encountered great numbers of young cod fry drifting in the water above the great depression in this region. It is possible that many individuals perish during such drift movements; nothing is, however, definitely known as to this. It would be especially desirable to ascertain the extent of such movement, and how far the young fry is able to return, of their own volition, to such localities as offer favorable conditions for their further growth.*" In other words, as a second alternative, if the pelagic juveniles in this western region attain a systematic and sustained swimming behavior toward the east they might return to the water masses that flow into the Barents Sea (e.g., Staaterman and Paris, 2013).

A third alternative is that the pelagic juveniles are successfully transported with the currents either back onto the eastern shelves or onto the large northeastern Greenland shelf where they might settle and grow up as a geographically separated component of NEA cod. Independent of this reasoning, a traditional folklore opinion in some Norwegian coastal fishing communities has been that Greenland cod occasionally spawn in Norwegian waters. This opinion might possibly be based on fishermen visiting Greenland waters observing specific morphometric (phenotypic) characteristics of the cod growing up in Greenland waters that they recognize in Norwegian spawning sites. In a possible support, of considering the northeastern Greenland shelf as being a distant part of NEA cod habitat, are recent findings of adult cod in the area (Christiansen et al., 2016), see **Figure 1**.

In this current study, we address the impacts of advection and dispersion of the offspring from the spawning area to the areas of subsequent settlement about half a year later. More specifically, we focus on the third alternative and address four main research questions related to the above outline by applying a state-of-the-art biophysical model coupled with *in-situ* data. (1) What fraction of the NEA cod spawned along the Norwegian coast is advected westward off the continental shelf, and how large is the variability in this off-shelf drift within and between years? (2) Which spawning grounds have the highest probability for off-shelf drift of cod offspring? (3) What are the mechanisms and forcing causing the off-shelf transport? (4) Where do the observed off-shelf pelagic juveniles finally end up, and what is the relative number of individuals following the alternative transport routes?

MATERIALS AND METHODS

Firstly, we modeled transport for the years 1978–2015 with particles initiated as eggs at 10 well-known spawning sites for NEA cod along the Norwegian coast (**Figure 1**; Sundby and Nakken, 2008) investigating questions 1–3. Particles are being transported by an individual-based particle tracking model (IBM) utilizing daily 3D oceanic currents from an ocean model archive resulting from simulations with the Regional Ocean Modeling System (ROMS) model[1] (Shchepetkin and McWilliams, 2005; Lien et al., 2014, 2016). Since transportation off the shelf and shelf circulation above complex topography might be significantly influenced by small-scale dynamics, this part of the study was done with two different ocean model

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[1] www.myroms.org

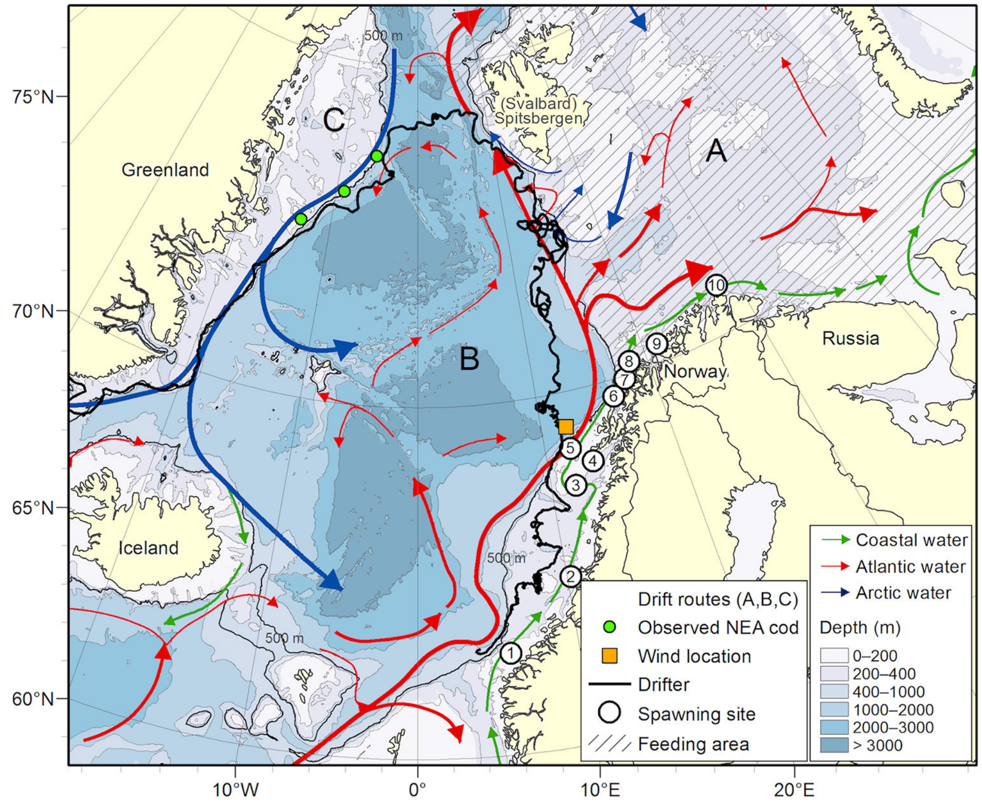

FIGURE 1 | Circles with numbers indicate the 10 spawning grounds where particles representing eggs are initiated. The orange square indicates the location from where winds are correlated with off-shelf transport of particles and ocean currents perpendicular to the shelf edge. The thin black line shows the 500 m isobath (here; the shelf edge). The thick black trajectory shows the 2009 drifter with arrival at the Greenland shelf as commented in section Connectivity Studies on Atlantic Cod. Locations of observed cod on Greenland are marked with green dots (taken from Christiansen et al., 2016). Currents are marked as NCC (green arrow), AW/NASC (red arrow), and Arctic water (blue arrow). Dashed area is the average long-term spatial extent of the NEA cod's feeding area, and modeled distribution areas (drift routes) are indicated with A, B, and C, see section Transport Pattern of Pelagic Juveniles Off the Shelf Edge for explanation.

archives; both the daily mean 3D circulation archive, and an hourly mean 3D archive with an even finer grid resolution.

The weighted (see section Individual-Based Model) model distributions from known spawning grounds were evaluated against observed pelagic juveniles (see section Pelagic Juvenile Observations). For each observation location, the weighted model distribution of pelagic juveniles was summarized across the nearest four by four grid cells, still less than the distance between observations, and compared to the observations. A match is accomplished when both or neither observed and modeled pelagic juveniles are present. However, results must be interpreted with care as the biophysical model do not include natural mortality. Furthermore, the transportation of NEA cod juveniles off the shelf was correlated with NORA10 wind (see section Ocean Model and Atmospheric Forcing). In addition, we correlated the wind forcing against the modeled current component perpendicular to the shelf edge at different depth intervals in order to evaluate the potential for transportation off the shelf.

Secondly, investigating question 4, we initialized particles according to the annual observed distributions of pelagic juvenile NEA cod off the continental shelf and followed their free pelagic drift toward nursery grounds for years with observations (1978–1991). The aim of this exercise was to investigate alternative drifts routes and new potential nursery habitats.

Ocean Model

The main ROMS model applications used here is the 4 by 4 km resolved horizontal grid covering the Nordic Seas and the Barents Sea for the period 1958–2015 with 32 vertical sigma layers forced by the Simple Ocean Data Assimilation data set (SODA; Carton and Giese, 2008) on the lateral boundaries and regional downscaled European Centre for Medium-Range Weather Forecasts (ECMWF) re-analysis (ERA-40; Uppala et al., 2005) combined with previous prognostic runs to a grid with 10 by 10 km resolution (hereafter denoted NORA10) at the sea surface (hereafter denoted SVIM, see Lien et al., 2014). In the vertical, the spatio-temporal eddy diffusivity terms from the local turbulence closure scheme were used (a Generic Length Scale mixing scheme with k-ω setup) in ROMS (Umlauf and Burchard, 2003; Umlauf et al., 2003). See Warner et al. (2005) for a thorough evaluation comparing different mixing schemes.

The ocean model archive, SVIM, has proven to reproduce many observed oceanographic features in the area (Lien et al., 2014, 2016) motivating its use for investigating intra- and inter-annual variations in drift trajectories from observed spawning grounds. In addition, we have used an 800 by 800 m horizontal resolution application with 35 sigma layers covering the entire Norwegian coast from the Skagerrak and the northern North Sea to the Barents Sea extending from the fjords out into the deep basin off the shelf edge (Albretsen et al., 2011, hereafter denoted the NorKyst800). The NorKyst800 hindcast covers the period 2005–2015 and has lateral boundary forcing from SVIM.

Atmospheric Forcing

Atmospheric forcing for the two ROMS applications were taken from NORA10 (Reistad et al., 2011), providing 6-hourly winds, temperature, pressure, humidity, cloud cover, and accumulated precipitation, while radiative forcing is computed internally in ROMS.

Individual-Based Model

Egg, larvae and pelagic juvenile drift are reproduced by particles advected by simulated currents in the IBM model "Lagrangian Diffusion Model" (Ådlandsvik and Sundby, 1994). The "Lagrangian Diffusion Model" is a simple particle-tracking model with a 4th order Runge-Kutta advection scheme and a sub-module handling individual physiological and behavioral responses to environmental forcing. It implies that the variable physical environment is included in the biological sub-module, but the variability in prey and predator field is uncertain and not known to a sufficient degree in relevant spatial and temporal scales to estimate the mortality and, hence, not included. Due to the horizontal resolution of the SVIM-archive (4 km), mesoscale vorticity is underestimated (Isachsen et al., 2012). Therefore, a horizontal eddy diffusive term (with turbulent diffusion coefficient $K = 1\ \mathrm{m}^2\ \mathrm{s}^{-1}$, chosen after testing different values) is included to compensate for the lack of resolving mesoscale processes. The same was included when using the NorKyst800 as forcing for particle dispersal. Vertical distribution of eggs is based on individual egg size and density (Sundby, 1983), modeled ocean densities and levels of turbulence in the water column at the individual time-varying location of each egg (based on Thygesen and Ådlandsvik, 2007; utilized in e.g., Opdal et al., 2011; Röhrs et al., 2014). The larval and juvenile growth function is taken from Folkvord (2005) and based on laboratory experiments for a range of temperatures under constant satiated feeding of the offspring. Vertical migration is included as a diel migration between upper and lower limits depending on light conditions and swimming capability (5–30 m during night and 10–40 m during day, with night defined as light levels below 1.0 micromole photons per $\mathrm{m}^2\mathrm{s}^{-1}$, see Opdal et al., 2011). A well-known challenge in Lagrangian particle-tracking models is the handling of particles advected near land. We tested different land-handling schemes to avoid abnormal stranding along the irregular coast. We decided to implement a solution where particles were only moved in the direction of the offshore velocity component if they were to be moved onto land in the next time step. The IBM was run with two different setups, one with particles initiated at well-known spawning grounds along the Norwegian coast for the years 1978–2015, and another with particles initiated according to observed offshore pelagic juveniles for the years 1978–1991. For both setups, the particles are initiated at 5 m depth.

When initiating eggs at the spawning grounds, we released 200 particles at each site every day during the known spawning period from March 1st until April 30th and followed each particle for 200 days to analyze dispersal. The model results were adjusted by weighting the importance of each particle to reflect a Gaussian spawning intensity in time with peak spawning at April 1st and by considering the yearly geographically distribution across spawning grounds using observations from egg surveys (Ellertsen et al., 1987; Sundby and Bratland, 1987; Sjølingstad, 2007; Sundby and Nakken, 2008) and observations on abundance of spawning NEA cod (see the supplementary section for complete references 1978–2004, and data from IMR's *spawning migration cruises* 2005–2015 held at IMR fish database). The particles are initiated as eggs and continue as hatched larvae after about 2–3 weeks depending on ambient temperatures.

To initiate the model with the observed distributions of pelagic juveniles we released 500 particles at each offshore station with observed NEA cod at the mid-date of the year-specific survey (**Table 1**) and followed each particle for 120 days until November when NEA cod reach the stage of settling to the bottom in the Barents Sea, i.e., their transition from a pelagic to a demersal habitat (Ottersen et al., 2014).

Pelagic Juvenile Observations

During the years 1977–1991 scientific surveys[2] covered year-specific observational grids towing trawls of various sizes at a speed of 2–3 knots (Bjørke and Sundby, 1984, 1987; Suthers and Sundby, 1993, 1996). The number of stations, geographic coverage and duration of the surveys varied between years (**Table 1**). The median spatial resolution between each station was 26 km. The surveys lasted from 16 to 49 days within the period June 18th to August 5th, with mid-date for offshore stations between June 28th and July 26th. The sampling gear used started with a pelagic meshed midwater trawl with an opening of 4 × 10 m in 1977, 18 × 18 m from 1978 until 1984, and finally a 29 × 29 m trawl opening from 1985 and onwards. Here, we have omitted the first year, 1977, since this is considered a test survey where the trawl used was too small. All trawls had diminishing mesh sizes toward the cod end and a 4 m long net with a mesh size of 4 mm (stretched) at the inner part of the cod end. During 1978 through 1984 two hauls were made at each station; one haul with the headline at 40 and 20 m depth, and a towing time of 15 min in each depth interval, and the second haul at the surface with five big floats on the headline and a towing time of 30 min. From 1985 through 1991 the depths were the same as the previous years, but the towing time at each depth interval was halved (Bjørke and Sundby, 1987).

General Circulation Features

The circulation features of the northeastern North Atlantic are governed by the two-branched northward flow of warm and salty Atlantic Water (AW) across the Faeroe-Shetland Channel (Hansen and Østerhus, 2007; Eldevik et al., 2009) along the

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[2] http://www.emodnet-biology.eu/data-catalog?module=dataset&dasid=4443

TABLE 1 | NEA cod pelagic juvenile survey details between 1978 and 1991 and corresponding modeling.

Observation information			Simulation information				
Year	**Number of stations in total/offshore with/offshore without presence of juveniles**	**Observed mean length in total/off-shelf [mm]**	**Start date [dd.mm]**	**Particles released**	**Area A [%]**	**Area B [%]**	**Area C [%]**
1978	120/22/34	28.7/28.8	09.07	11,000	24.7	75.3	0.0
1979	160/15/45	23.0/20.9	29.06	7,500	52.0	48.0	0.0
1980	127/1/35	20.6/22.0	28.06	500	99.0	1.0	0.0
1981	193/31/35	24.5/27.5	11.07	15,500	24.0	75.2	1.9
1982	155/8/7	27.2/33.3	21.07	4,000	35.8	63.6	0.6
1983	100/5/5	32.2/44.9	11.07	2,500	32.4	60.3	7.3
1984	145/29/3	34.4/40.0	14.07	14,500	41.4	56.6	1.9
1985	129/30/10	24.3/26.8	08.07	15,000	30.2	66.5	3.3
1986	197/16/30	27.0/29.3	13.07	8,000	21.6	66.3	12.1
1987	217/48/23	27.8/30.0	16.07	24,000	30.1	69.0	0.8
1988	242/41/57	34.8/38.5	17.07	20,500	22.1	77.8	0.1
1989	242/21/71	34.1/34.7	14.07	10,500	37.6	59.7	3.0
1990	111/35/8	47.3/57.7	26.07	17,500	35.8	64.2	0.0
1991	163/26/32	36.0/41.1	12.07	13,000	30.8	66.9	2.3

Left side: Total number of survey stations per year, number of stations offshore with and without observed presence of cod juveniles, and mean juvenile length offshore compared to all observations. Right side: Start-date for simulations, number of particles released (500 times per offshore station with observed pelagic juveniles), and the spatial distribution of juveniles per November 1st in the three areas (A–C), see explanation in text.

eastern continental slope, the NASC, and a second branch farther off the shelf. Eddy shedding brings AW off the upper shelf slope and into the Lofoten Basin (Rossby et al., 2009; Søiland et al., 2016) where it either recirculates or flows along the Mohn Ridge toward the Jan Mayen area (Isachsen and Nøst, 2012). Farther north the AW bifurcates at the entrance to the Barents Sea with one branch flowing to the northwest of Svalbard and the other entering the Barents Sea. Northwest of Svalbard AW either carries on northeast and east along the shelf north of Svalbard or eddy shedding brings it out into the Fram Strait and southwest along the Greenland Shelf (Hattermann et al., 2016). **Figure 1** shows the geographical extent of our study area including the main circulation features.

Predominant Wind Directions and Shelf Edge Orientation

The focus area of the present study is between 67.0 and 70.0° N, where the continental shelf is largely oriented to the northeast (42° from east). Therefore, wind sectors coming from the northerly-easterly/southerly-westerly (NE/SW), within the directional sector of ± 45° of the shelf edge orientation, gives opposite wind sectors against/with the predominating currents. For NE wind, it has the potential to create instability and/or Ekman transport off the shelf edge. We have defined off-shelf areas to include waters deeper than the 500-meter isobath (here named the "shelf edge"). To investigate this further, winds are extracted from NORA10 at a point location at the shelf edge outside Lofoten (69° N, 12° E, see **Figure 1**). Directions of wind with strength <5 m/s are not considered anticipating that such wind is insufficient to cause significant perturbations to the predominant along-shelf currents. The main period chosen is March through July since by then about 70% of the cod offspring have passed the area of interest (by then) according to the model mean.

RESULTS

Origin of the Pelagic Juveniles Off the Shelf Edge

Figure 2A shows the fractions of particles transported off the shelf by mid-September (based on SVIM) from each of the 10 spawning areas for the years 1978–2015. The mean off-shelf transport for these years is 11.5% with a minimum in 2002, and a maximum in 2008. **Figure 2B** is similar to **Figure 2A**, but here the particles are weighted according to observed spawning intensity in time and space (inter- and intra-annual, see section Individual-based Model). The mean off-shelf transport of NEA cod offspring then increases to 14.7%. The inter-annual variability also increases, reflecting the high weights added to the offspring originating from the Lofoten region (spawning sites 3–5 in **Figure 1**). In summary, **Figure 2A** illustrates the potential off-shelf transport from each spawning area, while **Figure 2B** shows the off-shelf transport based on the actual year-specific weighted spawning intensity from each spawning area. Increasing horizontal resolution in the ocean model (from SVIM to NorKyst800) for the years 2005–2015 resulted in a decreased mean off-shelf transport from 11.5 to 5.6%. However, the variations between the years have similar features between NorKyst800 and SVIM, with highest off-shelf transport in 2008 (2012) without (with) adding weights to the spawning grounds. According to Suthers and Sundby (1993), the fraction of pelagic juveniles found off shelf in mid-July 1988 was

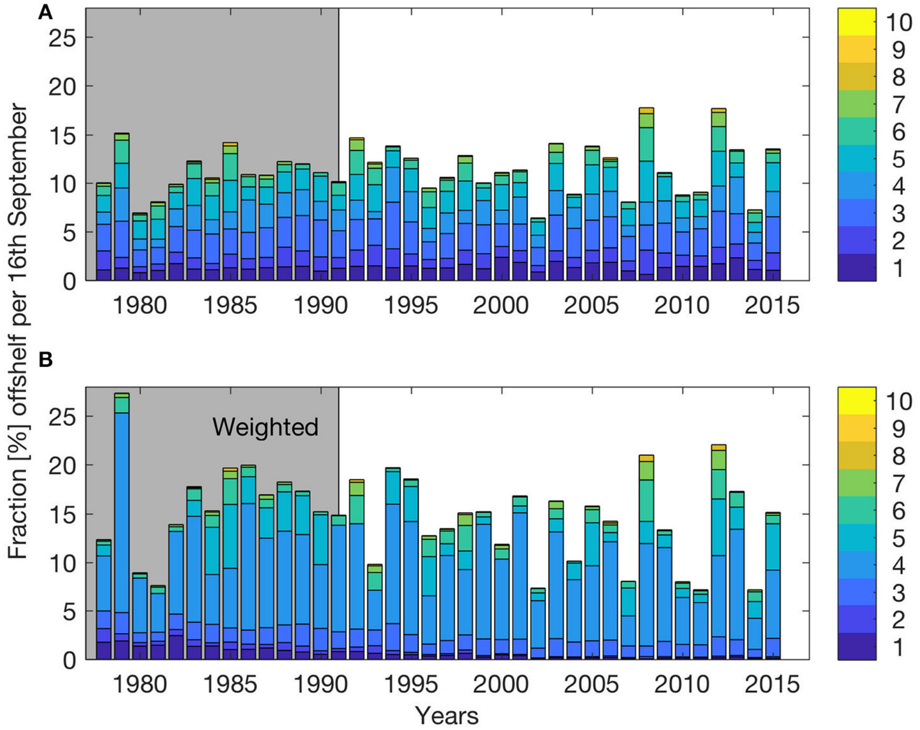

FIGURE 2 | Fraction (%) of particles initiated at the 10 spawning grounds along the Norwegian coast that are transported off the shelf edge (>500 m) per September 16th for the years 1978–2015. Particles are released between March 1st and April 31st. **(B)** is identical with **(A)** except that particles are weighting according to observed spawning intensity in space and time. Each bar differentiates between particles originating from the different spawning grounds, see colorbar and **Figure 1**. Gray shading indicates years with available pelagic juvenile observations.

35%. From our weighted simulations, the 1988 off-shelf transport was estimated to be 16.7%, about half of what was calculated from field observations, but close to the simulated average in our simulations. When averaged over all years, **Table 2** shows that the weighted model distributions of pelagic juveniles compare with observations in 62.4% of the observational stations, varying yearly between 40 and 79%.

Mechanisms Causing Off-Shelf Transport

Here, we propose two major causes of off-shelf flows; (1) mesoscale eddies related to baroclinic instability of the along-shelf flow, and (2) a larger-scale interior Ekman transport related to wind forcing (Brink, 2016). Since we have used either a model with horizontal resolution of 4 by 4 km, not properly resolving mesoscale variability (Isachsen et al., 2012), or a finer-resolved grid where the lateral boundary off shelf is close to the shelf edge, we focus on the effects of periodic wind forcing.

Figure 3 shows the number of particles (from non-weighted spawning grounds) displaced off the shelf edge per day for three sample years (1987–1989) between March 1st and July 31st. Here we have investigated the non-weighted model results since the focus is on understanding the physical forcing. The time series show that off-shelf transport is dominated by episodic events and that frequencies and timing varies significantly between years. In the area between 67 and 70° N (black line in **Figure 3**), 1987 has two main events (one late March and one mid-June; **Figure 3A**), 1988 has several events between late April to mid-June with a maximum at May 20th (**Figure 3B**), while in 1989 there are several small events from May to August (**Figure 3C**).

It seems that changing wind directions have a major impact on off-shelf transport of eggs, larvae and juveniles. Having identified off-shelf events (**Figure 3**), we correlated these events in the area between 67 and 70° N with the occurrence of two opposite wind sectors (the NE and SW sectors as described in section Predominant Wind Directions and Shelf Edge Orientation) for the period between March 1st and July 31st. Events are defined as days when the number of particles crossing the shelf edge is higher than one standard deviation of the variability for the year-specific period (see **Figure 3**). **Figure 4** shows the correlation between the frequency of such events and the NE and SW winds. There is a significant ($p = 0.003$) positive (negative) correlation with NE (SW) wind sector of $R^2 = 0.22$ (0.23).

A similar procedure is done correlating the frequency of winds directly against the modeled ocean currents at different depths. The correlation between NE (SW) wind sector and the current component perpendicular to the shelf edge (at the 500 m isobath), when the current component is above one standard deviation for the year-specific period, is $R^2 = 0.67$ (0.45) with significance for the surface current (**Table 3**). Corresponding correlations for currents in the depth intervals 5–10 m and 5–40 m are $R^2 = 0.48$ (0.28) and $R^2 = 0.20$ (0.06, though not significant), respectively. These depths are relevant because

TABLE 2 | Coinciding presence or absence of pelagic juveniles in modeled and observed data at the year-specific observation locations.

Year [19-]	78	79	80	81	82	83	84	85	86	87	88	89	90	91	Mean
Match [%]	71	58	64	68	53	40	72	73	50	49	57	75	65	79	62.4

Match (%) between the weighted model distributions and observations occur if both show presence or absence of pelagic juveniles within an area of four grid cells.

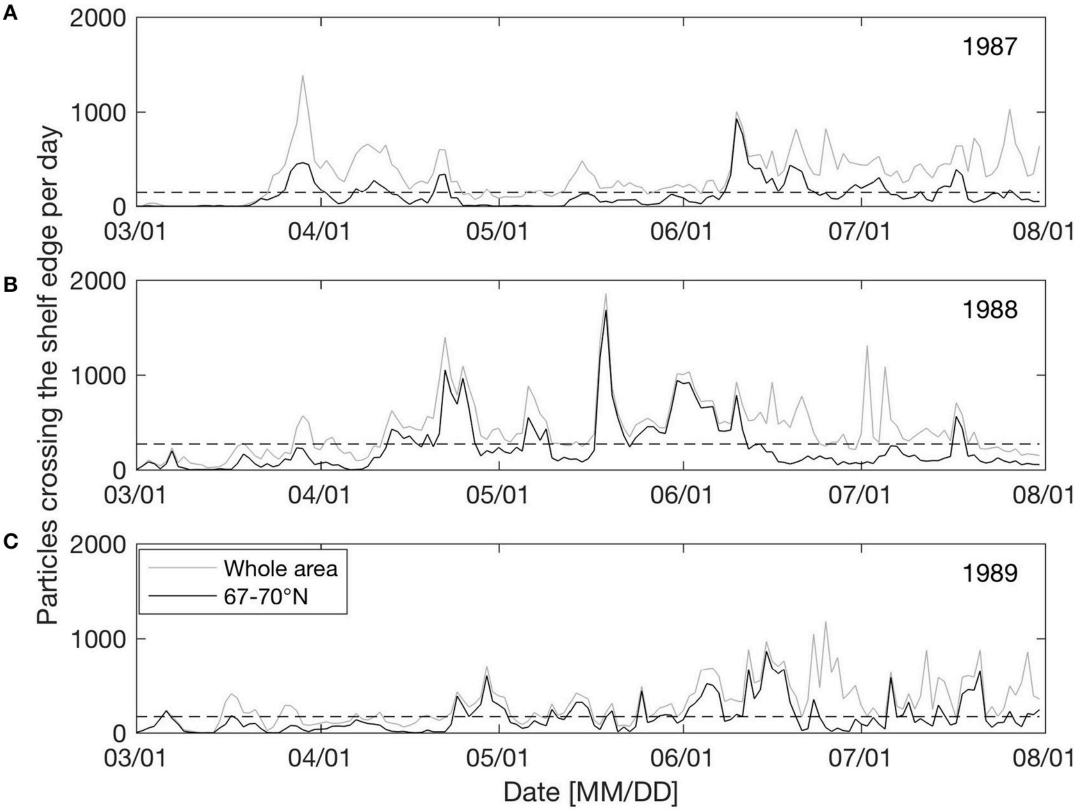

FIGURE 3 | Number of particles (from non-weighted spawning grounds) transported off shelf per day between March 1st and July 31st for the years 1987 **(A)**, 1988 **(B)**, and 1989 **(C)**, differentiating between off-shelf transport occurring in the whole model area (gray) and between 67 and 70° N (black). The black dashed horizontal line indicates one standard deviation of variability.

eggs are distributed with increasing concentrations toward the surface, while larvae avoid the surface layers and occupy the depths between 5 and 40 m (Ellertsen et al., 1984; Kristiansen et al., 2014) depending on various cues such as prey, predators, and light. Further analysis shows that 83.0% of the daily cross-shelf flow events coincides with the occurrence of NE wind (>5 m/s) during the previous 24 h. Comparing events of stronger cross-shelf currents and winds, show that NE winds above 7 m/s coincide with 90.3 or 97.6% of the cross-shelf currents above 11 or 20 cm/s.

On average for all years, 64.6% of the off-shelf (particle) events between March 1st and July 31st have mean winds coming from NE during the three prior days before each event (**Figure 5**). This result is even strengthened by comparing with winds preceding such events by 5–7 days (68.2–70.6% respectively). In particular, the years 1985, 1987, 1995, 2004, and 2014 have co-occurring mean 3-day NE winds in >80% of the events.

Transport Pattern of Pelagic Juveniles Off the Shelf Edge

Observations from the pelagic juvenile surveys (1978–1991) show that pelagic juveniles are variably present all years off the shelf and that the individual juveniles are larger than those on the shelf, except for the year 1979 (**Table 1**). Modeled dispersal of particles representing pelagic juvenile drift from the time of observations during summer to November 1st shows large inter-annual variations in distribution, but also characteristic features that are repeated between years (**Figure 6**). Pelagic juveniles drift with near-surface currents largely by the following main routes: back onto the adjacent eastern shelves and into the Barents Sea (south of Svalbard and in the Bear Island Trough), to the west and north of Svalbard with a fair chance of eventually ending up in the Barents Sea, west toward Jan Mayen, northwest toward the Greenland shelf, or recirculating within the Lofoten Basin. Separating particles by their position at November 1st into three

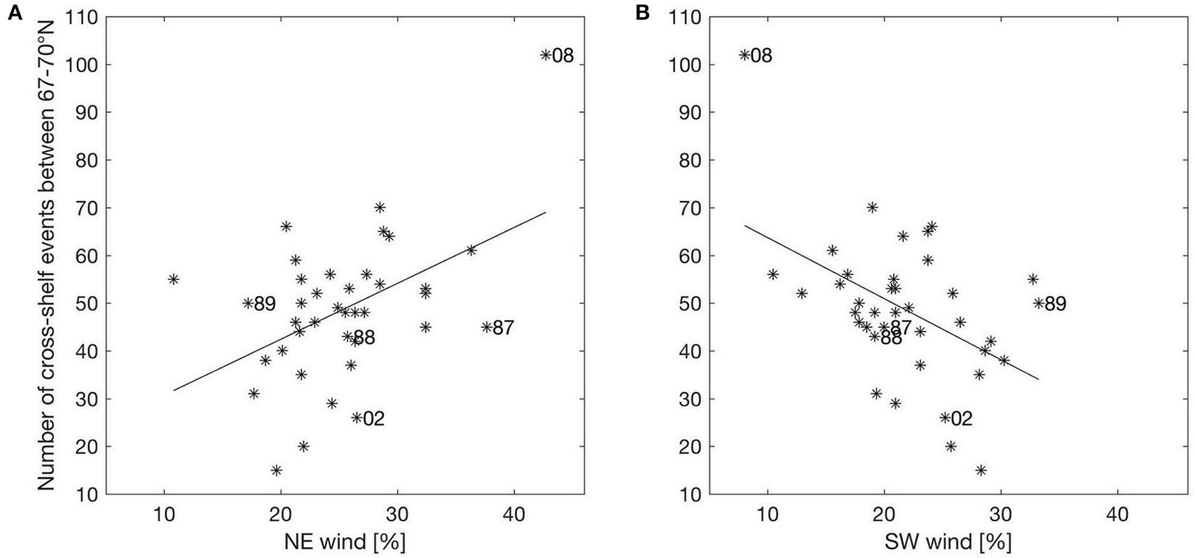

FIGURE 4 | Scatterplot of percentage wind in sectors NE **(A)** and SW **(B)** against number of events where transport of particles exceeds one standard deviation of variability from March 1st to July 31st between 67 and 70° N for the years 1978–2015. Years are marked with stars, where the linear regression lines are shown as solid black lines. The years discussed explicitly in the text are labeled.

TABLE 3 | The correlation (R^2) and significance (P) between wind sectors (northeastern NE or southwestern SW) and current components at three different depth intervals perpendicular to the shelf edge.

Depth	R^2/P (NE)	R^2/P (SW)
Current at top layer (3 m)	0.67/0.000	0.45/0.000
Current between 5 and 10 m	0.48/0.000	0.28/0.001
Current at 5–40 m	0.20/0.005	0.06/0.140

(A-C) areas enables quantification of inter-annual variability in the destiny of the pelagic juveniles off-shelf (**Figure 1**);

(A) The Barents Sea with depths shallower than 500 m.
(B) Deep ocean with depths deeper than 500 m, (depth > 500 m, lon > 2°E and lat > 73.5°N) | (depth > 500 m and lat < 73.5°N).
(C) Crossing the Fram Strait to northeastern Greenland (<2° E and >73.5° N).

Table 1 shows that on average 36.9% of the off-shelf juveniles are advected back onto the eastern shelf into the Barents Sea habitat (A), 60.7% remain in the open ocean (B), and 2.4% head toward the northeastern Greenland shelf (C). Inter-annual variation is large, especially for area C. The fraction of pelagic juveniles transported into C varies between 0.0 and 12.1%. NEA cod offspring advected off the shelf edge have a chance of being transported back onto the shelf (A) where the main nursery grounds are located (Olsen et al., 2010) without performing directional swimming, varying between 21.6 and 52.0% (except 1980, but this year only has a single observation of pelagic juveniles off-shelf and, hence, few particles are initiated for dispersal simulation).

DISCUSSION

A characteristic attribute of the NEA cod is that the mature part of the population migrates out of its feeding habitat in the Barents Sea to spawn along the Norwegian coast during spring. During the subsequent period from March until September, the pelagic offspring are transported northward by the NCC (and partly by the NASC) toward their feeding habitat in the Barents Sea. The present study has focused on the portion of this pelagic offspring that become advected off the shelf into the Norwegian Sea, and traditionally assumed to be lost for recruitment (defined as Hjort's 2nd hypothesis by Sinclair et al., 1985). We have investigated the origin of such juvenile loss, the driving mechanisms of this transport, and challenged Hjort's 2nd hypothesis with exploration of alternative fates of these individuals.

Our results show that off-shelf transport has strong inter-annual variations varying between 7.2 and 27.4% with an average of 14.7% during the years 1978–2015. Spawning grounds around Lofoten, especially the one located near the shelf edge (spawning site 5 in **Figure 1**) used by spawning cod in some years, contribute the most to off-shelf transport. The continental shelf is at its narrowest immediately downstream of this area (about 10 km wide at 69.5 °N), resulting in closer dynamic interactions between the NCC and the NASC branches manifested by enhanced mixing and current instabilities.

According to field observations (Suthers and Sundby, 1993), the fraction of pelagic juveniles found off shelf in mid-July 1988 was 35%. From our weighted simulation, the 1988 off-shelf transport was estimated to be 16.7%, about half of the field observation, and close to the simulated average of 14.7%. This indicate that our estimations of off-shelf transport might be an underestimation compared to what is

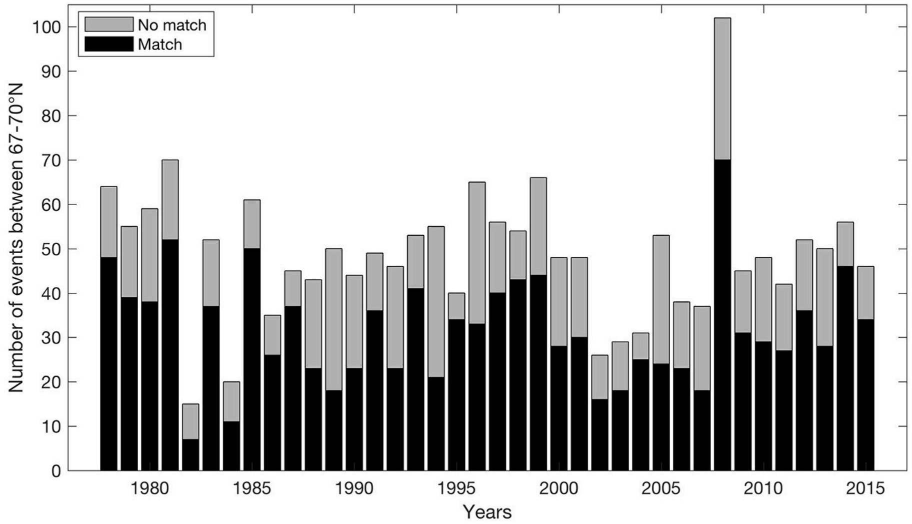

FIGURE 5 | Match between events where transport of particles off-shelf exceeds one standard deviation of variability from March 1st to July 31st between 67 and 70° N and occurrences of mean NE wind situations during the three proceeding days before each event.

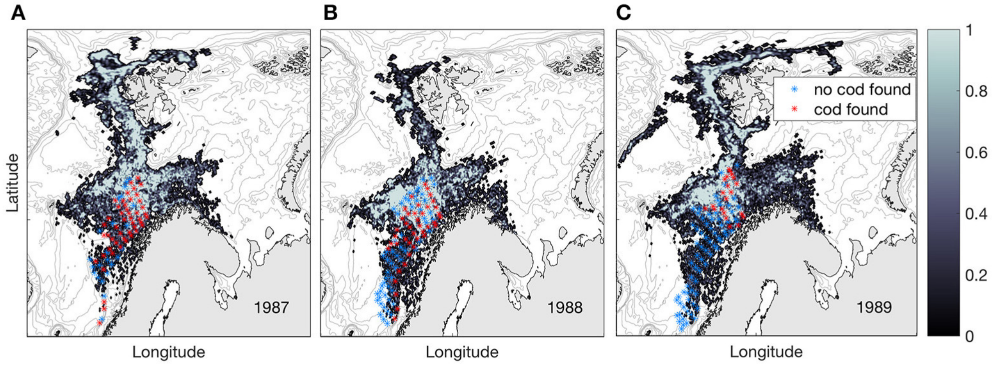

FIGURE 6 | Normalized concentrations of NEA cod pelagic juveniles per November 1st for years 1987 **(A)**, 1988 **(B)**, and 1989 **(C)** when originating from the year-specific observed pelagic juvenile distribution during summer (red stars). The years 1987–1989 have approximately an equal number of trawl stations during the pelagic juvenile cruises, here illustrated by red and blue stars indicating with and without cod in the trawl. Survey stations taken on the continental shelf is not included. Note that the modeled distributions are smoothed across 5 by 5 grid cells.

transported into the Norwegian Sea each year. It should be emphasized that not only advectional mechanisms may cause such differences between observed and modeled distributions. Offspring mortality differs substantially in time and space (e.g., Langangen et al., 2014) and will contribute to changes in spatial distributions. As demonstrated by Suthers and Sundby (1993) the main portion of the observed pelagic juveniles in 1988 originated from a spawning window 2 weeks after peak spawning implying an offspring mortality that differs substantially in time. Moreover, the fact that observed off-shelf juveniles in 1988 (Suthers and Sundby, 1993) were larger than those at the shelf they likely also had higher survival rates as they have outgrown some of their natural predators. Since mortality is not included in the biophysical model used here, this explains parts of the difference between modeled and observed off-shelf abundances.

Daily off-shelf advection of pelagic NEA cod offspring is dominated by episodic events where frequencies and timing varies between years. One important driving mechanism for these events are here shown to be fluctuating wind regimes, where northeasterly winds, especially winds blowing steadily over a period of several days (3–7 days), favor off-shelf transport. The correlation between NE winds and near-surface ocean currents weakens with depth down to 40 m, the depth-interval relevant for cod eggs and larvae drift, showing the importance of vertical placement of NEA cod offspring for off-shelf transport.

Based on observations of pelagic juvenile NEA cod in the Norwegian Sea we simulated the potential onward drift to explore possibilities of reaching other favorable destinations than the Barents Sea habitat, i.e., other shelf areas in the North Atlantic. An average of 36.9% are advected back onto the shelves of the Barents Sea by November 1st and thereby given the opportunity to re-enter the NEA cod stock in its natural habitat. This includes juveniles following AW north of Svalbard. Most pelagic juveniles (average of 60.7%) remain in the deep Norwegian Sea, thus not reaching areas where it is possible to bottom-settle due to the depths (>2,000 m). Hence, this portion of the offspring is confirming the destiny suggested by Hjort's second recruitment hypothesis. However, within the investigated period up to 12.1% (average of 2.4%) heads toward the northeastern Greenland shelf, pre-conditioning bottom-settlement if the conditions are otherwise good.

Connectivity Studies on Atlantic Cod

A recent model study (Myksvoll et al., 2014) indicates that exchange of pelagic offspring between Norwegian coastal cod and NEA cod may occur to a limited extent. However, the study indicates that exchange is dominated by export of offspring from the coastal cod populations to the NEA cod population (Myksvoll et al., 2011).

Connectivity studies over a larger geographical area were undertaken by researchers on Iceland in the 1970s (e.g., Jamieson and Jónsson, 1971). They found a West Greenland component of the spawning cod at Iceland from tagging experiments implying that connections between neighboring shelves are possible. Also here, the dominating exchange was from the Icelandic cod population to the West Greenland cod population. This is a result of the general circulation patterns where the pelagic offspring are advected downstream. Export the other way must be caused by active migration of the mature fish back to their origins of birth, i.e., natal homing.

During the previous warm period (1920s and 1930s) there was an increase of Atlantic cod in western Greenland. Cod appeared at the offshore banks and expanded their habitat northwards. This is believed to be caused by increased transport of larvae from Iceland as well as better survival due to higher abundance of zooplankton (Drinkwater, 2006).

Observational and modeling studies at Georges Bank in the northwestern Atlantic Ocean (e.g., Lough et al., 1994; Lough and O'Brien, 2012) showed that wind conditions leading to off-shelf Ekman transport is detrimental for survival in early life stages of cod. The Gulf stream is located just south of Georges Bank, and cod transported off the bank will be transported out in the large North Atlantic basin and become lost for recruitment, making this a straightforward example of Hjort's 2nd hypothesis.

Our results show similarities with the Greenland-Iceland study where most juveniles advected off-shelf are lost, but where a minor fraction may get back onto a shelf—either into the well-known nursery grounds or a new location. During the previous warm period in our focus area (the 1930s), Iversen (1934) summarized observations indicating cod could spawn as far north as west of Svalbard. If this re-occurs during the current or future warm periods, there is an even shorter distance from spawning grounds to potential nursery areas at the Greenland shelf.

From the Global Drifter Program[3], one drifter (id = 78758) from 2009 showed similar transport characteristics as here shown for young NEA cod pelagic juveniles reaching the northeastern Greenland shelf (see **Figure 1**). This drifter consisted of a surface buoy, a transmitter, a temperature sensor and a subsurface drogue of 15 m depth (Koszalka et al., 2011) representing a drift in the upper ocean comparable with NEA cod offspring (vertical migration between about 5 and 30 m). The drifter crossed the Norwegian continental shelf edge at February 8th 2009, and arrived at the northeastern Greenland shelf July 27th 2009, a journey of ∼6 months. This is well within the period when cod should locate the seabed and become stationary (the Greenland shelf has approximately the same depth as the Barents Sea ∼300 m). This observed drifter's trajectory is demonstrating the potential for drift of NEA cod pelagic juveniles to the northeastern Greenland shelf.

Growth, Predation, and Survival Conditions

In this study, we have not investigated food availability along alternative drift routes for pelagic juveniles drifting off the shelf edge from late summer and through fall. However, zooplankton studies in the Fram Strait confirm that the region is rich in arctic and arcto-boreal copepods in summer (Smith, 1988) as well as during early autumn (Svensen et al., 2011). These copepod species have been identified as the key size groups of prey for pelagic juvenile cod during the spring and summer (Sysoeva and Degtereva, 1965; Sundby, 1995). During late summer the growing juvenile cod switches to larger prey (Sundby, 1995) such as krill. These species are also abundant in the Fram Strait region (e.g., Hop et al., 2006). Consequently, there is a good reason to assume that there are suitable and sufficient prey items for pelagic juvenile cod to survive during summer and early autumn. Hence, the recent observations of immature cod at the northeastern Greenland shelf (Christiansen et al., 2016), coinciding spatially with the present modeled entering region of pelagic juveniles, support the conclusion that cod may be transported, in good condition, from spawning areas along the coast of North Norway.

We have focused on the physical processes affecting the young NEA cod offspring, only including simple biological behavior such as a diurnal vertical migration, growth dependent only on temperature and year-specific choice of spawning grounds (both in time and space). If we also had included mortality as a function of prey and predator availability, the estimate of the percentage of off-shelf transport would likely change. e.g., if individuals located on the shelf are more subject to predation, in addition to being smaller (Suthers and Sundby, 1993), this would lead to higher mortality on-shelf than off-shelf, and the off-shelf percentage would increase. As outlined in the introduction of the Discussion above it is also possible that the larger juveniles off the shelf would be in a better situation to resist and survive potential harsh conditions on their way across the Norwegian Sea. An inclusion of mortality in the model is also expected to change the match between modeled and observed juvenile distributions (**Table 2**) since observations are formed by the sum of transport, dispersion and site-specific mortality.

Homing from Northeastern Greenland to Norway?

What may happen to NEA cod arriving at the northeastern Greenland shelf? One possibility is that the shelf will function as a distant part of the NEA cod nursery habitat, while the

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[3] http://www.aoml.noaa.gov/envids/gld/krig/parttrk_id_temporal.php

Norwegian coast still is the preferred spawning habitat. This suggestion implies the occurrence of long-distance homing. The other possibility would be that the NEA cod settle along the eastern coast of Greenland, forming a separate sub-population. We will here focus on the first possibility, the long-distance homing strategy.

The Greenland shelf is large, with approximately the same depth as the Barents Sea (∼300 m), but much of the shelf area is covered with colder water masses resulting in slower growth and possibly also being exposed to waters of less prey productivity. Keeping in mind that high latitudes have experienced recent warming, with a subsequent northward shift in boreal species (Fossheim et al., 2015), there are reasons to believe that the northeastern Greenland shelf might get increased productivity if the warming trend continues.

Tagging experiments have already shown that NEA cod tends to return to the same spawning locations along the Norwegian coast where it was tagged, and that cod from different spawning locations occupies different areas of the Barents Sea (Godø, 1984). As mentioned in the introduction, a traditional folklore opinion in some fishing communities says that Greenland cod occasionally spawn in Norwegian waters. The hypothesis is that the Norwegian fishermen are recognizing specific phenotypic traits of the cod which are characteristic for cod growing up in Greenland waters, suggesting a long-distance homing strategy. Considering distances for such a migration pattern, the cod could either take a route directly across the Norwegian Sea (∼1,000 km), or crossing the Fram Strait following the continental shelf edge (against the NASC) toward Lofoten (∼1,500 km). Both routes are within the distance range of observed migration from the Barents Sea to the spawning sites along the Norwegian coast (Sundby and Nakken, 2008; Yaragina et al., 2011). As mentioned in section Connectivity Studies on Atlantic Cod, Jamieson and Jónsson (1971) found that connectivity (homing) between neighboring shelves are possible, and already happening between southwestern Greenland to spawning grounds at Iceland. The difference between our suggested migration and the one described by Jamieson and Jónsson (1971) is that cod from Greenland to Norway need to migrate over deep waters (deeper than 2,000 m). To our knowledge, there is no literature describing deep ocean migration of NEA cod or other cod populations, making our suggested migration unique. A recent study, however, discusses observations of cod in deep waters of the Fram Strait feeding on a mesopelagic layer, demonstrating its highly adaptive capacity (Ingvaldsen et al., 2017).

Model Uncertainties

In general, the ROMS model setup applied to produce the SVIM seems to overestimate topographic steering above steep slopes. Lien et al. (2014) reported extraordinary strong horizontal gradients in hydrography along the continental shelf slope and AW with a limited westward distribution as compared to observations. This is likely the reason for less stratification on the shelf and the shelf slope as compared to observations, and in turn a different vertical impact of wind stress than in reality. We believe this also affects the ability of the model to replicate eddies shedding off the shelf (Isachsen et al., 2012). Surprisingly, a higher horizontal grid resolution in NorKyst800, a comparable ROMS setup, did not improve the off-shelf transport, but instead reduced the percentage as compared to observations. Since NorKyst800 applies SVIM-results as forcing along its open boundaries and is thus highly affected by the density field in the coarser model, our results from both model runs are thus limited by the intense horizontal gradients in hydrography. We expect that utilizing forcing fields with improved stratification would give more accurate results. In comparison, the study by Hattermann et al. (2016) successfully quantified eddy-induced westward transport of AW across the Fram Strait and emphasized the need for high horizontal resolution in the ocean model. Their model setup was comparable to the ROMS setup in NorKyst800 but limited to the western shelf of Svalbard. In light of the results by Hattermann et al. (2016), showing that ROMS is capable of replicating eddy shedding, we expect that the relative intra- and inter-annual variation reported in our study are representative for the frequency of off-shelf transport but that the strengths are underestimated as compared to reality. Furthermore, if waves were included in the ocean circulation model, the wave-induced drift could lead to higher retention toward the coast for the cod juveniles (Röhrs et al., 2014). Also looking at ocean dynamics with time scales less than daily, tides would likely change the transport pathways in Vestfjorden implying a slightly different spread of cod eggs and larvae (Lynge et al., 2010).

If there are any errors in the setup of the biophysical model this could lead to systematic errors in the drift. For example, correlation between wind forcing and modeled ocean currents perpendicular to the shelf edge at three different depth intervals demonstrated that the vertical distribution of NEA offspring and their vertical migration affect the chance of being displaced off the shelf. The higher up in the water column, the higher chance of being transported off-shelf. We performed a sensitivity test, with particles drifting without any vertical movement but kept at fixed depths; surface, 5 and 40 m. Results from this showed that pelagic juveniles drifting close to the surface have a more dispersed horizontal distribution, while the deeper drift pattern was more trapped along topographic features following the Norwegian coast more closely. This is in accordance with Vikebø et al. (2005, 2007) and shows the importance of accurate description of the vertical placement of NEA cod to obtain correct pelagic drift pattern. Important factors to be determined are egg buoyancy (Sundby and Kristiansen, 2015), and realistic vertical migration of the larvae and juveniles (Kristiansen et al., 2014) as well as correct vertical current profile.

The number of observation sites, and observations with and without pelagic juveniles present varied a lot between years. Hence, the number of particles initiated at spawning grounds and dispersed until the time of observations should not introduce a bias in the comparison between model and observations. In contrast, if the stations were dominated by observations with (without) pelagic juveniles, a high (low) number of modeled particles would be beneficial for match. As expected, in years with a high number of observations, there is an increasing number of observations without presence of pelagic juveniles in the trawl, as the survey also covers areas beyond the extent of distribution of cod.

There are uncertainties associated with the origin of pelagic NEA cod juveniles, mainly due to observational limitations. In our study, we defined 10 different spawning grounds along the coast of Norway, and investigated dispersal of NEA cod offspring with and without weighted spawning grounds (**Figure 2**). The weighting is a continuation of Table 3.1 by Sjølingstad (2007) which divided NEA cod spawning into six spawning grounds. We refined these further into 10 spawning grounds and expanded the table until 2015 using available egg-survey observations (references described in Material and Methods). Four main considerations were done in accordance with Sundby and Nakken (2008); (1) spawning outside Møre decreases with time, (2) a northward shift in spawning locations from the early 1980s have been quantified, (3) for all years, we added highest weights to the spawning grounds around Lofoten, in accordance with well-established knowledge (Sundby and Bratland, 1987; Ottersen et al., 2014), (4) the spawning ground outside Lofoten, close to the shelf edge, only occurs occasionally (Sundby and Nakken, 2008), but increased spawning has been observed here during the recent decade, similar to the observations in the 1980s (Sundby and Bratland, 1987). The effect of weighting changed the estimated mean off-shelf amount from 11.5 to 14.7%. Any inaccurate quantification of the weighting would affect this estimation.

Recommendations for Future Work

Both observations and a biophysical model indicate that a significant part of the NEA cod offspring may be advected off-shelf away from the typical drift routes from the spawning grounds along the Norwegian coast toward the nursery grounds in the Barents Sea. Our modeling approach focuses mainly on the physical processes, but to investigate the fate of the off-shelf drifting offspring in a more biological context, it may be necessary to explore the capability and need for horizontal swimming to re-enter the nursery areas in the Barents Sea shelf area. This may be done in a combined effort including *in-situ* observations and biophysical models (Staaterman and Paris, 2013).

Furthermore, it is essential to determine the prey availability for offspring that are advected off-shelf. Is it sufficient for survival during pelagic free drift for durations up to several months? This may be studied through combined *in-situ* observations, biophysical models and remote sensing. Egg, larval and pelagic juvenile mortality involves the enigma of the recruitment problem. The main challenge of predicting the fate of the offspring is still on larval growth and survival basically involving food abundance and the distribution of predators. Site-specific mortality will clearly contribute to the variability in distribution of offspring in addition to the physical advection.

A current warming trend and subsequent northward shift in boreal species (Fossheim et al., 2015) give reasons to believe that NEA cod offspring transported off-shelf toward other shelf areas, specifically northeastern Greenland shelf, may successfully settle at the shelf. If this part of the NEA cod would be able to migrate back to its well-known habitat it will contribute to even higher recruitment to the stock if this warming trend continues. The other possibility would be that the NEA cod settle along the eastern coast of Greenland, not returning to the Norwegian coast to spawn. Observational cruises to the northeastern Greenland shelf together with tagging experiments may give better insight into this issue.

Finally, ongoing work in assimilating *in-situ* observations in local ocean model setups show promising features with respect to replicating vertical stratification of the upper ocean inhabited by NEA cod offspring (Sperrevik et al., 2017). We believe this may improve predictive capabilities for dispersal modeling of eggs, larvae and pelagic juveniles on their critical journey toward the favorable nursery grounds in the Barents Sea.

AUTHOR CONTRIBUTIONS

All authors listed have contributed substantially, both direct and intellectually, and approved it for publication. KS, SS, and FV was responsible for formulating the hypothesis. KS performed most of the direct contribution to the work. SS and FV was responsible for synthesizing the major part of the literature. JA set up the NorKyst800 hindcast.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: http://journal.frontiersin.org/article/10.3389/fmars.2017.00304/full#supplementary-material

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Cooperative Research to Evaluate an Incidental Catch Distribution Forecast

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Concern over incidental catches in commercial fisheries has been increasing, and while simple mitigation strategies have been effective, few effective mitigation strategies have been established for more complex species interactions. Incidental catches of alewife (*Alosa pseudoharengus*) and blueback herring (*A. aestivalis*) in the commercial Atlantic herring (*Clupea harengus*) fishery have received substantial attention on the Northeast U.S. continental shelf, despite an existing bycatch avoidance program. This study evaluates the utility of existing species distribution forecasts to predict river herring catches in the southern New England small mesh bottom trawl Atlantic herring fishery, with the ultimate goal of incorporating incidental catch forecasts into the bycatch avoidance program. Commercial Atlantic herring bottom trawl vessels assisted with field-based evaluation of alewife, blueback herring, and Atlantic herring species distribution forecast models. Vessels were equipped with conductivity, temperature, and depth probes, and sampling occurred throughout the fishery season (January–March). Locations of expected low and high forecasted incidental catches were sampled, as well as locations the captain expected to find low and high incidental catches. This allowed us to sample within the spatial area the fishery occurs, and to evaluate the forecasted conditions, and predictions, at the spatial scale of the fishery. Catch differences between high and low probability stations were small and variable, as were differences in modeled probability of species presence. No differences were observed between observations at model-predicted stations and captain-selected stations. The sampling provided a better understanding of the potential effectiveness of distribution forecasts for further reducing incidental catches. Existing models have limited use at the spatial scale of this fishery, but could be improved by developing models with fishery-dependent data. Collaborations between researchers, managers, and the Atlantic herring commercial fleet have improved relationships between the groups, and continued collaboration in the development and evaluation of incidental catch reduction tools is key for further reducing incidental catches.

Keywords: cooperative research, species distribution models, bycatch avoidance, river herring, oceanographic forecast

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INTRODUCTION

Flexible management strategies and cooperative research are becoming common tools in fisheries management, and can increase compliance and improve the economic and ecological efficiency of fisheries (Cox et al., 2007; O'Keefe et al., 2013). Flexible management strategies have become more widespread, especially over the last decade, and are facilitated by technology advancements (Gilman et al., 2006; Lewison et al., 2015; Little et al., 2015). While flexible strategies, such as "move-on rules," generally need to be combined with some broader scale management plan, these tools can allow fisheries to reduce their non-target catches, while minimizing the economic impacts on the fleet (Dunn et al., 2013; O'Keefe et al., 2013; Little et al., 2015). Many flexible strategies, especially those intended to reduce non-target catches, require regular communications between actively fishing vessels and scientists (Bethoney et al., 2013; O'Keefe et al., 2013; Lewison et al., 2015). A good relationship between managers and industry is key to a successful fleet communication program because of the need for regular communications of detailed information regarding fishing locations and catch compositions as well as high participation levels (O'Keefe et al., 2013; Lewison et al., 2015).

Cooperative research has been used in the development of a variety of tools for improving financial benefits and reducing ecological impacts, such as using industry to test new or modified fishing gear, or to develop and test tools to avoid catching non-target species (Johnson and van Densen, 2007; Lewison et al., 2015). When industry is included in the early stages of research projects, management changes, and policy development, they can contribute critical ideas and information that may have been overlooked by scientists and managers, improving the effectiveness (Hartley and Robertson, 2006; Johnson and van Densen, 2007). This collaboration can also increase industry buy-in for modifying gear or changing their fishing strategy, which drastically improves the success of new policies (Hartley and Robertson, 2006; Johnson and van Densen, 2007).

Recent advances in environmental forecast model accuracy and species distribution modeling have facilitated a shift in dynamic ocean management techniques, from "reactive" systems, where catches are regularly summarized and reported back to vessels, to "proactive" forecasting systems (Hobday and Hartmann, 2006; Manderson et al., 2011; O'Keefe et al., 2013; Eveson et al., 2015; Lewison et al., 2015). Species distribution models provide the foundation for most proactive dynamic management systems, as species distributions are directly or indirectly related to environmental conditions (Mann, 1993). Environmental forecasts can be combined with species distribution models to predict over relatively short (i.e., days to months) time scales to inform fisheries (Hartog et al., 2011; Eveson et al., 2015; Kaplan et al., 2016), or over longer (i.e., decadal) time scales to predict shifts in distributions related to climate change (Hare et al., 2010; Lynch et al., 2015).

In the Northeast U.S., the River Herring Bycatch Avoidance Program, a collaboration involving the Massachusetts Division of Marine Fisheries, the University of Massachusetts School for Marine Science and Technology, and the Atlantic herring (*Clupea harengus*) and Atlantic mackerel (*Scomber scrombus*) fisheries, has been operating since 2010 (Bethoney et al., 2013). The program began because of growing concern over incidental catches of river herring (alewife, *Alosa pseudoharengus*, and blueback herring, *A. aestivalis*) in the Atlantic herring and Atlantic mackerel fisheries (Bethoney et al., 2013). Participation in the program is voluntary, yet has grown to all of the mid-water fleet (11 vessels) and most of the bottom trawl fleet (6 of 8 vessels) since the implementation of river herring catch caps for all fishing areas (US DOC, 2015). The overall river herring catch cap is the weighted mean river herring catch estimate, with proportions specified for regions and gear types (US DOC, 2015). Many of the small mesh bottom trawl vessels are also part of the NOAA Northeast Fisheries Science Center's Cooperative Research Study Fleet (NEFSC Study Fleet), facilitating detailed data collection on catch composition and locations (Palmer et al., 2007). Preliminary analyses suggest that the Bycatch Avoidance Program has reduced river herring catches as a result of vessels avoiding areas with reported high river herring catches (NEFMC, 2014). The next step in further reducing incidental river herring catches is to develop a nowcast or forecast tool to inform industry of areas where higher river herring catches are likely, along with information on where they have been observed.

We previously developed and evaluated species' distribution models using fishery-independent data (Turner et al., 2015), which we then coupled with an ocean forecast model (FVCOM; Chen et al., 2006) and evaluated its accuracy using newly collected fishery-independent data (Turner et al., 2017). Species' distribution forecasts correctly predicted presence for 68–69% of fishery-independent observations, but given the substantially different spatial scales of the trawl survey used for model development and initial testing and the fishery, fishery-dependent evaluations were necessary. The goal of developing species' distribution forecasts is to create a product that can be incorporated into the existing River Herring Bycatch Avoidance Program to further reduce incidental catches of alewife and blueback herring. The next step in the development of a proactive tool is testing using the designed collection of fishery-dependent data. We contracted three commercial Atlantic herring bottom trawl vessels (members of the NEFSC Study Fleet) to perform directed sampling of the species' distribution forecasts. Our objectives were:

1) To evaluate the accuracy of the species' distribution forecasts over the spatial and temporal scales of the commercial Atlantic herring bottom trawl fishery; and
2) Compare the species' distribution forecasts with the captains' "mental models."

METHODS

Study Area

Species' distribution forecasts were previously developed and evaluated with fishery-independent data (Turner et al., 2015, 2017) for alewife, blueback herring, Atlantic herring, and Atlantic mackerel (not included in this study), encompassing most of the Northeast U.S. continental shelf (**Figure 1**). The spatial scale of this study (41.15–41.50°N, ⁻71.86–⁻71.40°W; **Figure 1**) was substantially smaller than for initial model development and evaluation because the vessels used by the Atlantic herring small mesh bottom trawl in this study typically only take 1 day trips because of limited carrying capacity. All three study species overwinter in Southern New England continental shelf habitats (Fay et al., 1983; Stevenson and Scott, 2005) and alewife and blueback herring are regularly caught by small mesh bottom trawl vessels targeting Atlantic herring during the winter; this study encompassed the fleets' fishing grounds (Bethoney et al., 2013; Cournane et al., 2013). The FVCOM forecast model domain completely encompasses the study area (**Figure 2**).

Directed Sampling

The dates selected for directed model sampling were days the vessels were not commercially fishing with favorable weather; a total of 10 trips were taken for this study (two vessels were contracted for 3 fishing days each, and one vessel was contracted for 4 fishing days). We aimed for one sampling trip each week, to sample most of the fishery season (January–March). Two ports in southern Rhode Island were used for all trips (**Figure 1**). Oceanographic forecasts coupled with species

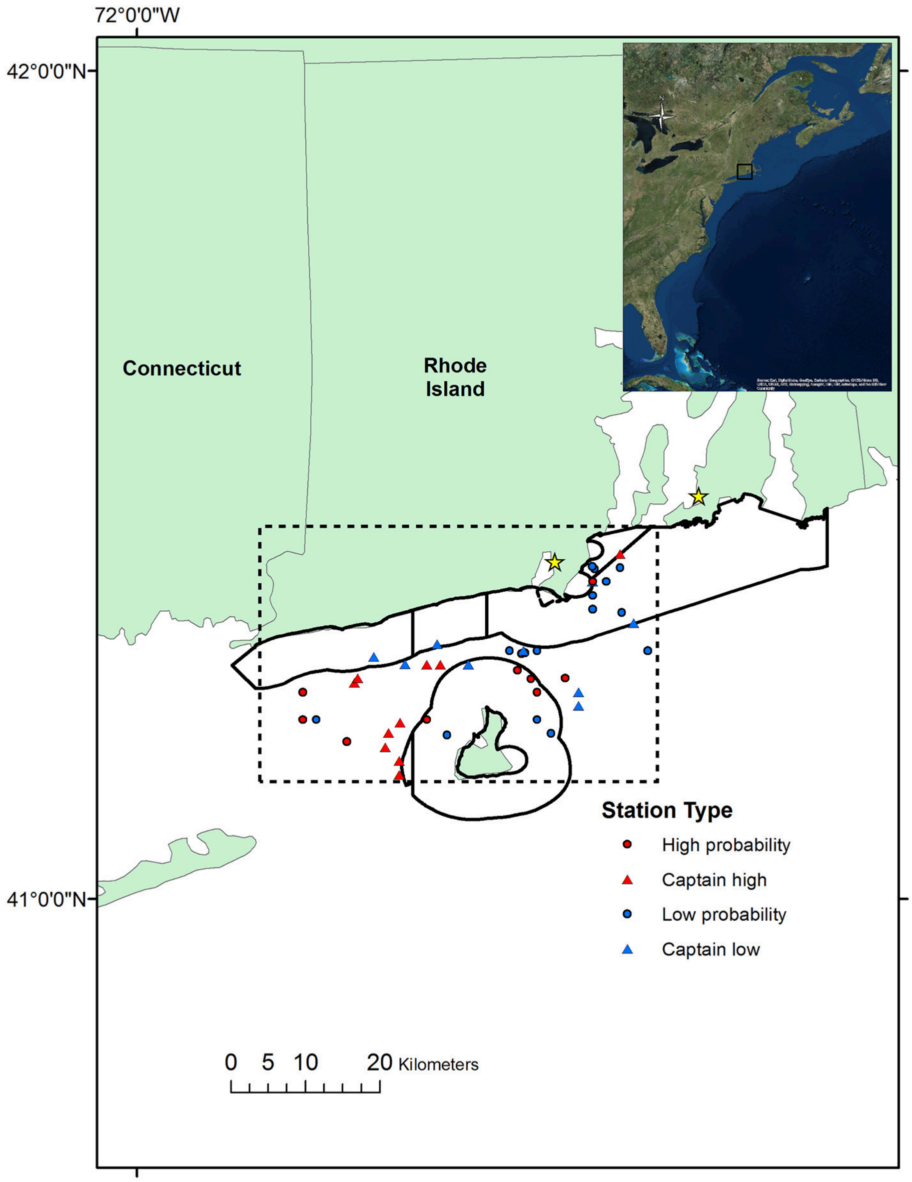

FIGURE 1 | Map of the study area, with Rhode Island state waters indicated with the black line and the spatial limits of the study indicated by the dashed line. Circles indicate model-selected high and low probability stations, triangles indicate captain-selected high and low probability stations; stars indicate the ports.

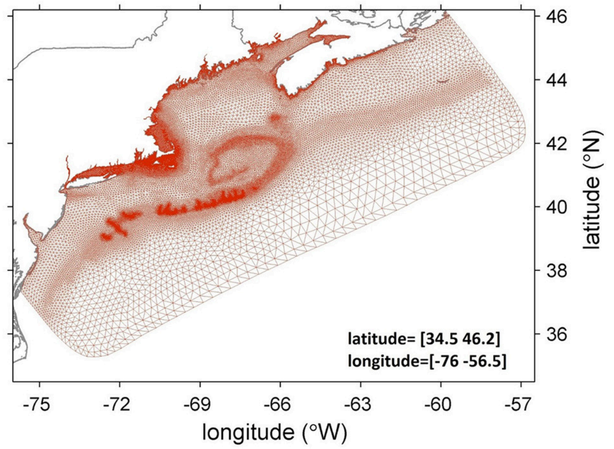

FIGURE 2 | Map of the finite-volume community ocean model (FVCOM) forecast grid; points indicate the forecast nodes, with distances between nodes varying by physical environment complexity (distance between nodes ranges from 0.3 to 15 km).

distribution models were used to select stations with high and low probability of catching alewife and/or blueback herring; ranges for high and low probability stations were dependent on the available ranges of probabilities on a given day. The area was restricted based on vessel capabilities (day boats) and permit allowances, depths greater than 18 meters, and areas with substrate suitable for trawling (**Figure 1**). Four station types were sampled: a model-based high probability station, a model-based low probability station, a captain-predicted high probability station, and a captain-predicted low probability station. Five sampling stations were the target for each trip, one of each type and a repeat of one of the two model-predicted stations (dependent on location relative to returning to port; see **Figure 1**) and this was achieved on most trips. Captains could select stations anywhere within the study region they would expect to see high or low river herring incidental catches. All sampling occurred on dedicated research trips, and was covered by a Scientific Research Permit issued by the NOAA Greater Atlantic Regional Fisheries Office Sustainable Fisheries Division; catches were not subject to fishery regulations (i.e., were excluded from quotas). This work was conducted as part of commercial fishing operations and all rules and regulations were followed under an Experimental Fishing Permit (no ethics approval was required as per institutional and national guidelines).

Three captains participated in the project; all are part of the NEFSC Study Fleet. For model selected stations, captains fished as close as safely possible to the coordinates provided (i.e., avoid locations that will damage their gear). Captains selected their fishing locations using their "mental models" of where they thought incidental catch would be high and low. At each station, a 20-min tow (beginning when proper door spread was achieved) was conducted, and a conductivity, temperature, and depth probe (CTD) was attached to the net for each trip to compare the forecasted conditions with those observed. A scientist sorted and weighed (in pounds) all fish caught in each tow to estimate catch composition; when the hail exceeded 1,000 pounds a subsample was taken and extrapolated. Atlantic herring were caught in all tows except one (49 of 50), alewife were caught in 48 of 50 tows, and blueback herring were caught in 40 of 50 tows (**Figure 3**; see Supplementary Table 1 for catch weights by tow). Other species caught were American shad (*A. sapidissima*; 31 tows), Atlantic mackerel (19 tows), Atlantic menhaden (*Brevoortia tyrannus*; 18 tows), butterfish (*Peprilus triacanthus*; 2 tows), silver hake (*Merluccius bilinearis*; 1 tow), and long-finned squid (*Doryteuthis pealeii*; 1 tow).

Evaluation and Analyses

While the FVCOM model has been thoroughly evaluated, evaluation of temperature and salinity errors at the spatial and temporal scales of the study was deemed useful. Forecasted and observed temperature and salinity were compared using paired *t*-tests. CTD data were limited to when the net was on the bottom based on the pressure, following protocols established for other bottom trawl surveys, by omitting data where the pressure is <15 decibars and where the rate of change exceeds 0.3 decibars/10 s (measurements were recorded at 10 s intervals). The mean observed temperature and salinity for each tow were used to predict the probability of species' presence for comparison with forecasted probabilities. FVCOM forecasts predict up to 2 days in advance, and 1 or 2 day advance forecasts were used for station selection depending on how far in advance a fishing day was scheduled (previous work found no significant differences in conditions from 1 or 2 day forecasts; Turner et al., 2017). The forecasted conditions used for evaluations were the FVCOM model forecast node nearest to the start of the tow. Linear models were used to test if the relationships between the forecasted and observed conditions were correlated with the distance between the FVCOM forecast node and the coordinates for the trawling start.

Generalized additive models for the habitat associations of alewife, blueback herring, and Atlantic herring, based on fishery-independent data, were previously developed using the R package "mgcv" v. 1.8-6 (Hastie and Tibshirani, 1990; Wood, 2006; Politis et al., 2014; R Development Core Team, 2014; Turner et al., 2015). Species' presence was the response variable, using a binomial link function, and all models included smooth functions of bottom temperature, bottom salinity, and depth, a tensor product smooth of solar azimuth and solar elevation, and region as a factor variable (Turner et al., 2015). Model probabilities of species presence using forecasted and observed conditions were evaluated for all three species using paired *t*-tests. Linear models were used to test if the relationships between the forecasted and observed predictions were correlated with the distance between the FVCOM forecast node and the coordinates for the trawling start. Model predictions were compared with observed catches by calculating the ratio of alewife or blueback herring weight to Atlantic herring weight (i.e., weight of alewife/weight of Atlantic herring). The differences in model probabilities and catch proportions at high and low probability stations for each day (repeat tows were excluded) were then calculated for alewife and blueback herring to understand how the differences in modeled probabilities compare with observed

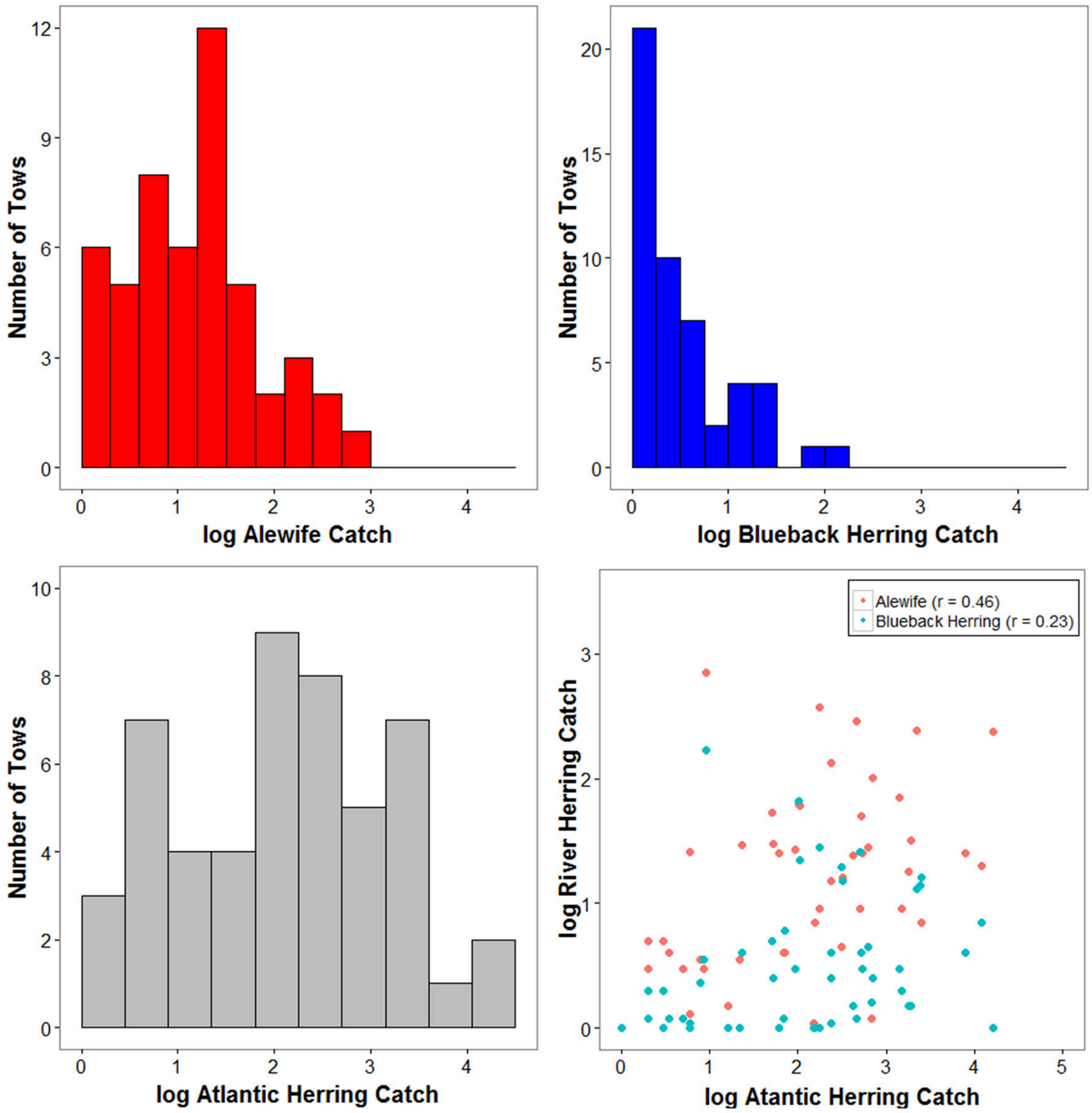

FIGURE 3 | Summary of the observed catches (in pounds) during directed sampling; histogram of the log-transformed alewife catch (upper left), histogram of the log-transformed blueback herring catch (upper right), histogram of the log-transformed Atlantic herring catch (lower left), and a scatterplot of log-transformed alewife (red), and blueback herring (blue) catches against the log-transformed Atlantic herring catch.

catch differences. Relationships between model probabilities and catch proportions were examined using FVCOM modeled fields and CTD measurement, for model and captain predicted stations.

To examine one potential discrepancy between catch and forecasted species distribution, we examined how the probabilities changed over the course of the tow track. The vessel records the GPS location every 20 s, and these coordinates were matched to the nearest temporal CTD conditions. Similarly, the closest FVCOM node was matched to each coordinate recorded throughout each tow. The probability of each species' presence was modeled for each observation within each transect using the observed and forecasted conditions, to identify if any substantial changes in the probability of species' presence occurred.

RESULTS

Deviations between forecasted and observed conditions, as well as the probabilities of species' presence based on the forecasted and observed conditions, were quantified to evaluate the ocean forecasts and species distribution forecasts. The differences between the forecasted and observed temperatures and salinities were significant (paired *t*-tests: $t = -9.9$ and 10.1, respectively; d.f. $= 49$; $p < 0.0001$; **Figure 4**). The correlation between the temperature deviation (forecasted–observed) and the distance between the FVCOM forecast node and the start location of each trawling station was marginally significant (d.f. = 48; $p = 0.0599$). The correlation between the salinity deviation and the distance between forecast and trawl stations was significant (d.f. = 48; $p = 0.0144$). Conversely, the correlation between the species' distribution model deviations and the distance between the FVCOM forecast node and the trawl start locations were not significant (d.f. = 48; $p > 0.2$). We also evaluated the differences in species distribution model probabilities derived using observed and forecasted conditions. Deviations between forecasted and observed species distribution model probabilities were significant for alewife and Atlantic herring ($t < -5$; d.f. = 49; $p < 0.0001$; **Figure 5**).

The differences were relatively small (average 0.06) between model probabilities of alewife or blueback herring presence for high and low probability stations using forecasted and observed conditions (**Tables 1, 2**).The differences in the catch proportions of alewife to Atlantic herring and blueback herring to Atlantic herring were generally small for each day (mean difference in proportion alewife = 0.27, mean difference in proportion blueback herring = 0.05; **Tables 1, 2**; **Figure 6**). There were weak correlations between the log-transformed alewife and blueback herring catches and the Atlantic herring catches (**Figure 3**). For 3 fishing days, the proportion of alewife to Atlantic herring catch was lower at the high probability station; the forecasted probability differences for these days ranged from 0.05 to 0.14. The observed condition probability differences on these days did not exceed 0.04 (**Table 1**; **Figures 7**, **8**). The proportion of blueback herring to Atlantic herring catch was also lower at high probability stations for three fishing days (**Table 2**; **Figures 7**, **8**). The blueback herring forecasted probability difference was small (<0.02) for all 3 of these days and negative (−0.01) for one. The observed probability differences for these days were similar (**Table 2**).

There were minimal differences in the skill of the forecast model compared to the captains' mental models of where high and low catches of river herring would be encountered. There was one exception where the difference for the captain-predicted stations was very large (**Figures 7**, **8**). There was a weak, non-significant, correlation between the catch proportions and forecast model predictions (i.e., alewife probability/Atlantic herring probability; alewife $r = 0.25$; blueback herring $r = 0.20$; **Figure 9**). No significant trends were identified between the differences in model probability and catch proportions between high and low probability stations for model or captain selected stations, using either FVCOM or CTD conditions (**Figures 7**, **8**).

The differences in forecasted and observed model probabilities for all species across each transect were relatively small (all < 0.1) and the median observed probability ranges were all below 0.03 and the median forecasted probability ranges were less than 0.02 (**Figure 10**). Most tows did not show strong trends in the probability of alewife or blueback herring presence from the start to the end (Supplementary Figures 1, 2).

DISCUSSION

Real-time spatial management (dynamic management) strategies have been demonstrated to be more effective than static time and area closures in a wide variety of fisheries (Lewison et al., 2015; Little et al., 2015; Dunn et al., 2016). Real-time management can now be taken a step further, as advancements in oceanographic forecasting permit forecasting species' distributions based on species' habitat associations (Eveson et al., 2015; Kaplan et al., 2016). This study illustrates how to integrate cooperative research for evaluating a potential real-time bycatch forecasting tool. We tested the potential for coupling ocean forecast models and species' distribution models to predict the likelihood of non-target catches of alewife and blueback herring in the winter Atlantic herring bottom trawl fishery at spatial and temporal scales relevant to the fishery. Our test showed little to no skill in our ability to predict high or low occurrence of river herring in the wintertime, small-mesh Atlantic herring bottom trawl fishery. However, the contrast between modeled high and low probability stations was also relatively small (<20%).

Model Evaluations

Forecasted temperature and salinity differed significantly from the observed conditions, but both deviations were related to the distance between the FVCOM forecast node and the trawl starting location. Thus, small spatial scale heterogeneity in conditions likely influences these deviations. The deviations observed here were similar to the deviations observed during fishery-independent model evaluations in Turner et al. (2017) for Southern New England. Forecasted and observed alewife and blueback herring distribution probabilities also differed significantly, but the differences were not related to the distances between FVCOM nodes and trawl start locations. Some additional improvements might be made through higher resolution numerical circulation models. However, the modeled probability of river herring occurrence was little affected by using forecast model based temperature and salinity or CTD-based temperature and salinity. This supports the conclusion of Turner et al. (2017) that much of the error in the model occurrence derives from the species distribution model and not the oceanographic forecasting model: it is the biology not the physics, where the majority of the uncertainty lies.

One weakness in our test of the models skill in predicting high and low incidental catches was the lack of contrast across the model domain. On any given day, the difference between modeled high and low probabilities never exceeded 0.25 and was 0.06 on average. This suggests that probabilities of alewife and blueback herring are relatively consistent within the study area (i.e., at the spatial scale of this fishery; **Figure 1**) on a given day. Sampling stations for the fishery-independent survey used for initial model development and testing are an average of 12 km apart and cover most of the Northeast U.S. continental shelf; probabilities of species presence at that spatial scale had ranges from 0.5 to 1.0. Despite small differences in probabilities and catches, weak positive correlations, albeit non-significant, were observed between the overall modeled probabilities of both

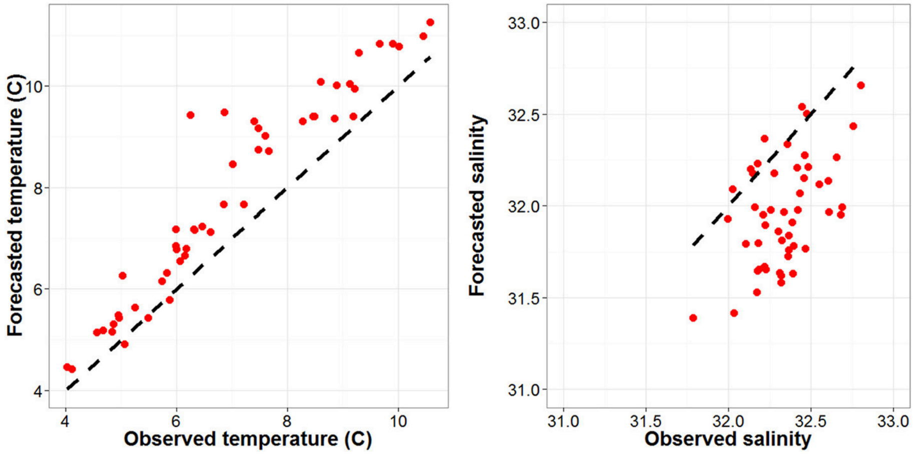

FIGURE 4 | Scatterplots of the forecasted against the observed temperature (left) and salinity (right) for each tow. The dashed line is the 1:1 line.

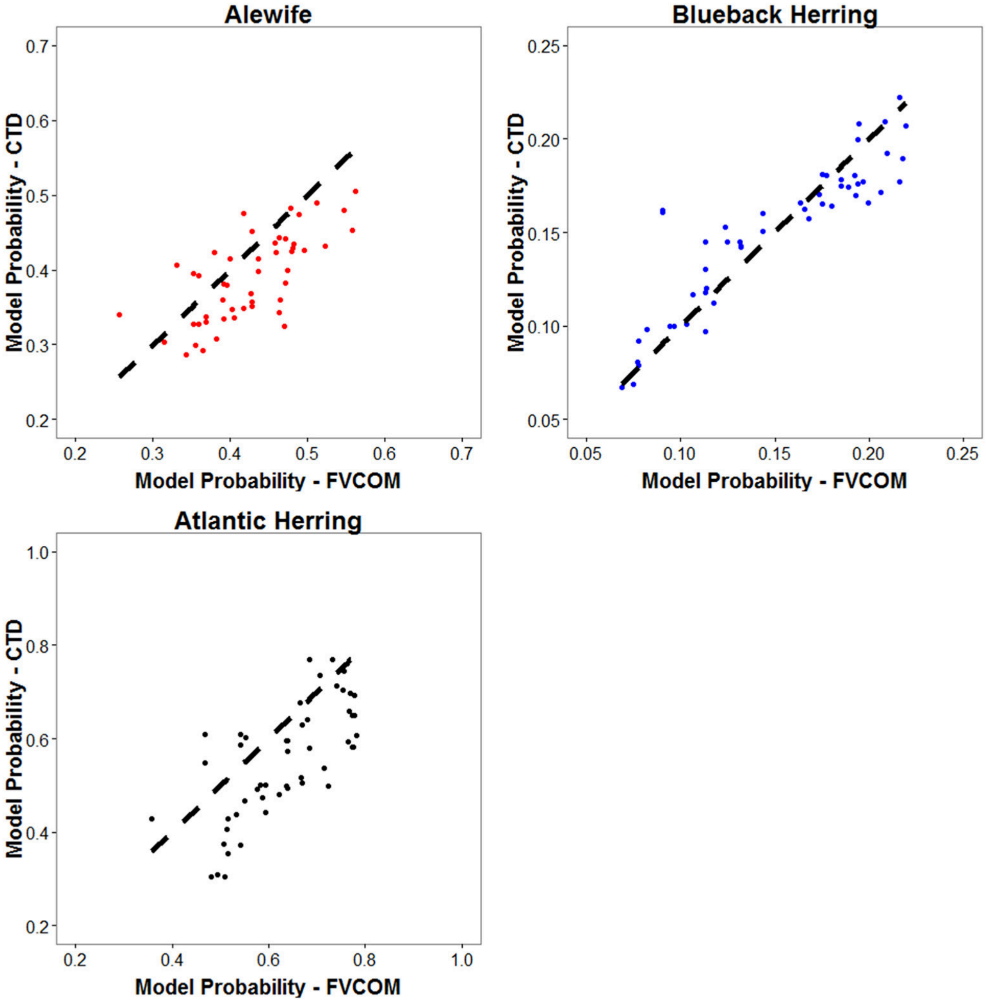

FIGURE 5 | Scatterplots of the model probability of species presence using observed (CTD) conditions against model probabilities using forecasted (FVCOM) conditions for alewife (upper left), blueback herring (upper right), and Atlantic herring (lower left).

TABLE 1 | Summary of the differences between high and low model probability stations for alewife based on forecasted and observed conditions, and observed difference in the proportion of alewife to Atlantic herring catch for each sampling trip.

Date	Forecast condition probability differences	Observed condition probability differences	Proportion of Atlantic herring catch differences
12/30/2015	0.0549	0.0339	−0.5610
1/6/2016	0.1391	0.0400	−0.2156
1/12/2016	0.0519	−0.0259	0.3599
1/21/2016	0.0809	0.0474	0.0331
1/28/2016	0.0598	0.0112	−0.0370
2/10/2016	0.0835	0.0370	0.5510
2/18/2016	0.1682	0.0931	1.7594
2/22/2016	−0.2223	−0.1656	0.0000
3/1/2016	0.0847	0.1226	0.5119

TABLE 2 | Summary of the differences between high and low model probability stations for blueback herring based on forecasted and observed conditions, and observed difference in the proportion of blueback herring to Atlantic herring catch for each sampling trip.

Date	Forecast condition probability differences	Observed condition probability differences	Proportion of Atlantic herring catch differences
12/30/2015	0.0008	−0.0017	−0.1442
1/6/2016	−0.0099	−0.0172	−0.2845
1/12/2016	−0.0200	−0.0074	0.0000
1/21/2016	0.0188	0.0117	−0.0486
1/28/2016	0.0148	0.0016	0.0032
2/10/2016	0.0225	−0.0146	0.0073
2/18/2016	0.0238	−0.0102	0.8895
2/22/2016	−0.0246	0.0007	0.0000
3/1/2016	−0.0079	−0.0131	0.0258

species' presence and the proportion of the Atlantic herring catch for alewife and blueback herring.

Environmental forecast models have been used to predict species' distributions and habitat overlap with other commercially valuable species months in advance for southern bluefin tuna, *Thunnus maccoyii* (Hartog et al., 2011; Eveson et al., 2015). These models have longer temporal accuracy than those used here, but the spatial resolution is coarser; also, the study species' thermal associations are more distinct than observed for Atlantic herring, alewife, and blueback herring (Hartog et al., 2011; Turner et al., 2015). The difference between the spatial scales of the fishery-independent trawl survey (roughly 20 km or more between stations) that was used for model development and the Atlantic herring small-mesh bottom trawl fishery (total area of roughly 60 by 40 km) may further complicate our model evaluations. When species distribution forecasts were evaluated with fishery-independent data, the forecast model skill ranged from 0.68 to 0.69 for Atlantic herring, alewife, and blueback herring (Turner et al., 2017). At the scale of the small mesh bottom trawl fishery, habitat associations could be dependent on variables not included in models, or relationships with some variables might vary between the spatial scale of the trawl survey compared with the fishery (Hirzel and Le Lay, 2008).

Conditions, and therefore probability of species' presence, changed during the course of each tow, and while the changes in probability were relatively small and generally lacked trends, the ranges observed within tows were similar to the differences observed between high and low probability stations. This heterogeneity in environmental conditions within tows likely affects species distributions, but occurs at a scale finer than the species distribution models and potentially the ocean forecast models as well. Given the relatively small range of probabilities observed within and between tows, and that tow durations for this study were short relative to regular fishing trips (20 min vs. 2 h), species mixing may occur at spatial scales finer than sampled here. Interestingly, the species distribution forecast models and the captains' "mental models" had fairly similar accuracy. This suggests that small-scale physical heterogeneity is not driving differences in catch; which raises the importance of small-scale unresolved aspects of the biological distribution.

Implications and Next Steps

Models developed using fishery-dependent data, as opposed to fishery-independent data might provide greater skill for predicting incidental catch in commercial fisheries. Fishery-dependent models could be developed by deploying CTD probes on commercial small mesh bottom trawl and mid-water trawl vessels. These oceanographic data could be used to further evaluate the accuracy of FVCOM forecasts. Previously collected tow-by-tow catch data can also be used by coupling with FVCOM hindcast data. Tow-by-tow data on catch composition only began being regularly collected within the past decade, thus further limiting the amount of existing data (Bethoney et al., 2013). These data could then be used to generate species distribution models, which could then be tested similar to the test reported here.

The models, in their current form, have limited applicability to the winter small mesh bottom trawl Atlantic herring fishery, but they were useful at the broader scale of the Northeast Fisheries Science Center fishery-independent bottom trawl survey (Turner et al., 2015, 2017). Therefore, we hypothesize that model accuracy is confounded by spatial scale differences in habitat associations, and can be improved for commercial fisheries by developing models using fishery-dependent data. If fishery-dependent models have predictive skill, the next step would be to collaborate with the River Herring Bycatch Avoidance Program to incorporate the forecast models into the program. Given that the existing Bycatch Avoidance Program uses an $\sim 5'$ latitude by $10'$ longitude grid (roughly 5 nautical miles by 8 nautical miles) for reporting, the forecasts will likely need to be adapted to the same scale to facilitate integrating forecasts models with current bycatch avoidance updates (Bethoney et al., 2013). While a lot of work remains, this tool has the potential to further reduce the ecological impacts of the fishery without large economic losses.

This study also paves the way for using oceanographic forecasting models to support fishery management in near-real time. While substantial work remains, the architecture of

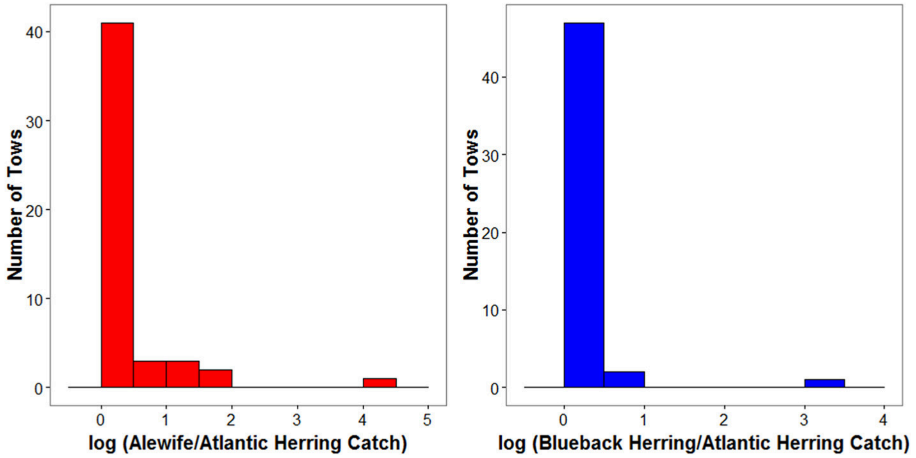

FIGURE 6 | Histograms of the log-transformed proportion of alewife/Atlantic herring catch in pounds (left) and blueback herring to Atlantic herring catch in pounds (right).

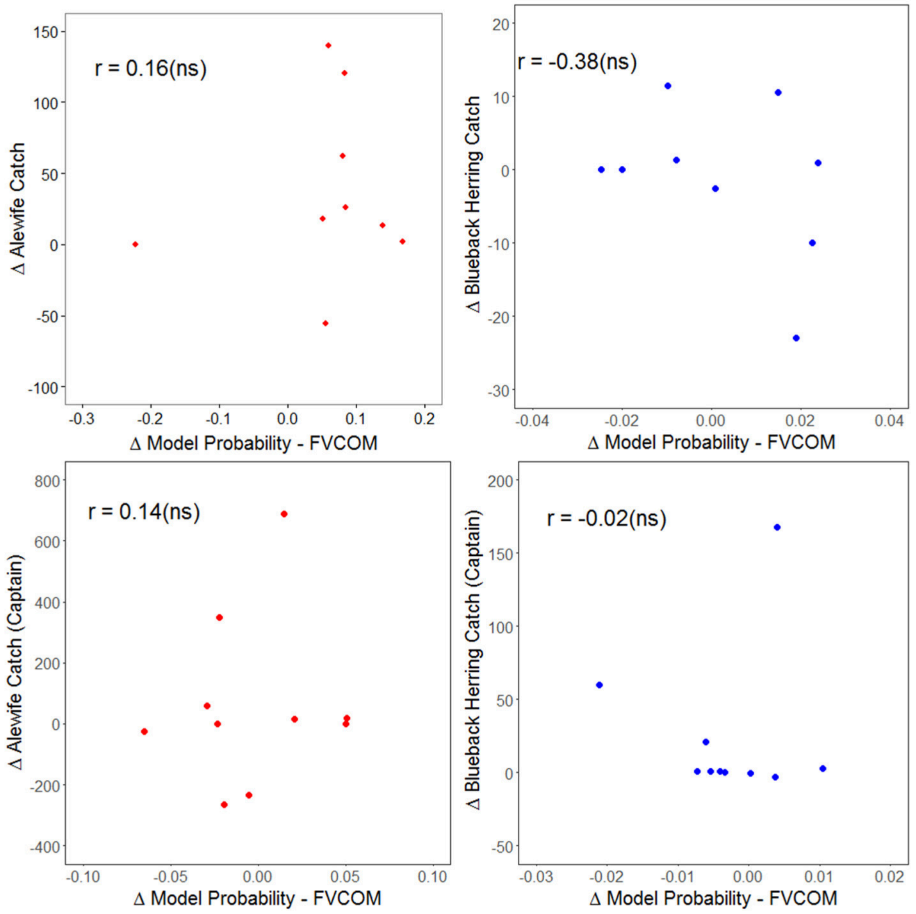

FIGURE 7 | Scatterplots of the observed difference in catch (in pounds) at high and low probability stations against the difference in FVCOM forecasted model probability of species presence for model-selected stations for alewife (upper left) and blueback herring (upper right) and for captain-selected stations for alewife (lower left) and blueback herring (lower right).

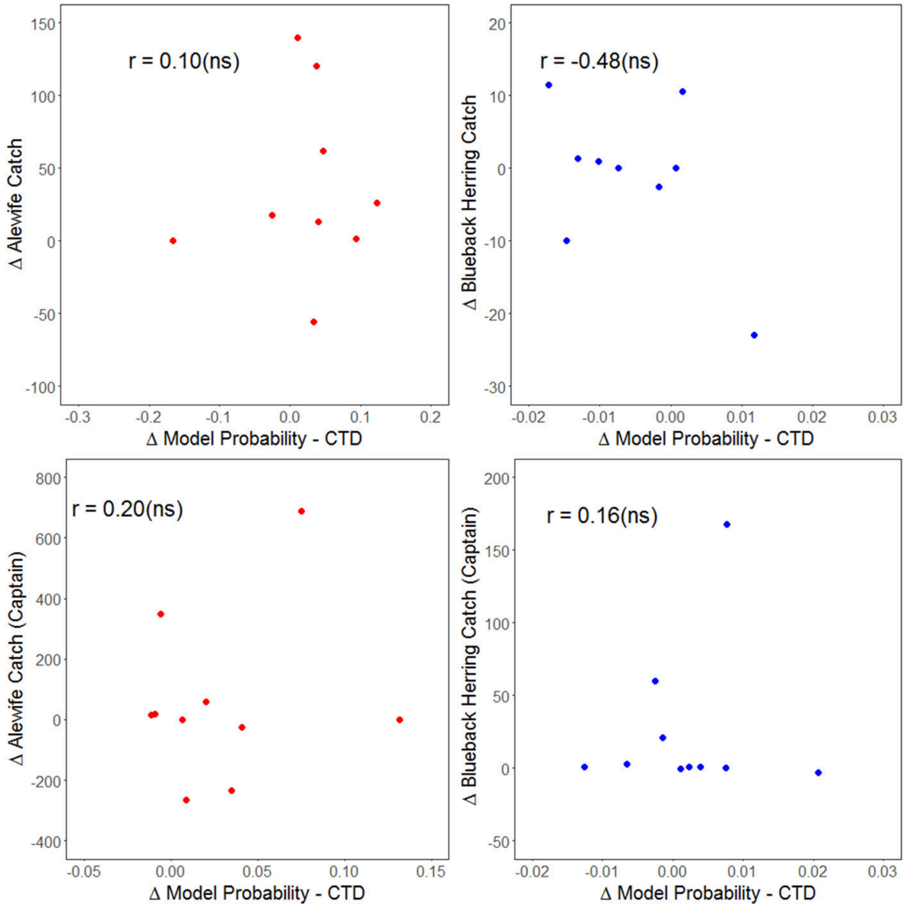

FIGURE 8 | Scatterplots of the observed difference in catch (in pounds) at high and low probability stations against the difference in observed (CTD) model probability of species presence for model-selected stations for alewife (upper left) and blueback herring (upper right) and for captain-selected stations for alewife (lower left) and blueback herring (lower right).

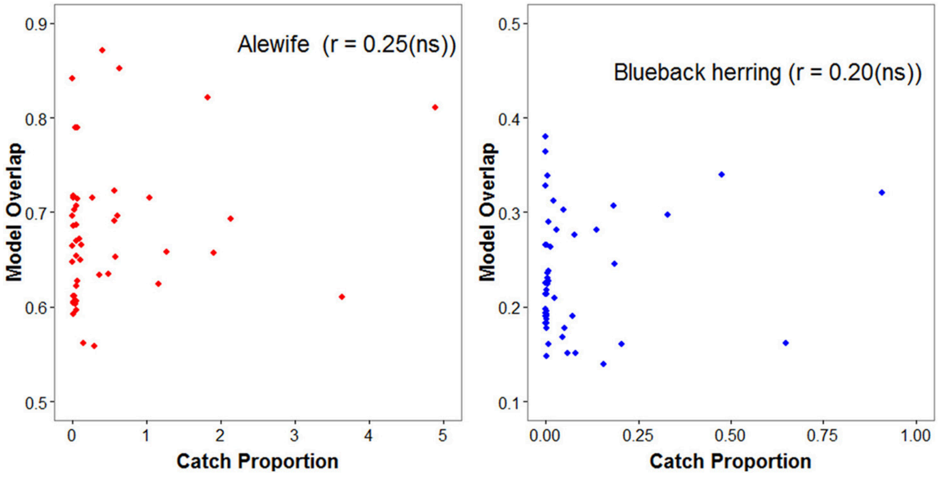

FIGURE 9 | Scatterplots of the proportion of model probability overlap against the catch proportion for alewife (left) and blueback herring (right).

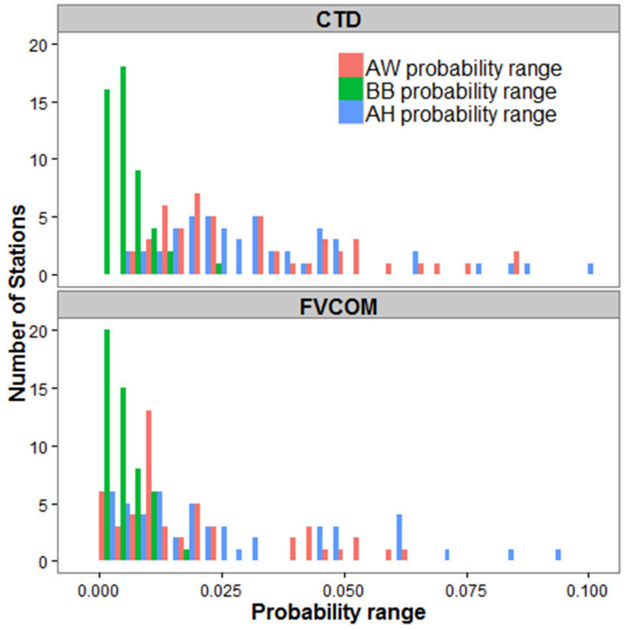

FIGURE 10 | Histograms of the ranges in model probabilities of each species observed within each tow. The upper panel shows the ranges for probabilities derived using observed (CTD probe) data, and the lower panel shows the ranges for probabilities derived using forecast model (FVCOM) data. Red bars represent ranges of alewife (AW) model probability, green bars represent blueback herring (BB) model probability, and blue bars represent Atlantic herring (AH) model probability.

coupling circulation models with species distribution models, and providing the output to fishermen in near-real time has been developed. Continued involvement of multiple stakeholders is needed to improve upon this idea. There are numerous by-catch and incidental catch issues in the Northeast region where this approach may contribute to meeting the goals of reducing incidental catch in a cooperative framework, and is a relatively inexpensive method of sampling that could inform stock assessments.

AUTHOR CONTRIBUTIONS

All authors contributed to the study design. CS performed data collection, and analyses were performed by ST and JH. The initial draft was drafted by ST and JH with input and critical feedback from all other coauthors. All authors approve the final submission.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: http://journal.frontiersin.org/article/10.3389/fmars.2017.00116/full#supplementary-material

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frontiers in Marine Science

METHODS
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A Framework for Combining Seasonal Forecasts and Climate Projections to Aid Risk Management for Fisheries and Aquaculture

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A changing climate, in particular a warming ocean, is likely to impact marine industries in a variety of ways. For example, aquaculture businesses may not be able to maintain production in their current location into the future, or area-restricted fisheries may need to follow the fish as they change distribution. Preparation for these potential climate impacts can be improved with information about the future. Such information can support a risk-based management strategy for industries exposed to both short-term environmental variability and long-term change. In southern Australia, adverse climate impacts on valuable seafood industries have occurred, and they are now seeking advice about future environmental conditions. We introduce a decision tree to explain the potential use of long-term climate projections and seasonal forecasts by these industries. Climate projections provide insight into the likely time in the future when current locations will no longer be suitable for growing or catching particular species. Until this time, seasonal forecasting is beneficial in helping industries plan ahead to reduce impacts in poor years and maximize opportunities in good years. Use of seasonal forecasting can extend the period of time in which industries can cope in a location as environmental suitability declines due to climate change. While a range of short-term forecasting approaches exist, including persistence and climatological forecasts, only dynamic model forecasts provide a viable option for managing environmental risk for marine industries in regions where climate change is reducing environmental suitability and creating novel conditions.

Keywords: climate risk management, emergence time, climate variability, climate change, ACCESS-S, climate-proofing

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INTRODUCTION

Marine industries such as fisheries and aquaculture have historically coped with interannual and seasonal environmental variability that affects the presence, growth, and survival of many species (Callaway et al., 2012; Hobday et al., 2016; Salinger et al., 2016). Optimal conditions for catching and farming fish are not always present at the desired time and location (Callaway et al., 2012; Bell et al., 2013; Brander, 2013), which has required development of skills and approaches to cope with environmental variability. For example, interannual changes in species distribution in response to climate drivers such as ENSO have required fishers to temporarily move to new grounds to access fish (e.g., Lehodey et al., 2006), or to delay aquaculture activities in that season (Spillman et al., 2015). However, under long-term climate change, new conditions will be encountered, and past experience may no longer be as useful in managing businesses (Hobday et al., 2016). Thus, new approaches to cope with future environmental conditions may be needed.

Information about future environmental conditions can be used to manage risk in environmentally-exposed industries (Chang et al., 2013; Little et al., 2015). Seasonal forecasting applications in Australia and elsewhere have been developed for a range of marine resource segments, including salmon and prawn aquaculture (Spillman and Hobday, 2014; Spillman et al., 2015), commercial tuna (Hobday et al., 2011; Eveson et al., 2015) and sardine fisheries (Kaplan et al., 2016), and recreational fisheries (Brodie et al., 2017). Depending on the application, these forecasting applications have delivered information on both environmental conditions, such as water temperature, rainfall, and air temperature, and habitat distribution, at lead times of up to 3 months (Hobday et al., 2016), helping managers and fishers to plan activities based on predicted conditions (Eveson et al., 2015; Spillman et al., 2015). These marine industries are thus in a position to make improved management decisions and perform better than those without information about the future environment.

In contrast, longer-term projections of environmental change that will impact the distribution and abundance of marine species, such as tuna (Hobday, 2010; Lehodey et al., 2010; Hartog et al., 2011; Dell et al., 2015; Robinson et al., 2015), have not been as useful to seafood businesses. While policy and management discussions can be informed by projections at long time scales (Bell et al., 2013; Brander, 2013), there are few operational business decisions made at time scales matching climate scale projections. Thus, while many highly cited papers describe changes in marine species distribution and abundance for the year 2100 (e.g., Cheung et al., 2010; Hobday, 2010; Lehodey et al., 2010), the timescale of these studies is less relevant for marine industries currently facing challenging environmental conditions (Spillman and Hobday, 2014). The goal of this paper is to propose one approach to help these industries manage climate variability in the short-term and adapt to climate change in the long-term.

Some marine industries are spatially restricted, including most ocean-based aquaculture businesses largely due to infrastructure associated with holding the farmed species, and so are particularly vulnerable to changing environmental conditions (e.g., Callaway et al., 2012). Likewise, coastal fisheries may have a restricted operating range from a port due to the vessel size, fishing technique, management restrictions, or product shipping requirements (e.g. access to road or air freight). Here we introduce a conceptual framework to help climate-proof these marine industries by using a combination of climate and seasonal forecasting that recognizes the influence of both long-term trends and short-term environmental variability. In this regard, we define climate-proofing as the development of strategies that can equip businesses with skills or information to manage or reduce the risk from climate change. This approach builds on recent development and application of seasonal forecasting tools, which represent one risk-based approach used by the marine resource sector to manage future uncertainty (Battaglene et al., 2008; Hobday et al., 2016; Payne et al., 2017).

We illustrate this framework using long-term climate projections and seasonal forecast examples from southern Australia, where marine-based industries are worth more than A$10B per annum (Bennett et al., 2016). Economically important aquaculture industries worth close to A$1B per annum include salmon, tuna, abalone, oyster, and mussel and are all exposed to environmental change (Savage and Hobsbawn, 2015). This region is experiencing rapid change in terms of ocean warming (Hobday and Pecl, 2014) as well as in the number of extreme events such as marine heatwaves (Oliver et al., 2017), both of which are projected to continue (Oliver et al., 2014). Thus, there is growing interest in forecasting applications to help marine industries in this region (Hobday et al., 2016). Here we focus on forecasts of sea surface temperature (SST), a primary environmental variable that is changing and is influential on aquaculture production via direct impacts on growth and survival and indirect impacts through disease, pests, and equipment fouling (Hobday et al., 2016), and on fisheries through changes in distribution and abundance of the target species (e.g., Madin et al., 2012; Frusher et al., 2016).

THE APPROACH TO CLIMATE-PROOFING

To understand the potential environmental conditions at seasonal and long-term time scales, information from seasonal-scale and climate-scale models, respectively, is needed. We first provide a brief description of a seasonal-scale and climate-scale model used in Australia, with a focus on SST, whilst noting that each model provides a range of other projected variables that may be useful for different situations and species. We then describe a novel framework that uses information from these two forecasting time scales to support decision makers seeking to manage risk under both climate variability and change.

To generate illustrative long-term projections, we use output from the CSIRO Ocean Downscaling Project (hereafter CSIRO-Downscaling). A global high-resolution (0.1°) ocean general circulation model (OGCM) is used to dynamically downscale climate changes in the twenty-first century derived from Coupled Model Intercomparison Project Phase 5 (CMIP5) climate models (Taylor et al., 2012). The OGCM is the Ocean Forecasting Australia Model Version 3 (OFAM3, Oke et al., 2013), based on version 4p1d of the GFDL Modular Ocean Model (Griffies, 2009), which is configured to have 0.1° grid spacing for all longitudes between 75°S and 75°N, and 51 vertical layers. The global OGCM is integrated over the historical period (1979–2014) driven by 3-h Japanese 55-year Reanalysis (JRA-55, Kobayashi et al., 2015) through bulk formula. Details about model set-up of this historical experiment and validation with observations are provided in Zhang et al. (2016). The model is further integrated from 2006 to 2101, driven by merged atmospheric forcings which include a high-frequency (daily to interannual) part from current-day JRA-55 reanalysis and a long-term climate change part from the ensemble of 17 CMIP5 models under a high emission scenario (RCP8.5) (Zhang et al., 2017). High-resolution (0.1°) model results provide downscaled climate change projections in the twenty-first century for all common ocean state variables including sea level, temperature, and currents.

Example seasonal forecasts are derived here using the new ACCESS-S1 (the seasonal prediction version of the Australian Community Climate and Earth-System Simulator; version 1) seasonal prediction system, developed by the Australian Bureau of Meteorology in collaboration with the UK Met Office (UKMO), CSIRO and universities. ACCESS-S1 is a coupled ocean-atmosphere prediction system comprising the UKMO coupled model GC2, which consists of the latest UKMO atmospheric model, European ocean model NEMO (Nucleus for European Modeling of the Ocean) and sea-ice model CICE (Los Alamos sea ice model), together with land surface model JULES (Joint UK Land Environment Simulator; Lim et al., 2016; Hudson et al., 2017). ACCESS-S1 has considerable enhancements compared to its operational predecessor POAMA-2 (Spillman and Hobday, 2014), including higher ocean grid resolution of 25 km compared to 100–200 km. This marked increase in resolution means that impacts of local weather and climate of narrow features of coastal currents such as the East Australian Current could be resolved and may provide new opportunities for coastal forecasting applications. Example SST forecast skill as a measure of predictive performance for this seasonal model is illustrated here.

Both climate- and seasonal-scale information can be used to manage future environmental risk (**Figure 1**). Climate projections can help to assess regional suitability from the present time to many decades into the future. For example, given a desired SST range for a farmed or fished species, climate models can give an indication as to if and when SST in a particular region will become unsuitable. If environmental conditions in the region are suitable now and remain so in future, then managing for climate variability with accurate seasonal forecasts will suffice. However if the current region is not suitable now, or will become unsuitable in future, it may be necessary to relocate to a new region based on climate projections, or develop other adaptation strategies (e.g., develop a genetically-adapted lineage if sufficient time exists until the site becomes unsuitable; investigate ways to modify the environment to make it suitable; switch to farming/catching a different species).

In southern Australia, SST is projected to warm rapidly over the next 60-80 years, particularly in south-east Australia (**Figure 2**), which is consistent with climate projections reported in previous studies (Hobday and Lough, 2011; Hobday and Pecl, 2014; Popova et al., 2016). These climate projections indicate that seafood industries across southern Australia will need to consider climate-proofing strategies. For example, eastern Tasmania is already warming rapidly (Hobday and Pecl, 2014), with warming projected to continue (**Figure 2;** Popova et al., 2016). The upper limit of a representative temperature (e.g., 13–18°C, representing typical maximum summer and winter temperatures) for an indicative species fished or farmed in this region is currently regularly exceeded in north-east Tasmania (Zone 4, **Figure 3**). To compare between regions, we use as a measure "time of exceedance," analogous to "time of emergence" used in climate studies (Hawkins and Sutton, 2012; Lyu et al., 2014). While summer temperatures receive attention, cooler temperatures in winter are important for recruitment of some wild species, and can also prevent disease persisting year round in cultured species, thus warmer winters may bring challenges, just as do warm summers. For regions to the south, climate projections indicate the year of *first exceedance* of unsuitable summer (winter) conditions increases from north (Zone 3) to south (Zone 1): 2018 (2010), 2024 (2030), and 2037 (2032), respectively (**Figure 3**—middle column). In each region, even as the average SST for a month exceeds a threshold, there will still be areas that may be cooler (**Figure 3**—right two columns). The time of *permanent exceedance* (all subsequent summers above the threshold) is 30–45 years later than the year of first exceedance for the summer threshold, and 14–30 years later for the winter threshold, depending on location (**Figure 3**). If the particular aquaculture or fishing operation needs to have both summer and winter temperatures below these example thresholds, then the time period of suitable conditions is abbreviated. These results should be considered indicative, as they are the results from a single model run with no estimate of uncertainty (Stock et al., 2011), but they illustrate how the time between first and permanent exceedance represents a window in which to use seasonal forecasting, whilst developing a solution for when conditions become permanently unsuitable (**Figure 1**).

Future sites can be assessed by considering their suitability under future conditions. For example, as the most northern region (Zone 4) warms, suitable locations based on SST conditions can be found to the south (**Figure 3**). Thus, in 2048, when the average conditions become permanently unsuitable (outside the range 13–18°C) in Zone 3, there are still some locations within Zone 3 that are suitable, and there are more areas with suitable conditions further to the south. If only a small southward relocation distance is selected by a fishing or aquaculture business, it will likely be necessary to relocate again in future, while a move too far south may be premature for best conditions.

BENEFIT OF SEASONAL FORECASTING AS THE CLIMATE CHANGES

Seasonal forecasts can be used to manage risk due to environmental variability both when the current location is expected to remain suitable in future and when it is expected to become unsuitable (**Figure 1**). In the first case the main objective is to use short-term forecasts to improve efficiency and increase profits, while in the second case the aim is more to minimize costs and increase the time period over which the current region remains viable for the fishing or farming activity while developing long-term adaptation options.

Specifically, in areas where the environmental suitability for the focal species is good, profits are high relative to costs (**Figure 4**). If conditions are always suitable (e.g., always between the upper and lower SST threshold), the benefits

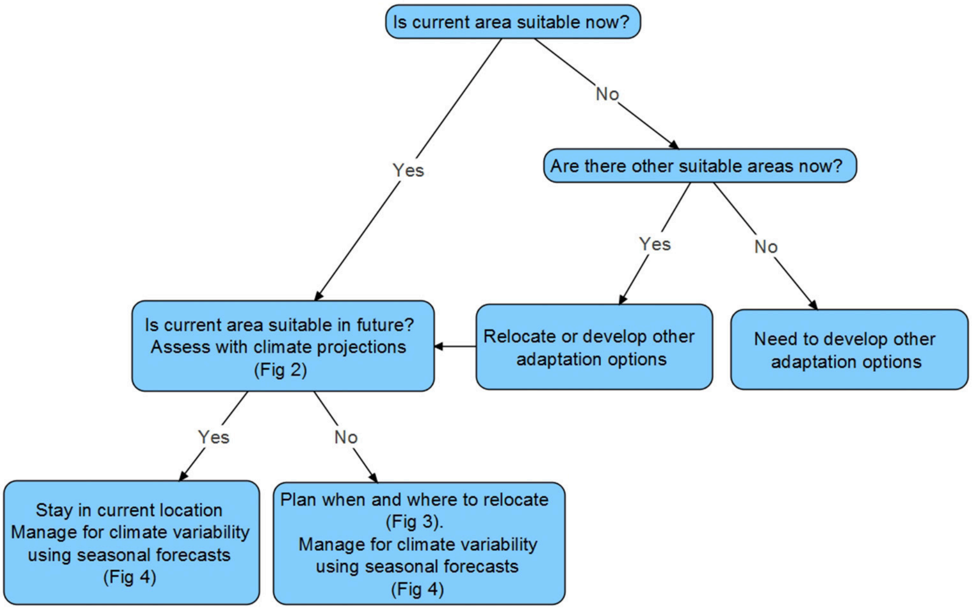

FIGURE 1 | Decision tree to guide climate-proofing approach by aquaculture businesses. Figure numbers refer to subsequent figures.

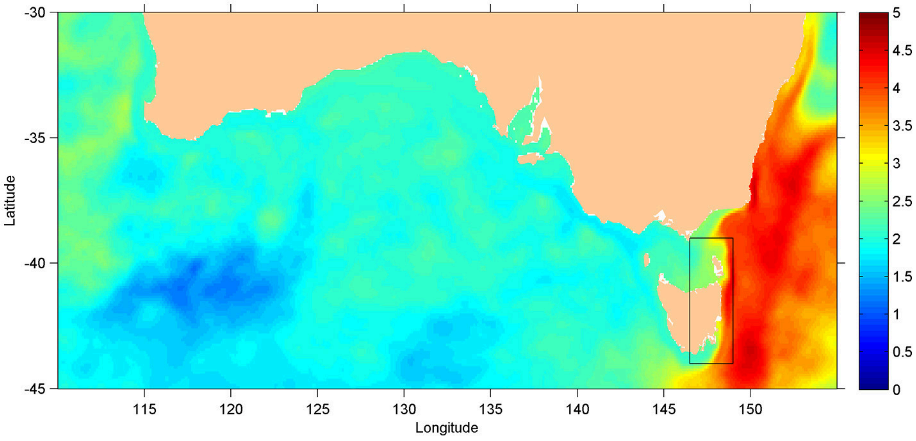

FIGURE 2 | Projected SST change over the period 2081-2100 relative to 1986-2005 for southern Australia based on output from the CSIRO-Downscaling project described in the text. Box shows the area considered in **Figure 3**.

from seasonal forecasting might not be significant. However, if environmental variability sometimes exceeds the suitable range, even if there is no long-term trend, seasonal forecasts will be beneficial. If the environmental suitability at a location is predicted to decline over time under climate change, operational costs are expected to increase and profits decrease, until business would not be viable. Seasonal forecasts can provide information on upcoming environmental conditions so individual businesses have increased potential to reduce costs and increase profits, relative to no forecast (Hobday et al., 2016). This can allow these businesses to implement proactive response options to remain viable during periods when less suitable environmental conditions occur, even if there is no significant climate change trend (e.g., Spillman and Hobday, 2014; Spillman et al., 2015). Depending on the business, these options might include modifying the environment, changing the fishing or harvesting schedule, increasing or decreasing the production volume, or adjusting the maintenance schedule. As climate change continues, major business change is likely needed (e.g., transformational adaptation; Kates et al., 2012), such as relocation or selection of a species for which the environmental conditions are more suited (**Figure 4**). Previous work has shown that provision of seasonal forecasts to seafood businesses have led operators to make different decisions on the basis of the

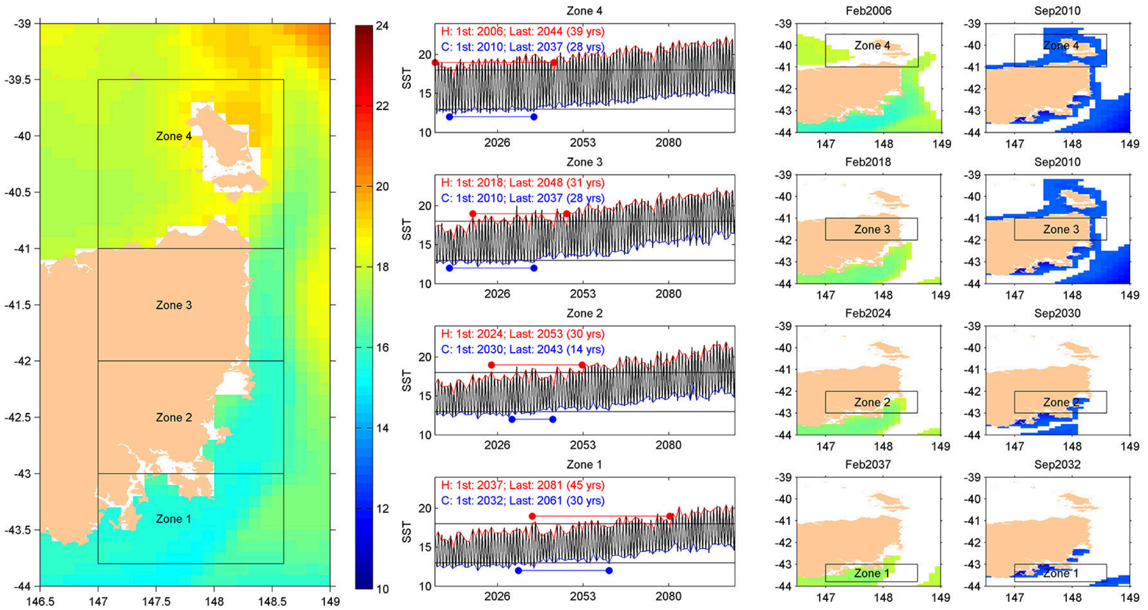

FIGURE 3 | First column: Model sea surface temperature (SST) in eastern Tasmania for February 2016. **Middle column:** Monthly SST time series for the period 2006-2101 (black line) for the four zones with example warm (18°C) and cold thresholds (13°C) in horizontal black lines, corresponding to maximum tolerances for a hypothetical species in summer and winter, and the average SST for February (Austral summer, red line) and September (Austral winter, blue line), typically the warmest and coldest month respectively. The first and permanent exceedance times for the summer (red dots) and winter (blue dots) are shown for each zone, and provided on each panel (red and blue text), along with the period between first and permanent exceedance. **Final two columns**: February and September SST maps for the year of first exceedance, showing that in each region, there are pixels where SST is below the threshold values for summer and winter (shaded). Color scale is the same in all maps. Data are from modeling experiments run by the CSIRO-downscaling project.

forecasts. For example, tuna fishers in the Great Australia Bight adjusted the timing of their fishing activity based on forecasts of environmental conditions in the upcoming season (Eveson et al., 2015), while prawn farmers in Queensland changed their stocking times based on seasonal rainfall forecasts (Spillman et al., 2015). Thus, seasonal forecasting will be most useful to businesses after the environmental conditions first exceed a threshold (first exceedance time) and before conditions are permanently unsuitable (permanent exceedance time; **Figure 3**). Over this period, there will be good and bad seasons, and information on the likely conditions at these short time scales can help minimize costs.

A seasonal forecast system can only be useful if it produces reliable and accurate forecasts. For example, in southern Australia, model forecast skill, persistence forecast skill, and SST variability all vary across the region (**Figure 5**). Model skill here is quantified using Pearson's correlation, correlating monthly model and observed SST anomalies (i.e. deviations from the long-term monthly model/observed mean), where the observed dataset is Reynolds OISST v2 SST (Reynolds and Smith, 1994; Reynolds et al., 2002). A persistence forecast uses the current observed anomaly conditions as a predictor of future conditions; e.g., for a forecast beginning on 1 February 1990, the SST anomaly for January 1990 is used as the forecast and persisted for the duration of the forecast period (Spillman and Alves, 2009). In this example, persistence skill is quantified using Pearson's correlation, as per model skill. The performance of persistence forecasts is generally higher in areas of low intra-annual SST variability, i.e., where SST conditions vary little from month to month. For areas of low inter-annual monthly SST variability, i.e., SST for a particular month varies little from year to year, a climatological forecast (long-term monthly mean) can be useful.

In the locations where inter-annual SST variability is low, such as during July in the inshore Great Australia Bight (∼130–137°E) (**Figure 5**), a forecast may not be necessary (Case 1, **Table 1**). The most challenging case is when SST variability is high, and persistence and model skill is low. In these situations, forecasting may be very hard (Case 2, **Table 1**), such as in January off the Bonney Coast (∼140°E), and real-time monitoring and rapid responses should be developed. If the persistence skill is high and model skill is low in a region (Case 3, **Table 1**), such as in July off south-west Western Australia (∼115°E), real-time observations can also be used and future planning at a seasonal time scale based on the assumption that anomalous conditions will continue. These approaches (Cases 1–3, **Table 1**) are not climate-proof, as they do not account for trends in a changing environment. If model forecast skill is high (such as around Tasmania ∼150°E in winter or in the Great Australian Bight ∼130–137°E in summer), then a model forecast can be used in preference to a persistence forecast (whether high or low persistence skill and regardless of SST variability; Case 4 and Case 5, **Table 1**), since a dynamic model (e.g., ACCESS-S1) can account for trends in the changing environment and thus provides a climate-proof approach.

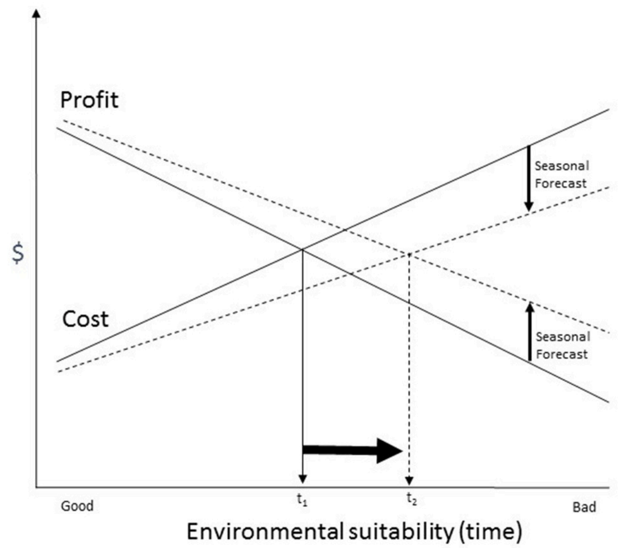

FIGURE 4 | Benefit of seasonal forecasting under changing environmental suitability. In areas where the environmental suitability for the species under consideration is good, profits are high relative to costs. If the environmental suitability at a location declines over time under climate change, costs are expected to increase and profits decrease until a time at which a business would not be profitable (t1). Using seasonal forecasts to provide information on upcoming conditions, businesses should be able to reduce costs and increase profits, relative to no forecast such that they can remain profitable under less suitable environmental conditions for longer (until t_2). Beyond this point, conditions are such that relocation (or another adaptation option) is necessary.

RISK MANAGEMENT FOR CLIMATE-EXPOSED SEAFOOD BUSINESSES

Marine industries, particularly seafood businesses, are exposed to environmental variability and long-term climate change, such that the future carries risks to production. While the focus here is on fisheries and aquaculture, this approach may also be useful for other applications: guiding external investment decisions in these marine industries; the insurance industry; and international seafood supply businesses that seek products from many regions who might be managing production risks across many locations in the same way that large agricultural companies manage supply chain risk.

Decision makers in aquaculture or marine management agencies often require information from a range of time scales in their decision making (Hobday et al., 2016; Tommasi et al., 2017). Fisheries managers can use forecast information to plan distribution of fishing effort, as has been proposed for the Californian sardine fishery based on forecasts with a downscaled regional ocean model (Kaplan et al., 2016). Aquaculture managers might be charged with managing production and harvest schedules, which can be informed by knowledge of likely (and unlikely) conditions over the coming months (i.e., seasonal forecasts). At longer time scales, they may use climate-scale forecasts to assess the need to seek new sites, and if necessary, to negotiate with coastal planning agencies for access to new regions. In the same way, coastal management agencies may use long-term climate projections to develop zoning plans.

While more mobile than aquaculture, fisheries are still relatively site attached with regard to access to fixed infrastructure such as ports, product transport and processing plants; thus, information on future environmental conditions at a local scale is still important for short and long-term planning. For example, the southern bluefin tuna (SBT) fishery in the Great Australia Bight currently utilizes seasonal forecasts to plan the timing and location of fishing operations, workforce management, and equipment deployment (Eveson et al., 2015). This fishery is more site-attached than most in that captured fish are towed back to farm sites near Port Lincoln, South Australia, for grow-out in cages (Ellis and Kiessling, 2016). If climate change results in conditions at the current catch locations becoming unsuitable for SBT, fish may move too far from the farm sites for this system to be viable. Alternatively, conditions at the farm sites could become unsuitable. In both cases, climate forecasts could be used to assess future viability of alternative farm sites, with seasonal forecasts used in the interim to manage risks due to changing fish distribution or unsuitable grow-out conditions.

For marine industries provided with environmental information about the future, such as warming waters in the examples presented here, there are a range of risk management options. Most simplistic is a movement to new regions that meet the required environmental conditions. Given the long-term persistence of climate change (e.g., many centuries of temperature and sea level rise; Meehl et al., 2012), industries may have to relocate more than once in the future to stay within an environmental suitability envelope. If the changes are such that relocation is not possible or not cost-effective, an adaptation response could be to change the focal species of the fishery or aquaculture operation. For example, in eastern Tasmania, SST conditions may begin to suit other species for farming or wild fisheries, such as kingfish (*Seriola lalandi*). This species is currently exploited by aquaculture and fishery industries further north in Australia, and its distribution is already expanding further south (Stuart-Smith et al., 2016).

Here we have focused on SST as a dominant driver of marine production, but the same approach could be used for other critical variables such as upwelling strength, eddy activity, oxygen concentration or primary production. In order to deliver information for variables that have greater spatial variability and projection uncertainty, seasonal and climate models will need to improve and be validated. Thus, any decisions made on the basis of climate forecasts available today may need to be revisited with revised forecasts over the coming years, as predictive skill improves. While we have considered just a single set of climate projections and a single variable (SST), other studies show that the uncertainty of climate scale forecasts can be relatively large, and this uncertainty increases further into the future (Payne et al., 2017). Thus, a business may need to deal with the case where the upper temperature threshold for their species/situation is expected to be permanently exceeded anywhere from, say, 2040 to 2060. This is where the power of considering seasonal

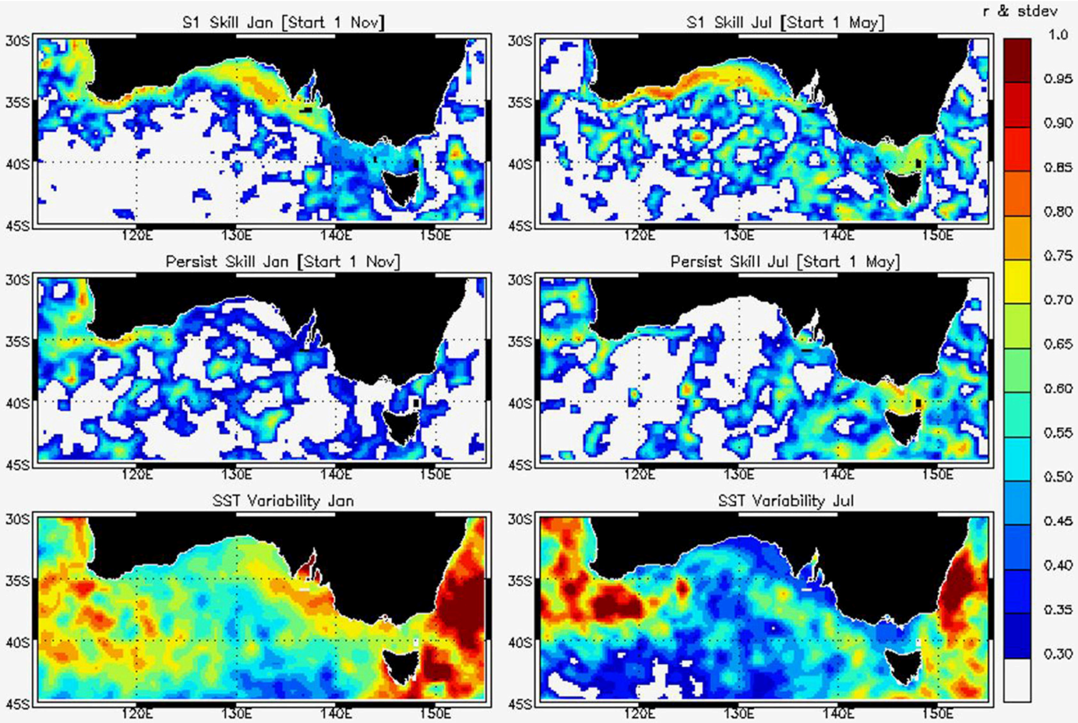

FIGURE 5 | Skill of alternative seasonal forecast approaches in summer (January) and winter (July), illustrated for southern Australia. **Row 1**: skill for ACCESS-S1 forecasts issued 1 November and 1 May; **Row 2**: skill for persistence forecasts issued 1 November and 1 May; **Row 3**: inter-annual SST variability for January and July (standard deviation for January or July across 1991–2012). In all cases, values were calculated over the time period 1990–2012.

TABLE 1 | Managing environmental variability at the present location is possible with several different approaches, depending on the historical environmental variability (in this case SST), the skill of a persistence forecast, and the skill of the dynamic model forecast.

Case	Inter-annual SST variability	Persistence forecast skill	Model forecast skill (ACCESS-S1)	Best approach at this time	Climate-proof?
1	Low	NR	NR	May not need a forecast. Use climatology to infer conditions for the near future.	No
2	High	Low	Low	Difficult—this is an uncertain environment for businesses. Develop rapid responses to real-time monitoring.	No
3	Low/High	High	Low	Use real-time observations. If above average at the current time, assume will be above average for the near future.	No
4	Low/High	Low	High	Use dynamic model forecast.	Yes
5	Low/High	High	High	Either dynamic model or persistence forecast useful, but dynamic model forecast more robust under climate change.	Yes

Not all these approaches will be climate-proof. NR indicates "not relevant" to decision process.

forecasting at the same time is demonstrated. The risk due to uncertainty with long-term projections (i.e., conditions will become unsuitable, but when?) can be reduced with information on shorter time scales.

Additional research is needed to evaluate the cost-benefit of future climate-proofing, such as examining the risk of following a new strategy too soon. For example, a pre-emptive move from warming conditions may result in a better environment for the activity, but may result in a business being too far from existing infrastructure. Integrated responses to climate risk are needed, with strong engagement across the range of stakeholders involved, from the primary fishers to the managers and policy makers. All these groups should work together to consider the appropriate responses to future climate risk, how it can be reduced with future information, and how to plan for transitions to new ways of doing business. Providing information for regional planning agencies is particularly important, as many government agencies have not yet begun to recognize the need for changes in the regional marine industries. Long-term projections can help with development of parallel responses. Thus, a combination of seasonal and long-term forecasting tools will allow entire regions to undergo spatial planning at time scales previously considered separately.

AUTHOR CONTRIBUTIONS

AH and CS: Conceived paper; XZ: Contributed analyses; AH, CS, JE, JH, XZ and SB: All co-wrote paper.

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Projecting Marine Mammal Distribution in a Changing Climate

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Climate-related shifts in marine mammal range and distribution have been observed in some populations; however, the nature and magnitude of future responses are uncertain in novel environments projected under climate change. This poses a challenge for agencies charged with management and conservation of these species. Specialized diets, restricted ranges, or reliance on specific substrates or sites (e.g., for pupping) make many marine mammal populations particularly vulnerable to climate change. High-latitude, predominantly ice-obligate, species have experienced some of the largest changes in habitat and distribution and these are expected to continue. Efforts to predict and project marine mammal distributions to date have emphasized data-driven statistical habitat models. These have proven successful for short time-scale (e.g., seasonal) management activities, but confidence that such relationships will hold for multi-decade projections and novel environments is limited. Recent advances in mechanistic modeling of marine mammals (i.e., models that rely on robust physiological and ecological principles expected to hold under climate change) may address this limitation. The success of such approaches rests on continued advances in marine mammal ecology, behavior, and physiology together with improved regional climate projections. The broad scope of this challenge suggests initial priorities be placed on vulnerable species or populations (those already experiencing declines or projected to undergo ecological shifts resulting from climate changes that are consistent across climate projections) and species or populations for which ample data already exist (with the hope that these may inform climate change sensitivities in less well observed species or populations elsewhere). The sustained monitoring networks, novel observations, and modeling advances required to more confidently project marine mammal distributions in a changing climate will ultimately benefit management decisions across time-scales, further promoting the resilience of marine mammal populations.

Keywords: marine mammal distribution and abundance, climate-change, marine ecosystems, predicting and forecasting, Marine mammal conservation

INTRODUCTION

Marine mammals are exposed to a variety of threats and habitat perturbations from human activities (e.g., by-catch incidental to commercial fisheries, industrial noise, ship-strike) on regional and global scales. Human activities can lead to changes in marine mammal distribution, such as extirpation due to whaling or hunting [e.g., southern right whales (*Eubalaena australis*) in New Zealand Patenaude et al., 1998; Carroll et al., 2014] and temporary abandonment of portions of a range [e.g., gray whales (*Eschrichtius robustus*) in Laguna Guerrero Negro, Baja California, Mexico Bryant et al., 1984]. Alteration of oceanographic conditions and processes due to anthropogenic global climate change are expected to profoundly influence ecosystems (i.e., ocean warming, acidification, and deoxygenation) (Burrows et al., 2011; IPCC, 2014) and, in turn, marine mammal distributions in the foreseeable future (Learmonth et al., 2006; Schumann et al., 2013; Laidre et al., 2015). While the full nature and scope of climate-driven impacts on marine mammals are unclear, changes in population ranges and regional abundance are expected (Learmonth et al., 2006).

Shifting ranges of various marine species have been observed across all ocean regions (Poloczanska et al., 2016). Integration of long time series and modeling studies have demonstrated climate change-associated distributional changes in numerous marine fish and invertebrate populations (e.g., Perry et al., 2005; Nye et al., 2009; Pinsky et al., 2013; Poloczanska et al., 2013; Walsh et al., 2015), including commercially important North Atlantic Ocean species in multi-billion dollar fishing industries (NMFS, 2016). Additional shifts in these taxa, as well as the potential for accelerated rates of change, are expected as warming continues (Hazen et al., 2013; Lynch et al., 2015; Hare et al., 2016).

Shifts have included important prey items for marine mammals. Rising temperatures in the Gulf of Maine, for example, have prompted *Calanus finmarchicus*, a major food source for herring, mackerel, and North Atlantic right whales (*Eubalaena glacialis*), to prematurely exit winter dormancy, denying key predators a lipid rich food source in spring and summer (Runge et al., 2015). Such changes in the quality, timing, and abundance of key zooplankton and forage fish species may confound efficient transfer of marine primary and secondary production to higher trophic levels with corresponding cascading implications for food webs (Peterson, 2009; Lauria et al., 2012; Sydeman et al., 2015), including those involving marine mammals (Trathan et al., 2007; Moore and Huntington, 2008).

Range shifts associated with climate change have been observed in some marine mammal populations (e.g., Kovacs et al., 2011; Clarke et al., 2013; Hamilton et al., 2015). Substantive shifts in the distribution of marine mammals and other large marine vertebrates have been predicted (e.g., IWC, 2010; Gilles et al., 2011; Becker et al., 2012; Hezel et al., 2012; Keller et al., 2012; Gregr et al., 2013; Hazen et al., 2013; Mannocci et al., 2014). As such shifts occur in novel environments expected under climate change, protective measures for marine mammals will need to be adapted. However, capabilities available to managers to anticipate and react to such changes are currently limited.

MARINE MAMMAL MANAGEMENT–AUTHORITIES AND MANDATES

Conservation of marine mammals and their habitats is generally the responsibility of federal, state, and provincial governments, in some cases working with co-management partners. Anthropogenic threats to marine mammal populations are largely managed in the United States through policies and conservation activities developed under the Marine Mammal Protection Act (MMPA) and Endangered Species Act (ESA) and in other nations through similar statutes (e.g., Canada's Species at Risk Act; Australia's Environment Protection and Biodiversity Conservation Act). Under these statutes, agencies are required to develop programs to assess and permit various ocean-use activities (e.g., oil and gas development and production, renewable energy facility siting, and development), minimize threats to marine mammal habitat, engage in endangered species recovery planning, and assess global climate change as it impacts the ecology and health of marine mammal populations. In addition, marine mammals can be large consumers of commercially important fish species, and any shifts in their distribution may therefore be of concern to fisheries management programs that also will need to adapt to such changes. Moreover, marine mammals are integral parts of their ecosystems—as both predators and prey—and ecosystem-based fishery management will need to take into account any changes in marine mammal distribution, abundance and predator-prey relationships. Agencies involved in marine mammal management and conservation, as well as those engaged in managing subsistence harvests, will increasingly need means to anticipate shifts in marine mammal distribution and abundance resulting from climate change (e.g., Laidre et al., 2015).

While most agencies have broad authority to reduce anthropogenic threats (e.g., those arising from commercial, industrial, or military activities), agencies charged with management do not currently have the ability to regulate greenhouse gases, the primary driver of global climate change (IPCC, 2014). Thus, limited resources, regulatory inertia, and lack of public consensus constrain many agencies' abilities to react with appropriate protective measures to climate-driven changes in marine mammal distribution. In addition, as centers of abundance or areas of aggregation shift when existing habitats undergo change, existing threat-reduction measures may become obsolete or require modification as marine mammal distributions shift. For example, the location of a renewable energy or other industrial facility may be selected based on an assessment that its effects on marine mammal populations are anticipated to be relatively low. However, if the composition and regional abundance of those populations change, the facility may have greater overall impact than originally expected, and permitting of the facility may need to be re-assessed with a substantial investment of time and resources and lost opportunities to protect key species. Marine Protected Areas (including for marine mammals; Hoyt, 2011) and critical habitats are also established based on the existing occurrence of marine taxa; but these areas would have little conservation value if key species undergo shifts in distribution. An ability to track and anticipate such changes would aid in the protection of those species.

In rapidly changing ecosystems, including those in high-latitudes (Forcada et al., 2006; Laidre et al., 2008, 2015; Ragen et al., 2008), or in instances where populations are already in decline (e.g., Shelden et al., 2015), managers face a heightened need to respond with appropriate protective measures. Near- and long-term conservation planning would be enhanced by increased capacity to anticipate marine mammal response to changes in habitats brought about by climate change. Long-term planning may be particularly important given the long lifespans, long maturation periods, and low recruitment rates of many marine mammal species and will be important for those with complex social structures.

Conservation and planning actions occur on various spatial scales and temporal planning horizons (**Figure 1**), motivating marine mammal distribution and abundance predictions across a similar range of space and time-scales. These may include nowcasts and short-term (<1 week) forecasts (Hazen et al., 2016), to seasonal predictions up to 6 months in the future, to multi-year forecasts, increasing to decadal or century-scale projections. In the United States for example, endangered species recovery plans are updated on 5-year cycles, while permitting for industrial activities, such as the siting or construction of offshore renewable energy facilities and oil and gas exploration and development activities, tends to be on the order of decades (BOEM, 2016; **Figure 1**). On even longer time scales, designation of endangered status often necessitates evaluation of species persistence on the order of a century (e.g., Angliss et al., 2002). Conversely, measures developed to reduce the risk of whales being struck by ships (e.g., Silber et al., 2012) or limit marine mammal exposure to military operations (e.g., NOAA, 2015) may be established in finite areas and be implemented only for seasons to a few years (NOAA, 2013). While the emphasis here is meeting the challenge of projecting marine mammal distributions in a changing climate on multi-decadal to century time-scales, we note that decisions across multiple time-scales can contribute to the long-term resilience of marine mammal populations. We will thus discuss and contrast approaches across time-scales.

MARINE MAMMAL ECOLOGY AND CLIMATE CHANGE

Marine mammals have unique ecologies with complex life cycles that make predicting responses to climate change more difficult and, in some cases, make the species especially vulnerable to climate change impacts. Perhaps most notable amongst these traits in the context of climate change is endothermy, which provides for a broader range of temperature tolerance in marine mammals relative to fish. This could be a mechanism that adds resilience in marine mammal populations, but also makes for less predictable responses relative to fish or invertebrates that show isotherm-following behaviors (Pinsky et al., 2013).

Endothermy also elevates the importance of predicting changes in food resources relative to warming signals. While progress has been made in projecting large-scale prey resource changes (e.g., Stock et al., 2014; Lefort et al., 2015), marine mammal species such as blue whales (*Balaenoptera musculus*) show tight coupling to smaller scale oceanographic features (Fiedler et al., 1998; Moore et al., 2002; Croll et al., 2005) associated with high euphausiid (krill) abundance (Santora et al., 2011). Similar relations have been exhibited by bowhead whales (*Balaena mysticetus*) across the Arctic (Laidre et al., 2007; Citta et al., 2015; George et al., 2015) and North Atlantic right whales (Baumgartner et al., 2003; Baumgartner and Mate, 2005). Such aggregations remain poorly resolved in even high-resolution models and may exhibit climate change responses that differ from large-scale changes.

Other common traits are long lifespan, low birth rate, and long generation time. These traits are not conducive to rapid evolutionary adaptation (Trathan et al., 2007), making behavioral flexibility critical for adaptation to changing climatologies. Fortunately, some marine mammals have exhibited substantial behavioral and prey selection flexibility (Palacios et al., 2013). For example, humpback whales (*Megaptera novaeangliae*) remained abundant and were suspected to adapt foraging behavior to new prey species when climate conditions were unfavorable to common target prey species (Benson et al., 2002; Fleming et al., 2016). Failure to account for such flexibility could lead to unrealistically pessimistic projections.

Alternatively, many marine mammal species exhibit strong dependence on habitat types or oceanographic features that may be highly vulnerable to climate change, or high fidelity to particular sites or migration routes. For example, ringed seals (*Pusa hispida*) rely on sea ice habitat for pupping and sufficient snow to hide young from predators (Smith and Stirling, 1975; Laidre et al., 2008; Kovacs et al., 2011; NOAA, 2012). Hawaiian monk seals (*Neomonachus schauinslandi*) may lose haul-out sites to sea level rise; thus, understanding the climate-related threats to

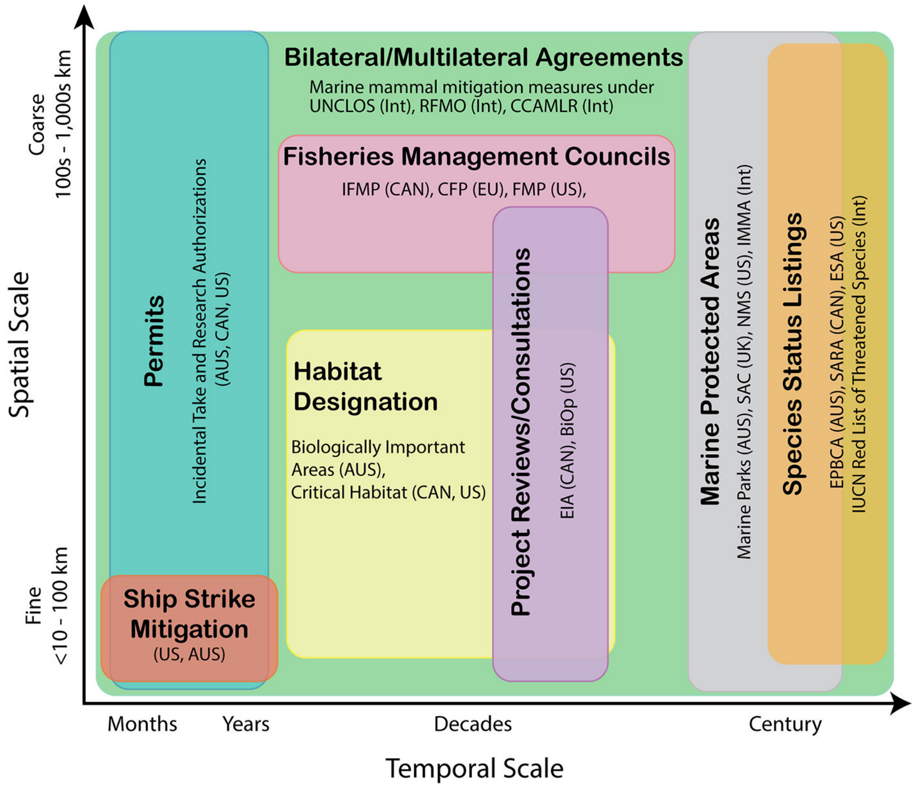

FIGURE 1 | Various examples of national and international management activities mapped conceptually along generalized temporal and spatial (both granularity and extent) scales. Management and research objectives on appropriate spatial/temporal scales will dictate model type selection and data requirements. AUS, Australia; BiOp, Biological Opinions; CFP, Common Fisheries Policy; CCAMLR, Commission for the Conservation of Antarctic Marine Living Resources; ESA, Endangered Species Act; EIA, Environmental Impact Assessments; EPBCA, Environment Protection and Biodiversity Conservation Act; EU, European Union; FMP, Fishery Management Plans; IFMP, Integrated Fisheries Management Plans; IMMA, Important Marine Mammal Areas; Int, International; IUCN, International Union for Conservation of Nature; NMS, National Marine Sanctuaries; RFMO, Regional Fishery Management Organizations; SAC, Special Areas of Conservation; SARA, Species at Risk Act; UK, United Kingdom; UNCLOS, United Nations Convention of the Law of the Sea.

this species might require a different type of model (e.g., dynamic shoreline evolution) for forecasting its distribution (Baker et al., 2006). Failure to account for unique vulnerabilities arising from such life-cycle strategies may result in unrealistically optimistic projections.

Lastly, some marine mammals are near the top of marine food webs, introducing a potentially strong dependence on integrated food web effects (Doney et al., 2012; Sydeman et al., 2015). Recent studies suggest robust amplification of productivity changes at higher trophic levels (Chust et al., 2014; Stock et al., 2014, 2017; Lefort et al., 2015). This potential sensitivity is further heightened by mid-trophic level fishing (Forcada et al., 2012), motivating work to analyze marine mammal responses in a food web context.

CURRENT APPROACHES FOR PREDICTING AND PROJECTING MARINE MAMMAL OCCURRENCE AND DISTRIBUTION

Two components are essential for predicting marine mammal occurrence and distribution. The first is a model capable of estimating marine mammal distribution and/or abundance given a set of physical and/or ecological variables (e.g., ocean temperature, food resources). The second is the capability to project the states of the relevant physical and ecological variables at the time and space scales of interest. Models are designed to address a variety of research questions (Guisan and Thuiller, 2005), and a range of model types have been used for the first component (Gregr et al., 2013; Palacios et al., 2013). Early efforts employed simple visual mapping to describe marine mammal seasonal occurrence. For example, Winn et al. (1986) used North Atlantic right whale sighting records to develop a simple conceptual model of the species' seasonal distribution.

Statistical habitat models use environmental data and species occurrence data to generate predictions of the distribution of the species. The environmental predictors chosen for these models usually pertain to biological mechanisms (e.g., temperature is an important physiological constraint; chlorophyll-*a* has often proved to be a meaningful proxy for ocean productivity and food resources), which helps to avoid spurious correlations. For example, Baumgartner and Mate (2005) used water depth, depth gradient, bottom hydrographic properties, sea surface temperature (SST), chlorophyll concentration, and other features to characterize North Atlantic right whale habitat. Becker et al. (2016) developed predictive habitat-based models of cetacean density and distribution for a number of species in the California Current System using a variety of dynamic environmental variables, including temperature, salinity, sea surface height, and mixed layer depth. Models used to predict distribution patterns, given observed environmental variables, may also be used to project a species' distribution using expected future values of the environmental variables (Becker et al., 2012).

In Panels 1 and 2, we highlight two examples of such statistical models in detail. Case study 1 describes "nowcasts" (i.e., estimates of the current ocean state) and seasonal predictions for 11 marine mammal species in the California Current based on habitat-based density models (Becker et al., 2016). Case study 2 applies similar empirically-driven approaches to assess potential challenges for ringed seal pup survival related to sea-ice and snowpack changes projected over the next century due to global warming (Hezel et al., 2012).

There are several limitations associated with statistical correlative models when used in a predictive context (Elith and Graham, 2009; Monahan, 2009; Webber et al., 2011). First, the relationships inferred from field data may not adequately describe the critical factors determining species distributions. Existing data on species distributions reflect the realized rather than potential habitat (i.e., the area where the intrinsic rate of population growth is >0; Araujo and Guisan, 2006; Soberon and Nakamura, 2009). This realized habitat implicitly reflects interactions with predators, prey species, and barriers to movement and comprises a level of structural detail not generally included in sets of climate predictors or even present in climate change projections. Predictions and projections based on realized niches thus presume that the impacts of these implicit factors act to maintain present realized habitat boundaries.

A second limitation is that, although the mechanisms by which environmental conditions affect biology and species distributions are considered, these relationships are empirically-defined from available data on past conditions and may not represent future conditions. Stationarity of these relationships is assumed when such models are used in a predictive context. This is clearly reasonable when predicting for conditions that have analogs in the historical record, but becomes less reliable for responses to extreme events or for the novel conditions expected under climate change (Williams et al., 2007; Hothorn et al., 2011).

Relatively recent advances in observational data collection and access to large marine environmental databases (e.g., the National Oceanographic Data Center; NCEI, 2017 or the Southwest Fisheries Science Center's ERDDAP site, SWFSC, 2017) provide an improved foundation for statistical habitat models, but would not address structural uncertainties in models that arise from incomplete understanding of species interactions and physiological thresholds. This level of knowledge would instead require a shift from reliance on correlations between marine mammals and their environment toward models that more clearly establish functional relationships with the physical and biological underpinnings of habitat utilization (Gregr et al., 2013; Cribb et al., 2015). These relationships enable development of process-based models that yield robust predictions of species distributions rooted in ecological understanding (Palacios et al., 2013). While such models have been traditionally developed for a broad range of zooplankton and higher trophic level species, including forage fish (e.g., Ito et al., 2015; Rose et al., 2015), migratory predators (e.g., Lehodey et al., 2008) and other commercially and ecologically important species (e.g., Cury et al., 2008; Fiechter et al., 2015), marine mammal case studies are also starting to appear. For example, California sea lion (*Zalophus californianus*) foraging patterns and feeding success were simulated using sub-models for biogeochemical processes, regional ocean circulation, and forage fish abundance (Fiechter et al., 2016). The parameterization of more mechanistic models is challenging, but will also benefit from data collection advances referenced above. In data-poor situations, mechanistic models informed by general principles can help define the scope of potential marine mammal responses by testing the implications of general principles drawn from theory or data-rich regions (Friedrichs et al., 2007). While such exercises inevitably lead to large uncertainty bounds, they can help prioritize future observations on quantities or processes within existing uncertainty bounds (Plaganyi et al., 2011).

Predictions and projections for future states of drivers of marine resource abundance and distribution are generally derived from global climate and earth system models (Stock et al., 2011; Hobday et al., 2016; Tommasi et al., 2017a). Several characteristics of global climate and earth system models have shaped their application in projecting marine mammal distribution and abundance under climate change (Stock et al., 2011). The coarse resolution of global climate models (often 1–2°, or 100–200 km ocean grids in past assessments of the Intergovernmental Panel on Climate Change, IPCC) can generate significant coastal biases (Scales et al., 2017). Large inter-model differences in regional climate change projections limit confidence in scenarios for the future states of drivers of marine resource distribution and abundance (Hawkins and Sutton, 2009; Frölicher et al., 2016). Limited resolution of marine food webs in most earth system models may under-estimate the potential amplification of climate change effects for higher trophic levels, particularly at regional scales (Chust et al., 2014; Stock et al., 2014, 2017; Lefort et al., 2015). As a result of these limitations, confidence in predicting the magnitude and direction of climate change trends that are capable of altering marine resource distributions is generally greatest at ocean-basin spatial scales and multi-decadal to century time-scales. In the absence of refined resolution via downscaling or high-resolution global models (see below), regional inferences must focus on the magnitude and direction of changes due to large-scale greenhouse gas accumulation, and include the caveat that unresolved regional responses may significantly modify these trends (e.g., Hare et al., 2012; Lynch et al., 2015).

Global climate model configurations similar to those used for long-term climate change projections are also applied to short-term predictions on seasonal to multi-annual scales that have proven valuable for a range of marine resource applications

(Hobday et al., 2016; Tommasi et al., 2017a). Analysis to date has suggested that skillful seasonal and, in some cases, multi-annual sea surface temperature predictions are possible for many regions despite coarse model resolution (Stock et al., 2015; Tommasi et al., 2017b). Seasonal to multi-annual predictions of ocean productivity, oxygen and other potential factors important to marine resource distributions and abundance have provided some cause for optimism (Séférian et al., 2014; Gehlen et al., 2015), but have not been assessed with the same rigor as ocean temperatures, in part due to the sparsity of data with which to robustly characterize the model skill. The use of short-term forecasts in dynamic management approaches (Maxwell et al., 2015; Dunn et al., 2016; Tommasi et al., 2017b) may also contribute to building long-term resilience (Hobday et al., 2016; Tommasi et al., 2017a).

IMPROVING MARINE MAMMAL DISTRIBUTION PROJECTIONS

Uncertainty in projected marine mammal distributions ultimately reflects the integration of uncertainties in climate, food resources and marine mammal ecology, physiology and behavior (Cheung et al., 2016; Payne et al., 2016). Each of these components is likely to make a significant contribution to the combined uncertainty. The complexity of marine mammal ecology, physiology and behavior (see "Marine Mammal Ecology and Climate Change"), however, suggests that marine mammal responses to changing habitat and prey distributions may be a dominant uncertainty source for climate change projections. This suggests the importance of: (a) better understanding marine mammal behavior in order to improve the ecological and mechanistic underpinning of statistical habitat models; and (b) continued development and application of mechanistic population models as critical steps to increasing confidence in marine mammal projections under climate change. Confidence in physical climate change projections rests in large part on the foundation of climate models on robust physical principles that are expected to hold as climate changes (Randall et al., 2007). Solidifying the ecological and physiological principles upon which marine resource projections are based is equally critical (Stock et al., 2011).

Key requirements for credible mechanistic models are observations that provide the understanding and constraints necessary to build and validate such models. To support modeling efforts, research plans are needed that extend beyond the collection and dissemination of marine mammal occurrence and environmental correlate data, particularly where critical management needs exist or where correlative modeling studies are already underway. For example, improved understanding of how prey resources drive marine mammal distribution as well as the underlying physical and biological features that dictate prey occurrence (Fiedler et al., 1998; Croll et al., 2005; Santora et al., 2013; Schroeder et al., 2014) will likely lead to advances in marine mammal distribution modeling.

Monitoring of marine mammals and their habitats has become increasingly sophisticated, yet despite the broad distribution of many species well outside continental shelves, most monitoring programs are largely focused in coastal and nearshore areas, where most anthropogenic activities are concentrated. As a result, validating models and detecting changes in distribution and regional abundance of many species may be difficult. Monitoring networks are needed that incorporate additional assets outside areas where marine mammals are traditionally studied. Research vessel surveys allow the collection of broad-scale data on marine mammals and their environment, but such surveys are costly and often limited by ship-time availability. Technologies such as passive acoustics, satellite telemetry, remote sensing, and autonomous underwater vehicles (AUVs) are also well-suited for collecting data on marine mammal occurrence and important physical and oceanographic data and may provide cost-effective alternatives, especially in remote areas. As such, long-term planning for data collection and monitoring is needed, accompanied by fiscal planning for access to appropriate platforms for gathering priority data.

Another critical challenge in projecting marine mammal responses to climate change is uncertainty in regional climate and earth system projections (Hawkins and Sutton, 2009; Frölicher et al., 2016). Improved resolution of regional climate processes is a focal point of current climate research (Xie et al., 2015). Refined resolution in global climate models has allowed them to better resolve coastal processes and, in some cases, to reduce regional model biases (Saba et al., 2016). Dynamical downscaling offers a second means of improving coastal process resolution (e.g., Hermann et al., 2016; Holt et al., 2016), but the underlying global climate models are still subject to biases that propagate through regional model boundaries (e.g., Meier et al., 2006). Lastly, climate variability, which present-day models suggest has limited predictability beyond a year for all but a few regions of the ocean (Meehl et al., 2014), will continue to contribute uncertainty to future climate states (e.g., Deser et al., 2012). These results suggest that some gains in the accuracy and precision of regional climate change projections are likely, but progress will be difficult. Future marine mammal projections at regional scales must thus prioritize using a range of climate projections to ensure the best possible estimate of the range of potential marine mammal responses.

To be effective, future modeling efforts must involve researchers from diverse disciplines, including climate science, ecology, physical oceanography, marine mammal biology, and marine resource management. These multidisciplinary research efforts will be essential to identify how ongoing marine mammal modeling studies might be refined, better characterized to reduce the uncertainties in projections on different time and spatial scales, and build their value in informing pressing management decisions—both relating to marine mammals directly as well as for other interacting ecosystem components. Thus, marine mammal populations of highest concern, settings where protective measures are needed most, and the temporal and spatial scales for management actions need to be identified. In addition, biological and climate change modelers must provide feedback on the limits of modeling efforts and describe likely levels of uncertainty in model outputs.

PRIORITY ACTIONS AND EXEMPLAR SPECIES

The broad scope of the challenges identified above ("Current Approaches for Predicting and Projecting Marine Mammal Occurrence and Distribution") and the limited resources available to meet these challenges suggests initial prioritization of species/populations that represent a high management need and represent a high suitability to be modeled. Species that represent high management need are: (a) depleted or currently undergoing declines in abundance; (b) exposed to multiple (and perhaps compounding) anthropogenic threats; or (c) occur in high latitudes or other regions undergoing rapid change. Species with a high modeling suitability may: (a) already have multiple aspects of their ecology quantified; or (b) occur in ecosystems modeled by previous or ongoing efforts. In contrast, it may be of relatively limited value to devote resources to populations that are abundant and increasing in number [e.g., sperm whales (*Physeter macrocephalus*)] or of relatively low management priority, or for which modeling suitability may be limited (**Figure 2**).

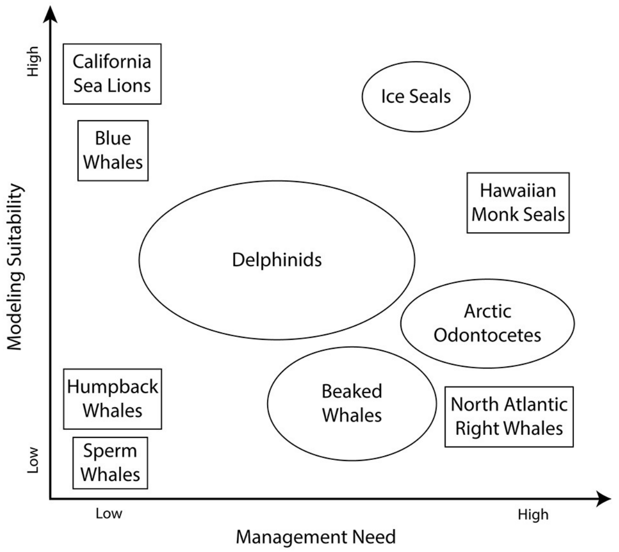

FIGURE 2 | The range of increasing modeling suitability and management need for some illustrative marine mammal populations. Species and their relative positions are provided for illustration purposes and may not indicate an official agency prioritization.

Some marine mammal populations with limited ranges are exhibiting slow population growth or undergoing declines in abundance, such as the Cook Inlet beluga whale (*Delphinapterus leucas*) and vaquita (*Phocoena sinus*) (NMFS, 2016; Jaramillo-Legorreta et al., 2017). Note that for these species, fisheries bycatch and other factors may be the proximal cause for the severe depletion or extinction. However, given their highly-limited ranges, vulnerability to climate change is heightened as habitat and ecosystem perturbations become added stressors. Other species or populations with limited ranges, specialized diets, or similarly limiting ecological features may also be particularly vulnerable to habitat perturbations or large-scale ecological shifts. These populations, in addition to those exposed to the effects of various human activities such as bycatch in fisheries, underwater industrial noise, or competition for commercially valuable fish species, are high-priority candidates for refining forecast modeling studies. Ongoing efforts are focused on developing approaches to identify which protected marine vertebrates (i.e., pinnipeds, cetaceans, and turtles) are likely to be vulnerable to climate change and the attributes that make them vulnerable (Link et al., 2015), using an approach similar to that used for commercial fisheries (Pecl et al., 2014; Morrison et al., 2015; Hare et al., 2016). Such vulnerability assessments can inform decisions regarding priorities for assessing future impacts on marine mammals.

High-latitude marine systems are among the regions responding most rapidly to climate change (e.g., Doney et al., 2012; Hobday and Pecl, 2014; Thomas et al., 2016). As a result, marine mammal populations in these regions are likely to undergo range expansions/contractions or changes in local abundance sooner and perhaps more profoundly than in other regions, particularly those at lower latitudes (e.g., Laidre et al., 2008; Moore and Huntington, 2008; Gilg et al., 2012). These changes may lead to novel species interactions (Doney et al., 2012). Shifts in occurrence or availability of key prey species may also be expected in these high-latitude areas (McBride et al., 2014; Thomas et al., 2016). Ice-obligate species that use ice as a platform for raising young (e.g., ringed seal pupping lairs) (NOAA, 2012) or for hunting (e.g., for polar bears, *Ursus maritimus*), or whose prey species are closely or directly linked to ice [e.g., Antarctic fur seals (*Arctocephalus gazella*) (Forcada et al., 2008)] may be particularly vulnerable to declines in the extent of seasonal and multi-year ice. While some forecasting work has already been done for polar bears, ice seals, and walruses (*Odobenus rosmarus*) in the context of endangered species determinations under the ESA (Jay et al., 2011; Regehr et al., 2016), additional work is required to develop and refine models for species residing or occurring seasonally in high latitudes.

Forecast uncertainties will be less in cases where the species' ecology is relatively well understood and plentiful occurrence and environmental data exist than for data-poor populations. Thus, modeling populations about which much is already known is of particular importance because such studies may help elucidate potential climate change sensitivities that can strategically guide conservation and management efforts for less well observed regions.

Given the level of effort that has been devoted to characterizing their marine mammal populations and physical and biological components, the California Current and Bering Sea ecosystems are particularly important areas for such modeling efforts (Moore, 2008; Friday et al., 2013; Redfern et al., 2013; Dransfield et al., 2014; Becker et al., 2016). Continuation of these studies should be encouraged because ample environmental and species distribution data already exist, linkages between species occurrence and their environmental drivers have been explored, and these systems have been extensively modeled. Modeling studies of multiple trophic levels, species complexes, and well-understood systems (predator-prey relationships in particular) are a means to capitalize on interdisciplinary work already underway, represent cost-effective ways to maximize use of limited analytical resources, and provide opportunities for model validation with application to other taxa. They also help foster collaborative work with other modeling studies (e.g., fisheries, ecosystem) in the region studied. This will be most effective in regions where species interactions and relations to the physical environment are already well known. Thus, candidates for exploratory study of species complexes might include biogeographic provinces such as along shelf breaks, and portions of Bering Sea, Gulf Stream, and Antarctic ecosystems.

Therefore, key candidate marine mammal populations for future modeling studies are those particularly vulnerable to climate change, with high management priorities, and/or for which ecological data already exist. Among these are ice seal species [e.g., ringed seals and bearded seals (*Erignathus barbatus*)], Arctic odontocetes [beluga, narwhal (*Monodon monoceros*), and killer whales (*Orcinus orca*)], bowhead whales, North Pacific right whales (*Eubalaena japonica*), North Atlantic right whales, and cetacean species occurring in the Bering Sea [e.g., humpback and gray whales or California Current ecosystems [gray, fin (*Balaenoptera physalus*), and blue whales]; **Figure 2**].

CONCLUSIONS

Climate change presents unprecedented challenges for managers responsible for developing and implementing conservation measures for marine mammals. As marine mammals respond to climate change, protective measures must be developed that are responsive to provide adequate protection, which requires the ability to anticipate changes in occurrence, distribution, phenology, and relative abundance of populations. A range of models, varying in levels of complexity and with varying informational and computational requirements, have been developed to project climate change impacts on marine organisms. These models can be adjusted to appropriate temporal and spatial scales and use new and existing species-related data (e.g., life history, distributional ecology, behavioral responses, and population dynamics) to be more effective under projected climate conditions. Ongoing modeling studies can be strengthened by improving predictive capacities, increasing data available for marine mammals and their habitats, particularly in areas poorly-sampled in the past.

Marine resource managers and modelers need to work together to identify priority management needs and the strengths and weaknesses inherent in modeling studies. Agencies should engage in long-term fiscal planning to equip scientists and managers with tools and resources needed to increase data collection, enhance ongoing studies, and refine current models, particularly as they pertain to appropriate temporal and spatial scales relevant to conservation/management actions in settings where needs are greatest. Given the global scale and complexity of both climate change impacts and marine mammal distributions, multidisciplinary collaborations are necessary to develop new, and improve existing, models to better address conservation of living marine resources in an uncertain future.

AUTHOR CONTRIBUTIONS

GS and ML: Lead authors and workshop co-convenor. PT: Author, workshop co-convenor. JB, MB, EB, PB, DD, JeF, JaF, KF, RG, JH, AH, DH, KL, NM, LQ, JS, KS, PS, CS, WS, KV, and RW: workshop participants and contributing authors. All authors made substantial contributions to the workshop content and discussion of ideas, drafting and revising the manuscript, providing final approval of submitted version and agree to be accountable for the work.

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APPENDIX: PANEL

Case study 1. Modeling Cetacean Density in the Pacific Ocean

Predictive habitat-based density models were developed for 11 marine mammal species or species assemblages in the California Current Ecosystem, eastern tropical Pacific, and central Pacific Ocean (**Figure A1**). Models used a generalized additive modeling framework at ecosystem-dependent scales (2–120 km) and extensive line-transect survey data (e.g., Ferguson et al., 2006; Redfern et al., 2008; Forney et al., 2012; Becker et al., 2016). This approach has enabled comparisons of modeling framework effectiveness, evaluation of predictor variables at differing spatial and temporal resolutions, development of methods to characterize uncertainty in model predictions, and model validation (Barlow et al., 2009; Becker et al., 2010, 2014; Forney et al., 2015).

Dynamic environmental covariates included sea surface temperature (SST), salinity (SSS) and height (SSH), chlorophyll concentration (CHL),thermocline depth and strength, and mixed layer depth (MLD) collected *in situ* during transect surveys and sensed remotely. In addition, dynamic variables (including SST, SSS, MLD, and SSH) from ocean models have been used as potential predictors in habitat models (Becker et al., 2016). Habitat predictors from ocean circulation models all served as proxies for unmeasured underlying ecological processes linking cetaceans to their prey, and they provide opportunities for dynamic predictions.

Models have successfully captured variability in cetacean density and distribution at seasonal and interannual time scales (e.g., **Figure A2**, Forney et al., 2012; Becker et al., 2014, 2016), but they only reflect historical data and the variation therein and do not take into account current or future conditions. Becker et al. (2012) demonstrated that advanced satellite data and forecasts from ocean models allow "nowcasts" of marine mammal distributions on time scales of days to weeks and forecasts on time scales of 3–4 months. Ocean circulation models provide robust predictive models of cetacean distributions (Becker et al., 2016), showing promise for future predictions of marine mammal distributions in a changing climate. However, these models rely on proxy variables, and future forecasts can fail if the proxy relationships change; likewise, modeling marine mammal distribution in one area may not be readily transferable (i.e., may perform poorly) to other locations. Future steps require additional model validation, particularly at different spatial resolutions and longer temporal scales.

Case Study 2. Projecting Ringed Seal Distributions

In the context of a biological review regarding the listing of the ringed seal as threatened or endangered under the ESA, ringed seal distributions were projected through the twenty-first century using a highly-simplified definition of habitat required by the species for the critical life history functions of whelping, nursing, and weaning pups. These functions occur in spring, a period when the pups are highly vulnerable to predation and hypothermia if there is insufficient snow cover for mothers to construct and maintain lairs on top of the ice. Studies of lair construction indicated that accumulated snow depths of at least 20 cm are required for drifts to form that are sufficiently deep (50–65 cm) for adequate birth lairs (NOAA, 2012). Therefore, ringed seal habitat and breeding distribution were assumed to be those areas of the Arctic where at least 20 cm of snow depth could be expected in the month of April. Output from global climate models predicts that although precipitation in the Arctic is expected to increase, much of it will fall as rain. Delayed autumn ice formation will mean that some of the snow that does fall will fall into open water rather than accumulating on the ice surface. Consequently, the area with snow depths above 20 cm in April was projected to decline under a broad range of plausible greenhouse gas emission scenarios, with the greatest decline up to 70% by the end of the twenty-first century under one emissions scenario (Hezel et al., 2012). This would result in a substantial loss of ringed seal reproductive habitat.

One strength of this approach is that it is built on climate projections that are, qualitatively at least, broadly agreed to represent the best available science and project robust large-scale trends in Arctic sea ice. A significant limitation of this method for ringed seal habitat projection is that the species' habitat has been reduced to just two dimensions (sea ice extent and snow accumulation), a drastic oversimplification. Another limitation is that regional and finer scale variability may not be adequately reflected in the coarse resolution of the global circulation models used for the climate projections (Stock et al., 2011).

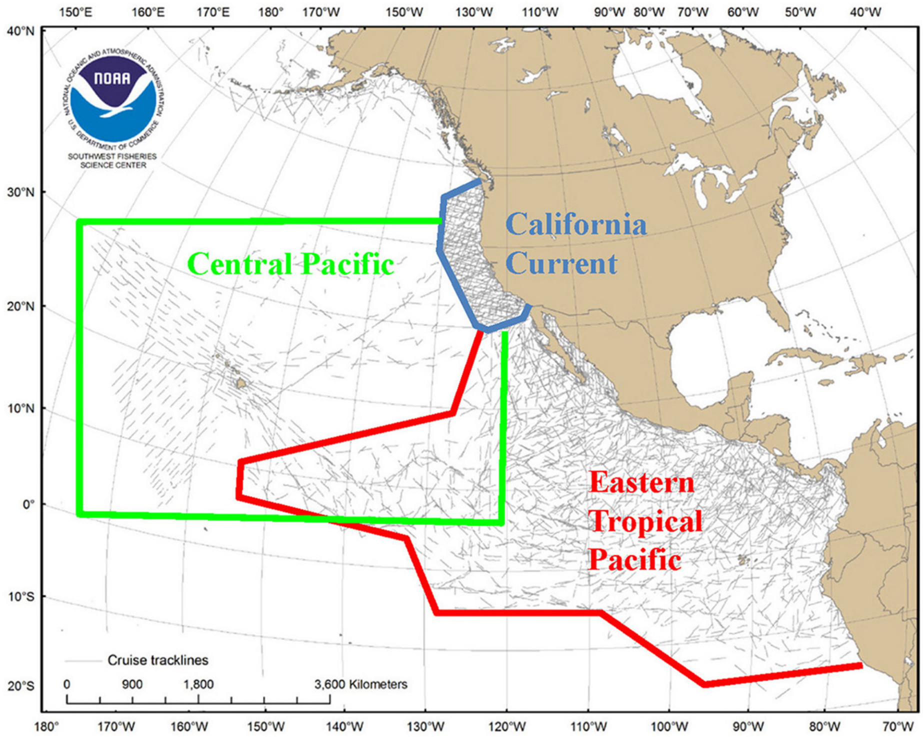

FIGURE A1 | (Case study 1) Transect coverage for surveys conducted by SWFSC between 1986 and 2006 in three broad study areas in the eastern North Pacific. Modified from Hamilton et al. (2009).

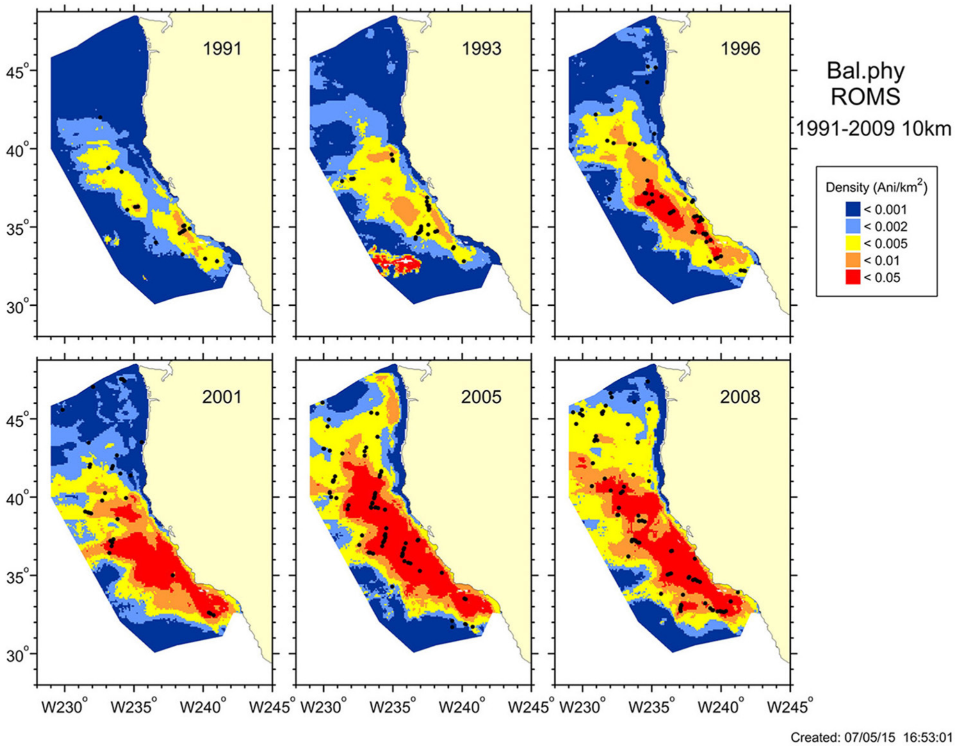

FIGURE A2 | (Case study 1) Model-based estimates of fin whale summer/fall density (animals/km^{-2}) and distribution for six different years, 1991–2009, in the California Current Ecosystem. Black dots show actual sighting locations during ship surveys conducted in each year. (Details provided in Becker et al., 2016).

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REVIEW
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Lessons from the First Generation of Marine Ecological Forecast Products

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Recent years have seen a rapid expansion in the ability of earth system models to describe and predict the physical state of the ocean. Skilful forecasts ranging from seasonal (3 months) to decadal (5–10 years) time scales are now a reality. With the advance of these forecasts of ocean physics, the first generation of marine ecological forecasts has started to emerge. Such forecasts are potentially of great value in the management of living marine resources and for all of those who are dependent on the ocean for both nutrition and their livelihood; however, this is still a field in its infancy. We review the state of the art in this emerging field and identify the lessons that can be learnt and carried forward from these pioneering efforts. The majority of this first wave of products are forecasts of spatial distributions, possibly reflecting the inherent suitability of this response variable to the task of forecasting. Promising developments are also seen in forecasting fish-stock recruitment where, despite well-recognized challenges in understanding and predicting this response, new process knowledge and model approaches that could form a basis for forecasting are becoming available. Forecasts of phenology and coral-bleaching events are also being applied to monitoring and industry decisions. Moving marine ecological forecasting forward will require striking a balance between what is *feasible* and what is *useful*. We propose here a set of criteria to quickly identify "low-hanging fruit" that can potentially be predicted; however, ensuring the usefulness of forecast products also requires close collaboration with actively engaged end-users. Realizing the full potential of marine ecological forecasting will require bridging the gaps between marine ecology and climatology on the one-hand, and between science and end-users on the other. Nevertheless, the successes seen thus far and the potential to develop further products suggest that the field of marine ecological forecasting can be expected to flourish in the coming years.

Keywords: ecological forecasting, seasonal-to-decadal-forecasting, spatial distribution, recruitment, Phenology, marine ecological forecasting, ecological prediction

INTRODUCTION

Rapid recent advances in observing and modeling the earth system have driven a quiet revolution in our ability to forecast the evolution of our planet's weather and climate (Bauer et al., 2015). Some of the most impressive results have been seen in the oceanic domain (Meehl et al., 2014), where the slow dynamics and long memory of the ocean readily lend themselves to forecast timescales dramatically longer than in the atmosphere. Skilful forecasts on the annual and even decadal scale of sea surface temperature (SST) and upper ocean heat and salt content (Smith et al., 2007; Keenlyside et al., 2008; Doblas-Reyes et al., 2011; Corti et al., 2012; Matei et al., 2012b; van Oldenborgh et al., 2012), the Atlantic Meridional Overturning Circulation (e.g., Matei et al., 2012a), net primary productivity (e.g., Séférian et al., 2014), the north Atlantic sub-polar gyre (e.g., Wouters et al., 2013), and the uptake of CO_2 from the atmosphere (e.g., Li et al., 2016) have all been demonstrated thus far, and this list is expected to continue to grow.

This newfound predictive skill of the ocean represents a tremendous opportunity for society as a whole, and particularly for the parts of it that are most closely linked to the ocean. The high variability of living marine resources is widely recognized as arising in part from interactions with the physical environment (e.g., temperature, salinity, currents) (Drinkwater et al., 2010; Hollowed et al., 2013; Petitgas et al., 2013). This variability manifests itself not just in terms of productivity (e.g., yield of fisheries) but also in terms of spatial distribution (e.g., shifts of fish into new jurisdictions) and the timing of key events (e.g., migrations, spawning), and even propagates further into the human systems dependent on the ocean (e.g., fishing practices, community revenue, and employment associated with commercial and recreational fisheries). In principle, the predictability of the physical system could allow much of this variability to be foreseen: such predictions could be used to both adapt to and mitigate the worst impacts of variability for individual stakeholders and society alike, and to optimize monitoring, exploitation, and management of these resources (Hobday et al., 2016; Tommasi et al., 2017a).

Unfortunately, generating such forecasts of biological systems is not entirely straightforward. Most climate models only produce forecasts of physical variables, such as temperature, salinity, and ocean currents, rather than the variables of direct interest to marine resource management and ecosystem applications. An intermediate "translation" step is therefore usually required, where biological models convert forecasts of the physical environment to forecasts of the biological environment. However, the biological knowledge required to make this linkage is often either poor, or entirely absent; fisheries scientists, for example, have been trying to generate environmentally-driven predictions of fish stock recruitment for close to a century now with little success (e.g., Myers, 1998). In fact, just 15 out of 1,250 fish stocks globally (<2%) incorporate any form of environmental information in the generation of their tactical advice and management (Skern-Mauritzen et al., 2016). Nevertheless, the first generation of forecast products for applications to marine living resources is now appearing, starting in Australia nearly a decade ago (Hobday et al., 2011; Eveson et al., 2015) and more recently in North America (**Table 1**).

Here we take stock of the progress made thus far in applied forecasting of marine ecological quantities, with a view toward the next steps. We focus our review away from the predictability of the physical components of the system, for which the reader is referred to numerous reviews already covering the topic (Meehl et al., 2014; Bauer et al., 2015; Stock et al., 2015) and thus do not comment on the improvements needed for the physical side of marine prediction models. We also restrict our focus to applications of relevance to the management and exploitation of living marine resources and therefore exclude human-health related forecasts (e.g., of harmful algal blooms (e.g., NOAA, 2016), outbreaks of *Vibrio* sp.) and marine pathogen outbreaks (e.g., Constantin de Magny et al., 2009; Maynard et al., 2016). Instead, we focus here on examples of forecast products relating to living marine resources, covering their productivity, spatial distribution and phenology and associated human systems in turn. The strengths, weaknesses, lessons learned, and future prospects of each of these types of forecasts are examined. We then synthesize these experiences into a set of recommendations to facilitate the field's future advancement, including the identification of research priorities. Through this review, we lay out a roadmap for the future development of this new and promising field.

WHAT FORECAST PRODUCTS EXIST?

As a starting point for this review, we have collated and summarized currently available forecast products relating to living marine resources (**Table 1**, **Figure 1**). We collected forecast products that the authors were familiar with, and complemented this with a brief literature search: while this is by no means an exhaustive list, we believe that it nevertheless covers the majority of products available today. We restricted the results to examples of products that are currently being produced and updated regularly and that are publicly available. Long-term biological responses to a changing climate were excluded as they are projections rather the predictions: instead the focus was on nowcast-to-decadal scale forecasts. We also only focus on products where environmental or ecological factors outside the system of interest drive the forecast, thereby excluding persistence forecasts and projections based on population dynamics (as is common in e.g., fisheries management). Similarly, we restrict the focus to situations where there are specific ecological *forecasts* made. As a result, some examples of environmentally-informed fisheries management in which the management might be informed based on relationships between a physical variable and a biological response (eg., Skern-Mauritzen et al., 2016), but where these relationships are not (yet) used in forecasting stock dynamics, are excluded.

The results provide several clear insights into the current state of forecasting of living marine resources. Firstly, there are distinct spatial patterns in the distribution of these forecast products,

TABLE 1 | Overview of operational nowcast and forecast ecological products for application in the management of living marine resources found by the authors.

Key	Forecast product	Basis for forecast	How far into the future is the forecast made?
	1. Name/forecasted variable 2. URL (if appropriate) 3. References	1. which physical variables are used? 2. how are they generated/forecast? 3. how are physics and biology linked?	
PRODUCTIVITY			
1	Returns of Salmon along US West Coast http://www.nwfsc.noaa.gov/research/divisions/fe/estuarine/oeip/g-forecast.cfm (Burke et al., 2013; Pacific Fishery Management Council, 2016)	1. Ensemble of ecosystem indicators combined using PCA. 2. Observations 3. Empirical relationship between returns and environment indicators	∼1 year
SPATIAL DISTRIBUTIONS			
2	WhaleWatch—distribution and numbers of blue whales in California current http://www.westcoast.fisheries.noaa.gov/whalewatch/ (Hazen et al., in press)	1. SST, chlorophyll-a, SSHa standard deviation, bathymetry, standard deviation of bathymetry 2. Satellite data observations 3. Satellite-telemetry-based habitat model	Near real-time
3	TurtleWatch—spatial areas where there is a high risk of loggerhead turtles bycatch http://www.pifsc.noaa.gov/eod/turtlewatch.php (Howell et al., 2008, 2015)	1. SST 2. Satellite data observations 3. Empirical model	Near real-time
4	Great Australian Bight tuna distributions http://www.cmar.csiro.au/gab-forecasts/ (Eveson et al., 2015)	1. SST 2. Satellite data 3. Empirical model	Forecast from 0 to 3 months ahead
5	SE Australia long-line tuna fishery http://www.afma.gov.au/fisheries-services/sbt-zones/ (Hobday et al., 2011)	1. SST and Temperature at depth 2. Satellite and ocean model data 3. Empirical model	Forecast from 0 to 3 months ahead
6	California Sardine distribution http://www.nanoos.org/products/j-scope/forecasts.php (Kaplan et al., 2016; Siedlecki et al., 2016)	1. SST, salinity, chlorophyll 2. Dynamical biogeochemical downscaling of global forecast system 3. Empirical habitat model	Skilful up to a 5-month lead time
PHENOLOGY			
7	Timing of Gulf of Maine lobster landings http://www.gmri.org/lobster-forecast (Mills et al., in review)	1. 50-m ocean temperature 2. Observations from coastal buoys in NERACOOS network 3. Empirical model	Landings forecast based on temperatures 3–4 months prior
8	Columbia river salmon run timing http://www.cbr.washington.edu/inseason (Anderson and Beer, 2009)	1. Oceanic upwelling, Columbia river flows, timing of juvenile arrival 2. Observations 3. Empirical regression model of timing	Up to 3 months ahead, updated daily during run
OTHER			
9	Coral Reef Watch's Heat Stress Outlook http://coralreefwatch.noaa.gov (Liu et al., in review)	1. Global daily SST forecast up to 9 months. 2. Accumulated heat stress conducive to mass coral bleaching is predicted and bleaching risk is forecasted based on an established relationship between the amount of accumulated heat stress and severity of coral bleaching 3. Anomalously warm temperatures above coral's tolerance level cause heat stress potentially leading to mass coral bleaching	Weekly and composite forecast up to 4 months; updated weekly

The geographical location of these products is mapped in ***Figure 1*** *using the number in the "Key" column. Products are grouped into broad categories reflecting the response variable being forecast.*

with the majority occurring in North America (**Figure 1**). Models also tended to be almost exclusively empirical (correlative) in nature: a notable exception are the forecasts of the intensity and spatial distribution of coral bleaching (forecast product 9), which have a strong mechanistic underpinning. Variables predicted could otherwise be grouped into predictions of productivity, spatial distribution or phenology: of these, forecasts of spatial distributions were clearly the most common. We examine these products in more detail below.

PREDICTING PRODUCTIVITY CHANGES

Changes in the productivity of fisheries result from changes in all processes that affect current and future exploitable biomass and fishery yields (e.g., growth, survival, and reproduction). The relative importance of these factors is strongly linked to the life-history and fishery of the stock. For long-lived and late-maturing species that have fisheries targeting many age-groups (e.g., temperate-boreal gadoids and flatfishes), changes in

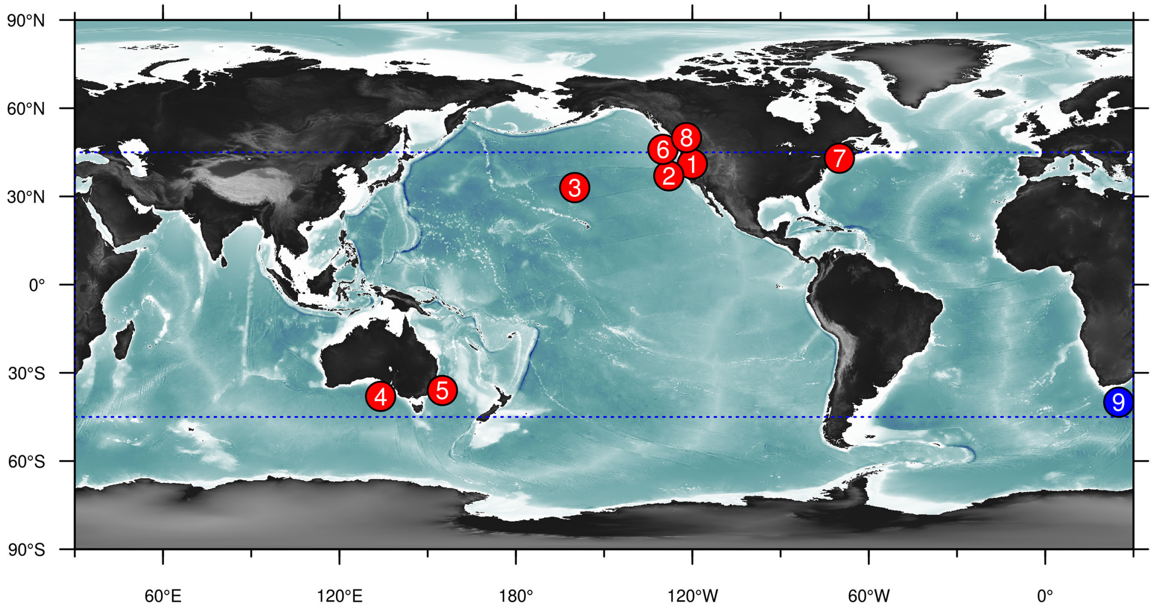

FIGURE 1 | Map of known examples of marine ecological nowcast and forecast products listed in **Table 1**. Details of these products are given in this table for the corresponding number. Note that the Coral Reef Watch forecast product (number 9, blue circle) covers the globe between 45°N and 45°S (dotted blue box).

growth and mortality of fish *currently in the water* are critical: in these cases young fish are recruited to the fishery at age 2 or later, and their impact on yield therefore occurs 1–2+ generations into the future (Basson, 1999; Brander, 2003; Planque et al., 2003; Tommasi et al., 2017a), while recruitment forecasts do not become useful until 5–10+ years into the future (Basson, 1999; Brander, 2003; Planque et al., 2003). Forecasting changes in growth and natural mortality 1–5 years ahead would be of more immediate benefit to the management of such species. For shorter-lived species, and those captured at young ages (e.g., sardine, anchovy, sprat, sandeel, and capelin), however, the need for predictability is reversed: fisheries for these stocks often depend on a very small number of age groups (e.g., 1–2) and large inter-annual variations in year-class strength are more important for the future fishery yields than changes in growth and mortality.

Recruitment forecasting, however, has been, and still is, a major challenge in fisheries oceanography and management (Houde, 2008; Hare, 2014). Numerous published relationships between recruitment and environmental variables have broken down when updated with new data (Myers, 1998), and few such relationships are used in operational fisheries management (Skern-Mauritzen et al., 2016). However, links between recruitment and the environment are nevertheless well-recognized: for example, environmental variability has been shown to be more influential in the recruitment of many fish stocks than spawner biomass (Szuwalski et al., 2015), and explains more variation in productivity than either density-dependent or random processes (Vert-pre et al., 2013). Advances in recruitment process modeling also demonstrate the sensitivity of recruitment to oceanographic variability, including how environmental conditions affect larval food resources and mortality rates (Daewel et al., 2015).

In addition, there are (at least) two broad patterns in recruitment-environment relationships that could provide potential avenues for future forecasting attempts. First, some of the published relationships re-evaluated by Myers (1998) continued to be valid with updated data: those cases tended to be stocks located near limits of species ranges where recruitment processes for those stocks might be particularly sensitive to environmental variations (Myers, 1998). Subsequent updates of previously published relationships for stocks near range limits have also remained valid (Lindegren et al., 2010; Margonski et al., 2010; MacKenzie et al., 2012). Second, biogeographic patterns in the recruitment-environment (temperature) relationship for stocks throughout a species range indicate increases in recruitment for stocks located in cold regions and decreases for stocks in warm regions when temperatures rise (Brander, 2000; Mueter, 2002; MacKenzie and Köster, 2004; Mantzouni and Mackenzie, 2010). Both of these patterns demonstrate some persistent environmental impacts on recruitment and suggest that there may be forecast potential for recruitment in some stocks. Moreover, as recruitment process knowledge increases, this potential is likely to increase in the future.

The future sustainability of all fisheries depends on successful recruitment: clearly, a prolonged decline or downward shift in production of recruits will eventually erode the basis for a fishery and require fishery management actions to prevent local collapse or extinction. Multiple fishery management decisions and strategies such as short-term yield forecasts, fishery, and biomass reference points, recovery plans, and long-term climate change impacts on yields, therefore depend on assumptions (expectations) of future recruitment. Several stocks recognize this fact in their management, and while they do not forecast recruitment directly, exploitation is nevertheless adjusted according to the state of the environment: see (Skern-Mauritzen et al., 2016) for an overview of these stocks. The management of such stocks is therefore potentially amenable to forecast information: for example, the harvest guideline for Pacific sardine, already influenced by sea surface temperature (SST), has been shown to be more effective when informed by short-term recruitment forecasts driven by seasonal SST predictions (Tommasi et al., 2017b). Improvements in the reliability and timing of forecasts of recruitment could therefore have major impacts on different aspects of fishery management across the diverse spectrum of time scales and life-histories (Tommasi et al., 2017a).

While recruitment forecasts would be a key component in forecasting productivity changes, forecasted changes in growth or mortality rates would also be beneficial for fishery management. Changes in biological parameters depend on changes in the biota, not only the abiotic properties of the oceans. For example variations in growth, condition, fecundity, and recruitment can all be influenced by availability of prey and predators, how the prey and predators overlap in time and space (Neuenfeldt and Beyer, 2006) and the relative size distributions of the prey and predators (Golet et al., 2015). New operational forecast models that link the spatial distributions of interacting species (competitors, prey-predators) and use these distributions to forecast feeding, growth and mortality rates could thereby generate forecasts of productivity changes. Indeed, existing multispecies assessment models (e.g., ICES, 2017) contain all of these elements and could therefore be extended into the future to predict productivity changes. Such a step would represent a major scientific advance toward developing and implementing integrated ecosystem-based approaches to management.

In summary, developing productivity forecasts requires identification of the relevant scales and life-histories where predictive skill is needed and available. For example, a zooplankton abundance or a mean temperature averaged over a specific depth range in a specific place and time may be more relevant for larval fish mortality or juvenile growth rates than averaged over some other (e.g., larger) scale. Acquiring the scale-relevant knowledge will require process-oriented field, experimental, and modeling studies. However, recognizing and exploiting the (rare) situations where predictive skill is needed and available and linking them to fishery management systems may lead to valuable new marine ecological forecast products.

PREDICTING SPATIAL DISTRIBUTION CHANGES

Within fisheries management, questions around the productivity (and thus quotas and sustainability) of a fish stock typically gather substantial attention and energy, both from the scientific community and the general public. However, the distribution of the resource in both time and space ultimately sets the framework within which fisheries operate and is thus a second question of critical importance to both fishers and managers.

The first wave of marine ecological forecast products to become fully operationalised has been strongly biased toward prediction of spatial distributions. Seasonal forecasts of the spatial distribution of southern bluefin tuna in the Great Australian Bight (Eveson et al., 2015) have been used to support the strategic planning of fisheries in this region for nearly a decade (Hobday et al., 2016) and were amongst the very first such forecast products to become operational. Distribution forecasts are also actively used in this region in a dynamic management context to close areas with the aim of avoiding by-catch (Hobday et al., 2011). In the United States, nowcasts of sea turtle distributions in the Pacific Ocean north of the Hawaiian Islands were amongst the first dynamic spatial management applications (Howell et al., 2008), and forecasts of the spatial distribution of sardines and blue whales in the California Current ecosystem have recently followed (Kaplan et al., 2016; Hazen et al., in press).

The relative success of spatial distribution forecasts most likely reflects a number of features that make this response variable well-suited to prediction. Spatial distribution studies typically have access to a relative wealth of observational data from scientific surveys, fisheries and other sources (e.g., Eveson et al., 2015 used tagging data) that allow relationships between the environment and the organism to be well-characterized. In contrast, recruitment studies are limited to one realization per year, with a typical time series being <30 years (Ricard et al., 2012). Furthermore, many living marine resources actively respond to environmental variability by shifting their distribution, either to avoid unfavorable conditions (e.g., temperatures that are too warm/cold) or to seek out optimal conditions (e.g., to reproduce or feed). In many cases, these constraints have a physiological basis (e.g., thermal or salinity tolerances) making for particularly robust and mechanistically-rooted links between the environment and the distribution. Finally, at least some, although not all, of the variables by which organisms sense and modulate their spatial distributions, such as temperature and salinity, are also the variables that are predicted directly by forecast systems, simplifying the "translation" from physics to biology tremendously.

Nevertheless, the ability to forecast spatial distributions is also subject to several important limitations. While we observe and are interested in distribution (where the organisms actually are), current forecasting systems are centered on the idea of habitat or ecological niche (where they could potentially be). However, these concepts are not interchangeable, and many processes (often outside of the modeling framework) govern the subset of potential habitats that are utilized and thereby yield the distribution (Dormann, 2007; Araújo and Peterson, 2012; Urban et al., 2016). For example, the dynamics of movement and migration can be important or even dominating: inter-annual shifts in the distribution of herring in the NE Atlantic of up to several thousand kilometers have been shown to be driven by the peculiarities of schooling dynamics (Huse et al., 2010). Similarly, two regions of space that are environmentally comparable may both offer suitable habitat, but one may be inaccessible due to the presence of environmental or physical barriers or extreme distances (Briscoe et al., 2017). Life-history dynamics are also critical to consider (Petitgas et al., 2013), as distributions at a given time point are strongly determined by both what has gone before and the need to close the life-cycle. Furthermore, not all of the variables that are potentially important in shaping distributions are currently measured or forecasted: the distributions of relevant predators, prey, and competitors are also critical (Elith and Leathwick, 2009). Correlative niche models using definitions of habitat based on the variables that we can observe and forecast are therefore inherently weakened by their narrow view of the processes shaping distribution (Warren, 2012, 2013; McInerny and Etienne, 2013).

Future research can help improve upon these early products. An important step in this direction is moving toward more mechanistic representations of distribution by increasing the biological realism of the models (Urban et al., 2016) e.g., explicitly incorporating movement and life-cycle with the limitations imposed by habitat. Suitable frameworks for this type of work already exist within the marine community (Lehodey et al., 2008; Ito et al., 2013) and operational applications are now being developed (Gehlen et al., 2015). Such a transition from empirical toward more mechanistic models would parallel the development pathway seen in terrestrial distribution modeling (Guisan and Zimmermann, 2000; Pearson et al., 2014).

Realizing the full potential of spatial distribution forecasts, will require close collaboration between developers and end-users. Spatial forecasts are already being used for dynamic spatial management (Hobday et al., 2011) based on close interaction with managers and fishers (Hobday et al., 2016). The use of forecast information to design monitoring programmes is also a particularly obvious application, as there are few barriers between the forecast developers and the scientists performing the surveys. However, the most important application will likely continue to be in direct collaborations with the fishing and shipping industries to forecast the distribution of both target and non-target/protected species. In these cases, where forecast users have an economic incentive to increase their effectiveness, a high degree of flexibility to use such information, and in some cases a legal imperative, it is not unreasonable to expect substantial growth in the number, and variety of spatial forecast products in the near future.

PREDICTING PHENOLOGICAL CHANGES

Physical forcing of ecosystem dynamics, particularly in high latitude environments, varies seasonally, and animal populations have adapted their phenology (i.e., the timing of life history events) to follow peaks in the seasonal cycles of physical drivers (e.g., temperature) and prey abundance. Variability in phenology affects the reproductive success of marine species (Hjort, 1914; Cushing, 1990; Platt et al., 2003; Durant et al., 2007) and influences their availability to fisheries.

Several examples of phenological forecasts now exist. For instance, the availability of lobsters to the Maine fishery varies between years following temperature-driven changes in their molting and inshore migration phenology (Mills et al., 2013). In 2012, during a marine heatwave, temperatures warmed 3 weeks earlier than normal, and lobster landings subsequently also increased sharply 3 weeks early, leading to a large influx of lobster, and a subsequent drop in price and economic challenges for the fishers (Mills et al., 2013). This event motivated the development of a forecast for the timing of the lobster fishery, which has been provided to the industry since 2015 to improve their operational planning and climate-readiness (Mills et al., in review). Timing forecasts of anadromous fish migration are also available (Anderson and Beer, 2009; Burke et al., 2013; Pacific Fishery Management Council, 2016). Other types of forecasts can also have a strong temporal element without being explicit forecasts of phenology, e.g., forecasts of seasonally-dependent high mortality conditions such as disease outbreaks (Maynard et al., 2016) or coral-bleaching risk (Liu et al., in review).

A successfully adopted ecological forecast is one that clearly addresses stakeholders' needs (Hobday et al., 2016). Phenological processes are non-linear, and subtle changes in climate drivers can lead to marked changes in the timing of management- and industry-relevant biological events. Since stakeholders are aware of and affected by the timing of certain ecological events at short time scales, phenological forecasts may be more easily adopted as compared to other types of ecological forecasts. On the other hand, because phenological events are discrete and non-linear, forecast errors are more evident. Binning the forecast into longer temporal bins (e.g., weekly instead of daily) and using probabilistic predictions can help reduce this problem (Mills et al., in review).

A forecast also needs to be skilful in order to be considered successful (Murphy, 1993). Seasonal forecasts of SST have skill in some regions at the coastal scales relevant to stakeholders' needs (Stock et al., 2015), but seasonal prediction skill of other phenologically-relevant physical variables (e.g., onset of upwelling) has not been adequately assessed (Tommasi et al., 2017a). Furthermore, biogeochemical forecasts (e.g., nutrients, chlorophyll, primary production) are still experimental but show some potential (Séférian et al., 2014; Li et al., 2016; Siedlecki et al., 2016). Thus, phenological forecasts that depend on temperature-driven physiological mechanisms (e.g., Liu et al., in review) may more quickly be operationalized than those requiring predictions of prey conditions.

Another challenge in the development of phenological forecasts is the limited availability of long time series of high-temporal-resolution data needed to quantify phenological changes. Integration of phenological forecasts into fisheries opening/closure decisions, survey planning, coastal management, or industry operations will require maintenance and expansion of observing systems for continuous-high resolution climate and biological data. Ensuring spatial constancy is also critical in this context, to allow spatial and temporal shifts to be separated from each other (de Keyzer et al., 2017). In addition, an improved process understanding of the drivers of phenological changes, assessment of physical prediction skill with a phenology focus (i.e., timing of specific events), and development of seasonal biogeochemical forecast capabilities will all represent valuable advances.

PREDICTING THE HUMAN PART OF THE SYSTEM

While our survey of existing marine ecological forecast products revealed examples of forecasts of species distribution, productivity, and phenology, it did not reveal any examples of forecasts of the human part of the system. However, without an understanding of the human responses to changes in a system, unanticipated consequences can occur, such as shifts in fishing effort following declaration of marine protected areas (e.g., Ward et al., 2001; Abbott and Haynie, 2012), concentration of fishing effort in particular areas (e.g., Parnell et al., 2010), changes in illegal behavior (Österblom and Bodin, 2012), and quota shifts (Emery et al., 2014). Here we examine the potential for developing such forecasts.

Unfortunately, even defining the human component is challenging, which partly explains why exploration of future human behaviors and responses has received considerably less attention than biological responses. The human part of the marine system may include direct participants in marine activities (e.g., fishers, tourists), downstream participants (e.g., fish processors), resource managers, and policy makers. The human system may also include the economic market (e.g., Mullon et al., 2017), or non-consumptive actors (Sanchirico et al., 2013; e.g., Tracey et al., 2013). Defining the relevant human sub-system is the first challenge.

Including humans is seen as an important challenge when modeling marine systems (e.g., Fulton, 2010), and this will increase further in importance when forecasting ecosystem changes. Managers of marine systems may be interested in a range of issues that involve humans, including trade-offs in ecosystem-based fisheries management (EBFM) as a result of environmental change, planning for infrastructure (e.g., in locations where fish are projected to move, fisheries and the necessary infrastructure will need to adjust), and minimizing unanticipated consequences (e.g., that can result from ignoring the people). Social and economic sustainability are now seen as central goals alongside ecological sustainability, and forecasts may provide valuable new insights into how ecosystem changes and management actions will differentially affect multiple objectives (Fulton et al., 2014; Jennings et al., 2016).

In constructing models of human systems, there are several advantages compared to the "biological" part of the system. Humans can talk and be observed (e.g., via observer and vessel monitoring systems), they are relatively easy to sample and census, and extensive historical data are often available (e.g., price, employment, catch, effort) to condition and test models. At times control groups of vessels or fleets are available that allow controlled studies to be performed (e.g., Essington, 2010; Abbott et al., 2015). On the negative side, humans can be deliberately or accidently unreliable or strategic in describing their behavior. They may have preferences which are not revealed until a situation actually occurs, particularly for problems that result from a combination of physics (ocean change), biology (dynamic species responses), and humans (behavioral responses). As a result, there are considerable challenges in building mathematical descriptions of human behavior, and gathering information on people in a systematic way such that it can be included in marine models (Fulton, 2010). For example, in a study of the eastern Bering Sea ecosystem and the response of extensive commercial fishery and subsistence harvests, Haynie and Huntington (2016) found the influence of ecosystem conditions on the outcomes of human activities was weaker than anticipated. They attributed this loose coupling to the ability of fishers and hunters to adjust to variable conditions, and the role of social systems, the market economy, and management in moderating the direct effects of changes in the ecosystem.

Development of predictive models of human behavior has thus been considered challenging, with marine examples to date consisting mostly of models that characterize fleet behavior (e.g., Eales and Wilen, 1986; Michael et al., 2017) or that assess outcomes of conservation or resource management decisions (Fulton et al., 2015). These modeling tools allow a range of options to be explored, and support evaluation of alternative interventions under differing conditions. Model results can be presented at multiple spatial and temporal scales, and relative to ecological, economic, and social objectives. Results can also reveal potential "surprises", such as bottlenecks in human responses (Fulton et al., 2015). Predicting how fleets will respond to changes in management such as catch shares is particularly challenging, as the observed behavior is a response to environmental, market, and management conditions and changes (e.g., Abbott et al., 2015; Reimer et al., 2017).

HOW TO GO FORWARD

While marine ecological forecasting is clearly still a field in its infancy, it is also extremely diverse in the range of issues considered. Although each of the response variables and associated forecast products described has their own strengths and weaknesses, there are also clear trends and commonalities between them. Here we synthesize these lessons with the aim of highlighting the way forward on a broad scale.

Firstly, it is important to remember that it may not be necessary to invoke the complex machinery of a fully-coupled climate model to produce useful forecasts. Many physical, biological and social systems have inherent lags that can be exploited to produce useful forecasts based on observed (rather than forecasted) environmental conditions, an approach used by the Gulf of Maine lobster and Pacific salmon return forecasts (**Table 1**). Similarly, the influence of environmental factors on year-class strength of a fish stock typically occurs very early in life (Hjort, 1914; Houde, 2008) but in many cases it can take several years before these individuals become important for the fishery. Fraser River salmon forecasts and Gulf of Maine lobster timing have both used this approach to give appreciable forecast horizons without the need for a climate model.

Similarly, the long-term memory of the ocean and its slow dynamics can also be exploited. Statistical forecasts of the physical environment can be produced by assuming persistence of either absolute values, of anomalies or of a trend (e.g., climate warming) into the future. For example, in the North Sea, anomaly persistence forecasts of SST readily give appreciable skill at a one-year lead time (Stock et al., 2015). This approach is implicit in several of the examples noted previously, where exploitation of the fishery is adjusted to the local environmental regime e.g., Pacific sardine management. While such forecasts may not have the elegance or technical bravado of applying a fully coupled climate model, the important question from an end-user's perspective is the presence (or absence) of useful skill, rather than how the forecast is generated.

Where such simple approaches are insufficient and fully coupled climate models are required, a good place to start is by focusing on the predictability of major modes of variability in the ocean, and their biological consequences. Much of the skill of seasonal and, in part, multi-year forecasts at management-relevant local scales arises from the ability of the forecast systems to capture the evolution of predictable basin-scale patterns (e.g., associated with the El Niño-Southern Oscillation, ENSO) and their regional imprints (Goddard et al., 2001; Stock et al., 2015). Thus, some of these types of events may be more predictable than average conditions. For example, in the California Current, skill of seasonal SST predictions is higher during El Niño events (Jacox et al., 2016). This is beneficial for fisheries managers and industry stakeholders, as El Niño events can have dramatic impacts on the California Current ecosystem (Chavez et al., 2002; Jacox et al., 2016). Similarly, there is evidence that the strong and abrupt contraction of the North Atlantic sub-polar gyre in the mid-1990s could have been foreseen with a sub-decadal lead time (Yeager et al., 2012; Wouters et al., 2013; Msadek et al., 2014). These oceanographic changes also have had well-documented effects on the ecosystems of the North Atlantic (Hátún et al., 2009a,b). In both cases, a valuable first step may be to build simple conditional ecological forecast systems (so-called "if-then" forecasts or "forecasts by analogy") whereby a list of ecosystem responses seen in prior analogous events can be produced: a forecast need not be quantitative in nature to be valuable.

While these simplistic approaches can quickly yield useful forecasts in some situations, the most comprehensive results will ultimately require coupling of biological models to physical forecast systems. In developing such forecast products, it is tempting to focus on a specific response variable or species, driven by the nexus of commercial and academic interests, together with available funding. However, there is no guarantee that such an approach will lead to forecast systems that are both *skilful* and *useful*. Instead, we propose that the question should be reversed: rather than asking "how do we predict a particular variable", it is useful to consider asking "what can we predict?" We propose three concepts that we believe can be valuable in identifying systems and variables that can be predicted *skilfully*.

Firstly, mechanistic understanding, where available, is clearly favored over empirically derived models when building forecasts (Levins, 1966; Urban et al., 2016). This is not to say that useful forecasts cannot be built upon empirical knowledge: indeed nearly all of the products highlighted here are based on correlations between physical variables in the ocean and biological responses. However, mechanistic knowledge is generally regarded as providing a strong footing for forecasting both biological (Guisan and Zimmermann, 2000; Dickey-Collas et al., 2014) and economic (e.g., Haynie and Pfeiffer, 2012) aspects of marine systems, particularly in cases where extrapolation beyond the range of conditions seen in the training set (e.g., under climate change) is required. Nevertheless, it is important to note that there is often little choice but to employ correlative approaches: while the difficulties of predicting fish-stock recruitment based on empirical relationships with the environment have long been recognized (e.g., Myers, 1998), skilful mechanistic solutions to this problem still appear far off.

Secondly, it is necessary to focus on developing biological forecast products around physical variables that can themselves be predicted. A forecast system based on SST, which can readily be predicted on seasonal and even decadal time scales in many marine ecosystems (Kirtman et al., 2014; Meehl et al., 2014; Stock et al., 2015), is much more likely to yield success than one that requires estimates of food abundance, which at the moment cannot be forecasted skilfully. Similarly, it is important to recognize that the spatial forecast skill of a given variable differs across space (**Figure 2**) and across time scales (**Figure 3**). For example, while there is multi-annual SST forecast skill in the North Atlantic (Matei et al., 2012b; Meehl et al., 2014), prediction skill at a multi-annual scale is low over the Pacific Ocean (**Figure 3**). This contrasts with the seasonal scale, where ENSO provides high seasonal forecast skill to the eastern tropical Pacific Ocean (**Figure 2**). A full assessment of the predictability of the physical-system at biologically-relevant spatial and temporal scales (Stock et al., 2015) could eliminate areas where forecasts are not possible and is therefore a critical first step in narrowing down the range of skilfully-predictable biological quantities.

Thirdly, researchers should focus on biological responses where there is a high proximity between the biological response and the physical driver, i.e., tight cause-and-effect relationships. For example, a large body of knowledge exists about correlations between large-scale climate indices, such as the North Atlantic Oscillation (NAO) and Atlantic Multidecadal Oscillation (AMO), and biological responses (Ottersen et al., 2001; Stenseth et al., 2003; Alheit et al., 2014; Nye et al., 2014). However, while these indices can potentially be well-predicted by coupled forecast systems (García-Serrano et al., 2012), it seems unlikely that they can be used to build skilful predictive systems of the marine environment due to the large number of steps between the predictor and the response, each of which adds noise to the predictive process. Similarly, biological responses to physical processes that are filtered through multiple processes and trophic levels (e.g., from upwelling to nutrient concentration to primary productivity to secondary productivity to survival of juvenile fish) seem less likely to yield skilful predictions than situations where there is a direct response to the physical driver (e.g., egg mortality due to low salinity, avoidance of waters that are too cold).

However, and most importantly, while these three concepts can help focus on identifying "low-hanging fruit" that it may be possible to predict *skilfully*, there is no guarantee that these quantities will be *useful* to end-users. The ultimate value and success of a forecast is determined by whether it is (actively) used by end-users in their decision making process and whether its use results in economic or other benefits (Murphy, 1993). Active engagement with the end-users of the predictions from the very start of the project to co-develop forecast products is therefore key to ensure that their potential value to the end-user is realized (Hobday et al., 2016). While this may necessarily entail a deviation from the approach given above, worsen the forecast

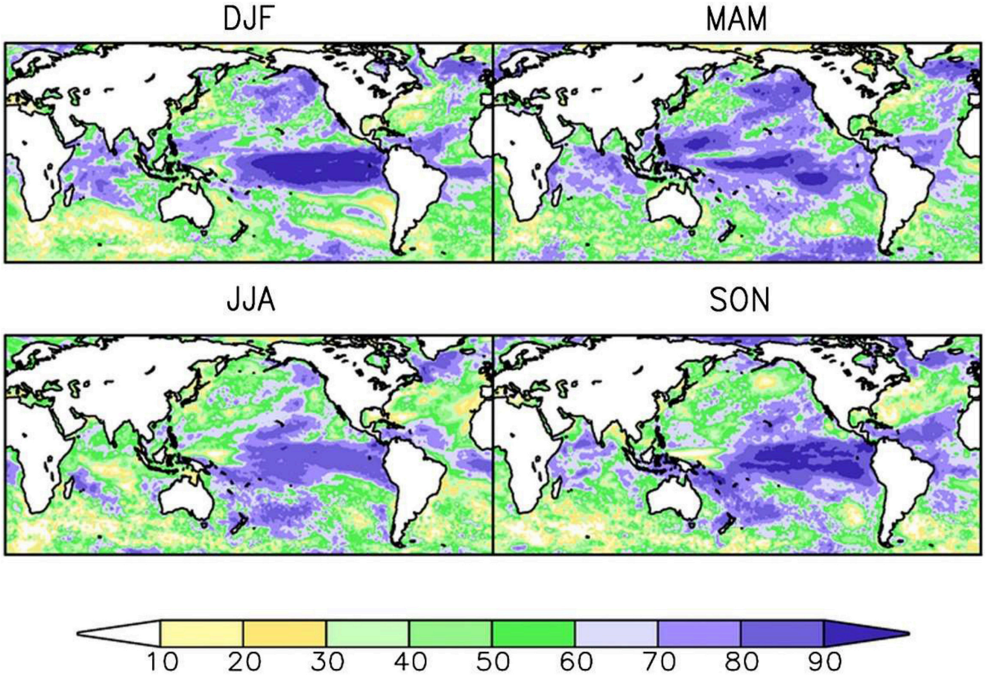

FIGURE 2 | Seasonal-scale sea surface temperature (SST) forecast skill. Skill is shown here for the North American Multi-model Ensemble (NMME) as the correlation coefficient (as a percentage) between observed and forecast seasonal anomalies for a 1 month forecast lead time. Correlation coefficients are shown for temperature anomalies averaged over each of four seasons. **Top-left**: December, January, February (DJF). **Top-right**: March, April, May (MAM). **Bottom-left**: June, July, August (JJA). **Bottom-right**: September, October, November (SON). Modified from (Becker et al., 2014). © 2014 American Meteorological Society. Used with permission.

skill, or complicate the development process, a forecast product without an end-user is ultimately a waste of effort. Striking the balance between what is feasible and what is useful will therefore be essential to push marine ecological forecasting forward in the future.

FUTURE NEEDS

While the forecast products highlighted here have successfully shown that forecasting of marine ecological variables is possible, realizing the full potential of this field will require more than just coupling existing biological or socio-economic knowledge to existing climate forecast systems. Developing the next generation of forecast products that moves beyond these initial proof-of-concept examples necessitates further developments in both research and management, as we discuss here.

Perhaps the greatest factor limiting the development of marine ecological forecast products is the gap between the climate modeling and marine science communities. This gap is multidimensional in its nature. Climate modelers and marine scientists, for example, are rarely employed at the same institute and have very different educations and ways of thinking and working. The nature of climate model output is a particularly challenging aspect of this disjoint; while climate scientists routinely work with extremely large data sets on large computing clusters, many analyses and datasets in marine science have historically not required the use of a formal programming language and are stored in a spreadsheet (Berx et al., 2011). Bridging this gap is challenging, and the main linkage between the two disciplines is currently in the form of relatively few individuals that are capable of moving between them. Fortunately, climate-model and climate-data literacy can be learned. The development of training courses to increase the proficiency of both marine biological researchers and students in the use and application of climate-model data should therefore be seen as a simple but high priority action to help bring these two fields closer together. Similarly, the climate data needs in marine science can be better communicated to climate scientists so they can provide output that facilitates the uptake of climate information into marine ecological forecasts. Overall, large projects that bring together researchers across disciplines for sustained periods of time should be encouraged as they facilitate the exchange of expertise in both directions (e.g., Van Pelt et al., 2016).

A second key factor limiting the development and eventual uptake of climate-model forecasts in fisheries and marine science, even for those that are adept with climate-data, is access to forecast data. Getting access to such data for marine scientists typically requires establishing close collaborations with climate modelers directly: on the one hand, this brings new and critical expertise into the project, but on the other hand is not an option available to all. Availability of climate-forecast data on both the seasonal and decadal timescales, including both hindcasts and routine delivery of updated forecasts, is nevertheless critical for the continued development and production of marine

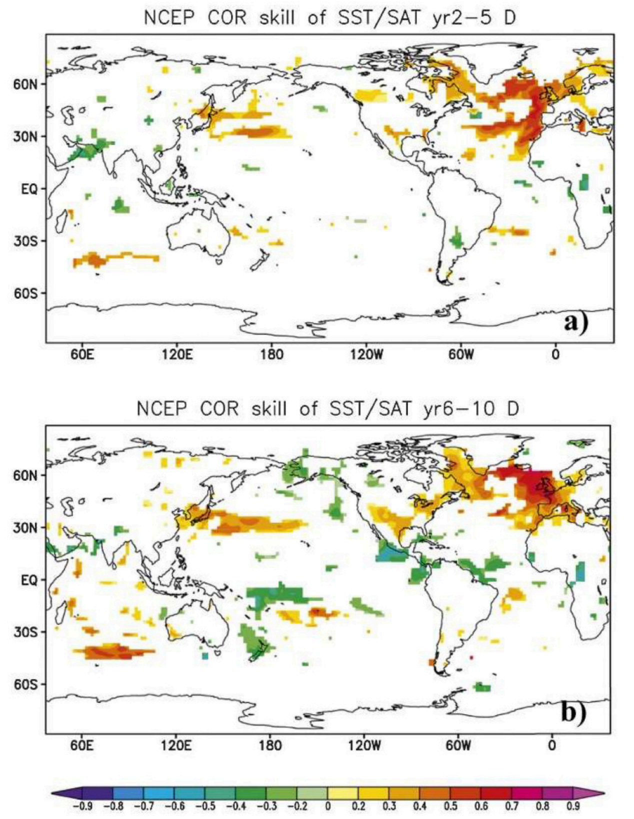

FIGURE 3 | Decadal-scale sea surface temperature (SST) forecast skill. Skill is shown as the temperature predictability beyond the global warming trend for the ECHAM5/Max Planck Institute Ocean Model (MPI-OM) coupled model with initial conditions provided by the NCEP reanalysis. Correlation coefficients between linearly-detrended observations and forecasts are shown for forecast lead times of **(a)** 2–5 years and **(b)** 6–10 years. Only the significant correlations (at the 5% level) are plotted. Modified from (Matei et al., 2012b). © 2012 American Meteorological Society. Used with permission.

ecological forecast products. Fortunately, this problem has been well-recognized for some time now in the climate-modeling community and initiatives aimed at improving access (e.g., the WCRP Grand Challenge on Near Term Climate Predictions) are starting to deliver results. Seasonal scale forecasts are available from the North American Multi-Model Ensemble (NMME: Kirtman et al., 2014) and analogous projects are currently in progress in Europe (e.g., Copernicus C3S). Some decadal forecast products are also openly available e.g., via CMIP5 (IPCC, 2013) and can be used to develop products, although given that most of the models stop around 2005, these cannot be used to produce regularly updated predictions.

From a biological point of view, there is a continuing need to improve the quality of our biological models. Marine science has been limited for many years by its focus on describing, rather than predicting, systems. Expanding our knowledge beyond the empirical toward the mechanistic can be expected to greatly improve the quality of our understanding and our predictive capability (Dickey-Collas et al., 2014; Urban et al., 2016). Incorporating behavior, allowing for adaptive responses, and modeling organisms in terms of their full life-cycle are all key elements that can be expected to be seen in the next generation of models and deliver gains in predictive skill, challenges in parameterising such models notwithstanding (Urban et al., 2016). Similarly, the importance of social science in understanding the marine system is gaining increasing recognition and can be expected to drive important modeling developments in the future as well as to inform the features that make a management system effective (Fulton, 2010; Bundy et al., 2017).

For economics and social sciences, modeling, and data collection are expanding significantly but the integration of these models with biophysical models is nascent. Economic models are both structural and empirical, but even when predictions can be made about how fish populations and market conditions will change, the ability to predict what will occur across large policy changes that alter fishers' incentives is limited (Reimer et al., 2017). However, as more research is conducted and the lessons learned integrated across management systems, better assumptions will be able to be made about the combined impacts of environmental, market, and policy variability and change.

Improvements in applying this knowledge are also needed to take advantage of the potential offered by marine ecological forecasts. Foremost amongst this is the need to further develop frameworks to assess and quantify the value of forecast knowledge. Potential applications of forecast information could be run through a simulation procedure, similar to a Management Strategy Evaluation (MSE) to quantify both the benefits and risks associated with the forecast product. Importantly, the level of forecast skill required of the forecast product to "break-even" (i.e., where the benefits outweigh the risks) can be established within such a framework and used to determine when the procedure should be adopted, modified or potentially rejected. Examples of such analyses can be found in the literature already (e.g., Basson, 1999) and at least one example of the analysis of a forecast system, for the management of the Pacific sardine fishery, has emerged (Tommasi et al., 2017b).

Finally, the role of stakeholders in the development of these forecast products is often easy to overlook, but is also critical (Hobday et al., 2016). Stakeholder participation is crucial at all phases of developing forecast products, and should be involved all the way from the scoping of the project through its development to its evaluation and into operational delivery (e.g., Liu et al., in review). Support to train stakeholders on how to interpret and use this forecast information is therefore also essential: engaged and informed stakeholders will ultimately both inspire the development of new forecast products that the scientific community cannot foresee and ensure their success. Efforts to increase and support stakeholder engagement are therefore expected to yield large dividends.

DISCUSSION AND CONCLUSIONS

This review of the current state of the marine ecological forecast products shows a field that is developing quickly. Within the last 5 years, many products have come online and are now being produced in an operational manner, with many more still under development. A number of these products are quite mature, and have been in operation for close to a decade: it therefore seems safe to say that the field has moved beyond the "proof-of-concept" phase and is now preparing to roll-out the technology on a much larger scale.

Realizing the full potential offered by marine ecological forecasting can, however, seem like a daunting task, currently available forecast products notwithstanding. The underlying complexity of biological systems and the difficultly of observing life in the ocean are particularly challenging obstacles. Nevertheless, it is worth remembering the tremendous progress that has been made in other fields: meteorology, in particular, makes for a particularly inspirational example. Starting from the early numerical experiments of Lorenz in the 1950s, weather forecasting has progressed steadily and surely to the point where reliable 5 and 7 day forecasts are now a reality (**Figure 4**), a situation that was pure fantasy just a few decades ago (Bauer et al., 2015). These advances have occurred in spite of challenging observational difficulties and the inherent complexity and chaotic nature of weather systems. Marine biological science faces many similar problems today. While it is tempting to despair of the complexity of ecosystems, the lessons from the history of numerical weather prediction teach us that useful products can be developed in the face of complexity.

The pathway followed by marine ecological forecasting, however, will likely be different from the incremental progress of numerical weather prediction (**Figure 4**). We expect the next few years to exhibit a form of "Cambrian explosion" in the number and variety of such forecast products, as marine researchers become aware of the potential of forecasting and start to populate the "niche." We expect that this second generation of products will be dominated by direct use of the available model outputs: this is the approach advocated in the section "How to go forward." However, once the initial "low-hanging fruit" products have come online, progress can be expected to be more incremental in nature, as the joint development of forecast systems between physical modelers and marine scientists starts to address the more challenging problems; indeed, such collaborations are already starting to emerge e.g., the J-SCOPE forecasting system in the California Current (Kaplan et al., 2016; Siedlecki et al., 2016).

The marine ecological forecast products that have emerged thus far are by no means distributed uniformly across the globe, or even across the developed world. While Australia has clearly been the pioneer, with multiple mature operational products, and the United States has also seen rapid development of operational products within the last few years, Europe has yet to see the first such products emerge. Counterintuitively, the waters surrounding Europe have some of the longest forecast horizons in the world (**Figure 3**), particularly in the North Atlantic sub-polar gyre region where decadal-scale forecasts are a reality (Matei et al., 2012b; Meehl et al., 2014), but also in its shelf seas (Stock et al., 2015). Moreover, many of its seas have a long history of scientific investigation and some of the key hypotheses about fish stock productivity were inspired by variations in European stocks (Hjort, 1914; Paasche et al., 2015). We postulate two potential explanations for this discrepancy. Firstly, while local fisheries in Australia and the USA essentially are governed by one national agency, management of European fisheries needs to balance the

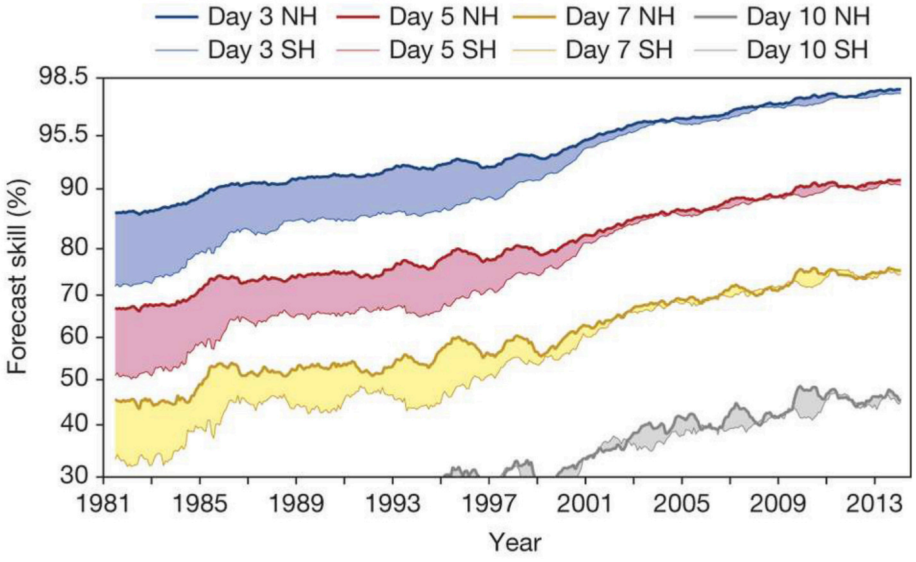

FIGURE 4 | Development of weather forecast skill since 1981 for 3, 5, 7, and 10 day lead times for the northern (NH) and southern hemispheres (SH). Forecasts are regarded as being useful if they exceed a skill of 60%, while >80% is considered to be of high accuracy. Forecast skill is the correlation between the forecasts and the verifying analysis of the height of the 500-hPa level, expressed as the anomaly with respect to the climatological height. The collapse of the curves in the late 1990s is due to advances in incorporating satellite observations into forecast models. Reprinted by permission from Macmillan Publishers Ltd, Nature (Bauer et al., 2015) copyright 2015.

interests of many nations at the same time, and therefore may be less flexible and slower to respond to new opportunities. Secondly, both Australia and the USA border the Pacific Ocean and their waters are influenced by strong and regular variability in the form of both ENSO and the Pacific Decadal Oscillation (PDO). Furthermore, many of the first seasonal forecasts of the ocean (for ENSO) were developed in this area more than a decade ago, while the dominate mode of variability in the North Atlantic (the NAO) has until recently been thought to be unpredictable (Scaife et al., 2014; Smith et al., 2016), again giving the Pacific a natural advantage in this respect. Nevertheless, the high predictability of the front doorstep of Europe represents a tremendous potential that we expect to see tapped in the future.

As marine forecasts become more common, we can also expect to see both dramatic failures and unintended consequences emerge. These negative outcomes may result if a forecast fails in a technical sense, but they will also arise if forecasts are not used or interpreted properly. As the technical potential for forecasting in marine systems becomes more tangible, the need is rising for systematic processes to engage end-users in designing forecasts that can effectively support their specific decision-making requirements. In addition, information that is understandable to stakeholders about what the forecast provides, temporal and spatial scales at which it is relevant, its associated levels of uncertainty and its limitations is also critical. In many cases, successful use of a forecast will require that stakeholders beyond the immediate users are capable of interpreting the forecast correctly, so as not to disrupt highly connected systems in which actors may have competing interests, such as fishery governance systems and seafood supply chains. Active engagement with end-users to communicate the limitations and assumptions inherent in these forecasts is therefore critical to minimize the problems created when forecasts inevitably fail or are misused.

In conclusion, we have reviewed and highlighted the lessons learned so far from this first generation of forecast products. While the recommendations made here will not guarantee the successful development of other popular prediction systems in the future, they can nevertheless be used to increase the rate of development, identify "low-hanging fruits" where there is a good chance of developing forecast systems and ensure the relevance of the products to end-users. Following such an approach will, we believe, lead to a rapid blooming of forecast products that can close the gap between the potential and the reality of marine ecological forecasting.

AUTHOR CONTRIBUTIONS

All authors contributed to the initial discussions shaping this manuscript. MRP, AJH, BRM, and DT lead the drafting of the manuscript. All authors contributed to the revision of the manuscript and approved the final version.

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