Frontiers | Frontiers in Marine Science

TYPE Original Research
PUBLISHED 29 May 2025
DOI 10.3389/fmars.2025.1551352

OPEN ACCESS

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RECEIVED 25 December 2024
ACCEPTED 07 April 2025
PUBLISHED 29 May 2025

CITATION
Wang Z, Cai Z and Li Y (2025) Prediction and analysis of China's coastal marine economy: an innovative grey model with the best-matching data-preprocessing techniques. *Front. Mar. Sci.* 12:1551352. doi: 10.3389/fmars.2025.1551352

Prediction and analysis of China's coastal marine economy: an innovative grey model with the best-matching data-preprocessing techniques

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China's coastal marine economy, a key part of the national economy, exhibits complex temporal evolution and regional heterogeneity, posing challenges for accurate forecasting. To address these challenges, this study employs advanced data-preprocessing techniques, accumulating generation operators (AGO) in grey prediction models, to tackle the nonlinear, volatile, and heterogeneous gross ocean product (GOP) data. Specifically, an accumulating generation operator matching mechanism that utilizes a pool of seven advanced AGOs is incorporated into the discrete grey prediction model. The proposed best-matching discrete grey prediction model can accurately describe the GOP system in China's 11 coastal provinces. Furthermore, the experimental results indicate that the proposed model achieves 5.09% average forecasting mean absolute percentage error, demonstrating 46.65% and 61.73% improvement rates over the single AGO-based and benchmark models, respectively. Consequently, the proposed model is deployed to forecast China's provincial GOP up to 2025, offering insights into the national development strategies, regionally tailored policies, and inter-provincial coordination in the marine sector.

KEYWORDS

marine economy forecasting, gross ocean product, grey prediction model, accumulating generation operator, data preprocessing

1 Introduction

The marine economy refers to the various industries and economic activities associated with the development (Fang et al., 2024), utilization (Tang et al., 2022; Xin et al., 2024), and protection of marine resources (Yusheng et al., 2024; Zhang, 2024). It encompasses a wide range of sectors, including marine fisheries, marine transportation, offshore oil and gas extraction, shipbuilding, marine engineering, and marine tourism. At the core of measuring the marine economy's contribution, the gross ocean product (GOP) represents the total economic output of these marine sectors (Pan et al., 2024). The GOP is made up of three primary components: (1) the primary sector, which includes marine fishing and aquaculture; (2) the secondary sector, encompassing industries like offshore oil and gas extraction, shipbuilding, and marine engineering; and (3) the tertiary sector, which involves services such as marine transportation, coastal tourism, and maritime logistics. Together, these sectors capture the economic value generated from marine resources and associated industries, making GOP a critical indicator of the strength and growth of the marine economy.

In recent years, according to the Ministry of Natural Resources of the People's Republic of China (https://www.mnr.gov.cn/), China's gross ocean product reached 10.54 trillion yuan, accounting for 7.8% of the country's total gross domestic product (GDP) in 2024, maintaining the similar ratio as in 2022. Thus, the marine economy has played an increasingly vital role in national economic growth, contributing to a significant share of China's GDP.

Consequently, the marine economy plays a pivotal role in China's broader economic development, influencing multiple dimensions of national progress (Xu et al., 2024). Its importance is reflected in its contributions to economic growth, industrial structure optimization, regional development, foreign trade expansion, and social welfare improvement (Santos et al., 2024). As a driver of economic growth, the marine economy fuels sectors such as marine transportation, fisheries, and offshore energy, while also fostering high-tech industries like marine biotechnology and renewable energy, supporting China's shift toward innovation-driven growth (Liu et al., 2021). Additionally, the marine economy plays a key role in promoting regional coordination, especially among coastal provinces (Prince et al., 2023). The marine economy also serves as a critical pillar of China's international engagement, with maritime trade and initiatives like the Belt and Road enhancing global economic ties (Turschwell et al., 2020).

Given these multifaceted roles and the increasing complexity of marine economic systems, there is a growing need to anticipate future developments and manage growth proactively through forecasting tools. Accurate forecasts provide essential insights for economic planning and industrial layout (Nguyen and Hoang, 2024), enabling policymakers to optimize resource allocation, guide the growth of marine industries, and plan effectively for the future (Zheng et al., 2023). Moreover, GOP forecasting aids in the rational development and utilization of marine resources, ensuring that economic exploitation is balanced with environmental sustainability. In addition to fostering sustainability, reliable forecasts help enhance the economy's resilience to risks, such as market fluctuations or environmental disruptions, by anticipating future trends and challenges. As such, strengthening GOP forecasting becomes vital for advancing the high-quality development of China's marine economy and positioning it for long-term success in a dynamic global landscape (Ji et al., 2024).

Therefore, this work aims to contribute to the growing body of research on marine economic forecasting by developing a novel forecasting model tailored to China's coastal provinces. Given the diverse economic conditions and unique marine resource endowments of each region, a customized approach is essential for producing accurate and reliable forecasts. By utilizing advanced data processing techniques and dynamic modeling methods, this study provides a comprehensive analysis of future gross ocean product trends. The insights generated will support policymakers and industry leaders in making informed decisions, promoting sustainable development, and enhancing China's position as a global leader in the marine economy.

The core contributions of this work are summarized as follows:

1. This study provides an in-depth analysis of the current state of gross ocean product across China's coastal provinces, revealing a range of complex characteristics unique to each region. The analysis highlights the presence of significant nonlinearities, high volatility, and diverse noise perturbations in the data series, also underscoring the regional heterogeneity in the developmental patterns of the GOPs.
2. This study proposes a novel model that employs an mechanism to identify the best-matching advanced accumulating generation operator (AGO) method within the grey prediction model for each region, leveraging the distinct attributes of each province's marine economic data. This tailored approach ensures the highest possible accuracy in forecasting, and the results demonstrate a significant improvement in predictive precision compared to other benchmark models.
3. This study projects the future Gross ocean product in China's 11 coastal provinces, offering valuable insights that can inform regionally personalized policy decisions. The forecast results enable regional policymakers to craft sustainable growth strategies tailored to each province's unique strengths, while also advancing coordinated national development goals.

The remaining article is organized as follows. Section 2 reviews the existing literature on marine economy forecasting and grey prediction methods. Section 3 details the methodology employed, focusing on data preprocessing techniques and the newly proposed best-matching AGOs-DGM(1, 1) model. Section 4 presents the data analysis and experimental results, highlighting the model's predictive performance. Section 5 presents and discusses future projections based on the forecasting outcomes and explores policy implications. Finally, Section 6 concludes the paper.

2 Literature review

2.1 Progress on marine economy forecasting

Accurate marine economy forecasting (e.g., achieving a forecasting mean absolute percentage error below 10% or 5%) is crucial for the growth and strategic planning of coastal regions (Kong et al., 2024). As forecasting methodologies have become more refined, they now offer significantly improved accuracy (Shi et al., 2024; Wang et al., 2024), enabling coastal regions to allocate resources more effectively and plan strategically for evolving marine economic trends.

In recent years, diverse mathematical, machine learning, and grey system models have advanced marine economic forecasting applications, addressing the unique challenges of forecasting in the marine sector. Initially, mathematical models are valued for their low data requirements, allowing for effective short- and medium-term predictions even with limited historical data. However, discrepancies between predicted and actual marine economic output indicate that there is still a need to better align inputs like talent, capital, and marine research to enhance the added value of marine production (Ma et al., 2020). Subsequently, backpropagation (BP) neural networks have been utilized to construct forecasting index systems that capture the nonlinear and dynamic relationships within marine economies. By analyzing multiple indicators, BP neural networks reveal the causal relationships that underpin marine economic development, offering precise predictions that align closely with actual observed trends. This approach has demonstrated high predictive accuracy, highlighting its value in regional economic forecasts (Shi, 2019). Lastly, grey models have become increasingly popular due to their robustness in handling small samples and uncertain data. These models are particularly suited to analyzing the marine economy system, which evaluates the system against economic shocks and regional disparities. For instance, the nonlinear fractional grey model, combined with optimization algorithms, has been used to forecast marine economy resilience across China's coastal regions (A CRITIC-TOPSIS and optimized nonlinear grey prediction model: A comparative convergence analysis of marine economic resilience, 2024).

Additionally, grey prediction models have shown remarkable utility in addressing the unique challenges of marine economic forecasting, particularly where data availability is constrained or uncertain (Xuemei et al., 2019). These models have been applied to evaluate and predict the growth trajectories of regional marine economies, such as those in China's coastal areas. Through grey forecasting, researchers can gain insights into the system's evolutionary trends that would otherwise be difficult to predict due to data limitations (Zhang et al., 2003). For instance, grey prediction models are used to reflect the developmental dynamics of regional marine economies, providing an informed basis for policy formulation and sustainable growth strategies (Zhang, 2020). Moreover, grey models also facilitate comprehensive assessments that highlight potential areas for economic improvement, thereby assisting regional governments in aligning their policies with long-term development goals (Kedong et al., 2021).

Given the advancements in model accuracy and complexity, these forecasting models have become indispensable tools for regional economic planning. Marine economic forecasting has been extensively applied to coastal provinces to predict economic outcomes such as GOP growth and the performance of marine industries. Forecasts for provinces like Guangdong have identified key growth drivers, including marine technological innovation and infrastructure investment, providing insights into long-term regional economic strategies (Ma et al., 2020). The ability to forecast regional marine economies has helped coastal governments tailor their development plans, ensuring that policies are aligned with the unique needs and potential of each region (Shi, 2019; Kedong et al., 2021). By applying advanced forecasting models, local governments can better anticipate economic fluctuations and plan for sustainable marine growth.

In conclusion, the progress made in marine economy forecasting has equipped coastal regions with powerful tools for economic planning and strategic decision-making. The continued evolution of grey system models and hybrid forecasting methods reflects a growing capacity to accurately predict complex marine economic trends. As these models are increasingly applied to regional contexts, they enable tailored development strategies that align with each region's unique economic profile.

However, existing research on marine economy forecasting has primarily focused on model development or national-level analysis, with limited attention to region-specific forecasting strategies that account for the heterogeneous economic dynamics of individual coastal provinces. This highlights the need for adaptive forecasting frameworks capable of tailoring predictions to diverse regional marine economies.

2.2 Grey prediction methods

Grey prediction methods have emerged as a valuable tool in economic forecasting (Deng, 1982), particularly for fields where data limitations are a common challenge. These methods are well-suited to environments with small sample sizes and uncertain or incomplete information, making them an effective choice for forecasting in the marine economy and other sectors characterized by data scarcity (Li et al., 2023a). Initially, Grey models offer a unique advantage in their ability to generate reliable predictions even with minimal data, as they require fewer observations than traditional statistical methods. This adaptability allows them to handle non-linear relationships and dynamic changes within a system, providing robust predictions in situations where other models might struggle. Subsequently, compared with hybrid approaches, grey prediction models offer significant advantages in computational efficiency and model transparency, enabling faster implementation and easier interpretation. Therefore, the versatility of grey prediction methods has led to their widespread application across various domains. Specifically, grey prediction methods have been utilized in engineering, environmental studies, healthcare, and retail sales management (Ye et al., 2024), showcasing their broad applicability. Their ability to forecast with limited data has made grey models particularly popular for emerging sectors and regions with underdeveloped data infrastructure. As for marine economic forecasting, grey models are frequently employed to predict marine economic (Li et al., 2023b) and environmental (Tian et al., 2020; Li et al., 2024) systems, aiding in regional marine development.

Building on their established strengths, grey prediction methods have evolved through several key enhancements to improve accuracy and adaptability. (1) Background value optimization is one such area, focusing on refining the approximation of adjacent values to reduce jump errors between continuous and discrete data. For example, Simpson's background values are utilized in place of the traditional adjacent average (Ding et al., 2024c). Another crucial enhancement is (2) initial condition optimization, which improves the solution of time response equations by optimizing the initial conditions of differential or difference equations to better match the evolving behavior of the target system (Ding and Li, 2021). (3) model structure optimization aims to increase the flexibility of grey models by modifying differential or difference equation structure (Ding et al., 2024d) or incorporating elements from other techniques (Ding et al., 2024a), creating adaptive model structures or hybrid models that are more responsive to complex data. Together, these advancements in background values, initial conditions, and model structure significantly enhance the effectiveness of grey prediction methods, broadening their application across various domains.

Additionally, the construction of the Accumulating generation operator has been a major focus among the advancements in grey prediction methods (Ding et al., 2024b). AGO is central to grey models, as it transforms raw data into a form that emphasizes trends and reduces the influence of random fluctuations. This process of accumulation is particularly valuable for small-sample and poor-information environments, which are typical in marine economic forecasting.

Currently, the improvements in AGO have involved optimizing its configuration to further enhance the model's predictive power. Ding et al (2022) observed that the grey model often leads to projections that increase or decrease too steeply, due to its nature as a time series model with coefficients that vary over time. To address this, the study incorporated a damping trend parameter within the accumulating generation operator to adjust and moderate the forecast outcomes. He et al (2022) introduced a fractional dynamic weighted coefficient system that adheres to normalization, creating a new information-prioritized s-order weighted accumulation operator. This approach allows the parameter to assign varying levels of priority to data, thereby adjusting the relative influence of both recent and older information during sequence generation. Zhang et al (2023) identified that certain existing AGOs may aggregate errors from irrelevant grey data, which can impair the model's accuracy. In response, a probabilistic operator (PAGO) was devised to process grey information more effectively, thus isolating and utilizing only the relevant data.

As a result, the refinement of AGO has significantly boosted the accuracy and versatility of grey prediction models, enabling them to offer more reliable forecasts across diverse applications. The ongoing focus on AGO's structure and application underscores its importance in maintaining the robustness and adaptability of grey prediction methods.

Despite substantial advancements in AGO design, current studies rarely address the challenge of selecting the most appropriate AGO for different data environments. There remains a research gap in developing systematic, data-driven mechanisms to match AGO variants with specific regional characteristics, especially within complex systems like marine economies.

3 Methodology

To accurately forecast the Gross ocean product of China's coastal provinces, this section employs a novel grey prediction framework, best-matching AGO-DGM(1, 1), tailored to address the complexities and heterogeneities of the provincial marine economic systems. The proposed methodology leverages advanced accumulating generation operators to preprocess sparse and noisy data, enhancing trend extraction and noise reduction. Furthermore, by integrating a best-matching AGO selection mechanism, the model adapts to the unique dynamics of each region, optimizing its forecasting accuracy. This section details the data preprocessing techniques used, the establishment of the AGO-DGM(1, 1) model, and the procedures for selecting the best-matching AGO for each province. The overall procedure of the proposed model is illustrated in Figure 1.

3.1 Data preprocessing techniques in grey theory

The marine economy, represented by Gross ocean product, is a grey economic system characterized by sparse data and insufficient information. This data scarcity, combined with the inherent complexity and volatility of marine economic activities, makes it highly suitable for grey system theory. Furthermore, the grey prediction model, as a crucial component of grey system theory, specializes in handling uncertain, incomplete, and poor information, representing an effective tool to model and predict such economic behaviors.

Specifically, the AGO represents a key data preprocessing technique within grey prediction models. The AGO plays a critical role in transforming raw data into a more suitable format for grey system modeling, particularly in the context of small-sample, poor-information marine economy data environments. This technique offers several advantages:

- Enhancing evolutionary patterns: The AGO enhances the underlying evolutionary trends of small samples by accumulating data, allowing the model to better capture the long-term development of the marine economy system.
- Mitigating external random disturbances: Through accumulation, AGO reduces the effects of external random disturbances and shocks. This is particularly useful for stabilizing volatile data series, such as marine economic outputs, which are often influenced by external factors like policy changes and natural events.
- Reinforcing quasi-exponential characteristics: By applying AGO, the behavior of the system's data sequence is

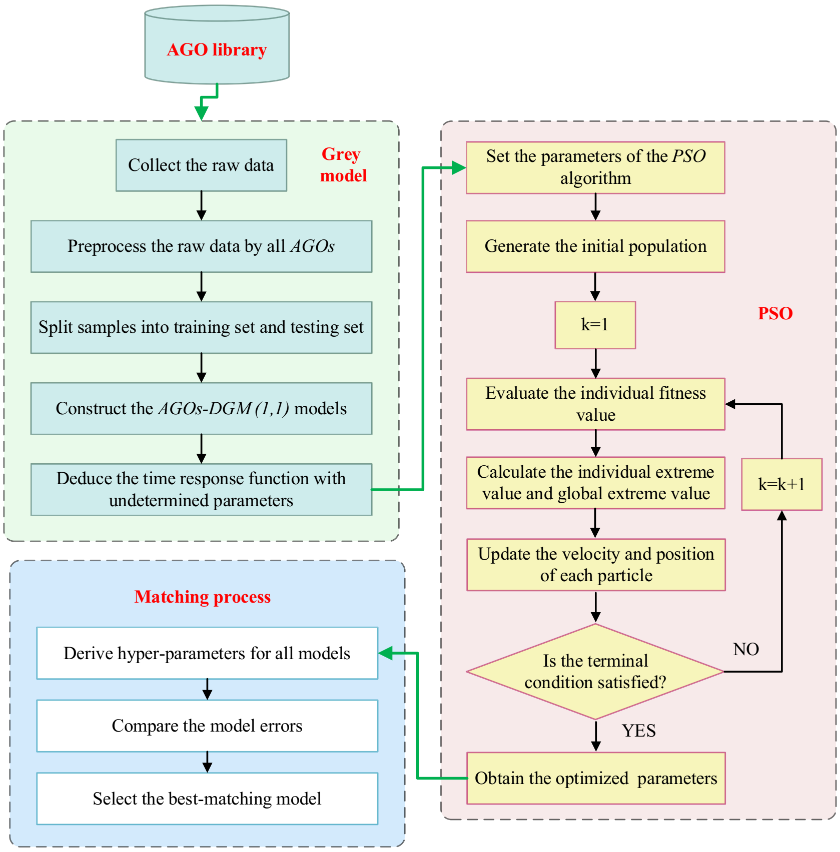

FIGURE 1
Methodological framework of the proposed model.

transformed to exhibit an approximate exponential characteristic. This transformation makes the sequence more compatible with differential equation modeling, which is the mathematical foundation of many grey prediction models, including the DGM(1, 1) model.

Therefore, the AGO data preprocessing technique enables more accurate forecasting by strengthening the marine economic system's inherent dynamics while simultaneously reducing noise and randomness. Thus, it presents an ideal tool for handling the marine economy's nonlinear, volatile, and stochastic data characteristics, ultimately enhancing prediction accuracy.

So far, many advanced AGO methods have been developed to improve upon the traditional AGO, with one of the most notable advancements being the information-prioritized accumulating generation operator. This method is a significant refinement that addresses some of the limitations of the conventional AGO. Subsequently, several crucial new-information-priority AGO methods will be introduced.

3.1.1 Conventional AGO

Assuming that $\mathbf{Y}^{(0)} = [y^{(0)}(1), y^{(0)}(2), \ldots, y^{(0)}(n)]^{\mathrm{T}}, y^{(0)}(i) \geq 0, \mathrm{i}, 1, 2, \ldots, \mathrm{n}$. represents the original Gross ocean product sequence, the conventional 1-AGO process is defined as follows:

$$\mathbf{Y}^{(1)} = [y^{(1)}(1), y^{(1)}(2), \ldots, y^{(1)}(n)]^{\mathrm{T}}$$
$$y^{(0)}(k)d = \sum_{i=1}^{k} y^{(0)}(i)\,;\; k = 1, 2, \ldots, n\,. \tag{1}$$

where, $\mathbf{Y}^{(1)}$ represents the accumulated sequence worked by the conventional 1-AGO and d stands for the operator that works on $y^{(0)}(k), k = 1, 2, \ldots, n$.

3.1.2 New information priority operator (NIPO)

Building on the traditional 1-AGO framework, NIPO enhances the accumulation process by utilizing variable weights (Wu et al., 2022), distinguishing it from the equal-weight accumulation characteristic of 1-AGO. Specifically, it introduces a breakpoint in the accumulation process and employs an adaptive parameter κ that adjusts the accumulation weights $\eta_i k$ before and after this breakpoint:

$$\mathbf{Y}^{(NIPO)} = [y^{(NIPO)}(1), y^{(NIPO)}(2), \ldots, y^{(NIPO)}(n)]^{\mathrm{T}}$$
$$y^{(NIPO)}(k) = \sum_{i=1}^{k} \eta_{ik} y^{(0)}(i), \quad \eta_i k = \begin{cases} 1, i = k \\ \kappa, i \leq k-1 \end{cases}, \kappa \in (0,1)\,. \tag{2}$$

where $y^{(v)}(k)$ indicates the processed sequence employing the variable weight AGO. Equation 2 indicates that when generating the k-th data point in the accumulated sequence ($y^{(v)}(k)$), the weight assigned to the k-th data point ($y^{(0)}(k)$) is 1, while the data points prior to $y^{(0)}(k)$ ($y^{(0)}(1), y^{(0)}(2)\ldots, y^{(0)}(k-1)$) receive an accumulation weight less than 1, which is controlled by the parameter κ. This approach ensures that the processed marine economy sequence adheres to the principle of new information priority.

3.1.3 R-order adjacent accumulating generation operator (RAAGO)

Unlike the NIPO's weight allocation, RAAGO divides the accumulation process with nonlinearly correlated accumulation weights (Wang et al., 2022):

$$\begin{aligned}\mathbf{Y}^{(RAAGO)} &= [y^{(RAAGO)}(1), y^{(RAAGO)}(2), \ldots, y^{(RAAGO)}(n)]^{\mathrm{T}}\\ y^{(RAAGO)}(k) &= \sum_{i=1}^{k} \eta_{ik} y^{(0)}(i), \quad \beta_{\eta_{ik}} = \begin{cases} \frac{1}{r^2+1}, i = k \\ \frac{r}{r^2+1}, i \le k-1 \end{cases}.\end{aligned} \tag{3}$$

Here, $\mathbf{Y}^{(RAAGO)}$ represents the accumulated sequence processed by RAAGO. This AGO approach can make accumulation with less fluctuations. Additionally, when $r = 0$, the accumulated sequence is reduced to the original sequence. When $r \in (0,1)$, RAAGO conforms to the principle of new information priority. And when $r > 1$, the historical accumulating weight is greater than the current accumulating weight.

This AGO method facilitates accumulation with reduced fluctuations. Additionally, when $r = 0$, the accumulated sequence reverts to the original sequence. When $r \in (0,1)$, RAAGO adheres to the principle of prioritizing new information. When $r > 1$, the weight of historical accumulation exceeds that of the current accumulating weight.

3.1.4 Accumulated generating operation with the new information priority principle (NAGO)

NAGO, in contrast to NIPO and RAAGO, does not divide accumulation weights into two discrete segments (Wu and Zhang, 2018). Instead, it assigns continuously varying weights to the data across all time points:

$$\begin{aligned}\mathbf{Y}^{(NAGO)} &= \left[y^{(NAGO)}(1), y^{(NAGO)}(2), \ldots, y^{(NAGO)}(n)\right]^{\mathrm{T}}\\ y^{(NAGO)}(k) &= \sum_{i=1}^{k} \eta_{ik} y^{(0)}(i), \quad \eta_{ik} = \rho^{k-i}, \rho \in (0,1).\end{aligned} \tag{4}$$

where $\mathbf{Y}^{(NAGO)}$ represents the accumulated sequence utilizing the NAGO and ρ indicates the parameter adjusting the consequtive accumulating weights.

Equation 4 indicates that, during the accumulation for the data point $y^{(NAGO)}(k)$ at the time k, the original observations $y^{(0)}(i), i = 1, 2\ldots, k$'s accumulating weights increase exponentially concerning the time points i. Moreover, a smaller value of ρ results in a faster increase in the accumulating weights. This weight assignment not only renders new information priority but also enhances the exponential developmental pattern within the processed marine economy series.

3.1.5 Adaptive exponential accumulated generation operator (AEAGO)

Expanding on NAGO's continuously variable accumulation weights, AEAGO applies a scaling factor to modify the exponential pattern of the accumulation weights (Ye et al., 2022).

$$\begin{aligned}\mathbf{Y}^{(AEAGO)} &= [y^{(AEAGO)}(1), y^{(AEAGO)}(2), \ldots, y^{(AEAGO)}(n)]^{\mathrm{T}}\\ y^{(AEAGO)}(k) &= \sum_{i=1}^{k} \eta_{ik} y^{(0)}(i), \quad \eta_{ik} = \begin{cases} 1, k = 1 \\ (1-\rho)\rho^{k-i}, k \ge 2 \end{cases}, \rho \in (0,1].\end{aligned} \tag{5}$$

Here, the parameter ρ functions as the exponential base, while its linear form $(1-\rho)$ functions as a scaling factor of the exponent. When the value of ρ is relatively small, the exponential growth rate is accelerated and the scaling effect is amplified. Moreover, η_{11} is set to be one to construct a buffer operator. By introducing the scaling effect, AEAGO can be seen as an enhanced version of NAGO.

3.1.6 New information priority generalized accumulation generation operator (NGAGO)

NGAGO is derived from the Wei-bull distribution to grant the accumulation weight a life distribution function (Li et al., 2022). Contrasting to AEAGO, it offers nonlinear constraints between the scaling factor and the exponent:

Initially, the Wei-bull distribution describes the service lifetimes of the system components, which is expressed as:

$$f(t) = \frac{a}{m}\left(\frac{t}{m}\right)^{a-1} e^{-\left(\frac{t}{m}\right)^{a}}. \tag{6}$$

Particularly, when $a = 1$, Equation 6 is reduced into an exponential function of time with a nonlinear scaling factor:

$$f(t) = \rho e^{-\rho(t-i)}. \tag{7}$$

Considering the accumulation weight η_{ik} as the system component, NGAGO gives the following transformation:

$$\begin{aligned}\mathbf{Y}^{(NGAGO)} &= [y^{(NGAGO)}(1), y^{(NGAGO)}(2), \ldots, y^{(NGAGO)}(n)]^{\mathrm{T}}\\ y^{(NGAGO)}(k) &= \sum_{i=1}^{k} \eta_{ik} y^{(0)}(i), \quad \eta_{ik} = \rho e^{-\rho(k-i)}, \rho > 0.\end{aligned} \tag{8}$$

Likewise, $\mathbf{Y}^{(NGAGO)}$ represents the preprocessed sequence and ρ stands for the parameter adjusting the accumulation weights.

3.1.7 Unified new-information-based accumulating generation operator (UNAGO)

UNAGO is inspired by the aforementioned AGO methods (Ding et al., 2024b). Initially, the constraint between the exponential and scaling coefficients limits weight variability in AEAGO and NGAGO. To overcome this, the exponential and scaling effects are decoupled by introducing them as independent hyperparameters. Additionally, the above AGOs do not integrate both variable and equal weight accumulation.

Thus, UNAGO attends to these problems to create a unified framework:

$$\mathbf{Y}^{(UNAGO)} = [y^{(UNAGO)}(1), y^{(UNAGO)}(2), \ldots, y^{(UNAGO)}(n)]^{\mathbf{T}}$$
$$y^{(UNAGO)}(k) = \sum_{i=1}^{k} \eta_{ik} y^{(0)}(i), k = 1, 2, \ldots, n, \quad \eta_{ik} = \rho_1 \rho_2^{k-i} + \rho_3 \tag{9}$$

Here, ρ_1, ρ_2, and ρ_3 represent the scaling, exponential, and equal-accumulation coefficients, respectively. By decoupling those weight adjustment effects, the UNAGO obtains a unified mechanism.

Generally, the development of various AGO methods demonstrates the continuous improvement of grey prediction models in handling sparse and uncertain data. These advanced techniques have enhanced the ability to capture the evolutionary trends of marine economy systems, by refining the accumulation process. Thus, these data preprocessing techniques result in more accurate and reliable forecasts, making the grey prediction model an invaluable tool for predicting the Gross ocean product in China's coastal provinces. Nonetheless, China's coastal provinces' marine economy systems exhibit regional heterogenous characteristics. Consequently, the best-matching AGO approaches should be employed to accurately describe the evolutions of China's coastal provinces' Gross ocean product.

3.2 The model implementation of AGOs-DGM(1, 1) model

Due to the heterogeneous characteristics of marine economic systems across China's coastal provinces, a tailored approach is necessary to accurately describe the unique evolution of each province's gross ocean product. These provinces vary significantly in terms of economic structure, geographic conditions, resource availability, and policy impacts, making a one-size-fits-all model insufficient for precise forecasting. Therefore, it is essential to customize models that can capture the distinctive growth patterns, fluctuations, and disturbances within each regional economy to improve prediction accuracy.

In response to this need, we propose the best-matching AGOs-DGM(1, 1) model. This model selects the most appropriate AGO method for a given coastal region, ensuring that the chosen preprocessing technique best fits the unique dynamics of the area's marine economy. By utilizing this data-driven approach, the model adapts to the evolutionary characteristics of the economic system, mitigating the effects of volatility and noise while enhancing the underlying trend signal.

Subsequently, the establishment of the AGO-improved version of the DGM(1, 1) model is introduced.

Assuming that $\mathbf{Y}^{(0)}$ is as defined in Equation 1 and $\mathbf{Y}^{(AGO)}$ represents the preprocessed marine economy series with an *AGO* method, the corresponding *AGO-DGM(1, 1)*'s basic difference function is described as:

$$y^{(AGO)}(k+1) = \lambda_1 \cdot y^{(AGO)}(k) + \lambda_2 \tag{10}$$

where λ_1 and λ_2 represent the developmental and grey constant coefficients, respectively.

Let

$$\mathbf{B} = \begin{bmatrix} y^{(AGO)}(1), & x^{(AGO)}(2), & \ldots, & y^{(AGO)}(n-1) \\ 1 & 1 & \ldots, & 1 \end{bmatrix}^{\mathrm{T}} \tag{11}$$
$$\mathbf{C} = \left[y^{(AGO)}(2), y^{(AGO)}(3), \ldots, y^{(AGO)}(n) \right]^{\mathrm{T}}$$

the estimated parameters $\hat{\lambda}_1$ and $\hat{\lambda}_2$ are calculated by the ordinary least square approach:

$$[\hat{\lambda}_1, \hat{\lambda}_2]^{\mathbf{T}} = (\mathbf{B}^{\mathbf{T}}\mathbf{B})^{-1}\mathbf{B}^{\mathbf{T}}\mathbf{C} \tag{12}$$

Given the initial condition: $\hat{x}^{(u)}(1) = x^{(u)}(1)$, the analytical time response equation is derived as

$$\hat{y}^{(AGO)}(k+1) = \hat{\lambda}_1^k \cdot y^{(AGO)}(1) + \frac{1-\hat{\lambda}_1^k}{1-\hat{\lambda}_1} \cdot \hat{\lambda}_2, k = 1, 2, \ldots, n-1 \tag{13}$$

Take UNAGO as an instance, the restored series from the accumulation process is

$$\hat{y}^{(0)}(k) = \frac{\hat{y}^{(AGO)}(k) - \sum_{i=1}^{k-1} (\rho_1 \rho_2^{k-i} + \rho_3) \hat{y}^{(0)}(i)}{\rho_1 + \rho_3}. \tag{14}$$

Equation 14 represents the generation process of the simulative and forecasting sequence by the UNAGO-DGM(1, 1) model. The other AGOs-DGM(1, 1) models follow the similar procedures.

3.3 The hyper-parameter solution and AGO-matching process

This Section demonstrates the hyper-parameter solution and AGO-matching process to establish the proposed best-matching AGOs-DGM(1, 1) model.

Initially, the hyper-parameters regarding the accumulation weight adjustment parameters (referring to ρ_1, ρ_2, and ρ_3 in UNAGO, ρ in AEAGO and NGAGO, r in AEAGO, and κ in NIPO) need to be optimized. In this work, a heuristic intelligent algorithm, particle swarm optimization algorithm (PSO), is applied to search the self-adaptive weight adjustment parameters. The PSO algorithm iteratively updates the particles' velocities (directions and magnitude) and positions (parameter value). Assuming that $v_i^{(t)}$ and $u_i^{(t)}$ represent the current velocity and position of the particle i at the t^{th} iteration, respectively. The following equation describes the rules for updating the particles' velocities and positions:

$$v_i^{(t+1)} = w \cdot v_i^{(t)} + c1 \cdot rand_1 \cdot (P_{best,i} - u_i^{(t)}) + c2 \cdot rand_2 \cdot (G_{best} - u_i^{(t)})$$
$$u_i^{(t+1)} = u_i^{(t)} + v_i^{(t+1)}$$
$$P_{best,i} = u_i^{(t+1)} \text{ if } J(P_{best,i}) > J(u_i^{(t+1)}) \tag{15}$$

where w is the inertial weight, $c1$ and $c2$ are the acceleration coefficients. $rand_1$ and $rand_2$ are random numbers between 0 and 1. $P_{best,i}$ and G_{best} are currently the best position of the particle and the best position among all particles, respectively. Upon the termination criteria of satisfactory fitness level, G_{best} is outputted as the optimal parameters for the AGOs-DGM(1, 1) model.

Furthermore, the proposed best-matching AGOs-DGM(1, 1) model utilizes the mean absolute percentage error (MAPE) as the objective function for both the PSO algorithm and AGOs' matching process:

$$\begin{aligned} sMAPE &= \sum_{k=1}^{n-h} \left| \frac{\hat{y}(k) - y(k)}{y(k)} \right| / (n-h) \\ fMAPE &= \sum_{k=n-h+1}^{n} \left| \frac{\hat{y}(k) - y(k)}{y(k)} \right| / h \end{aligned} \tag{16}$$

Here, h notes the forecast horizon within the test set and $n - h$ represents the training data length. $\hat{y}(k)$ and $y(k)$ stand for the forecasted gross ocean product and the ground truth, respectively. Moreover, $sMAPE$ and $fMAPE$ represent the simulating and forecasting MAPE, respectively. Furthermore, the $sMAPE$ is employed to search the best self-adaptive weight adjustment parameter(s) while the $fMAPE$ is applied to match the best AGO methods for the specific coastal provinces.

Therefore, after obtaining the model parameters from the training set, we construct the forecasting models under different AGO configurations for the GOP data. We then compare their forecasting errors during the prediction period, allowing us to select the AGO that yields the lowest out-of-sample error. This process enables us to theoretically and empirically identify the best-matching model for each province. The rationale behind this approach lies in that it serves as a benchmark for evaluating competing AGO variants after the model has been fully trained. Since each AGO transformation defines a distinct model structure. This allows for a data-driven, yet methodologically sound, selection of the AGO method that best fits the underlying data characteristics of each province.

In summary, the proposed best-matching AGOs-DGM(1, 1) model provides a robust and adaptive framework tailored to the heterogeneous marine economic systems of China's coastal provinces. By selecting the most appropriate AGO method and optimizing the best-matching model's self-adaptive parameters, the proposed model can effectively capture the complex, nonlinear, and dynamic characteristics of each region's marine economy. This enhances both the accuracy and reliability of predictions, making it a valuable tool for forecasting the gross ocean product in coastal areas. Furthermore, the integration of advanced preprocessing techniques and adaptive parameter adjustments ensures that the model remains flexible and responsive to the evolving economic conditions across different provinces, ultimately aiding in informed decision-making and policy formulation.

4 Data analyses and experimental results

In this section, we present the data and experimental results used to evaluate the effectiveness of the proposed best-matching AGO-DGM(1, 1) model in forecasting the Gross ocean product of China's coastal provinces. The analysis begins with a collection of provincial GOP data, highlighting the regional heterogeneity and temporal variability that the model must accommodate. Subsequently, this section conducts multi-step forecasting experiments, assessing the model's performance across different horizons, and comparing its accuracy with that of several benchmark models. Through this comparative analysis, we aim to demonstrate the superior predictive capabilities of the best AGO-matching grey prediction framework in handling sparse, nonlinear, volatile, and heterogeneous data typical of marine economic systems.

4.1 Data collections and analyses

This study compiles Gross ocean product data from the coastal provinces of China, as shown in Figure 2. The data sources include the China Marine Statistical Yearbook and the Marine economy statistical bulletins published by the provincial natural resources (marine) administrative departments and statistical agencies. The data sets begin at 2005, but the most recent data varies between provinces due to data availability. For example, gross ocean product data for some provinces, such as Shandong, is available up to 2023, whereas for others, like Hebei, it only extends to 2021.

Figures 2, 3 display the time series of gross ocean product for each coastal province and the spatial distribution of gross ocean product in 2021, respectively. Several key insights emerge from these figures:

1. Small sample and poor information system: The gross ocean product data for each province is a classic example of a small sample and poor information system. As illustrated in Figure 2, the time series consists of only 17–19 data points, making it a grey system problem rather than a traditional statistical analysis issue. Such small-sample data, compared to large datasets typically used in statistical and machine learning models, require specific forecasting techniques like the grey prediction model and the data preprocessing approach to handle the uncertainty and limited information effectively.
2. Nonlinear evolution and data volatility: The GOP data exhibits a high degree of complexity, with notable nonlinear trends, significant volatility, and abundant noise. As observed in Figure 3, each province follows a distinct nonlinear growth pattern, with fluctuations in growth rates across the years. These fluctuations likely stem from a combination of factors, including changes in local policies, natural resource availability, external economic influences, and environmental disruptions. The irregular disturbances and oscillations in the data further underline the challenge of making accurate forecasts, reinforcing the need for sophisticated models like the proposed best-matching AGOs-DGM(1, 1) that can account for such dynamic behaviors.
3. Significant spatial distribution disparities and temporal heterogeneity: As shown in Figure 3, there are

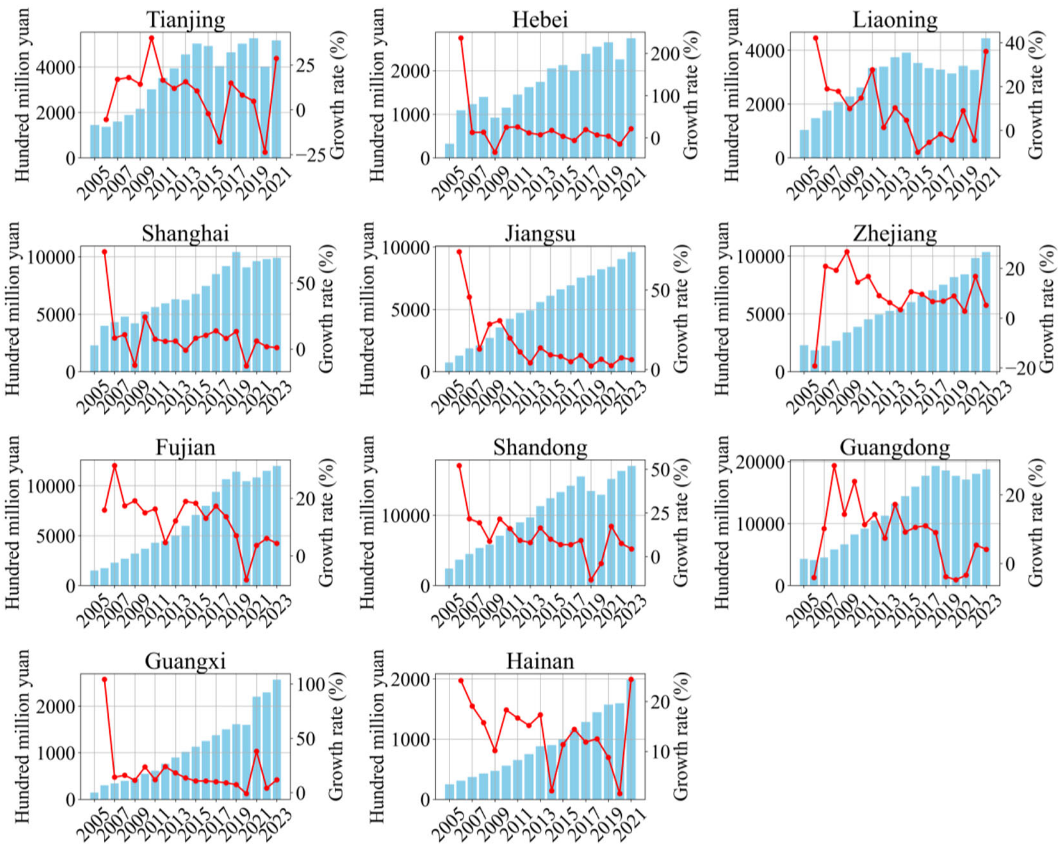

FIGURE 2
Gross ocean product series from 11 coastal provinces in China.

considerable differences in the spatial distribution of gross ocean product across the provinces. Provinces like Guangxi, Hainan, and Hebei have relatively low GOP levels, all below 3000 hundred million yuan. In contrast, Shanghai and Zhejiang reach 9621.3 and 9841.2 hundred million yuan, respectively, while Shandong and Guangdong exceed 15,000 hundred million yuan. This phenomenon indicates substantial regional variation, with different provinces at distinct stages of marine economic development, necessitating region-specific analysis. In addition to spatial differences, Figure 2 highlights the temporal heterogeneity in the evolution of marine economies across provinces. The time series data reveals divergent nonlinear dynamics, with varying levels of growth volatility and randomness. Some provinces show smoother, more consistent growth patterns, while others exhibit more erratic fluctuations. This heterogeneity in both spatial and temporal dimensions underscores the need for a customized predictive model that can account for each province's unique characteristics, ensuring accurate forecasts that reflect their specific developmental trajectories and fluctuations.

In summary, the collected gross ocean product data from 11 coastal provinces of China highlights the need for specialized forecasting techniques due to the small-sample, poor-information nature of the system. The marine economy system exhibits significant nonlinear evolution and volatility. Furthermore, the spatiotemporal analysis shows marked disparities in GOP levels and distinct temporal developmental behaviors across the provinces.

Thus, the above data characteristics of the marine economy system emphasize the necessity of a customized grey system model, such as the proposed best-matching AGOs-DGM(1, 1) model, which can tailor predictions to the specific dynamical characteristics of each province's marine economy, ensuring more accurate and region-specific forecasts, which is essential for effective policy-making and marine economic planning.

4.2 Experimental results

This section presents the experimental results to validate the effectiveness of the proposed best-matching AGOs-DGM(1, 1) model in accurately forecasting the provincial gross ocean product in China.

Firstly, the multi-step ahead forecasting experiments are conducted to evaluate the predictive performance of the model across different forecast horizons. Specifically, in the one-step ahead forecasting, the latest available GOP value from each region's time

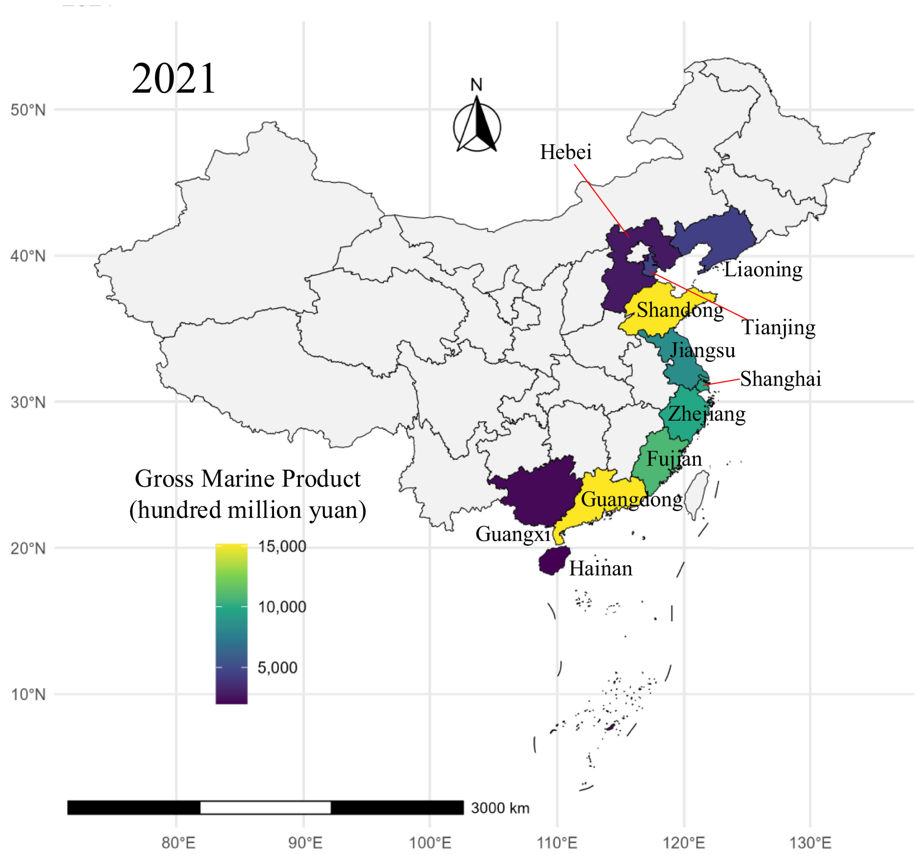

FIGURE 3
Regional distribution of the coastal provinces' gross ocean product in China.

series is used as the test data, while the preceding data is treated as the training set to calibrate the models. This setup allows for an assessment of the model's ability to forecast near-term values. Similarly, in the three-step ahead forecasting, the last three data points are reserved as the test set to evaluate the model's performance over a longer horizon, while the earlier data serves as the training set. Additionally, the accuracy of the forecasts is evaluated using the MAPE criterion. Lastly, given the varying data availability across provinces, Tianjin, Hebei, Liaoning, and Hainan used a total sample length from 2005 to 2021, while other regions used a total sample length from 2005 to 2023 for the train-test data split.

Secondly, this study includes several benchmark models for comparison to highlight the superior predictive capabilities of the proposed model. Specifically, the autoregressive integrated moving average (ARIMA) and exponential smoothing (ETS) models, which are widely used statistical time series forecasting methods, are included. Furthermore, advanced machine learning models such as the long short-term memory model (LSTM) and Transformer, known for their effectiveness in handling sequential data, are also employed as benchmark models. By comparing the performance of the best-matching AGOs-DGM(1, 1) model against these traditional and modern approaches, we aim to demonstrate its advantages in forecasting the gross ocean product of China's coastal provinces

Table 1 records the forecasting MAPEs of all competing models across one- to three-step prediction horizons for China's coastal provinces. Figure 4 provides a visual representation of these results by presenting box plots of the MAPEs, where the forecasting errors for one- to three-step predictions are consolidated into a single box to illustrate the overall distribution of forecasting errors. From the analysis of both the table and figure, several key observations can be made:

1. The AGO-enhanced grey prediction models achieve higher accuracies: The DGM(1, 1) models enhanced by the advanced AGO methods, including UNAGO, NAGO, NGAGO, AEAGO, NIPO, and RAAGO, consistently exhibit superior forecasting accuracy across all prediction steps and coastal provinces. Specifically, these models achieved average fMAPE values of 8.66%, 8.97%, 6.63%, 6.48%, 11.95%, and 7.67%, respectively. These accuracy levels surpass the performance of the traditional 1-AGO-based DGM(1, 1) model, indicating that the advanced AGOs significantly improve the forecasting precision of the conventional one. The enhanced models demonstrate their ability to better capture the underlying nonlinear trends and mitigate the noise present in the small-sample data, leading to more reliable predictions. This validates the effectiveness of AGO optimizations in grey models, as they

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TABLE 1 Forecasting MAPEs (%) of all competing models across all prediction horizons for the coastal provinces.

Models		AGOs-							Benchmarks			
Provinces	Horizons	*UNAGO*	*NAGO*	*NGAGO*	*AEAGO*	*NIPO*	*RAAGO*	*1-AGO*	*ARIMA*	*ETS*	*LSTM*	Transformer
Fujian	1	2.45%	4.28%	1.52%	0.53%	0.53%	0.53%	25.70%	0.73%	27.20%	6.44%	43.10%
	2	6.76%	11.11%	2.91%	0.78%	31.11%	0.78%	31.11%	0.36%	5.12%	9.44%	3.36%
	3	20.61%	22.29%	11.28%	6.20%	39.98%	1.94%	39.98%	26.93%	27.20%	6.05%	4.44%
Guangdong	1	0.99%	2.48%	0.59%	0.66%	0.66%	0.66%	24.77%	0.32%	11.38%	3.22%	0.37%
	2	4.82%	7.08%	2.48%	1.89%	1.89%	1.89%	32.44%	10.14%	13.66%	3.24%	3.14%
	3	15.23%	20.60%	12.44%	6.45%	45.31%	6.31%	45.31%	8.14%	11.38%	1.71%	3.49%
Hainan	1	9.56%	8.18%	11.55%	12.49%	13.06%	13.06%	1.51%	16.37%	4.56%	14.57%	17.54%
	2	6.19%	6.21%	6.56%	6.35%	6.19%	6.39%	9.16%	8.05%	6.08%	17.21%	10.91%
	3	5.25%	4.38%	4.39%	4.78%	5.51%	4.80%	9.41%	6.21%	4.56%	8.62%	9.49%
Guangxi	1	0.43%	3.23%	1.85%	1.51%	1.39%	0.02%	4.71%	5.81%	11.86%	11.52%	29.76%
	2	3.18%	4.19%	1.13%	1.11%	4.20%	6.90%	5.28%	13.26%	4.23%	94.15%	69.17%
	3	15.99%	16.93%	21.17%	20.61%	24.24%	24.24%	2.65%	27.15%	11.86%	63.00%	5.29%
Hebei	1	4.68%	4.64%	15.00%	10.04%	4.67%	2.29%	4.68%	13.89%	7.97%	30.41%	18.24%
	2	21.70%	21.70%	9.08%	9.47%	21.70%	20.91%	21.70%	15.15%	11.63%	15.55%	9.72%
	3	16.63%	16.63%	9.49%	7.55%	16.63%	16.12%	16.63%	12.70%	7.97%	88.36%	6.87%
Jiangsu	1	1.06%	2.00%	2.28%	1.87%	1.88%	1.87%	14.48%	0.75%	3.88%	9.46%	4.31%
	2	3.18%	3.59%	2.78%	3.98%	4.08%	3.98%	17.95%	1.98%	2.93%	5.76%	3.00%
	3	1.61%	1.62%	1.43%	1.61%	1.65%	1.61%	23.98%	2.17%	3.88%	3.10%	5.62%
Liaoning	1	26.12%	20.85%	20.33%	21.59%	27.39%	22.61%	11.44%	26.19%	22.77%	1.19%	22.67%
	2	14.17%	14.20%	14.22%	14.19%	14.26%	14.20%	14.32%	13.06%	14.71%	17.12%	15.31%
	3	12.24%	10.02%	10.43%	9.54%	13.97%	9.54%	15.83%	19.64%	22.77%	12.16%	12.36%
Shandong	1	4.39%	4.14%	4.17%	3.06%	2.26%	2.80%	11.10%	0.59%	36.73%	23.52%	14.28%
	2	8.54%	7.08%	7.78%	6.86%	6.48%	6.92%	12.89%	1.90%	1.65%	25.69%	11.17%
	3	8.78%	8.95%	10.44%	14.40%	14.47%	14.47%	17.79%	12.09%	36.73%	17.18%	15.02%
Shanghai	1	12.32%	12.10%	1.51%	2.02%	13.52%	6.73%	14.35%	3.30%	10.95%	2.02%	3.93%
	2	15.51%	15.29%	1.83%	3.05%	15.58%	12.59%	15.81%	4.55%	10.32%	2.68%	0.86%

(Continued)

TABLE 1 Continued

Models		AGOs-							Benchmarks			
Provinces	Horizons	*UNAGO*	*NAGO*	*NGAGO*	*AEAGO*	*NIPO*	*RAAGO*	*1-AGO*	*ARIMA*	*ETS*	*LSTM*	Transformer
	3	17.09%	17.41%	1.85%	5.99%	17.41%	13.81%	17.41%	2.68%	10.95%	5.26%	3.37%
Tianjin	1	4.35%	4.15%	4.17%	3.06%	2.17%	2.86%	11.10%	25.03%	16.46%	1.78%	6.49%
	2	7.04%	7.08%	7.78%	6.86%	6.61%	6.93%	12.89%	21.67%	22.03%	19.64%	12.54%
	3	7.66%	8.83%	10.44%	14.37%	14.47%	14.47%	17.79%	15.13%	16.46%	23.65%	10.05%
Zhejiang	1	4.52%	2.32%	3.18%	6.32%	6.81%	6.32%	12.06%	0.41%	4.14%	42.31%	1.16%
	2	1.52%	1.52%	1.64%	1.98%	3.92%	1.98%	11.14%	11.09%	5.47%	25.85%	2.54%
	3	1.34%	1.09%	1.15%	2.64%	10.39%	2.64%	13.60%	6.61%	4.14%	8.10%	7.84%
Average		8.66%	8.97%	6.63%	6.48%	11.95%	7.67%	16.39%	10.12%	12.53%	18.79%	11.74%
Average of model class		9.54%							13.30%			

enhance the model's capability to adapt to the complexities of marine economic data.

2. Benchmark models underperform in comparison: The benchmark models—ARIMA, ETS, LSTM, and Transformer—achieved average fMAPE errors ranging from 10.12% to 18.79%, which are substantially higher than the AGO-enhanced DGM(1, 1) models. This stark difference highlights the limitations of conventional statistical and machine learning models in handling the sparse, volatile, and noisy nature of marine economic data. While ARIMA and ETS models are effective in forecasting linear time series data, they struggle with the nonlinear and fluctuating characteristics of the GOP data. Similarly, although LSTM and Transformer models are known for their strength in sequential data processing, they were less effective in this context, likely due to the small sample size and the requirement for data pre-processing, such as the AGO techniques employed by grey models.

These results underscore the superiority of AGO-enhanced DGM(1, 1) models for forecasting gross ocean product in China's coastal provinces, particularly in environments characterized by sparse, uncertain, and non-linear data. By utilizing advanced AGO methods, the grey models can better capture the dynamics of each province's marine economy, providing more accurate and reliable forecasts than traditional models.

Lastly, the proposed best-matching AGO-DGM(1, 1) model leverages the best matching AGO technique to forecast the GOPs of China's coastal provinces. It is important to emphasize that the best-matching AGO-DGM(1, 1) model is not focused on re-evaluating forecasting performance during the testing stage. Instead, it identifies and applies the best-matching AGO method tailored to each specific coastal province. The rationale behind this approach lies in the fact that the superior performance of the AGO-enhanced DGM(1, 1) models has been validated in our experiments. Consequently, the model directly selects the optimal AGO method based on the unique characteristics of each province's data.

Table 2 presents the best-matching AGOs for each coastal province, determined by minimizing the forecasting errors (fMAPEs). These AGOs were selected through the models' selection processes, ensuring that each region's specific dynamics —such as its growth pattern, volatility, and data structure—are accurately captured. This allows the model to provide highly accurate and region-specific forecasts, further confirming the versatility and effectiveness of the AGO-DGM(1, 1) framework in addressing the heterogeneous nature of marine economic systems across China's coastal regions.

To further illustrate the effectiveness of the proposed a best-matching AGO-DGM(1, 1) model, Table 3 and Figure 5 compare its performance with that of the benchmark models. Therein, the proposed best-matching AGO-DGM(1, 1) model consistently outperforms the benchmark models in terms of forecasting accuracy. The lower average error and more concentrated error distribution of the AGO-DGM(1, 1) model indicate a higher level of precision and consistency. This result suggests that the proposed

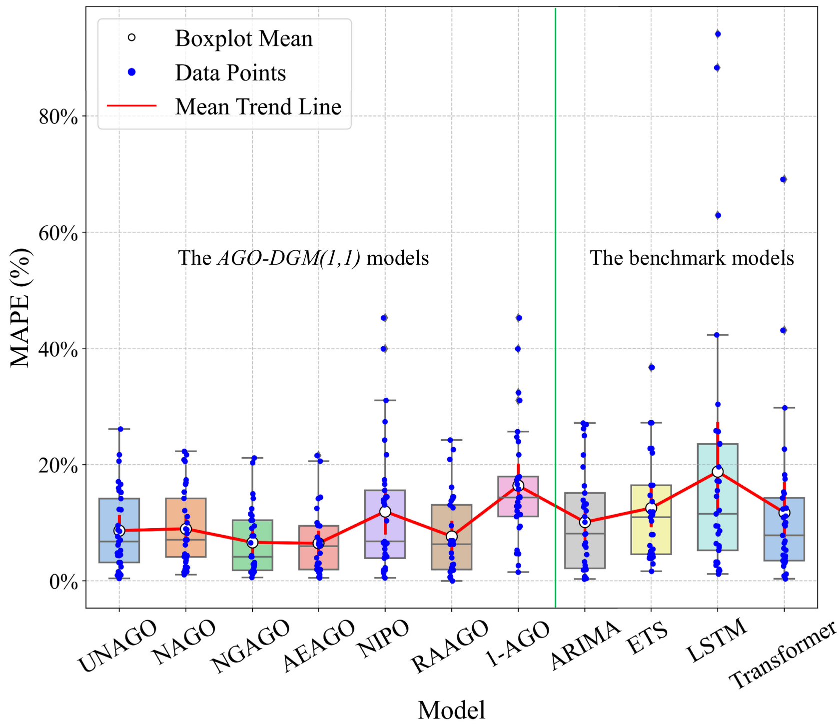

FIGURE 4
fMAPEs of all competing models across all prediction horizons.

model is not only better at handling the overall trends but also more robust in managing outlier predictions. The fewer outliers observed in the results point to the model's capacity to mitigate extreme fluctuations and irregularities, which are common in volatile and nonlinear marine economic data. Additionally, the tight clustering of errors demonstrates the model's adaptability to the specific economic dynamics of each coastal province, ensuring reliable forecasts across different regions and time horizons.

TABLE 2 Best matching AGOs for the coastal provinces.

Provinces	*fMAPEs*	Best *AGOs*
Tianjin	6.35%	*UNAGO*
Hebei	9.02%	*AEAGO*
Liaoning	13.86%	traditional *AGO*
Shanghai	1.73%	*NGAGO*
Jiangsu	2.16%	*NGAGO*
Zhejiang	1.64%	*NAGO*
Fujian	1.08%	*RAAGO*
Shandong	6.73%	*NAGO*
Guangdong	2.95%	*RAAGO*
Guangxi	4.21%	traditional *AGO*
Hainan	6.26%	*NAGO*
Average	5.09%	

In contrast, the benchmark models, such as ARIMA, ETS, LSTM, and Transformer, show a wider spread of errors and more frequent outliers, revealing their limitations in capturing the complexity of small-sample, poor-information systems like gross ocean product data. These comparisons clearly affirm that the best-matching AGO-DGM(1, 1) model provides superior forecasting performance, making it an ideal choice for such challenging datasets.

In conclusion, the experimental results demonstrate the crucial role of the advanced AGO methods in enhancing prediction reliability for marine economy systems. By optimizing data preprocessing, the AGO reduces noise and amplifies key trends, laying a strong foundation for accurate modeling. Additionally, the best-matching AGO approach further refines this process, adapting to the unique regional characteristics and diverse dynamics of each province. This tailored, region-specific adaptation significantly boosts the proposed model's predictive accuracy, ensuring robust forecasts.

5 Future projections and policy implications

5.1 Projecting the future gross ocean product in China

This section presents the forecasted results of the gross ocean product across China's 11 coastal provinces. As recorded in Table 4, the gross ocean product of China's coastal provinces shows a steady

TABLE 3 Forecasting errors of the proposed model and the benchmark models.

Provinces\Models	*ARIMA*	*ETS*	*LSTM*	*Transformer*	Proposed
Tianjin	20.61%	18.31%	15.02%	9.69%	6.35%
Hebei	13.91%	9.19%	44.77%	11.61%	9.02%
Liaoning	19.63%	20.08%	10.16%	16.78%	13.86%
Shanghai	3.51%	10.74%	3.32%	2.72%	1.73%
Jiangsu	1.63%	3.56%	6.11%	4.31%	2.16%
Zhejiang	6.04%	4.58%	25.42%	3.85%	1.64%
Fujian	9.34%	19.84%	7.31%	16.97%	1.08%
Shandong	4.86%	25.04%	22.13%	13.49%	6.73%
Guangdong	6.20%	12.14%	2.73%	2.33%	2.95%
Guangxi	15.41%	9.32%	56.22%	34.74%	4.21%
Hainan	10.21%	5.07%	13.47%	12.65%	6.26%

growth trend from 2022 to 2025, with regional variations that reflect differing levels of economic development, industrial capacity, and natural resource management. Additionally, Figure 6 depicts the regional distribution of the forecasted GOPs in 2025. The following provides a detailed analysis of the projected growth in each region, along with a discussion of the potential economic and ecological implications of these forecasts:

5.1.1 Strong growth in southern coastal provinces

Guangdong, the province with the largest marine economy, is projected to grow from 18,033.4 hundred million yuan in 2022 to 19,889.6 hundred million yuan in 2025, with a consistent annual increase. This stable growth highlights Guangdong's well-established marine industries, particularly in sectors such as marine equipment manufacturing, logistics, and biopharmaceuticals. The province's continued expansion indicates its dominant position in China's marine economy. While this growth is promising economically, it also raises concerns about the sustainability of marine resources. Efforts to ensure the sustainable use of marine resources, such as implementing stricter fishing quotas and promoting the restoration of marine ecosystems, will be crucial to prevent overexploitation.

Fujian is also set to see significant growth, with its GOP increasing from 11,500 hundred million yuan in 2022 to 13,099.39 hundred million yuan in 2025. This reflects the province's increasing investment in marine fisheries, tourism, and renewable energy. Fujian's strategic location and access to rich marine resources contribute to its steady development. While these industries present opportunities for growth, they also place pressure on marine biodiversity, especially in the case of fisheries and tourism.

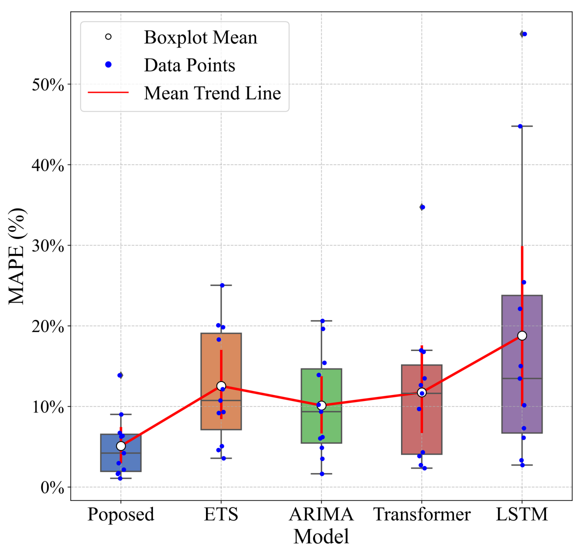

FIGURE 5
fMAPEs of the DGM(1, 1) model with the best-matching AGOs and the benchmarks.

5.1.2 Emerging growth in underdeveloped regions

Hainan and Guangxi are among the fastest-growing provinces in terms of GOP percentage increase. Hainan is projected to grow from 2,094.82 hundred million yuan in 2022 to 2,767.54 hundred million yuan in 2025, a 32% increase over the forecast period. This significant growth is largely driven by Haina's focus on becoming a global center for marine tourism, marine conservation, and low-carbon marine industries. This growth offers significant potential for ecological restoration projects, as the province is increasingly integrating biodiversity conservation into its economic development plans.

Guangxi shows a similar upward trajectory, growing from 2,296.9 hundred million yuan in 2022 to 3,363.1 hundred million yuan in 2025, representing a 46% increase. The province's marine economy, which is less developed compared to other coastal regions, is expected to benefit from new investments in port infrastructure, maritime logistics, and aquaculture, making it an emerging player in China's marine sector.

TABLE 4 Forecasted coastal provincial gross ocean product (hundred million yuan) from 2022-2025 in China.

Provinces\Years	2022	2023	2024	2025
Fujian	11500	12000	12543.81	13099.39
Guangdong	18033.4	18778.1	19363.8	19889.6
Hainan	2094.818	2301.268	2525.026	2767.543
Guangxi	2296.9	2568.4	3000.505	3363.104
Hebei	2650.073	2705.054	2755.805	2802.651
Jiangsu	9046.2	9606.9	9949.512	10354.45
Liaoning	4248.918	4421.125	4600.313	4786.763
Shandong	16302.9	17018.3	17182.81	17687.81
Shanghai	9792.4	9901.6	9880.278	10014.89
Tianjin	4641.827	4657.148	4661.049	4654.627
Zhejiang	10355	10881.83	11557.7	12253

The provinces that contain available data during a specific year use the fitting results of the proposed model. For instance, Shandong's data is available up to 2023, and thus the forecasted values in 2022 and 2023 represent the fitting result while the forecasted values in 2024 and 2025 stand for the out-of-sample results.

5.1.3 Steady growth in central and northern provinces

Jiangsu, another economic powerhouse, is projected to increase its GOP from 9,046.2 hundred million yuan in 2022 to 10,354.45 hundred million yuan in 2025, reflecting moderate but steady growth. Jiangsu's marine industries, particularly in shipbuilding and marine engineering, continue to play a crucial role in its economic performance. The province's focus on technological innovation and marine ecosystem management will likely sustain this growth.

Shandong is expected to maintain its position as one of the leading marine economies, with its GOP rising from 16,302.9 hundred million yuan in 2022 to 17,687.81 hundred million yuan in 2025. While growth in Shandong is slightly slower compared to southern provinces, its established marine industries, including fisheries, offshore oil, and ocean-based manufacturing, ensure its continued economic contribution.

Liaoning is forecasted to grow from 4,248.92 hundred million yuan in 2022 to 4,786.76 hundred million yuan in 2025, reflecting moderate growth in the marine sector. Liaoning's focus on heavy marine industries, including shipbuilding and port logistics, will drive this expansion, although the province faces challenges related to environmental sustainability and industrial upgrading. Liaoning will need to adopt innovative practices that reduce pollution and promote the sustainable use of marine resources to ensure the long-term health of its marine economy.

5.1.4 Slower growth and stagnation in Hebei and Tianjin

Hebei is expected to see only modest growth, increasing from 2,650.07 hundred million yuan in 2022 to 2,802.65 hundred million yuan in 2025. This slow growth suggests that Hebei's marine economy is encountering structural issues, such as over-reliance on traditional industries and limited innovation in emerging sectors. Hebei may need to focus on modernizing its marine sectors and diversifying its economic base to achieve more robust growth.

Tianjin, in contrast, shows signs of stagnation. The projected GOP grows slightly from 4,641.83 hundred million yuan in 2022 to 4,654.63 hundred million yuan in 2025, indicating almost no growth after 2023. This stagnation reflects Tianjin's reliance on legacy marine industries and its struggles with industrial restructuring. Without strategic interventions to foster innovation and revitalize its marine sector, Tianjin may continue to experience stagnant growth.

5.1.5 Dynamic growth in Zhejiang and Shanghai

Zhejiang is projected to experience robust growth, with its GOP increasing from 10,355 hundred million yuan in 2022 to 12,253 hundred million yuan in 2025. This substantial rise reflects Zhejiang's diversified marine economy, which includes marine tourism, fisheries, and high-tech marine industries. As one of the fastest-growing regions, Zhejiang's development underscores the success of its innovation-driven growth model.

Shanghai, although experiencing slower growth than Zhejiang, is still projected to increase its GOP from 9,792.4 hundred million yuan in 2022 to 10,014.89 hundred million yuan in 2025. Shanghai's marine economy is mature, with strong contributions from international shipping, port management, and ocean-related financial services. However, its slower growth reflects the challenges of maintaining rapid expansion in a highly developed marine economy. Policies that promote the greening of Shanghai's marine sectors—such as stricter environmental regulations and investments in marine conservation—will be crucial to maintaining the city's competitive edge while ensuring the sustainability of its marine ecosystems.

Overall, from 2022 to 2025, most provinces are expected to see continuous growth in their marine economies, though at varying rates. The southern and eastern coastal provinces—such as Guangdong, Fujian, and Zhejiang—will remain leaders in China's marine economy, driven by innovation, diversified industries, and strong financial support. Meanwhile, provinces like Hainan and Guangxi will emerge as growth centers, leveraging their untapped potential and benefiting from increased investment and development. In contrast, northern provinces such as Hebei and Tianjin face slower growth, signaling a need for structural reforms and innovation-driven policies to revitalize their marine sectors. Without such interventions, these regions may lag behind their southern counterparts.

5.2 Policy implications

The forecasted growth of gross ocean product across China's coastal provinces highlights several key areas where targeted policy interventions can ensure sustained growth, promote regional synergy, and drive sustainable development. The following policy recommendations are structured at the national and regional levels

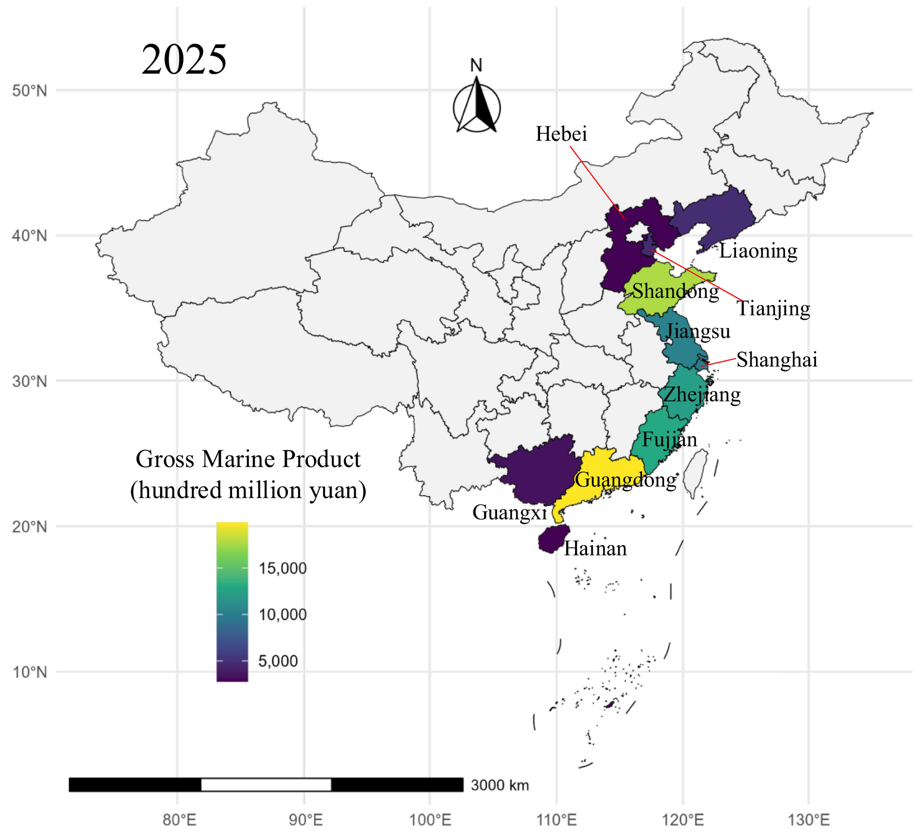

FIGURE 6
Regional distribution of the forecasted provincial gross ocean product in China.

and focus on inter-provincial coordination to address the diverse needs of China's marine economy, while also considering the potential impacts of marine economic growth on biodiversity, fishing policies, and ecosystem services.

5.2.1 Strengthen national-level marine economic strategies

At the national level, China's marine economy must be aligned with broader national economic and sustainability goals to ensure long-term prosperity. This requires the central government to implement cohesive policies that drive innovation, ensure environmental sustainability, and provide strategic financial support for marine development.

National innovation agenda: A comprehensive national policy should prioritize innovation in marine industries by incentivizing research and development (R&D) in areas such as marine biotechnology, renewable energy, and smart shipping. Establishing national marine research institutes can further accelerate innovation and foster partnerships between academia, industry, and government. These innovations must also be coupled with efforts to integrate biological sustainability into economic policies, ensuring that technological advancements do not come at the cost of marine biodiversity or ecosystem health.

Green marine development: To mitigate environmental degradation, the government should enforce national environmental standards across all coastal provinces. Centralized policies that promote green marine technologies and sustainable marine practices will ensure that the marine economy grows while protecting marine ecosystems. This can be supported through green finance mechanisms such as subsidies for low-carbon technologies and investments in eco-friendly infrastructure. Additionally, national policies should explicitly address the importance of preserving marine biodiversity and regulating industries such as fishing and tourism, which can often lead to habitat degradation and overexploitation of marine resources.

National marine investment funds: The government should establish national-level marine investment funds to support provinces at different stages of development. These funds would provide capital for provinces with both mature and emerging marine sectors, helping to finance projects that enhance marine infrastructure, port modernization, and marine environmental conservation. It is crucial that these investments also focus on sustainable marine practices that ensure the protection of marine biodiversity and ecosystem services.

5.2.2 Tailor regional policies to address provincial needs

Given the heterogeneity of China's coastal provinces, regional policies should be tailored to reflect the specific needs and growth patterns of each province. Fast-growing provinces require policies that support innovation and sustainability, while slower-growing regions need targeted investments and restructuring programs.

Support innovation in leading provinces: Provinces like Guangdong, Fujian, and Zhejiang—which lead China's marine economy—should focus on enhancing high-tech marine industries such as marine biopharmaceuticals and renewable energy. However, alongside rapid growth, these provinces must prioritize sustainability by adopting green technologies and enforcing strict environmental regulations to mitigate potential ecological damage. Policy measures should also encourage these provinces to incorporate biodiversity conservation into their economic plans, ensuring that marine development does not compromise the health of ecosystems.

Drive growth in emerging regions: Hainan and Guangxi are poised for substantial growth but need strategic investments to fully realize their potential. Special economic policies that provide tax incentives, simplified regulatory frameworks, and infrastructure investments can accelerate their growth. Additionally, the government should invest in marine tourism and aquaculture in these regions, sectors that are primed for expansion and can drive long-term economic development.

Revitalize stagnating economies: Northern provinces such as Hebei and Tianjin face slower growth, highlighting the need for industrial restructuring. Policies should focus on transitioning from traditional marine industries to more modern, tech-driven sectors, such as marine environmental services and clean energy. To encourage this shift, innovation hubs can be established in these provinces, fostering entrepreneurship and attracting investment in emerging marine sectors.

5.2.3 Promote inter-provincial coordination for balanced growth

One of the key challenges highlighted by the growth projections is the disparity between fast-growing southern provinces and slower-growing northern regions. To ensure cohesive development across all coastal provinces, the government must foster greater inter-provincial coordination. This will promote balanced economic growth and reduce regional disparities.

Facilitate knowledge and technology sharing: Leading provinces such as Guangdong, Zhejiang, and Shandong can play a pivotal role in sharing knowledge and technology with slower-growing regions like Hebei and Tianjin. Establishing inter-provincial research collaborations and marine technology transfer programs will allow slower-growing provinces to benefit from the advancements made in more developed areas, promoting a more uniform growth trajectory across the country.

Create regional marine innovation hubs: The government can establish regional innovation hubs that facilitate cross-provincial partnerships between industry, academia, and research institutions. These hubs would focus on marine-related R&D, providing shared resources and infrastructure for provinces to collaborate on key projects, such as marine biopharmaceuticals, smart ports, and renewable energy. These hubs will help bridge the gap between leading and lagging provinces, driving overall marine economic development across the nation.

In summary, the future of China's marine economy depends on a multifaceted policy approach that integrates national-level strategies, region-specific interventions, and inter-provincial coordination. By promoting innovation, ensuring sustainable development, and addressing the unique challenges faced by each coastal province, China can achieve balanced growth across its marine sectors. Facilitating cooperation between provinces will also allow for the sharing of sustainable practices and ensure that all regions benefit from the country's expanding marine economy without compromising its marine biodiversity. A coordinated effort will position China as a global leader in marine innovation and sustainable development, creating a model for other nations to follow.

6 Conclusion

This study developed an best-matching AGOs-DGM(1, 1) model to forecast the gross ocean product of China's coastal provinces, effectively addressing the complexities of marine economic data with an approach tailored to each region's unique characteristics. By applying an adaptive AGO matching mechanism that includes seven distinct AGOs, including some of the most advanced optimized versions, the model effectively captures the nonlinear trends, volatility, and regional heterogeneity inherent in marine economic systems.

Firstly, an in-depth analysis of GOP data across 11 coastal provinces revealed significant variations in economic trajectories, reflecting unique local characteristics such as regional heterogeneity, nonlinear growth patterns, and a range of external disturbances. These complexities underscore the need for specialized forecasting methodologies tailored to the marine economic context.

Secondly, the proposed model leverages an adaptive AGO matching mechanism utilizing seven types of AGOs, including advanced optimized versions, significantly enhancing forecasting precision. This tailored AGO selection enabled the model to align more closely with the specific data profiles of each province, leading to superior forecasting performance compared to traditional models like ARIMA and LSTM, particularly in scenarios involving limited data samples.

Thirdly, the forecasting outcomes provide valuable insights for policymakers aimed at promoting sustainable development and fostering regional coordination. By aligning provincial strategies with both local economic strengths and overarching national goals, the model aids in crafting policies that advance balanced growth and resilience within China's marine economy.

In conclusion, this research delivers robust forecasts of the complex marine economy, employing adaptive grey prediction models with optimized best-matching AGOs as critical instruments. This approach notably enhances forecasting accuracy for regions with limited data and diverse developmental pathways, delivering more dependable projections to inform strategic planning and policy formulation for sustainable economic development.

Nevertheless, several limitations should be acknowledged. While the model performs well under stable data conditions, it may have limited capacity to account for unforeseen economic shocks, abrupt policy changes, or extreme events. Future research could address this limitation by integrating external shock indicators or developing hybrid models that incorporate real-time policy or risk signals into the forecasting framework.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/supplementary material.

Author contributions

LX: Conceptualization, Formal analysis, Methodology, Resources, Writing – original draft. ZC: Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Validation, Writing – original draft, Writing – review & editing. YL: Data curation, Formal analysis, Methodology, Visualization, Writing – review & editing. ZW: Data curation, Formal analysis, Resources, Visualization, Writing – review & editing, Writing – original draft.

Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

Acknowledgments

Thanks for the reviewers and editors.

Conflict of interest

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

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

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