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HIGH-QUALITY MARINE ECONOMIC DEVELOPMENT IN CHINA FROM THE PERSPECTIVE OF GREEN TOTAL FACTOR PRODUCTIVITY GROWTH: DYNAMIC CHANGES AND IMPROVEMENT STRATEGIES

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Abstract. High-quality marine economic development (HMED) is regarded as a new development pattern of the marine economy in China. This paper aims to examine the dynamic changes and improvement strategies of HMED from the perspective of the green total factor productivity (GTFP) growth. First, the GTFP growth of the marine economy in China's coastal regions for the period 2007–2020 is calculated using the bootstrapped Malmquist index. Second, the dynamic changes and spatial impacts of the GTFP growth are characterized using kernel density estimation (KDE). Moreover, a novel analytical framework to study the improvement strategies of the GTFP is developed. Within this framework, the fuzzy set qualitative comparative analysis (fsQCA) method is used to explore the paths to achieve HMED. The findings show that: (i) the GTFP growth for coastal regions shows significant fluctuations, suggesting that a stable pattern of marine economic development has yet to be established; (ii) the regional distribution of GTFP growth varies significantly, with provinces with fast GTFP growth gathering resources from neighboring provinces, resulting in a siphon effect; (iii) for coastal provinces that lack certain development conditions, the combined effect of other advantageous factors can be used to achieve HMED. Finally, this study presents policy recommendations for achieving HMED, which can provide insights into the design of China's future marine economic policies.

Keywords: marine economy, high-quality marine economic development, green total factor productivity, kernel density estimation, fuzzy set qualitative comparative analysis.

JEL Classification: O47, Q56.

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1. Introduction

With land-based resources becoming increasingly scarce, the Chinese Government realizes that marine resources can bring enormous economic benefits to society (Jiang et al., 2014). Driven by national strategies, the marine economy has already become a vital component of China's national economy (Ding et al., 2020b). Currently, China's marine economy is evolving from extensive growth relying on the consumption of material resources to high-quality marine economic development (HMED) (Liu et al., 2021). In 2018, the *Opinions on Promoting the*

HMED (hereinafter referred to as the "Opinions") were issued, which clearly put forward the goal of promoting HMED. Therefore, there is a practical necessity to clarify the connotation of HMED, demonstrate the dynamic changes of HMED and identify strategies to enhance HMED, which can effectively contribute to the further formulation of marine economic policies by the government.

As a consequence of the lack of a clear definition of HMED, we can explore the connotation of HMED through the relevant policies issued by the government. The "Opinions" point out that the focus will be on promoting the upgrade of traditional marine industries, fostering the newly emerging marine industry, and forming a green development pattern. The traditional marine industry exhibits low-value-added products and high energy consumption, resulting in environmental pollution. In contrast, the newly emerging marine industry features higher levels of technology and efficiency, while keeping pollution levels low. An important feature of HMED is the reduction of marine environmental pollution (Ren et al., 2018). The "Opinions" also underscore that HMED should be propelled by the reasonable allocations of production factors, instead of relying solely on expanding factor inputs. Specifically, increasing capital and labor investment will not improve HMED, and such an extensive development model may cause further marine ecosystem degradation (Ren et al., 2018). The improvement of factor productivity can organically link the economic benefits of micro-entities (e.g., sea-related enterprises) with the overall HMED. Notably, this process of efficiency improvement will further contribute to the structural upgrading through the optimization of factor allocation and production technology. Factor productivity improvements are a core component of HMED.

As a result, numerous scholars have undertaken in-depth investigations into factor productivity within the marine economy. Some contributions assess marine economic development by measuring a single-factor indicator such as labor productivity (Karim et al., 2018). Since input factors in the marine economy include a variety of resources, such as capital and labor, relying solely on a single indicator to measure its development may lead to significant biases (Liu et al., 2021). An increasing number of scholars are measuring the development of the marine economy using total factor productivity (TFP), which refers to the growth rate of output resulting from all factors except labor and capital (Ren et al., 2018). When evaluating economic growth, researchers tend to focus on changes in TFP, also known as the TFP index or TFP growth, as it can shed light on the sources of economic growth (Estache et al., 2004). Although the TFP index is a useful tool for measuring the growth of the marine economy, accurately measuring HMED is challenging because the index does not take environmental factors into account in the economic efficiency measurement framework. This limitation can potentially mislead the formulation of marine policies (Liu et al., 2021). To address these issues, the green total factor productivity (GTFP) index, which includes environmental factors, is becoming a mainstream method for measuring HMED (Ren & Ji, 2021; Ye et al., 2021).

For policymakers, the formulation of marine economic policy requires clear strategies to improve the GTFP of the marine economy. While previous studies have extensively examined the important role of various influencing factors, including scientific and technological innovation, industrial structure upgrading, and openness level, in the growth of GTFP (Liu et al., 2021; Ren & Ji, 2021; Wei et al., 2021), the following problems still exist. First, existing studies lack a systematic framework for analyzing the factors affecting the growth of GTFP in the marine economy. The selection of relevant influencing factors is inadequate and not systematic. Second, most existing studies use regression analysis to examine the linear or non-linear relationship between a single factor and GTFP growth, lacking the analysis of the synergistic and joint effects of multiple influencing factors on GTFP growth under a configuration perspective. In the configuration perspective, the synergistic and joint effects of multiple antecedent conditions influence the HMED (Liang et al., 2023; Prokop et al., 2021). Compared to examining the effect of a single condition on HMED, exploring what combinations of antecedent conditions can generate the outcome of HMED is more instructive for the formulation of marine economic policy.

In view of the above, we first apply the bootstrapped Malmquist index to calculate the GTFP growth of the marine economy and use the index as a measure of HMED. Then, kernel density estimation (KDE) is employed to characterize the dynamic changes and spatial impacts of the GTFP growth in China's coastal regions. Finally, a policy implementation framework named SIEO based on scientific and technological innovation, industrial structure, environmental regulation, and openness level is constructed. Within this framework, the fuzzy set qualitative comparative analysis (fsQCA) method is adopted to explore the synergistic and joint effects of various influencing factors on GTFP growth, to find specific strategies to promote HMED and offer a theoretical basis for policymakers to formulate marine economic policies. This study contributes to the literature in three aspects. First, we use the bootstrapped Malmquist index to measure the GTFP growth of the marine economy, which can overcome the bias caused by small sample size and sampling variability to obtain a more realistic GTFP growth than the measurement models used in existing studies. Second, the results of the KDE analysis reveal the existence of a siphon effect in the GTFP growth in China's coastal regions, providing a reference for the government to strengthen the top-level design of regional coordinated development mechanisms. Third, compared to using regression analysis to explore HMED improvement strategies, this study examines the synergistic and joint effects of multiple antecedent conditions on HMED from a configuration perspective, providing differentiated improvement strategies for HMED in coastal regions.

The remainder of this paper is organized as follows. Section 2 presents the theoretical background. Section 3 discusses the bootstrapped Malmquist index, the KDE methods, and the fsQCA method. Section 4 describes the study materials. Section 5 brings the results and discussion, and Section 6 presents the conclusions and policy implications.

2. Theoretical background

2.1. Measurement of HMED

At the beginning of the 21st century, the government of China gradually recognized the importance of the marine economy and increased investment in resources in the marine sector, and the Gross Ocean Product (GOP) developed rapidly. However, a series of incidents of marine environmental pollution led to the realization that this extensive development pattern, which only emphasized factor inputs, could not achieve sustainable growth. As a result, the government and academics began to investigate the sustainability of the marine economy under resource and environmental constraints, aiming to achieve sustainable growth and reduce environmental pollution through cleaner production methods and innovative technologies (Lee et al., 2020).

In recent years, as China's economic development speed has changed from high-speed to medium-speed, the factor-driven economic development pattern is no longer able to achieve long-term development goals. The marine economy's development model is shifting from the pursuit of GOP growth towards enhancing factor productivity (Li et al., 2020). Factor productivity is a measure of the productive effectiveness of an economic unit (e.g., coastal provinces) at obtaining output with certain factor inputs. Single-factor productivity measures the unilateral factors that affect productivity growth, such as capital productivity or labor productivity (Makieła et al., 2021). But in reality, there are many observable factor resources other than capital and labor, and using only single-factor productivity to measure the productive efficiency of an economic unit is inevitably biased (Ding et al., 2020a). Therefore, scholars mostly use TFP to measure the productive efficiency of economic units. In the measurement of marine economic growth, they have placed increasing emphasis on the TFP index. This index is regarded as an effective tool for evaluating the sustainability of marine economic development (Solís et al., 2015). Moreover, the GTFP index, which incorporates environmental pollution factors, better aligns with the concept of high-quality development and is increasingly being recognized as a mainstream tool for measuring HMED (Liu et al., 2021).

Given that the marine economic system involves multiple inputs and outputs, it is essential to consider a model that can handle such complexity for calculating the marine economic GTFP index. Data Envelopment Analysis (DEA) is widely acknowledged as the most effective model to deal with multiple input and output problems, as it does not require assumptions regarding specific forms of production functions and estimated parameters. Additionally, DEA exhibits strong applicability in the calculation of the GTFP index. Several existing DEA-based models have been proposed for measuring the GTFP index, including the directional distance function (DDF) (Xia & Xu, 2020), the slacks-based measure (SBM) (Jiang et al., 2021), and the super-SBM model (Liu et al., 2021).

2.2. Improvement strategies for the HMED

The transformation of the marine economic growth pattern from factor-input driven extensive growth to GTFP-driven intensive growth is the key to achieving HMED (Ren et al., 2018). Numerous studies have been conducted on enhancing the GTFP of the marine economy. These studies primarily focus on analyzing the factors that have impact on GTFP growth (S. Wang et al., 2021). The decomposition of the GTFP index reveals that technological progress is a crucial driver of GTFP growth. Consequently, several studies have examined the mechanism by which technological innovation impacts GTFP growth. For example, Liu et al. (2021) have discussed the non-linear relationship between technological innovation and GTFP growth, characterized by a "positive weakening" effect. Ren and Ji (2021) suggest that technological innovation will contribute to GTFP growth by improving the level of technological production, creating environment-friendly products and changing the supply of production factors. In addition, under the GTFP growth perspective, environmental pollution factors are included as undesired outputs in the production efficiency measurement framework, and governments have made efforts to regulate the discharge of pollutants through the implementation of environmental regulations. Ye et al. (2021) argue that the GTFP growth of the marine economy requires environmental regulations of the appropriate intensity. Ren and Ji (2021) show that environmental regulations increase marine economy GTFP by eliminating highly polluting enterprises, injecting foreign capital and improving resource allocation efficiency. It is worth noting that increasing the level of openness and optimizing the industrial structure can also benefit GTFP growth (L. Wang et al., 2021; Wei et al., 2021). Increasing the openness level, on the one hand, brings advanced technology and management experience to marine enterprises and sectors and improves their productivity, while on the other hand, it improves the competitive market environment and enables enterprises to maintain their competitive dynamics, thus increasing GTFP. Optimizing the industrial structure will result in a greater allocation of resource factors to the more efficient marine sector and an overall increase in GTFP (L. Wang et al., 2021).

2.3. Research gaps

While the previous review highlights advancements in measuring HMED and promoting GTFP growth, some gaps remain in research that require further attention. First, traditional DEA models may be biased when measuring efficiency due to the small sample size covered by China's coastal regions. Given that the data for computing the GTFP index are mainly derived from census sampling estimates, addressing statistical issues like sampling variability in the measurement process is crucial. However, the existing literature overlooks the bias caused by sampling variability. Second, the analysis of dynamic changes in the GTFP growth of the marine economy is insufficient, and there is a lack of examination of the spatial impacts of such growth. Third, there is currently no systematic framework for analyzing the factors that influence GTFP growth. Additionally, binary statistical methods that only examine the relationships between independent and dependent variables are insufficient for revealing strategies to improve GTFP. These methods make it difficult to analyze the synergistic and joint effects of three or more factors on GTFP growth.

This paper aims to address the above gaps by making the following contributions:

(i) The bootstrapped Malmquist index is used to measure the GTFP growth of the marine economy. The estimators are applied to the simulated sample, overcoming the bias caused by the small sample size and sampling variability, and allowing for results that are closer to the actual GTFP growth.

(ii) KDE methods are used to characterize the dynamic changes and spatial impacts of the GTFP growth of the marine economy. We first use the traditional KDE method to examine the evolution of GTFP growth and the presence of regional differences. Then, we apply the spatially conditioned KDE method to analyze the impacts of spatial factors on GTFP growth in China's coastal regions. The results of the KDE provide a reference for the government to strengthen the top-level design of regional coordinated development mechanisms.

(iii) A novel analytical framework called SIEO for GTFP improvement strategies is constructed. This framework encompasses several factors that impact GTFP growth, including technological innovation, upgrading of industrial structure, environmental regulation, and openness level. Within the SIEO framework, the fsQCA method is applied to investigate the strategies to achieve HMED by examining the multiple concurrent causal relationships among multiple factors. Importantly, fsQCA can identify asymmetric antecedents that contribute to differences in HMED, enabling policymakers to sufficiently understand the differentiated driving mechanisms of HMED in coastal regions.

3. Methodologies

3.1. Bootstrapped Malmquist index

The bootstrap method is a non-parametric statistical bias correction method that overcomes the bias caused by small sample sizes and the inherent dependency of DEA efficiency values. Based on the bootstrap method, Simar and Wilson (1998) proposed the bootstrapped DEA model to correct for bias in DEA efficiency measurements. Further, Simar and Wilson (1999) extended it to the bootstrapped Malmquist index, which compensates for the fact that bootstrapped DEA can only be used for static analyses. The main steps of calculating the bootstrapped Malmquist index are described below.

Step 1. Consider a scenario where there are n decision-making units (DMUs), each characterized by m inputs that are utilized to produce s desirable outputs and p undesirable outputs. The inputs, desirable outputs, and undesirable outputs of the j-th DMU (j = 1, 2, ..., n) are represented by three vectors: $\mathbf{x}_j = (x_{1j}, x_{2j}, ,..., x_{mj})$, $\mathbf{y}_j = (y_{1j}, y_{2j}, ,..., y_{sj})$, $\mathbf{z}_j = (z_{1j}, z_{2j}, ,..., z_{pj})$). The GTFP $\hat{\theta}_k$ for the k-th DMU (k = 1, 2, ..., n) can be calculated with Eqs (1)–(2):

$$\begin{aligned} & \max \beta_k \\ & \text{s.t.} \sum_{j=1}^{n} \lambda_j x_{ij}^t + \beta_k x_{ik}^t \le x_{ik}^t,\ i = 1,2,\dots,m, \\ & \sum_{j=1}^{n} \lambda_j y_{rj}^t - \beta_k y_{rk}^t \ge y_{rk}^t,\ \ r = 1,2,\dots,s, \\ & \sum_{j=1}^{n} \lambda_j z_{qj}^t + \beta_k z_{qk}^t \le z_{qk}^t,\ \ q = 1,2,\dots,p, \\ & \sum_{j=1}^{n} \lambda_j = 1, \\ & \beta_k \ge 0, \\ & \lambda_j \ge 0,\ \ j = 1,\dots,n, \end{aligned} \tag{1}$$

where β_k is the inefficiency value of the k-th DMU, λ_j is the intensity variable associated with the j-th DMU, x_{ik}^t, y_{rk}^t and z_{qk}^t represent inputs, desirable outputs, and undesirable outputs for the k-th DMU in period t, respectively. Efficiency values θ_k can be obtained using $\theta_k = \left(1-\beta_k\right)/\left(1+\beta_k\right)$. To render efficiency values θ_k comparable across time, the global Malmquist index (MI) (Pastor & Lovell, 2005) is used to calculate $\hat{\theta}_k$, which can be represented as follows:

$$\mathrm{MI}_t^{t+1} = \frac{E^g\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}{E^g\left(x^t, y^t, z^t\right)}, \tag{2}$$

where E^g represents the efficiency value of a DMU, with the superscript g denoting the reference to the global frontier. A value of MI greater than one indicates an increase in GTFP, while a value of MI smaller than one suggests a decrease. Additionally, the decomposition of MI into the efficiency change (EC) index and technological change (TC) index is demonstrated in Eqs (3) to (5).

$$\mathrm{MI}_t^{t+1} = \frac{E^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}{E^t\left(x^t, y^t, z^t\right)} \times \frac{E^g\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}{E^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}\right)} \times \frac{E^t\left(x^t, y^t, z^t\right)}{E^g\left(x^t, y^t, z^t\right)}; \tag{3}$$

$$\mathrm{EC}_t^{t+1} = \frac{E^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}{E^t\left(x^t, y^t, z^t\right)}; \tag{4}$$

$$\mathrm{TC}_t^{t+1} = \frac{E^g\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}{E^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}\right)} \Big/ \frac{E^g\left(x^t, y^t, z^t\right)}{E^t\left(x^t, y^t, z^t\right)}. \tag{5}$$

A value of EC greater than one indicates an improvement in efficiency, while a value of EC smaller than one suggests a decrease in efficiency. Similarly, a value of TC greater than one indicates technological progress, while a value of TC smaller then one suggests a deterioration.

Step 2. For the GTFP $\hat{\theta}_k$ (k = 1, 2, ..., n) calculated in Step 1, the bootstrap method is used to simulate n-dimensional samples $\bar{\theta}_{kb}^*$ (b = 1, 2, ..., M), where b represents the b-th bootstrap iteration and $\bar{\theta}_{kb}^*$ represents the k-th GTFP in $\theta_1^*, \ldots, \theta_n^*$ generated by the b-th bootstrap iteration.

Step 3. The results of Step 2 are used to obtain pseudo-samples of $\left(\mathbf{x}_{jb}^*, \mathbf{y}_j, \mathbf{z}_j\right)$, j =1, 2, ..., n, where

$$\mathbf{x}_{jb}^* = \left(\hat{\theta}_k / \bar{\theta}_{kb}^*\right)\mathbf{x}_j. \tag{6}$$

Step 4. For each simulated sample, the GTFP $\tilde{\theta}_{kb}^*$ (k = 1, ..., n) is calculated using Eqs (1)–(2).

Step 5. Steps 2–4 are repeated M times, obtaining M efficiency values $\tilde{\theta}_{kb}^*$ (b = 1, 2, ..., M) for each DMU.

Step 6. The bootstrap method allows to simulate the distribution of the original sample estimates, so that the DEA-Malmquist estimation bias can be corrected using Eq. (7):

$$\mathrm{Bias}\left(\hat{\theta}_k\right) = \frac{1}{M}\sum_{b=1}^{M}\left(\tilde{\theta}_{kb}^*\right) - \hat{\theta}_k. \tag{7}$$

Step 7. The GTFP index θ_k^* after correcting for bias using the Bootstrapped Malmquist index is:

$$\theta_k^* = \hat{\theta}_k - \mathrm{Bias}\left(\hat{\theta}_k\right) = 2\hat{\theta}_k - \frac{1}{M}\sum_{b=1}^{M}\left(\tilde{\theta}_{kb}^*\right). \tag{8}$$

The number of iterations of the bootstrap method is positively correlated with the accuracy of the results, and the value of M is set to 2000 in this paper, which ensures coverage of the confidence interval.

3.2. Traditional KDE and spatially conditioned KDE

To present the distribution of the GTFP index, we utilize the traditional KDE method to generate a visual density function curve. By observing the changes in the position and shape of these curves, we can gain insights into the dynamic changes of the GTFP index over time. Specifically, we represent the density function curve of x in period t as $f(x_t)$, which can be expressed as follows:

$$f\left(x_t\right)=\frac{1}{nh}\sum_{i=1}^{n}K\left(\frac{x_t-x_{it}}{h}\right); \tag{9}$$

$$K\left(x_t\right)=\left(\frac{1}{\sqrt{2\pi}}\right)\exp\left(-\frac{{x_t}^2}{2}\right). \tag{10}$$

The observed value x_{it} for the i-th coastal area in period t is used in conjunction with the kernel function $K\left(\cdot\right)$ and bandwidth h. Then, we specifically utilize the Gaussian kernel function to analyze the dynamic changes of the GTFP index, as given by Eq. (10).

Then, the spatially conditioned KDE is used to examine the spatial impacts of the GTFP growth in coastal regions, i.e., whether the GTFP growth of a particular province is influenced by its neighboring provinces (Quah, 1997). For example, the GTFP growth in Shandong Province may be influenced by the GTFP growth in neighboring provinces (e.g., Hebei, Tianjin, and Liaoning) within the Circum-Bohai Sea Region. The formulas of the spatially conditioned KDE are shown in Eqs (11)–(12):

$$f\left(x_t,y_t\right)=\frac{1}{nh_xh_y}\sum_{i=1}^{n}K_x\left(\frac{x_t-x_{it}}{h_x}\right)K_y\left(\frac{y_t-y_{it}}{h_y}\right); \tag{11}$$

$$g\left(y_t|x_t\right)=\frac{f\left(x_t,y_t\right)}{f\left(x_t\right)}, \tag{12}$$

where x_t is the GTFP growth of other provinces in the same region in period t, and y_t is the GTFP growth of the province considered in period t. $f\left(x_t,y_t\right)$ is the joint probability density of x_t and y_t. $g\left(y_t|x_t\right)$ represents conditional probability density of y_t given x_t.

3.3. Identification of improvement strategies for HMED: fsQCA

In this study, we employ the fsQCA approach to investigate what configurations of antecedent conditions can generate the outcome of HMED within the SIEO framework, thereby exploring improvement strategies for HMED (Liu et al., 2022; Llopis-Albert et al., 2021). The fsQCA approach proposed by Ragin (2009) is an analytical method that combines set theory and Boolean algebra. Due to the advantages in the following three aspects, it has gained widespread attention from scholars in recent years. First, fsQCA has relatively minimal constraints on sample size, making it suitable not only for addressing research issues with small- and medium-sized samples but also for application in large dataset environments (Kraus et al., 2018). Second, fsQCA can reveal multiple concurrent relationships and asymmetries between antecedent conditions and outcomes through the relationships among sets (Tekic & Tekic, 2024). Third, fsQCA combines the advantages of qualitative and quantitative analysis, allowing for the exploration of the heterogeneity and complexity of cases (Liang et al., 2023). A step-by-step procedure is provided below to clearly present the manner by which we used the fsQCA approach. Figure 1 illustrates the research process used in this study.

Step 1. *Case selection*. Based on the research background of this study, we chose the 11 coastal regions of China as cases.

Step 2. *Data calibration*. Each condition and outcome was considered a set, and the data of each case were calibrated by assigning a membership score from 0 to 1 to these sets.

Step 3. *Analysis of necessary conditions*. When the consistency value of a condition exceeds 0.9, then the condition is considered necessary for the outcome.

Step 4. *Construction of the truth table*. Each row in a truth table represents a combination of the conditions. Three parameters, i.e., the minimum case frequency, consistency threshold, and proportional reduction of inconsistency (PRI), were used to simplify the rows of the truth table.

Step 5. *Sufficiency analysis*. After performing a sufficiency analysis, we used intermediate and parsimonious solutions to determine the core and peripheral conditions.

Step 6. *Robustness test*. A robustness test was performed by adjusting the consistency level, i.e., by increasing the consistency threshold from 0.8 to 0.85.

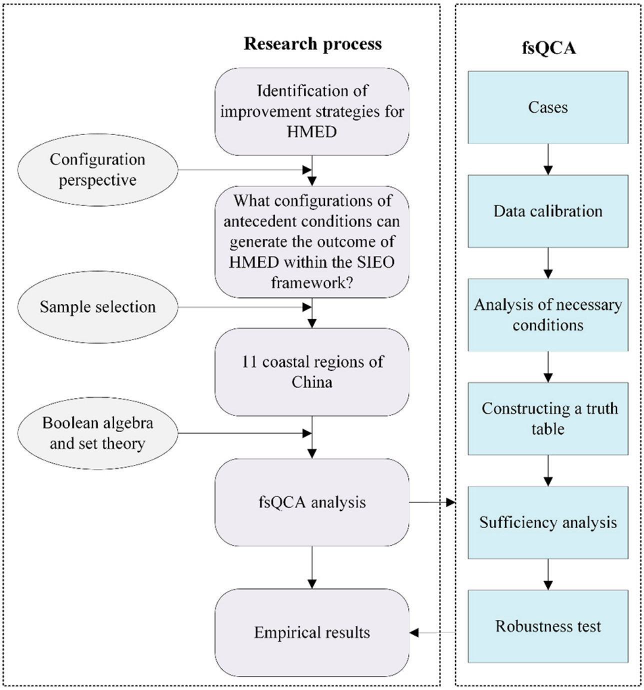

Figure 1. Research process and basic steps of fsQCA

4. Materials

4.1. Selection and processing of variables

4.1.1. Variables for measuring the GTFP index

The basic variables for calculating the TFP index of the marine economy include capital input, labor input, and GOP output. In this paper, we extend the calculation of the GTFP index for the marine economy beyond these basic variables to include additional factors such as resource input, environmental protection input, and undesirable output. Table 1 provides the relevant variables.

Table 1. Variables for measuring the GTFP index of marine economy

Function layer	Dimension layer	Indicator layer
Inputs	Capital	Marine capital stock
	Labor	Marine-related employed personnel
	Resource	Area of confirmed sea area
	Environmental governance	Investment in marine industrial wastewater pollution treatment
Outputs	Desirable output	Gross Ocean Product
	Undesirable output	Chemical oxygen demand in marine economic systems

Note: We deflate the variables involving price factors using 2006 as the base period.

(1) Input variables

- **Marine capital stock.** Given the lack of official statistics on marine capital stock, we estimate the total capital stock of coastal provinces using the perpetual inventory method (Liu & Zhu, 2022). Next, we calculate the marine capital stock by multiplying the total capital stock with the proportion of GOP to gross domestic product (GDP).
- **Marine -related employed personnel.** This indicator represents the number of people in marine-related employment in each region.
- **Area of confirmed sea area.** This indicator refers to the area of the sea approved for use by the government.
- **Investment in marine industrial wastewater pollution treatment.** This indicator tracks the investment in the treatment of marine industrial wastewater pollution. To account for the long-term impact of these projects, we use the perpetual inventory method to estimate the stock data of investment in marine industrial wastewater pollution treatment.

(2) Output variables

- **Gross Ocean Product.** GOP is used as desirable output to reflect the total output of marine economic activities in coastal regions.
- **Chemical oxygen demand (COD) in marine economic systems.** This indicator is used as the undesirable output variable to reflect environmental constrains. We calculate the COD in the marine economic system by multiplying the COD in wastewater by the pro-

portion of the GOP of a certain coastal region to the GDP. The higher the COD value, the greater the pollution level in the water.

4.1.2. Analytical framework of the improvement strategies of HMED

In terms of improvement strategies for HMED, most of the existing studies are based on correlation theory to identify the factors with a positive impact on HMED, such as scientific and technological innovation, industrial structure upgrading, environmental regulations, and openness level (Liu et al., 2021; Ren & Ji, 2021; Wei et al., 2021). However, these studies primarily focus on the net effect of individual factors on HMED, utilizing regression analysis methods based on the independent variable and dependent variable binary relationship to investigate the factors promoting HMED. However, the marine economic system is a complex, nonlinear system, and synergistic and joint effects may exist among multiple factors to affect HMED. To examine the synergistic and joint effects among multiple factors on HMED, an analytical framework called SIEO is developed in Figure 2 based on configuration theory. Configurational theory is used to explore what combination of antecedent conditions can generate a specific outcome, and this combination of antecedent conditions is referred to as a configuration. In the SIEO analytical framework, we focus on the synergistic and joint effects on HMED between the factors of science and technology innovation, industrial structure upgrading, environmental regulations and openness level. Table 2 provides details on the conditions and outcomes.

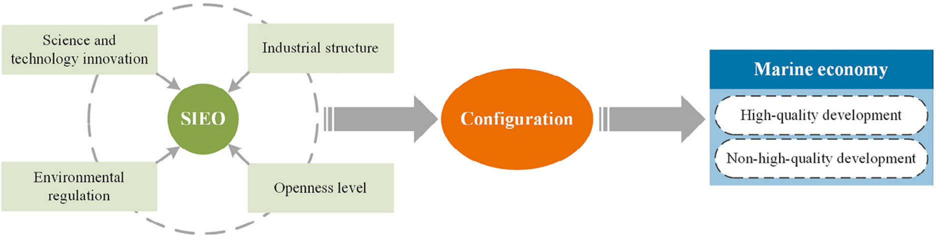

Figure 2. Analysis framework of GTFP growth path of the marine economy

Table 2. Results and conditional variables

Variable Types	Codes	Variable Definitions	References
Outcome variable	MI	HMED	Ren and Ji (2021), Ye et al. (2021)
Marine scientific and technological conditions	Hum	Marine human capital	Jiang et al. (2014), Liu et al. (2021)
	R&D	R&D investment	L. Wang et al. (2021), Zhang (2021)
Industrial structure conditions	Sec	Proportion of secondary industry	Su et al. (2021), L. Wang et al. (2021)
	Ter	Proportion of tertiary industry	G. Li et al. (2021), Su et al. (2021)
Environmental regulation condition	Env	Environmental protection investment	Ren and Ji (2021), Ye et al. (2021)
Openness conditions	Por	Port economic activity index	Liu et al. (2021), Santos et al. (2018)
	Tra	Proportion of total import and export trade in GDP	Y. Li et al. (2021), Liu et al. (2021)

(1) Result variable

- HMED: HMED is used as the outcome variable, and MI is its proxy variable.

(2) Marine scientific and technological conditions

- Marine human capital (Hum): We use the proportion of marine scientific and technological personnel in sea-related employment as a variable to measure marine human capital, which can properly reflect the input of the human factor in scientific and technological innovation activities.
- Marine R&D investment (R&D): To make it comparable between coastal regions with different scales of economic development, we use the proportion of marine research institutions' R&D expenditure in GOP to measure marine R&D investment.

(3) Industrial structure conditions

- The proportion of secondary industry (Sec) and the proportion of tertiary industry (Ter): The Petty-Clark theorem suggests that, as the marine economy develops, the industrial structure tends to be dominated by secondary and tertiary industries. Therefore, we utilize the proportion of marine secondary and tertiary industries as proxy variables to measure the upgrading of the marine industrial structure.

(4) Environmental regulation condition

- Marine environmental protection investment (Env): Environmental protection investment is regarded as the most important indicator to measure the intensity of environmental regulation. We multiply the environmental protection investment in coastal regions by the ratio of GOP to GDP to reflect the state of environmental regulation in the marine economic system.

(5) Openness conditions

- Port economic activity index (Por): The port economic activity of coastal provinces is measured by using the port economic activity index, which is calculated by fitting the cargo throughput and passenger throughput with the entropy method.
- The proportion of total import and export trade in GDP (Tra): We use the proportion of total import and export trade in GDP as another proxy variable to measure the openness level.

4.2. Study areas and data sources

The data for this study were collected from 11 coastal regions in China from 2007 to 2020. To address missing data, linear interpolation and proximal point averaging techniques were used. The 11 coastal regions in China, from north to south, are Liaoning, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi, and Hainan. The relevant data were obtained from various sources published by the National Bureau of Statistics [NBS] and the Ministry of Natural Resources [MNR], including the *China Statistical Yearbook* (NBS, 2020b), *China Regional Economic Statistical Yearbook* (NBS, 2020a), and *China Marine Statistical Yearbook* (MNR, 2020).

5. Results and discussion

5.1. Dynamic changes of the GTFP growth of the marine economy

5.1.1. The GTFP index and its decomposition index

Figure 3 displays the temporal trends of MI, EC, and TC from 2007 to 2020. To facilitate trend analysis, the study period is divided into 2007–2015 and 2016–2020 based on the changes in MI.

(I) In the period 2007–2015, MI exhibited significant fluctuations, with the minimum value (in 2007) and maximum value (in 2012) both occurring within this time frame. During this period, MI exhibited relatively large fluctuations. In 2007, 2009, 2011, and 2014, the values of MI were less than 1, indicating a decline in GTFP. In 2008, 2010, 2012, 2013, and 2015, the values of MI were greater than 1, indicating GTFP growth. The fluctuating pattern of MI during the period from 2007 to 2015 could be attributed to the implementation of China's 11th Five-year Plan and 12th Five-year Plan by the government. During this period, the Chinese government introduced a series of policies supporting the development of the marine economy, implemented the strategy of promoting technology-driven maritime development, and significantly improved the efficiency of marine resource utilization. However, due to the impact of the international financial crisis, marine environmental pollution, and adjustments in the marine industry structure, MI did not sustain a stable upward trend and experienced declines in some years. From the decomposition of MI, it can be observed that the fluctuations in EC are greater than those in TC – the mean value of TC was higher than the mean value of EC- indicating that technological progress had a greater impact on GTFP than efficiency improvement.

(II) In the period 2016–2020, MI entered a phase of slight fluctuations. Compared to the period 2007–2015, the value of MI has remained above 1, indicating a steady growth of GTFP during this period. A possible reason for this is that during this period, the Chinese government implemented the 11th Five-year Plan, emphasizing the guidance

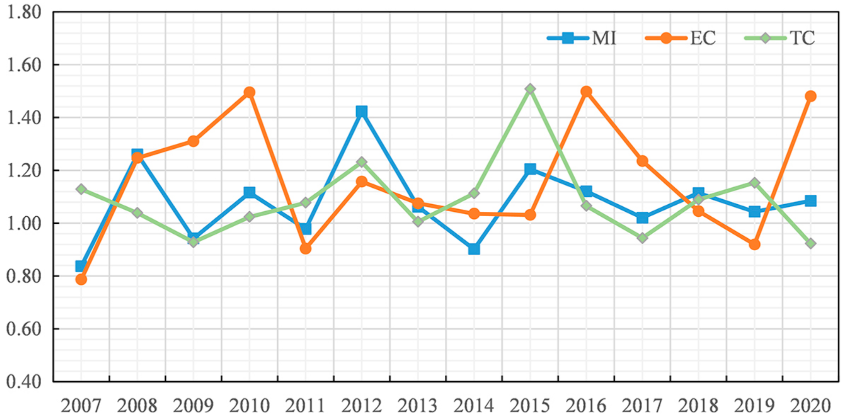

Figure 3. The temporal trends of the average MI, EC and TC in the period 2007–2020

of the development of the marine economy by the new development philosophy, focusing on innovation, coordination, green, openness, and sharing across these five dimensions. After the optimization and upgrading of the marine industry structure during the 12th Five-year Plan period, the industrial structure of the marine economy tended to become more reasonable during the 13th Five-year Plan period. Additionally, a gradual establishment of the marine ecological environmental governance system occurred, leading to effective control of marine environmental pollution. Therefore, during the period 2016–2020, the development of the marine economy entered a phase of quality improvement. Additionally, in this period, the average value of EC exceeded that of TC, indicating that the impact of efficiency improvement on GTFP growth was higher than that of technological progress.

The preceding analysis indicates that the growth and decline of GTFP in the marine economy were more pronounced during the period 2007–2015, while the changes during 2016–2020 were slight and in a growth phase. Overall, during the 13th Five-year Plan period and guided by the new development philosophy, the Chinese government's efforts to combat marine environmental pollution have yielded significant results in recent years. After controlling for environmental pollution variables, GTFP showed a slight increase, indicating an improvement in the quality of China's marine economic development.

Figure 4 depicts the changes in the GTFP index across the 11 coastal regions during the period 2007–2020. Due to differences in geographical location and environmental resources, the GTFP index exhibited significant variations among the coastal provinces. To provide a clearer presentation of the changes in the GTFP index for each coastal province, we used vertical axes with varying scales. The red line represents the mean value of MI, while the value 1 on the vertical axis is denoted in green.

Overall, the GTFP growth of the marine economy showed fluctuations across all coastal regions. Among the 11 coastal regions, the average GTFP of Fujian, Guangdong, and Zhejiang ranked in the top three, while the GTFP averages of Hainan, Liaoning, and Jiangsu ranked in the bottom three. Taking Fujian as an example, during the 13th Five-year Plan period, Fujian's annual average growth of GOP was 8.2%. In 2020, Fujian's GOP reached 1.05 trillion yuan, ranking third in the nation. Furthermore, Fujian's primary, secondary, and tertiary marine industry structures changed from 7.3:37.1:55.6 in 2015 to 6.5:31.7:61.8 in 2020, indicating a significant achievement in the upgrading of the marine industry structure. Furthermore, Fujian actively promoted the protection of the marine ecological environment by designating 32.9% of the sea area as the red line zone for marine ecological protection. Although the average GTFP index value for the 11 regions remained greater than 1, the GTFP index development in all coastal provinces displayed a fluctuating trend. This indicates that a stable model for the development of the marine economy has yet to be established.

5.1.2. The regional differences and spatial impacts of the GTFP growth

To gain a deeper understanding of the dynamic changes in the GTFP index, we utilize the KDE method to present the KDE curves of the GTFP index, as illustrated in Figure 5.

The distribution of the KDE curves shows that the main body of the curves is located in the MI < 1 region, indicating an unfavorable status of the GTFP index in that particular year.

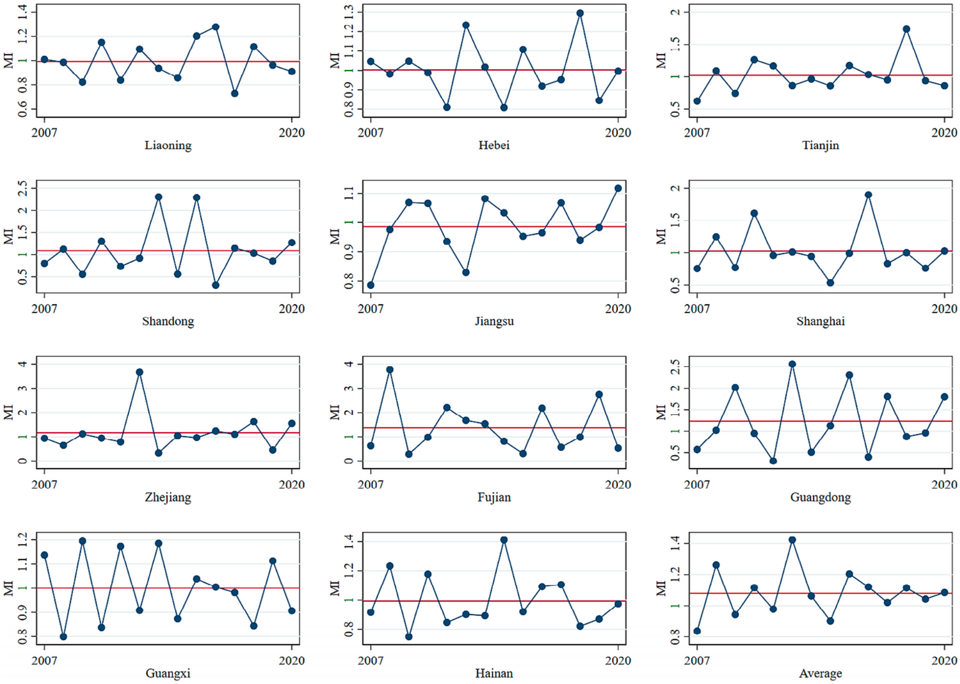

Figure 4. The GTFP index in 11 coastal regions in the period 2007–2020

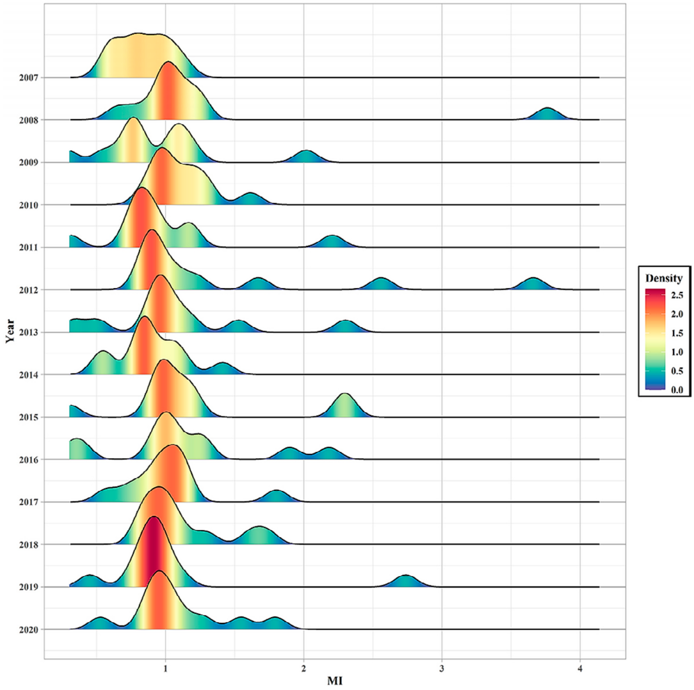

Figure 5. The traditional KDE of MI

For example, in 2007, the main body of the KDE curve was situated in the MI < 1 part, indicating that GTFP was at a low level. Conversely, the main body of the KDE curve located in the MI > 1 region indicates an increase in GTFP for that year. For instance, in 2008, the main body of the KDE density curve was situated in the MI > 1 region, suggesting that the growth of the marine economy was good that year. Compared to the position of the KDE curve from 2007 to 2014, the position of the KDE curve from 2015 to 2020 has remained more stable, indicating increased stability in recent years.

The peak distribution of the KDE curve suggests that the differences in HMED among coastal regions have exhibited a pattern of initial expansion followed by subsequent narrowing. In 2008, the right-hand trailing trend of the KDE curve suggested that the GTFP index in some coastal regions was significantly higher than in others. Similar trends were observed in other years such as 2009, 2011, 2012, and 2013. Although the right-hand trailing pattern of the KDE curve disappeared by 2020, the primary peak density of the KDE curve was larger compared to 2007. Additionally, peaks were observed in both the MI<1 and MI>1 regions, indicating an imbalanced pattern of GTFP growth in coastal regions.

To sum up, the GTFP index in coastal regions has fluctuated, but regional imbalances in development have become a concern.

Additionally, we utilize spatially conditioned KDE to investigate the influence of spatial factors on the GTFP index in China's coastal regions. The findings are illustrated in Figure 6,

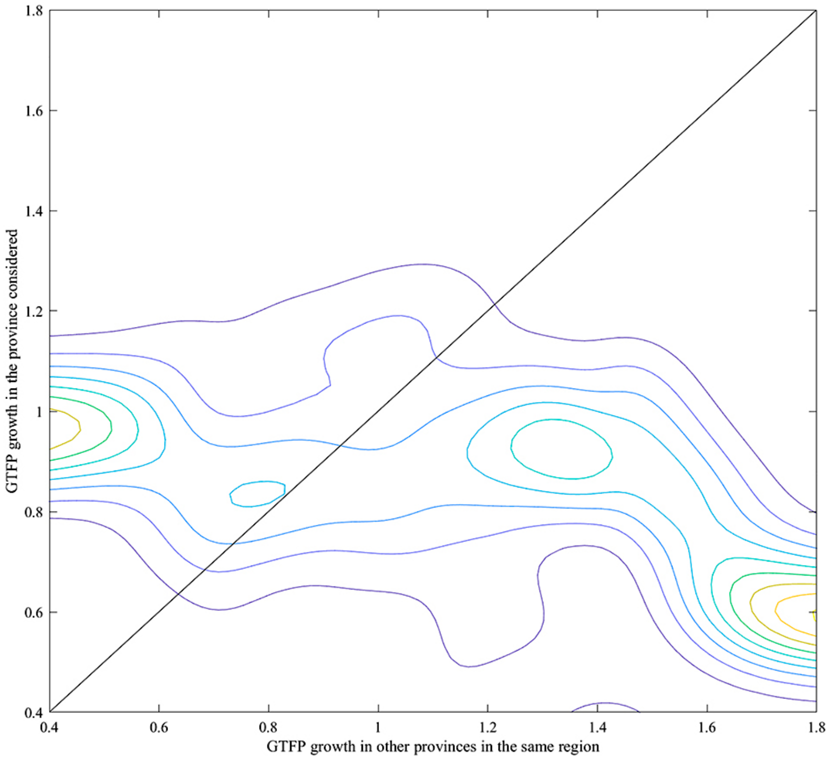

Figure 6. Spatially conditioned KDE contours of the GTFP growth for 11 coastal regions

which demonstrates the trend of GTFP growth in the province considered under the influence of GTFP growth of other provinces in the same region. In Figure 6, the Y-axis represents the GTFP growth of the province considered, while the X-axis represents the GTFP growth of other provinces in the same region. The density curve depicts the conditional probability density, where the contour lines closer to the center indicate higher probability density values. The density of the contour lines reflects the degree of probability density variation, and the corresponding kernel density graph appears steeper as the density of the contour lines increases. If the spatial impact is strongly positive, then the probability density distribution should concentrate along the diagonal from the bottom left to the top right. However, as shown in Figure 6, the distribution is oriented in the opposite direction to the diagonal line, indicating that provinces with faster GTFP growth within the same region negatively affected GTFP growth in their neighboring provinces. Specifically, the faster GTFP growth in the marine economy of certain provinces has led to the attraction of production factors from neighboring provinces, resulting in a siphon effect that negatively affected the GTFP growth in their neighboring provinces. For example, Guangdong's GTFP grew faster and ranked second out of 11 provinces, but its neighbor, Guangxi, had a slower GTFP growth and ranked tenth. The siphon effect of Guangdong on Guangxi was manifested in the following aspects. First, in terms of resource attraction, Guangdong, a province with fast GTFP growth, possessed advanced technology, equipment, and management experience in the development of marine resources and coastal tourism. This led Guangxi's resources to flow to Guangdong for better investment opportunities and returns. Second, in terms of talent mobility, Guangdong offered a wealth of sea-related scientific research platforms and job opportunities, which attracted those talents with marine-related skills from Guangxi Province to relocate to Guangdong. Furthermore, Guangdong had already established a relatively mature marine industry cluster, which attracted maritime enterprises from Guangxi to engage in investment cooperation or establish branch offices in Guangdong.

5.2. Improving HMED: strategies within the SIEO framework

5.2.1. Data calibration

The fsQCA method treats each antecedent and outcome variable as a set, and calibrates the data based on specific rules to assign membership scores to the cases (Schneider & Wagemann, 2012). Membership scores, which range from 0 to 1, are assigned using three threshold points. This paper uses a direct calibration method based on previous studies and descriptive statistics of cases. Specifically, the full membership point is set as the upper quartile (75%) of the sample data, the crossover point is set as the median (50%), and the full non-membership point is set as the lower quartile (25%). The data for antecedent and outcome variables are based on average values from 2007 to 2020. To avoid cases with a membership score of 0.5 being excluded from subsequent analysis, a constant of 0.001 is added to antecedent conditions with a membership score of 0.5 (Campbell et al., 2016). We perform the data calibration process using the fsQCA 3.0 software and present the threshold points for each variable in Table 3.

Table 3. Data calibration of each variable

Variables	75%-Full membership	50%-Crossover point	25%-Full non-membership
MI	1.128	1.020	0.997
Hum	0.079	0.049	0.035
R&D	2.827	2.036	1.347
Sec	46.389	38.043	37.357
Ter	55.707	50.500	47.593
Env	86634.900	38980.100	28954.100
Por	0.007	0.006	0.006
Tra	0.088	0.066	0.039

5.2.2. Analysis of necessary conditions

Before conducting configuration analyses, it is necessary to test whether individual conditions constitute necessary conditions for either HMED or non-HMED. If a specific condition consistently co-occurs with the occurrence of HMED or non-HMED, then this condition is considered a necessary condition for that outcome. When analyzing necessary conditions, any conditions with a consistency value above 0.9 can be regarded as necessary conditions for a specific outcome (Fiss, 2011). As shown in Table 4, the values of consistency for all condition variables are less than 0.9 and there are no necessary conditions affecting HMED or non-HMED. According to Table 4, the consistency values for all condition variables are below 0.9, indicating that there are no necessary conditions for the outcome of HMED or non-HMED.

Table 4. Analysis of the necessary conditions

Condition	HMED		Non-HMED	
	Consistency	Coverage	Consistency	Coverage
Hum	0.443	0.415	0.602	0.647
~Hum	0.623	0.577	0.456	0.485
R&D	0.467	0.426	0.590	0.619
~R&D	0.582	0.553	0.452	0.493
Sec	0.610	0.529	0.500	0.498
~Sec	0.422	0.423	0.527	0.608
Ter	0.707	0.623	0.424	0.429
~Ter	0.352	0.347	0.627	0.711
Env	0.744	0.670	0.362	0.375
~Env	0.305	0.294	0.680	0.753
Por	0.740	0.702	0.337	0.367
~Por	0.332	0.304	0.726	0.763
Tra	0.707	0.656	0.367	0.391
~Tra	0.344	0.321	0.677	0.726

Note: The notation ~ indicates the absence/negation of a condition.

5.2.3. Sufficiency analyses of configurations

In this section, we employ sufficiency analysis of configurations to determine the strategies for enhancing HMED within the SIEO framework. The analysis enables us to reveal how scientific and technological innovation, industrial structure, environmental regulation, and openness level synergistically and jointly contribute to the achievement of HMED. Considering the small number of cases (11 coastal regions), we set the minimum case frequency to 1 and the consistency threshold to 0.8 in the sufficiency analysis of configurations (Fiss, 2011). Additionally, we set the proportional reduction in inconsistency (PRI) to 0.75 to prevent conflicting configurations (Frambach et al., 2016). The results of the sufficiency analysis are classified into three types: complex, intermediate, and parsimonious solutions. Intermediate and parsimonious solutions are used to determine the core and peripheral conditions. A large black circle (●) is used to label the core conditions because they have a significant causal relationship with the outcome. A smaller black circle (•) is used to indicate edge conditions with weaker causal relationships with the outcome. If a core condition is absent, then an × in a circle (⨂) is typically written down. Similarly, if a peripheral condition is absent, then a smaller version of the symbol (⊗) is written down. A blank in the relevant cell of the table indicates that having a high or non-high condition is not important. Table 5 presents the results of the sufficiency analysis of configurations for the outcomes of HMED and non-HMED within the SIEO framework.

As shown in Table 5, within the SIEO framework, there are two configurations driving HMED, which reflect the multiple and concurrent causal relationships between the factors of science and technology innovation, industrial structure upgrading, environmental regulation and openness level and HMED. The two configurations exhibit consistencies of 1 and 0.921, respectively, both exceeding the consistency threshold of 0.8, thereby demonstrating their sufficiency as conditions for achieving HMED within the SIEO framework. The consistency of the overall solution is 0.975, which is also greater than the consistency threshold of 0.8.

Table 5. The sufficiency analysis of configurations for HMED and Non-HMED

Configurations	HMED		Non-HMED			
	1	2	3	4	5	6
Hum	⊗	•	⊗	●	●	●
R&D	⊗	•	•	⊗	•	•
Sec		•	⊗	•	⊗	•
Ter	•	⊗	⊗	•	⊗	⊗
Env	●	●	●	⨂	⨂	●
Por	●	●	⨂	⨂	•	⨂
Tra	•	⊗	⨂	⨂	⨂	•
Consistency	1	0.921	0.985	1	0.981	1
Raw coverage	0.408	0.158	0.109	0.089	0.089	0.165
Unique coverage	0.385	0.135	0.085	0.085	0.068	0.146
Overall solution consistency	0.975		0.992			
Overall solution coverage	0.543		0.409			

The raw coverages for the two configurations are 0.408 and 0.158. Additionally, the overall solution coverage is 0.543, indicating that each configuration explains a certain amount of the outcome of HMED. In summary, Table 5 shows that the configuration paths are highly explicable, and the results are reliable.

The two configurations of HMED can provide valuable insights for policymakers to understand the distinct contributions of science and technology innovation, industrial structure, environmental regulation, and openness level to the achievement of HMED. The specific details are outlined below:

- **(i)** In Configuration 1, high levels of investment in environmental protection and a robust port economy play a central role in driving HMED, while a higher proportion of tertiary industry and trade serve as supportive factors. The path highlighted by Configuration 2 indicates that achieving HMED is contingent on a combination of factors, including environmental regulation, upgrading of industrial structure, and increased openness. In other words, provinces that lack capabilities in marine science and technology innovation should prioritize strengthening their environmental regulations, expanding their openness, and increasing the proportion of tertiary industry in their GOP.
- **(ii)** In Configuration 2, similar to Configuration 1, high-level environmental protection investment and port economic activities play a core role in HMED, while high-level marine human capital, R&D, and the secondary industry play a supportive role. The result of Configuration 2 provides a strategy for improving HMED for provinces with low levels of marine tertiary industry and import and export trade, which is to strengthen environmental regulation and port construction while enhancing marine technology innovation capabilities and developing the marine secondary industry.

Typical cases covered by Configuration 1, which refers to cases in which both the antecedent membership degree and the outcome membership degree exceed 0.5, include the provinces of Guangdong, Fujian, and Zhejiang. Taking Guangdong province as an example, it is noteworthy that in recent years the local government has made significant efforts to combat pollution in nearshore waters, with a particular emphasis on addressing pollution in rivers that flow into the sea. By establishing a marine ecological environment zoning and control system, a portion of the marine environmental problems have been effectively resolved. In 2020, the proportion of good water quality in Guangdong Province reached 87.3% under the national monitoring program for surface water. Moreover, Guangdong Province has a significant degree of openness, and its provincial government is actively developing a world-class port cluster that centers around Guangzhou Port, Shenzhen Port, Zhuhai Port, and Dongguan Port. Despite the low proportion of marine scientific and technological personnel in sea-related employment and marine R&D investment in GOP, the high level of marine environmental governance, openness, and proportion of marine tertiary industry have driven the marine economy of Guangdong province.

The typical case covered by Configuration 2 is Shandong. Located in Shandong Province, Qingdao City has gathered 30% of China's marine academicians and 40% of the high-end research and development platforms related to the marine industry, giving Shandong province a high level of marine innovation capacity. Additionally, the government of Shandong province places significant emphasis on marine environmental protection. In 2020, the offshore waters of Shandong Province achieved 91.5% good water quality. Moreover, Shandong province boasts important ports such as Qingdao Port, Yantai Port, and Rizhao Port, which have fostered a thriving port economy. Despite the marine tertiary industry accounting for a relatively small proportion of Shandong's GOP, Shandong has achieved HMED due to its high-level environmental governance, marine technology innovation, and marine secondary industry.

In this paper, the configurations that generate non-HMED are also examined. Configuration 3 indicates that high levels of environmental protection and marine R&D alone cannot achieve HMED. Configuration 3 covers the case of Guangxi. Configuration 4 states that for provinces with a high-level of marine industry structure, high-level human capital alone cannot achieve HMED. The case covered by Configuration 4 is Hebei. For Configuration 5, even with high-level marine science and technology innovation and a high-level port economy, HMED cannot be achieved if the marine industry structure is unreasonable. The case covered by Configuration 5 is Liaoning. Configuration 6 indicates that even with high levels of investment in marine technology innovation and ocean environmental governance, HMED cannot be achieved without a reasonable marine industry structure and an active port economy. Configuration 6 covers the typical case in Jiangsu.

5.2.4. Robustness test

The fsQCA approach, being set-based, is considered robust when the findings of a study remain unchanged with slight variations in manipulation. Following a study by Schneider and Wagemann (2012), the consistency threshold in the sufficiency analysis was increased from 0.8 to 0.85, and the configurations for HMED and Non-HMED outcomes remained the same, as shown in Table 6. This suggests that the study findings are robust.

Table 6. Robustness test with improved consistency threshold of 0.85

Configurations	HMED		Non-HMED			
	1	2	3	4	5	6
Hum	⊗	•	⊗	●	●	●
R&D	⊗	•	•	⊗	•	•
Sec		•	⊗	•	⊗	•
Ter	•	⊗	⊗	•	⊗	⊗
Env	●	●	●	⨂	⨂	●
Por	●	●	⨂	⨂	•	⨂
Tra	•	⊗	⨂	⨂	⨂	•
Consistency	1	0.921	0.985	1	0.981	1
Raw coverage	0.408	0.158	0.109	0.089	0.089	0.165
Unique coverage	0.385	0.135	0.085	0.085	0.068	0.146
Overall solution consistency	0.975		0.992			
Overall solution coverage	0.543		0.409			

6. Conclusions and policy implications

This paper aimed to investigate the dynamic changes and improvement strategies of HMED in China's 11 coastal regions from the perspective of GTFP growth. We first calculated the proxy variable GTFP index for HMED using the bootstrapped Malmquist index, and then described the development dynamics and spatial impacts of the GTFP growth using the traditional KDE and the spatially conditioned KDE, respectively. The application of fsQCA within the proposed SIEO framework was further utilized to explore the improvement strategies of GTFP growth. The primary conclusions drawn from this study are as follows:

(i) Based on the results obtained from the bootstrapped Malmquist index, we found that the GTFP index displayed considerable fluctuations during the period 2007-2015, with a tendency to stabilize and exhibit an upward trend (greater than 1) during 2016-2020. Although the mean GTFP index for coastal regions was greater than 1, the index displayed wide fluctuations, indicating that a stable pattern of marine economic development had not yet been firmly established.

(ii) The traditional KDE analysis showed significant regional differences in the growth of GTFP among coastal regions, with a pattern of widening and then narrowing of the differences over time. The spatially conditioned KDE analysis revealed that provinces with higher GTFP growth rates within the same region inhibited the GTFP growth of neighboring provinces, due to the attraction of resources from those provinces. This phenomenon, known as the siphon effect, was observed in the study.

(iii) The two configurations for increasing the GTFP growth of the marine economy within the SIEO framework illustrate the various interrelated causal relationships between the factors of technological innovation, industrial structure, environmental regulation and openness and HMED. Coastal provinces with limited development conditions can still achieve HMED by leveraging the combined effects of other advantageous factors.

Some policy implications can be drawn from the above conclusions to promote the HMED. First, the performance assessment objectives of local governments should encompass not only the development of marine industries but also the enhancement of GTFP. The government must commit to transforming the extensive marine economic growth model into a high-tech, high-value-added model by improving GTFP. In addition, the government should avoid over-investment in production factors while formulating marine economic policies and instead focus on strengthening research, development, and implementation of sea-related technologies to foster technological progress and improve efficiency, thus creating a high-quality marine economic development model.

Second, given the lack of coordination in the development of the marine economy across coastal regions, the government should strive for a more balanced and integrated approach to foster growth. This includes providing stronger policy support to coastal provinces with low GTFP growth to narrow the development gaps among them, and avoiding the siphon effect of provinces with high GTFP growth on their neighboring provinces. To achieve a well-coordinated growth of the marine economy in the entire region, the government should design distinct development strategies based on the regional characteristics of neighboring provinces, prioritize the cultivation of marine industries with comparative advantages, and ensure an equitable distribution of these industries across different regions.

Third, it is essential for policymakers to explore different paths for HMED, taking into consideration the unique characteristics of each coastal province, and accordingly designing marine economic policies. Provinces lacking in technological innovation capacity must prioritize strengthening environmental regulations, increasing the proportion of tertiary industry in the GDP, and improving openness levels. Meanwhile, provinces with a low proportion of tertiary industries can focus on upgrading their industrial structure through the complementation of the secondary industry. In addition, enhancing technological innovation, reinforcing environmental regulations, prioritizing port construction, and increasing openness are all crucial factors in promoting the development of HMED. The government needs to recognize the multiple roles played by factors such as technological innovation, industrial structure, environmental regulation, and openness levels in achieving this goal.

The limitations of this study should be highlighted and addressed in future studies. First, the conclusions of this study are derived from the perspective of the GTFP growth of the marine economy. Due to different ways of measuring HMED, different results may be obtained. Therefore, future research should attempt to assess HMED through the construction of a multi-criteria evaluation system and validate the research findings. Second, this paper explored the improvement strategies of HMED within the SIEO framework, and future research should incorporate more antecedent conditions to expand on our findings. Third, in the part of identifying improvement strategies for HMED, we used fsQCA to process the averaged dataset. In future studies, the improvement strategies for HMED with temporal effects should be further explored.

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Author contributions

Peide Liu and Baoying Zhu conceived the study and were responsible for the design and development of the data analysis. Mingyan Yang was responsible for data collection and analysis. Bernard De Baets was responsible for modification and supervision. Baoying Zhu wrote the first draft of the article.

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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