

The Impact of Digital Economy Development on Marine Fishery Carbon Emission Efficiency: Evidence and Differentiated Policy for Coastal Provinces in China

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Abstract:

The low-carbon transformation of marine fisheries is critical for sustainable development of the sector, with digital economy development emerging as a promising pathway for enhancing production and carbon emission efficiency. This study constructs a comprehensive digital economy index (DEI) and evaluates the impacts on marine fishery carbon emission efficiency (MFCEE) by utilizing panel data from 11 Chinese coastal provinces from 2011 to 2023. Spatial econometric analyses reveal that digital economy development significantly improves local MFCEE and generates substantial positive spatial spillover effect across neighboring coastal provinces, indicating strong transboundary synergy. However, structural heterogeneity assessments indicate critical boundaries to these benefits. Digitalization significantly improves MFCEE in low capture-dependence areas, where modernized aquaculture systems readily absorb smart technologies, but its impact is not evident in high capture-dependence regions heavily reliant on fuel-intensive marine capture fisheries. Furthermore, the effects exhibit regional variations, presenting distinct interaction dynamics in the eastern and southern coastal regions compared to the north. These findings suggest that digital economy development is an important driver for decarbonizing marine fisheries, but its effectiveness is contingent upon regional conditions and underlying production structure. Consequently, this study provides robust empirical evidence for implementing regionally differentiated, cross-provincial digital and green transformation strategies.

Keywords: Sustainable fisheries, Decarbonization, Carbon emission efficiency, Spatial Durbin model (SDM), Super-efficiency SBM, Spatial spillover effects, Structural heterogeneity

1 Introduction

2 Since the beginning of the 21st century, emissions of greenhouse gases, particularly
3 carbon dioxide emissions, have continued to increase. According to the International
4 Energy Agency, global energy review 2025 revealed total energy-related CO₂ emissions
5 reached a record high of 37.8 Gt in 2024, indicating the energy consumption remains a
6 major source of global carbon emissions (IEA, 2025). Global warming has become
7 increasingly severe and has emerged as a major challenge threatening the sustainable
8 development of human society (Zheng *et al.*, 2024). In this context, promoting low-
9 carbon economic development, improving resource utilization efficiency, and reducing
10 carbon emission intensity have become important pathways for countries to achieve
11 green transformation and respond to climate change. While the manufacturing and
12 energy sectors have traditionally been the primary targets for emission reductions, the
13 blue economy and marine food systems are increasingly recognized as critical
14 components of global carbon budgets. As an important component of the marine
15 economy, marine fisheries not only play an important role in ensuring the supply of
16 aquatic products and promoting economic development in coastal regions but also serve
17 as a key part of the strategy of building a strong maritime country. However, marine
18 fisheries also face multiple pressures related to energy consumption, carbon emissions,
19 and green transformation during their development (Cao and Fan, 2022). For example,
20 Sala *et al.* (2022) showed that some trawl fisheries are highly fuel-intensive, with
21 substantial CO₂ emissions generated during fishing operations. Therefore, how to
22 improve marine fishery carbon emission efficiency (MFC EE) has become an important
23 issue for promoting the high-quality development and low carbon sustainable
24 transformation of marine fisheries (Li *et al.*, 2025).

25 However, the low-carbon transformation of marine fisheries faces distinct regional
26 and structural challenges. Gao *et al.* (2022) measured the carbon emission efficiency of
27 marine fisheries in China's eastern coastal provinces and analyzed its spatial-temporal
28 differentiation characteristics. The results indicate that marine fishery carbon emission
29 efficiency is not homogeneous across coastal provinces, but instead shows certain
30 spatial differences. Zhu *et al.* (2023) examined the spatial-temporal characteristics of
31 marine fishery ecological efficiency in China's coastal regions and found that, although
32 the ecological efficiency of coastal fisheries has generally improved, distinct regional
33 disparities still exist. In addition, Zhang *et al.* (2025) analyzed carbon emissions from
34 China's marine fisheries from a long-term perspective, focusing on the effects of
35 different operation modes and production structures on carbon emissions, and pointed
36 out that operation structure is one of the important factors affecting marine fishery
37 carbon emissions. Meanwhile, the spatial relationship between the digital economy and
38 green development has attracted increasing attention. Sun *et al.* (2023) found that the
39 digital economy has significant direct and spatial spillover effects on green total factor

1 productivity. Zou *et al.* (2024) used the Spatial Durbin model (SDM) to analyze the
2 spatial spillover effect of the digital economy on urban total factor productivity and
3 found that the digital economy not only improves local urban total factor productivity,
4 but also generates spatial spillover effects through the digital economy development of
5 neighboring regions. This literature indicates that the improvement of marine fishery
6 carbon emission efficiency may be affected by regional development conditions,
7 fishery production structure, and spatial linkage effects. Therefore, it is necessary to
8 further examine the impact of digital economy development on marine fishery carbon
9 emission efficiency from the perspectives of spatial effects and heterogeneity.

10 The digital economy, as a new economic form, relies on digital technologies, data
11 resources, and information networks to promote digital industrialization and industrial
12 digitalization. It continuously improves the level of digitalization, networking, and
13 intelligence in economic activities, thereby contributing to high-quality economic
14 development, innovation capacity enhancement, and environmental performance
15 improvement (Dong *et al.*, 2022). For the marine economy, problems such as the
16 imbalance between growth speed and development quality, low marine innovation
17 efficiency, and insufficient allocation of marine-related resources and factors still exist
18 (Zhang and Li, 2024). Under increasing resource and environmental constraints, digital
19 economy development provides a new pathway for promoting the green and low carbon
20 transformation of marine fisheries. Specifically, in the marine fishery sector, the digital
21 economy may improve MFCEE through multiple channels. First, digital technologies
22 can improve the monitoring and management of fishery production activities. From a
23 governance perspective, integrating advanced vessel tracking systems and digital
24 monitoring enables policymakers to precisely regulate fishing efforts, manage quotas,
25 and monitor fuel consumption. This policy-driven oversight can systematically
26 optimize energy use and production scheduling, and thereby reduce inefficient energy
27 consumption. Second, digital innovation can promote the upgrading of traditional
28 fishery production modes and improve production and resource utilization efficiency.
29 Third, digital financial services can provide more convenient financial support for low-
30 carbon equipment renewal, technological innovation, and green transformation.
31 Therefore, digital economy development may help reduce carbon emission inefficiency
32 in marine fisheries and further improve MFCEE.

33 Existing studies have extensively examined the relationship between the digital
34 economy and green low-carbon development. Most studies suggest that digital
35 economy development can improve carbon emission efficiency, reduce carbon
36 emissions, and promote green total factor productivity. For example, Qin *et al.* (2023)
37 examined the effects and mechanisms of digital economy development on urban carbon
38 emissions and found that digital economy development significantly improves urban
39 carbon emission performance, making it an important support for achieving China's
40 dual-carbon goals in the new era. Huang *et al.* (2023), based on data from 273 Chinese

cities, investigated the impact of the digital economy on urban green economic efficiency and found that digital economy development has a positive effect on urban green economic efficiency. Xie *et al.* (2025) further explored how the digital economy affects carbon emission efficiency in the logistics industry and found a nonlinear relationship between the digital economy and carbon emission efficiency. These studies indicate that the digital economy can promote green and low-carbon development through resource allocation optimization, technological progress, and regional linkages. While current research predominantly examines the manufacturing, logistics, and agricultural industries, the marine fisheries sector has remained largely underexplored.

In recent years, however, this field has seen increased emphasis on carbon footprints, ecological efficiency, and sustainable growth. Shao *et al.* (2018) calculated carbon emissions and carbon sinks from marine capture and mariculture in Shandong Province and found that marine fisheries in Shandong were still in a carbon deficit state, indicating that the tasks of emission reduction and carbon sink enhancement remain challenging. Chen *et al.* (2024), using data from China's coastal provinces, measured marine fishery carbon emissions and eco-efficiency, and further analyzed their spatiotemporal evolution and influencing factors. Other studies have examined marine fisheries from the perspectives of carbon trading, carbon emissions, and carbon sinks, suggesting that marine fishery activities have both carbon source and carbon sink attributes. These studies provide an important basis for understanding the green development performance of marine fisheries. However, existing research on marine fishery predominantly focuses on tracking carbon emission, estimating carbon sink, and analyzing the spatiotemporal evolution of eco-efficiency. However, these studies overlook how digital economy development enhances MFCEE, its potential spatial spillover effects, and structural heterogeneity of these impacts across different production levels. Consequently, it is necessary to incorporate digital economy development, spatial spillover effects, and production-structure heterogeneity into the analytical framework of MFCEE.

Based on this, this study uses panel data from 11 Chinese coastal provinces from 2011 to 2023, constructs a comprehensive index of digital economy development, and applies the super-efficiency SBM model to measure marine fishery carbon emission efficiency. On this basis, a two-way fixed-effects model is first employed to examine the direct impact of digital economy development on MFCEE, and robustness and endogeneity tests are conducted to verify the reliability of the results. Second, considering the potential spatial autocorrelation among coastal provinces, this study constructs four spatial weight matrices and applies the Spatial Durbin Model (SDM) to examine both the local effect and spatial spillover effect of digital economy development on MFCEE. Finally, heterogeneity analysis is conducted from the perspectives of geographical location and capture-dependence level to reveal how the impact of digital economy development on MFCEE differs across regional conditions

1 and marine fishery production structures.

2 The marginal contributions of this study are mainly reflected in three aspects. First,
3 this study extends the literature on the digital economy and carbon emission efficiency
4 to the marine fishery sector, thereby enriching research on the role of the digital
5 economy in promoting green and low-carbon development. Second, based on the
6 measurement of MFCEE, this study introduces spatial econometric models to identify
7 both the local and spatial spillover effects of digital economy development on MFCEE,
8 providing empirical evidence for understanding digital linkages and low-carbon
9 efficiency improvement among coastal provinces. Third, this study examines
10 heterogeneity from the perspectives of geographical location and capture-dependence
11 level. In particular, incorporating capture-dependence level into the analytical
12 framework helps reveal how differences in marine fishery production structure shape
13 the effect of digital economy development on MFCEE. The subsequent sections are
14 structured as follows: Section 2 establishes the theoretical framework and research
15 hypotheses. Section 3 introduces the research methods, variable selection, and data
16 sources. Section 4 presents the empirical results. Section 5 concludes the study by
17 offering policy implications.

20 **Theoretical analysis and research hypotheses**

21 As a new form of economic development, the digital economy is characterized by
22 strong permeability, sharing, and integration, which can promote the deep integration
23 of digital technologies, data elements, and real industries (Shi and Cao, 2023). In
24 general, the development of the digital economy is reflected not only in the expansion
25 of digital industries themselves, but also in the digital transformation of traditional
26 industries. Through digital industrialization and industrial digitalization, the digital
27 economy can improve information transmission efficiency, optimize resource
28 allocation, promote technological innovation and industrial structure upgrading, and
29 further affect energy utilization efficiency and environmental governance in economic
30 activities (Wang and Shao, 2023; Maiurova *et al.*, 2022). Therefore, under the
31 background of green and low-carbon development, the digital economy has gradually
32 become an important factor in improving industrial carbon emission efficiency (Dong
33 and Zhang, 2023).

34 For marine fisheries, production activities involve multiple stages, including
35 capture, aquaculture, processing, circulation, and management. These activities are
36 characterized by strong resource dependence, wide spatial distribution, and relatively
37 distinct energy consumption. With the development of smart fishery technologies, such
38 as the Internet of Things, big data, artificial intelligence, multi-source sensing, and
39 digital management have gradually been applied to breeding, aquaculture, resource

conservation, capture, and processing, which helps improve fishery production efficiency and promote the modernization of fisheries (Liu and Liu, 2025). Therefore, digital economy development may support the transformation of marine fisheries from traditional extensive production toward intelligent, refined, and green development. First, the digital economy can improve through technological progress. Digital monitoring and management technologies can improve production decisions, reduce monitoring costs, strengthen resource protection, and lower resource waste and energy consumption. Meanwhile, digital training can enhance fishers' ability to adopt advanced technologies and provide human capital support for the digital transformation of fisheries (Li and Wei, 2025). Second, the digital economy can improve MFCEE through the resource allocation optimization. In traditional marine fishery production, problems such as information asymmetry, delayed market response, and imbalanced allocation of production factors may lead to resource mismatch, repeated input, and energy waste. The development of the digital economy can strengthen information sharing and data flows, improve the matching among fishery production, market demand, logistics circulation, and management decisions, and promote the more reasonable allocation of capital, labor, technology, energy, and fishery resources across different regions and production links. Previous studies have also emphasized that optimizing the allocation of fishery production factors is important for improving the green total factor productivity and high-quality development of marine fisheries (Fu *et al.*, 2023). Third, the digital economy can improve MFCEE through industrial structure optimization and green transformation. With the improvement of digitalization, the development of marine fisheries is no longer limited to traditional capture and aquaculture activities, but gradually extends toward the coordinated development of processing, cold-chain logistics, market circulation, fishery services. Existing studies have emphasized that green technological progress and the optimization of production factor allocation are important for improving the green development level of aquaculture (Yang *et al.*, 2023).

Based on this analysis, this study proposes the following hypothesis:

Hypothesis 1. The development of the digital economy exerts a positive effect on MFCEE.

The digital economy has strong cross-regional permeability and information diffusion capacity, which can, to some extent, break through the constraints of traditional geographical boundaries on the flow of knowledge, technology, and information. This helps reduce interregional information transmission costs and strengthen the connections among regional economic activities (Shahnazi, 2021; Zhou *et al.*, 2024). With the continuous improvement of digital infrastructure, digital platforms, and information networks, digital technologies, management experience, and green production models can spread more easily across regions. Therefore, the influence of the digital economy may not be limited to the local region, but may

1 generate spatial spillover effects on neighboring regions through interregional linkages
2 (Liu *et al.*, 2022; Sergio *et al.*, 2023). Meanwhile, the digital economy is characterized
3 by replicability, strong permeability, and instantaneous dissemination, which can form
4 certain economic synergies among different regions, thereby making its impact on
5 carbon emission efficiency spatially transmissible (Yang and Zhao, 2024).

6 For marine fisheries, coastal provinces are connected in terms of fishery resource
7 utilization, industrial chain division, technology application, market circulation,
8 processing trade, and policy implementation. Marine fishery production is not a
9 completely isolated regional activity. Capture fisheries, aquaculture, processing, cold-
10 chain logistics, and aquatic product trade often involve cross-regional coordination
11 beyond administrative boundaries. The improvement of digital economy development
12 in one region may affect marine fishery production modes and resource utilization
13 efficiency in surrounding regions through information sharing, technology diffusion,
14 industrial coordination, and policy learning, thereby influencing MFCEE in
15 neighboring regions. Existing studies have also found that the digital economy has
16 significant spatial effects on urban carbon emissions, and its spillover effects may differ
17 across regions (Xu *et al.*, 2022).

18 Specifically, the spatial impact of the digital economy may be reflected in two
19 aspects: spillover effects and siphon effects. On the one hand, when spillover effects
20 dominate, digital infrastructure construction, smart fishery technologies, digital
21 management platforms, and green production experience can diffuse among
22 neighboring coastal provinces. This may help surrounding regions improve marine
23 fishery production organization and resource utilization efficiency, thereby enhancing
24 their carbon emission efficiency. On the other hand, when siphon effects dominate,
25 regions with higher levels of digital economy development may attract talent, capital,
26 technology, and data resources from surrounding regions, leading digital resources to
27 concentrate in advantaged regions and weakening the digital transformation and low-
28 carbon development capacity of neighboring regions (Sun and Kim, 2021; Cheng *et al.*,
29 2023). These findings suggest that the spatial impact of the digital economy on MFCEE
30 may not be unidirectional, but may be influenced by regional development stages,
31 digital foundations, industrial structure, and the strength of spatial correlation.

32 Therefore, when analyzing the impact of the digital economy on MFCEE, it is
33 necessary to further consider spatial correlation and spatial spillover effects.

34 Based on the above analysis, this study proposes the following hypothesis:

35 **Hypothesis 2. The development of the digital economy has spillover effects on the**
36 **carbon emissions efficiency of marine fisheries across neighboring regions.**

37
38 The impact of the digital economy on MFCEE may not be completely consistent
39 across all regions and industrial structures. Existing studies have shown that the effects
40 of the digital economy on carbon emission performance, carbon efficiency, and carbon

reduction performance are influenced by regional development levels, resource endowments, industrial foundations, and policy environments, showing a certain degree of regional heterogeneity (Zhang *et al.*, 2022; Lv *et al.*, 2025; Yu, 2024).

For marine fisheries, coastal provinces differ in economic development levels, digital infrastructure, technological absorption capacity, fishery resource endowments, and industrial structures. Related studies have found that China's provincial total carbon emission efficiency of fishery shows distinct spatial temporal differentiation, MFCEE also exhibits significant spatial and regional heterogeneity, and marine fishery eco-efficiency presents significant spatiotemporal evolution characteristics and regional differences (Li *et al.*, 2018; Di *et al.*, 2023). This indicates that differences in fishery development foundations, economic development levels, and carbon reduction conditions across regions may further affect the role of the digital economy.

From the perspective of regional differences, regions with higher economic development levels and more complete digital infrastructure usually have stronger technological absorption capacity, industrial transformation capacity, and green governance capacity. In such regions, the digital economy is more likely to be integrated with marine fishery production, processing, circulation, and management, thereby more effectively promoting the improvement of MFCEE. In contrast, in regions with relatively weak digital foundations, insufficient technological application capacity, or limited conditions for industrial transformation, the role of the digital economy in promoting low-carbon development in marine fisheries may be constrained to some extent. Therefore, the impact of the digital economy on MFCEE may exhibit regional heterogeneity.

From the perspective of marine fishery industrial structure, the development priorities of marine fisheries differ across provinces. Some regions are dominated by marine capture fisheries, while others rely more on mariculture, aquatic product processing, or related services. Existing studies have shown that embodied carbon emissions in China's fishery production system exhibit structural differences across different industrial sectors. The primary fishery industry has long accounted for the major share of embodied carbon emissions in fishery production system, while the proportions of embodied carbon emissions from the secondary and tertiary fishery industries have also changed over time (Li *et al.*, 2021). This suggests that different fishery industrial structures correspond to different energy consumption patterns, carbon emission sources, and emission reduction potentials; therefore, the pathways and intensity through which the digital economy plays a role may also differ.

Therefore, the impact of the digital economy on MFCEE may show heterogeneity due to differences in regional development conditions and marine fishery industrial structures.

Given this analysis, this study proposes the following hypothesis:

Hypothesis 3. The impact of digital economy on MFCEE varies across

geographical locations and production structures.

Methods

Variable construction and measurement

Marine fishery carbon emission efficiency (MFCEE)

In this study, marine fishery carbon emissions are calculated for 11 coastal provinces in China from the perspective of the marine fishery production process. Based on the research by He *et al.* (2026), marine fishery carbon emissions are measured by the fuel consumption of marine fishing vessels, the fuel consumption of mariculture vessels, and electricity consumption during aquaculture production. To further evaluate MFCEE, this study employs the super-efficiency SBM model with undesirable outputs proposed by Tone and Tsutsui (2010); Zhang *et al.* (2024). The detailed input-output indicator system is provided in Supplementary Table S1. The super-efficiency SBM model with undesirable outputs can be written as:

$$\rho = \min \frac{\frac{1}{m} \sum_{i=1}^m \frac{\bar{x}}{x_{ik}}}{\frac{1}{q1 + q2} (\sum_{s=1}^{q1} \frac{\bar{y}^d}{y_{sk}^d} + \sum_{t=1}^{q2} \frac{\bar{y}^u}{y_{tk}^u})} \quad (1)$$

$$s. t. \begin{cases} \bar{x} \geq \sum_{j=1, j \neq k}^n \phi_j x_{ij}, i = 1, 2, \dots, m \\ \bar{y}^d \leq \sum_{j=1, j \neq k}^n \phi_j y_{sj}^d, s = 1, 2, \dots, q1 \\ \bar{y}^u \geq \sum_{j=1, j \neq k}^n \phi_j y_{tj}^u, t = 1, 2, \dots, q2 \\ \bar{x} \geq x_k, \bar{y}^d \leq y_k^d, \bar{y}^u \geq y_k^u, \phi_j \geq 0 \end{cases} \quad (2)$$

where ρ denotes the MFCEE value of each decision-making unit (DMU), and its value may exceed 1 in the super-efficiency SBM model. n represents the number of DMUs, with the marine fishery sector of each coastal province regarded as one DMU. The model includes three components: inputs (m), desirable outputs ($q1$), and undesirable outputs ($q2$). Specifically, x denotes the elements of the input matrix, y^d denotes the elements of the desirable output matrix, and y^u denotes the elements of the undesirable output matrix. In addition, $\bar{x}$, $\bar{y}^d$, and $\bar{y}^u$ represent the slack-related variables corresponding to inputs, desirable outputs, and undesirable outputs, respectively. The

super-efficiency SBM model with undesirable outputs is suitable for this study because it can incorporate undesirable outputs into the efficiency evaluation framework, effectively address the slackness problem, and further rank efficient DMUs with efficiency scores greater than 1. Therefore, it provides a more accurate measurement of MFCEE (Zhou *et al.*, 2019).

In the baseline model, total marine fishery carbon emissions are used as the undesirable output. For robustness testing, net carbon emissions are further used as an alternative undesirable output to re-measure MFCEE (Gao *et al.*, 2024). Net carbon emissions are calculated as total marine fishery carbon emissions minus carbon sinks generated from algae and shellfish mariculture (Wang and Feng, 2023).

Digital economy index (DEI)

The level of digital economy development is used as the core explanatory variable in this study. Based on previous studies and data availability, this paper constructs a digital economy development comprehensive index from three dimensions: Internet development, digital innovation capability, and digital finance (Ma *et al.*, 2025; Zhang and Avas, 2026; Zhou *et al.*, 2024). In Table S2 in Supplementary, we construct the digital economy development evaluation indicators.

To measure the digital economy development level of China's 11 coastal provinces from 2011 to 2023, this study uses the entropy method to construct the comprehensive index of the digital economy (Chen *et al.*, 2023). In this paper, the comprehensive digital economy index is denoted as DEI. The main steps of the entropy method are as follows:

First, the data are standardized.

$$Y_{ij} = \begin{cases} \frac{X_{ij} - \min(X_{ij})}{\max(X_{ij}) - \min(X_{ij})}, & \text{Positive indicators} \\ \frac{\max(X_{ij}) - X_{ij}}{\max(X_{ij}) - \min(X_{ij})}, & \text{Negative indicators} \end{cases} \quad (3)$$

Where i denotes the sample observation of each province in a given year, j denotes the indicator. X_{ij} Y_{ij} denote the indicator values before and after standardization, respectively.

Second, the information entropy of each indicator is calculated.

$$E_j = -\frac{1}{\ln n} \sum_{i=1}^n [(Y_{ij} / \sum_{i=1}^n Y_{ij}) \times \ln \frac{Y_{ij}}{\sum_{i=1}^n Y_{ij}}] \quad (4)$$

Third, the weight of each indicator is determined.

$$W_j = (1 - E_j) / \sum_{j=1}^m (1 - E_j) \quad (5)$$

Finally, the comprehensive evaluation index is obtained.

$$DEI_{ij} = \sum_{j=1}^n (W_j \times Y_{ij}) \quad (6)$$

Meanwhile, the entropy value TOPSIS method is employed to reconstruct the digital economy development index for robustness test (Wang *et al.*, 2024)

Control variables

Referring to related studies, this study selects six control variables: The level of economic development is measured by the disposable income of the population (Zhang *et al.*, 2025). Industrial structure is represented by the ratio of the output value of the tertiary sector of marine fisheries to the total output value of marine fisheries (Zheng and Dai, 2019). Environmental regulation is measured by the ratio of investment in environmental pollution control to GDP (Xu and Ji, 2023). Marine fishery production scale is measured by total marine fishery production (Zhang *et al.*, 2020). Technological innovation is proxied by aquatic technology extension expenditure (Wang and Yuan, 2023). Opening-up is measured by the ratio of marine fishery import and export trade to the total output value of the fishery economy (Zhang, 2021). The variable definitions and measurements are shown in Table 1.

Data sources

In this study, data for 11 coastal provinces in China from 2011 to 2023 were collected, including Northern region (Tianjin, Hebei, Liaoning, Shandong); Eastern region (Jiangsu, Zhejiang, Shanghai); Southern region (Guangdong, Guangxi, Hainan, and Fujian). Specifically, data related to marine fisheries, the digital economy, and control variables were mainly obtained from the China Fishery Statistical Yearbook, the China Statistical Yearbook, and the China Environmental Statistical Yearbook. The China Digital Inclusive Finance Index was obtained from the Institute of Digital Finance Peking University, and Ant Financial Services Group. In terms of data processing, missing values were filled using linear interpolation, and all price-related variables were adjusted to 2011 as the base year. Some variables were logarithmically transformed to reduce data fluctuations and improve data stability. The descriptive statistics of the variables are shown in Table 2.

Table 1 Variable definitions and measurements

Variable type	Variable name	Variable symbols	Description
Explained variable	Marine fishery	<i>MFCEE</i>	Super-efficiency

Explanatory variable	carbon emission efficiency		<i>DEI</i>	SBM model calculation
	Digital economy			Entropy value method calculation
	The level of economic development			Per capita income of fishermen
Control variable	Marine fishery industrial structure		<i>STRU</i>	Tertiary sector output value of marine fisheries to total marine fishery output value
	Environmental regulation			Ratio of investment in environmental pollution control to GDP
	Marine fishery production scale			Total marine fishery production
	Technological innovation		<i>TI</i>	Expenditure on aquatic technology extension
	Opening-up			Ratio of marine fishery import and export trade to the total output value of the fishery economy

Table 2 Descriptive statistics of variables

Variable type	Symbols	Obs.	Mean	Std. Dev.	Min	Max
Explained variable	<i>lnMFCEE</i>	143	0.422	00.147	0.148	0.744
Explanatory variable	<i>lnDEI</i>	143	0.273	00.151	0.027	0.608
	<i>lnFS</i>	143	130.952	10.959	90.169	150.82
	<i>lnED</i>	143	90.885	00.310	90.125	100.422
Control variable	<i>lnSTRU</i>	143	0.160	00.110	0.002	0.395
	<i>lnER</i>	143	0.643	00.235	0.252	10.638
	<i>lnTI</i>	143	90.064	10.035	50.962	100.67
	<i>Open</i>	143	0.330	00.672	0.011	30.758

Evolutionary characteristics of MFCEE and the digital economy development

To further examine the dynamic changes and distribution characteristics of MFCEE and the digital economy development, this section conducts a visual analysis based on the sample data of 11 coastal provinces in China from 2011 to 2023. Specifically, dual-axis line charts are used to describe the temporal changes in the average levels of the two variables, while 3D kernel density estimation is applied to reveal their distribution dynamics and regional differences. Through these analyses, this section provides a preliminary understanding of the changing patterns of MFCEE and digital economy development, laying a foundation for the subsequent empirical analysis.

Figure 1 shows the temporal evolution of the mean values of MFCEE and the (DEI) in China's coastal provinces from 2011 to 2023. Overall, both MFCEE and DEI show an upward trend during the study period, indicating that MFCEE and digital economy development have improved simultaneously in coastal regions. Specifically, the mean MFCEE increased from a relatively low level in 2011 to a higher level in 2023. Although a slight decline occurred around 2020, the overall trend remained upward, suggesting a continuous improvement in the coordination between marine fishery production and carbon emission reduction. The mean DEI also increased steadily throughout the sample period, with a more pronounced growth after 2017, reflecting improvements in internet development, digital innovation capability, and digital finance in coastal provinces. The shaded areas represent one standard deviation above and below the annual mean values. The relatively wide shaded areas indicate that there are still distinct interprovincial differences in both MFCEE and DEI. In particular, the dispersion of MFCEE is relatively large in some years, suggesting that the improvement of MFCEE is uneven across coastal provinces. Similarly, the widening shaded area of DEI in the later period implies that digital economy development has improved overall, but regional disparities remain.

Figure 2 shows the three-dimensional kernel density evolution of MFCEE and DEI in China's 11 coastal provinces from 2011 to 2023. The distribution of MFCEE gradually shifts to the right, indicating an overall improvement in MFCEE. However, the relatively dispersed distribution suggests that interprovincial differences still exist. Similarly, the distribution of DEI also moves toward higher values over time, reflecting the continuous improvement of digital economy development in coastal provinces. Nevertheless, the density surface shows certain fluctuations and dispersion, implying that regional differences in digital economy development remain among coastal provinces. Overall, the results show that both MFCEE and DEI improved during the study period, but their regional differences have not been completely eliminated

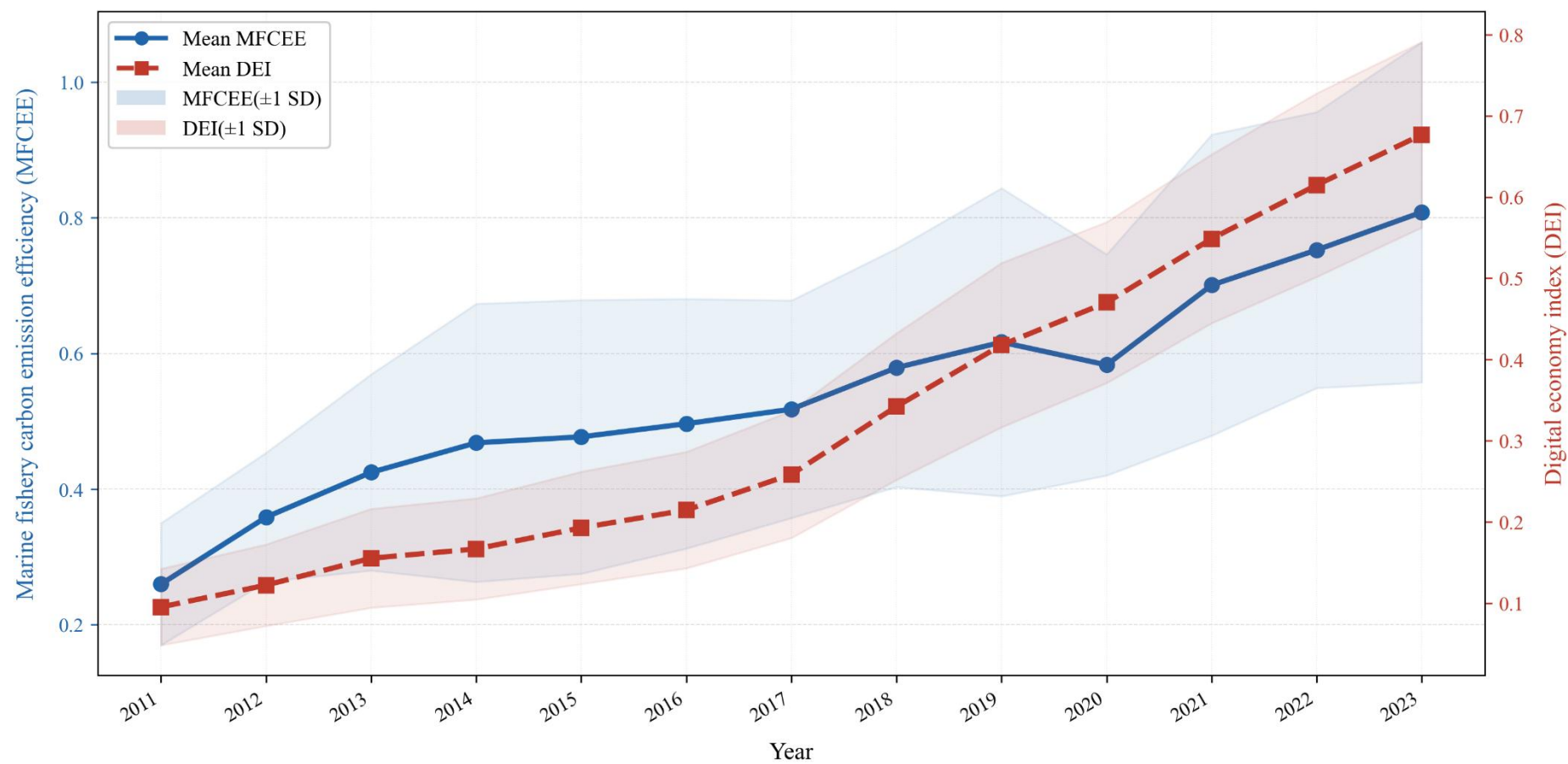


Figure 1 Temporal evolution of MFCEE and DEI in China's coastal provinces (2011–2023)

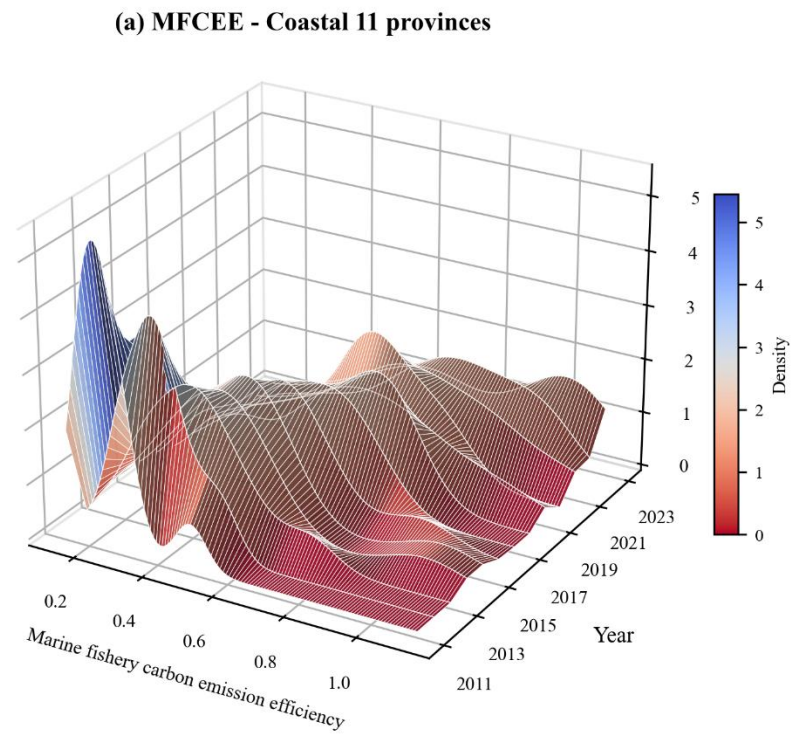
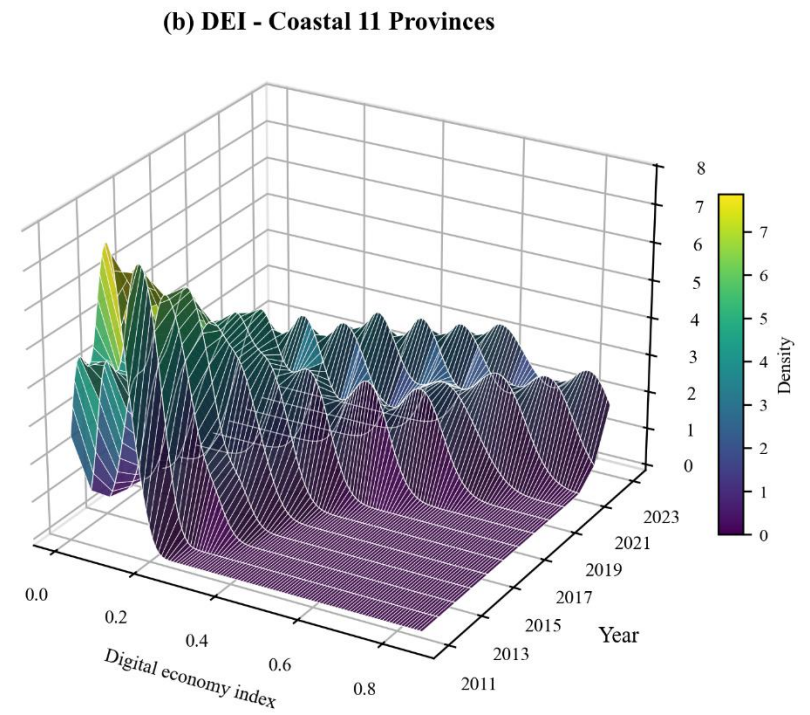


Figure 2 3D kernel density evolution of MFCEE and DEI in China's coastal provinces (2011-2023)

1 Econometric model specification

2 Baseline regression model

3 To examine the impact of digital economy development on MFCEE, this study
4 constructs a baseline regression model. The model is specified as follows:

$$\ln MFCEE_{it} = \alpha + \beta \ln DEI_{it} + \theta Controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (7)$$

5
6 Where $MFCEE_{it}$ denotes MFCEE of province i in year t . DEI_{it} represents the level of
7 digital economy development in province i in year t . $Controls_{it}$ is a series of control
8 variables. μ_i denotes individual fixed effects. δ_t denotes time fixed effects. ε_{it} is the
9 random error term.

11 Spatial spillover effect model

12 Considering the potential spatial association among coastal provinces, MFCEE
13 may not be independent across regions. According to the theoretical analysis and
14 research hypothesis proposed above, the development of the digital economy may not
15 only affect local MFCEE, but may also generate spatial spillover effects on neighboring
16 regions. Therefore, this study adopts a spatial econometric model to examine the
17 relationship between digital economy index and MFCEE. The spatial econometric
18 models include the spatial error model, spatial lag model, and Spatial Durbin Model
19 (SDM). Based on the results of the LM test and related model selection tests, this study
20 selects the SDM, which can simultaneously consider the spatial lag of the dependent
21 variable and the autocorrelation of the spatial error term (Ma *et al.*, 2025). The model
22 is specified as follows:

$$\ln MFCEE_{it} = \alpha + \rho W \ln MFCEE_{it} + \beta_1 \ln DEI_{it} + \beta_2 W \ln DEI_{it} \\ + \theta_1 Controls_{it} + \theta_2 W Controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (8)$$

24
25 Where W is the spatial weight matrix, $W \times \ln MFCEE_{it}$ represents the spatial lag term
26 of MFCEE, and $W \times \ln DEI_{it}$ denotes the spatial lag term of the DEI. ρ is the spatial
27 autoregressive coefficient, β_1 and β_2 denote the coefficients of the DEI and its spatial
28 lag term, respectively, θ_1 and θ_2 denote the coefficient vectors of the control variables
29 and their spatial lag terms, respectively.

30 Regarding the selection of spatial weight matrices, this study refers to previous
31 literature and considers the possible spatial correlation of marine fishery carbon
32 emission among coastal provinces (Zheng *et al.*, 2023; Zhou *et al.*, 2024; Wang *et al.*,
33 2024). In addition, coastal provinces may also be spatially associated due to
34 geographical proximity and similarity in economic development levels. Considering
35 the unbalanced economic development among coastal provinces, an asymmetric
36 economic-geographical nested matrix is further constructed to better reflect the

direction and intensity of interregional spatial interactions (Chen et al., 2022).

Therefore, this study constructs four spatial weight matrices to capture different forms of spatial dependence and to test the robustness of the spatial econometric results.

The matrices are presented as follows:

$$W_1 = \begin{cases} 1/d_{ij} & i \neq j \\ 0 & i = j \end{cases} \quad (9)$$

$$W_2 = \begin{cases} 1/d_{ij}^2 & i \neq j \\ 0 & i = j \end{cases} \quad (10)$$

Where d_{ij} denotes the geographical distance between the capital cities of province i and province j , calculated based on their longitude and latitude coordinates. Compared with W_1 , W_2 is constructed using the inverse squared geographical distance.

$$W_3 = W_1 \times \text{diag}(\frac{\bar{y}_1}{\bar{y}}, \frac{\bar{y}_2}{\bar{y}}, \dots, \frac{\bar{y}_i}{\bar{y}}) \quad (11)$$

$$W_4 = W_2 \times \text{diag}(\frac{\bar{y}_1}{\bar{y}}, \frac{\bar{y}_2}{\bar{y}}, \dots, \frac{\bar{y}_i}{\bar{y}}) \quad (12)$$

Where $\text{diag}(\frac{\bar{y}_1}{\bar{y}}, \frac{\bar{y}_2}{\bar{y}}, \dots, \frac{\bar{y}_i}{\bar{y}})$ is the diagonal matrix, $\bar{y}_i$ is the average per capita GDP of province i during the sample period, $\bar{y}$ is the average GDP per capital of all sample provinces.

Before applying the spatial econometric model, this study first employs Moran's I to examine the spatial autocorrelation of MFCEE and the DEI (Chen and Wang, 2022). The calculation formula is expressed as follows:

$$\text{Moran's } I = \frac{n}{\sum \sum w_{ij}} \times \frac{\sum \sum w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum (x_i - \bar{x})^2} \quad (13)$$

Where x_i, x_j represent the observed value of the MFCEE or DEI in region i and j , $\bar{x}$ represents the mean value of the MFCEE or DEI, w_{ij} is the element of spatial weight matrix W , reflecting the spatial association between region i and j .

Results

Baseline regression results

Before conducting the baseline regression, this study uses the variance inflation factor (VIF) to test for multicollinearity among all variables. The results are presented in Table S3 in Supplementary.

The baseline regression results for the impact of digital economy development on MFCEE are presented in Table 3. Columns (1)-(7) gradually add control variables, while province fixed effects and year fixed effects are controlled in all models. The coefficient of core explanatory variable is positive and statistically significant in all specifications. After gradually adding marine fishery production scale, the level of economic development, Marine fishery industrial structure, environmental regulation, technological innovation, opening-up, the coefficient of *lnDEI* remain significantly positive, suggesting that the baseline regression results are robust. Specifically, after controlling for all control variables and two-way fixed effects, the coefficient of core explanatory variable (*lnDEI*) in column (7) is 1.077 and significant at the 1% level. This indicates that digital economy development has a positive promoting effect on MFCEE. In other words, the development of the digital economy can effectively promote the improvement of MFCEE. Therefore, Hypothesis 1 is verified.

Robustness tests

To verify the robustness of the baseline results, this study conducts two robustness tests. First, MFCEE is re-estimated using net carbon emissions, rather than total carbon emissions, as undesirable output. Second, the digital economy development index is reconstructed using the entropy-TOPSIS method instead of the entropy-weight method. The results remain consistent with the baseline finding, indicating that the main conclusions are robust. Detailed results are presented in Supplementary Tables S4-S5.

Table 3 Baseline regression results.

Variables	<i>lnMFCEE</i>						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>lnDEI</i>	0.737** (0.291)	0.989*** (0.307)	1.132*** (0.266)	1.184*** (0.264)	1.171*** (0.285)	1.065*** (0.263)	1.077*** (0.262)
<i>lnFS</i>		0.203*** (0.059)	0.170*** (0.062)	0.183*** (0.060)	0.183*** (0.060)	0.179*** (0.058)	0.252*** (0.058)
<i>lnED</i>			0.177** (0.080)	0.161* (0.082)	0.158* (0.081)	0.167** (0.084)	0.183** (0.086)
<i>lnSTRU</i>				-0.131 (0.151)	-0.132 (0.151)	-0.186 (0.151)	-0.146 (0.154)
<i>lnER</i>					0.007 (0.035)	0.001 (0.033)	-0.002 (0.032)
<i>lnTI</i>						0.047*** (0.015)	0.045*** (0.015)
<i>Open</i>							0.042* (0.025)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143	143	143	143	143	143	143
R-squared	0.826	0.854	0.861	0.862	0.862	0.874	0.879

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. The standard errors are in parentheses.

Endogeneity test

The baseline regression results in the previous section may be affected by potential endogeneity problems. First, there may be reverse causality between digital economy development and MFCEE. Specifically, the improvement of MFCEE may also promote the development of the digital economy, which may lead to biased estimation results. Second, although this study has controlled a series of influencing factors in the model specification, unobservable omitted variables or model specification bias may still exist, thereby causing endogeneity problems. To alleviate the above potential endogeneity concerns, this study further adopts two approaches. First, the one-period and two-period lagged terms of the core explanatory variable are used for regression analysis (Yin *et al.*, 2025). Since the one-period and two-period lagged digital economy development levels preceded current MFCEE in time, this method can reduce the potential influence of reverse causality on the estimation results to some extent. Second, following the approach of related studies (Hu and Shen, 2023; Huang *et al.*, 2019), this study constructs an instrumental variable and applies the two-stage least squares (2SLS) method. Specifically, the interaction term between the number of post offices per million people in 1984 and the one-period lagged Internet penetration rate is used as the instrumental variable for digital economy development. The results are listed in Tables S6-S7 in Supplementary.

Spatial spillover effect analysis

Spatial correlation test and model selection

To examine the spatial spillover effect of digital economy development on MFCEE, this study first uses global Moran's I to test whether spatial correlation exists between DEI and MFCEE before conducting the spatial econometric analysis. The results are presented in Table 4. The global Moran's I indices of MFCEE and DEI indicate certain spatial correlation characteristics during the sample period. Specifically, the Moran's I value of MFCEE are mainly negative from 2011 to 2019, suggesting that MFCEE exhibits a certain negative spatial correlation among coastal provinces in the early period. This implies that high-efficiency and low-efficiency regions tend to be spatially adjacent. After 2020, the Moran's I value of MFCEE gradually turn positive, indicating that the spatial distribution pattern of MFCEE has changed over time and has begun to show a certain positive spatial clustering trend in the later period. In contrast, the global Moran's I value of DEI are positive throughout 2011-2023, and most of them pass the significance test. This suggests that digital economy development among coastal provinces exhibits relatively stable positive spatial correlation, indicating that regions with higher digital economy development levels are more likely to be adjacent to regions with similar development levels. Overall, both MFCEE and DEI show certain spatial correlation characteristics, indicating the necessity of considering spatial dependence when examining the impact of digital economy development on MFCEE.

During the model selection stage, this study further conducts a series of spatial econometric model tests, as shown in Table S8 in Supplementary.

Estimation results of the Spatial Durbin Model (SDM)

The estimation results of spatial regressions are shown in Table 5, which presents the SDM estimation results and spatial effect decomposition under four spatial weight matrices. The results show that the coefficients of *lnDEI* are significantly positive under all four spatial weight matrices, indicating that digital economy development significantly improves local MFCEE. Specifically, the coefficients of *lnDEI* under W1-W4 are 1.073, 0.839, 1.152, and 0.930, respectively, suggesting that the positive effect of DEI on MFCEE is relatively stable across different spatial weight settings.

In addition, the coefficients of $W * \ln DEI$ are also significantly positive across the four spatial weight matrices, indicating that DEI in neighboring regions has a positive impact on local MFCEE. This suggests that digital economy development not only improves local MFCEE but also generates significant spatial spillover effects.

The effect decomposition results further support this finding. The direct effects of *lnDEI* are significantly positive under all spatial weight matrices, indicating that DEI directly promotes the improvement of local MFCEE. Meanwhile, the indirect effects are also positive and significant at the 1% level, suggesting that DEI can improve MFCEE in neighboring regions through spatial spillover channels. The total effects are also significantly positive, further confirming the overall positive impact of digital economy development on MFCEE.

It is worth noting that the spatial autoregressive coefficient ρ is negative under all four matrices and significant under W1 and W3, suggesting that MFCEE may exhibit a certain degree of spatial competition or differentiation among coastal provinces. However, this does not change the main conclusion, as the direct, indirect, and total effects of digital economy development remain significantly positive across different spatial weight matrices. Therefore, DEI not only improves local MFCEE but also promotes efficiency improvement in neighboring regions through spatial spillover effects. Thus, Hypothesis 2 is supported.

Table 4 Moran's I index of MFCEE and DEI

MFCEE		DEI					
Year	Moran's I	Year	Moran's I	Year	Moran's I	Year	Moran's I
2011	-0.231*	2018	-0.098	2011	0.051*	2018	0.147**
2012	-0.233*	2019	-0.253**	2012	0.065*	2019	0.153**
2013	-0.270**	2020	0.048*	2013	0.092**	2020	0.092*
2014	-0.254**	2021	-0.218*	2014	0.093**	2021	0.053*
2015	-0.256**	2022	0.077**	2015	0.138**	2022	0.063*
2016	-0.28**	2023	0.108**	2016	0.139***	2023	0.080*
2017	-0.191			2017	0.155***		

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively

Table 5 Estimation results of SDM

	(1)	(2)	(3)	(4)
	W1(SDM)	W2(SDM)	W3(SDM)	W4(SDM)
Main	1.073***	0.839***	1.152***	0.930***
<i>lnDEI</i>	(4.70)	(3.50)	(5.00)	(3.91)
W _X	4.171***	2.123***	4.198***	2.115***
W* <i>lnDEI</i>	(4.95)	(4.55)	(4.77)	(4.46)
	0.927***	0.811***	1.038***	0.923***
Direct effect	(3.77)	(3.27)	(4.32)	(3.83)
	3.080***	1.964***	3.261***	2.026***
Indirect effect	(3.95)	(4.21)	(3.80)	(4.10)
	4.007***	2.774***	4.299***	2.950***
Total effect	(5.15)	(6.03)	(4.94)	(5.83)
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	143	143	143	143
	-0.339*	-0.079	-0.272*	-0.043
Spatial-rho	(-1.88)	(-0.76)	(-1.65)	(-0.44)
	0.002***	0.002***	0.002***	0.002***
sigma2-e	(8.38)	(8.45)	(8.40)	(8.45)

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. z statistics are in parentheses.

Heterogeneity analysis

To further examine whether the impact of DEI on MFCEE varies across geographical location and marine fishery production structures, this study conducts heterogeneity analysis from two perspectives: regional heterogeneity and capture-dependence level heterogeneity.

Regional heterogeneity

There are significant regional differences in MFCEE and DEI across coastal provinces. Based on geographical location, this study divides the 11 coastal provinces into three groups: northern, eastern, and southern regions. To avoid the statistical instability and reduced degree of freedom associated with running separate regressions on small regional subsamples, which contain only three or four provinces each, this study adopts the interaction-term approach proposed by Ding *et al.* (2025). Specifically, we introduce interaction terms between regional dummy variables and digital economy development into the full-sample model. Specifically, the northern region is used as the benchmark group. Two regional dummy variables $East_i$ and $South_i$ are constructed for the eastern and southern regions, respectively. Their interaction terms with digital economy development, namely $lnDEI \times East_i$ and $lnDEI \times South_i$ are then included in the model. In this specification, $lnDEI$ captures the effect of DEI on MFCEE in the northern region, while the two interaction terms capture the differences in the effects for the eastern and southern regions relative to the northern region.

Column (1)-(3) of Table 6 present the results of regional heterogeneity analysis. Based on the estimated coefficients of the interaction-term model, the effects of digital economy development on MFCEE are -0.166, 0.381, and 0.323 for the northern, eastern, and southern regions, respectively. However, none of these region-specific effects is statistically significant, indicating that the within-region effects are not sufficiently stable in statistical terms. Nevertheless, the inter-group difference tests provide further evidence of regional heterogeneity. The difference between the eastern and northern regions is statistically significant ($F=17.29$, $p=0.0001$), and the difference between the southern and northern regions is also significant ($F=14.80$, $p=0.0002$). In addition, the joint Wald test of the regional interaction terms is significant ($F=9.36$, $p=0.0002$), confirming the existence of regional heterogeneity in the effect of digital economy development on MFCEE. By contrast, the difference between the eastern and southern interaction coefficients is insignificant ($F=0.38$, $p=0.5410$), suggesting that the heterogeneity mainly arises from the differences between the northern region and the other two regions, rather than from a significant difference between the eastern and southern regions.

Overall, the results indicate that the effect of DEI on MFCEE is regionally uneven. Compared with the northern region, the estimated effects are higher in the eastern and southern regions. However, since the region-specific effects are not statistically

significant, the results should be interpreted as evidence of relative regional differences rather than strong within-region promoting effects.

Heterogeneity by marine capture-dependence level

In this study, marine fishery production structure refers to the composition of marine fishery production activities across different production types, specifically the relative shares of marine capture and mariculture in total marine fishery production. Since marine capture and mariculture differ substantially in production methods, energy-use patterns, and carbon emission sources, the effect of DEI on MFCEE may vary across provinces with different production structures. Therefore, this study uses the share of marine capture production in total marine fishery production to measure marine capture-dependence level.

In this study, marine capture-dependence level is measured by the share of marine capture production in total marine fishery production. For each province, the average capture share over the sample period is calculated to reflect its overall production structure. Provinces with an average capture share above the median are classified as high capture-dependence regions, while those below the median are classified as low capture-dependence regions. Based on this classification, this study examines whether the effect of DEI on MFCEE differs between high and low capture-dependence regions.

As shown in columns (4) and (5) of Table 6, the results present clear heterogeneity across different marine fishery production structures. In low capture-dependence regions, the coefficient of DEI is significantly positive at the 1% level, with a coefficient of 1.756 and a t-statistic of 7.58. This indicates that DEI significantly improves MFCEE in regions where marine fisheries are relatively less dependent on capture production. In contrast, in high capture-dependence regions, the coefficient of DEI is negative but statistically insignificant, with a coefficient of -0.729 and a t-statistic of -0.90. This suggests that the positive effect of DEI on MFCEE is not evident in regions with relatively high dependence on marine capture production. The number of observations is 65 for the low capture-dependence group and 78 for the high capture-dependence group, with R-squared values of 0.970 and 0.823, respectively.

This difference may be related to the characteristics of different marine fishery production structures. In low capture-dependence regions, marine fishery production is more closely associated with mariculture and related modernized production activities. Digital technologies can be more easily applied to production monitoring, resource allocation, energy management, and efficiency improvement. Therefore, DEI is more likely to be transformed into improvements in carbon emission efficiency. By contrast, high capture-dependence regions rely more heavily on fishing vessels, fuel consumption, and offshore fishing operations. In these regions, digital technologies may be more closely related to improving fishing information acquisition, expanding operational capacity, or enhancing fishing intensity, rather than directly improving

1 carbon emission efficiency. As a result, the efficiency-enhancing effect of DEI may be
2 weaker in high capture-dependence regions.

3 Overall, the heterogeneity results show that the effect of DEI on MFCEE varies
4 across geographical locations and capture-dependence levels. From the perspective of
5 geographical location, although the region-specific effects are not individually
6 significant, the Wald tests indicate significant differences between the eastern and
7 northern regions and between the southern and northern regions. This suggests that the
8 impact of DEI on MFCEE differs across coastal regions. From the perspective of
9 capture-dependence level, DEI significantly improves MFCEE in the low capture-
10 dependence group, while its effect is not statistically evident in the high capture-
11 dependence group. These findings indicate that the effect of DEI on MFCEE is shaped
12 by both regional conditions and marine fishery production structure. Therefore,
13 Hypothesis 3 is verified.

14 It should be noted that the sample size of this study is relatively limited, as the
15 analysis is based on 11 coastal provinces in China. After further dividing the sample by
16 geographical location or capture-dependence level, the number of observations within
17 each group becomes smaller. Consequently, the heterogeneity findings should be
18 interpreted with caution due to the constraints of a relatively small sample size. Further
19 studies should validate these insights by utilizing extended time-series data or highly
20 disaggregated, fine-grained datasets.

21

Table 6 Heterogeneity analysis results

Variables	(1)	(2)	(3)	(4)	(5)
	Geographical location			Marine capture-dependence level	
	Northern	Eastern	Southern	Low	High
<i>lnDEI</i>	-0.166(-0.37)	0.381(1.11)	0.323(0.89)	1.756*** (7.58)	-0.729 (-0.90)
Controls	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	143	143	143	65	78
R-squared	0.911	0.911	0.911	0.976	0.823
East = North	17.29***				
South = North	14.80***				
Joint test of regional interaction terms	9.36***				
Test: Eastern = Southern	0.38				

Notes: Robust t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Columns (1)-(3) report the heterogeneity results by geographical location, and columns (4)-(5) report the heterogeneity results by capture-dependence level. The bottom rows report F-statistics from Wald tests for regional differences.

1 **Conclusions and policy implications**

2 **Conclusions**

3 Digital economy development has become an important pathway for promoting the
4 green and low-carbon transformation of marine fisheries. This study constructs a
5 comprehensive index to assess the level of digital economy development and applies
6 the super-efficiency SBM model to evaluate MFCEE. Based on panel data from 11
7 Chinese coastal provinces from 2011 to 2023, this study first examines the direct effect
8 of digital economy development on MFCEE using a two-way fixed-effects model, and
9 then investigates its spatial spillover effects through the Spatial Durbin Model (SDM).
10 Furthermore, heterogeneity analysis is conducted from the perspectives of geographical
11 location and capture-dependence level. The principal findings are as follows:

12 First, digital economy development has a significant positive effect on MFCEE.
13 The baseline regression results indicate that DEI significantly enhances MFCEE, and
14 this conclusion remains robust after a series of robustness and endogeneity tests.

15 Second, MFCEE and digital economy development exhibit spatial correlation, and
16 the Spatial Durbin Model (SDM) results further reveal significant spatial spillover
17 effects. The spatial correlation tests indicate that spatial econometric analysis is
18 necessary, and the model selection results support the use of the Spatial Durbin Model
19 (SDM). The SDM estimation results show that the coefficients of DEI are significantly
20 positive under all four spatial weight matrices, confirming the robust positive effect of
21 digital economy development on local MFCEE. Moreover, the coefficients of the
22 spatially lagged DEI are also significantly positive, indicating that digital economy
23 development in neighboring provinces can promote the improvement of local MFCEE.
24 The effect decomposition results further show that the direct, indirect, and total effects
25 of DEI are all significantly positive, suggesting that digital economy development not
26 only improves local MFCEE but also generates positive spillover effects across
27 neighboring coastal provinces.

28 Third, the effect of digital economy development on MFCEE differs across
29 geographical locations and marine capture-dependence levels. From the perspective of
30 geographical location, the effect of DEI is relatively stronger in the eastern and southern
31 regions than in the northern region, reflecting regional differences in the transformation
32 of digital economy development into MFCEE improvement. From the perspective of
33 capture-dependence level, DEI significantly improves MFCEE in low capture-
34 dependence regions, whereas its effect is not evident in high capture-dependence
35 regions. This indicates that the role of digital economy development in improving
36 MFCEE is closely related to regional development conditions and marine fishery
37 production structure. In particular, regions with lower dependence on marine capture
38 production may be better able to transform digital economy development into efficiency
39 gains in low-carbon marine fishery development.

1 **Policy implications**

2 The transition toward low-carbon and sustainable marine fisheries requires policy
3 frameworks that integrate digital economy development with marine fishery carbon
4 emission reduction. Our empirical outcomes highlight the pivotal role of digital
5 economy development in improving MFCEE, while simultaneously demonstrating that
6 the efficacy of this impact is contingent upon regional attributes, transboundary spatial
7 linkages, and capture-dependence levels. Therefore, targeted and coordinated policies
8 are needed to fully release the efficiency-enhancing effect of the digital economy in
9 marine fisheries. Based on these findings, the following policy implications are
10 proposed:

11 First, coastal governments should further promote the digital transformation of
12 marine fisheries by strengthening digital infrastructure and data-governance capacity
13 throughout the entire industrial chain. Digital infrastructure should extend beyond
14 general communication networks to fishing vessels, fishing ports, aquaculture areas,
15 seafood-processing facilities, cold-chain logistics, and market circulation. In particular,
16 integrated fishery data platforms should be developed to connect information on
17 production activities, marine environmental conditions, meteorological changes,
18 energy consumption, market demand, and regulatory supervision. From a marine
19 governance perspective, seamlessly integrating Vessel Monitoring Systems (VMS) and
20 Automatic Identification System (AIS) data into these platforms can significantly
21 enhance fishing effort estimation and precise regulatory oversight. Common data
22 standards and interoperable information systems should also be established among
23 fishery authorities, environmental agencies, maritime departments, and local
24 governments. These measures can reduce information fragmentation and transaction
25 costs, improve production and regulatory efficiency, and provide a reliable data
26 foundation for monitoring marine fishery carbon emissions. Moreover, the wider
27 application of intelligent monitoring, digital management, and digital financial services
28 can optimize the allocation of production factors and continuously improve marine
29 fishery carbon emission efficiency. To ensure an inclusive digital transition, public
30 support should be provided to small-scale fishers and aquaculture operators through
31 equipment subsidies, technical services, and digital training, thereby preventing
32 unequal access to digital technologies and promoting the low-carbon development of
33 marine fisheries.

34 Second, regional coordination in digital economy development should be
35 strengthened. The spatial econometric results show that digital economy development
36 not only improves local MFCEE but also generates positive spillover effects on
37 neighboring coastal provinces. Therefore, Coastal provinces should move beyond
38 isolated province-based policies and establish cross-regional cooperation mechanisms
39 for digital infrastructure investment, fishery data sharing, environmental early warning,
40 vessel monitoring, carbon accounting, joint enforcement, and low-carbon governance.

1 Unified technical standards should be adopted for data collection, carbon emission
2 measurement, and digital fishery platforms to facilitate the cross-regional diffusion of
3 digital technologies, management experience, and low-carbon production models.
4 Provinces with relatively advanced digital economy development should play a
5 demonstration and leading role by sharing technologies and governance practices with
6 neighboring regions. Such cooperation is particularly important for fishing activities
7 and marine ecological problems that cross administrative boundaries. Meanwhile,
8 coordinated supervision should be strengthened to prevent high energy consuming
9 fishing, aquaculture, and processing activities from shifting from regions with stricter
10 environmental regulations to neighboring provinces with weaker governance capacity,
11 thereby improving the overall carbon emission efficiency of coastal marine fisheries.

12 Third, differentiated digital development strategies should be implemented
13 according to regional conditions. The heterogeneity results indicate that the effect of
14 digital economy development on MFC EE varies across geographical locations. Given
15 the eastern and southern regions exhibit more pronounced impacts compared to the
16 northern region, policy designs should avoid uniform implementation and instead
17 embrace localized differentiation. For eastern and southern coastal provinces, the focus
18 should be on deepening the integration of digital technologies with marine fishery
19 production, aquaculture management, processing, and supply chains, so as to further
20 release the efficiency-enhancing effect of the digital economy. For northern coastal
21 provinces, more attention should be given to improving digital infrastructure,
22 strengthening digital technology application capacity, and promoting the digital
23 upgrading of traditional marine fishery activities. Policy design should also reflect
24 differences in marine fishery production structures. Capture-dominated regions should
25 prioritize the replacement of old and energy-intensive fishing vessels, intelligent route
26 planning, fuel-use monitoring, fishing-ground information services, and VMS.
27 Crucially, to prevent digitalization from merely increasing fishing effort and
28 exacerbating resource depletion, these smart technologies must be strictly coupled with
29 Total Allowable Catch (TAC) allocations and the restructuring of fuel subsidies. These
30 measures should be coordinated with seasonal fishing bans, and resource conservation
31 policies to align operational efficiency with long-term ecological sustainability. By
32 contrast, regions dominated by mariculture, seafood processing, and fishery services
33 should focus on intelligent feeding, water-quality monitoring, disease-warning systems,
34 energy-efficient processing, cold-chain management, and digital product traceability.
35 Such differentiated policies can better exploit the efficiency-enhancing effects of the
36 digital economy, narrow regional disparities in digital development, and promote the
37 low-carbon transformation of marine fisheries.

38 Fourth, a long-term policy framework integrating digital economy development
39 and low-carbon marine fishery governance should be established. Digital fishery
40 policies should be coordinated with technological innovation, environmental regulation,

fiscal incentives, industrial upgrading, and green financial instruments. Government subsidies and concessional loans for digital equipment should be linked to measurable environmental outcomes, such as reductions in fuel consumption, electricity use, carbon intensity, and resource waste, rather than being evaluated solely by the number of devices or platforms installed. A standardized monitoring, reporting, and verification system for marine fishery carbon emissions should also be developed to improve policy accountability and provide a reliable basis for green credit, low-carbon certification, ecological compensation, and blue-carbon programs. Governments should further encourage the participation of enterprises, research institutions, and financial organizations in the digital and low-carbon transformation of marine fisheries. For mariculture, greater support should be directed toward low-carbon farming models and the development of shellfish and algae aquaculture, while digital technologies can be used to strengthen the monitoring and verification of carbon sequestration. Through the coordinated use of digital innovation, green finance, environmental regulation, and regional cooperation, coastal provinces can gradually establish a more efficient, coordinated, and sustainable marine fishery development system.

Finally, policymakers must preemptively address the potential rebound and distributional effects of digitalization to ensure a timely transition within the marine economy. Although digital technologies can improve production efficiency, they risk increasing fishing intensity or reinforcing the market dominance of large-scale enterprises if appropriate regulatory and social safeguards are absent. Therefore, particular attention should be given to mitigating the digital divide for small-scale fishers, elderly workers, and economically less-developed coastal areas. By embedding capacity-building programs and inclusive financial mechanisms into policy design, governments can ensure that the benefits of digital and low-carbon transformation are distributed more equitably, contributing to both ecological resilience and social equity in marine governance.

Data availability

The datasets generated and/or analyzed in this study are available from the corresponding author on request.

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E.H.: writing original draft, writing review & editing, data acquisition, data curation, formal analysis, software, visualization. H.J.: conceptualization, supervision, investigation, funding acquisition, writing review & editing, formal analysis. C.Z.: conceptualization, supervision, investigation. Y.L.: data acquisition, data curation, software. All authors reviewed the manuscript.

Competing Interests

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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