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China's ocean carbon sink capacity and its spatial spillover effects in the context of carbon neutrality

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Abstract

Purpose – As a critical component of the global carbon cycle, ocean carbon sinks under the "carbon neutrality" target require scientific estimation of regional capacities and exploration of their spatial correlations. These efforts serve as an essential basis for formulating differentiated carbon sink development policies. This study aims to measure China's ocean carbon sink capacity (OCSC) in the context of carbon neutrality and to investigate its spatial spillover effects. By revealing regional disparities and cross-regional dependencies, the research provides a scientific basis for formulating differentiated and coordinated policies to enhance ocean carbon sequestration.

Design/methodology/approach – Based on panel data of blue carbon ecosystems in 11 coastal provinces of China from 2008 to 2022, this study measures China's ocean carbon sink capacity and employs a spatial econometric model to analyze the spatial spillover effects of various influencing factors.

Findings – Local governments should fully consider the integrity of ocean ecosystems and regional disparities when formulating ocean carbon sink policies, further coordinating interregional factors to enhance carbon sink capacity. (1) China's total OCSC showed a consistent upward trend from 2008 to 2022, with salt marshes becoming the dominant contributing system. Regionally, the capacity ranked Eastern Ocean Economic Circle > Southern Ocean Economic Circle > Northern Ocean Economic Circle, with significant inter-provincial heterogeneity. (2) The global Moran's I exhibited an inverted U-shaped pattern, indicating significant positive spatial autocorrelation. Local indicators confirmed that high-high and low-low clusters dominated. (3) Spatial spillover effects revealed that ocean technology innovation, environmental regulation, and economic development generated significant positive cross-regional impacts, whereas ocean disasters and sea level rise produced negative spillovers. Ocean labor input had positive direct effects but insignificant indirect effects.

Originality/value – Local governments should fully consider the integrity of ocean ecosystems and regional disparities when formulating ocean carbon sink policies, further coordinating interregional factors to enhance carbon sink capacity.

Keywords Carbon neutrality, Ocean carbon sink capacity, Spatial correlation, Spatial spillover

Paper type Research paper

1. Introduction

Global climate change is one of the most severe challenges in the 21st century. The intergovernmental panel on climate change (IPCC) 's Sixth Assessment Report shows that

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from 2011 to 2020, the global surface temperature was 1.09°C higher than pre-industrial levels. Meanwhile, atmospheric carbon dioxide (CO_2)concentration hit a record high of 413.2 ppm in 2020 – the highest in two million years (CINRDT, 2021). This warming trend has triggered a cascade of impacts, including frequent extreme weather events, rising sea levels and ecosystem degradation, posing significant threats to sustainable development. Against this backdrop, reducing greenhouse gas emissions and achieving carbon neutrality have become shared responsibilities of the international community. As the world's largest developing country and carbon emitter, China formally announced its strategic goal of "peaking carbon emissions by 2030 and achieving carbon neutrality by 2060" in 2020. This commitment not only reflects China's role as a major player in global climate governance but also demands higher standards for domestic economic restructuring and sustainable development. Among the pathways to carbon neutrality, enhancing carbon sink capacity is regarded as a critical component.

The ocean is Earth's largest active carbon reservoir. It stores about 39 trillion tons of carbon – 20 times more than terrestrial carbon pools and 50 times more than atmospheric carbon pools (Jingming *et al.*, 2024). Coastal zones (encompassing blue carbon ecosystems such as mangroves, salt marshes, seagrass beds and coastal wetlands) are particularly noteworthy. Despite covering only 0.2% of the ocean's surface area, their carbon sequestration rate is 30–50 times higher than that of terrestrial forests (Kirwan *et al.*, 2023). As a nature-based solution, coastal ocean carbon sinks demonstrate tremendous potential for mitigating climate change. Moreover, these ecosystems provide co-benefits such as coastal protection, water purification, biodiversity conservation and enhanced fishery resources, offering significant ecological and economic value. Thus, coastal ocean carbon sinks hold irreplaceable strategic importance in achieving China's dual carbon goals (peak carbon and carbon neutrality), necessitating further optimization and enhancement of their carbon sequestration functions.

Ocean carbon sinks, which absorb and store atmospheric CO_2 through biological, chemical and physical processes (Gruber *et al.*, 2023), have become a critical research area in global carbon cycle studies. The Paris Agreement explicitly incorporates ecosystem carbon sinks into the scope of Nationally Determined Contributions (NDCs), providing policy legitimacy for blue carbon. The United Nations Framework Convention on Climate Change and related bodies encourage parties to integrate the protection and restoration of blue carbon ecosystems – such as mangroves, salt marshes and seagrass beds – into their emission reduction commitments. China possesses vast maritime territories and over 18,000 kilometers of continental coastline, with abundant carbon-sequestering ecosystems such as mangroves, salt marshes, seagrass beds and macroalgae distributed along its coasts, demonstrating significant potential for ocean carbon sequestration. Preliminary estimates indicate that China's coastal wetlands sequester approximately 0.94–1.65 Tg C/yr, offsetting 0.5%-1% of the nation's annual carbon emissions (Wang *et al.*, 2021). However, due to anthropogenic disturbances like rapid urbanization, land reclamation and ocean pollution, the area of coastal wetlands declined by about 53% between 1984 and 2015 (Chen *et al.*, 2019), leading to a marked degradation of their carbon sink function. Thus, analyzing the Ocean Carbon Sink Capacity (OCSC) of coastal zones is of practical significance. Current research on ocean carbon sinks has limitations. It lacks complete quantitative assessments, a full understanding of regional variations and driving mechanisms and exploration of spatial spillover effects – how neighboring areas' environments, economies or policies affect local carbon sink capacity. Understanding such spatial interdependencies is crucial for formulating regionally coordinated policies to enhance ocean carbon sinks. Moreover, ocean carbon sinks involve ecological, economic and social dimensions, requiring interdisciplinary approaches for comprehensive evaluation and spillover analysis. Yet existing studies remain fragmented, lacking systematic integration. Therefore, effectively utilizing ocean ecosystems and accurately assessing their carbon sequestration potential is vital for boosting OCSC and supporting China's dual carbon goals (peak carbon and carbon neutrality).

Against this backdrop, this study investigates the spatiotemporal evolution of China's OCSC and its spatial spillover effects, aiming to provide a scientific basis for optimizing management strategies and promoting regional collaborative emission reduction. Specifically, we integrate remote sensing data, ocean observations and socioeconomic statistics to construct an evaluation model for OCSC, analyzing its spatiotemporal patterns. Furthermore, spatial econometric methods are employed to examine spatial dependencies and spillover mechanisms, revealing cross-regional drivers.

Compared to existing research, this study contributes in three key aspects: Calculating the OCSC of 11 coastal provinces and the national total to better understand sequestration potential. Analyzing evolutionary trends at national, regional and provincial levels. Applying a Spatial Durbin Model (SDM) to investigate spatial correlations and decompose the spatial effects of influencing factors.

2. Literature review

The study of ocean carbon sinks originated from scientific investigations into the global carbon cycle. Early research primarily focused on two key mechanisms: the physical pump and the biological pump. The physical pump refers to the process whereby carbon dioxide dissolves at the air-sea interface and is subsequently transported to deep ocean storage through ocean circulation. The biological pump, on the other hand, involves phytoplankton absorbing CO_2 through photosynthesis, with carbon then being transferred through the food chain and ultimately sequestered via particle sedimentation (Koeve *et al.*, 2024). Since the 1980s, as climate change emerged as a pressing global issue, ocean carbon sinks have progressively become an interdisciplinary research focus bridging oceanography and climate science (Damien *et al.*, 2024). The IPCC assessment reports have repeatedly emphasized the critical role of oceans in the global carbon cycle, noting that oceans absorb approximately 30% of anthropogenic CO_2 emissions, playing a vital role in mitigating global warming (CINRDT, 2021). However, significant uncertainties remain regarding the spatiotemporal heterogeneity and long-term stability of ocean carbon sinks. These knowledge gaps have motivated researchers to pursue more comprehensive and refined studies across broader spatial and temporal scales.

In the quantitative assessment of ocean carbon sinks, early research primarily relied on ship-based observations and laboratory analyses (Takahashi *et al.*, 2009). However, limited by data coverage and costs, large-scale continuous monitoring was difficult to achieve. With the advancement of remote sensing technology, satellite-derived parameters such as sea surface temperature and chlorophyll concentration have provided new tools for estimating ocean primary productivity and carbon flux (Sabine *et al.*, 2004). In recent years, scholars have begun integrating multi-source data and combining machine learning methods to improve assessment accuracy. Watson *et al.* (2020) developed a dynamic model of ocean carbon sinks using global buoy data and satellite remote sensing, revealing that the carbon sequestration capacity of coastal areas has long been underestimated. Regarding ocean carbon accounting methods, as a critical step in evaluating the carbon sequestration capacity of ocean ecosystems, research has mainly focused on the carbon storage method for coastal wetlands (Jie *et al.*, 2019) and the material quantity assessment method (Wenhan, 2021; Ai *et al.*, 2022) for measuring carbon sequestration by algae and shellfish. In terms of overall estimates of China's ocean carbon sinks, Ai *et al.* (Ai *et al.*, 2022) estimated that the carbon sequestration of mangroves, salt marshes and seagrass beds in China from 1997 to 2019 ranged between 0.033–0.078 Tg C/year, 0.234–0.646 Tg C/year and 0.012–0.018 Tg C/year, respectively. However, other studies, considering the accounting boundaries of ocean carbon sinks, estimated China's ocean carbon sinks at approximately 69.83–106.46 Tg C/year when including offshore carbon sequestration (Chang *et al.*, 2022).

Regarding the influencing factors of ocean carbon sinks, existing research primarily examines natural and anthropogenic dimensions. Natural factors include seawater temperature, salinity, nutrient supply and ocean currents. Li *et al.* (2024) found that global warming may reduce ocean carbon sink efficiency, as rising water temperatures decrease CO_2 solubility and enhance ocean stratification. Gruber *et al.* (2019) noted that upwelling zones (e.g. the Eastern Pacific) bring carbon-rich deep water to the surface, turning these areas into CO_2 sources. Moore (2018) conducted a global analysis showing that marginal seas like the East China Sea experienced a 30–40% decline in primary productivity due to nitrogen-phosphorus imbalance. Anthropogenic factors mainly focus on economic development, industrial structure and policy interventions. Qiu and Lin (2024) employed a material quantity assessment method to estimate carbon sequestration in mariculture across different regions, identifying technology adoption, fishery output share and relative humidity as the most critical influencing factors. Qifei *et al.* (2024) highlighted spatial location and local economic development levels as key determinants of ocean fishery carbon sinks. Macreadie (2021) demonstrated that ocean-protected areas could accelerate the recovery rate of blue carbon ecosystems by 2–3 times. Chen *et al.* (2024), through a case study in China, revealed that the "Blue Bay Remediation" project restored degraded wetland carbon sinks to 80% of their original capacity. These findings not only provide empirical support for formulating targeted strategies to enhance ocean carbon sinks but also advance China's regional ocean carbon sink research, contributing to ocean ecological conservation and climate mitigation goals.

Spatial spillover effects are a key concept in regional environmental economics, but their application in ocean carbon sink research remains in its early stages. Traditional studies often assume that the carbon sequestration capacities of different ocean regions are independent, overlooking spatial interdependencies. However, the dynamic nature of ocean environments means that carbon sink processes in adjacent waters may be closely linked. Grizzetti *et al.* (2021) employed the SDM to investigate the transboundary transmission of nitrogen pollution in European waters and found that the benefits of pollution control policies exhibit significant cross-border spillover effects.

In recent years, the spatial effects perspective has gained increasing attention, opening new avenues for a more refined understanding of ocean carbon sinks. Jingjun *et al.* (2020) constructed a spatial econometric model using panel data from China's coastal provinces, revealing that factors such as economic output, technology adoption and labor input significantly influence carbon sink capacity through spatial spillover effects. Peng *et al.* (2024) focused on the spatial correlation characteristics of coastal carbon sinks, finding that fishery economic development, labor input, aquaculture area, fishery disasters, technology promotion and R&D investment all exhibit notable spatial spillover effects. Yixuan *et al.* (2025) conducted a spatial analysis of blue carbon ecosystems in China's coastal provinces, demonstrating significant spatial spillover effects in the carbon sequestration capacities of salt marshes and mangroves. However, such studies have mostly been limited to specific ecosystems rather than encompassing the entire ocean carbon sink system. Moreover, the mechanisms underlying spatial spillover effects in ocean carbon sinks remain insufficiently explored – particularly how natural processes and human activities interact to shape these effects. Furthermore, research is needed to deepen our understanding in this area.

In summary, although significant progress has been made in ocean carbon sink research, several understudied areas remain within the Chinese context. On one hand, existing assessments are mostly confined to localized sea areas or single time points, lacking long-term dynamic analyses at a national scale. On the other hand, the spatial interdependencies of ocean carbon sinks and their underlying driving mechanisms have not yet received sufficient attention, despite their substantial impact on optimizing and enhancing carbon sequestration capacity. This study aims to address these gaps, providing a more comprehensive scientific basis for the management and policy-making of ocean carbon sinks in China.

3. Research methodology and data sources

3.1 Ocean carbon sink capacity estimation method

This study adopts the calculation formula for OCSC from "Ocean Carbon Sink Accounting Methodology" (HY/T 0349–2022) (Ministry of Natural Resources of the People's Republic of China, 2022). This standard delineates the processes, activities and mechanisms through which ecosystems such as mangroves, salt marshes, seagrass beds, phytoplankton and macroalgae absorb and store carbon dioxide from the atmosphere or ocean. This research estimates China's overall OCSC to provide a scientific basis for selecting appropriate ocean carbon sink assessment methods. The specific calculation formula is shown as formula (1):

$$C_{ocean} = C_{mangroves} + C_{saltmarsh} + C_{seagrass} + C_{phytoplankton} + C_{macroalgae} \tag{1}$$

In the formula: C_{ocean} represents the total OCSC, $C_{mangroves}$, $C_{saltmarsh}$, $C_{seagrass}$, $C_{phytoplankton}$, $C_{macroalgae}$ denote the carbon sink capacities of distinct ocean ecosystems, corresponding to mangroves, salt marshes, seagrass beds, phytoplankton and macroalgae, respectively.

3.1.1 Mangrove carbon sink capacity. China's mangroves are predominantly distributed in tropical to subtropical coastal intertidal zones, with these wetland systems primarily composed of salt-tolerant woody plant communities. Their spatial distribution is mainly concentrated in coastal provinces such as Hainan, Guangxi, Guangdong, Fujian and Zhejiang. As a typical coastal ecosystem, mangroves provide vital ecological services, including water purification and biodiversity conservation. They also exhibit significant carbon sink effects through long-term carbon capture, transformation and storage processes. The mangrove carbon sink capacity comprises two components: sediment and vegetation. The specific calculation formula is shown as formula (2):

$$\begin{aligned} C_{mangroves} = C_{ms} + C_{mp} = \rho_{mangroves} \times S_{mangroves} \times R_{mangroves} \times A_{mangroves} \\ + \sum\left(A_i^{mp} \times P_i^{mp} \times CF_i^{mp}\right) \end{aligned} \tag{2}$$

In the formula:

C_{ms}: Mangrove sediment carbon sink capacity;C_{mp}: Mangrove plant carbon sink capacity;$\rho_{mangroves}$: Bulk density of mangrove sediments (Hui *et al.*, 2024; Jiao *et al.*, 2025); $S_{mangroves}$: Organic carbon content in mangrove sediments (Chang *et al.*, 2022; Hui *et al.*, 2024);$R_{mangroves}$: Sedimentation rate of mangrove sediments (Jiao *et al.*, 2025); $A_{mangroves}$: Mangrove area; A_i^{mp}: Mangrove area at the *i* sampling station; P_i^{mp}: Annual net primary productivity of mangrove plants at the *i* station (Chang *et al.*, 2022; Jiao *et al.*, 2025); CF_i^{mp}: Average carbon fraction of mangrove plants at the *i* station (Jiao *et al.*, 2025).

3.1.2 Salt marsh carbon sink capacity. Salt marshes, as the most widely distributed coastal wetland type in China, are primarily found in estuarine and coastal intertidal zones at mid-to-high latitudes, influenced by periodic tidal cycles and the interaction of saline and freshwater inundation. Research indicates that the biological carbon sequestration of salt marsh ecosystems accounts for approximately 50% of global ocean sediment carbon storage, demonstrating significant carbon sink potential. The estimation formula for salt marsh carbon sink capacity is shown as formula (3):

$$C_{saltmarsh} = C_{ss} + C_{sp} = \rho_{saltmarsh} \times S_{saltmarsh} \times R_{saltmarsh} \times A_{saltmarsh} + \sum\left(A_i^{sp} \times P_i^{sp} \times CF_i^{sp}\right) \quad (3)$$

In the formula:

C_{ss}: Salt marsh sediment carbon sink capacity; C_{sp}: Salt marsh vegetation carbon sink capacity; $\rho_{saltmarsh}$: Bulk density of salt marsh sediments (Ruixia *et al.*, 2008; Jianlong *et al.*, 2023; Wan *et al.*, 2023); $S_{saltmarsh}$: Organic carbon content in salt marsh sediments (Chang *et al.*, 2022; Ruixia *et al.*, 2008; Jianlong *et al.*, 2023; Wan *et al.*, 2023; Xiuqiang *et al.*, 2023); $R_{saltmarsh}$: Sedimentation rate of salt marsh sediments (Yining and Luzhen, 2023); $A_{saltmarsh}$: Salt marsh area (Ai *et al.*, 2022; Chang *et al.*, 2022; Delu *et al.*, 2024; Shasha *et al.*, 2025); A_i^{sp}: Salt marsh area at the *i* sampling station; P_i^{sp}: Annual net primary productivity of salt marsh vegetation at the *i* station (Chang *et al.*, 2022; Wan *et al.*, 2023); CF_i^{sp}: Average carbon fraction of salt marsh vegetation at the *i* station (Wan *et al.*, 2023).

3.1.3 Carbon sequestration capacity of seagrass beds. The carbon sequestration in seagrass beds is achieved through two primary mechanisms: the formation of primary productivity carbon sinks via carbon fixation through photosynthesis by seagrass plants, epiphytic algae and symbiotic algae; and the development of sedimentary carbon sinks through metabolic activities of associated biological communities such as bed-dwelling fish and benthic mollusks. Remarkably, this ecosystem, which occupies less than 0.2% of the total ocean area, stores approximately 19.9 petagrams of carbon, with sediment carbon pools accounting for over 90% of this storage capacity. This substantial carbon storage potential makes seagrass beds particularly effective in mitigating global climate change. The formula for estimating the carbon sequestration capacity of seagrass beds is shown as formula (4):

$$C_{seagrass} = C_{sgs} + C_{sgp} = \rho_{seagrass} \times S_{seagrass} \times R_{seagrass} \times A_{seagrass} + \sum\left(A_i^{sgp} \times P_i^{sgp} \times CF_i^{sgp}\right) \quad (4)$$

In the formula:

C_{sgs}: Seagrass sediment carbon sink capacity; C_{sgp}: Seagrass plant carbon sink capacity; $\rho_{seagrass}$: Bulk density of seagrass bed sediments (Xi *et al.*, 2022); $S_{seagrass}$: Organic carbon content in seagrass bed sediments (Chang *et al.*, 2022; Xi *et al.*, 2022); $R_{seagrass}$: Sedimentation rate of seagrass bed sediments (Yaping *et al.*, 2022); $A_{seagrass}$: Total seagrass bed area (Jie *et al.*, 2019; Ai *et al.*, 2022; Chang *et al.*, 2022; Delu *et al.*, 2024; Shasha *et al.*, 2025; Yaping *et al.*, 2022; Chenhao *et al.*, 2016; Zheng *et al.*, 2013); A_i^{sgp}: Seagrass bed area at the *i* sampling station; P_i^{sgp}: Annual net primary productivity of seagrass plants at the *i* station (Chang *et al.*, 2022; Guoxu *et al.*, 2024); CF_i^{sgp}: Average carbon fraction of seagrass plants at the *i* station (Chenhao *et al.*, 2016).

3.1.4 Carbon sequestration capacity of phytoplankton. As the primary producers in ocean ecosystems, phytoplankton are characterized by their unicellular algal features, which enable widespread spatial distribution and exceptionally high biomass, making them a crucial component of the ocean's biological carbon pool. The carbon sequestration mechanism of phytoplankton involves CO_2 fixation through photosynthesis. By integrating assessment parameters from China's ocean waters with phytoplankton carbon content data, we can quantitatively evaluate their carbon sequestration capacity using the following formula (5):

$$C_{phytoplankton} = A_{sea} \times P_{phytoplankton} \times CF_{phytoplankton} \quad (5)$$

In the formula:

A_{sea}: Area of assessment zone (Using ocean ecological monitoring area); $P_{phytoplankton}$: Annual net primary productivity of phytoplankton (Wei *et al.*, 2024); $CF_{phytoplankton}$: Average carbon fraction of phytoplankton (Wei *et al.*, 2024).

3.1.5 Carbon sequestration capacity of macroalgae. In ocean aquaculture systems, macroalgal carbon sequestration primarily consists of two components: sediment carbon fixation and algal biomass carbon storage. Macroalgae efficiently absorb dissolved inorganic carbon (DIC) and CO_2 from seawater through photosynthesis, converting them into particulate organic carbon (POC) and dissolved organic carbon (DOC) (Matthias and Guillermo, 2021). These ocean plants possess the ecological function of rapidly accumulating carbon storage within short timeframes and play a pivotal regulatory role as biological carbon sinks in ocean carbon cycles (Tsai *et al.*, 2017). The calculation formula for macroalgal carbon sequestration capacity is shown as formula (6):

$$C_{macroalgae} = C_{mas} + C_{map} = \rho_{macroalgae} \times S_{macroalgae} \times R_{macroalgae} \times A_{macroalgae} + \sum \left(P_i^{ma} \times K_i^{ma} \times CF_i^{ma}\right) \quad (6)$$

In the formula:

C_{mas}: Sediment carbon sink capacity of macroalgae; C_{map}: Macroalgal biomass carbon sink capacity; $\rho_{macroalgae}$: Bulk density of macroalgal sediments; $S_{macroalgae}$: Organic carbon content in macroalgal sediments; $R_{macroalgae}$: Sedimentation rate of macroalgal sediments; $A_{macroalgae}$: Macroalgal coverage area; P_i^{ma}: Biomass (wet weight) of the i macroalgal species; K_i^{ma}: Wet-to-dry weight conversion coefficient for the i species; CF_i^{ma}: Carbon fraction in dry mass of the i species. The coefficients for different algal species are detailed in Table 1.

3.2 Spatial econometric model specification

3.2.1 Spatial correlation analysis. Based on the OCSC estimates derived above, this section constructs a SDM to reveal its spatial correlation characteristics. Prior to spatial econometric modeling, the incorporation of spatial effects requires verification of spatial autocorrelation in the study variables. This is typically quantified using global and local Moran's I indices as spatial correlation metrics. The global Moran's I measures overall spatial association across the study area, while the local Moran's I focuses on correlation analysis between individual regions and their neighboring areas (Shuai *et al.*, 2024). This testing approach determines whether OCSC exhibits spatial dependence characteristics.

Moran's I evaluates the overall spatial correlation and clustering patterns of variables, with values typically ranging [−1, 1]. Values > 0 indicate positive spatial autocorrelation (high-value clusters adjacent to other high-value areas and low-value clusters near other low-value areas); values < 0 demonstrate negative spatial autocorrelation (high-value areas adjacent to low-value areas and vice versa); values = 0 suggest random spatial distribution without significant spatial correlation. The calculation formula is shown as formula (7):

$$\text{Moran's I} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}\left[\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)\right]}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \quad (7)$$

Table 1. Coefficients of different algae (%)

Coefficient	Kelp	Ulva lactuca	Gracilaria tikvahiae	Porphyra yezoensis	Gracilaria lemaneiformis	Undaria pinnatifida	Gelidium amansii	Sargassum thunbergii	Others
Dry-wet ratio coefficient	20	20	20	20	20	20	20	20	20
Algae mass ratio	1	1	1	1	1	1	1	1	1
Algae carbon Content coefficient	31.2	27.1	28.4	41.96	31.93	28.81	26.37	30.97	30.36

Note(s): The data is sourced from the "Accounting methods for ocean carbon sink"

In the formula:

x_i and x_j represent specific attribute values of provincial units i and j($i \neq j$);n denotes the number of provincial-level units; $\bar{x}$ is the mean value; S^2 and w_{ij} correspond to the squared variance and spatial weight matrix elements, respectively:

$$I_i = \frac{(x_i - \bar{x})}{S^2} \sum_{j=1}^{n} w_{ij}(x_j - \bar{x}) \tag{8}$$

In the formula (8), I_i represents the specific Local Moran's Index value for the province.

3.2.2 Construction of the spatial econometric model. After incorporating various influencing factors, the SDM is considered, as the spatial effects of the explained variable (OCSC) depend on both the local and neighboring regions' explanatory variables. This model can more effectively assess spillover effects between regions. In light of this, this study selects the SDM as the spatial econometric model, with the specific model formulation as formula (9):

$$OCSC_{it} = \rho \sum_{j=1}^{n} w_{ij} OCSC_{it} + \beta X_{it} + \theta \sum_{j=1}^{n} w_{ij} X_{it} + \varphi_i + \delta_t + \varepsilon_{it} \tag{9}$$

In the formula, X represents the factors influencing OCSC. θ represents the spatial lag term coefficients of each explanatory variable; φ_i denotes the fixed effect of the study province; δ_t indicates the year fixed effect; ε_{it} is the random disturbance term.

3.3 Selection of influencing factors

In addition to analyzing the spatial spillover effects of OCSC, it is essential to consider its various influencing factors. This study examines the factors affecting OCSC from the following six dimensions:

(1) Ocean disaster level (ODL): The severity of ocean disasters is typically measured by economic losses, a key indicator of concern for local governments and the public. This study uses the economic losses caused by ocean disasters as an evaluation metric to quantify disaster severity.

(2) Ocean technology innovation (OTI): To assess the innovation level in ocean technology across provinces, this study employs the number of authorized ocean technology patents as a proxy indicator.

(3) Ocean environmental regulation (OER): Common measurement methods for environmental regulation include input-based, performance-based and multi-dimensional comprehensive evaluation approaches (Gang and Ying, 2012). This study selects the logarithm of total investment in environmental pollution control to quantify the economic commitment and priority given by local governments to ocean ecological protection.

(4) Ocean economic development (OED): Ocean economic development has a dual impact on carbon sink capacity. On one hand, ocean economic activities may exacerbate pollution and ecological damage, thereby weakening carbon sequestration. On the other hand, factors such as policy support, capital investment and technological innovation associated with ocean economic development facilitate resource allocation and ecological monitoring/restoration efforts, ultimately enhancing OCSC. This study uses the ratio of gross ocean product to

regional gross domestic product (GDP) as an indicator of ocean economic development.

(5) Sea level rise (SLR): As a critical marker of global climate change, the rate of sea level rise alters seawater properties, directly affecting ocean habitats and causing fluctuations in coastal blue carbon and fishery-related carbon sequestration. This study adopts year-on-year sea level rise as the evaluation metric.

(6) Ocean labor input (OLI): The number of maritime employees serves as an indicator of labor investment in ocean sectors, reflecting human resource participation in carbon sequestration activities.

3.4 Data sources and processing

This study focuses on 11 coastal provinces and municipalities in China during the period from 2008 to 2022. The research data were systematically collected from multiple authoritative sources, including the China Fishery Statistical Yearbook (2008–2023), China Fishery Yearbook (2008–2023), China Environmental Statistical Yearbook (2008–2023), China Natural Resources Statistical Yearbook (2008–2023), China Ocean Economic Statistical Yearbook (2008–2023), the 2023 China Ocean Ecological Early Warning and Monitoring Bulletin and the EPS data platform. To ensure data completeness, missing values were appropriately addressed using interpolation methods. Furthermore, all measured data underwent necessary preprocessing procedures, including logarithmic transformations, before formal analysis to meet the requirements of the analytical models. See Table 2 for details.

Table 2. Variable definitions and data sources

Variable symbol	Variable name	Definition	Data source	Processing method
OCSC	Ocean carbon sink capacity	Total carbon sink volume of the Five major ecosystems calculated by formula (1) (10,000 tons of carbon/year)	China fishery statistical yearbook	Logarithmic transformation
ODL	Ocean disaster level	Economic losses caused by marine disasters (100 million yuan)	China natural resources statistical yearbook	Take the logarithm
OTI	Ocean technology innovation	Number of marine technology patents granted (items)	China ocean economic statistical yearbook	Take the logarithm
OER	Ocean environmental regulation	Total investment in environmental pollution control (100 million yuan)	China environmental statistical yearbook	Take the logarithm
OED	Ocean economic development	Proportion of gross ocean product in regional GDP (%)	China ocean economic statistical yearbook	Original value
SLR	Sea level rise	Year-on-year rise in sea level (mm)	China natural resources statistical yearbook	Original value
OLI	Ocean labor input	Number of employees in marine-related sectors (10,000 persons)	China ocean economic statistical yearbook	Take the logarithm

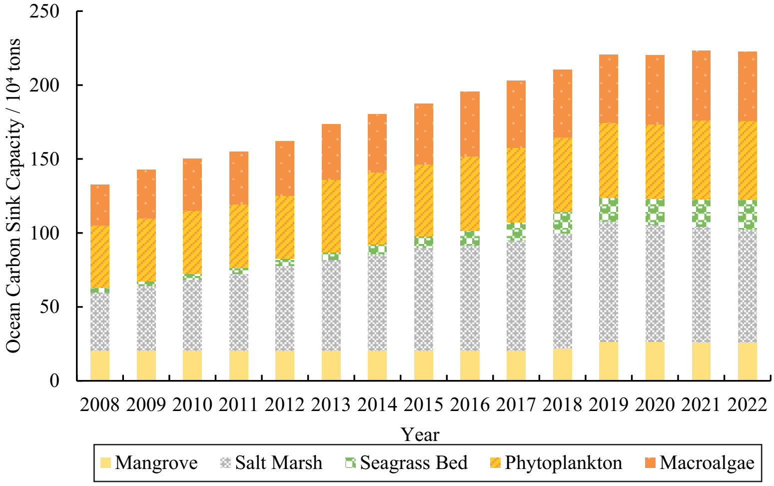


Figure 1. China's total ocean carbon sink capacity

4. Results analysis

4.1 Trend analysis of China's ocean carbon sink capacity

4.1.1 National-level trend analysis of ocean carbon sink capacity. Figure 1 presents the evolution of OCSC across five key ecosystems - mangroves, salt marshes, seagrass beds, phytoplankton and macroalgae – during the 2008–2022 period. The analysis reveals a consistent upward trajectory in China's overall ocean carbon sequestration capacity. The total capacity increased from 1.3265 million tons in 2008 to 2.2249 million tons in 2022. This represents a substantial 67.73% growth with an average annual growth rate of 3.79%. This growth was particularly robust during 2008–2019, when capacity expanded at 4.74% annually to reach 2.2065 million tons by 2019. Although the post-2019 period witnessed a moderated growth rate of 0.28% annually, the overall upward trend remained intact.

A detailed ecosystem-level examination shows uniform growth patterns: mangroves (202,100–260,400 tons; 1.96% annual growth), salt marshes (398,600–760,400 tons; 4.82%), seagrass beds (27,100–201,800 tons; 15.63%), phytoplankton (426,000–535,100 tons; 1.72%) and macroalgae (272,800–467,200 tons; 4.03%). Notably, seagrass beds demonstrated exceptional performance with sustained double-digit annual growth rates (over 10%), underscoring their significant potential for enhancing ocean carbon sequestration. Salt marshes emerged as particularly influential, establishing themselves as the predominant ocean ecosystem in terms of carbon sink contribution. The proportional contributions of these ecosystems underwent notable shifts between 2008 and 2022. Initial contribution shares of 15.23% (mangroves), 30.05% (salt marshes), 2.04% (seagrass beds), 32.12% (phytoplankton) and 20.56% (macroalgae) evolved to 11.70%, 34.18%, 9.07%, 24.05% and 21.00%, respectively. Coastal salt marshes, as China's primary coastal wetland type, increased their contribution share to 34.18%, solidifying their position as the leading contributor within the blue carbon ecosystem (Guangxuan *et al.*, 2022). While seagrass beds maintained the smallest share at 9.07%, they exhibited the most dramatic increase in proportional contribution among all ecosystems. In conclusion, salt marshes currently represent the principal contributor to China's OCSC. Although seagrass beds account for a relatively modest proportion, their remarkable growth trajectory suggests substantial

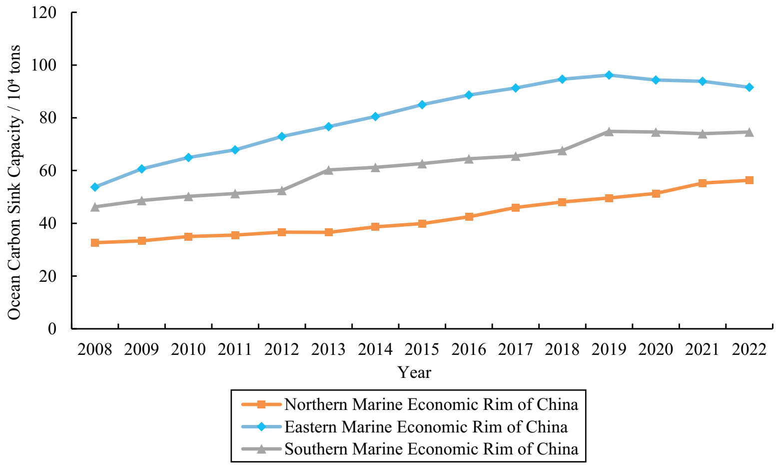


Figure 2. Regional ocean carbon sink capacity

untapped potential that warrants close attention in future ocean carbon sequestration strategies.

4.1.2 Regional trends in ocean carbon sink capacity. Based on the regional classification in the China Ocean Statistical Yearbook, China's 11 coastal provinces and municipalities are divided into three major ocean economic zones from north to south: The Northern Ocean Economic Zone includes Liaoning, Hebei, Tianjin and Shandong; the Eastern Ocean Economic Zone comprises Jiangsu, Shanghai and Zhejiang; and the Southern Ocean Economic Zone encompasses Fujian, Guangdong, Guangxi and Hainan.

Figure 2 illustrates the temporal evolution of OCSC across these coastal regions. All three ocean economic zones demonstrated increasing carbon sequestration capacity, though with notable inter-regional variations, showing the following hierarchy: Eastern Ocean Economic Zone > Southern Ocean Economic Zone > Northern Ocean Economic Zone. The Eastern Ocean Economic Zone maintained consistent leadership in carbon sink capacity, with its values surpassing those of both northern and southern zones throughout the study period, achieving an average annual growth rate of 3.95%. This region reached a peak capacity in 2019 before entering a declining phase, fluctuations attributable to the spatial distribution characteristics of coastal wetland resources and regional variations in ocean resource development intensity and industrial utilization patterns among its constituent provinces/ municipalities. The Southern Ocean Economic Zone exhibited more moderate growth, with capacity increasing from 462,500 tons in 2008–746,000 tons in 2022, representing an average annual growth rate of 3.55%. Although the Northern Ocean Economic Zone showed growth momentum, it remained the weakest performer among the three zones. Its capacity grew from 326,500 tons in 2008 to 563,100 tons in 2022, with an annual growth rate of 3.99% - the fastest growth rate across all zones despite its lower absolute capacity.

4.1.3 Provincial trends in ocean carbon sink capacity. Figure 3 illustrates the temporal evolution of OCSC at the provincial level. The development of ocean carbon sequestration capacity across China's provinces exhibits distinct spatial heterogeneity, with pronounced disparities observed among regions. Jiangsu Province demonstrates robust OCSC with a steady year-on-year growth trend, owing to its abundant ocean ecological resources. Similarly, Fujian, Shandong and Shanghai also display upward trajectories in their

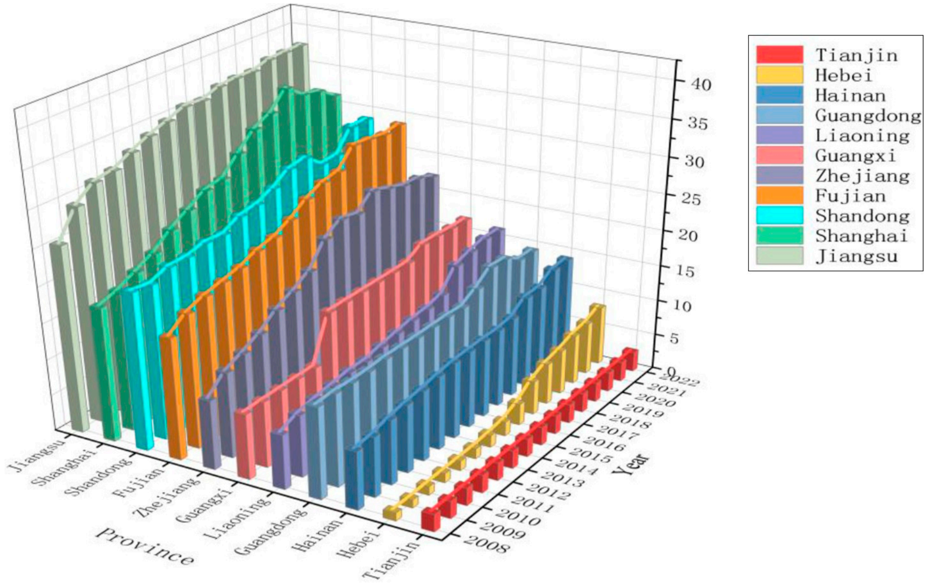


Figure 3. Provincial ocean carbon sink capacity

carbon sequestration capacities. Notably, both Shandong and Fujian possess inherent advantages in blue carbon ecosystems, endowing them with natural strengths in ocean carbon sequestration. Zhejiang Province has achieved remarkable progress in enhancing its carbon sink capacity, with a substantial increase from 95,400 tons in 2008 to 223,800 tons in 2022. This significant growth vividly reflects the province's proactive measures and outstanding accomplishments in advancing ocean carbon sequestration. In contrast, Tianjin and Hebei maintain relatively lower levels of OCSC. Hebei Province, constrained by its heavy industry-oriented economic structure (Chunrui and Xin, 2025) and evident environmental challenges, faces significant bottlenecks in developing and utilizing its ocean carbon sequestration potential, which severely limits the full realization of its blue carbon capabilities.

4.1.4 Uncertainty analysis. To assess the impact of key parameter selection on the estimation results of OCSC, this study employs a one-factor sensitivity analysis method, selecting sediment carbon content (S), sedimentation rate (R) and the macroalgae carbon fraction coefficient (CF) as key sensitive parameters. Based on the range of variation reported in the literature (Hui *et al.*, 2024; Jiao *et al.*, 2025; Xiuqiang *et al.*, 2023; Yining and

Table 3. Sensitivity analysis results of key parameters

Parameter	Range (%)	Change in total OCSC (%)	Most sensitive ecosystem
S_mangroves	±20	−3.2 ~ +3.8	Mangroves
S_saltmarsh	±20	−8.6 ~ +9.4	Salt marshes
S_seagrass	±25	−2.1 ~ +2.5	Mangroves and salt marshes
R	±30	−24.6 ~ +28.3	Mangroves and salt marshes
CF_ma	±10	−3.2 ~ +3.5	Macroalgae

Luzhen, 2023; Xi *et al.*, 2022; Yaping *et al.*, 2022), each parameter was adjusted upward and downward from its baseline value (mangroves and salt marshes: ±20%; seagrass beds: ±25%; sedimentation rate: ±30%; macroalgae carbon fraction coefficient: ±10%). The total OCSC for each province and the nation as a whole from 2008 to 2022 was recalculated, with the results shown in Table 3.

Overall, although the estimation results exhibit a certain degree of sensitivity to the key parameters, the overall upward trend of China's OCSC from 2008 to 2022 remains unchanged under all parameter variation scenarios and the inter-regional ranking (Eastern Ocean Economic Circle > Southern Ocean Economic Circle > Northern Ocean Economic Circle) does not alter. This result indicates that the core conclusions of this study possess good robustness.

4.2 Spatial correlation analysis of China's ocean carbon sink capacity

4.2.1 Global spatial correlation analysis. To examine the spatial autocorrelation of OCSC, this study employs the Global Moran's I for global spatial autocorrelation testing. Addressing the potential "island effect" observed in Hainan Province, we adopt the Rook contiguity matrix for constructing the spatial weight matrix, following the methodology of Bin *et al.* (2005), by considering Hainan as adjacent to Guangdong and Guangxi. The results of the Global Moran's I test for OCSC are presented in Table 4. The analysis reveals that from 2008 to 2022, the p-values of the Global Moran's I for China's OCSC were consistently below 0.05, with statistically significant positive values. This indicates the existence of significant positive global spatial autocorrelation in OCSC across the study period.

From the dynamic trend of Moran's I index, China's OCSC exhibited a general "rise-decline" fluctuation pattern in its spatial distribution characteristics during 2008–2022 (Figure 4). This fluctuation pattern reveals regional disparities in the implementation intensity of ocean ecological protection policies and the resulting spatial agglomeration characteristics of OCSC. During 2008–2016, the Moran's I index showed continuous growth. From 2018 to 2022, although the index displayed a downward trend, it remained positive throughout, indicating that coastal provinces and municipalities maintained positive spatial correlation in their OCSC. The comprehensive analysis demonstrates that OCSC exhibited significant spatial agglomeration characteristics across different regions during the

Table 4. Global Moran's I test for ocean carbon sink capacity

Year	I	E (I)	Sd (I)	*Z*-value	*p*-value
2008	0.440	−0.100	0.266	2.029	0.021
2009	0.486	−0.100	0.260	2.255	0.012
2010	0.502	−0.100	0.259	2.325	0.010
2011	0.537	−0.100	0.260	2.448	0.007
2012	0.583	−0.100	0.262	2.608	0.005
2013	0.590	−0.100	0.261	2.644	0.004
2014	0.613	−0.100	0.263	2.715	0.003
2015	0.662	−0.100	0.264	2.880	0.002
2016	0.680	−0.100	0.269	2.900	0.002
2017	0.652	−0.100	0.271	2.779	0.003
2018	0.683	−0.100	0.271	2.888	0.002
2019	0.635	−0.100	0.268	2.743	0.003
2020	0.608	−0.100	0.267	2.657	0.004
2021	0.586	−0.100	0.268	2.564	0.005
2022	0.553	−0.100	0.266	2.454	0.007

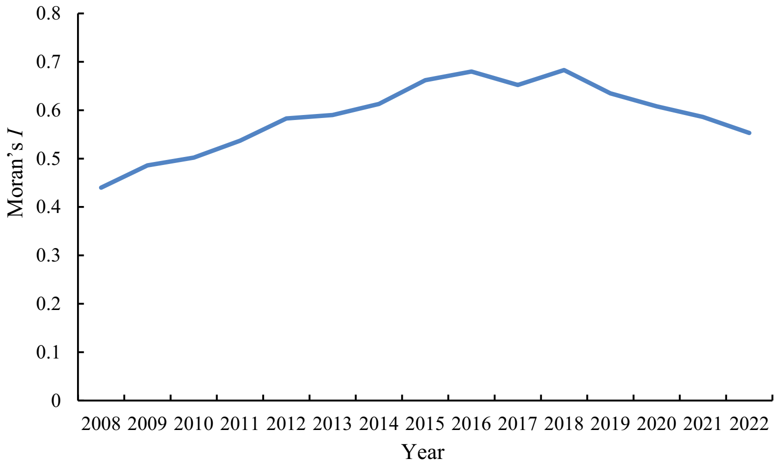
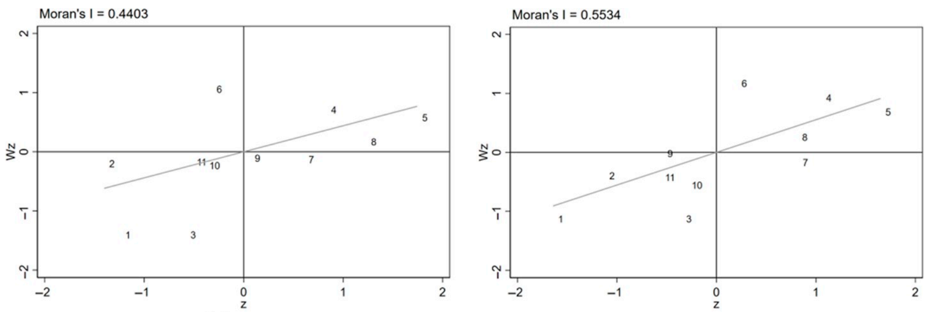


Figure 4. Moran's I index trend



(a) 2008 **(b)** 2022

Figure 5. Local Moran's I scatter plot

entire study period. Therefore, it is necessary to employ spatial econometric models for subsequent research on spatial spillover effects.

4.2.2 Local spatial autocorrelation analysis. While global Moran's index analysis cannot precisely characterize the local spatial autocorrelation of OCSC among regions (Yanfen *et al.*, 2025), we constructed local scatter plots for 2008 and 2022 to conduct in-depth analysis of local MoranËs I correlations (Figure 5), thereby avoiding the potential distortion of global MoranËs I values caused by offsetting effects between positive and negative correlations across different spatial units.

The MoranËs I scatter plot visually displays four distinct spatial clustering patterns through its quadrants, representing different local spatial relationships between observation units and their neighboring regions. These four quadrants correspond to: high-high clustering (H-H), low-high clustering (L-H), low-low clustering (L-L) and high-low clustering (H-L) patterns. The first and third quadrants indicate significant positive spatial autocorrelation, while the second and fourth quadrants reflect negative spatial correlations. Analysis of Figure 5 reveals that data points are predominantly concentrated in the first and third quadrants. Regarding positive spatial clustering, most of China's 11 coastal provinces/ municipalities were located in these quadrants. In 2008, three regions (Shandong, Jiangsu and Shanghai) appeared in the first quadrant (H-H), while five (Tianjin, Hebei, Liaoning, Guangxi and Hainan) were in the third quadrant (L-L), collectively accounting for 72.73% of all coastal regions. By 2022, this proportion increased to 90.91%, indicating strengthened spatial dependence. In contrast, negative spatial clustering was less prevalent, with only Zhejiang, Fujian and Guangdong distributed in the second/fourth quadrants in 2008 and just Fujian remaining in the fourth quadrant by 2022. These results demonstrate that OCSC in China's coastal regions exhibits significant positive spatial clustering characteristics, with this autocorrelation pattern becoming more pronounced over time. The spatial patterns revealed provide important insights for developing regionally differentiated ocean carbon management strategies and coordinated environmental policies.

4.3 Analysis of spatial spillover effects on China's ocean carbon sink capacity

4.3.1 Regression results analysis of the spatial Durbin model. This study employed multiple statistical tests, including the Hausman test, LR and Wald tests, with detailed results presented in Table 5. The Hausman test yielded a statistic of 91.66, which was significant at the 1% level, supporting the superiority of the fixed effects model over the random effects model. Furthermore, both the LR test and Wald test demonstrated significance at the 1% level, confirming that the SDM could not be simplified to either a Spatial Lag Model (SLM) or Spatial Error Model (SEM). Based on these test results, we selected the fixed effects SDM as the foundational model for subsequent empirical analysis.

The regression results of the spatial econometric model (Table 6) reveal a spatial autoregressive coefficient of 0.1538, which is statistically significant at the 1% level, indicating that OCSC exhibits significant and positive spatial spillover effects. After applying the spatial weight matrix to each explanatory variable, the analysis shows that *ODL*

Table 5. Results of Hausman, LR and Wald tests

Test type	Statistic value	*p*-value
Hausman	91.66	0.00
LR-lag	68.60	0.00
LR-error	59.30	0.00
Wald-lag	81.26	0.00
Wald-error	69.86	0.00

Table 6. Spatial econometric model regression results

Variable	SDM		Spatial effect
ODL	−0.8795 (−1.5164)		−1.6158*** (−3.5789)
OTI	0.3497 (1.3375)		0.4543*** (2.6730)
OER	0.0913 (0.3422)		0.6291*** (3.0644)
OED	−1.9529*** (−3.1867)		2.9705*** (6.0835)
SLR	−0.7053 (−1.2122)		−1.5477*** (−3.9197)
OLI	2.5879* (1.8082)		0.4802 (0.5639)
rho		0.1538*** (4.6502)	
sigma2_e		1.7047*** (8.6624)	

and *SLR* exert negative impacts on neighboring provinces, while *OTI*, *OER*, *OED* and *OLI* demonstrate positive spillover effects on adjacent regions. Notably, the spatial effect direction of *OED* contradicts preliminary estimation results. In light of these findings, we plan to conduct further analysis through spatial effect decomposition of each contributing factor.

4.3.2 Analysis of spatial spillover effects. The regression coefficients of the SDM fail to directly reveal the marginal effects of various influencing factors on OCSC. To address this limitation, our study employs the spatial effects decomposition approach developed by Lesage and Pace (2010), utilizing partial differentiation methods to systematically decompose the spatial effects of each determinant. The decomposition yields three distinct effect components:

(1) Direct effects, which quantify how changes in local factors influence OCSC within their own administrative regions;

(2) Indirect effects (spillover effects), capturing the cross-border radiative impacts that regional factors exert on neighboring areas through spatial connectivity mechanisms; and

(3) Total effects, representing the aggregate outcomes derived from the summation of direct and indirect effects.

These comprehensive decomposition results are presented in Table 7, providing nuanced insights into the complex spatial transmission dynamics of ocean carbon sequestration processes.

The analysis of direct effects reveals several noteworthy patterns in local impacts on OCSC. As demonstrated by the results, *ODL* exhibits statistically significant negative effects, indicating its substantial adverse impact on coastal carbon sequestration. In contrast, *OTI* shows significantly positive spatial influences, suggesting that technological advancements effectively enhance local carbon absorption capabilities. *OER* displays negative yet statistically insignificant coefficients, implying that the outcomes of pollution control investments may not be immediately observable due to constrained resource allocation and implementation lags. Similarly, *OED* presents negative but insignificant effects, reflecting the complex duality of economic activities where potential benefits may be counterbalanced by detrimental practices, including resource overexploitation, suboptimal industrial distribution, excessive fishing and coastal industrial expansion - all of which potentially compromise ocean ecosystem carbon sequestration. Particularly noteworthy are the significantly negative direct effects of *SLR*, which align with existing literature documenting how rising sea levels degrade critical coastal ecosystems such as mangroves and salt marshes through habitat deterioration and biodiversity depletion (Rongshuo and Hongjian, 2020). On the positive side, *OLI* demonstrates statistically significant beneficial effects, as workforce investments in coastal wetland monitoring and

Table 7. Spatial spillover effect decomposition results

Variable	Direct effect	Indirect effect	Total effect
ODL	−1.5709** (−2.4701)	−5.3579*** (−4.1061)	−6.9288*** (−4.0827)
OTI	0.5104** (2.0694)	1.4482*** (3.2433)	1.9586*** (3.2009)
OER	0.3631 (1.1991)	1.9529*** (3.5792)	2.3160*** (2.9747)
OED	−0.8138 (−1.1237)	8.2182*** (4.5854)	7.4043*** (3.2932)
SLR	−1.4981* (−1.9088)	−5.1168*** (−3.3430)	−6.6149*** (−3.1204)
OLI	2.9904* (1.9168)	2.6655 (1.0035)	5.6558 (1.5070)

mariculture operations serve as essential production factors that contribute to ocean ecosystem stabilization and carbon sequestration enhancement. These findings collectively underscore the complex interplay between anthropogenic factors and natural processes in shaping regional ocean carbon sink dynamics.

The analysis of indirect effects yields several significant findings regarding cross-regional impacts on OCSC. First, *ODL* demonstrates statistically significant negative spillover effects, suggesting that extreme ocean events (e.g. storm surges, red tides and typhoons) can synchronously degrade ecological environments in adjacent regions through damaging critical blue carbon ecosystems, including mangroves, salt marshes and mariculture systems, thereby reducing their carbon sequestration functionality. Conversely, both *OED* and *OTI* exhibit significantly positive spatial spillovers, attributable to the cross-border diffusion of information and technology that enables neighboring provinces to benefit from knowledge sharing and "free-rider" effects (Jingjun *et al.*, 2020), ultimately fostering a virtuous cycle of regional technological advancement and industrial upgrading. Notably, *OER* shows particularly strong positive spillover effects, indicating that stringent pollution standards and governance requirements can generate substantial transboundary benefits. The implementation of such measures leads to gradual ocean ecosystem improvements, with adjacent waters experiencing synchronous environmental quality enhancement due to oceanic connectivity through currents. However, sea level rise presents significantly negative spatial externalities, as excessive elevation drives coastal carbon sink degradation via mechanisms like saline intrusion and wetland deterioration, with impacts extending beyond administrative boundaries. Interestingly, *OLI* shows statistically insignificant spillover effects, implying that workforce investments in ocean sectors do not generate measurable cross-regional impacts on carbon sink capacity. These findings collectively highlight the complex spatial dynamics of ocean carbon sink systems, where certain factors (e.g. technological diffusion and environmental regulation) create positive regional synergies, while others (e.g. ocean disasters and sea level rise) generate negative transboundary externalities. It is particularly worth noting that the direct effect of OED on local areas is negative (−0.8138, not significant), while its indirect effect on neighboring regions is significantly positive (8.2182, $p < 0.01$). This contrast may stem from the fact that local marine development activities (e.g. land reclamation and aquaculture pollution) exert negative impacts on blue carbon ecosystems, offsetting the financial and technological dividends brought by economic development in the short term. In contrast, the positive spillover effects are realized through pathways such as technological diffusion, industrial transfer and ecosystem connectivity. It should be noted that the significance of spillover effects depends on interregional policy coordination and ecological linkages and the boundaries of these effects still require further validation.

5. Conclusions and recommendations

5.1 Main conclusions

This study systematically evaluates China's OCSC using panel data from 11 coastal provinces (2008–2022), examining spatial correlations through global and local Moran's I indices and investigating determinants and spatial spillover effects via a SDM. Three key findings emerge from our analysis:

First, China's ocean carbon sequestration demonstrated a consistent growth trajectory (2008–2022), with salt marshes constituting the primary contributor. Regional disparities were evident, showing a distinct hierarchy in carbon sink capacity (Eastern > Southern > Northern Ocean Economic Circles) alongside significant interprovincial heterogeneity. Second, robust spatial dependence was identified among coastal provinces, with global Moran's I revealing an inverted U-shaped temporal pattern (2008–2022) and local indicators confirming positive spatial autocorrelation. Third, factor analysis revealed ocean technology innovation and labor input as significant local enhancers, while ocean disasters and sea level rise functioned as inhibitors. Spatial spillover effects were particularly noteworthy, with technology diffusion, environmental regulation and economic development generating positive cross-border externalities, contrasted by ocean disasters and sea level rise producing significant negative spillovers. These findings underscore the complex spatial dynamics of ocean carbon sequestration. They highlight the need for coordinated regional governance strategies that account for both synergistic and competitive interjurisdictional effects in coastal ecosystem management.

5.2 Policy recommendations

Building upon the research findings, this study proposes a three-pronged policy framework to enhance China's OCSC through targeted ecosystem management, regional cooperation mechanisms and technological-institutional synergies:

First, prioritizing the conservation and enhancement of dominant carbon sink ecosystems is critical. Given salt marshes' substantial contribution (accounting for 34.18% of total capacity), stringent enforcement of ecological protection redlines must be implemented to prohibit unauthorized reclamation and development, complemented by active restoration initiatives including native vegetation rehabilitation and water quality improvement programs. Recognizing the distinct resource endowments across China's three major ocean economic zones – the Eastern, Southern and Northern Ocean Economic Circles – differentiated policy approaches should be developed to capitalize on regional comparative advantages, such as intensifying mangrove conservation in southern provinces while optimizing phytoplankton productivity in eastern waters through nutrient management.

Second, establishing an interregional collaborative governance framework is essential to address spatial imbalances. This requires creating a transboundary ecological compensation mechanism incorporating fiscal transfers and technical assistance to support underperforming regions, coupled with joint conservation planning and coordinated management of shared ocean ecosystems. Key initiatives should include developing interconnected ocean protected area networks, implementing knowledge-sharing platforms for best practices in coastal restoration and instituting performance-based fiscal incentives to reward cross-jurisdictional carbon sink enhancement efforts.

Third, advancing ocean carbon sink technologies while optimizing policy instruments can amplify positive spillover effects. Strategic priorities include:

(1) accelerating R&D in ecosystem monitoring (e.g. AI-powered seagrass mapping), restoration techniques (e.g. salt marsh sediment augmentation) and carbon sequestration assessment methodologies;

(2) strengthening regulatory frameworks through real-time pollution monitoring networks and market-based mechanisms like blue carbon credit trading; and

(3) establishing regional risk governance systems featuring early warning networks for sea level rise impacts and standardized emergency response protocols for ocean disasters.

These measures should be underpinned by innovative public-private partnerships to mobilize corporate participation in carbon sink projects, ultimately creating a virtuous cycle of technological innovation, policy refinement and capacity building across coastal regions.

Author contributions

Fang Ye Manuscript Preparation, Literature Search; Xiaodong Sun Data Interpretation and Study Design.

Data availability

The data sets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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