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Temporal-spatial evolution analysis of carbon emission efficiency in the logistics industry of coastal provinces in China based on the super-efficiency SBM model

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Abstract

Background The logistics industry is a pillar industry of China's national economic development, and coastal provinces, as the core of China's economic development, have highly developed logistics industry. However, the rapid development of the logistics industry in China's coastal provinces is usually accompanied by high carbon emissions. Therefore, improving the carbon emission efficiency of the logistics industry (LCEE) in China's coastal provinces is one of the main contents to achieve "China's dual carbon goals". Existing research indicates that LCEE is closely related to the efficiency levels of neighboring regions, and its temporal and spatial evolution characteristics are also influenced by the change of neighborhood efficiency. However, less attention has been given to the role of geographic proximity in analyzing the temporal and spatial evolution characteristics. Thus, this paper introduces the spatial lag factor into the Markov chain (MC) to obtain the spatial Markov chain (SMC), examining the influence of neighboring provinces' LCEE on the spatial evolution of the local LCEE in China's coastal provinces.

Results The results show that: For most years between 2007 and 2022, in China's eleven coastal provinces, the LCEE values were less than one. These low LCEE values indicated that the potential for emission reduction had not been fully tapped, and low-carbon development faced significant challenges. The primary obstacle to improving LCEE during the study period was low technical efficiency, and the development of the technology level was crucial for enhancing LCEE. In 2007–2011 and 2015, the spatial distribution of LCEE exhibited significant spatial clustering features. The primary type of spatial clustering was high-high clustering, which indicated there was an obvious trend of regional coordinated development. The LCEE of neighboring provinces influenced the state transition probabilities of their own states, and spatial spillover effects in these provinces were very evident.

Conclusions This study conducted an in-depth analysis of the temporal-spatial evolution characteristics of LCEE in China's coastal provinces. There are significant differences in LCEE among these provinces. Each province needs to reduce the carbon dioxide emissions of the logistics industry and improve the LCEE through regional cooperation, technological investment, and targeted policies, so as to promote the sustainable development of the logistics industry in China's coastal provinces.

Keywords Logistics carbon emission efficiency, Temporal-spatial evolution, Super efficiency SBM model, Kernel Density Estimation, Markov chain

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Introduction

The eleven coastal provinces of China serve as foundational economic regions within the nation, occupying approximately 1,303,200 square kilometers, which constitutes 13.58% of China's total land area [1]. Figure 1 presents the geographic distribution of these provinces. According to the China Statistical Yearbook, in 2022, China's logistics industry generated an added value of RMB 476.864 billion, with coastal provinces contributing RMB 250.20 billion, accounting for 52.47% of the national total. Therefore, the growth of the logistics in coastal provinces profoundly affects China's development. However, significant progress in the logistics industry has been accompanied by high consumption, with the logistics industry leading in energy consumption across all sectors [2]. In 2022, China's energy consumption reached 5.40956 billion tons of standard coal, with the logistics sector alone consuming 404.34 million tons, representing 7.47% of the national total. All aspects of logistics activities, including transportation, warehousing, loading and unloading, distribution processing, and distribution, rely heavily on fossil fuels or electricity, leading to significant carbon dioxide emissions and environmental strain [3, 4]. In 2021, China's coastal provinces emitted a total of 5.25108 billion tons of carbon dioxide, of which 323.97 million tons were attributed to the logistics, accounting for 6.17% of the total emissions from all industries in this region [5]. China has committed to peak carbon emissions by 2030 and achieve carbon neutrality by 2060, as announced at the 75th United Nations General Assembly [6]. In this context, promoting sustainable growth within the logistics sector in coastal regions is crucial to achieving "China's dual carbon goals".

Logistics carbon emission efficiency (LCEE) is a crucial metric for assessing the sustainability of a region's logistics sector, as it links input–output processes with carbon dioxide emissions [7]. To harmonize the contradiction between input–output and carbon emissions of logistics industry, it is necessary to accurately measure LCEE and master its development law. Although LCEE in China has gained considerable scholarly attention and a series of research results have been achieved,

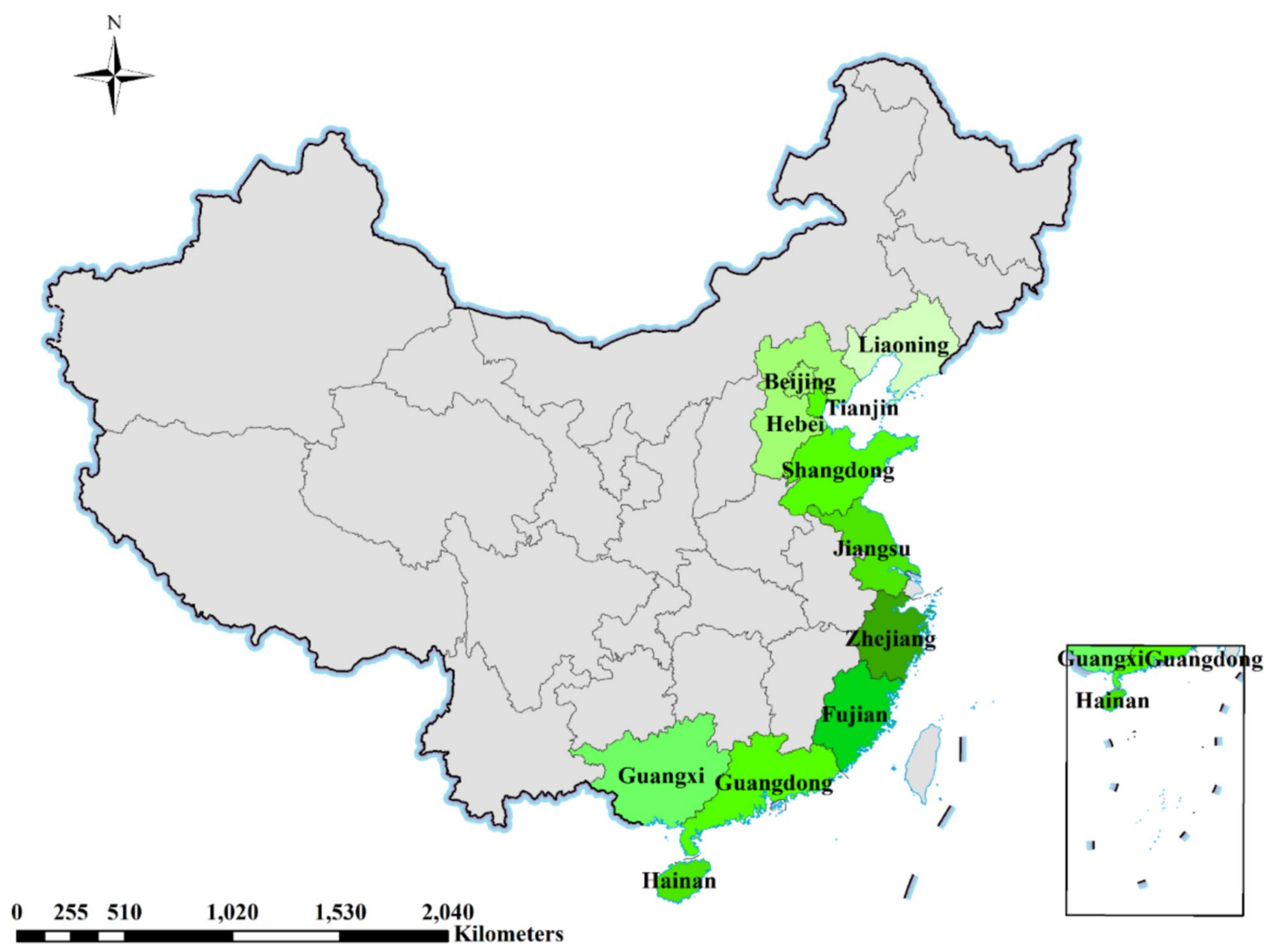

Fig. 1 Geographical location of China's eleven coastal provinces Map based on standard base map from the National Geomatics Center of China. Map review number: GS(2023)2767

some limitations still persist. Firstly, current research mainly focuses on national level and other broad regions to explore the temporal and spatial evolution of LCEE [8], with limited attention to China's coastal provinces' temporal and spatial evolution of LCEE. Secondly, most LCEE measurement methods rely on traditional Data Envelopment Analysis (DEA) models, like Banker, Charnes, and Cooper model and SBM model. However, these models present notable limitations in their application. They cannot effectively differentiate or compare decision-making units (DMU) with efficiency values greater than one, nor can they track changes in efficiency over time or explain the underlying reasons for these changes [9]. Additionally, the current study seldom concentrates on the China's coastal provinces' spatial correlation of LCEE, lacking correlation analysis from a spatial perspective. Finally, existing research indicates that LCEE is closely linked to the efficiency levels of neighboring regions, and its temporal and spatial evolution characteristics are also influenced by the change of neighborhood efficiency, but less attention is paid to the role of geographic proximity in analyzing the temporal and spatial evolution characteristics, which may lead to the trends of LCEE being under-analyzed.

By analyzing the temporal and spatial variations of LCEE in China's coastal provinces, this paper will examine the development disparities among different provinces and reveal the problems in the development of LCEE. However, less attention has been given to the role of geographic proximity in analyzing the temporal and spatial evolution characteristics. Thus, this paper introduces the spatial lag factor into the Markov chain (MC) to obtain the spatial Markov chain (SMC), examining the influence of neighboring provinces' LCEE on the spatial evolution of the local LCEE in China's coastal provinces, elucidating the temporal and spatial evolution characteristics in China's coastal provinces. This paper further investigates the carbon reduction strategies that should be implemented in various dimensions across these provinces, aiming to promote regional sustainable development. Analyzing the temporal and spatial evolution of LCEE in China's coastal provinces holds considerable importance. On the one hand, it helps clarify the current state of LCEE development in these provinces and uncovers potential issues, providing a scientific basis for policymaking. On the other hand, it enables the identification of trends in the evolution of LCEE across the provinces, supporting the region's coordinated development.

The following parts of this paper are organized in the following way: In "Methodology" section, the research methods used in this paper are explained. These include the super-efficiency slack-based measure (SSBM) model, the Global Malmquist-Luenberger (GML) index model, Moran's I, Kernel Density Estimation (KDE), and the MC model. In "Construction of an evaluation system for LCEE" section, we talk more about how to choose logistics input–output indicators, data sources, and how to handle the data in China's coastal provinces. In "Empirical analysis" section, the LCEE of China's coastal provinces is measured from 2007 to 2022, and its temporal and spatial evolution characteristics is analyzed. Finally, "Conclusions and policy suggestions" section is a summary of the study conclusion and policy suggestions.

Literature review

Current research on LCEE primarily focuses on accurate measurement, employing single-factor and total-factor approaches. The single-factor method measures LCEE through indicators such as carbon intensity, carbon productivity, and carbon emissions per unit of GDP [10, 11]. For instance, Zhang et al. [12] applied the Generalized Divisia Index Method to examine the key drivers of carbon emissions in China's logistics industry from 2000 to 2019, while Sun et al. [13] used input–output models to estimate embedded carbon emissions and emission intensity at multiple time points. Ferreira et al. [14] assessed the carbon intensity of logistics operations among the world's 242 highest revenue retail companies, evaluating their sustainability performance. The study found that food retailers exhibit significantly higher carbon intensity in logistics compared to non-food retailers, primarily due to the influence of refrigeration systems, energy supply sources, and energy efficiency strategies. However, the single-factor approach is limited to considering the proportionate relationship between a single input and carbon emissions, ignoring the interaction effects among input factors in the logistics operation process [15]. To address this limitation, researchers have shifted towards the total-factor approach, which considers several input–output systems like energy and labor. From a total factor perspective, carbon emission efficiency (CEE) is the ability to raise economic output and lower carbon emissions without increasing inputs like labor and capital [16]. And it incorporates the interconnections among several elements like capital, labor, energy, and CEE [17]. According to the current study on measuring LCEE, scholars primarily employ parametric and non-parametric methods in the total-factor approach. Aigner et al. [18] came up with the Stochastic Frontier Analysis method, which is the most common parametric method. To analyze China's CEE, Sun and Huang [19] used stochastic frontier analysis. Wang et al. [20] applied panel data from 2000 to 2019, covering eleven provinces within the Yangtze River Basin, and used stochastic frontier analysis in conjunction with carbon productivity to quantify the effectiveness of green technology. However, the stochastic frontier analysis method exhibits inherent stochastic characteristics and requires the explanatory variables to be independent, which introduces certain limitations. In contrast, as a widely used non-parametric method, DEA addresses these limitations and provides distinct advantages in assessing CEE with several inputs and outputs. Because DEA has no requirement on the number of samples and can directly carry out the efficiency analysis without dimensionless processing of indicators, it is frequently used in CEE evaluation of different industries [21]. Ibrahim et al. [22] employed a Network Data Envelopment Analysis model to evaluate the LCEE across 48 countries. The study revealed that 36% of the assessed countries exhibited below-average efficiency levels, with innovation and energy sustainability identified as critical drivers for enhancing the LCEE. However, traditional DEA models, such as BCC and CCR, do not account for slack variables, which may lead to an overestimation of efficiency scores. The SSBM model overcomes the constraints of DEA models by considering slack variables and undesirable outputs. This model allows for further comparison among units on the efficiency frontier and distinguishes and ranks DMU with efficiency values above one. Consequently, it provides a more precise measurement of LCEE [23]. Gao et al. [24] used a non-competitive input–output model to estimate embodied carbon emissions across 28 industries in China, followed by SSBM modeling to assess their CEE from 2005 to 2017. Chen et al. [25] adopted SSBM model to measure CEE in China, so as to achieve more accurate and efficient carbon emission quota allocation results. Wang et al. [26] analyzed changes in LCEE from two perspectives. Rashidi and Cullinane [27] used super-SBM model to assess logistics sustainability in OECD countries, incorporating greenhouse gas emissions as an undesirable output. Results showed significant performance variations, with the U.S. and Slovenia excelling, while Greece and Italy underperformed. The study highlights the need for integrated economic, environmental, and social metrics in logistics evaluations, providing insights for improving LCEE. Wang and Li [28] used the SSBM-GML model to evaluate the Marine CEE of eleven coastal provinces from 2001 to 2019, conducted an empirical analysis of the dynamic association among Marine CEE, trade openness, and financial development. Furthermore, Yuan et al. [29] employed the SSBM model to measure construction sector carbon efficiency across 30 provinces in China and applied Tobit regression to identify influencing factors.

Temporal-spatial evolution analysis is a critical area of research on LCEE. At present, most studies analyze the evolution characteristics of LCEE from both temporal and spatial perspectives [30]. In the analysis of temporal evolution, the Malmquist index based on the DEA method is a common method to measure the LCEE. Zhang et al. [31] applied the SSBM and the Malmquist index model to analyze the temporal evolution of CEE in 108 Chinese cities from 2005 to 2020, concluding that overall efficiency was insufficient and fluctuated over the study period. However, the Malmquist-Luenberger (ML) index model lacks cyclic multiplicative property and may have linear programming without solutions, which can easily lead to errors in the measurement. To address these limitations, Oh [32] established the GML index model, which resolves the absence of solutions of the ML index model and allows for cyclic multiplication. Long et al. [33] further applied the SSBM model and Malmquist index to assess the temporal evolution of logistics eco-efficiency across eleven Chinese provinces from 2004 to 2016, providing insights into long-term trends. In the analysis of spatial evolution, most scholars have used the KDE and MC methods. Liu and Zhu [34] used KDE to examine the spatial evolution of green total factor productivity in Chinese coastal cities, revealing a declining trend and widening regional disparities. Similarly, Cui et al. [35] utilized KDE and the MC model to explore the spatial distribution and regional variation of urban green space use efficiency in China, finding clear evidence of spatial polarization. He and Meng [36] used KDE and the MC model to investigate the dynamic spatial distribution trends in China's public service quality. The findings indicated that China's public service quality presented a "spatial spillover" effect, and the probability of upward shift of public service quality in provinces near to high-level provinces increased, the probability of upward shift of public service quality in provinces adjacent to lower-level provinces decreases.

In general, numerous studies have investigated the temporal and spatial evolution characteristics in LCEE, but several research gaps remain: Most of the current contributions on the temporal and spatial characteristics in LCEE focus on a detailed description of the evolution characteristics, ignoring the spatial correlation prevalent in economics. Few studies address the spatial effect of LCEE itself, and there is a lack of correlation analysis based on the spatial perspective.LCEE's value is not only related to its own level of development but also constrained by the environment of the neighboring area. Existing studies treat each DMU as independent, ignoring the influence of geographical proximity on the spatial characteristics of LCEE, which may result in measurement bias in the findings.

To bridge the above research gaps, the following research is conducted in this paper: Firstly, a spatial weight matrix founded on geographic distance is constructed, and the spatial correlation of LCEE in China's coastal provinces is explored by using the Global Moran I and Local Moran I. Secondly, KDE and traditional MC are adopted to comprehensively investigate the dynamic evolution trends of the spatial and temporal distribution of LCEE, revealing the mechanism of the changes in LCEE across different efficiency levels in China's coastal provinces. A spatial Markov chain is constructed by integrating spatial lag factors into the traditional MC, to investigate the impact of neighboring provinces on the spatial evolution of LCEE in China's coastal provinces.

Methodology

LCEE measurement methods

Super-efficiency SBM model

Traditional DEA models tend to overestimate the efficiency of DMU, leading to biased results [37]. When multiple DMU are efficient (with LCEE value of one), it cannot be further distinguished. Tone [38] proposed the SSBM model, it is a kind of DEA model, which considers undesirable outputs and allows for further differentiation and ranking of DMU with efficiency scores greater than one. This approach addresses the shortcomings of traditional DEA models. Consequently, this paper adopts the SSBM model to measure the LCEE.

Suppose there are n DMU, m inputs, s_1 desirable outputs, and s_2 undesirable outputs. The SSBM model considering undesirable outputs is shown in Eq. (1):

$$\rho^* = \min \frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}}{1-\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^+}{y_{ro}}+\sum_{k=1}^{s_2}\frac{s_k^-}{b_{ko}}\right)}$$

$$s.t.\begin{cases} x_{io} \geq \sum_{j=1,j\neq o}^{n}\lambda_j x_{ij} - s_i^-(i=1,2,...,m) \\ y_{ro}^g \leq \sum_{j=1,j\neq o}^{n}\lambda_j y_{rj} + s_r^+(r=1,2,...,s_1) \\ b_{ko}^b \geq \sum_{j=1,j\neq o}^{n}\lambda_j b_{kj} - s_k^-(k=1,2,...,s_2) \\ \sum_{j=1,\neq o}^{n}\lambda_j = 1 \\ \lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0, s_k^- \geq 0 \end{cases} \tag{1}$$

where x represents the inputs; y^g represent the desirable outputs; and b^b represents the undesirable outputs of each DMU; $x \in R^m$, $y^g \in R^{s_1}$, $b^b \in R^{s_2}$. The matrices X, Y^g, B^b denote the input matrix, desirable output matrix, and undesirable output matrix, respectively, where $X=[x_1,\ldots,x_n] \in R^{m\times n}$, $Y^g=\left[y_1^g,\ldots,y_n^g\right] \in R^{s_1\times n}$, and $B^b=\left[b_1^b,\ldots,b_n^b\right] \in R^{s_2\times n}$; λ_j is the weight vector; s_i^-, s_r^+, and s_k^+ are the slack variables for inputs, desirable outputs, and undesirable outputs. The efficiency score ρ indicates the target LCEE value; when $\rho \geq 1$, the DMU is considered efficient; when $0<\rho<1$, it indicates that there is a loss of LCEE in the DMU.

Global Malmquist-Luenberger index model

Static LCEE is weak to directly reflect the changes across different years, while dynamic LCEE allows for a more comprehensive examination of fluctuations in efficiency over time. Malmquist [39] established the Malmquist index model, which tracks changes in LCEE, enabling dynamic analysis for LCEE. But the traditional Malmquist index model fails to tackle the issue of undesirable outputs. To solve this problem, Chung et al. [40] combined the directional distance function with the traditional Malmquist index, creating the ML index model that considers undesirable outputs. However, ML index model has the disadvantages of not having circular cumulative multiplication and may have no solution for linear programming, which is prone to lead to errors in measurement results [41]. Expanding upon this, Oh established GML index model, this model addresses the infeasibility of solutions in the ML model's linear programming and constructs a global technology frontier. This allows for better comparisons across different time periods and mitigates the influence of shifts in the technology frontier on LCEE measurements. Consequently, this paper adopts GML index model to examine the dynamic changes of LCEE in China's coastal provinces. The GML index is further decomposed into the technical efficiency change index (GEC) and the technical change index (GTC). The GML index model is shown in Eq. (2):

$$GML = GEC \times GTC = \frac{E^g\left(x^{t+1},y^{t+1}\right)}{E^g\left(x^t,y^t\right)} = \frac{E^{t+1}\left(x^{t+1},y^{t+1}\right)}{E^t\left(x^t,y^t\right)} \times \left[\frac{E^g\left(x^{t+1},y^{t+1}\right)}{E^{t+1}\left(x^{t+1},y^{t+1}\right)} \times \frac{E^t\left(x^t,y^t\right)}{E^g\left(x^t,y^t\right)}\right] \tag{2}$$

$$GEC == \frac{E^{t+1}\left(x^{t+1},y^{t+1}\right)}{E^t\left(x^t,y^t\right)} \tag{3}$$

$$GTC == \frac{E^g\left(x^{t+1},y^{t+1}\right)}{E^{t+1}\left(x^{t+1},y^{t+1}\right)} \times \frac{E^t\left(x^t,y^t\right)}{E^g\left(x^t,y^t\right)} \tag{4}$$

where x^t and y^t represent the logistics industry input and output values of the evaluated unit in period t, E^g and E^t

denote the LCEE values of the global frontier in period t and $t+1$.

Based on the non-parametric framework and the SSBM model considering undesirable output, we construct a non-radial GML index model with reference to Yu and Wei's research [42]. This model is applied to capture the dynamic changes in LCEE across China's coastal provinces, as presented in Eq. (5):

$$GML_o^{t,t+1} = \frac{\rho_o^{t+1}\left(x_o^{t+1}, y_o^{g,t+1}, y_o^{b,t+1}\right)}{\rho_o^{t}\left(x_o^{t}, y_o^{g,t}, y_o^{b,t}\right)} \times \left[\frac{\rho_o^{g}\left(x_o^{t+1}, y_o^{g,t+1}, y_o^{b,t+1}\right)}{\rho_o^{t+1}\left(x_o^{t+1}, y_o^{g,t+1}, y_o^{b,t+1}\right)} \times \frac{\rho_o^{t}\left(x_o^{t}, y_o^{g,t}, y_o^{b,t}\right)}{\rho_o^{g}\left(x_o^{t}, y_o^{g,t}, y_o^{b,t}\right)}\right] \tag{5}$$

where $\rho_o^t\left(x_o^t, y_o^{g,t}, y_o^{b,t}\right)$ and $\rho_o^{t+1}\left(x_o^{t+1}, y_o^{g,t+1}, y_o^{b,t+1}\right)$ represent the LCEE values in China's coastal provinces in periods t and$t+1$; $\rho_o^g\left(x_o^t, y_o^{g,t}, y_o^{b,t}\right)$ and $\rho_o^g\left(x_o^{t+1}, y_o^{g,t+1}, y_o^{b,t+1}\right)$ represent the LCEE values based on the global production technology in each period and the input–output values in period t and$t+1$. $\frac{\rho_o^t\left(x_o^t, y_o^{g,t}, y_o^{b,t}\right)}{\rho_o^g\left(x_o^t, y_o^{g,t}, y_o^{b,t}\right)}$ and $\frac{\rho_o^g\left(x_o^{t+1}, y_o^{g,t+1}, y_o^{b,t+1}\right)}{\rho_o^{t+1}\left(x_o^{t+1}, y_o^{g,t+1}, y_o^{b,t+1}\right)}$ represent the proximity of the frontier t and $t+1$ to the global frontier respectively. $\mathrm{GML}_o^{t,t+1} = 1$ indicates LCEE has not changed; $GML_o^{t,t+1} > 1$ indicates LCEE is improved; $GML_o^{t,t+1} < 1$ indicates LCEE is decreased.

Spatial analysis method

Spatial autocorrelation model

Tobler's First Law of Geography says that all things in space are connected, but things that are geographically closer to each other are linked more strongly than things that are geographically farther away. Spatial autocorrelation analysis is primarily used to examine the regional connections and spatial relationships between nearby elements, measuring the degree of spatial clustering and correlation within the study subject. Big differences in logistics across different areas suggest that LCEE may have a lot of spatial autocorrelations. Moran [43] proposed Moran's I, which is widely adopted to test spatial dependence between neighboring regions' statistical indicators. Therefore, Moran's I is used in this paper to investigate and analyze the spatial autocorrelation of LCEE in China's coastal provinces from 2007 to 2022.

The Global Moran's I can show the main features of LCEE and check for spatial autocorrelation. The calculation is presented in Eq. (6):

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})\left(x_j - \overline{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{6}$$

where I represents the value of the Global Moran's I, n represents the number of subjects studied, x_i and x_j represent LCEE values in the studied provinces, and $\overline{x}$ represents the average LCEE value in the studied region; $\mathrm{W_{ij}}$ represents the spatial weight matrix. The value range of Global Moran's I is [−1, 1]. Due to the limitation of adjacency spatial weight matrix in analyzing interactions between non-adjacent regions, this paper constructs a spatial weight matrix based on the geographical distance of each province, as shown in Eq. (7):

$$W = \begin{cases} \frac{1}{d_{ij}}, i \neq j \\ 0, i = j \end{cases} \tag{7}$$

where, $\mathrm{d_{ij}}$ denotes the latitude and longitude distance between province i and province j.

While Global Moran's I tests for spatial correlation, it cannot identify clusters or dispersions within a region. Therefore, Local Moran's I is calculated to explore spatial agglomeration in LCEE and assess spatial autocorrelation between local provinces and their neighboring regions. The calculation formula is provided in Eq. (8):

$$I_i = \frac{(x_i - \overline{x})}{\sum_i (x_i - \overline{x})^2}\sum_{j=1}^{n} W_{ij}\left(x_j - \overline{x}\right) \tag{8}$$

where I_i represents the value of Local Moran's I, the meanings of the other variables are the same as those in Eq. (6).

Kernel Density Estimation Method

Rosenblatt [44] and Parzen [45] proposed the KDE method. This method relies on the data and constructs a continuous and smooth density curve to illustrate the distribution shape, thereby estimating the probability density. This paper utilizes KDE to uncover the dynamic evolution trends of LCEE in China's coastal provinces. Assuming the random variable X has the density form presented in Eq. (9), the commonly used Gaussian kernel function is applied, with its formula provided in Eq. (10):

$$f(x) = \frac{1}{nh}\sum_{j=1}^{n} K\left(\frac{x - x_j}{h}\right) \tag{9}$$

$$K(x) = \left(\frac{1}{\sqrt{2\pi}}\right) \exp\left(-\frac{x^2}{2}\right) \quad (10)$$

where n represents the number of Chinese coastal provinces; h represents the bandwidth, x_j represents the observed value of the j-th Chinese coastal province.

Markov chain

(1) Traditional Markov chain

The MC can effectively capture the dynamic changes in LCEE across China's coastal provinces. By analyzing the transition probabilities, it can reveal the evolution trends of LCEE. In this paper, the MC principles are applied to construct a traditional Markov transition probability matrix, which investigates how LCEE evolves over time in China's coastal provinces.

First, a $1 \times k$ matrix $P_t = P_{1,t}, P_{2,t}, \ldots, P_{k,t}$ is built to reflect the transition probabilities of LCEE in China's coastal provinces for period t. The changes of LCEE across China's coastal provinces over different time periods are depicted with a $k \times k$ matrix, as presented in Table 1. According to the quartile method, LCEE is divided into four categories. From small to large, the categories are Low (L), Medium–low (M-L), Medium–high (M-H), and High (H) [46]. The element m_{ij} in the matrix denotes the probability of being assigned to category i during period t but being assigned to category j during period $t+1$. For example, m_{13} indicates the probability that LCEE in coastal provinces belongs to the L level in period t but belongs to the M-H level in period $t+1$. The probability of state transition of LCEE in China's coastal provinces is calculated as shown in Eq. (11):

$$m_{ij} = \frac{n_{ij}}{n_i} \quad (11)$$

Here, n_{ij} represents the total number of provinces where LCEE belonged to category i in period t but transitioned to category j in period $t+1$; n_i denotes the coastal provinces total number with LCEE belonged to category i.

(2) Spatial Markov chain

The traditional MC model treats each province as an independent entity; however, provinces are influenced by their neighboring states, affecting the state transfer process. To account for this, the SMC model incorporates a spatial lag term into the standard MC transition probability matrix, where the neighboring state serves as the spatial lag term [47], as shown in Table 2. If the LCEE in the neighboring province is k, the element $m_{ij(k)}$ shows the chance of being in category i during period t but in category j during period $t+1$. As an example, $m_{13(1)}$ shows the chance of being at L level in period t but at M-H level in period $t+1$ if the spatial lag term of LCEE in nearby provinces is L level. The spatial lag value of LCEE for each coastal province is calculated as the weighted average of data from neighboring geographic units, as shown in Eq. (12):

$$Lag_i = \sum_{j=1}^{n} Y_j W_{ij} \quad (12)$$

where Lag_i denotes spatial lag value in China's coastal province i; Y_j represents LCEE value in coastal province j; n refers to the total number of coastal provinces in China; W_{ij} denotes the spatial weight matrix, capturing the spatial relationship between coastal provinces. As the influence between provinces diminishes with increasing spatial distance, this paper constructs an inverse-distance spatial weight matrix based on the distances between coastal provinces [48]. The spatial weight matrix calculating formula is presented in Eq. (7).

Construction of an evaluation system for LCEE

Indicator selection

The logistics industry in China, as an emerging composite sector, has not been classified under a single category within the national economic classification, which leads to a shortage of specific statistical data. Given that transportation, storage, and postal services are the core of logistics sector and there are specific metrics available in China, this paper adopts the approach commonly used by most scholars and references the statistical data for transportation, storage, and postal services as proxies for logistics industry data.

According to the principles of data availability and scientific and quantitative construction of indicators, this paper builds an indicator system for logistics industry by referencing previous studies, as shown in Table 3. The types of inputs include capital, labor, energy, and infrastructure. As for the output indicators, they cover desired and undesired outputs. Capital input is the capital stock, labor input is the number of employees, energy input is the amount of energy used, and infrastructure input is represented by the mileage of transportation lines.

Table 1 The traditional Markov transition probability matrix (k = 4)

t/t + 1	1	2	3	4
1	m_{11}	m_{12}	m_{13}	m_{14}
2	m_{21}	m_{22}	m_{23}	m_{24}
3	m_{31}	m_{32}	m_{33}	m_{34}
4	m_{41}	m_{42}	m_{43}	m_{44}

Table 2 Spatial Markov transition probability matrix(k=4)

Spatial lag	t/t+1	1	2	3	4
1	1	$m_{11\,(1)}$	$m_{12\,(1)}$	$m_{13\,(1)}$	$m_{14\,(1)}$
	2	$m_{21\,(1)}$	$m_{22\,(1)}$	$m_{23\,(1)}$	$m_{24\,(1)}$
	3	$m_{31\,(1)}$	$m_{32\,(1)}$	$m_{33\,(1)}$	$m_{34\,(1)}$
	4	$m_{41\,(1)}$	$m_{42\,(1)}$	$m_{43\,(1)}$	$m_{44\,(1)}$
2	1	$m_{11\,(2)}$	$m_{12\,(2)}$	$m_{13\,(2)}$	$m_{14\,(2)}$
	2	$m_{21\,(2)}$	$m_{22\,(2)}$	$m_{23\,(2)}$	$m_{24\,(2)}$
	3	$m_{31\,(2)}$	$m_{32\,(2)}$	$m_{33\,(2)}$	$m_{34\,(2)}$
	4	$m_{41\,(2)}$	$m_{42\,(2)}$	$m_{43\,(2)}$	$m_{44\,(2)}$
3	1	$m_{11\,(3)}$	$m_{12\,(3)}$	$m_{13\,(3)}$	$m_{14\,(3)}$
	2	$m_{21\,(3)}$	$m_{22\,(3)}$	$m_{23\,(3)}$	$m_{24\,(3)}$
	3	$m_{31\,(3)}$	$m_{32\,(3)}$	$m_{33\,(3)}$	$m_{34\,(3)}$
	4	$m_{41\,(3)}$	$m_{42\,(3)}$	$m_{43\,(3)}$	$m_{44\,(3)}$
4	1	$m_{11\,(4)}$	$m_{12\,(4)}$	$m_{13\,(4)}$	$m_{14\,(4)}$
	2	$m_{21\,(4)}$	$m_{22\,(4)}$	$m_{23\,(4)}$	$m_{24\,(4)}$
	3	$m_{31\,(4)}$	$m_{32\,(4)}$	$m_{33\,(4)}$	$m_{34\,(4)}$
	4	$m_{41\,(4)}$	$m_{42\,(4)}$	$m_{43\,(4)}$	$m_{44\,(4)}$

The capital stock of the logistics industry reflects the accumulation and operation status of capital in the logistics sector. Fixed asset investment, as an input factor of industrial capital, is the main way for the formation of capital in the logistics industry. Based on the data of fixed asset investment in the logistics industry, this paper estimates the capital stock of the logistics industry in terms of comparable prices by using the perpetual inventory method and takes it as the capital input indicator. Talent in the logistics industry is one of the important indicators promoting the rapid development of the logistics industry. Therefore, this paper selects the annual employment number in the logistics industry as the labor input indicator of the logistics industry. The nine most used energy consumption volumes in the logistics industry are selected as the energy input indicators of the logistics industry. The mileage of logistics transportation routes reflects the basic situation of the economic and industrial foundation of the logistics industry. The development and improvement of logistics infrastructure can reduce logistics costs, improve logistics efficiency, thereby enhancing logistics benefits and promoting economic development. Therefore, the mileage of logistics transportation routes is selected as the infrastructure input indicator. The added value of the logistics industry is one of the core indicators reflecting the development status of the logistics industry, and it is the intuitive output of various inputs in the logistics industry. The volume of freight reflects the size of transportation business volume of the logistics industry within a certain period and is one of the important indicators for measuring the development status of the logistics industry and a direct manifestation of logistics development. Therefore, this study selects the added value of the logistics industry and the volume of freight in coastal provinces as the desirable output indicators. The carbon emissions of the logistics industry mainly come from energy consumption. To measure the impact of the logistics industry on the environment, this paper selects the carbon emissions of the logistics industry in coastal provinces as the undesirable output indicator and calculates the carbon emissions based on the energy consumption of the logistics industry.

Data source and processing

Data source

This paper collects data of transportation, storage, and postal services across eleven provinces in China's coastal areas from 2007 to 2022. From the China Statistical Yearbook (2008–2023), China Energy Statistical Yearbook (2008–2023), the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, and the Guidelines for the Preparation of Self-Assessment Reports on the Responsibility of Provincial People's Governments to Control Greenhouse Gas Targets Detailed data of indicators. The data used is complete and does not contain any outliers or missing values.

Table 3 Input–output indicator system for LCEE

Index type	Primary index	Secondary index	Unit
Input indicators	Capital input	Capital stock of the logistics industry	Billion yuan
	Labor input	Number of employees in the logistics industry	Ten thousand people
	Energy input	Energy consumption of the logistics industry	Million tons of standard coal
	Infrastructure input	Mileage of transportation lines in the logistics industry	Million km
Output indicators	Desirable output	Added value of logistics industry	Billion yuan
		Freight volume of the logistics industry	Million tons
	Undesirable output	Carbon emissions of the logistics industry	Million tons

Data processing

(1) Measurement of capital stock. The calculation of the capital stock of fixed asset investment in the logistics industry is represented by Eq. (13):

$$K_{it} = I_{it} + (1 - \delta_{it})K_{it-1} \tag{13}$$

where K_{it} and K_{it-1} represent the capital stock of province i in period t and period t − *1*; I_{it} denotes the fixed asset investment in the logistics industry of province i during period t; and δ_{it} denotes the capital depreciation rate. Based on the research conclusion of Li [49] and Zhang et al. [50], this paper uses the perpetual inventory method to calculate the capital stock of fixed assets in the logistics industry. The initial capital stock for each province is estimated by dividing the 2005 fixed asset investment in transportation, storage, and postal services by 10%. The economic depreciation rate is chosen to be 9.6%.

(2) Calculation of carbon emissions. The carbon emission factor method is the most utilized approach to measuring carbon emissions. Based on earlier research, this paper calculates carbon emissions based on the nine energy sources most used in the logistics industry. All data used in our calculation are obtained from the China Energy Statistical Yearbook. Equation (14) shows the method for the calculation:

$$CO_2 = \sum_{i=1}^{n} CO_{2,i} = \sum_{i=1}^{n} E_i \times NCV_i \times CEF_i \times COF_i \times \frac{44}{12} + E_9 \times \delta_j \tag{14}$$

where i denotes the type of energy; E_i denotes the consumption of the i-th energy type; E_9 denotes the electricity consumption; NCV_i denotes the low calorific value of the i-th energy type; CEF_i denotes the carbon content per unit heat value of the i-th energy type; COF_i denotes the carbon oxidation rate of the i-th energy type; δ_j denotes the electricity emission factor for province j. Table 4 presents the carbon emission coefficients, while Table 5 presents the average carbon dioxide emission coefficients for provincial power grids.

Empirical analysis

Static analysis results

This paper collects 16 years of data on input–output indicators for logistics in China's coastal provinces. Using the SSBM model that considers undesirable outputs, this paper calculates and analyzes static LCEE in these coastal provinces during the study period. The results of LCEE measurements are presented in Fig. 2, the quartile method is employed to classify the LCEE in China's coastal provinces during the study period into four categories: L efficiency (0.3241–0.6042), M-L efficiency (0.6042–0.7581), M-H efficiency (0.7581–1.0017), and H efficiency (1.0017–1.4638).

From the measurement results in Fig. 2, static LCEE values in different provinces vary greatly over various years. From 2007 to 2022, Tianjin, Hebei, Shandong, and Liaoning consistently exhibited higher LCEE in most years, with Tianjin, Hebei, and Shandong taking the lead in low carbon logistics development among coastal regions. LCEE in Jiangsu, Shanghai, and Zhejiang steadily improved, maintaining relatively high levels. In contrast, LCEE in Fujian, Guangdong, Guangxi, and Hainan remained low, with these provinces often positioned in the low or medium efficiency levels for a long time with a small change, showing that these provinces are lagging in low carbon logistics development.

From the time series perspective, LCEE exhibited a fluctuating trend from 2007 to 2022, formed a W-shaped pattern characterized by four stages of decline-growth-decline-growth. The first stage is from 2007 to 2009, in which the average LCEE showed a declining tendency, from 0.7063 in 2007 to the lowest point of 0.6551 during the study period. The reason for the decline in LCEE

Table 4 Carbon emission coefficients of nine energy types

Energy type	Low calorific value (kJ/kg)	Carbon content per unit heat value (kgC/GJ)	Carbon oxidation rate (%)	Standard coal conversion coefficient	Carbon emission factor ($kgCO_2$/kg)
Raw coal	20,908	26.37	94	0.7143	1.9003
Crude oil	41,846	20.10	98	1.4286	3.0202
Gasoline	43,070	18.90	98	1.4714	2.9251
Kerosene	43,070	19.50	98	1.4714	3.0179
Diesel oil	42,652	20.20	98	1.4571	3.0959
Fuel oil	41,816	21.10	98	1.4826	3.1705
Liquefied petroleum gas	50,179	17.20	98	1.7143	3.1013
Natural gas	38,931(kJ/m^3)	15.30	99	1.2150	2.1622
Electricity	–	–	–	0.4040	–

Data resource: National Greenhouse Gas Inventory Guidelines during this period may be the global financial crisis that erupted during 2007–2009, and China's coastal provinces' logistics industry was also affected. Although China's economy generally maintained growth, the sharp decline in external demand led to the problem of excess capacity in the logistics industry. Particularly in the coastal provinces, the reduction in demand for logistics dependent on international trade, the lower utilization of cargo transportation and the reduced efficiency of the logistics network led to lower LCEE.

In the second stage, starting from 2009, the average LCEE increased significantly, reaching a relatively high point of 0.8777 in 2012. The rise in LCEE during this period may be attributed to the fact that after 2009, the global economy began to gradually recover from the financial crisis and China's economic growth re-accelerated. The Chinese government launched the China's four-trillion economic stimulus plan, and through large-scale infrastructure investment and domestic demand, manufacturing and trade in coastal provinces rebounded rapidly, and logistics demand rebounded strongly. Against the backdrop of this rebound in demand, the logistics industry has seen an increase in equipment utilization and transportation efficiency, which in turn has led to an increase in LCEE.

However, in the period from 2012 to 2015, LCEE in China's coastal provinces decreased again, from 0.8777 in 2012 to 0.6891 in 2015. This may be because China's coastal provinces' economic growth entered a 'New Normal' after 2012 and slowed down significantly. The logistics industry in coastal provinces is highly sensitive to economic fluctuations, and with industrial overcapacity and weakening external demand, the growth rate of the logistics business has slowed down, leading to an overall overcapacity in the logistics industry. In the context of unstable logistics demand, the utilization rate of transport vehicles has declined, leading to wasted resources and increased energy consumption, as well as reduced LCEE.

Table 5 Average carbon dioxide emission factors of provincial power grids in coastal provinces

Provinces	Carbon dioxide emission factors ($kgCO_2/kWh$)	Provinces	Carbon dioxide emission factors ($kgCO_2/kWh$)
Fujian	0.3910	Liaoning	0.7219
Guangdong	0.4512	Shandong	0.8606
Guangxi	0.3938	Shanghai	0.5641
Hainan	0.5147	Tianjin	0.8119
Hebei	0.9029	Zhejiang	0.5246
Jiangsu	0.6829	–	–

Data resource: Guidelines for the Preparation of Self-Assessment Reports on Provincial Government's Greenhouse Gas Emission Control Targets.

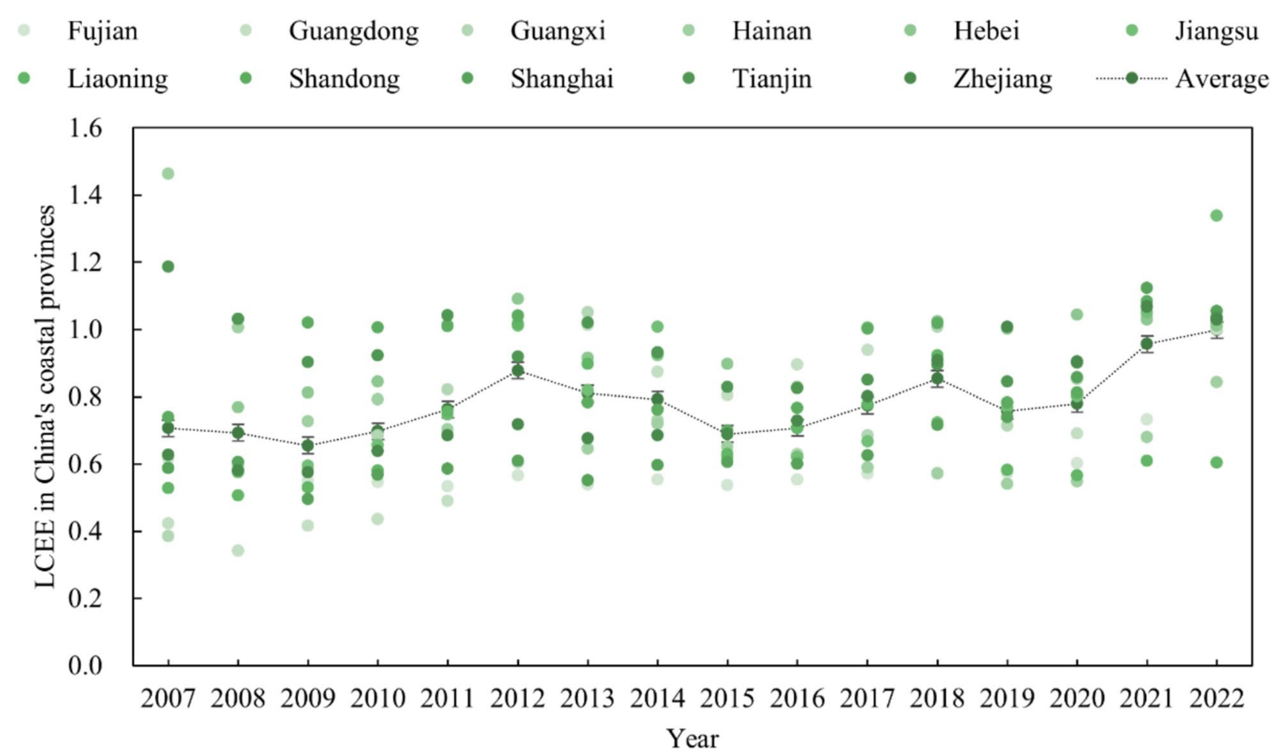

Fig. 2 Trend of LCEE in China's coastal provinces from 2007 to 2022

The last stage is from 2015 to 2022, during this period, the average LCEE in China's coastal provinces in all other years showed an upward trend except for 2018, which decreased slightly. The LCEE value increased from 0.6891 in 2015 to 0.9973 in 2022, reaching the peak in sixteen years. The average LCEE fluctuates but overall level remains high, indicating that the logistics industry in these provinces has achieved low-carbon sustainable development at this stage. During this period, the Chinese Government vigorously promoted energy conservation, emission reduction and green development, especially in the logistics industry in China's coastal provinces, and introduced a series of policies to encourage green logistics. For example, the 13th Five-Year Plan for the Development of a Modern Comprehensive Transportation System, the 14th Five-Year Plan, and the Peak Carbon and Carbon Neutral Action Plan have set out clear energy-saving and emission reduction targets and measures. The government's policy support and supervision of logistics enterprises has increased, especially in coastal provinces, and the implementation of the policies has been effective, which has promoted the improvement of LCEE. The short-lived decline in LCEE in 2018 may be related to the external economic fluctuations and changes in the international trade environment. The outbreak of trade friction between the United States and China and the uncertainty of global trade may have led to fluctuations in China's foreign trade logistics, particularly affecting exports in coastal provinces. This fluctuation in foreign trade demand increases the uncertainty in the logistics chain, leading to a decrease in the utilization of some logistics resources, which temporarily affects LCEE. Overall, however, the impact was relatively short-lived, with LCEE picking up again in subsequent years. Throughout the study period, the lowest average LCEE was recorded in 2009 at 0.6551, while the highest was in 2022 at 0.9973, close to the efficiency level, marking an improvement of 0.3422. This result indicates there is significant progress.

To better analyze the trend of LCEE, the eleven coastal provinces are grouped into three regions according to their geographic locations and similarities in LCEE: the Bohai Rim Region, the Yangtze River Delta Region, and the Pan-Pearl River Delta Region. The specific provinces within every region are listed in Table 6.

From a regional perspective, as shown in Fig. 3, the trends in LCEE across the three regions are broadly similar. And all three regions have seen significant improvements in the LCEE from 2007 to 2022. The average LCEE in the Bohai Rim region has always been at a relatively high level, higher than that in the other two regions. Except for 2021 and 2022, in all other years within the study period, it has consistently been higher than the overall average LCEE. This regional disparity may be attributed to factors such as the logistics industry structured the geographical environment. From the fluctuation trends perspective, the Yangtze River Delta Region has experienced the most rapid enhancement in LCEE with the most pronounced growth trend. In contrast, the other two regions have shown a slight upward trend with minor fluctuations. The average LCEE in the Yangtze River Delta Region improved from 0.6007 in 2007 to 1.1400 in 2022, a growth of 0.5393. In the Bohai Rim Region, the average LCEE rose from 0.7699 in 2007 to 0.9198 in 2022, an increase of 0.1499. Meanwhile, in the Pan-Pearl River Delta Region, the average LCEE improved from 0.7219 in 2007 to 0.9679 in 2022, an increase of 0.2460. The Yangtze River Delta region has seen the fastest improvement in LCEE, benefiting from strong economic development, technological advances, policy support and the wide application of new energy sources; the Pan-Pearl River Delta region has seen a steady improvement through internationalized logistics demand, modern logistics technology and the development of multimodal transportation at ports; and the Bohai Rim region, due to its heavy traditional industrial structure and relatively lagging technological advances, has seen the improvement of LCEE is slower, but still maintains a small growth.

From the perspective of LCEE in different provinces, as shown in Fig. 4, there are great differences in different provinces. From 2007 to 2022, the average LCEE in Tianjin, Hebei, and Shandong remained high, surpassing the average LCEE in China's coastal provinces. This means that in these three provinces, the logistics industry is paying more attention to the effective management of carbon emissions while maintaining rapid development. The average LCEE in Fujian was the lowest, at just 0.6019. In most provinces within the study region, the average LCEE ranged between 0.6 and 0.8, which is below the overall mean of 0.7818. This suggests that there is considerable potential for improving the LCEE.

In summary, this paper reveals significant fluctuations and regional differences in LCEE in China's coastal provinces from 2007 to 2022. During these sixteen years, LCEE shows a W-shaped trajectory, with stages of decline and growth influenced by external economic

Table 6 Three regions of China's coastal provinces

Regional division	Corresponding China coastal provinces in the region
The Bohai Rim Region	Liaoning, Hebei, Tianjin, Shandong
The Yangtze River Delta Region	Jiangsu, Shanghai, Zhejiang
The Pan-Pearl River Delta Region	Fujian, Guangdong, Guangxi, Hainan

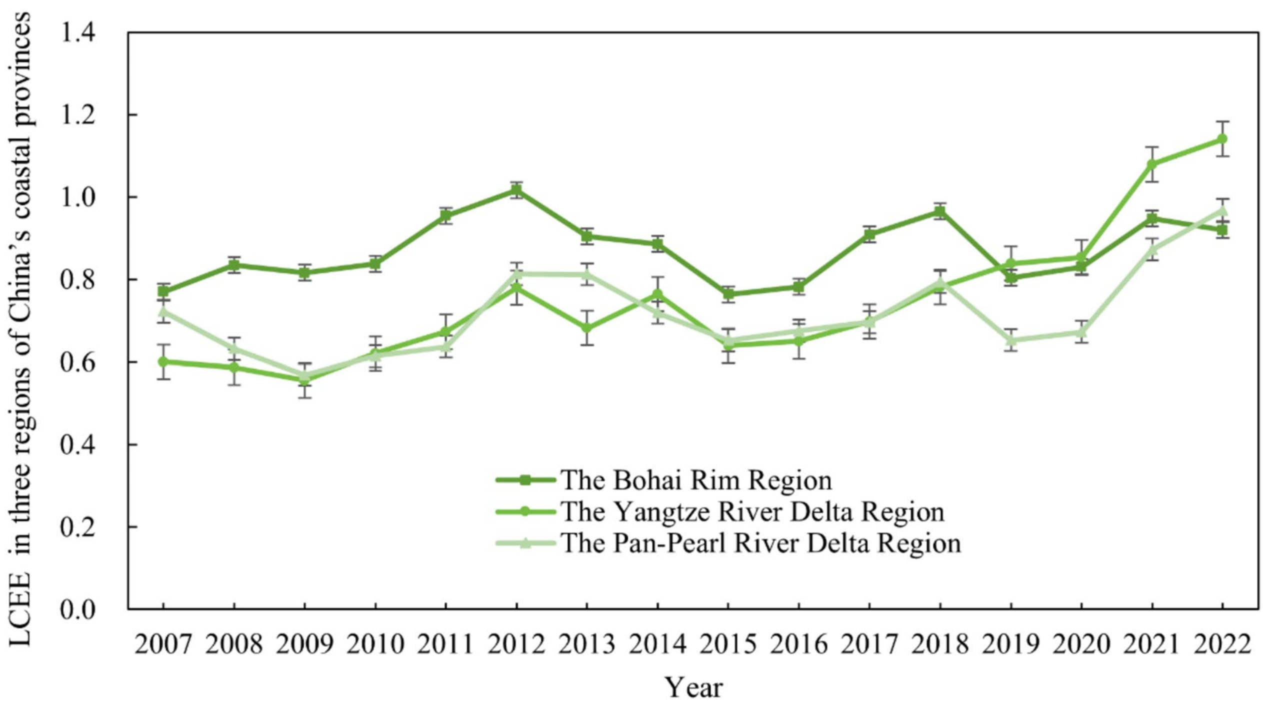

Fig. 3 Trend of LCEE in three regions of China's coastal provinces from 2007 to 2022

factors, government policies and industry adjustments. The analysis shows that the LCEE value of the Bohai Rim region has been higher than that of the Yangtze River Delta and Pan-Pearl River Delta regions due to its mature logistics structure and geographical advantages. However, the Yangtze River Delta region has experienced the most significant growth, driven by rapid economic development and the adoption of advanced green technologies. Despite the improvement, LCEE in provinces such as Fujian is still below average, highlighting that there is still considerable room for industry to improve its LCEE. The findings suggest the need for continued support for green logistics practices to reduce carbon emissions, especially in underperforming regions like Fujian, to promote the sustainable development of the logistics industry in China's coastal provinces.

Dynamic analysis results

Figure 5 illustrates that the GML index of LCEE in China's coastal provinces exhibited fluctuations between 2007 and 2022. The GML index remained between 0.8 and 1.2 overall, with some fluctuations in individual years, but no major declines. The overall trend from 2007–2008 to 2021–2022 shows a slow increase in fluctuation. There are large differences in LCEE among coastal provinces. 2020–2021 had the highest average GML index, suggesting relatively better low-carbon economic efficiency compared to other years. which may be attributed to the policy support, technological innovation, and industrial restructuring, which have promoted the decarbonization and green transformation of the logistics industry.

To investigate the factors influencing changes in LCEE across coastal provinces in China from 2007 to 2022, the GML index is decomposed into GEC and GTC. From Fig. 6, it can be observed that the growth of LCEE in seven coastal provinces, including Guangdong, Guangxi, Hebei, Jiangsu, Shandong, Shanghai, and Zhejiang, all benefited from the promotion effect of technical efficiency and logistics technology. Among them, Guangxi has a catch-up effect; that is, the technical efficiency of this province is steadily converging toward the production frontier. Despite a decrease in logistics technical efficiency in Fujian and Shandong, their overall LCEE still increased, owing to advancements in logistics technology. The growth of LCEE in Liaoning is because the increase in GEC is greater than the decrease in GTC. This indicates that the province has certain strengths in logistics management level, but there is a need to further enhance the logistics technology level by adopting advanced technologies. Hainan's GEC and GTC have both seen a certain decline, so on the one hand, Hainan should focus on the training logistics professionals, adopting successful enterprise management practices to elevate its management standards, and pay attention to the allocation of logistics resources for maximum efficiency. On the other

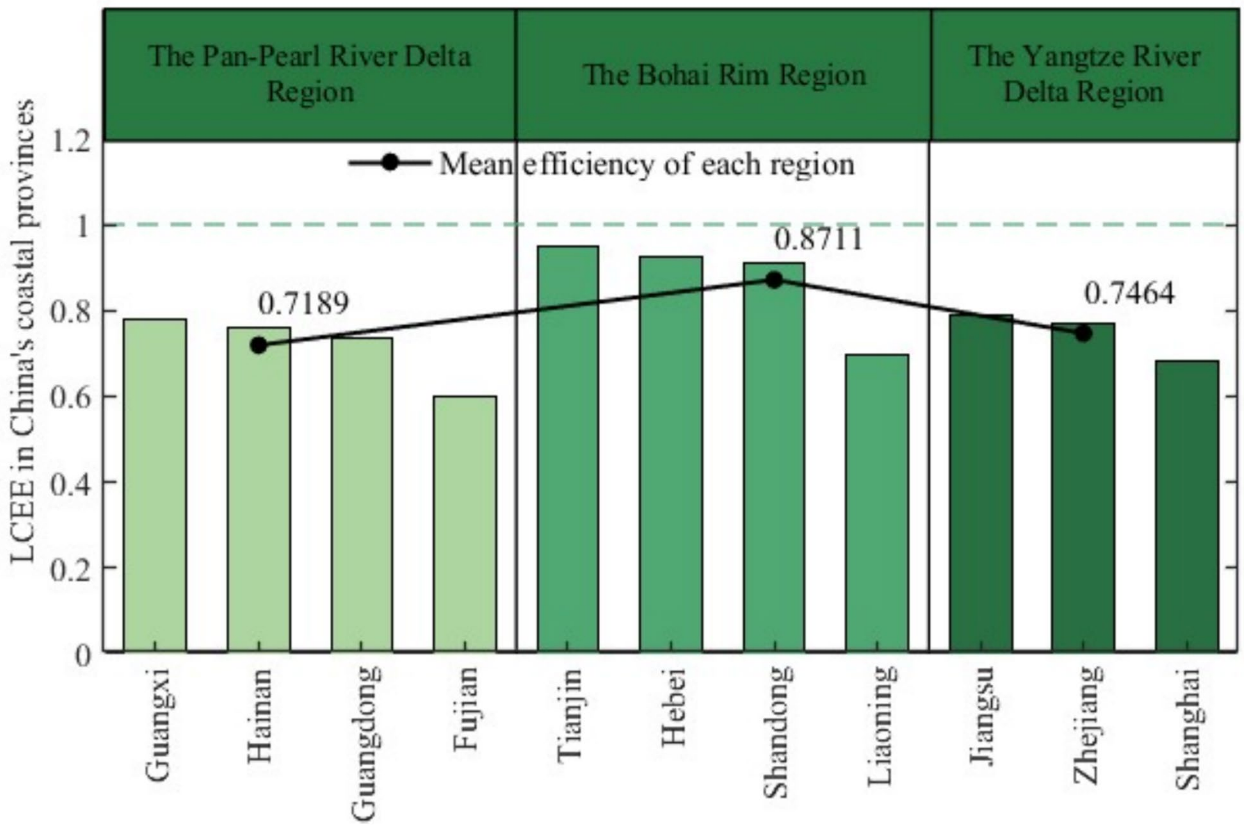

Fig. 4 Provincial differences in LCEE of China's coastal provinces from 2007 to 2022

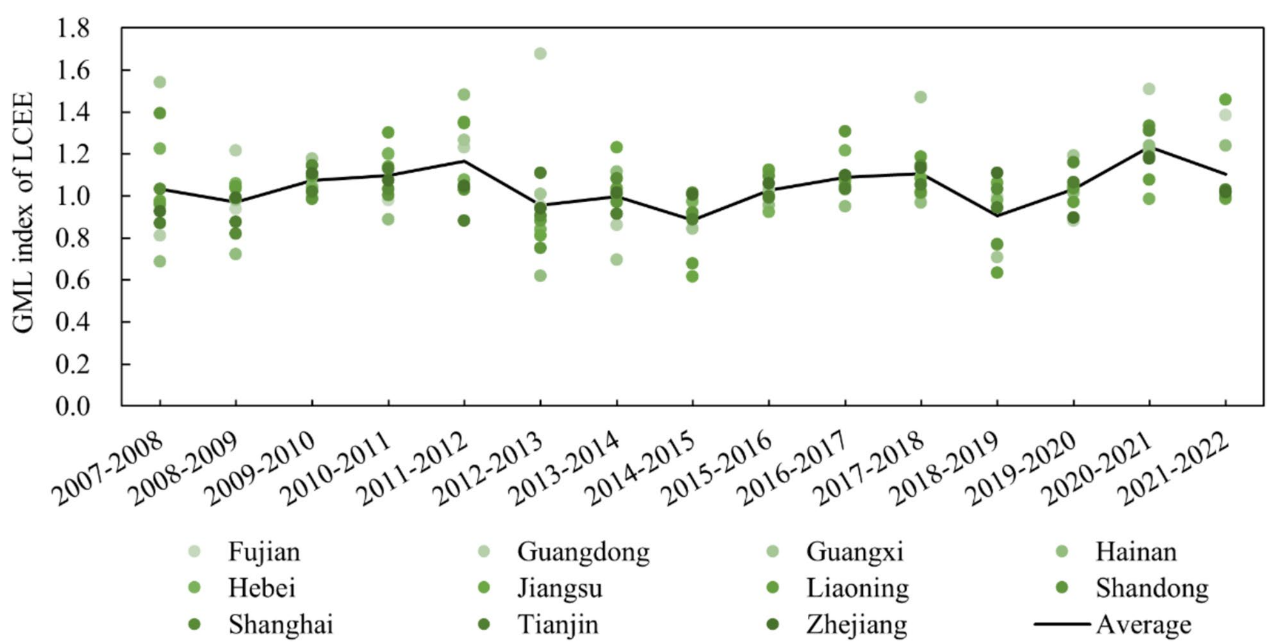

Fig. 5 GML index of LCEE in China's coastal provinces from 2007 to 2022

hand, Hainan must further strengthen logistics technology by incorporating advanced innovations.

From Fig. 7, it can be seen the fluctuation range of GEC is relatively small. Most provinces remain around 1.0, indicating that the changes in technical efficiency are relatively stable. However, there are significant peaks in some years. Liaoning reached 1.5398 in 2008–2009, and Guangdong reached 1.8816 in 2012–2013. This phenomenon may be closely related to the policy support in these two provinces, the adjustment of industrial structure, and the optimization of green management measures. It reflects that in certain periods, the driving force for the improvement of LCEE is the improvement of technical efficiency.

The fluctuation range of the GTC index is much larger than that of the GEC, indicating the uncertainty and cyclical characteristics of technological progress. Especially in Guangdong, it reached 2.2240 from 2008 to 2009, which might be attributed to the significant breakthroughs in green technologies of the logistics industry at that time, such as the promotion of new energy transportation tools and the optimization of logistics information systems. Overall, the changes in GEC are relatively stable, while GTC shows significant fluctuations. This indicates that the improvement of LCEE largely depends on the breakthroughs and promotion of technological innovation rather than merely relying on the optimization of existing technologies.

In summary, the LCEE of China's coastal provinces has changed to varying degrees from 2007 to 2022, and the reasons for the changes in each province also differ. For most provinces, logistics technical efficiency has become a bottleneck constraining the growth of LCEE.

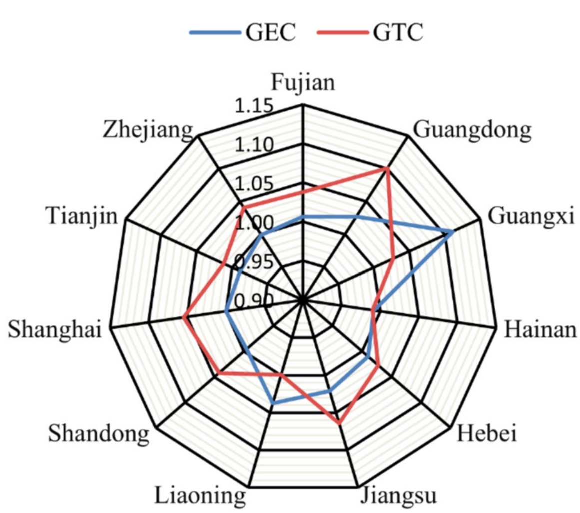

Fig. 6 GEC and GTC of the logistics industry in China's coastal provinces

These provinces should increase investment in logistics technology innovation and upgrading. For provinces constrained by logistics technological progress, improvements should focus on enhancing management capabilities, achieving economies of scale, and improving resource allocation efficiency to boost LCEE.

Spatial pattern analysis

Temporal-spatial distribution characteristics analysis

To further reveal the spatial distribution characteristics of LCEE in China's coastal provinces, ArcGIS 10.8 was utilized to generate spatial distribution maps for the years 2007, 2012, 2017, and 2022 in China's coastal provinces, as illustrated in Fig. 8.

From the point of view of the spatial distribution patterns, there were a lot more H efficiency provinces in 2022 than there were in 2007. This means that the LCEE of the coastal areas of China has gotten better over time. At the regional level, the Pan-Pearl River Delta and the Yangtze River Delta have much lower LCEE than the Bohai Rim area. The LCEE in the Bohai Rim region has mostly stayed at an H level of efficiency, while it has slowly gone up in the other two regions. From the provincial perspective, Shandong consistently maintained an H level throughout the four representative years. Hebei and Tianjin were also at H level most of the time. Jiangsu, Shanghai, Zhejiang, Guangdong, and Guangxi have seen their LCEE values increase across efficiency intervals from 2007 to 2022, reaching the H level by 2022. However, Fujian's logistics sector has consistently exhibited L or M-L LCEE across these years. which may be because logistics enterprises generally rely on traditional transportation modes, and the promotion of the application of green logistics technology is insufficient. Fujian should strengthen policy support and guidance for the logistics industry, accelerating the transition to low-carbon practices to improve LCEE. Hainan's LCEE has decreased in these years, shifting from the H level in 2007 to the L level in 2017, and then to the M-L level in 2022, likely driven by rapid growth in logistics demand alongside lagging infrastructure development, which has hindered effective carbon emission control. Therefore, Hainan should accelerate the application of green technology and infrastructure development to meet the growing demand for logistics. Notably, LCEE in Liaoning initially rose from an L level in 2007 to a H level, then decreased to an M-H level in 2017, and further declined to an M-L level in 2022. This trend may be attributed to advancements in logistics technology and supportive policies in Liaoning during the early years, which led to improvements in LCEE. However, as logistics demand in Liaoning grew, the pressure on resources and the environment escalated,

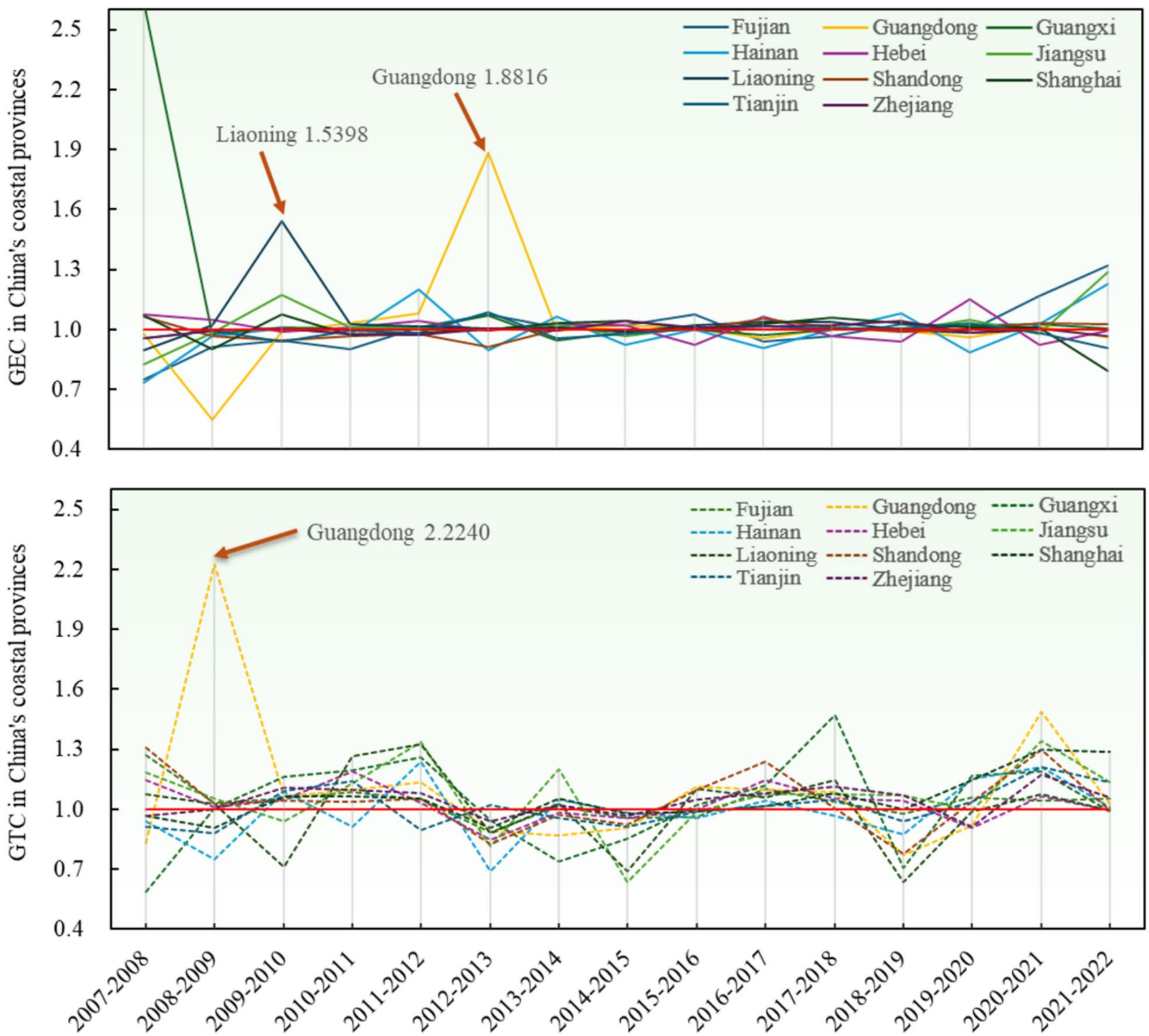

Fig. 7 GML index decomposition

which progressively diminished LCEE levels. As Liaoning's logistics industry continues to expand rapidly, measures should be implemented to control carbon emissions and improve LCEE to ensure the sustainable development of the logistics.

Spatial autocorrelation analysis

Global Moran's I can reveal the spatial autocorrelation of LCEE in China's coastal provinces. This paper employs the Global Moran's I to analyze the spatial autocorrelation of the LCEE in China's coastal provinces from 2007 to 2022. The Global Moran's Index is calculated using ArcGIS 10.8, and the results are presented in Table 7. In both 2009-2011and2015, Global Moran's I values were positive and passed the 10% significance test. This indicates that in these years, there was a pattern of regional clustering in the spatial distribution of LCEE in China's coastal provinces, which showed positive spatial autocorrelation. In other words, LCEE in China's coastal provinces was influenced by neighboring provinces, and LCEE presented a phenomenon of "high-high" or "low-low" agglomeration in geographical space. In 2007, 2012 to 2014, and 2016 to 2022, the spatial distribution of LCEE in China's coastal provinces revealed a random trend, did not show obvious spatial autocorrelation characteristics, and the efficiency values of each province were not significantly influenced by neighboring provinces.

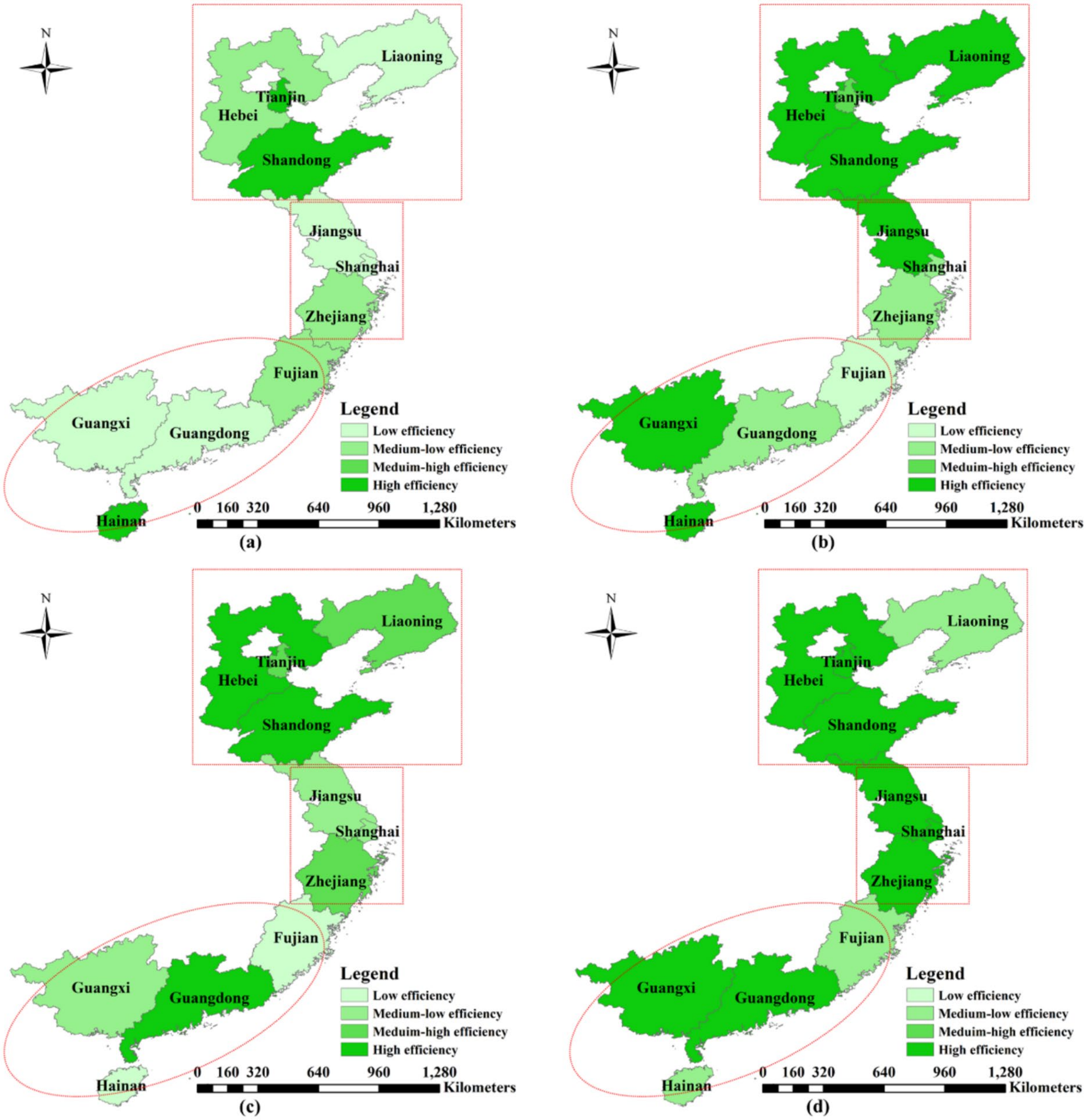

Fig. 8 Spatial distribution patterns of LCEE across China's coastal provinces for the years. 2007 (**a**), 2012 (**b**), 2017 (**c**), and 2022 (**d**).

The Global Moran's I can show how LCEE is spatially related across coastal provinces, but it can't show how provinces are geographically clustered. Therefore, this paper employs Local Moran's I to conduct a local spatial autocorrelation analysis of LCEE in China's coastal provinces.

To further analyze the clustering degree in neighboring spaces of local regions in China's coastal provinces, this paper selected the years with significant spatial clustering characteristics to conduct a local spatial autocorrelation analysis of LCEE. The outcomes can be seen on Fig. 9. Although the Global Moran's I index was insignificant in certain years, it does not necessarily imply the absence of spatial dependence, as local clustering may still be present. Therefore, the local spatial autocorrelation analysis helps identify specific provinces or regions where high-efficiency or low-efficiency clusters exist, offering insights into regional disparities and potential spillover effects. However, given the relatively small sample size of coastal provinces, the results should be interpreted with caution.

The Local Moran's I cluster map analysis shows that LCEE in most of China's coastal areas does not have significant clustering features. In 2009, only Shandong displayed the spatial characteristics of high-high clustering. This means that LCEE in Shandong was high, with similarly high LCEE observed in the surrounding provinces. In 2010, both Hebei and Shandong showed high-high clustering spatial characteristics. In 2011, Hebei, Tianjin, and Shandong had high-high clustering, while Liaoning had low–high outliers spatial characteristics. In 2015, Hebei and Tianjin showed high-high clustering characteristics, while Fujian showed low-low clustering spatial characteristics. Overall, high-high clustering was the main type of clustering for LCEE in China's coastal provinces from 2007 to 2022. Shandong showed high-high clustering characteristics from 2009 to 2011, indicating that its LCEE was at a H efficiency level and among the top in China's coastal provinces, exerting a certain radiating effect.

Dynamic evolution trend of temporal-spatial distribution analysis

Kernel Density Estimation analysis

To examine the dynamic evolution characteristics and regional differences of LCEE in China's coastal provinces, this paper adopts KDE to explore the distribution position, main peak evolution trend, distribution extensibility, and polarization trend of LCEE from 2007 to 2022. The results are presented on Fig. 10.

Table 7 Global Moran's I of LCEE in China's coastal provinces from 2007 to 2022

Year	Global Moran's I	*P*-value	Z-score
2007	−0.1833	0.7672	−0.2960
2008	0.3187	0.1901	1.3103
2009	0.7085	0.0094	2.5986
2010	0.6341	0.0202	2.3220
2011	0.8845	0.0022	3.0584
2012	0.2232	0.3241	0.9860
2013	0.4043	0.1211	1.5503
2014	0.1331	0.4704	0.7218
2015	0.6877	0.0118	2.5194
2016	0.3830	0.1340	1.4986
2017	0.3772	0.1420	1.4686
2018	0.0667	0.6047	0.5177
2019	0.0985	0.5291	0.6294
2020	0.2826	0.2301	1.2002
2021	0.1397	0.4443	0.7650
2022	0.0846	0.4422	0.7685

From the distribution position of the kernel density function curves, the kernel density curves of LCEE in China's coastal provinces showed a rightward shift. This indicates that there was a fluctuating rising tendency in LCEE. From the evolution trend of the main peak, the kernel density curve of LCEE initially declined and subsequently rose, reaching its lowest point in 2013. At the same time, the curve's width increased first and then decreased, indicating that the agglomeration level of LCEE weakened between 2007 and 2013. However, after 2013, LCEE across various regions once again showed a trend of agglomeration, with more regions exhibiting convergence in LCEE. From the distribution extensibility, the kernel density curve of LCEE exhibited a double-sided tailing pattern. This indicates that, overall, there were both exemplary regions with advanced LCEE and regions with relatively low development levels in China's coastal provinces. The contraction of extensibility revealed that the absolute difference in LCEE between different regions had decreased. From the polarization trends, the kernel density curve of LCEE transitioned from a multimodal to a bimodal distribution. This indicates a transition from a multipolar to a bipolar trend, suggesting that LCEE across different regions in China's coastal provinces is becoming more diversified, with efficiency levels converging and becoming more similar across regions.

Overall, LCEE in China's coastal provinces exhibited a fluctuating pattern. Over time, the kernel density curve gradually shifted rightward, signifying an increase in LCEE values. The main peak of the curve first declined and subsequently rose, reflecting a similar trend in the level of spatial agglomeration. The contraction in extensibility indicated a reduction in the absolute differences between provinces. The kernel density curve transitioned from a multimodal to a bimodal distribution, indicating a shift from multipolar to bipolar differentiation. Although the absolute differences in LCEE between provinces diminished, the polarization in efficiency levels remained evident.

Markov chain analysis

The kernel density function can capture the overall dynamic distribution and evolution trends of LCEE in China's coastal provinces, but it cannot determine the transition laws between different efficiency intervals. In order to further reveal the transfer rules and characteristics of LCEE in China's coastal provinces, this paper uses traditional MC and SMC methods to analyze the evolution process. Here are the results of the calculations for the traditional MC transition probability matrix and the SMC transition probability matrix based on the above classification of LCEE levels, they are shown in Tables 8

Fig. 9 Agglomeration map of LCEE in coastal provinces of China. 2009 (**a**), 2010 (**b**), 2011 (**c**), and 2015 (**d**)

and 9. A change from a lower value to a higher value is called an upward transition, a change from a higher value to a lower value is called a downward transition. The main diagonal represents the probability that the current state of LCEE remains unchanged, while the off diagonal represents the probability of an upward or downward shift.

There is a standard Markov transition probability matrix. In this matrix, the probability values for L, M-H,

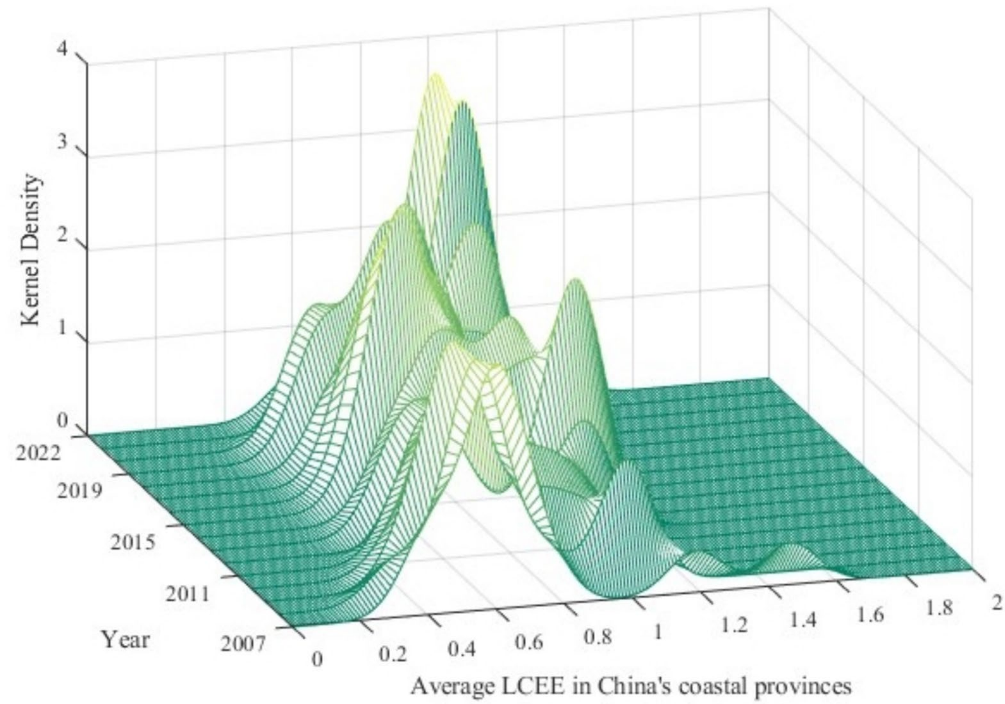

Fig. 10 KDE of LCEE in China's coastal provinces from 2007 to 2022

and H levels are consistently higher on the main diagonal than those on the non-diagonal lines. This indicates that the provinces at these three efficiency levels are more inclined to maintain their original efficiency levels unchanged, with a relatively high probability of convergence and a relatively low probability of hierarchical transition. The LCEE in China's coastal provinces demonstrated stability, with the probabilities of maintaining the same efficiency level after one year being 72.73, 52.38, and 55.55%, respectively. The state transitions in LCEE in China's coastal provinces were primarily concentrated in transitions from M-H level to H level and from H level to M-H level, with transition probabilities of 35.72 and 30.56%, respectively. Most state transitions occurred between adjacent categories, indicating that the development of LCEE in China's coastal provinces is a gradual process, making leapfrog transitions difficult to achieve. Meanwhile, the probabilities of upward transition by one level after one year for L, M-L, and M-H levels were 27.27, 39.53, and 35.72%, respectively. This indicates that the development process of LCEE is dynamic and characterized by fluctuations, with varying probabilities of upward transitions across different efficiency levels. Conversely, the probabilities of downward transition by one level for M-L, M-H, and H efficiency levels were 13.95, 11.90, and 44.45%, respectively, suggesting that there was a potential downward trend in the development of LCEE in China's coastal provinces.

The traditional MC does not account for spatial interactions between different provinces, treating the eleven coastal provinces of China as independent entities. However, the logistics industry is closely connected across China's coastal provinces, so it is essential to study the transition process of LCEE under the various spatial lags in China's coastal provinces. In this paper, the SMC, which is based on the traditional MC, is used to investigate the effect of neighboring provinces on the spatial evolution of LCEE and to further analyze the dynamic evolution trend of spatial distribution in China's coastal provinces.

As shown in Table 9, geographical factors had a big effect on the transition process. The LCEE transition probability changed a lot when there was a change in

Table 8 Traditional Markov transfer probability matrix of LCEE in China's coastal provinces from 2007 to 2022

t/t+1	n	L	M-L	M-H	H
L	44	0.7273	0.2500	0.0000	0.0227
M-L	43	0.1395	0.4651	0.2558	0.1395
M-H	42	0.0238	0.0952	0.5238	0.3572
H	36	0.0000	0.1389	0.3056	0.5555

Table 9 Spatial Markov transfer probability matrix of LCEE in China's coastal provinces from 2007 to 2022

Spatial lag	t/t+1	n	L	M-L	M-H	H
L	L	2	1.0000	0.0000	0.0000	0.0000
	M-L	1	1.0000	0.0000	0.0000	0.0000
	M-H	1	0.0000	0.0000	1.0000	0.0000
	H	0	0.0000	0.0000	0.0000	0.0000
M-L	L	22	0.7273	0.2727	0.0000	0.0000
	M-L	20	0.1500	0.4500	0.3000	0.1000
	M-H	23	0.0000	0.0870	0.6087	0.3043
	H	17	0.0000	0.0588	0.3529	0.5883
M-H	L	20	0.7000	0.2500	0.0000	0.0500
	M-L	21	0.0952	0.5238	0.1905	0.1905
	M-H	18	0.0556	0.1111	0.3889	0.4444
	H	19	0.0000	0.2105	0.2632	0.5263
H	L	0	0.0000	0.0000	0.0000	0.0000
	M-L	1	0.0000	0.0000	1.0000	0.0000
	M-H	0	0.0000	0.0000	0.0000	0.0000
	H	0	0.0000	0.0000	0.0000	0.0000

spatial lag compared to the standard MC. There were big differences between the traditional and spatial Markov transition probability matrices in China's coastal provinces because the LCEE levels of neighboring provinces affected the chances of each province making a shift. From the spatial Markov transition probability matrix, it can be observed that:

The LCEE of neighboring provinces in China's coastal areas affected the transfer probability of their own LCEE state. The spatial Markov transition probability matrix was very different from the traditional Markov transition probability matrix because of the effect of the LCEE of neighboring provinces. In the traditional MC matrix, for example, 72.73% of areas with low LCEE would stay at the low efficiency level in the next period. Taking into account the impact of nearby provinces, however, the chances of staying in the L efficiency level were 100, 72.73, 70.00, and 0%.

LCEE in China's coastal provinces exhibited a clear spatial spillover effect. Specifically, neighboring regions with lower LCEE enhanced the probability of a downward transition in a province's LCEE, while neighboring regions with high LCEE increased the probability of an upward transition. For example, under the influence of L LCEE neighboring regions, the probability of L LCEE regions remaining at a L level was 100%, and the probability of M-L efficiency regions declining to a L level was also 100%. Conversely, under the influence of M-H efficiency neighboring regions, the probability of L efficiency regions moving up increased to 30.00%, and the probability of M-L efficiency regions moving up was 38.1%, with a 19.05% chance of directly jumping to the H efficiency level.

Conclusions and policy suggestions

Reducing carbon emissions from logistics in China's coastal provinces has become an urgent task in the context of the "China's dual carbon goals". It means that studying LCEE in China's coastal provinces is necessary for change and sustainable growth in the logistics industry. This paper first applies the SSBM model to calculate the static LCEE in China's coastal provinces. And then, the model of GML index is used to figure out the reason that causes the change of LCEE. Moreover, spatial autocorrelation analysis is used to examine spatial correlation relationships. Finally, KDE is used to analyze the LCEE's overall dynamic evolutionary trends. This paper integrates spatial lag factors into the traditional MC to construct the SMC, further explores the temporal and spatial evolution characteristics of LCEE in China's coastal provinces from a spatial perspective. The main conclusions are as follows:

From the calculation results in LCEE in China's coastal provinces, it was observed that the overall LCEE level in China's coastal provinces during the period from 2007 to 2022 remained relatively low, albeit exhibiting a fluctuating upward tendency. Notably, there were pronounced variations in the spatial distribution of LCEE across different provinces at diverse stages, and significant disparities also emerged in the LCEE of the same province over different periods. Tianjin, Hebei, and Shandong were at the forefront of the health development of LCEE in China's coastal provinces, while Fujian, Shanghai, and Liaoning had great potential for carbon emission reduction in the logistics industry. LCEE in Bohai Rim region was substantially higher than the other two regions, the Yangtze River Delta Region has experienced the most rapid enhancement with the most pronounced growth trend. This all points to the fact that there was a comprehensive disequilibrium in the progression of LCEE within the coastal provinces of China.

From the perspective of the factors that contribute to change, the primary constraint on the overall development of LCEE in China's coastal provinces from 2007 to 2022 was attributed to technical efficiency. Technological progress was identified as a cardinal and pivotal constituent of LCEE.

From the point of view of spatial autocorrelation, during the periods from 2007 to 2011 and 2015, the distribution of LCEE in the coastal provinces demonstrated both positive spatial autocorrelation characteristics and spatial clustering features. Among them, the high-high agglomeration constituted the predominant type of spatial agglomeration. It was evident that China's coastal provinces presented a distinct trend of coordinated regional development.

The KDE results showed that the LCEE in China's coastal provinces had changed from multilevel differentiation to polarization in the trend of temporal and spatial dynamic development. Despite the fact that the absolute disparity in LCEE among the provinces was on the decline, the polarization of the LCEE levels persisted. MC analysis revealed that spatial factors had substantial influence on the temporal and spatial evolution characteristics of LCEE in China's coastal provinces. LCEE in neighboring provinces affected the transition probability of its own LCEE state, and LCEE in China's coastal provinces exhibited an obvious spatial spillover effect.

In light of the above-mentioned conclusions and the disparities in regional development within China's coastal regions, the following suggestions are put forward to promote the sustainable development of logistics in the coastal provinces:

Firstly, the logistics industry in China's coastal provinces ought to transition from an extensive growth pattern to an intensive and sustainable one. At present, the technical level of logistics industry in coastal provinces is insufficient, and relying on extensive development mode, it cannot meet the demand of green logistics. The logistics industry in China's coastal provinces should increase investment in logistics technology, introduce advanced logistics technology, and give full play to the engine role of technological progress in the high-quality development of logistics industry.

Secondly, the government should prioritize narrowing the differences in the development of LCEE and achieve coordinated development of the logistics industry in China's coastal provinces. Significant variations in LCEE exist among the eleven coastal provinces at the provincial level. The government ought to strongly support the coordinated development, formulate efficient policies, and create a sustainable environmental framework for the logistics industry in coastal provinces with low LCEE such as Fujian, Shanghai, and Liaoning. And these low LCEE provinces' government should eliminate facilities with high carbon emission characteristics and cultivate green logistics development models. The Yangtze River Delta Region has the advantages of developed economy and technological innovation, so it should increase investment in the research and development of green logistics technology, such as supporting the research and development and promotion of new energy logistics vehicles and building intelligent logistics and storage systems. At the same time, take advantage of the large number of universities and scientific research institutions in the region to establish an industry-university-research cooperation platform to accelerate the transformation of green logistics technology achievements. The Bohai Rim Region is characterized by a heavy traditional industrial structure, so it should implement industrial green transformation strategies, such as encouraging the deep integration of traditional manufacturing and green logistics and reducing carbon emissions in the transportation process of raw materials and products through logistics optimization. The Pan-Pearl River Delta Region is characterized by an export-oriented economic feature. It should implement measures to strengthen the alignment with international green logistics standards. For example, it should promote cross-border logistics enterprises to adopt internationally advanced carbon emission management systems. At the same time, the region should encourage the development of multimodal transport, especially low-carbon transport models such as sea-rail combined transport and river-sea combined transport.

For Fujian, Guangdong, Hebei, Jiangsu, Shanghai, Tianjin and Zhejiang, technological progress is the main driving force for enhancing the LCEE. Considering the conclusion and current national policies, these provinces should increase their investment in the research and development of green logistics technologies and promote the transformation of the logistics industry towards a green and low-carbon direction. Specific measures include promoting green logistics technologies, encouraging enterprises in coastal provinces to adopt low-carbon technologies such as new energy vehicles, intelligent warehousing systems, and green packaging materials, and reducing energy consumption and carbon emissions in logistics processes.

LCEE in coastal provinces is characterized by obvious spatial agglomeration, with efficiency levels exhibiting significant interdependence and spillover effects among neighboring provinces. In this regard, it is suggested that the relevant departments should guide the formation of "high–high agglomeration" areas to give full play to the spatial spillover effect among regions. A regional low-carbon logistics cooperation alliance can be established to further promote interregional technology exchanges, resource integration and market co-construction, to realize the goal of carbon emission reduction through regional linkage. Shandong Province has demonstrated remarkable high-high agglomeration spatial characteristics in terms of LCEE. This phenomenon not only effectively enhances the LCEE of the region itself but also has a positive radiation effect on the green development of the logistics industry in surrounding areas. This successful experience provides a demonstrative model that other coastal provinces can learn from. Based on this, other provinces can learn from Shandong Province's experience and combine policy guidance with technological innovation to further improve the LCEE. A series of measures such as improving transportation infrastructure, promoting green logistics technologies, and optimizing logistics resource allocation can be adopted to achieve continuous improvement in LCEE.

Finally, according to the results of the MC and SMC analysis, the state transfer of LCEE in each province is affected by spatial factors, so a mechanism for resource sharing and policy synergy across provinces should be established to promote the regional coordinated development of LCEE in China's coastal provinces. According to the spatial spillover effect revealed by the MC, the linkage and cooperation between high-efficiency and low-efficiency regions should be supported, and neighboring provinces should be encouraged to jointly carry out pilot and demonstration projects on low-carbon logistics, to further promote the overall improvement of LCEE.

Discussion

The study of the temporal and spatial evolution of LCEE can reveal trends among China's coastal provinces, provide a scientific basis for carbon reduction policies, and promote the development of the logistics industry towards sustainable and low-carbon growth. The results of this study highlight significant regional disparities in the LCEE among China's coastal provinces. These differences can be attributed to various underlying factors, including policy variations and economic development levels, which shape the carbon reduction capacity and efficiency improvements across regions.

Policy differences are the cause of LCEE of coastal provinces in China. Empirical research in the Bohai Rim region shows that strict environmental regulations, carbon trading mechanisms, and fiscal incentives implemented in provinces such as Tianjin, Hebei, and Shandong have significantly promoted the transformation of green logistics, and the LCEE in these provinces has been maintained at a high level. Due to weak environmental law enforcement, insufficient incentives for green technology innovation, and limited financial support, provinces such as Fujian and Liaoning have relatively low LCEE levels, resulting in poor policy implementation effects. This regional difference highlights the different abilities of local governments in policy refinement, resource allocation, and implementation supervision, emphasizing that the effectiveness of local policy implementation is a key factor affecting the LCEE in coastal provinces.

The level of economic development has a significant impact on LCEE in coastal provinces. The research results indicate that the logistics industry in the Yangtze River Delta region has the fastest growth rate in LCEE. This is due to the high level of economic development in the region, where digital logistics and green transportation systems have been widely applied. Provinces with strong economic foundations such as Shanghai, Jiangsu, and Zhejiang are vigorously implementing green logistics technologies such as automated warehousing and intelligent logistics platforms. These green logistics activities based on a higher level of economic development have continuously improved LCEE in the Yangtze River Delta region. Provinces with relatively low levels of economic development, such as Guangxi and Hainan, still face challenges in improving LCEE due to insufficient investment in green logistics infrastructure, limited financial support for carbon emission reduction measures, and a low level of modernization in the logistics industry. These economic constraints hinder the large-scale application of efficient energy logistics solutions, resulting in lower energy logistics efficiency in these regions compared to provinces with stronger economic strength.

Although the research in this paper has reached a more meaningful conclusion, there remain certain shortcomings as follows:

First, China currently does not have any departments or organizations that are solely responsible for gathering data about the logistics business. This paper uses data from the postal, transportation, and warehousing businesses instead of logistics data because logistics data is hard to come by. This may make the empirical study less objective.

Second, this paper only talks about the provincial level because there are not any public numbers on how much energy the logistics industry uses at the prefecture level. It doesn't go into detail about cities at the prefecture level. Moreover, since energy consumption data for 2023 are not yet available at the time of writing, the study period is only extended to 2022.

Abbreviations

LCEE	Logistics carbon emission efficiency
MC	Markov chain
SMC	Spatial Markov chain
SSBM	Super-efficiency slack-based measure
GML	Global Malmquist-Luenberger
KDE	Kernel Density Estimation
DMU	Decision-making units
DEA	Data Envelopment Analysis
CEE	Carbon emission efficiency
ML	Malmquist-Luenberger
GEC	Technical efficiency change index
GTC	Technical change index
L	Low logistics carbon emission efficiency
M-L	Medium-low logistics carbon emission efficiency
M-H	Medium-high logistics carbon emission efficiency
H	High logistics carbon emission efficiency

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Author contributions

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

Ethics approval was not required for this research.

Consent for publication

The authors declare that written informed consent for publication was obtained from all participants involved in the study.

Competing interests

The authors declare no competing interests.

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