RESEARCH ARTICLE

Spatial–temporal characteristics and regional differences of the freight transport industry's carbon emission efficiency in China

Xiyang Zhao[1] · Jianwei Wang[2] · Xin Fu[2] · Wenlong Zheng[1] · Xiuping Li[1] · Chao Gao[2]

Abstract

The freight transport industry is an important field in which to achieve the goal of carbon emission reduction within the transportation industry. Analyzing the spatial–temporal characteristics and regional differences in the freight transport industry's carbon emissions efficiency (CEE) is an essential prerequisite for developing a reasonable regional carbon abatement policy. However, few studies have conducted an in-depth analysis of the freight transport industry's CEE from the perspective of geographic space. This study combines the super-efficiency slack-based measure (SBM) model and the window analysis model to measure the freight transport industry's CEE in 31 Chinese provinces from 2008 to 2019. We then introduced a spatial autocorrelation analysis and the Theil index to analyze the spatial–temporal evolution characteristics and regional differences in the freight transport industry's CEE in China. The results show that (1) the overall level of the freight transport industry's CEE is low, with an average of 0.534, which showed a weak downward trend during the study period. This indicates that the freight industry's CEE has not improved, and there is a massive requirement for energy conservation and emission reduction. (2) From 2008 to 2019, CEE gradually shows a spatial distribution pattern of being "low in the west and high in the east," with a significant, positive spatial correlation (all passed the significance level test at $P < 0.01$). This indicates that the spatial diffusion and inhibition of the freight transport industry's CEE in adjacent areas cannot be ignored. (3) The overall differences in the freight transport industry's CEE show a fluctuating upward trend from 2008 to 2019. The inter-regional differences of the three regions (east, central, and west) are the main contributors of the total differences. Therefore, narrowing inter-regional gaps in CEE is one of the main ways to improve the freight transport industry's CEE.

Responsible Editor: Eyup Dogan

✉ Xin Fu
  fuxin@chd.edu.cn

  Xiyang Zhao
  zhaoxiyang@chd.edu.cn

  Jianwei Wang
  wjianwei@chd.edu.cn

  Wenlong Zheng
  zhwenlong@chd.edu.cn

  Xiuping Li
  lixiuping1988@sina.com

  Chao Gao
  489686122@qq.com

[1] School of Economics and Management, Chang'an University, Xi'an 710064, Shaanxi, China

[2] School of Transportation Engineering, Chang'an University, Xi'an 710064, Shaanxi, China

Introduction

With the rapid growth of the world's economy, global warming has seriously threatened human survival and sustainable social development (Wang and He 2017). Since China's economic reform and its opening up, its economy has developed rapidly to become the world's second largest in 2011. With its rapid economic growth, China's carbon emissions have also increased significantly. According to the CO_2 Emissions and Fuel Combustion Highlights 2009 Edition, China's energy-related carbon emissions surpassed those of the USA in 2007, becoming the world's largest emitter of greenhouse gas (GHGs) (IEA 2009). To reduce carbon emissions and encourage global GHG emissions to peak as early as possible, most countries have adopted the Paris Agreement. China has pledged to adopt strong measures to continuously reduce

carbon emissions and achieve the peak by 2030 (Wang et al. 2021).

The transportation industry is essential for economic development yet is a crucial contributor to carbon emissions (Van Fan et al. 2018), producing about one-quarter of the total worldwide carbon emissions (IEA 2019). In China in 2019, according to national statistics, the transportation industry's energy consumption accounted for 9.02% of the total energy consumption, while its direct carbon emissions accounted for approximately 10% of the total emissions. Following the 13th Five-Year Plan for the Development of a Modern Comprehensive Transportation System issued in 2016 (Ministry of Transport of the People's Republic of China), which proposed to promote energy-saving and the low-carbon development of the transportation industry, the 14th Five-Year Plan, issued in 2021, further proposed to comprehensively promote said industry's green and low-carbon transformation and implement the objectives of carbon peak and carbon neutralization. Therefore, the transport industry has become a key industry in which China can fulfill its carbon emission reduction commitments (Peng et al. 2020), and its energy conservation and emission reduction have become important research issues (Li et al. 2019; Liu et al. 2021; Peng et al. 2020; Wang and He 2017).

However, few scholars studied energy conservation and emission reduction of the freight transport industry. In recent years, China's freight transport industry has developed rapidly, owing to the fast growth of economic aggregates. In 2019, China's freight turnover reached 19,939.4 billion tkm, an 80.8% increase from 2008 (China Statistical Yearbook 2020). Relevant studies show that in 2013, the GHG emissions of China's freight industry accounted for about 8% of the country's total GHG emissions, and it is predicted that by 2050, its GHG emissions will be 2.4 times those of 2013 (Hao et al. 2015). The report Research on Strategy and Policy of China's Freight Transportation Energy Conservation and Emission Reduction, issued by the Energy Conservation and Emission Reduction Research Group of the Chinese Academy of Engineering, also pointed out that the carbon dioxide emissions of China's freight transportation industry were 675 million tons in 2014, accounting for 61% of those of China's transportation industry and predicted that the carbon emissions of the said industry would reach 1.04 and 1.27 billion tons in 2030 and 2050, respectively. Therefore, the freight transport industry has become a significant contributor to the fast growth of transport carbon emissions and is thus a key focus area for emission reduction in China. Accordingly, the sustainable development of both the transportation industry and society must consider minimizing the impact of freight transport on the environment. Simultaneously, since sustainable energy conservation and emission reduction are closely related to the improvement of energy utilization and CEE in the production process (Jebaraj and Iniyan 2006), it is of great practical importance to study the freight transport industry's CEE.

Since there is significant disparity in natural resources, geographical location, and market environment across China's various regions, regional economic development is unbalanced, which also leads to substantial disparity in regional energy utilization and CEE. Freight transport is a derivative demand of economic development. Therefore, along with the regional differences in economic development, there is regional heterogeneity in the freight transport industry's energy use and CEE. Studying the spatial–temporal distribution characteristics and regional differences in the freight transport industry's CEE in different regions will not only reveal the changes in the distribution of CEE in different areas, but will also enable further exploration of the causes of regional differences, to ultimately provide a basis for developing regional carbon abatement policies.

Accordingly, this study selected 31 regions in China as research areas in which to explore the spatial–temporal distribution characteristics and regional differences in China's freight transport industry's CEE from 2008 to 2019. First, we used the super-efficiency slack-based measure (SBM) window model to calculate the CEE and analyzed the spatial characteristics of CEE using a spatial autocorrelation analysis. Second, we used the Theil index to analyze the total, inter-regional, and intra-regional differences in the freight transport industry's CEE to understand the degree of regional differences in China and identify the main contributors to the total differences. Finally, some useful policy implications are provided for the improvement of the freight transport industry's CEE in different regions of China, aiming to provide a reference for government departments to draft freight transport's CEE policies to achieve the goal of carbon emissions peak and carbon neutralization.

Compared with previous studies, the main contributions of this study are as follows: (1) different from previous studies using the single-factor method or traditional data envelopment analysis (DEA) method to evaluate the efficiency of carbon emission, this study calculated the CEE of China's freight transportation industry by using a calculation method combining super-efficiency SBM model and the window analysis model. (2) Based on the perspective of geographical space, this study undertook an in-depth analysis of the temporal and spatial characteristics and regional differences in the freight transport industry's CEE at the provincial and regional levels. It provided a more comprehensive perspective for the government to understand the Chinese freight transport industry's CEE, which could help regional and provincial decision-makers draft differentiated strategies for improving the freight transport industry's CEE.

Literature review

Prior research has mainly focused on analyzing the transportation industry's driving factors and reduction strategies regarding carbon emissions (Isik et al. 2020; Mustapa and Bekhet 2016; Zhang et al. 2019), the relationship between the transportation industry's development and carbon emissions (Li et al. 2019; Wang et al. 2019), and the transportation industry's energy and environmental efficiency (Wei et al. 2021; Zhu et al. 2020). However, the aforementioned studies considered the transportation industry as an entire system and did not distinguish between passenger and freight transport. Regarding freight transport, Tian et al. (2014) studied the characteristics of freight carbon emissions in various provinces, Luo et al. (2016) conducted research on the driving forces of carbon dioxide emissions from freight transport in China, and Hao et al. (2015) estimated the GHG emissions of freight transport in China from the perspective of life cycle and scenario-based predictions. Other studies have calculated and analyzed the GHG emissions of China's road freight industry (Fu et al. 2020; Li et al. 2013). However, these studies only calculated and analyzed carbon emissions without considering the efficiency of carbon emissions.

The calculation methods of carbon emissions and energy efficiency mainly include single-factor and total-factor indicator methods. Single-factor indicator methods, such as energy and carbon emissions intensity, only measure part of the carbon emissions performance; that is, they cannot comprehensively evaluate the entire production system's carbon emissions and energy efficiency (Feng and Wang 2018). Therefore, the DEA method, based on total-factor indicators, has become the primary evaluation method of carbon emissions and energy efficiency (Zhang and Wei 2015). This method is also widely used in transportation systems. For instance, Cui and Li (2014) and Zhou et al. (2013) used the DEA method to calculate the transport industry's carbon emissions and energy efficiency. However, the traditional radial DEA model does not consider relaxation variables, and the model's calculation deviation is large (Liu et al. 2016). Therefore, Tone (2001) extended the traditional DEA method and proposed an SBM model that considered slack variables to reduce measurement bias. Chu et al. (2018) and Park et al. (2018) applied the SBM model to the transportation system to effectively measure the transportation industry's carbon emissions and energy efficiency and showed that it was more suitable for scenarios that had undesirable outputs. However, the ordinary SBM model's maximum value is 1, while decision-making units (DMUs) that have an efficiency value of 1 cannot be effectively distinguished. In the super-efficiency SBM model, since the efficiency value of the evaluated DMU is obtained by referring to the frontier composed of other DMUs, the efficiency value of the effective DMU will be greater than 1, so the effective DMU can be distinguished (Cheng 2014). Therefore, the super-efficiency SBM model is widely applied to estimate carbon emissions and ecological efficiency (Bai et al. 2021; Tang et al. 2021). However, the super-efficiency SBM model only performs static analysis on cross-sectional data and cannot dynamically analyze time series. The DEA window model dynamically measures the efficiency of DMUs based on the moving average method. It takes all DMUs in a certain width period as a reference set so as to multiply the number of DMUs in the reference set. For instance, assuming there are n DMUs and t periods, the total number of DMUs is $n \times t$. If the window width is set to d, the number of DMUs in each window is $n \times d$, which is d times the number of DMUs in each time (Cheng 2014; Peykani et al. 2021). Therefore, the combination of the super-efficiency SBM and window DEA models not only solves the problem of undesired output and distinguishes effective DMUs, but also effectively increases the number of DMUs (thus solving the efficiency evaluation problem regarding panel data) and makes the calculation results more reliable and accurate (Song et al. 2016).

Given the disparity in the resource, technology, and economic levels, there is a notable disparity in the development level of transportation and freight transport among the different regions of China. However, most study outcomes on the transportation system's carbon emissions have regarded each area independently and ignored the spatial interaction among various areas. Lesage and Pace (2009) believe that the region's characteristics are not spatially independent and will be affected by its neighbors. Some research results have also shown that the transportation system's carbon emissions have spatial agglomeration and regional differences characteristics (Bai et al. 2020; Peng et al. 2020). However, prior studies on the transportation industry's carbon emissions and energy efficiency have not considered the two major geographical characteristics of spatial correlation and regional differences. Moreover, they have neglected the influence of spatial factors on the freight transport industry's CEE. As freight transport is a key contributor to the transportation industry's carbon emissions, an in-depth analysis of freight transport's CEE from the point of spatial correlation and regional differences is necessary.

In sum, there are few studies on the carbon emissions of freight transport, and most of them focus on the calculation and analysis of carbon emissions, while only a few explore the freight transport industry's CEE. In addition, previous research has mainly used the traditional DEA model or the super-efficiency SBM model to measure CEE. The combination of the super-efficiency SBM and window analysis models can consider the undesired output, distinguish the

effective DMUs, and increase the number of DMUs to solve the problem regarding panel data and make the calculation results more accurate. Finally, most prior studies have treated each province or region as an independent individual and ignored the spatial interaction and regional differences between them; thus, they have failed to conduct an in-depth analysis of CEE from the perspective of geographical space. However, the spatial correlation and regional differences among the regions are of great significance for government departments aiming to formulate carbon emissions reduction policies. Thus, we adopt the super-efficiency SBM window model, spatial autocorrelation analysis, and the Theil index to analyze the spatial–temporal evolution and regional differences in China's freight transport industry's CEE. This topic has theoretical and practical significance, as it can be a reference for drafting carbon reduction policies for the freight transport industry.

Methodology

Calculation of the freight transport industry's carbon emissions

There are two main methods for estimating the transport system's carbon emissions. The first is to estimate the emissions according to the industry terminal energy consumption and carbon emissions factor data, that is, the "top-down" calculation method. The second is based on vehicle mileage, fuel consumption per unit mileage, and carbon emissions factor, that is, the "bottom-up" calculation method. Because the energy consumption data of the freight transportation industry cannot be directly obtained, this study adopted the second method by referring to the research methods of Ou and Xu (2020), Wang (2012), and Tian et al. (2014). This study estimated the carbon emissions of freight transport based on the turnover of goods in different transportation modes, the energy consumption of unit turnover, and the carbon emission factors of various energy sources, as follows:

First, the freight transport industry's energy consumption can be estimated based on the freight turnover of different transportation modes and the energy consumption per turnover unit of transportation tools. The calculation is shown in Formula (1):

$$E_{h,l} = V_{h,l} CF_{h,l} \tag{1}$$

where h and l represent the mode and means of transport, respectively; $E_{h,l}$ signifies the energy consumption of transport means l in transport mode h; $V_{h,l}$ indicates the freight turnover of transport means l in transportation mode h; and $CF_{h,l}$ denotes the energy consumption per turnover unit of transport means l under transportation mode h.

Second, we calculated the carbon emissions of different transportation modes according to the energy consumption obtained by Formula (1). The calculations are shown in Formulas (2) and (3):

$$C_{h,l} = E_{h,l} f_{h,l} \tag{2}$$

$$C = \sum_h \sum_l C_{h,l} \tag{3}$$

where $C_{h,l}$ signifies the carbon dioxide emissions of transport means l in transport mode h, $E_{h,l}$ has the same meaning as Formula (1), and $f_{h,l}$ is the carbon emissions factor of the fuel or electricity consumed by transport means l in transport mode h. C denotes the total emissions of the freight transport in each administrative region.

Calculation of the freight transport industry's CEE

By combining and analyzing the research results regarding the efficiency measurement methods from the literature review, we introduced the super-efficiency SBM window model to measure the CEE of provincial freight transport in China. The super-efficient SBM model is used to better distinguish the effective DMUs. The main limitation of this model is that a value of 0 should be avoided in input–output data. If the input or output index in the relevant model is 0, the DMU or relevant index that does not meet the conditions must be deleted. The input and output index values of the measured data in this study are not 0; therefore, they do not need to be processed. The model is shown in Formula (4):

$$\min \rho = \frac{1 + \frac{1}{m} \sum_{i=1}^{m} s_i^- / x_{ik}}{1 - \frac{1}{q_1 + q_2} \left(\sum_{r=1}^{q_1} s_r^+ / y_{rk} + \sum_{t=1}^{q_2} s_t^{b-} / b_{tk} \right)}$$

$$s.t. \begin{cases} \sum_{j=1, j \neq k}^{n} x_{ij} \lambda_j - s_i^- \leq x_{ik} \\ \sum_{j=1, j \neq k}^{n} y_{rj} \lambda_j + s_r^+ \geq y_{rk} \\ \sum_{j=1, j \neq k}^{n} b_{tj} \lambda_j - s_t^{b-} \leq b_{tk} \\ 1 - \frac{1}{q_1 + q_2} \left(\sum_{r=1}^{q_1} s_r^+ / y_{rk} + \sum_{t=1}^{q_2} s_t^{b-} / b_{tk} \right) > 0 \\ \lambda, s^-, s^+ \geq 0 \\ i = 1, 2, \cdots, m; r = 1, 2, \cdots, q; j = 1, 2, \cdots, n (j \neq k) \end{cases} \tag{4}$$

where ρ denotes the CEE of freight transport; x_{ik}, y_{rk}, and b_{rk} are the input and desirable and undesirable output

indicators of the k th DMU, respectively; m, q_1, and q_2 denote the number of input and output indicators of each DMU, respectively; and s_i^-, s_r^+, and s_t^{b-} are the slack variables. R is the constraint.

The DEA window analysis model needs to evaluate the CEE by setting the window width to select different reference sets. Referring to the research results of Halkos and Tzeremes (2009), Wang et al. (2013), and Wu et al. (2020), we set the width of the window to 3 to obtain a reliable and stable CEE value. Accordingly, by using the super-efficiency SBM window model, we obtained the CEE of each window in the 31 Chinese regions. With the exception of only one CEE value in 2008 and 2019 and two values in 2009 and 2018, each region has three efficiency values from 2010 to 2017. Then, by calculating the average annual CEE of each area, new results for the CEE of the 31 regions were obtained.

Spatial autocorrelation analysis

Spatial autocorrelation analysis is used to distinguish spatial correlation patterns and can effectively distinguish the spatial correlation model (spatial agglomeration, discrete or random distribution model) of the CEE of freight transport in relation to geographical location. It includes global and local spatial autocorrelation. Global spatial autocorrelation is the overall analysis of the geographic spatial distribution characteristics of CEE and the spatial correlation mode between regions. It is commonly measured using global Moran's I. The calculation is shown in Formula (5):

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{5}$$

$$w_{ij} = \begin{cases} 1, & \text{if share a common border or a single common point} \\ 0, & \text{else} \end{cases} \tag{6}$$

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{7}$$

The value of I ranges from -1 to 1. $-1 < I < 0$ and $0 < I < 1$ indicate a spatial negative and positive correlation distribution, respectively. When I is close to 0, there is no spatial correlation. n denotes 31 Chinese provinces; w_{ij} is shown in Formula (6); and x_i and x_j indicate the CEE of the freight transport in the i and j regions, respectively.

Global Moran's I cannot determine the specific aggregation region or the correlation mode of the CEE of a specific area. Therefore, the Moran scatter plot and local spatial autocorrelation should be combined to identify the specific location of agglomeration and determine the correlation mode of the CEE between regions. Local Moran's I is commonly used for the local spatial autocorrelation index, and its calculation is shown in Formula (8):

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

where $I_i > 0$ indicates that the study area presents "high-high" (HH) or "low-low" (LL) clustering, while $I_i < 0$ signifies that the study area shows "high-low" (HL) or "low–high" (LH) clustering. The meanings of the other variables are the same as in Formula (5).

Theil index

Theil (1967) proposed the Theil index based on the concept of entropy in information theory. It was initially used to measure the degree of income inequality between regions and was later developed as an important index to evaluate area disparities. This study utilized the Theil index to assess the area differences of freight transport's CEE. The calculation is shown in Formula (9):

$$T = \frac{1}{n} \sum_{i=1}^{n} \frac{x_i}{\bar{x}} \ln(\frac{x_i}{\bar{x}}) \tag{9}$$

where T is the Theil index of China's freight transport industry's CEE, n denotes 31 Chinese provinces, x_i indicates the CEE of the freight transport in province i, and $\bar{x}$ represents the average value of the CEE of all provinces.

According to China's three major economic regions (eastern, central, and western China), the Theil index can be decomposed into intra- and inter-area components, as shown in Formula (10):

$$T = Tw + Tb \tag{10}$$

where Tw and Tb indicate the intra- and inter-area Theil index, respectively. The calculations are shown in Formulas (11) and (12):

$$Tw = \sum_{k=1}^{3} \frac{n_k}{n} \frac{\bar{x}_k}{\bar{x}} T_k \tag{11}$$

$$Tb = \sum_{k=1}^{3} \frac{n_k}{n} \frac{\bar{x}_k}{\bar{x}} \ln(\frac{\bar{x}_k}{\bar{x}}) \tag{12}$$

where k represents the three economic regions; n_k indicates the number of provinces in the k th region; n denotes 31 Chinese provinces; $\bar{x}_k$ indicates the average CEE of

freight transport in the k th economic area; $\overline{x}$ denotes the average value of the national CEE of freight transport; and T_k is the Thiel index of the CEE of freight transport in the k th economic region.

Variable selection and data sources

Research area

The statistical caliber of China's road and water transport changed in 2008, while data fluctuated greatly, and some data were not available due to the impact of the COVID-19 pandemic in 2020. Therefore, to maintain data consistency, this study examined the spatial characteristics and regional differences in the freight transport industry's CEE in 31 Chinese provinces based on data from 2008 to 2019. Hong Kong, Macau, and Taiwan were excluded due to missing data. By referring to relevant studies (Feng and Wang 2018; Feng et al. 2017), this study divided the samples into three regions (east, central, and west) according to geographical adjacency (Table 1).

China has five main modes of freight transport: roads, railways, waterways, air, and pipeline. Owing to the particularity of pipeline transport, relevant data are difficult to obtain. Meanwhile, the proportion of air freight turnover in the total freight turnover is small—accounting for only 0.13% in 2019 (China Statistical Yearbook 2020)—and the airline mileage of each province cannot be accurately counted. Therefore, this study only considered roads, railways, and waterways as its three modes of transportation.

Data sources for the freight transport industry's carbon emissions

The data on the freight turnover of the three transport modes were from the China Statistical Yearbook (2009–2020). The freight turnover of the diesel and electric locomotives in railway freight transport was calculated according to the proportion data on their completed workloads from the China Railway Yearbook (2009–2020). The freight turnover of the diesel and gasoline vehicles in road freight was calculated based on the proportion data on their completed workloads from the China Motor Vehicle Environmental Management

Annual Report. According to the average values, the proportion of the completed workloads is 75% for diesel vehicles and 25% for gasoline vehicles. The energy consumption data per turnover unit of the different means of transport were from Ou and Xu (2020), the China Railway Yearbook (2009–2020), and China Transportation Yearbook. The missing data were calculated based on the target value of the 13th Five-Year Development Plan for Transportation Energy Conservation and Environmental Protection. The carbon emission factors of fuel and electricity were derived from the Provincial GHG Inventory Guidelines, and the electricity carbon emission factor was calculated on the annual average value. The specific data are shown in Tables 2 and 3.

Index selection and data source for the CEE estimation

In addition to research methods, variable selection is another key issue in the evaluation of freight transport's CEE. Referring to prior studies, combined with the actual situation of freight transportation and data availability, the variables of this study were selected as follows:

Input variables

Considering that capital and labor are the essential, core input elements in economic principles (Zhu et al. 2020) and the development of the freight transport industry cannot proceed without consuming energy, we selected capital, labor, and energy as the input variables. Since there are no statistical data on the capital stock of the transportation industry, by referring to the existing literature (Chen et al. 2018; Cui and Li 2014; Lei et al. 2021), we replaced capital stock with fixed asset investments. Bian and Yang (2010) also confirmed the rationale for using fixed asset investments as an input variable. However, freight transport is a subsystem of the transportation industry, and there are no statistical

Table 2 Energy carbon emission factors

Energy types	Diesel oil	Gasoline	Kerosene
Carbon emission factors (kg/kg)	3.0960	2.9251	3.0179

Table 1 The three regions and their provinces

Region	Provinces
East	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Central	Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan
West	Inner Mongolia, Chongqing, Sichuan, Guizhou, Yunnan, Guangxi, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang

Table 3 Electricity carbon emission factors

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Electricity carbon emission factor (kg/kWh)	1.131	1.028	1.003	0.980	0.973	0.971	0.974	0.963	0.941	0.922	0.903	0.895

data on fixed asset investments. Therefore, we used fixed asset investments in transportation, warehousing, and postal services as the capital inputs. Meanwhile, the fixed asset investment price index was used to convert the data into constant prices in 2008 to eliminate the impact of price changes. By drawing from the literature (Sun et al. 2018), we used the sum of employees in the road, railway, and waterway transportation industries as the labor input for the freight transport industry. We used the energy consumption data of the freight transport that were calculated using Formula (1) as the energy input.

Output variables

Song et al. (2016) and Liu and Lin (2018) believe that the freight turnover is a comprehensive indicator of the freight transport industry's output and also reflects society's cargo traffic services. Therefore, this study selected freight turnover as a desirable output variable for freight transport. When consuming energy, the freight transport industry inevitably produces various pollutants such as carbon dioxide—the main target for emission reduction by the government (Lv et al. 2019). Therefore, in combination with the purpose of this study, carbon dioxide was selected as an undesirable output variable.

Results and analysis

The overall characteristics of CEE

Based on the super-efficiency SBM window model that considered undesired outputs and the selected index data, we estimated the freight transport industry's CEE in 31 Chinese provinces from 2008 to 2019. The calculation results are

Fig. 1 Average national-level and provincial-level CEE
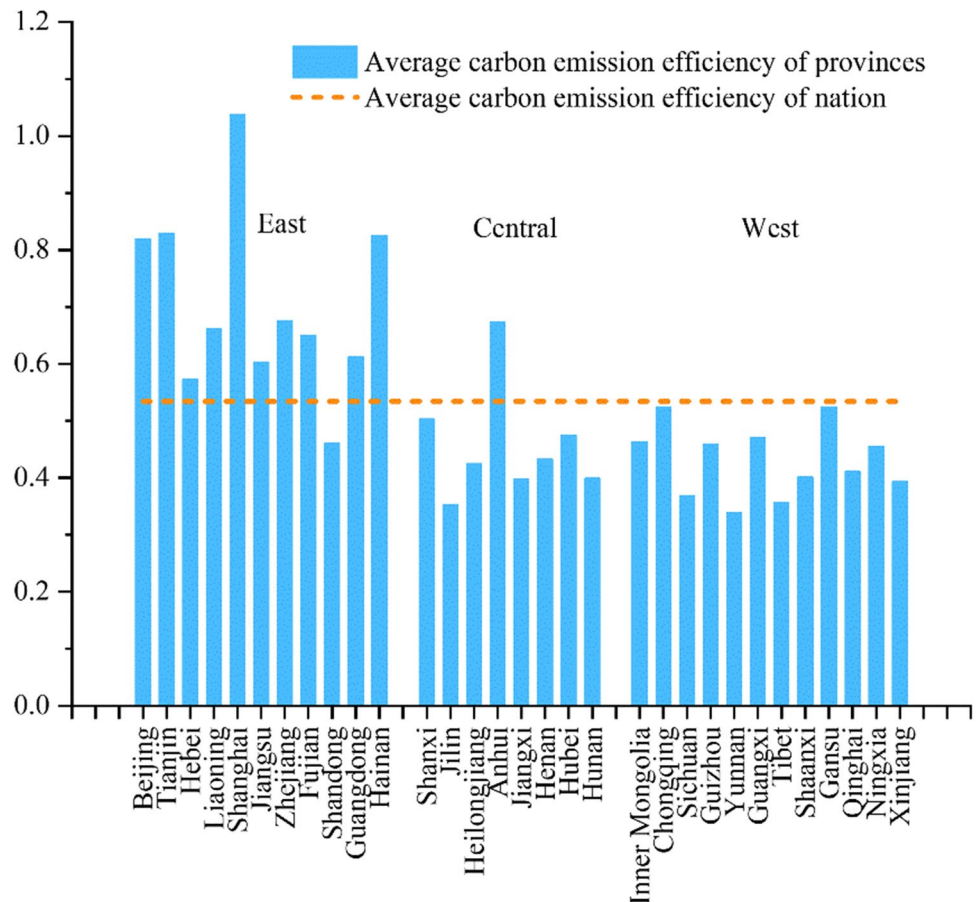
presented in Table 5 in the Appendix. Figure 1 displays the average CEE of the Chinese provinces from 2008 to 2019.

The average CEE of freight transport in the provinces is between 0.338 and 1.038, while the national average value is 0.534. This shows that China's freight transport industry's overall CEE level is low, so there is plenty of room for energy conservation and emission reduction. This result is very similar to the results of the transportation industry's CEE in 2004–2016 and 2010–2016 calculated by Peng et al. (2020) and Zhao et al. (2022), respectively. This also proves the accuracy of the measurement results.

Figure 1 shows that among the 31 provinces, only 11 (35.48%) have higher average efficiency values than the national average. Only Shanghai's CEE average is greater than 1, which is above the efficiency frontier, indicating that the resource allocation of Shanghai's integrated freight system is relatively reasonable. The average freight emission efficiency values for the other 10 provinces, including Tianjin, Beijing, and Hainan, are above the national average, indicating that these areas have a relatively reasonable allocation of resources and a small gap between input and output. However, there remains ample space for further improvement.

Figure 2 displays the spatial distribution of the freight transport industry's average CEE in the provinces, which was generated using quantile classification in ArcGIS 10.2

software. Figure 2 shows that the freight transport industry's CEE presents a gradually increasing distribution pattern from west to east. The Xinjiang, Qinghai, Tibet, and other western regions show low CEE, while Beijing, Tianjin, and the southeast coastal areas show high CEE. This indicates that the freight transport industry's CEE in China has the characteristics of spatial agglomeration and regional differences, which need to be further analyzed.

Spatial–temporal evolution characteristics of CEE

### Temporal evolution characteristics

Figure 3 shows the changing trend of the mean value, standard deviation (SD), and coefficient of variation (CV) of CEE over time. Overall, the CEE of freight transport shows a weak downward trend from 2008 to 2019. Specifically, the average CEE shows a fluctuating upward trend from 2009 to 2014 and 2018 to 2019, as well as a downward trend from 2015 to 2018, and is the highest in 2014. Meanwhile, the SD and CV also show a fluctuating trend. First, the SD presents a fluctuating upward trend in 2008–2011, 2013–2014, and 2015–2019 and reaches its maximum in 2014. This indicates that in the three given periods, the absolute difference in the freight transport's CEE shows an increasing trend and reaches

Fig. 2 Distribution of freight transport industry's average CEE
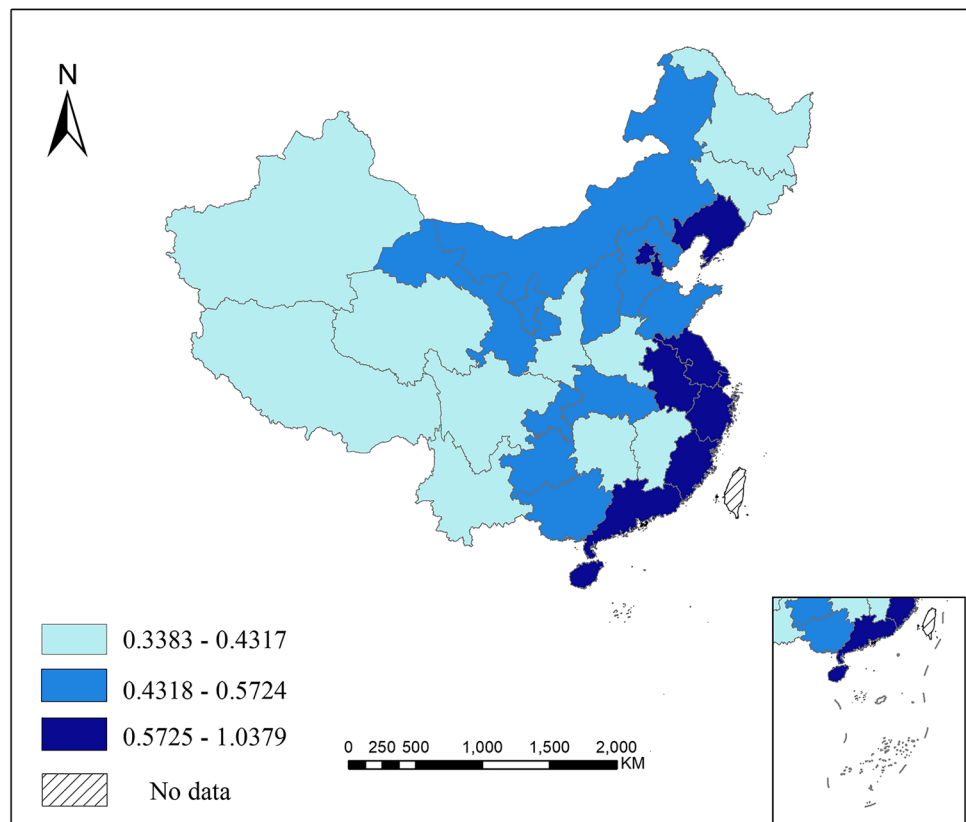
Fig. 3 The evolution trend of the national average, standard deviation, and coefficient of variation
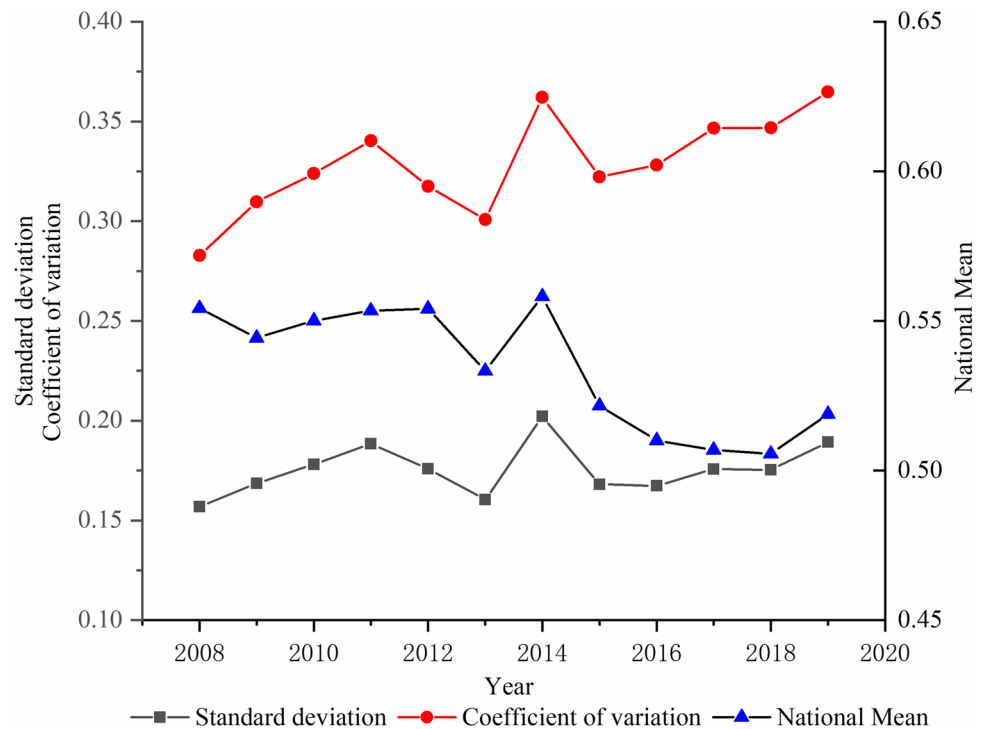
the maximum in 2014. Second, the SD shows a downward trend in 2012–2013, indicating that the absolute difference in the CEE shows a downward trend in 2012–2013. The CV's variation trend is consistent with the SD. The overall trend shows that the significant difference in the freight transport's CEE has not improved but shows an increasing trend.

Then, we analyzed the temporal evolution characteristics of the CEE of freight at the regional level. Figure 4 shows the changing trends of freight transport's CEE nationwide and the three regions from 2008 to 2019.

Regarding the specific regions, freight transport's CEE has obvious gradient characteristics of being "low in the west and high in the east." Freight transport's CEE in the eastern region is significantly higher than that in the central and western regions, and the difference between the regions tends to increase. This gradient feature is consistent with the research results of Tang et al. (2019) regarding the environmental efficiency of the freight transport industry, as well as those of Bai et al. (2021) regarding the ecological efficiency of the logistics industry. From 2008 to 2019, except for the apparent decline and increase in 2013 and 2014, the CEE of the eastern region is stable and fluctuates around 0.70. The average CEE of the central and western regions is relatively low, at 0.457 and 0.430, respectively, and shows a downward trend, while a declining trend is evident in the western region. This indicates that the freight transport industry's energy conservation and emission reduction strategies in the central and western areas have not been well implemented,

the resources have not been optimized, and the output efficiency is low.

There are three possible causes for freight transport's high CEE in the eastern area. First, the east area's economy is developed and coupled with the inclination of policies and capital investment so that its technical level is continuously improved, the comprehensive freight system's resource allocation is reasonable, and the energy utilization rate is high. Second, the eastern coastal areas are less dependent on road freight transport, compared with the central and western regions; however, their dependence on waterways is rather high, and the freight structure is relatively reasonable. Therefore, freight transport's CEE is relatively high in the eastern region. However, because of the backward economic development and technological levels of central and western areas, as well as the unreasonable allocation of resources in the freight transport industry's structure and system, the freight transport industry's CEE is relatively low, and the pressure of carbon emissions reduction is significant. For instance, in 2019, the road freight volume in Shanghai accounted for 41.8% of the total freight volume, while that in Guizhou and Qinghai accounted for 91.4% and 77.8%, respectively (China Statistical Yearbook 2020). Furthermore, the road freight volume of these two provinces is also much higher than that of Shanghai. Third, the eastern region has issued a series of policies to reduce carbon emissions from transportation and improve its CEE. For example, since 2015, the Shanghai Municipal Development and Reform Commission has

Fig. 4 The average CEE trends nationwide and in the east, central, and west from 2008 to 2019
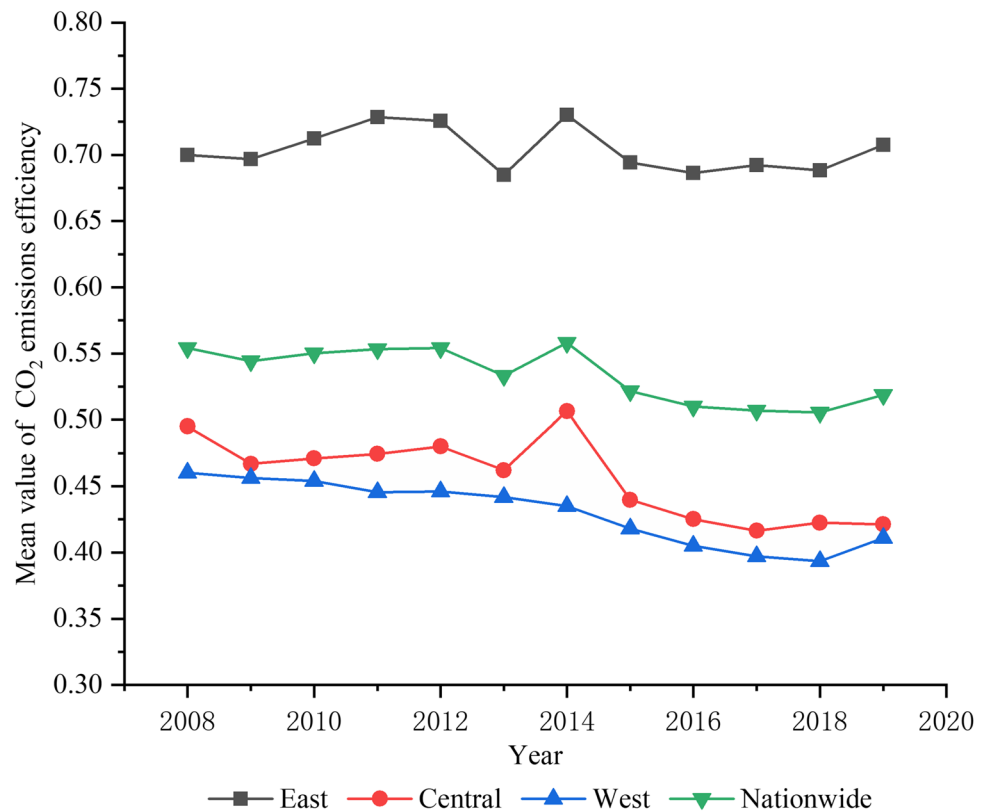
annually issued a notice on Shanghai Municipality's Key Work Arrangements for Energy Conservation and Emission Reduction and Addressing Climate Change, which focuses on energy conservation and emission reduction in key industries, including the transportation industry. In addition, Shanghai has also issued the Shanghai Implementation Plan for Promoting Transport Structural Adjustment (2018–2020) to promote "road-to-railway, sea-rail intermodal transport, etc., to accelerate the adjustment of the city's transportation structure, and to create a green transportation system."

In addition, Fig. 4 shows that during the observation period, freight transport's CEE both in the eastern and central regions, as well as nationwide, fluctuated significantly in 2013 and 2014, when it reached the trough and peak, respectively. This may be because 2013 was a mid-term assessment year of the 12th Five-Year Plan for National Environmental Protection, and the completion of indicators in 2013 lagged behind the progress requirements; therefore, the situation was very serious. In response, the State Council issued the 2014–2015 Energy Conservation, Emission Reduction, and Low-Carbon Development Action Plan, which required strengthening energy conservation and carbon reduction in the transportation industry. Therefore, freight transport industry's CEE shows a noticeable uptick in 2014 and reaches the peak.

Spatial evolution characteristics

According to the CEE calculation results in Table 5 in the Appendix, we used ArcGIS 10.2 software to select the efficiency values in 2008, 2012, 2015, and 2019 to create a spatial distribution evolution map of the freight transport industry's CEE. Figure 5 shows that, overall, the regions that have similar CEE are gradually concentrated. High-efficiency areas are mainly concentrated in the eastern and southeastern coastal areas, and low-efficiency areas are mainly concentrated in the northwestern and southwestern regions. Thus, the spatial distribution characteristics are "low in the west and high in the east." For example, the CEE of freight transport in Shanghai, Hainan, Beijing, and Fujian is high, while that in Yunnan, Tibet, Sichuan, and Xinjiang is low. Therefore, there are apparent spatial differences and agglomeration characteristics in freight transport's CEE among the regions in China.

Comparing 2008 and 2019, the freight transport's CEE in seven of the 11 provinces in the eastern region shows an increasing trend, indicating that the eastern region had a positive spatial effect. Guangdong, Hainan, and Fujian have a relatively high growth rate, indicating their focus on resource allocation, low-carbon emissions, and management technology development to improve
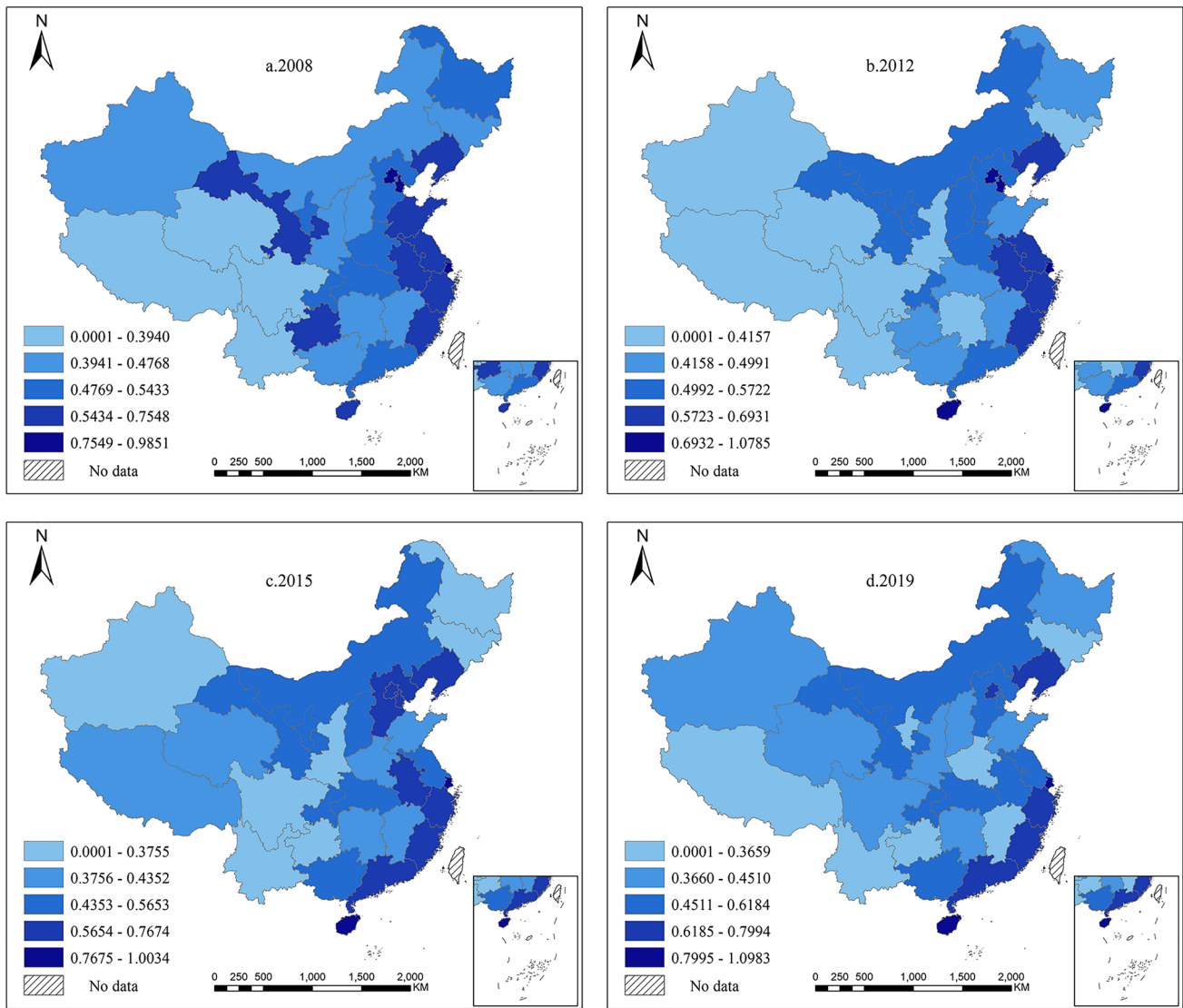
Fig. 5 Spatial distribution of freight transport's CEE in 2008, 2012, 2015, and 2019

freight transport and economic development, while also enhancing CEE. However, freight transport's CEE in most of the central and western areas presents a downward trend. Guizhou, Ningxia, and Gansu show a significant decline, with Guizhou showing the largest decline. The main reason for this may be that, following the implementation of the Western Development Strategy, energy-intensive industries in the western region have flourished, foreign investment has also increased rapidly, and the proportion of secondary industries has continued to increase, which has caused significant increases in these regions' freight turnover and energy consumption. However, the low-carbon technologies and management levels in these areas are relatively low, which results in a serious waste of resources and declining CEE. The proportion of coal consumption in Guizhou is relatively large, and, after 2010, with the accelerated

development in the western region and the continuous promotion of Guizhou province's policy to strengthen industry, the proportion of high-carbon emission fossil energy increased further, while the emission reduction technology and energy use efficiency were lower (Lu et al. 2018), resulting in a significant decline in CEE.

Spatial autocorrelation analysis

The global spatial autocorrelation analysis

According to Formula (5), and based on the spatial adjacency weight matrix, we calculated the global Moran's I of freight transport's CEE using GeoDA software. The results

Table 4 The global Moran's *I* of the freight transport's CEE in 2008–2019

| Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Moran's *I*	0.361	0.301	0.318	0.357	0.425	0.420	0.339	0.426	0.415	0.393	0.391	0.359
Z value	3.452	3.051	3.010	3.221	4.085	3.838	3.289	3.791	3.839	3.702	3.666	3.424
P value	0.001	0.003	0.003	0.002	0.001	0.000	0.003	0.000	0.000	0.001	0.000	0.002

are listed in Table 4 and show that the global Moran's *I* is positive and passes the 1% significance test; therefore, the CEE shows an obvious spatial positive correlation. Meanwhile, the global Moran's *I* of the CEE increases from 0.361 in 2008 to 0.425 in 2012 and then decreases to 0.359 in 2019. This shows that the spatial positive agglomeration trend of freight transport's CEE first increases and then decreases slightly.

The local spatial autocorrelation analysis

It is impossible to determine the local spatial agglomeration between the provinces with the global Moran's *I*. Therefore, this study used the Moran scatter plot and local indicators

of spatial association (LISA) cluster map to compare and analyze the local spatial dependence of freight transport's CEE in 31 Chinese provinces. Figures 6 and 7 illustrate the Moran scatter plot and the LISA cluster map, respectively, of the freight transport industry's CEE in 2008, 2012, 2015, and 2019.

Figure 6 shows that the number of provinces in the HH and LL quadrants in 2008, 2012, 2015, and 2019 accounted for 77%, 87%, 87%, and 81% of the national total, respectively. Moreover, Tianjin, Shanghai, Jiangsu, Zhejiang, and Fujian in the eastern region have always belonged to the HH quadrant, whereas provinces such as Tibet, Xinjiang, Ningxia, and Qinghai in the northwest region have always belonged to the LL quadrant. This indicates an unbalanced development pattern of freight

Fig. 6 Moran scatter plot of freight transport's CEE in 2008, 2012, 2015, and 2019
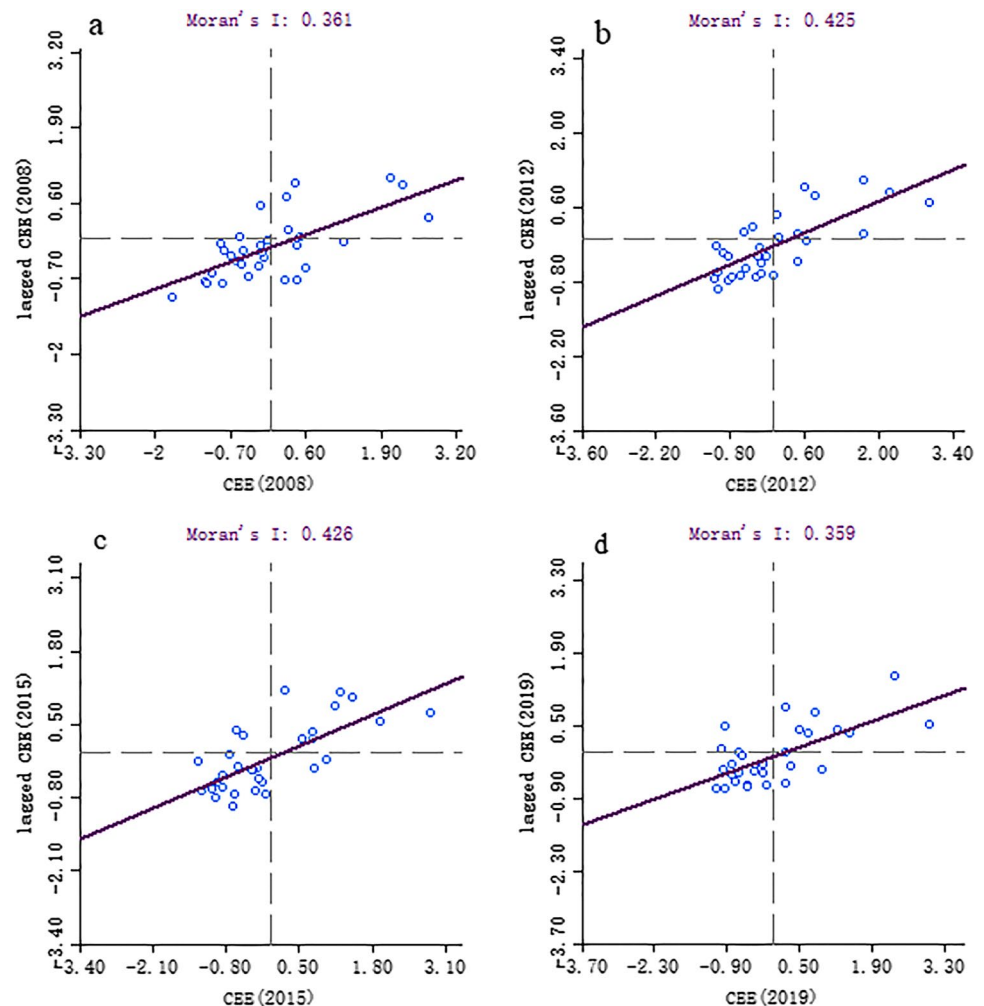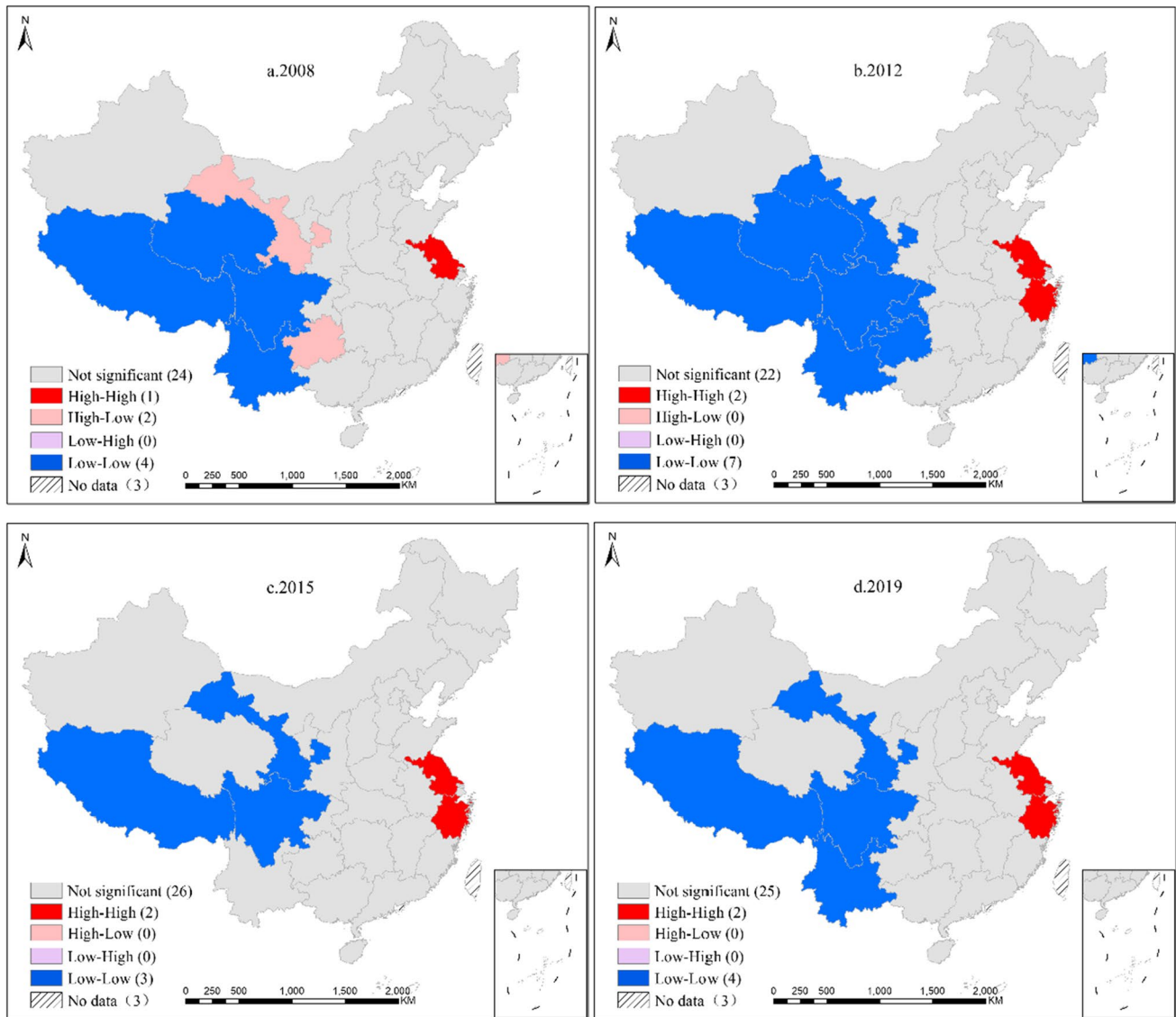
Fig. 7 LISA cluster map of freight transport's CEE in 2008, 2012, 2015, and 2019

transport's CEE, and there is a relatively high spatial dependence in local areas. Specifically, Hebei changed from the LH cluster in 2008 to the HH cluster in 2012 by strengthening both the carbon emissions technology level and the driving role of the neighboring provinces and has since remained a continuous HH cluster. However, Shandong changed from the HH cluster in 2008 to the LH cluster in 2012. Guizhou and Gansu changed from the HL-type agglomeration in 2008 to the LL-type agglomeration in 2012, Jilin changed from the LL-type agglomeration in 2015 to the LH-type agglomeration in 2019, and the agglomeration types of the other provinces remained relatively stable.

To determine whether the four cluster types (HH, HL, LH, and LL) were statistically significant, we used

the LISA cluster map (see Fig. 7) for further analysis. Figure 7 shows that at the 5% significance level, there were mainly HH and LL clusters in 2012, 2015, and 2019, except for Guizhou and Gansu, which were in the HL cluster in 2008. Among them, the provinces in the HH agglomeration are all located in the eastern coastal regions, including Jiangsu and Zhejiang. These provinces have a positive radiation effect and a strong driving effect on the surrounding provinces and can further improve the CEE by strengthening provincial cooperation. The provinces in the LL cluster are majorly distributed in western areas, including Tibet, Sichuan, Gansu, and Yunnan. The economic and technological levels of these regions

are underdeveloped, while the environmental protection systems are not sound enough, leading to low CEE. Based on their resource advantages, these regions can improve their CEE by updating their equipment, improving their environmental protection systems and energy utilization efficiency, and strengthening regional cooperation.

Regional difference analysis of CEE

To further analyze the regional differences in freight transport's CEE and the changes in the contribution of intra- and inter-regional differences to the total difference, we calculated the Theil index of freight transport's CEE from 2008 to 2019 according to Formula (9). We decomposed the Theil index into intra- and inter-regional Theil indexes of the east, central, and west economic zones and calculated the contribution of the two indexes to the total difference. The results are shown in Table 6 in the Appendix and Figs. 8 and 9.

The Theil index of freight transport's CEE shows a fluctuating upward trend from 0.0377 in 2008 to 0.0602 in 2019. This indicates that because of the disparity in the economic development, resources, and geographic locations of the various provinces, the national freight transport industry still shows uneven development characteristics, and the overall difference in the freight

transport industry's CEE is still expanding. Figure 8 shows that the inter-regional and overall Theil indexes have the same trend of change and present a fluctuating upward trend during the study. This suggests that the gap in the CEE among areas is still widening. In addition to the apparent rise in 2014, the intra-regional Theil index remains stable and fluctuates around 0.02, indicating that the difference in the CEE in each region remains stable and neither increases nor decreases. In addition, Fig. 8 shows that the overall and inter-regional Theil indexes present an apparent upward trend in 2014, which is consistent with the CEE trend. Owing to the introduction of relevant policies, the CEE of some regions rapidly increases in 2014 and slowly increases in other areas, leading to the widening of differences in the CEE, both nationwide and inter-regionally.

The average contribution rates of the inter- and intra-regional differences to the total differences during the study period are 54.81% and 45.19%, respectively. This indicates that the differences between regions are the major component of the differences in the freight transport industry's CEE. Figure 9 shows that in terms of specific trends, the contribution rate of intra-regional differences to the total differences shows a downward trend from 50.30% in 2008 to 41.91% in 2019. Simultaneously, the contribution rate of inter-regional differences to total

Fig. 8 The overall, inter-regional, and intra-regional Theil index change trends
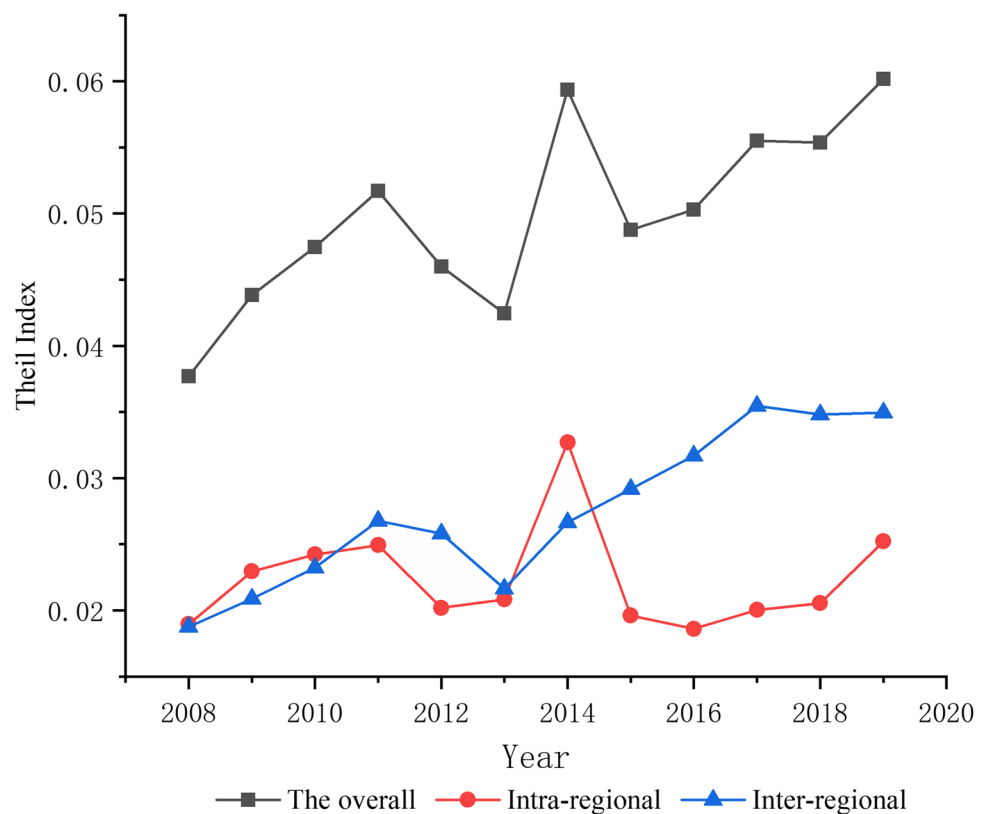
Fig. 9 The contribution of inter-regional and intra-regional differences to the overall differences
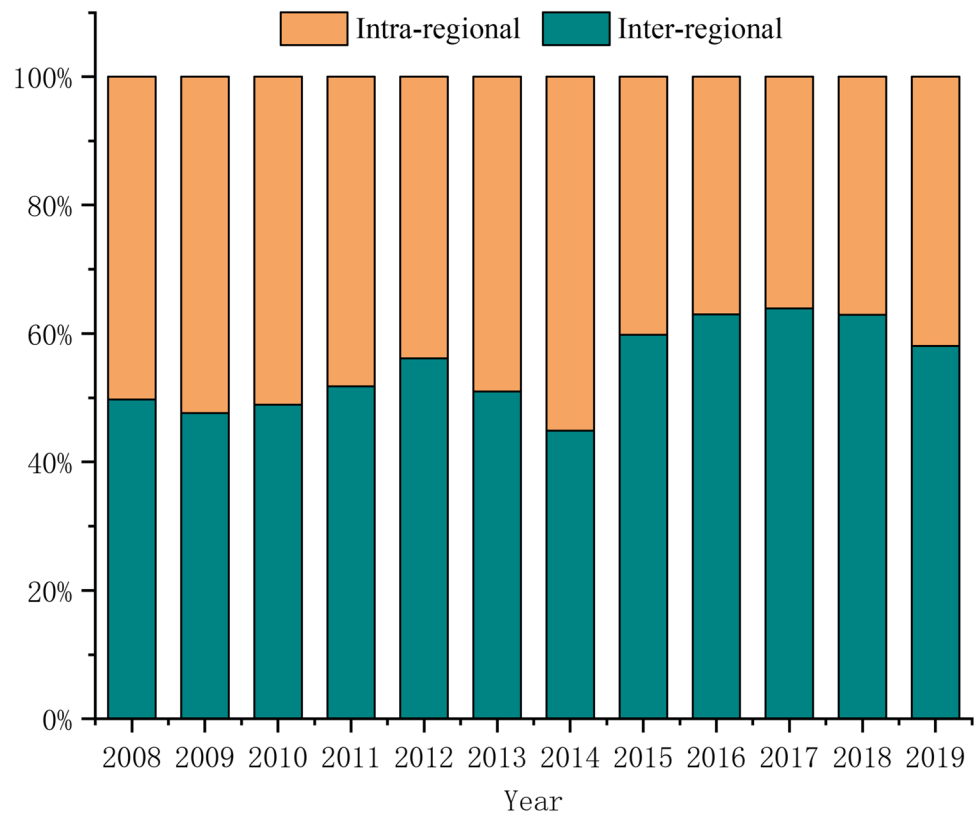
differences shows an upward trend from 49.70% in 2008 to 58.09% in 2019. This is because there are significant differences among the regions in terms of the natural resources, economic development, carbon emissions reduction technology, and the freight transport industry's development. Therefore, it is necessary to explore differentiated carbon reduction policies for the freight transport industry based on the different characteristics of each region, so as to gradually reduce the regional differences in the freight transport industry's CEE and achieve coordinated development among the regions.

Conclusions and policy implications

This study explores temporal and spatial characteristics as well as regional differences in the Chinese freight transport industry's CEE. Its aim was to analyze the spatial agglomeration characteristics of the provinces' CEE and identify the causes of regional differences in CEE, which could provide the government with useful information to formulate differentiated carbon emission reduction policies for freight transportation. The major conclusions and policy implications are as follows:

(1) The overall level of the Chinese freight transport industry's CEE is low, while the unbalanced development of the freight transport industry was prominent during the study period. The freight transport industry's CEE presents the spatial distribution features of "low in the west and high in the east." In terms of changing trends, the overall CEE showed a weak decreasing trend, while the significant difference showed an increasing trend. The eastern region's CEE had a steady development trend, the central and western regions showed a decreasing trend, and the western region declined significantly.

This indicates that the state has recently issued a series of policies to achieve energy conservation and emission reduction of the transportation industry and improve its CEE. However, these policies have not shown the effect of energy conservation and emission reduction in the freight industry, whose CEE has not improved. Therefore, the government should pay more attention to energy conservation and emission reduction in the freight industry and promptly draft special energy conservation and emission reduction schemes and strategies to realize the sustainable development of China's freight industry. Simultaneously, differentiated emission reduction policies should be formulated according to each region's resource,

economic, and technological levels. For the eastern coastal provinces, attention should be paid to enhancing management efficiency and low-carbon technology, improving the energy consumption structure, and strengthening the use of clean energy. Provinces in the central and western areas should focus on strengthening the utilization of energy-saving technologies and optimizing traditional industries to improve energy efficiency.

(2) The freight transport industry's CEE had a stable spatial positive correlation. The Moran scatter plot shows that more than 80% of the provinces belonged to the HH and LL clusters. The LISA cluster map shows that the CEE has significant spatial agglomeration characteristics. The HH clustering areas were primarily clustered in the eastern coastal regions; the LL clustering areas were mostly concentrated in the central and western regions.

This indicates that neighboring provinces with high CEE have strong cooperation and connections in space, thereby forming obvious diffusion and driving effects. Provinces with low CEE have an inhibiting effect on neighboring provinces. Therefore, the government should take into account the spatial interaction of adjacent regions when formulating carbon emission reduction policies for the freight industry, encourage provinces with resources and low-carbon technology advantages to take the lead in development, and use the space-driven effect to promote the improvement of the freight transport industry's CEE in surrounding provinces.

(3) The freight transport industry's CEE showed clear differences, while the overall differences presented a fluctuating upward trend. The decomposition results of the Theil index showed that the differences in the freight transport industry's CEE originated from inter-regional differences between the three major regions (east, central, and west), while the degree of influence of inter-regional differences on the overall difference gradually increased.

This indicates that the development of China's freight industry is not coordinated across different regions. Narrowing the CEE gap between different regions is one of the main ways to improve the freight transport industry's CEE. Therefore, future policies should focus on reducing the inter-regional differences in the freight transport industry's CEE. On the one hand, while promoting eastern provinces' CEE to the forefront of production, the government should increase its investment in funds and technology to focus on supporting the development of freight transport in the western provinces. On the other hand, the government should focus on establishing regional cooperation mechanisms to promote inter-regional exchange and cooperation and enable the proliferation and demonstration effects of the eastern region, which has a greater CEE.

In addition, the contribution of the freight transport industry's structural optimization to improve CEE should be given full play (Chang and Lai 2013). All regions should thoroughly implement the Outline for Building a Powerful Transportation Country; optimize the structure of freight transport and promote the orderly transfer of bulk cargo and medium- and long-distance freight transportation to railway and water transportation; and promote the development of railway–waterway, highway–railway, highway–waterway, and other multimodal transportation. Simultaneously, the government should deepen the multimodal transport demonstration project and the urban green distribution demonstration project, promote the advanced transportation organization model, and accelerate the transformation and upgrade of the road freight industry.

This study also had the following limitations, which may be overcome in further research: first, this study focused on the CEE of the entire freight industry but has not explored the CEE of freight sub-sectors such as the road, railway, and waterways, which can be studied in the future. Second, due to the unavailability of data, this study did not cover changes in the freight transport industry's CEE during the COVID-19 pandemic. Therefore, special research on the impact of the COVID-19 pandemic on the carbon emissions of the freight industry should be conducted in the future.

Appendix

Table 5 Calculation results of the freight transport industry's CEE

	Region	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean
East	Beijing	0.914	0.898	0.914	0.877	0.860	0.836	0.807	0.767	0.727	0.783	0.795	0.648	0.819
	Tianjin	0.881	0.995	1.006	1.111	0.944	0.809	0.809	0.734	0.693	0.669	0.674	0.618	0.829
	Hebei	0.525	0.449	0.460	0.496	0.563	0.621	0.677	0.646	0.618	0.631	0.618	0.564	0.572
	Liaoning	0.651	0.641	0.630	0.623	0.635	0.648	0.663	0.653	0.690	0.712	0.695	0.702	0.662
	Shanghai	0.985	0.983	1.052	1.052	1.078	0.967	1.148	1.003	0.993	1.045	1.050	1.098	1.038
	Jiangsu	0.620	0.620	0.626	0.649	0.659	0.658	0.641	0.565	0.538	0.555	0.535	0.566	0.603
	Zhejiang	0.599	0.616	0.657	0.684	0.693	0.722	0.728	0.719	0.687	0.655	0.665	0.674	0.675
	Fujian	0.626	0.624	0.640	0.642	0.637	0.622	0.623	0.649	0.659	0.651	0.665	0.758	0.650
	Shandong	0.600	0.550	0.529	0.516	0.483	0.401	0.438	0.435	0.411	0.388	0.376	0.388	0.460
	Guangdong	0.543	0.509	0.524	0.519	0.572	0.506	0.618	0.615	0.697	0.729	0.712	0.799	0.612
	Hainan	0.755	0.779	0.800	0.846	0.858	0.747	0.879	0.850	0.837	0.798	0.786	0.967	0.825
East mean		0.700	0.697	0.712	0.729	0.726	0.685	0.730	0.694	0.686	0.692	0.688	0.708	0.704
Central	Shanxi	0.460	0.502	0.542	0.544	0.528	0.530	0.515	0.479	0.474	0.518	0.495	0.451	0.503
	Jilin	0.418	0.407	0.397	0.384	0.362	0.342	0.340	0.303	0.307	0.316	0.319	0.323	0.352
	Heilongjiang	0.492	0.484	0.473	0.467	0.443	0.416	0.383	0.355	0.362	0.382	0.408	0.422	0.424
	Anhui	0.637	0.597	0.614	0.628	0.662	0.751	1.047	0.688	0.656	0.605	0.609	0.585	0.673
	Jiangxi	0.466	0.361	0.370	0.394	0.453	0.398	0.433	0.416	0.392	0.360	0.379	0.339	0.397
	Henan	0.525	0.487	0.474	0.484	0.505	0.402	0.423	0.397	0.370	0.358	0.390	0.366	0.432
	Hubei	0.534	0.491	0.503	0.513	0.499	0.450	0.468	0.462	0.447	0.430	0.424	0.478	0.475
	Hunan	0.428	0.407	0.395	0.382	0.387	0.408	0.443	0.419	0.393	0.363	0.357	0.404	0.399
Central Mean		0.495	0.467	0.471	0.474	0.480	0.462	0.507	0.440	0.425	0.417	0.422	0.421	0.457
West	Inner Mongolia	0.477	0.449	0.442	0.458	0.505	0.496	0.500	0.471	0.412	0.436	0.438	0.475	0.463
	Chongqing	0.521	0.523	0.527	0.523	0.554	0.528	0.519	0.507	0.507	0.507	0.505	0.563	0.524
	Sichuan	0.394	0.391	0.389	0.380	0.368	0.378	0.354	0.344	0.343	0.345	0.348	0.377	0.368
	Guizhou	0.594	0.631	0.604	0.555	0.495	0.435	0.400	0.372	0.368	0.353	0.342	0.363	0.459
	Yunnan	0.372	0.374	0.373	0.363	0.355	0.332	0.323	0.314	0.312	0.302	0.300	0.340	0.338
	Guangxi	0.476	0.465	0.465	0.449	0.460	0.462	0.502	0.497	0.472	0.454	0.459	0.482	0.470
	Tibet	0.283	0.313	0.326	0.332	0.365	0.390	0.400	0.408	0.401	0.373	0.381	0.309	0.357
	Shaanxi	0.445	0.435	0.426	0.407	0.405	0.412	0.391	0.375	0.377	0.376	0.373	0.389	0.401
	Gansu	0.627	0.580	0.591	0.570	0.513	0.542	0.517	0.476	0.452	0.458	0.460	0.495	0.524
	Qinghai	0.379	0.387	0.392	0.401	0.402	0.453	0.440	0.409	0.413	0.419	0.412	0.425	0.411
	Ningxia	0.531	0.497	0.483	0.489	0.515	0.463	0.490	0.484	0.452	0.383	0.344	0.334	0.455
	Xinjiang	0.422	0.427	0.429	0.421	0.416	0.409	0.386	0.357	0.353	0.358	0.362	0.380	0.393
West Mean		0.460	0.456	0.454	0.446	0.446	0.442	0.435	0.418	0.405	0.397	0.394	0.411	0.430
National Mean		0.554	0.544	0.550	0.553	0.554	0.533	0.558	0.522	0.510	0.507	0.506	0.519	0.534

Table 6 Theil indexes and contribution rates of intra-regional (Tw) and inter-regional (Tb) differences from 2008 to 2019

Year	Theil index	Tw	Tb	Tw contribution rate (%)	Tb contribution rate (%)
2008	0.0377	0.0190	0.0187	50.30	49.70
2009	0.0438	0.0229	0.0209	52.36	47.64
2010	0.0475	0.0242	0.0232	51.05	48.95
2011	0.0517	0.0249	0.0268	48.22	51.78
2012	0.0460	0.0202	0.0258	43.89	56.11
2013	0.0425	0.0208	0.0216	49.04	50.96
2014	0.0594	0.0327	0.0267	55.10	44.90
2015	0.0488	0.0196	0.0292	40.20	59.80
2016	0.0503	0.0186	0.0317	37.00	63.00
2017	0.0555	0.0200	0.0355	36.10	63.90
2018	0.0553	0.0205	0.0348	37.11	62.89
2019	0.0602	0.0252	0.0349	41.91	58.09

Author contribution Xiyang Zhao: conceptualization, methodology, and writing—original draft.

Jianwei Wang: data analysis and funding acquisition.

Xin Fu: review and supervision.

Wenlong Zheng: data analysis and visualization.

Xiuping Li: data collection and editing.

Chao Gao: validation and editing.

All authors have read and approved the final version of the manuscript.

Data availability The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

References

Bai C, Zhou L, Xia M, Feng C (2020) Analysis of the spatial association network structure of China's transportation carbon emissions and its driving factors. J Environ Manage 253:109765. https://doi.org/10.1016/j.jenvman.2019.109765

Bai D, Dong Q, Khan SAR, Chen Y, Wang D, Yang L (2021) Spatial analysis of logistics ecological efficiency and its influencing factors in China: based on super-SBM-undesirable and spatial Durbin models. Environ Sci Pollut Res: 1-19. https://doi.org/10.1007/s11356-021-16323-x

Bian Y, Yang F (2010) Resource and environment efficiency analysis of provinces in China: a DEA approach based on Shannon's entropy. Energy Policy 38:1909–1917. https://doi.org/10.1016/j.enpol.2009.11.071

Chang CC, Lai TC (2013) Carbon allowance allocation in the transportation industry. Energy Policy 63:1091–1097. https://doi.org/10.1016/j.enpol.2013.08.093

Chen X, Gao Y, An Q, Wang Z, Neralić L (2018) Energy efficiency measurement of Chinese Yangtze River Delta's cities transportation: a DEA window analysis approach. Energ Eff (1570646X) 11. https://doi.org/10.1007/s12053-018-9635-7

Cheng G (2014) Data envelopment analysis: methods and MaxDEA software. Intellectual Property Publishing House 8:151–154

Chu J-F, Wu J, Song M-L (2018) An SBM-DEA model with parallel computing design for environmental efficiency evaluation in the big data context: a transportation system application. Ann Oper Res 270:105–124. https://doi.org/10.1007/s10479-016-2264-7

Cui Q, Li Y (2014) The evaluation of transportation energy efficiency: an application of three-stage virtual frontier DEA. Transp Res Part d: Transp Environ 29:1–11. https://doi.org/10.1016/j.trd.2014.03.007

Feng C, Zhang H, Huang J-B (2017) The approach to realizing the potential of emissions reduction in China: an implication from data envelopment analysis. Renew Sustain Energy Rev 71:859–872. https://doi.org/10.1016/j.rser.2016.12.114

Feng C, Wang M (2018) Analysis of energy efficiency in China's transportation sector. Renew Sustain Energy Rev 94:565–575. https://doi.org/10.1016/j.rser.2018.06.037

Fu L, Sun Z, Zha L, Liu F, He L, Sun X, Jing X (2020) Environmental awareness and pro-environmental behavior within China's road freight transportation industry: moderating role of perceived policy effectiveness. J Clean Prod 252:119796. https://doi.org/10.1016/j.jclepro.2019.119796

Halkos GE, Tzeremes NG (2009) Exploring the existence of Kuznets curve in countries' environmental efficiency using DEA window analysis. Ecol Econ 68:2168–2176. https://doi.org/10.1016/j.ecolecon.2009.02.018

Hao H, Geng Y, Li W, Guo B (2015) Energy consumption and GHG emissions from China's freight transport sector: scenarios through 2050. Energy Policy 85:94–101. https://doi.org/10.1016/j.enpol.2015.05.016

IEA (2009) CO2 emissions and fuel combustion highlights. Office of Management and Administration, Paris

IEA (2019) CO2 emissions from fuel combustion highlights. Office of Management and Administration, Paris

Isik M, Sarica K, Ari I (2020) Driving forces of Turkey's transportation sector CO2 emissions: an LMDI approach. Transp Policy 97:210–219. https://doi.org/10.1016/j.tranpol.2020.07.006

Jebaraj S, Iniyan S (2006) A review of energy models. Renew Sustain Energy Rev 10:281–311. https://doi.org/10.1016/j.rser.2004.09.004

Lei X, Zhang X, Dai Q, Li L (2021) Dynamic evaluation on the energy and environmental performance of China's transportation sector: a ZSG-MEA window analysis. Environ Sci Pollut Res 28:11454–11468. https://doi.org/10.1007/s11356-020-11314-w

LeSage J, Pace RK (2009) Introduction to spatial econometrics. Chapman and Hall/CRC, New York

Li H, Lu Y, Zhang J, Wang T (2013) Trends in road freight transportation carbon dioxide emissions and policies in China. Energy Policy 57:99–106. https://doi.org/10.1016/j.enpol.2012.12.070

Li Y, Du Q, Lu X, Wu J, Han X (2019) Relationship between the development and CO2 emissions of transport sector in China. Transp Res Part d: Transp Environ 74:1–14. https://doi.org/10.1016/j.trd.2019.07.011

Liu W, Lin B (2018) Analysis of energy efficiency and its influencing factors in China's transport sector. J Clean Prod 170:674–682. https://doi.org/10.1016/j.jclepro.2017.09.052

Liu Y, Yang S, Liu X, Guo P, Zhang K (2021) Driving forces of temporal-spatial differences in CO2 emissions at the city level for China's transport sector. Environ Sci Pollut Res 28:25993–26006. https://doi.org/10.1007/s11356-020-12235-4

Liu Z, Qin C-X, Zhang Y-J (2016) The energy-environment efficiency of road and railway sectors in China: evidence from the provincial level. Ecol Ind 69:559–570. https://doi.org/10.1016/j.ecolind.2016.05.016

Lu Y, Li X, Yang Z (2018) Current situation and peak forecast of energy carbon emissions in Guizhou Province. Environ Sci Technol 41:173–180. https://doi.org/10.19672/j.cnki.1003-6504.2018.11.028

Luo X, Dong L, Dou Y, Liang H, Ren J, Fang K (2016) Regional disparity analysis of Chinese freight transport CO2 emissions from 1990 to 2007: driving forces and policy challenges. J Transp Geogr 56:1–14. https://doi.org/10.1016/j.jtrangeo.2016.08.010

Lv Q, Liu H, Yang D, Liu H (2019) Effects of urbanization on freight transport carbon emissions in China: common characteristics and regional disparity. J Clean Prod 211:481–489. https://doi.org/10.1016/j.jclepro.2018.11.182

Mustapa SI, Bekhet HA (2016) Analysis of CO2 emissions reduction in the Malaysian transportation sector: an optimisation approach. Energy Policy 89:171–183. https://doi.org/10.1016/j.enpol.2015.11.016

National Bureau of Statistics (2020) China Statistical Yearbook. http://www.stats.gov.cn/tjsj/ndsj/. Assessed 20 Nov 2020

Ou G, Xu C (2020) Analysis of Freight transport carbon emission efficiency in Beijing-Tianjin-Hebei: a study based on super-efficiency SBM model and ML index. J Beijing Jiaotong University (Social Sciences Edition) 19:48–57. https://doi.org/10.16797/j.cnki.11-5224/c.2020.0007

Park YS, Lim SH, Egilmez G, Szmerekovsky J (2018) Environmental efficiency assessment of US transport sector: a slack-based data envelopment analysis approach. Transp Res Part d: Transp Environ 61:152–164. https://doi.org/10.1016/j.trd.2016.09.009

Peng Z, Wu Q, Wang D, Li M (2020) Temporal-spatial pattern and influencing factors of China's province-level transport sector carbon emissions efficiency. Pol J Environ Stud 29:233–247. https://doi.org/10.15244/pjoes/102372

Peykani P, Farzipoor Saen R, Seyed Esmaeili FS, Gheidar-Kheljani J (2021) Window data envelopment analysis approach: a review and bibliometric analysis. Expert Syst: e12721. https://doi.org/10.1111/exsy.12721

Song M, Zheng W, Wang Z (2016) Environmental efficiency and energy consumption of highway transportation systems in China. Int J Prod Econ 181:441–449. https://doi.org/10.1016/j.ijpe.2015.09.030

Sun Q, Guo X, Jiang W, Wang C (2018) Study on efficiency evaluation and spatio-temporal evolution of freight transport in China with "one belt and one road" as the background. J Ind Technol Econ 37:53–61

Tang K, Xiong C, Wang Y, Zhou D (2021) Carbon emissions performance trend across Chinese cities: evidence from efficiency and convergence evaluation. Environ Sci Pollut Res 28:1533–1544. https://doi.org/10.1007/s11356-020-10518-4

Tang T, You J, Sun H, Zhang H (2019) Transportation efficiency evaluation considering the environmental impact for China's freight sector: a parallel data envelopment analysis. Sustainability 11:5108. https://doi.org/10.3390/su11185108

Theil H (1967) Economics and information theory. North Holland, Amsterdam

Tian Y, Zhu Q, Lai K-h, Lun YV (2014) Analysis of greenhouse gas emissions of freight transport sector in China. J Transp Geogr 40:43–52. https://doi.org/10.1016/j.jtrangeo.2014.05.003

Tone K (2001) A slacks-based measure of efficiency in data envelopment analysis. Eur J Oper Res 130:498–509. https://doi.org/10.1016/S0377-2217(99)00407-5

Van Fan Y, Perry S, Klemeš JJ, Lee CT (2018) A review on air emissions assessment: transportation. J Clean Prod 194:673–684. https://doi.org/10.1016/j.jclepro.2018.05.151

Wang K, Yu S, Zhang W (2013) China's regional energy and environmental efficiency: a DEA window analysis based dynamic evaluation. Math Comput Model 58:1117–1127. https://doi.org/10.1016/j.mcm.2011.11.067

Wang M 2012 Low carbon development model research on transportation sector in China. Dissertation Thesis, Dalian University of Technology, Dalian

Wang Q, Wang S, Li R (2019) Determinants of decoupling economic output from carbon emission in the transport sector: a comparison study of four municipalities in China. Int J Environ Res Public Health 16:3729. https://doi.org/10.3390/ijerph16193729

Wang R, Wang Q, Yao S (2021) Evaluation and difference analysis of regional energy efficiency in China under the carbon neutrality targets: insights from DEA and Theil models. J Environ Manage 293:112958. https://doi.org/10.1016/j.jenvman.2021.112958

Wang Z, He W (2017) CO2 emissions efficiency and marginal abatement costs of the regional transportation sectors in China. Transp Res Part d: Transp Environ 50:83–97. https://doi.org/10.1016/j.trd.2016.10.004

Wei F, Zhang X, Chu J, Yang F, Yuan Z (2021) Energy and environmental efficiency of China's transportation sectors considering CO2 emission uncertainty. Transp Res Part d: Transp Environ 97:102955. https://doi.org/10.1016/j.trd.2021.102955

Wu D, Wang Y, Qian W (2020) Efficiency evaluation and dynamic evolution of China's regional green economy: a method based on the super-PEBM model and DEA window analysis. J Clean Prod 264:121630. https://doi.org/10.1016/j.jclepro.2020.121630

Zhang K, Liu X, Yao J (2019) Identifying the driving forces of CO 2 emissions of China's transport sector from temporal and spatial decomposition perspectives. Environ Sci Pollut Res 26:17383–17406. https://doi.org/10.1007/s11356-019-05076-3

Zhang N, Wei X (2015) Dynamic total factor carbon emissions performance changes in the Chinese transportation industry. Appl Energy 146:409–420. https://doi.org/10.1016/j.apenergy.2015.01.072

Zhao P, Zeng L, Li P, Lu H, Hu H, Li C, Zheng M, Li H, Yu Z, Yuan D (2022) China's transportation sector carbon dioxide emissions efficiency and its influencing factors based on the EBM DEA model with undesirable outputs and spatial Durbin model. Energy 238:121934. https://doi.org/10.1016/j.energy.2021.121934

Zhou P, Chung W, Zhang X (2013) A study of carbon dioxide emissions performance of China's transport sector. Energy 50:302–314. https://doi.org/10.1016/j.energy.2012.11.045

Zhu Q, Li X, Li F, Wu J, Zhou D (2020) Energy and environmental efficiency of China's transportation sectors under the constraints of energy consumption and environmental pollutions. Energ Econ 89:104817. https://doi.org/10.1016/j.eneco.2020.104817