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A B S T R A C T

The threat of global climate change has caused the international community to pay close attention to atmospheric levels of greenhouse gases such as carbon dioxide. Transportation sector carbon dioxide emissions efficiency (TSCDEE) is a key indicator used to prioritize sustainable development in the transportation sector. In this paper, the epsilon-based measure data envelopment analysis model with undesirable outputs is applied to estimate TSCDEE for 30 provinces in China from 2010 to 2016. We also analyze influencing factors using the spatial Durbin model. Research shows that the overall TSCDEE of the Chinese provinces studied was 0.618, indicating that most regions are still in need of improvements. The provinces with the highest TSCDEE are located in developed coastal regions of China. This study shows that factors such as transportation structure, traffic infrastructure level, and technological progress have prominent positive effects on TSCDEE, while both urbanization level and urban population density exert significantly negative effects on TSCDEE. The findings should have a far-reaching impact on the sustainable development of global transportation.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) expected that the levels of emission of transport-related CO_2 would triple by 2100 if effective policies and measures were not implemented in the near future [1]. In this scenario, the average global temperature is expected to rise by over 4 °C above pre-industrial levels [2]. The transport sector is the third-largest source of CO_2 emissions in the world, ranking behind only the manufacturing sector and electricity production sector in 2016 [3]. Since the transportation sector is a main consumer of energy and contributor to CO_2 emissions, elevating transportation sector carbon dioxide emissions efficiency (TSCDEE) is of urgent importance.

Technical efficiency analysis was first reported by Ref. [4]; and it is the capacity of a decision-making unit (DMU) to achieve maximal output under a given set of inputs [5]. TSCDEE is a new framework for measuring the level of sustainable development in

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transportation. Relying on comprehensive and scientific principles, we define TSCDEE as the comprehensive transportation efficiency with which the transportation sector achieves more transportation outputs and creates much less carbon dioxide emissions; the definition assumes a condition of constant or decreasing input of the factors determining productivity in the transportation sector [6,7].

In 2016, the transportation sector in China consumed 271.831 million tons of standard coal, a level second only to that of the manufacturing sector [8]. From 1995 to 2017, the total energy consumption in China's transport sector grew by 639% [9]. This is the fastest-growing of all sectors, and the energy consumed by the transport sector is linked to significant increases in CO_2 emissions. In 2016, total traffic CO_2 emissions from China reached 851.2 million metric tons, accounting for 10.8% of global traffic CO_2 emissions and ranking second in the world after the USA (Fig. 1) [3]. It is, therefore, important to calculate China's TSCDEE accurately, since it can reveal the environmental impact arising from transportation in the second-largest transport carbon emitter in the word and ultimately promote global sustainable development of transportation. Moreover, analysis of the key factors influencing TSCDEE in China is beneficial and can assist in the development of scientific and practical tactics and steps.

Much of the earlier research reported estimated TSCDEE obtained with the data envelopment analysis (DEA) method, which use a linear programming scheme to calculate the technical efficiencies of a set of decision making units (DMUs). In the DEA method, multiple inputs and outputs are handled. Unlike the parametric efficiency evaluation approachs, some specific functional forms do not determine the efficient frontier [10]. The mian DEA methods for estimating TSCDEE includies the Charnes-Cooper-Rhodes (CCR) DEA model, the Banker-Charnes-Cooper (BCC) DEA model, and the slacks-based measure (SBM) DEA model, but these methods may overestimate or undervalue the efficiency value of a decision making unit (DMU) [11–13]. The epsilon-based measure (EBM) DEA model with undesirable outputs is a new method to measure the provincial carbon dioxide emissions efficiency; this method can address the defects of the CCR, BCC and SBM DEA models [12], which exhibit the potential for overestimation or underestimation of the efficiency value. [13]; therefore, this method was applied to estimate the provincial TSCDEE in China. As for the regression analysis, the Tobit model, spatial lag model (SLM), and spatial error model (SEM) are the major methods to analyze the factors affecting TSCDEE. In the traditional Tobit model, the spatial factors would not be taken into account. In SLM and SEM, the lags in both spatial independent variables and the dependent spatial variable are not considered at the same time, which may lead to an estimation error in the regression coefficient [14].

The major contributions of this article are: (1) We provide a more accurate method for calculating carbon dioxide emissions from the transport sector, which include fossil fuel and electrical carbon dioxide emissions. (2) We examine TSCDEE in Chinese 30 provinces from 2010 to 2016 and explore ways to achieve improvement in TSCDEE, a subject which few have examined in recent years. (3) We applied the SDM method, which contains spatial lags of the explained variable and explanatory variables and makes regression analysis more precise and reliable [15], to explore how five kinds of influencing factors affect TSCDEE. The findings should have a profound influence upon the policy making of transport sustainable development.

The rest of the article is composed by a few parts: Section 2 reviews and summarizes the relevant studies. The methodologies are briefly described in Section 3. Section 4 indicates the selection of relevant data and the sources for those data. Section 5 presents the characteristics of TSCDEE in China. In Section 6, the SDM method is applied to analyze the factors influencing TSCDEE, and Section 7 summarizes the article and offers suggestions for improvements.

2. Literature review

2.1. Calculation methodology

The basic methodology for estimating TSCDEE is the DEA method, which can handle multiple inputs and outputs and avoid inaccurate results arising from the use of incorrect functional forms [16]. There are two research approaches used in this field. The first

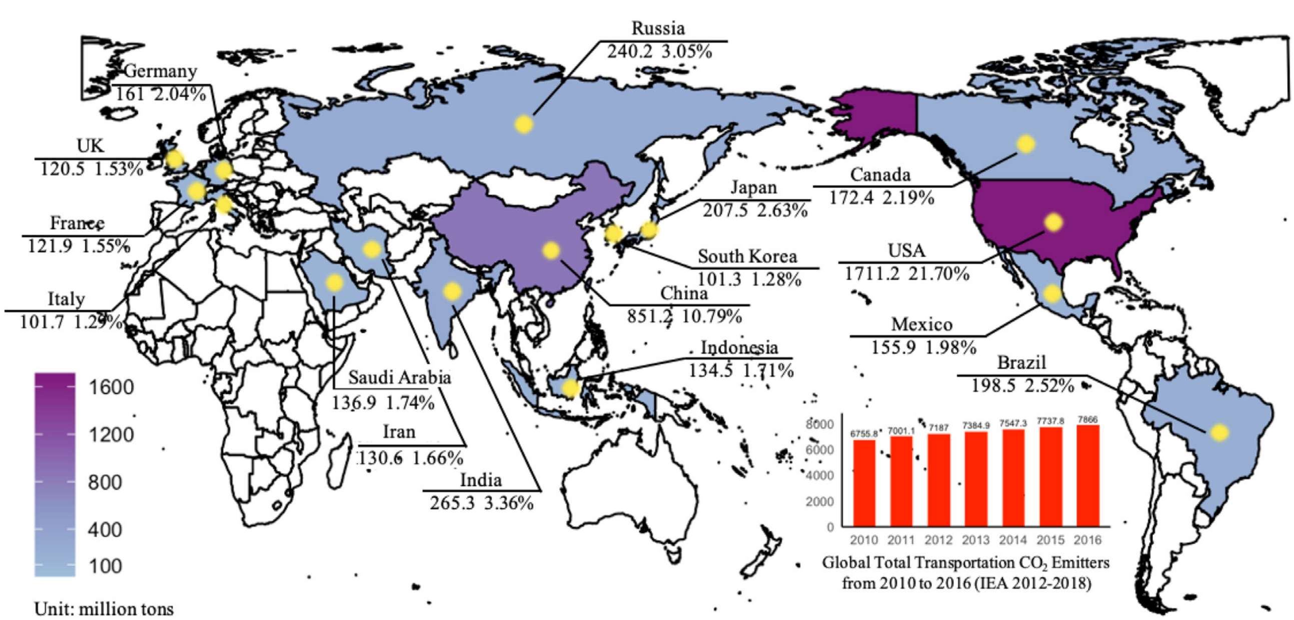

Fig. 1. Main transportation CO_2 Emitters in 2016.

takes carbon dioxide emissions as input by employing the radial DEA model, which includes the CCR DEA or BCC DEA model. The difference of two radial DEA models is that BCC can achieve the separation of technical and scale efficiencies [17]. In both models, the inputs and outputs were assumed to increase or decrease proportionally when estimating the efficiency [18]. Lan and Zhang [19] applied the CCR DEA model and treated capital stock, labor force, and the CO_2 emissions from the transportation sector as three inputs, while the value added by the transportation sector was treated as an output for evaluating the TSCDEEs of 30 Chinese provinces between 2006 and 2010. Chen et al. [20] regarded traffic CO_2 emissions as a key input indicator when using both the CCR DEA and BCC DEA methods to calculate TSCDEE in Beijing from 2000 to 2017. However, the radial DEA model is unable to consider the effect of non-radial slacks, which may overestimate the efficiency value of the DMU and cause a biased measure [13].

A second approach selects carbon dioxide emissions as an undesirable output and is based primarily on the non-radial DEA model with undesirable outputs. In dealing with the problem of the radial DEA model, Tone [18] put forward a non-radial SBM model that takes the input and the output slacks into account when calculating efficiency. However, the stranded SBM DEA cannot consider undesirable outputs. Tone [21] then proposed the SBM DEA model with undesirable outputs in 2004, and this can accommodate undesirable output factors. Considering the CO_2 emissions as the only variable of undesirable output and applying the SBM DEA model with undesirable outputs, Chang et al. [22] and Song et al. [23] calculated the environmental efficiency of the transportation sector of China, and Liu et al. [24] measured the environmental efficiency of the land transportation sector of China, and Park et al. [25] estimated the transportation sector of USA, respectively. Li et al. [26] and Ma et al. [27] applied the super-SBM DEA model with undesirable outputs to calculate the integrated transport efficiency in China based on CO_2 emissions, respectively. As for other DEA methods, Ren et al. (2017) applied a non-radial chance-constrained DEA model to measure the carbon emission efficiency of regional transportation systems in China, and Wang and He [28] used a non-radial directional distance function DEA models to measure the CO_2 emissions efficiency of the regional transportation sectors in China, and Feng and Wang [29] employed the Global meta-frontier DEA model based on CO_2 emissions to anaylze the energy efficiency in China's transportation sector.

2.2. Regression methodology

The main methods used to analyze the influencing factors are the traditional econometric methods and the spatial econometric methods. The former is essentially the Tobit model, which solves the problem of regression of truncated or restricted variables [30]. Cui and Li [6] applied the Tobit model to empirically analysis on the essential factors influencing carbon use efficiency in transportation. They found the technological and management factors to be the most important factors. The traditional econometric methods do not consider spatial autocorrelation. They do not recognize the existence of spatial heteroscedasticity, which may cause the estimated coefficients to be biased [31]. The various types of spatial econometric methods, such as SLM or SEM, can capture spatial factors and provide better accuracy than do traditional econometric methods when the dependent variable displays a certain degree of spatial autocorrelation in various research regions. SLM contains endogenous interaction effects and is appropriate for situations in which spatial autocorrelation can be explained through the lag effect of dependent variables [32]. SEM is suitable for situations in which the spatial interaction effects are the result of omitted variables that affect both local and adjacent areas [33]. Yuan et al. [34] used the SLM model and found that the level of energy savings had a prominent positive effect on transport carbon intensity, while transportation structure, income level, transportation intensity, and population scale had significant negative impacts on transport carbon intensity. After calculating the ecological environment efficiency of urban transport (EEUT) based on CO_2 emissions, Zheng and Yang [35] conducted SLM and SEM regression analyses on the EEUT in China's 30 major cities between 2007 and 2016. They discovered that per capita GDP, the use of urban public transport vehicles, and urban green areas had positive effects on EEUT, while the level of urbanization, the number of taxis, and the number of private cars had negative influences on EEUT.

2.3. General summary

The research reviewed demonstrates that the main methods for evaluating TSCDEE has become the non-radial SBM DEA models with undesirable outputs. Spatial econometric methods have replaced the traditional econometric methods to become the major methods for regression analysis. However, the current studies still have certain flaws: (1) The radial DEA models assume proportional changes of inputs or outputs [36]; they may therefore overvalue the efficiency value of the DMU. The non-radial SBM models has solved the potential problem of the radial DEA models, but they has been designed to achieve maximum reductions in inputs that discards varying proportions of original input resources and potentially contributes to the underestimation of the efficiency scores for the DMU [11,13]. The best way to resolve these issues is to combine the radial DEA and non-radial DEA features in a unified formula to consolidate their advantages [37]. (2) Existing literature focusing on the spatial autocorrelation analysis for the TSCDEE is scarce. The spatial autocorrelation analysis explores the correlation degree of attribute values for elements among some spatial areas in space and adjacent units [38]. If spatial autocorrelation of TSCDEE exists, it prompts the necessity of a spatial pattern analysis from the perspective of geography-aspect such as spatial heterogeneity, spatial homogeneity, or agglomeration. (3) The SLM and SEM models still exhibit a common weakness. The explained variable in these models may be explained, not only by a spatially lagged explained variable or spatially autocorrelated error term, but also by a spatially lagged explained variable and spatially lagged explanatory variable [14,39].

This paper has addressed the above-mentioned problems as follows. First, the present work is designed to update earlier methods and utilize the EBM DEA model with undesirable outputs to evaluate the provincial TSCDEE levels in China. This approach offers a significant improvement because it integrates the merits of radial and non-radial models and avoids the overestimation or underestimation the technical efficiency of the DMU [13]. It also allows the consideration of undesirable outputs [40,41]. Secondly, this paper attempts to study the spatial autocorrelation of the China's provincial TSCDEE and expects to contribute to relevant previous works. Thirdly, the paper also applies the SDM, which is an improvement over SLM and SEM, to analyze empirically the influential factors of TSCDEE. The SDM can capture both the spatial correlations between explained variables and spatial spillover effects of the explanatory variable [7,42,43]).

3. Methodology

3.1. The EBM DEA model with undesirable outputs

There are n DMUs ($j = 1, \ldots, n$) which have m inputs ($i = 1, \ldots, m$) and s outputs ($i = 1, \ldots, s$). The input matrices are indicated by $\mathbf{X} = \{x_{ij}\} \in R^{m \times n}$, and, in response to this, the output matrices are denoted by $\mathbf{Y} = \{y_{ij}\} \in R^{s \times n}$. The method assumes $\mathbf{X} > 0$ and $\mathbf{Y} > 0$. Variables *n, s, m* indicate the number of DMUs, the outputs, and the inputs, respectively, s^- denotes the input slacks, and x_{ij} and y_{ij} identify the *i*th input and the *i*th output of DMU_j, respectively. λ indicates the intensity vector. Under constant returns to scale, the formula of the EBM DEA model is written as:

$$\beta^* = \min\left(\gamma - \varepsilon x \sum_{i=1}^{m} \frac{w_i^- s_i^-}{x_{ik}}\right)$$
$$s.t.\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{ik}\ i = 1,2,\ldots,m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rk}\ r = 1,2,\ldots,s \\ \lambda \geq 0, s_i^- \geq 0 \end{cases} \tag{1}$$

In Eq. (1), β^* refers to the efficiency score of DMU_k. w_i^- is the weight of input *i* and satisfies $\sum w_i^{-1} = 1(\forall i w_i^- \geq 0)$. Parameter ε_x can combine the radial programming parameter γ and the non-radial slacks terms.

According to Tone and Tsutsui [11]; the CCR DEA model fails to consider the non-radial slacks factors, and then the efficiency value of the DMU_k may be overestimated [13]. As for the SBM DEA model, since the input slacks s^- is not necessarily proportion to the original x_k, the projected DMU may lose the proportionality present in the original x_k [37], and then the efficiency value may be understimateed [13].

From Eq. (1), the EBM DEA model will be simplified to the CCR DEA model when $\varepsilon_x = 0$, or transformed into the SBM DEA model when $\gamma = \varepsilon = 1$, therefore, the EBM DEA model can simultaneously take the radial and the non-radial information into consideration, it would get a more accurate and scientific result of the efficiency calculation [44].

Although significant progress has been made with the EBM DEA model proposed by Ref. [11]; there are still some problems that must be solved to allow practical implementation. The model neglects the undesirable outputs. It is, therefore, reasonable to combine the EBM DEA model and undesirable factors for the evaluation of efficiency when some by-products associated with beneficial output exist simultaneously [45]. To measure China's eco-efficiency, Chen et al. [46] and Ren et al. [40,41] in 2020 showed an improved EBM model that achieves the combination of both radial and non-radial DEA models and also takes the undesirable factors into account. The EBM DEA model with undesirable outputs is expressed as:

$$T^* = \min\left[\frac{\gamma - \varepsilon x \sum_{i=1}^{m} \frac{\omega_i^- s_i^-}{xik}}{\psi + \varepsilon y \sum_{r=1}^{s} \frac{\omega_r^{+good} s_r^{+bad}}{yrk} + \varepsilon y \sum_{p=1}^{q} \frac{\omega_p^{-bad} s_p^{-bad}}{b_{pk}}}\right]$$
$$s.t\begin{cases} \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \gamma x_{ik}\ i = 1,2,\ldots,m \\ \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^{+good} = \psi y_{rk}\ r = 1,2,\ldots,s \\ \sum_{j=1}^{q} b_{pj}\lambda_j + s_p^{-bad}\lambda = \psi b_{pk}\ p = 1,2,\ldots,q \\ \lambda_j \geq 0, s_i^- \geq 0, s_r^{+good} \geq 0, s_p^{-bad} \geq 0 \end{cases} \tag{2}$$

In Eq. (2), there are *m* inputs, *s* desirable outputs and *q* undesirable outputs in each DMU; the efficiency value *T** varies from 0–1; s_i^{-d}, s_r^{+good}, and s_p^{-bad} denote the slacks of the slacks of input *i*, desired output *r*, and undesired output *p*, respectively. ω_r^{+good} and ω_p^{-bad} represent the desired output weight and the undesired output weight, respectively. *b* stands for the *p*th undesirable output of the DMU_j, and *q* is the total number of undesirable outputs. ε_x stands for the set of radial γ and non-radial slacks; ε_y denotes the set of radial Ψ and non-radial slacks; εx and εy meet the conditions: $0 \leq \varepsilon_x \leq 1$ and $0 \leq \varepsilon_y \leq 1$. The definitions of the other variables are as described above.

For simplicity in calculating the technical efficiency, Cheng [47] invented the MaxDEA 7 Ultra software, which can run multiple DEA models, including the EBM DEA model with undesirable outputs. Therefore, this work involves the use of Cheng's MaxDEA 7 Ultra software to calculate the values of provincial TSCDEE employing the EBM DEA model with undesirable outputs. The method for applying Cheng's MaxDEA 7 Ultra software can be found in Cheng [48] and *MaxDEA 7 Manual* [47].

3.2. Spatial correlation analysis

Before the regression analysis, it is necessary to test whether there is spatial correlation in the variables. If the spatial correlation exists, a spatial econometric model needs to be established Otherwise non-spatial econometric methods need to be used [49].

The spatial autocorrelation analysis methods include global and local spatial autocorrelation. The global spatial correlation among all provinces could be judged by measuring the Global Moran's I, which is calculated as follows:

$$GlobalMoran'It = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} Wi,j(TSCDEEi,t - \overline{TSCDEE}t)(TSCDEEj,t - \overline{TSCDEE}t)}{\left[\frac{1}{n}\sum_{i=1}^{n}(TSCDEEi,t - \overline{TSCDEE}t)^2\right]\sum_{i=1}^{n}\sum_{j=1}^{n} Wi,j} \tag{3}$$

In Eq. (3), $TSCDEE_{i,t}$ indicates the value of TSCDEE for province i in year t. $\overline{TSCDEEt}$represents the average of the TSCDEE for all provinces in year t. I_t indicates the value of Global Moran's I in the year t, and the scale ranges over [-1,1]. If the result is greater than 0 and reaches significant level, the TSCDEE has an obviously positive spatial correlation. If the value is less than 0 and reaches a significant level, a negative spatial correlation is implied. If the value is 0 or if the significance test is failed, no spatial relationship is shown. n identifies the total number of provinces. W is the spatial matrix. i and j represent two adjacent provinces, respectively. If province i borders on j, $W_{i,j}$ equals 1; otherwise, $W_{i,j}$ equals 0.

Local spatial autocorrelation is mainly used to analyze the spatial autocorrelation characteristics of each region, by measuring the degree of local spatial correlation between each region and the surrounding region. This approach compensates the shortcoming of global autocorrelation, which ignores the instability of spatial processes. The local spatial autocorrelation analysis is able to measure the degree of local spatial clustering. The local Moran's I index of the provinces i is calculated as follows:

$$LocalMoran'Ii = \frac{(TSCDEEi,t-\overline{TSCDEEt})}{S^2}\sum_{i=1}^{n}Wi,j(TSCDEEj,t-\overline{TSCDEEt})$$
$$S^2=\frac{1}{n}\sum_{i=1}^{n}Wi,j(TSCDEEi,t-\overline{TSCDEEt})^2 \tag{4}$$

Positive local Moran's I index in the province i indicates that the TSCDEE in the province i is similar to its adjacent provinces, otherwise it is not similar. The local spatial autocorrelation could be usually measured by the Moran scatter plot (MSP) and Local Indicators of Spatial Association (LISA).

The MSPs can be divided into four quadrants as follow. The first quadrant (in which province with high TSCDEE is adjacent to the provinces with high TSCDEE, referred to as the High-High (H—H) agglomeration area) and the third quadrant (in which province with low TSCDEE is adjacent to the provinces with low TSCDEE, referred to as the Low-Low (L-L) agglomeration area) indicate positive spatial autocorrelations of the observed TSCDEE, while the second quadrant (in which province with low TSCDEE is adjacent to the provinces with high TSCDEE, referred to as the Low-High (LH) agglomeration area) and the fourth quadrant (in which province with high TSCDEE is adjacent to the provinces with low TSCDEE, referred to as the High-Low (HL) agglomeration area) denote negative spatial autocorrelations.

3.3. Spatial Durbin model

We analyze the driving factors of TSCDEE by applying the spatial Dubin model (SDM). In this section we introduce the SLM and SEM models, and analyze their advantage and disadvantage, and then indicates the rationality and practicability by applying SDM.

The spatial lag model (SLM) is given as:

$$Y = \rho WY + \beta X + \varepsilon \tag{5}$$

In Eq. (5), Y stands for the explained variable and X identifies the influencing variables. ρ is the spatial autocorrelation coefficient. W indicates the spatial weight matrix, WY represents the spatial lag of the explained variable. β stands for the spatial regression coefficient. ε is the random error and belongs to $N(0,\sigma^2 I_n)$. SLM contains endogenous interaction effects. From Eq. (5), it could be found that, in the SLM, the explained variable Y in the local area is explained by the spatially lagged explained variable, and could not be explained by the spatially explanatory variables in the adjoin area [7,39,43].

The spatial error model (SEM) is expressed as follows:

$$Y = \beta X + \lambda W\varepsilon + \mu \tag{6}$$

Where λ is the spatial error coefficient of the dependent variable vector, and μ stands for the random error vector of normal distribution. The SEM contains interaction effects among the error terms. From Eq. (6), it could be found that, in the SEM, the explained variable Y in the local area is affected by the spatially autocorrelated error term in the adjoin area; the SEM neglects the spatial lag of the explained variable [39].

The SDM can capture the spatial effects of both independent and dependent variables as well as the influence of variable error on observation values, rendering the results more accurate [50]. We therefore analyze the driving factors of TSCDEE by applying SDM.

The basic expression for SDM is:

$$Y = \rho WY + \beta X + \theta WX + \varepsilon \tag{7}$$

In Eq. (7), WX denotes the spatial lag effects associated with explanatory variables. Variables θ and β are vectors of regression coefficient estimates, respectively. I_n stands for an n-order identity matrix.

4. Research area and indicator selection

We include data from 30 mainland Chinese provinces (excluding Tibet), covering the period 2010 to 2016. As shown in Fig. 2, these provinces are divided into eight regions in accordance with Zhao et al. [51] and Zeng et al. [52].

Based on existing research results, such as those of Song et al. [53]; Wang and He [28]; and Feng and Wang [29]; this paper treats capital stock, labor force, and the energy consumption of the transportation sector as three inputs. The value added by transportation sector is a desirable output, while the CO_2 emissions of the transportation sector constitute an undesirable output (Table 1). The data for both the value added and capital stock of the transportation sector were converted to 2010 base period prices. Following the studies of Chang et al. [22] and Wang and He [28]; the transportation sector in this paper is taken to consist of the transportation, storage, and postal services industries.

The Chinese government does not publish data on the capital stock of the transportation sector. Referring to Wang and He [28]; Xie et al. [54]; Feng and Wang [29]; and Stefaniec et al. [55]; this article applies the perpetual inventory method to determine the capital stock of the transportation sector as follows: $C_{i,t} = I_{i,t} + (1\text{-}\delta) C_{i,t\text{-}1}$。 Here C and I indicate the capital stock and the fixed capital investment in the transportation sector. The subscripts i and t represent the province i and year t, respectively. δ indicates the

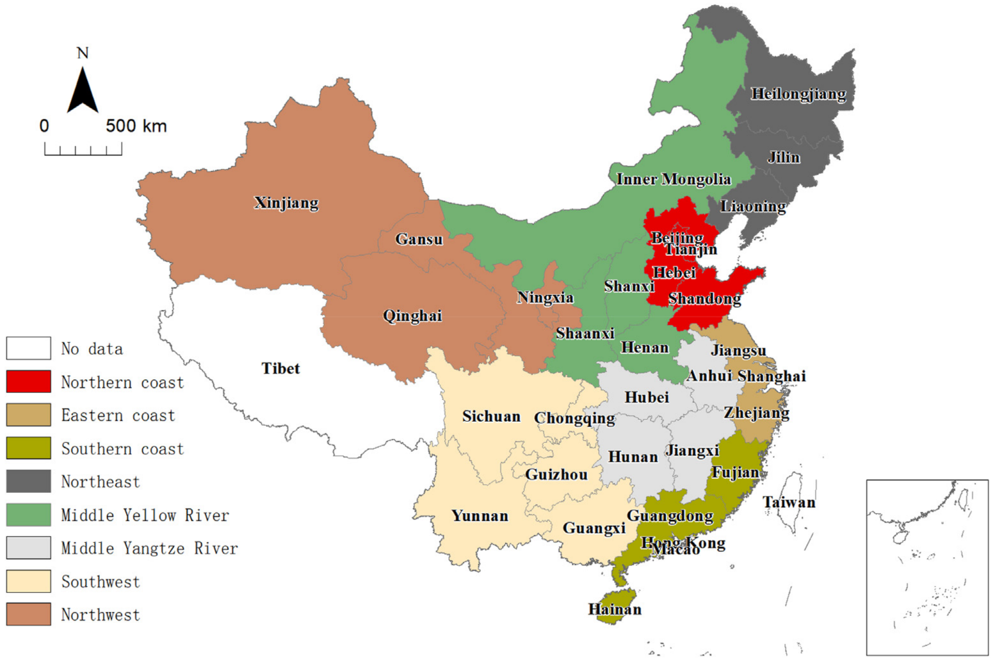

Fig. 2. Sketch map of Chinese eight economic zones.

Table 1
TSCDEE measurement index system.

Primary indices	Secondary-class indices	Third-class indices
Inputs	Capital	Capital stock of transportation sector (Unit: 100 million yuan RMB)
	Labour	Total number of employees in the transportation sector (unit: 10,000)
	Energy	Total energy consumption of the transportation sector (unit: 10,000 tons of standard coal)
Outputs	Desirable outputs	Added value of the transportation sector (unit: 100 million yuan RMB)
	Undesirable outputs	CO_2 emissions from the transportation sector (unit: 10^4 tons)

depreciation rate of capital stock, which is 8.76%, according to Li and Zhang [26]. Consistent with the study conducted by Zhang [56]; the capital stock of the transportation sector in 2010 is equal to the value of the gross fixed capital formation in 2010 divided by 10%. The data for fixed capital investments were taken from the National Bureau of Statistics of China (NBSC) [57].

We use the total number of employees in the transportation sector as the labor force variable, and data were taken from China Statistical Yearbooks (CSY) [58]. The energy consumption data were gathered from all provincial statistical yearbooks [59]. Data on the value added by the transportation sector were obtained from NBSC [57].

NBSC has not released data on the CO_2 emissions from the transportation sector, so these must be calculated. The transportation sector CO_2 emissions in this research consist of both fossil fuel and electrical CO_2 emissions.

With reference to the method in the IPCC Guidelines, the equation for counting CO_2 emissions from transportation fossil fuel consumption can be shown in Eq. (5) [60]:

$$CCi,t = \sum_{j=1}^{n}\left(Ei,t,j \times ALCVj \times CCFj \times COFj \times \frac{44}{12}\right) \tag{8}$$

In Eq. (8), $CC_{i,t}$ stands for the total CO_2 emissions from energy use by the transportation sector of province i in year t, j represents the different fossil fuel types, $E_{i,t,j}$ is the total consumption of fuel type j in province i in year t, $ALCV_j$ identifies the average low calorific value (ALCV) of fuel type j, CCF_j denotes the carbon content factor (CCF) of fuel type j, and COF_j stands for the carbon oxidation factor (COF) of the carbonaceous fuel j. The data on ALCV, CCF and COF were collected from Shan et al. [61] (Table 2). The data on fossil fuel consumption were obtained from CESY [9–62].

This work utilizes the carbon dioxide emission coefficient for electric power energy published by the National Development and Reform Commission (NDRC) [63] for calculating electricity carbon dioxide emissions; the estimation method is written as:

$$ECi,t = Ei,t \times EFgrid,OM,y,i,t \tag{9}$$

Here $EC_{i,t}$ refers to the total electrical CO_2 emissions resulting from the transportation sector of province i in year t. $EFgrid,OM,y,i,t$ denotes the total electric power consumed by the transportation sector in province i in year t, and the data were obtained from CESY [9–62]. $EF_{i,t}$ stands for the baseline emissions factors for regional power grids, which can be collected from NDRC [63] (Table 3).

Using the method described above, we have calculated the transportation sector CO_2 emissions for 30 Chinese provinces between the years 2010 and 2016. The International Energy Agency (IEA) is a monitoring organization that regularly releases data on CO_2 emissions. To check the reliability of our method for calculating CO_2 data from the transportation sector, we compared our results with those of the IEA [64] in Fig. 3. Clearly, the CO_2 data measured in this study for the transportation sector are similar to those of the IEA. From the comparison, we conclude that the method used herein is suitable for the accurate calculation of CO_2 emission levels.

Table 2
Fossil fuels and emissions factors (NCV_i, CC_i) [61].

Fuels in China's energy statistics	Fuels in this study	$ALCV_i$ (PJ/10^4 tonnes, $10^8 m^3$)	CCF_i (tonneC/TJ)	COF_i(%)
Raw coal	Raw coal	0.21	26.32	74
Cleaned coal	Cleaned coal	0.26	26.32	74
Other washed coal	Other washed coal	0.15	26.32	74
Briquettes	Briquettes	26.32	0.18	74
Gangue				74
Coke	Coke	0.28	31.38	89
Coke oven gas	Coke oven gas	1.61	21.49	91
Blast furnace gas	Other gas	0.83	21.49	91
Converter gas				91
Other gas				91
Other coking products	Other coking products	0.28	27.45	96
Crude oil	Crude oil	0.43	20.08	96
Gasoline	Gasoline	0.44	18.9	96
Kerosene	Kerosene	0.44	19.6	96
Diesel oil	Diesel oil	0.43	20.2	96
Fuel oil	Fuel oil	0.43	21.1	96
Naphtha	Other petroleum products	0.51	17.2	96
Lubricants				96
Paraffin				96
White spirit				96
Bitumen asphalt				96
Petroleum coke				96
Other petroleum products				96
Liquefied petroleum gas (LPG)	LPG	0.47	20	97
Refinery gas	Refinery gas	0.43	20.2	97
Nature gas	Nature gas	3.89	15.32	98

Table 3
Baseline emissions factors for regional power grids in China [63].

Provinces (EF_{grid}, OM, $_y$, tCO_2/MWh)	2010	2011	2012	2013	2014	2015	2016
Beijing, Tianjin, Hebei, Shanxi, Shandong, Inner Mongolia	0.9914	0.9803	1.0021	1.0302	1.058	1.0416	1
Liaoning, Jilin, Heilongjiang	1.1109	1.0852	1.0935	1.112	1.1281	1.1291	1.1171
Shanghai, Jiangsu, Zhejiang, Anhui, Fujiang	0.8592	0.8367	0.8244	0.81	0.8095	0.8112	0.8086
Henan, Hubei, Hunan, Jiangxi, Sichuan, Chongqing	1.0871	1.0297	0.9944	0.9779	0.9724	0.9515	0.9229
Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang	0.9947	1.0001	0.9913	0.972	0.9578	0.9457	0.9316
Guangdong, Guangxi, Guizhou, Yunnan	0.9762	0.9489	0.9344	0.9223	0.9183	0.8959	0.8676
Hainan	0.7972	0	0	0	0	0	0

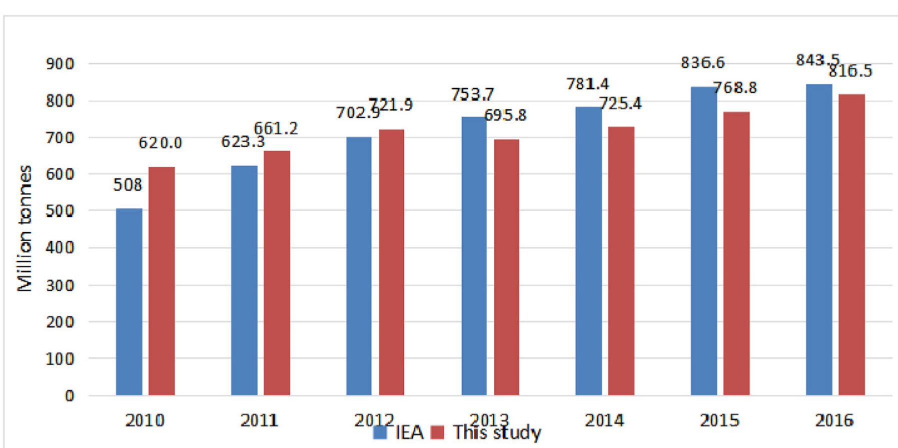

Fig. 3. Comparison of transportation CO_2 emissions in China as computed by IEA and this study.

5. Analysis of the characteristics of TSCDEE in China

Using MaxDEA 7 Ultra software, the TSCDEEs of 30 provinces in China between 2010 and 2016 were calculated as shown in Table 4.

5.1. National TSCDEE characteristics

Based on the mean value of TSCDEE for every province from 2010 to 2016, the spatial distribution map for TSCDEE levels was drawn using ArcGIS 10.3 software. As seen in Fig. 4, the overall national TSCDEE level was relatively low during the research

Table 4
The values of TSCDEE for 30 provinces in China (2010–2016).

Regions	Provinces	2010	2011	2012	2013	2014	2015	2016	Mean
Northern coast	Beijing	0.604	0.592	0.497	0.587	0.632	0.648	0.690	0.607
	Tianjin	0.831	0.787	0.726	0.758	0.784	0.777	0.810	0.782
	Hebei	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Shandong	1.000	0.923	0.877	0.784	0.855	0.882	0.932	0.893
Eastern coast	Shanghai	0.698	0.613	0.572	0.702	0.797	0.831	1.000	0.745
	Jiangsu	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Zhejiang	0.736	0.679	0.645	0.726	0.740	0.742	0.770	0.720
Southern coast	Fujian	0.715	0.619	0.637	0.655	0.651	0.712	0.783	0.682
	Guangdong	0.630	0.604	0.627	0.667	0.729	0.762	0.804	0.689
	Hainan	0.397	0.384	0.378	0.438	0.505	0.465	0.471	0.434
Northeast	Liaoning	0.545	0.551	0.548	0.638	0.650	0.756	0.751	0.634
	Jilin	0.488	0.467	0.463	0.486	0.491	0.497	0.523	0.488
	Heilongjiang	0.508	0.510	0.425	0.457	0.514	0.547	0.612	0.510
Middle Yellow River	Shanxi	0.535	0.510	0.532	0.529	0.551	0.631	0.697	0.569
	Inner Mongolia	0.700	0.659	0.657	0.767	0.765	0.661	0.782	0.713
	Henan	0.703	0.644	0.674	0.879	1.000	1.000	1.000	0.843
	Shaanxi	0.429	0.401	0.407	0.420	0.458	0.489	0.521	0.447
Middle Yangtze River	Jiangxi	0.756	0.632	0.601	0.676	0.671	0.643	0.619	0.657
	Anhui	0.682	0.605	0.702	0.725	0.726	0.728	0.765	0.705
	Hubei	0.519	0.480	0.463	0.544	0.556	0.553	0.530	0.521
	Hunan	0.579	0.525	0.560	0.590	0.604	0.597	0.631	0.584
Southwest	Guangxi	0.437	0.448	0.432	0.477	0.475	0.494	0.508	0.467
	Chongqing	0.493	0.456	0.454	0.538	0.533	0.538	0.564	0.511
	Sichuan	0.337	0.317	0.310	0.404	0.422	0.466	0.478	0.391
	Guizhou	0.725	0.713	0.703	0.721	0.698	0.685	0.715	0.709
	Yunnan	0.190	0.174	0.175	0.171	0.176	0.182	0.195	0.180
Northwest	Gansu	0.682	0.62	0.72	0.749	0.745	0.726	0.76	0.715
	Qinghai	0.757	0.645	0.613	0.691	0.677	0.632	0.612	0.661
	Ningxia	0.519	0.485	0.475	0.562	0.58	0.579	0.561	0.537
	Xinjiang	0.579	0.53	0.576	0.616	0.644	0.643	0.691	0.611
Average efficiency in Chinese provinces		0.613	0.577	0.568	0.613	0.634	0.644	0.673	0.617

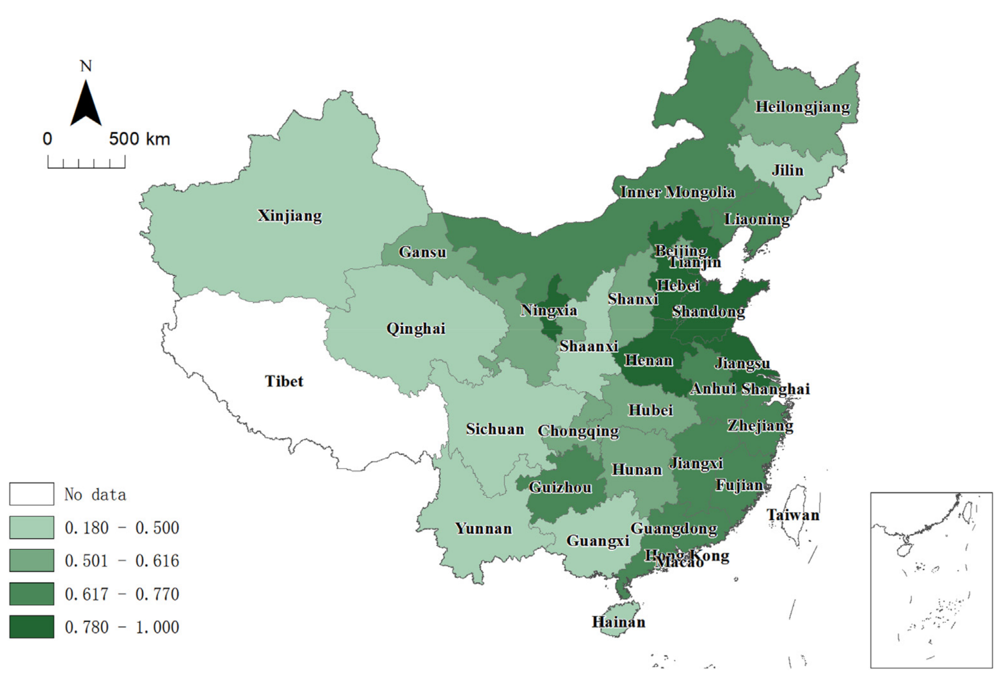

Fig. 4. Average TSCDEE values in 30 Chinese provinces (2010–2016).

period. The mean value of TSCDEE in Chinese provinces was 0.618, which illustrates that TSCDEE in China has substantial room for improvement. Furthermore, there was significant variation among provincial TSCDEEs. The TSCDEEs of the Yellow River downstream area and the southeastern areas were high, while low TSCDEEs were found for most of the western provinces (Table 5, Fig. 5). The trend in the national TSCDEE average consists of two phases. Phase one lasts from 2010 to 2012, when the national TSCDEE average exhibited a general downward trend and fell from 0.613 in 2010 to 0.568 in 2012. In the second phase, lasting from 2012 to 2016, the national TSCDEE average showed a steep upward trend, reaching a value of 0.673 in 2016 and thereby exceeding the initial TSCDEE

Table 5
TSCDEE values for eight Chinese regions (2010–2016).

Regions	2010	2011	2012	2013	2014	2015	2016	Mean
Northern coast	0.859	0.826	0.775	0.782	0.818	0.827	0.858	0.821
Eastern coast	0.811	0.764	0.739	0.809	0.846	0.858	0.923	0.822
Southern coast	0.581	0.536	0.547	0.587	0.629	0.646	0.686	0.602
Northeast	0.514	0.509	0.479	0.527	0.551	0.600	0.629	0.544
Middle Yellow River	0.592	0.554	0.567	0.649	0.694	0.695	0.750	0.643
Middle Yangtze River	0.634	0.561	0.582	0.633	0.639	0.630	0.636	0.616
Southwest	0.436	0.422	0.415	0.462	0.461	0.473	0.492	0.452
Northwest	0.538	0.502	0.495	0.511	0.510	0.512	0.509	0.511

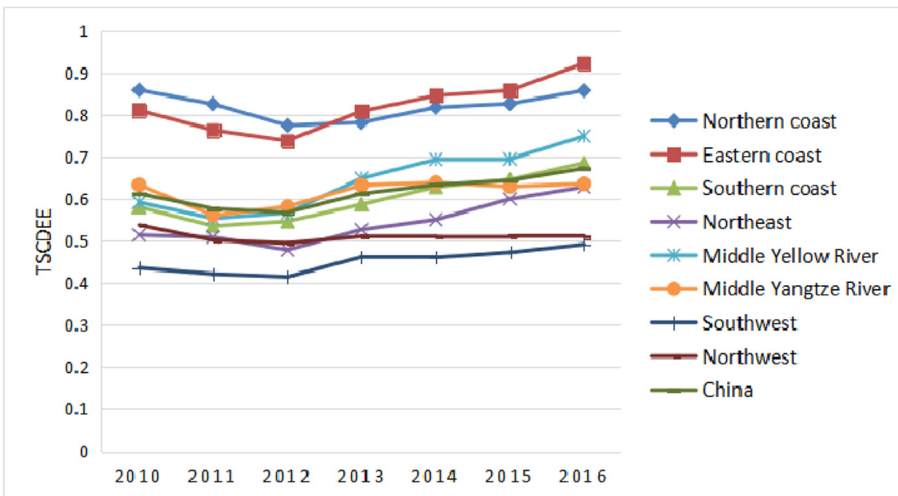

Fig. 5. The evolutionary trend of TSCDEE value in China and eight of its regions (2010–2016).

level.

In order to confront the global economic crisis of 2008, China executed an positive financial policy and permissive monetary policy. This allowed various provinces to increase their investments in transportation infrastructure, resulting in redundancies in capital investment in transportation [65–68]. Therefore, the national TSCDEE exhibited a downward trend from 2010 to 2012. In 2011, the Ministry of Transport of China (MOT) [69] developed many policies intended to curb the release of traffic pollutants. Notably, in 2013, the Communist Party of China (CPC) [70] promoted the building of an ecological civilization, and various provinces in China increased efforts to achieve energy conservation and emissions reductions. Many new energy-saving technologies were popularized and applied in the transportation sector; these were conducive to improving TSCDEE and can explain the upward trend in national TSCDEE after 2012.

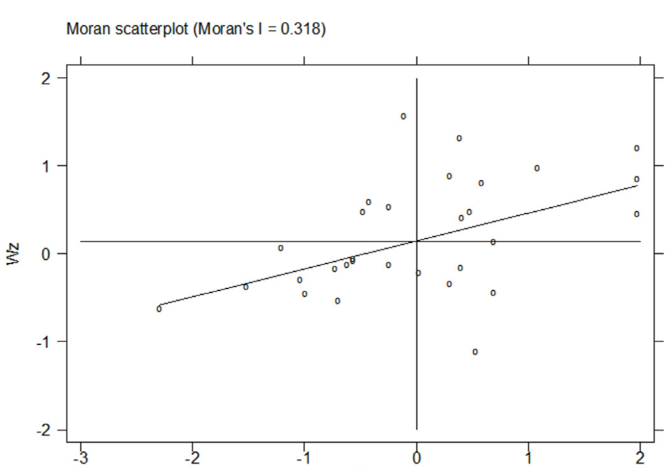

Fig. 6. The Moran's I scatterplot of 30 provincial TSCDEE in 2010.

5.2. Characteristics of TSCDEE in the different regions

A comparison of regions indicates that the Eastern coast has the highest level of TSCDEE, followed by the Northern coast, the Middle Yellow River, the Middle Yangtze River, the Southern coast, the Northeast, the Northwest, and the Southwest (Table 5, Fig. 6). Over time, all eight regions show trends that are consistent with the developmental trend of the national TSCDEE. Three additional factors are evident: (1) The coastal provinces enjoy geographical advantages and high levels of economic development. Their transportation industries are relatively highly developed, their education systems are advanced, they have large populations of professional and technical personnel, and they successfully implement and promote advanced foreign technologies and business ideas. These provinces have been at the forefront in implementing a number of energy-saving and emissions reduction measures, including many electrified modification projects for logistics parks, docks, and integrated transportation hubs. As a result, they may utilize transportation energy more efficiently and realize higher carbon dioxide emissions efficiencies than do other regions [29]. However, the TSCDEE level in Hainan Province, a coastal province, is relatively low. Although its geographical position is advantageous and it has been open since the 1990s, the output level of its transportation sector is low, resulting in low TSCDEE. (2) The Middle Yellow River and Middle Yangtze River regions closely follow the coastal areas and have been opened up to the outside world. The educational systems in these regions are also relatively developed, energy-saving technologies are fully applied, internal infrastructure is continuously improved, and traffic carbon dioxide emissions levels closely follow those of the coastal provinces. (3) As a result of geographical factors, leaders in the Northeast, Northwest and Southwest regions are less able to acquire and introduce advanced technologies. After the reform and opening, a large number of talented workers moved from the Northeast, Northwest, and Southwest to the coastal areas [71]. The resulting loss of talent has made it difficult to improve production technologies in various industries, and especially in transportation, where emission efficiency levels remain low.

5.3. Characteristics of TSCDEE in the different provinces

Using TSCDEE values, 30 Chinese provinces can be divided into four spatial regions exhibiting high TSCDEE, slightly high TSCDEE, medium TSCDEE, and low TSCDEE. Four additional observations follow: (1) For Hebei, Jiangsu, Shandong, Henan, Ningxia, and Tianjin, TSCDEEs were greater than 0.78. It is important to note that Ningxia is a western province. The reasons for its high TSCDEE level are that Ningxia has a relatively small geographical area, fewer transportation input resources, and higher output efficiency, as compared to other western provinces. (2) The annual mean value of the TSCDEEs of Shanghai, Zhejiang, Inner Mongolia, Guizhou, Jiangxi, Guangdong, Fujian, Anhui, and Liaoning ranged from 0.634 to 0.745 and fall in the category of slightly high TSCDEE. (3) The average annual TSCDEEs of Beijing, Hunan, Shanxi, Hubei, Gansu, Chongqing, and Heilongjiang ranged from 0.51 to 0.617, thereby placing them in the medium TSCDEE category. (4) The average annual TSCDEEs of Jilin, Guangxi, Xinjiang, Shaanxi, Hainan, Sichuan, Qinghai, and Yunnan are all below 0.5, and these provinces thus belong to the low TSCDEE region.

Analysis of trends shows that Hebei and Jiangsu remained at the production frontier level throughout the research period. However, the TSCDEEs of the remaining provinces exhibited different trends: (1) Shanxi, Liaoning, Guangdong, Guangxi, and Xinjiang show overall improvement in TSCDEE, indicating that their transportation sectors have made obvious improvements in energy conservation and emissions reductions. (2) Gansu and Qinghai show declining trends, meaning that these two provinces had unfavorable allocations of transport resources. (3) Inner Mongolia, Anhui, Guizhou, and Ningxia displayed significantly different fluctuation trends during the research period. (4) The remaining provinces are generally in line with the overall trend of the country, showing initial downward and subsequent rising trends.

6. The spatial autocorrelation of TSCDEE in China

6.1. The global spatial autocorrelation analysis

This work used Global Moran's I to examine the global spatial autocorrelation of provincial TSCDEEs further. Table 6 contains the results.

Table 6
Value of Moran's I of provincial TSCDEE in China (2010–2016).

Year	Moran's I	Z-score	P-value
2010	0.400	3.530	0.000
2011	0.352	3.170	0.002
2012	0.287	2.641	0.008
2013	0.319	2.883	0.004
2014	0.371	3.315	0.001
2015	0.385	3.436	0.001
2016	0.386	3.423	0.001

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

As shown in Table 6, there are significantly positive spatial autocorrelation of TSCDEEs among China's regions during the period 2010 to 2016, which indicates that provinces that are close to each other tend to exhibit similar TSCDEEs. More concretely, Global Moran's I showed changing dynamics from 2010 to 2016, with a downward trend from 2010 to 2012 indicating a weakened spatial autocorrelation. Global Moran's I displayed an upward trend after 2012, which indicates that the effect of spatial agglomeration gradually strengthened. Taken together, there were some potential biases in the regression analysis of the factors influencing TSCDEE when spatial effects were not considered.

6.2. The local spatial autocorrelation analysis

The Moran scatter plots (MSP) and Local Indicators of Spatial Association (LISA) were applied to explore the local spatial correlations of the local spatial autocorrelation of provincial TSCDEE in China. Figs. 6–8 report the MSP of TSCDEE in China in 2010, 2013 and 2016; most provinces are in the frist quadrant (H–H agglomeration area) and third quadrant (L-L agglomeration area), and only some provinces are located in the second quadrant (L-H agglomeration area) and the four quadrants (H-L agglomeration area), indicating that the spatial homogeneity is more significant than the spatial heterogeneity for TSCDEE in China.

The MSP maps in 2010, 2013, and 2016 indicate that Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Shandong, and Henan always belong to the first quadrant, meaning that these provinces have high TSCDEE and have diffusion effect on the surrounding areas. The above provinces are mainly located in Northern coast and Eastern coast of China. Heilongjiang, Hubei, Hunan, Guangxi, Chongqing, Sichuan, Yunnan, Shaanxi, and Ningxia are always the third quadrant in 2010, 2013 and 2016, meaning that these provinces have low TSCDEE and are surrounded by provinces with relatively low TSCDEE; these provinces are mainly western provinces; these provinces display a positive spatial autocorrelation. Beijing always distributed in the second quadrant in 2010, 2013 and 2016, representing that Beijing are always surrounded by province with higher TSCDEE level. The frequent occurrence of serious traffic congestions has become a major problem confronted by Beijing for a long time, which adds the difficulties to the low-carbon and energy-saving management of its transportation industry [72]. In 2010, 2013 and 2016, the fourth quadrant includes

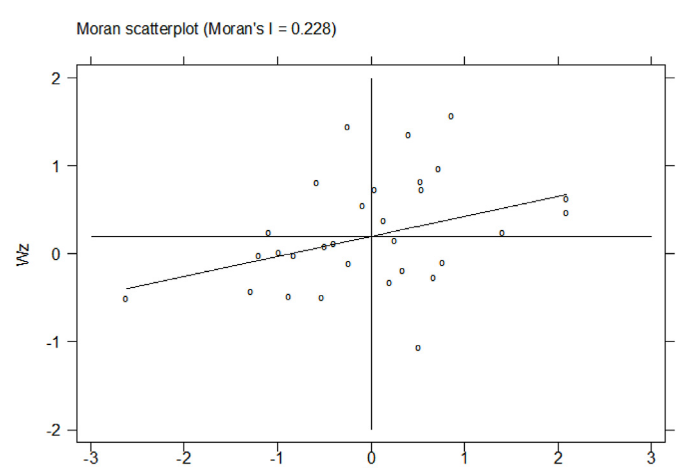

Fig. 7. The Moran's I scatterplot of 30 provincial TSCDEE in 2013.

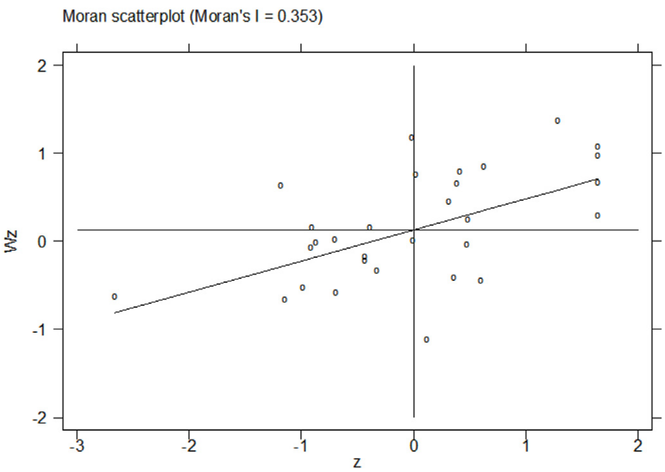

Fig. 8. The Moran's I scatterplot of 30 provincial TSCDEE in 2016.

Inner Mongolia, Gansu, Guangdong, and Guizhou that have high TSCDEE but are surrounded by provinces with low TSCDEE. It is remarkable that Inner Mongolia, Gansu, and Guizhou are belong to the western province. Based on the statistical data yearly, Inner Mongolia, and Guizhou have the high level of the transportation sector added value, which are at the forefront in Western China; compared with surrounding provinces, such as Inner Mongolia, Xinjiang or Shaanxi, Gansu has lower level of transportation production consumption factors and CO_2 emissions of transportation in Western China [57].

Figs. 9–11 depicted provinces with significant locations color-coded by different types of LISA coefficients of TSCDEE in China. As from the Figs, in 2010, 2013, and 2016, the provinces at the 5% significance level are in the H–H or L-L agglomeration areas. More specifically, In 2010, the H–H agglomeration area are composed by four obvious provinces: Tianjin, Hebei, Jiangsu, and Shandong, which passed the significant level test within 5%; Whereas the L-L agglomeration area exhibit an obvious small cluster area, which only includes two obvious provinces: Sichuan and Yunnan. By 2013, the H–H agglomeration area has decreased by three obvious provinces (Hebei, Jiangsu, and Shandong). By 2016, the H–H agglomeration area has increased compared with 2013, which are composed by four obvious provinces: Hebei, Shanghai, Jiangsu, and Shandong. The L-L agglomeration area remain unchanged across 2010, 2013 and 2016.

7. Factors influencing TSCDEE

7.1. Determinants of TSCDEE

After the systematic analysis of the regional TSCDEE features, we used the SDM method to explore the factors affecting TSCDEE. Based on previous studies, we selected transportation structure (TS), traffic infrastructure level (TIL), technological progress (TP), urbanization level (UL), and population density of urban area (PDUA) as independent variables (Table 7). The data were collected from CSY [58] and all provincial statistical yearbooks [59].

7.1.1. Transportation structure (TS)

The pollutant emissions per unit of highway freight were 7 times and 13 times greater than those of railway and waterway transportation, respectively (Ministry of Ecology and Environment of China [85] Waterway transportation is characterized as economical, secure, low polluting, and with low mass traffic, so it has become a significant alternative for the transport of dangerous goods. The idiographic measure of the optimization and adjustment of transportation structures is meant to establish a long-distance transportation system based on electrified trains and environmentally-friendly ships, as well as a short-distance transportation system based on low emission vehicles and alternative energy vehicles [85]. Moreover, Yuan et al. [34]; Wei et al. [73]; and Wang et al. [74] have suggested that a more reasonable transportation structure would prove beneficial in reducing carbon dioxide emissions from the transportation sector. Therefore, we apply

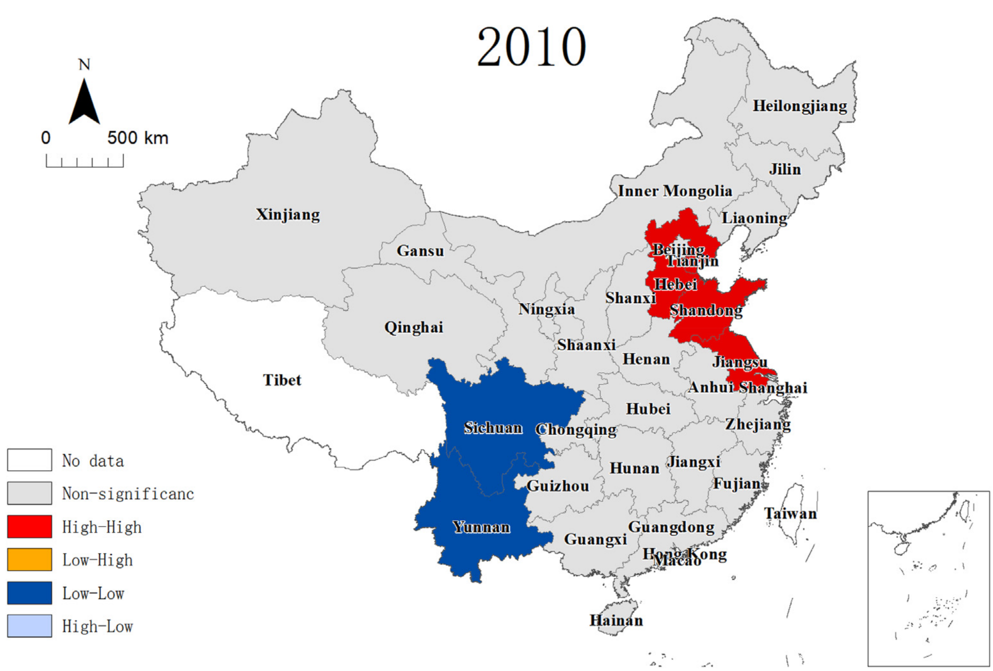

Fig. 9. LISA Diagrams of provincial TSCDEE in 2010.

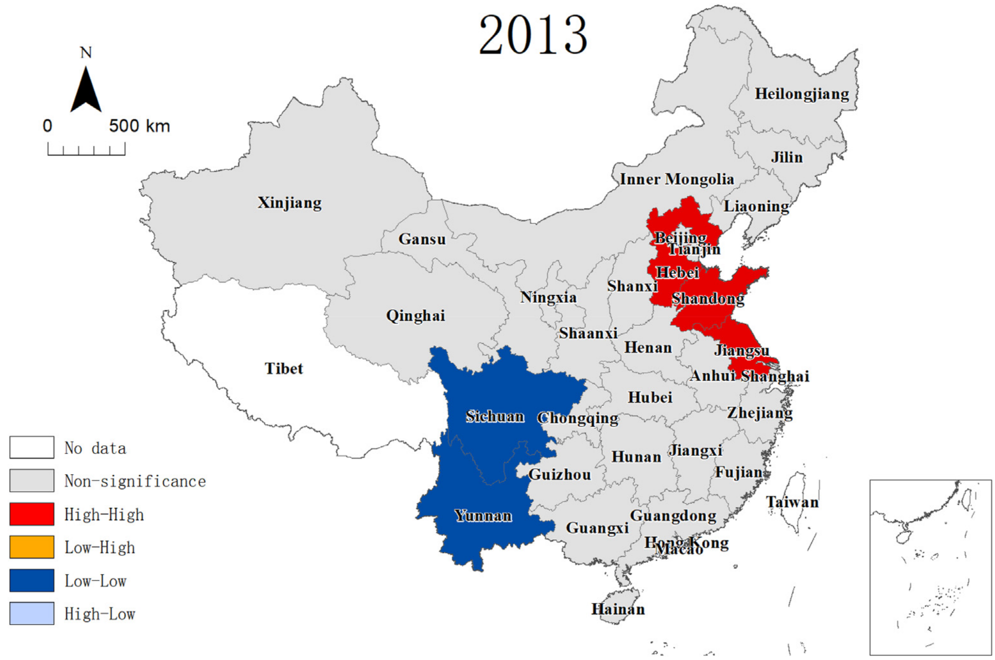

Fig. 10. LISA Diagrams of provincial TSCDEE in 2013.

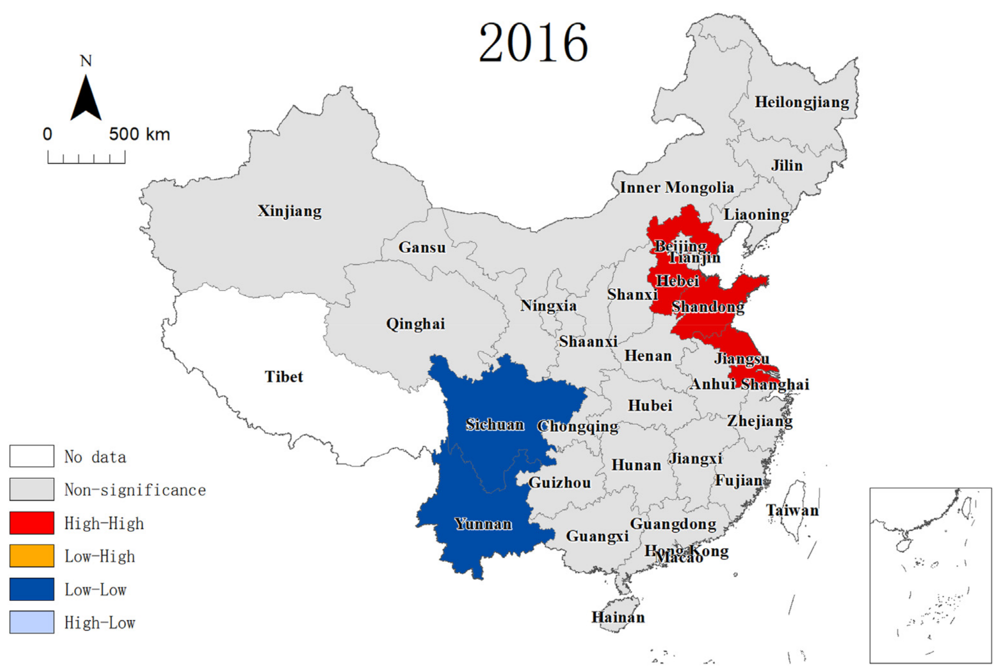

Fig. 11. LISA Diagrams of provincial TSCDEE in 2016.

the proportion of railway and water freight volume in the total freight volume to represent the transportation structure. Our prediction is that readjusting and optimizing the transportation structure would improve TSCDEE.

7.1.2. Traffic infrastructure level (TIL)

An excellent traffic infrastructure system can curb both energy consumption and the discharge of pollutants, but transportation planners should consider the level of per capita traffic infrastructure. Low per capita traffic infrastructure may lead to challenges in increasing transport loads. Traffic congestion has often been considered to be the major contributor to road traffic pollutant levels [86]. Therefore, an excellent transportation system requires adequate traffic infrastructure. Referring to Ma et al. [76]; Liu et al. [77]; Zhang [87]; and others, per capita road area was applied to measure the level of traffic infrastructure in this work. We offer the prediction that improvements in traffic infrastructure level would improve TSCDEE.

7.1.3. Technological progress (TP)

Technological progress in energy utilization is a key driver for reducing carbon dioxide emissions [88–91], and this has already

Table 7
Influencing factors.

Explanatory variables	Definitions of variables	Key references	Predicted effect
Transportation structure (TS)	Proportion of the total of railway and water freight volume to total freight volume (%)	Wei et al. [73]; Yuan et al. [34]; Wang et al. [74]	Positive
Traffic infrastructure level (TIL)	Per capita road area (km^2)	Zhang [75]; Ma et al. [76]; Liu et al. [77];	Positive
Technological progress (TP)	Ratio of GDP to energy consumption by the transportation industry (tons of standard coal/10^4 Yuan RMB)	Scholl et al. [78]; Wei et al. [73]; Yuan et al. [34]	Positive
Urbanization level (UL)	Proportion of city population in total population (%)	Wu et al. [79]; Xie et al. [80]; Lv et al. [81]	Unknown
Population density of urban area (PDUA)	Ratio of the total of urban population and urban transit to urban area (person/km^2)	Alford and Whiteman [82]; Modarres [83]; Hong [84]	Unknown

been widely considered and accepted. Generally, lower energy intensity signifies lower environmental costs and better technology for converting energy into economic outputs. In reference to the findings of Scholl et al. [78]; Wei et al. [73]; and Yuan et al. [34]; we have herein applied the reciprocal of transportation sector energy intensity as an indicator of technological progress (TP) and predict that improvements in technological progress would improve TSCDEE.

7.1.4. Urbanization level (UL)

Urbanization is thought to be correlated with the CO_2 emissions of the transportation sector. Wu et al. [79]; Xie et al. [80]; and Lv et al. [81] have conducted in-depth studies on urbanization and the CO_2 emissions of the transportation sector. Ongoing urbanization brings large-scale construction of urban residential housing and infrastructure and a notable increase in traffic demand. Conversely, the high traffic volume resulting from urbanization causes more energy consumption and release of gaseous pollutants. The relationship between urbanization level and TSCDEE, therefore, requires further empirical testing.

7.1.5. Population density of urban area (PDUA)

Because of the increasing returns resulting from scale or agglomeration effects, larger population can foster higher urban productive efficiency, which can bring higher profits that exceed the environmental external costs of the added transport. Alford and Whiteman [82] and Modarres [83] found that transport commuting in regions with higher population density can consume relatively less transport energy and release less CO_2. However, the additional emission reduction effects resulting from high population density were not significant after the population density reached a certain level [84]. Exorbitant population density may have a negative impact on traffic circulation, directly or indirectly, resulting in additional emissions of traffic pollutants. Therefore, the impact of population density on TSCDEE must be examined further.

7.2. Explaining TSCDEE: spatial Durbin regression results

To avoid the appearance of spurious regression and confirm the validity of the regression coefficient estimate, the LLC, IPS, ADF-Fisher and PP-Fisher methods are applied to perform a stationary analysis of all variable quantities. The results are shown in Table 8. The variables all pass the significance test at the second difference, which means that it is necessary to perform the cointegration test on all variable quantities.

The Kao and Pedroni cointegration tests were applied to determine whether all variables are cointegrated. The test outcome of the Kao method (t-Statistic: 1.941, P = 0.026) shows that the null hypothesis is rejected at the 5% significance level. The test outcome of the Pedroni method (Table 9) indicates that four of the seven

Table 8
Unit root test.

	LLC	IPS	PP - Fisher
lnTSCDEE	−5.760***	1.592	60.039
lnTS	−3.986***	0.844	67.354
lnTIL	0.756	3.121	25.419
lnTP	−28.910***	−2.290***	64.131
lnUL	−8.585***	−0.486	189.579***
lnPDUA	−3.986***	1.344	81.149**
△*lnTSCDEE*	−14.411***	−3.691***	157.892***
△*lnTS*	−0.6701	1.290	54.092
△*lnTIL*	0.094	1.320	51.490
△*lnTP*	−19.958***	−5.730***	193.394***
△*lnUL*	−9.890***	−2.217**	136.478***
△*lnPDUA*	−20.726***	−4.227***	137.397***
△△*lnTSCDEE*	−29.158***	−7.558****	134.718****
△△*lnTS*	−18.658***	−6.998***	136.933****
△△*lnTIL*	−14.087***	−2.525***	80.332**
△△*lnTP*	−18.781***	−6.775***	140.771***
△△*lnUL*	−20.451***	−5.162***	114.792***
△△*lnPDUA*	−29.337***	−7.361***	139.967***

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

statistics are significant at the 1% level. We are thus able to conclude that the panel data had cointegration relationships.

To decide which model is more appropriate for empirical investigation of the main determinants of TSCDEE, we carried out statistical tests. The Hausman test was applied to decide whether to use fixed or random effects models. The results (chi^2 (5) = 69.61, P = 0.000) demonstrated that the fixed effects model was preferred to the random effects model.

The next step was to conduct the Wald and Likelihood ratio (LR) tests to establish whether SDM can be simplified to SLM or SEM. The hypothesis that SDM can be degenerated into the SLM is rejected (Wald test: 30.26***, LR test: 57.57***). Moreover, the hypothesis that SDM can be simplified to the SEM is also rejected (Wald test: 46.17***, LR test: 58.01***). These results show that SDM is preferable to both SLM and SEM.

Based on Eq. (7), the explicit regression equation of the SDM with fixed effects is as follows:

$$\mathrm{TSCDEE}_{i,t} = \rho W^*\mathrm{TSCDEE}_{i,t} + \beta_1\mathrm{TS}_{i,t} + \beta_2\mathrm{TIL}_{i,t} + \beta_3\mathrm{TP}_{i,t} + \beta_4\mathrm{UL}_{i,t} + \beta_5\mathrm{PDUA}_{i,t} + \theta_1 W^*\mathrm{TS}_{i,t} + \theta_2 W^*\mathrm{TIL}_{i,t} + \theta_3 W^*\mathrm{TP}_{i,t} + \theta_4 W^*\mathrm{UL}_{i,t} + \theta_5 W^*PDUA_{i,t} + \varepsilon_{i,t}\ \varepsilon_{i,t} \sim N(0,\sigma^2_{i,t} I_n) \quad (10)$$

Table 10 displays the calculation results for the three SDM models: spatial fixed-effects, time fixed-effects, and spatial and time fixed-effects models, respectively. We performed the LR test to choose the most applicable model among them. The null hypothesis that the spatial fixed effects nested in spatial and time fixed-

Table 9
Cointegration test.

Alternative hypothesis: common AR coefs. (within-dimension) Statistic Weighted statistic		
Panel v-statistic	−570.643	−5.705
Panel rho-statistic	6.299	6.295
Panel PP-statistic	−6.958***	−15.552***
Panel ADF-statistic	−3.309***	−3.976***
Alternative hypothesis: individual AR coefs. (between-dimension) Statistic		
Group rho-statistic	8.706	
Group PP-statistic	−20.681***	
Group ADF-statistic	−3.709***	

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

effects is rejected at the 1% significance level (LR test: 40.23, P = 0.000). The null hypothesis that the time fixed effects nested in spatial and time fixed-effects is rejected at the 1% level of significance (LR test: 319.44, P = 0.000). Thus, spatial and time fixed-effects are acceptable. According to that results, we explain the deciding factors of TSCDEE.

The coefficient for transportation structure is notably positive, which illustrates that a higher proportion of rail and water traffic freight volume will lead to a higher TSCDEE, as expected. The amount of road freight transportation accounted for more than 74% of the total freight volume in China for every year of the study period. By contrast, both the railway and water traffic assumed a lower share of freight transportation during the same time period [58]. Therefore, it is very important to adjust the transportation structure policy by converting the long-distance transport model for bulk cargo from highway transport to railway and water transport [92].

The regression coefficient of the traffic infrastructure level is significantly positive, meaning that the increase in traffic infrastructure level can indirectly promote TSCDEE to some extent. The positive correlation does not indicate that the government should blindly increase investments in transportation infrastructure. Generally speaking, the traffic infrastructure levels in the western regions, especially in small and medium-sized cities, are comparatively lower. Therefore, the Chinese government should coordinate regional infrastructure construction.

Technological progress had a remarkably positive correlation with TSCDEE. From 2010 to 2016, transportation sector energy intensity gradually decreased from 1.48 TCE/10^4 yuan RMB to 1.2 TCE/10^4 yuan RMB [57], as the Chinese government enacted a range of energy-saving policies and technologies that have been widely implemented.

Urbanization level would significantly hinder the realization of local TSCDEE. Although urbanization can bring a notable increase in traffic demand, the irrationality of the regional transportation and energy consumption structures still appear in the utilization of the transportation production factors, which do not generate positive agglomeration effects.

Population density of urban area had a significant negative influence on TSCDEE. In the current period, the constant expansion of the population and urban land area is a common trend in China. The population density of urban area in China increased from 2209 person/km^2 in 2010–2408 person/km^2 in 2016 [57]. The regions in which the population density of urban area is developing rapidly should be given more attention. For example, both Guizhou and Qinghai have experienced rapid increases in population density of urban area from 2010 to 2016, and their TSCDEEs decreased rapidly.

8. Conclusions and policy implications

The accelerated transition to an energy system with low carbon emissions is demanded by society and the times [93], and China's TSCDEE data have grown at their fastest rates since 2012. In a political sense, it is possible to explain this acceleration in terms of a combination of the CPC's ecological civilization model and the MOT's green transport policies [75]. However, what does seem fairly clear is that the overall level of TSCDEE in China was low and total transport CO_2 emissions grew at the fastest rates seen for years. In the early developmental periods, factors including backward technology, insufficient environmental protection conscientiousness, and ‘extensive way’ of development had adverse impacts on the energy-saving and emission reduction efforts in the transportation sector. Although China has issued a series of policies to improve this situation, the effects of these policies have not emerged for a period of time due to intensive capitals and long circles nature of transportation industries [72,94]. To achieve the goals of the Paris Climate Accords, the Chinese government needed to focus on more effective and sustainable transportation development policies [28,31,95]. As shown by the SDM regression data, transportation structure, traffic infrastructure level, and technological progress all had significant positive effects on TSCDEE, while both urbanization level and population density of urban area had significantly negative effects on TSCDEE. It is noteworthy that the regression coefficient of technological progress is larger than that of the other two positive independent variables, which is consistent with the report of Cui and Li [6]. This shows that technological progress is a critical factor in achieving low-carbon transportation.

Urgent action by national governments is essential for realizing the mitigation commitments made in their respective Nationally Determined Contributions [96]. Based on the SDM regression results, this study suggests the need for a series of actions: (1) The

Table 10
Spatial Durbin model regression results.

	Spatial fixed-effects	Time fixed-effects	Spatial and time fixed-effects
TS	0.129***	0.038*	0.112***
TIL	0.038	0.041	0.040*
TP	0.509***	0.672***	0.452***
UL	−1.216***	0.097	−0.883***
PDUA	−0.207***	−0.013	−0.146 ***
*W*TS*	0.008	0.200***	−0.024
*W*TIL*	0.054	0.517***	0.031
*W*TP*	−0.081	0.250**	−0.132
*W*UL*	1.487***	0.068	1.435***
*W*PDUA*	0.337***	−0.078	0.393***
R-squared	0.643	0.443	0.632
Log-likelihood	289.945	94.093	320.174

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

government should rationally plan for local investment in transportation industries, and perfect an effective traffic infrastructure system, and improve the system of energy-saving emissions reductions in transportation industries. (2) Regional development disparity needs to be considered in formulating the targets and policies of emission reduction [97]. Every province should formulate a suitable transportation policy for emissions reduction based on its local economic development and technology levels. Coastal areas should assume more responsibility for energy conservation and emission reductions in their transportation industries and impose stricter restrictions on sewage discharge standards. China's inland areas must ensure that transportation sector growth and ecological protection in transportation can be achieved simultaneously. (3) Regional technical cooperation should be strengthened. A long-term communication mechanism is suggested to be established to connect regions. The coastal provinces are encouraged to intensify the technical support to the interior provinces, in order to balance regional development. (4) The government should accelerate the adjustment of the transportation structure by converting the bulk cargo transport mode from road transport to railway transport or water transport. (5) Currently, China is at a critical period of urbanization and industrialization [98]. The new urbanization process need to be coordinated with traffic infrastructure construction to avoid repeated construction or traffic undersupply. (6) Financial subsidies helps to gradually lower down the public transportation fare, thereby playing an important role in nudging urban residents to choose greener transportation mode, such as bus, rail and cycling [99,100]. The provinces with rapid urban population growth should actively adopt finance subsidy policies to promote the use of both urban public transportation means and new energy vehicles.

Several limitations in this paper point to a need for further study and future improvement. First, the study has used the province as the basic spatial unit. Future research could expand the research perspective from the province to the region and country, which could provide a more meaningful reference for global transportation sustainability. Second, subsequent research could focus more on specific traffic departments, by examining, for example, the carbon dioxide emissions efficiencies for railway, highway, waterway, and airline transport. Finally, we propose that the national statistics offices collect other transportation pollution data, such as those on the emissions of nitric oxides and carbon monoxide, to support a comprehensive study of the sustainable development of Chinese transportation.

Author contributions

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Declaration of competing interest

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

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