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TRANSPORT CARBON EMISSIONS REDUCTION EFFICIENCY AND ECONOMIC GROWTH: A PERSPECTIVE FROM NIGHTTIME LIGHTS REMOTE SENSING

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Abstract:

The carbon emissions are essential for climate change and 26% of the world's carbon emissions are related to transport. But focusing only on fewer carbon emissions might be biased at times. In order to keep a balance between economic growth and carbon emissions reduction, this paper evaluated the performance of carbon control by considering the input factors and output factors together, which is more comprehensive and reliable. Firstly, this paper has calculated the transport carbon emissions reduction efficiency (TCERE) based on the model of super SBM with undesirable outputs. The input factors include capital stock, labor force and fossil energy consumption. And the output factors include gross domestic product and carbon dioxide emissions. Then the influencing factors of TCERE were analyzed using econometric models. The economic growth, transport structure, technology level and population density were posited as influencing factors. This paper creatively proposed the per capita nighttime lights brightness as a new indicator for economic growth. An empirical study was conducted in East China from 2013 to 2017, and this study has found that the relationship between TCERE and economic growth shows an U-shape. Besides, transport structure and technology level both show a positive impact on TCERE. The implications of our findings are that: (a) The TCERE declines slower in East China, giving us reason to believe that the improvement of TCERE is predictable; (b) When economic growth exceeds the turning point, economic growth is conducive to the improvement of TCERE. We could develop the economy boldly and confidently; (c) Increased investment in railway and waterway transportation infrastructure projects is needed to strengthen the structure of the railway and waterway transportation systems. Furthermore, the general public and businesses should be encouraged to prefer rail or river transportation; (d) Investment in scientific and technological innovation should be enhanced in order to produce more efficient energy-use methods.

Keywords: *transport carbon emissions, data envelopment analysis, nighttime lights*

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1. Introduction

It is acknowledged that climate change is a global issue and carbon emissions play a significant role in it (Zhang et al., 2018). The Chinese government has enacted laws and implemented programs to develop a low-carbon economy and reduce carbon emissions in order to implement the Paris Agreement on Climate Change and the United Nations 2030 Agenda for Sustainable Development. 26% of the world's carbon emissions are related to transport (Cui et al., 2015). Reducing transport-related carbon emissions is crucial for low-carbon economy, and many nations have put limitations on transport-related carbon emissions, including Canada and Brazil (Cui et al., 2015). Some researchers also have studied the variation of transport carbon emissions (Blesl et al., 2007; Xu et al., 2014). But focusing only on fewer carbon emissions might be biased at times. In order to keep a balance between economic growth and carbon emissions reduction, we need to evaluate the performance of carbon control by considering the input factors and output factors together, which is more comprehensive and reliable. The input factors include capital stock, labor force and fossil energy consumption (Zhao et al., 2022). And the output factors include gross domestic product (GDP) and carbon dioxide (CO_2) emissions (Zhao et al., 2020; Zhao et al., 2022). Efficiency is an indicator that assesses a decision-making unit's (DMU's) ability to maximize outputs given a certain set of inputs, which is commonly applied in assessing the relationship between inputs and outputs (Zhao et al., 2022). Thus, this paper uses the transport carbon emissions reduction efficiency (TCERE) to evaluate the performance of transport carbon control.

With the purpose of better analyzing the impact of influencing factors (especially economic growth) on TCERE in East China, this paper intend to conduct an research using nighttime lights data and super slacks-based measure (SBM) model with undesirable outputs. First, a series of raw data in East China will be obtained through yearbooks, remote sensing images, etc. Next, the input and output variables for determining efficiency will be calculated using raw data. Then, the TCERE will be calculated using a super SBM with undesirable outputs model. Besides, the per capita brightness of nighttime lights, as well as other influencing factors, will be calculated using raw data. Lastly, we will establish an econometric model and intend to examine how influencing factors affect the TCERE. The main contributions and novelty of our work are that:

– We adopt an improved DEA model named the super SBM with undesirable outputs model to calculate TECRE, which is more reasonable.
– When analyzing the influencing factors of TCERE, we creatively use a new indicator derived from remote sensing images to represent economic growth.

The remaining parts are structured as follows. Section 2 is the literature review. Section 3 describes the processing methods. Section 4 describes the data. Section 6 presents the results and discusses the findings. Lastly, the conclusions are presented.

2. Literature review

In general, methods to evaluate efficiency can be divided into parametric and non-parametric models (Fan et al., 2017). Unlike parametric models, non-parametric models do not require to specify function forms (Cullinane et al., 2006; Zhao et al., 2022). Thus, non-parametric models can avoid causing model specification errors (Fan et al., 2017). Among various non-parametric models, the data envelopment analysis (DEA) is a common one. DEA employs a linear programming approach to determine the efficiency of each DMU, which has been extensively applied in various fields (Zhao et al., 2020). Tsolas (2022) applied DEA to assess regional entrepreneurship in Greece and demonstrated the viability. Wang et al. (2016) analyzed the green economic efficiency of Chinese cities using the traditional DEA model named BCC. Lan et al. (2014) assessed the efficiency of transport carbon emissions in 30 Chinese provinces from 2006 to 2010 using the traditional DEA model named CCR. However, the DEA models in the preceding research belong to radial DEA models. The radial DEA models have the disadvantage of not accounting for slacks, which might result in a biased evaluation (Zhao et al., 2022). Therefore, Chu et al. (2018) adopted the slacks-based measure (SBM) model, which is a type of non-radial DEA model and can handle slacks directly (Wang et al., 2019), to analyze the transport system environmental efficiency. The ordinary SBM model does not distinguish the outputs, whereas the outputs can be classified as desirable and undesirable (e.g., pollution) (Wang et al., 2019).

Neglecting undesirable outputs might lead to inaccurate analysis (Wang et al., 2012). Thus, Tian et al. (2022) used the SBM model with undesirable outputs to assess the urban green development efficiency of 277 Chinese cities. Park et al. (2018) adopted the SBM model with an undesirable output (CO_2) to analyze the environmental efficiency of US transport sector. However, the maximum value of a standard SBM model is 1.0, whereas many DMUs might reach the upper bound and cannot make a valid comparison (An et al., 2022). Therefore, we adopt an improved DEA model, i.e., the super SBM with undesirable outputs model. In this model, the efficiency value can exceed 1 so that the subsequent analysis is more effective (Zhang et al., 2022).
Many researchers have studied the influencing factors of TCERE (Cui et al., 2015). Understanding the influencing factors is important, because the government can use this information to formulate appropriate policies, balancing the economic development against TCERE. TCERE is an important indicator of environmental quality. According to the environmental Kuznets curve (EKC) hypothesis the economic growth is associated with environmental quality (Churchill et al., 2018). Thus, our paper mainly aims to examine the relationship between economic growth and TCERE. When testing the EKC hypothesis, many studies use per capita GDP to characterize the economics growth (Yan et al., 2020). However, it is unavoidable that certain mistakes may occur during the collection and compilation of GDP statistics (Xu et al., 2015; Wang et al., 2020). Additionally, the GDP data might be overstated because of the strive for economic growth success (Qin et al., 2019). Therefore, more and more researchers are using nighttime lights data to replace GDP when studying the economy. Chen et al. (2021) studied the relationship between light intensity and per capita income and found it is feasible to estimate living standards using nighttime lights. Gu et al. (2022) used DMSP/OLS and NPP/VIIRS nighttime lights data to predict economic development. Thus, we also use per capita nighttime lights brightness instead of GDP to characterize economic growth. The benefits of this approach are many. First, nighttime lights offer a consistent and long-lasting data source (Tan et al., 2018). Moreover, nighttime lights objectively capture economic activity and can represent information that typical GDP statistics cannot express (Qin et al., 2019). In this paper, the TCERE will be calculated using a super SBM model with undesirable outputs. Besides, the per capita brightness of nighttime lights, as well as other influencing factors, will be used to examine the impact on TCERE.

3. Methods

3.1. Input and Output Variables

In order to calculate TCERE, this article posits capital, labor force and energy as the inputs, gross domestic product (GDP) as the desirable output and carbon dioxide (CO_2) emissions as the undesirable output, in accordance with previous studies (Zhao et al., 2020; Zhao et al., 2022). Definitions of these variables are summarized in Table 1.
The detailed meanings of these variables are explained as follows.
(1) Capital
The indicator we chose to characterize capital is the capital stock of transport sector. Capital stock is measured in 10^8 CNY, which is calculated using the following formula:

$$C_t = C_{t-1}(1 - \delta_t) + I_t \tag{1}$$

where C_t denotes the capital stock of transport sector in year t, δ_t denotes the depreciation rate which is set to 8.76% (Zhao et al., 2022) and I_t denotes the investment in fixed assets of transport sector.
(2) Labor force
The indicator we choose to characterize labor force is the total number of transport employees in urban non-private units, private enterprises and self-employed individuals at year-end.
(3) Energy
The indicator we chose to characterize energy is the total energy consumption of transport measured in 10^4 tons of coal equivalent, which is calculated using the following formula:

$$E_t' = \sum_i (E_{it} \cdot c_i) \tag{2}$$

where t stands for year; i stands for energy type; E_t' is the total energy consumption of transport measured in coal equivalent; E_{it} is the energy consumption of transport measured in original physical unit; and c_i is the conversion factors from physical unit to coal equivalent, which is from the *China Energy Statistical Yearbook*, as shown in Table 2.

Table 1. Definitions of input and output variables

Type	Variable Name	Definition	Unit
Input	Capital	Capital stock of transport sector	10^8CNY
Input	Labor force	Total number of transport employees in urban non-private units, private enterprises and self-employed individuals at year-end	10^4persons
Input	Energy	Total energy consumption of transport measured in coal equivalent	10^4ton CE
Output	GDP	GDP of transport sector	10^8CNY
Undesirable output	CO_2	CO_2 emissions of transport sector	10^4ton

Notes: CNY denotes Chinese Yuan ; CE denotes coal equivalent.

Table 2. Conversion factor to coal equivalent

No.	Type	Factor	Unit
1	Raw coal	0.7143	kgCE/kg
2	Gasoline	1.4714	kgCE/kg
3	Kerosene	1.4714	kgCE/kg
4	Diesel	1.4571	kgCE/kg
5	Fuel oil	1.4286	kgCE/kg
6	Liquefied petroleum gas	1.7143	kgCE/kg
7	Natural gas	1.2150	kgCE/m^3
8	Liquefied natural gas	1.7572	kgCE/kg
9	Heat	0.03412	kgCE/MJ
10	Electricity	0.1229	kgCE/(kW·h)

(4) GDP
The indicator we used to characterize GDP is the GDP of transport sector, which has been transformed into 2010 price using deflators.
(5) CO_2
The indicator we chose to characterize CO_2 is the CO_2 emissions of transport sector, which is calculated using the following formula:

$$\Phi_t = \sum_i (E_{it} \cdot c_i \cdot k \cdot \alpha_i) \tag{3}$$

where k=29.307 GJ/tonCE and α_i stands for carbon dioxide emission factors, which is from the *2006 IPCC Guidelines for National Greenhouse Gas Inventories*, as shown in Table 3.

Table 3. Carbon dioxide emission factors

No.	Type	Factor	Unit
1	Raw coal	94.6	$kgCO_2$/GJ
2	Gasoline	69.3	$kgCO_2$/GJ
3	Kerosene	71.5	$kgCO_2$/GJ
4	Diesel	74.1	$kgCO_2$/GJ
5	Fuel oil	77.4	$kgCO_2$/GJ
6	Liquefied petroleum gas	63.1	$kgCO_2$/GJ
7	Natural gas	56.1	$kgCO_2$/GJ
8	Liquefied natural gas	56.1	$kgCO_2$/GJ
9	Heat	0	$kgCO_2$/GJ
10	Electricity	0	$kgCO_2$/GJ

3.2. Super SBM with Undesirable Outputs

DEA employs a linear programming approach to determine the efficiency (Cooper et al., 2007). Since the first DEA model, CCR, was proposed, a number of DEA models have been developed (Cheng, 2022). In DEA, each alternative under consideration is referred to as a Decision Making Unit (DMU). However, when estimating the efficiency, many DMUs might concurrently reach 1 because 1 is the upper bound. Hence, we elucidates an improved DEA model named the super SBM model with undesirable outputs. The super SBM model is developed by Andersen et al., which introduces a new concept of "super-efficiency" (Cooper et al., 2007). When calculating the efficiency, the DMU under study is omitted from the feasible solution set in constraints. Thus it might result in that some efficiency values exceed 1, which is referred to as "super-efficiency". Using super-efficiency to analyze DMUs can help to avoid the occurrence of massive DMUs reaching the upper bound of 1 at the same time.
Suppose there are n DMUs which have m inputs, s_1 desirable outputs and s_2 undesirable outputs. Let X stand for the input data matrix, Y^g for the desirable output and Y^b for the undesirable output, which are defined below:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{4}$$

$$Y^g = \begin{bmatrix} y_{11}^g & y_{12}^g & \cdots & y_{1n}^g \\ y_{21}^g & y_{22}^g & \cdots & y_{2n}^g \\ \vdots & \vdots & \cdots & \vdots \\ y_{s_1 1}^g & y_{s_1 2}^g & \cdots & y_{s_1 n}^g \end{bmatrix} \tag{5}$$

$$Y^b = \begin{bmatrix} y_{11}^b & y_{12}^b & \cdots & y_{1n}^b \\ y_{21}^b & y_{22}^b & \cdots & y_{2n}^b \\ \vdots & \vdots & \cdots & \vdots \\ y_{s_2 1}^b & y_{s_2 2}^b & \cdots & y_{s_2 n}^b \end{bmatrix} \tag{6}$$

Suppose DMU$_o$ is an alternative decision making unit where *o* ranges over 1, 2, ..., n. Let $\boldsymbol{x}_o$ be the input data for DMU$_o$, $\boldsymbol{y}_o^g$ be the desirable output data for DMU$_o$ and $\boldsymbol{y}_o^b$ be the undesirable output data for DMU$_o$, which are defined below.

$$\begin{aligned} \boldsymbol{x}_o &= [x_{1o}, x_{2o}, ..., x_{mo}]^{\bullet} \\ \boldsymbol{y}_o^g &= [y_{1o}^g, y_{2o}^g, ..., y_{s_1 o}^g]^{\bullet} \\ \boldsymbol{y}_o^b &= [y_{1o}^b, y_{2o}^b, ..., y_{s_2 o}^b]^{\bullet} \end{aligned} \quad (7)$$

In order to evaluate the super-efficiency value ρ^* of DMU$_o$, a convex optimization in $\boldsymbol{\lambda}, \overline{\boldsymbol{x}}, \overline{\boldsymbol{y}}^g, \overline{\boldsymbol{y}}^b$ is given below.

$$\rho^* = \min_{\lambda, \bar{x}, \bar{y}^g, \bar{y}^b} \frac{\frac{1}{m}\sum_{i=1}^{m} \frac{\bar{x}_i}{x_{io}}}{\frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1} \frac{\bar{y}_r^g}{y_{ro}^g} + \sum_{r=1}^{s_2} \frac{\bar{y}_r^b}{y_{ro}^b}\right)}$$

subject to

$$\begin{aligned} \bar{\boldsymbol{x}} &\geq \sum_{j=1,\neq o}^{n} x_j \lambda_j \\ \bar{\mathbf{y}}^g &\leq \sum_{j=1,\neq o}^{n} y_j^g \lambda_j \\ \bar{\mathbf{y}}^b &\leq \sum_{j=1,\neq o}^{n} y_j^b \lambda_j \\ \boldsymbol{\lambda} &\geq 0, \bar{\boldsymbol{x}} \geq \boldsymbol{x_o}, 0 \leq \bar{\mathbf{y}}^g \leq y_o^g, \bar{\mathbf{y}}^b \geq y_o^b \end{aligned} \quad (8)$$

where m=3, s_1=1, s_2=1 in this paper.

This model is called the super SBM with undesirable outputs. In this model, the efficiency value can be higher than 1. To implement a plausible approach of evaluating TCERE, we adopt the super SBM with undesirable outputs model in accordance with previous studies (Zhang, 2018), because it can be more effective.

3.3. Influencing factors

This paper also posits economic growth, transport structure, technology level and population density as influencing factors. Definitions of these influencing factors are summarized in Table 4.

In these influencing factors, PN (per capita nighttime lights brightness) is a new indicator for economic growth in individual provincial region. Here the PN value is the total DN (Digital Number) value of nighttime lights image in individual provincial region divided by population.

3.4. Econometric Models

The EKC model provides a theoretical framework to study the relationship between economic growth and environment (Yan et al., 2020). Thus, this paper extends the EKC model and establishes the following four econometric models:

$\boldsymbol{OLS_1}$:

$$TCERE = \alpha + \beta_1 \ln PN_{it} + \beta_2 (\ln PN_{it})^2 + \beta_3 TS_{it} + \beta_4 TL_{it} + \beta_5 PD_{it} + \varepsilon_{it} \quad (9)$$

$\boldsymbol{OLS_2}$:

$$TCERE = \alpha + \beta_1 \ln PN_{it} + \beta_2 (\ln PN_{it})^2 + \beta_3 TS_{it} + \beta_4 TL_{it} + \beta_5 PD_{it} + \mu_i + \xi_t + \varepsilon_{it} \quad (10)$$

$\boldsymbol{OLS_3}$:

$$TCERE = \alpha + \beta_1 \ln PN_{it} + \beta_2 (\ln PN_{it})^2 + \beta_3 TS_{it} + \beta_4 TL_{it} + \beta_5 PD_{it} + \xi_t + \varepsilon_{it} \quad (11)$$

$\boldsymbol{OLS_4}$:

$$TCERE = \alpha + \beta_1 \ln PN_{it} + \beta_2 (\ln PN_{it})^2 + \beta_3 TS_{it} + \beta_4 TL_{it} + \beta_5 PD_{it} + \mu_i + \varepsilon_{it} \quad (12)$$

where *i* denotes the data for the *i*-th region and *t* for the *t*-th year; α denotes the constant term; $\beta_1 - \beta_5$ denotes a series of unknown parameters; μ_i denotes an entity fixed effect; ξ_t denotes a time fixed effect and ε_{it} is the error term.

3.5. Technical Route

The process of calculating the TCERE and analyzing its influencing factors mainly consists of the following steps.

1. Acquiring raw data from relevant yearbooks, remote sensing images, etc.
2. According to Section 3.1, the raw data are processed to obtain the input and output variables.
3. The super SBM with undesirable outputs model is then used to evaluate the TCERE.
4. As described in Section 3.3, the raw data are processed to obtain the influencing factors.

Analyzing the relationship between TCERE and influencing factors based on econometric models.

Table 4. Definitions of influencing factors

Symbol	Variable	Indicator	Definition	Unit
PN	Economic growth	Per capita nighttime lights brightness	Total DN (Digital Number) value of nighttime lights image in individual provincial region divided by population.	nW/cm^2/sr/person
TS	Transport structure	Transport structure	Proportion of freight ton-kilometers in railway and waterway to total freight ton-kilometers	1
TL	Technology level	Technology level	Ratio of freight ton-kilometers to energy consumption in transport	10^4ton·km/tonCE
PD	Population density	Population density of urban area	Ratio of urban population to urban area	10^4persons/km^2

4. Data

4.1. Study Area

This paper studied the TCERE in East China. East China includes 7 provincial-level administrative regions, i.e., Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Fujian and Shandong. This paper selects these 7 provincial regions from 2013 to 2017 as samples. East China is the most technologically advanced economic zone, with superior natural environmental conditions, abundant natural resources, advanced commodities production, and a diverse variety of industrial sectors. The light industry, machinery, and electronics industries in East China maintain a dominant position in the whole country. It is also the most economically and culturally developed region in China, with well-connected railways, rivers, roadways, and shipping. Around 8.7% of China's total land area is located in East China (Kang, 2022). East China also ranked first among the seven major geographical regions of China in terms of GDP (43.8 trillion CNY) and GDP per capita (103,000 CNY) in 2021 (Kang, 2022). Fig. 1 shows the map of study area. The shapefiles of maps used in this paper are sourced from National Geomatics Center of China.

4.2. Data Sources

The raw data for calculating input and output variables are collected from the China Statistical Yearbook, China Price Statistical Yearbook, China Energy Statistical Yearbook, etc., in each year. Descriptive statistics for input and output varia-bles are reported in Table 5.

In this paper, the PN (per capita nighttime lights brightness) is a new indicator for the influencing factor of economic growth. To calculate this influencing factor, the nighttime lights remote sensing images of the Visible and Infrared Imaging Suite (VIIRS) were used here. The information about VIIRS nighttime lights images is available at (https://eogdata.mines.edu/products/vnl/) accessed on 10 June 2022. As for the product type, we select the "Annual VNL V2: average-masked". The relevant images can be downloaded at (https://eogdata.mines.edu/nighttime_light/annual/v20/) accessed on 10 June 2022. Fig. 2 shows the nighttime lights brightness images, and the PN value in individual provincial region is presented in Fig. 3.

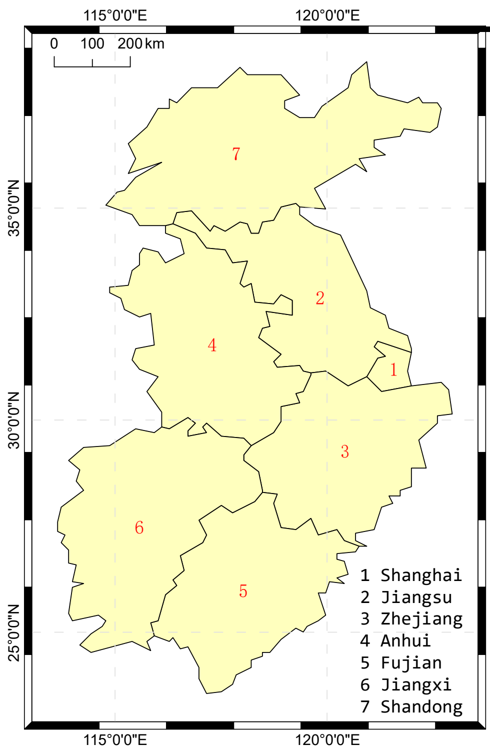

Fig. 1. Study area

Table 5. Descriptive statistics for input and output variables

Variable	Mean	Std. Dev.	Minimum	Maximum
Capital	7930.7332	3658.2812	2746.9216	16032.2708
Labor	57.0886	22.4914	30.6000	111.2000
Energy	1456.2384	555.3110	619.7023	2464.2623
GDP	1010.9361	496.2221	439.5809	2057.7745
CO_2	2970.8844	1142.1572	1272.9465	5201.9051

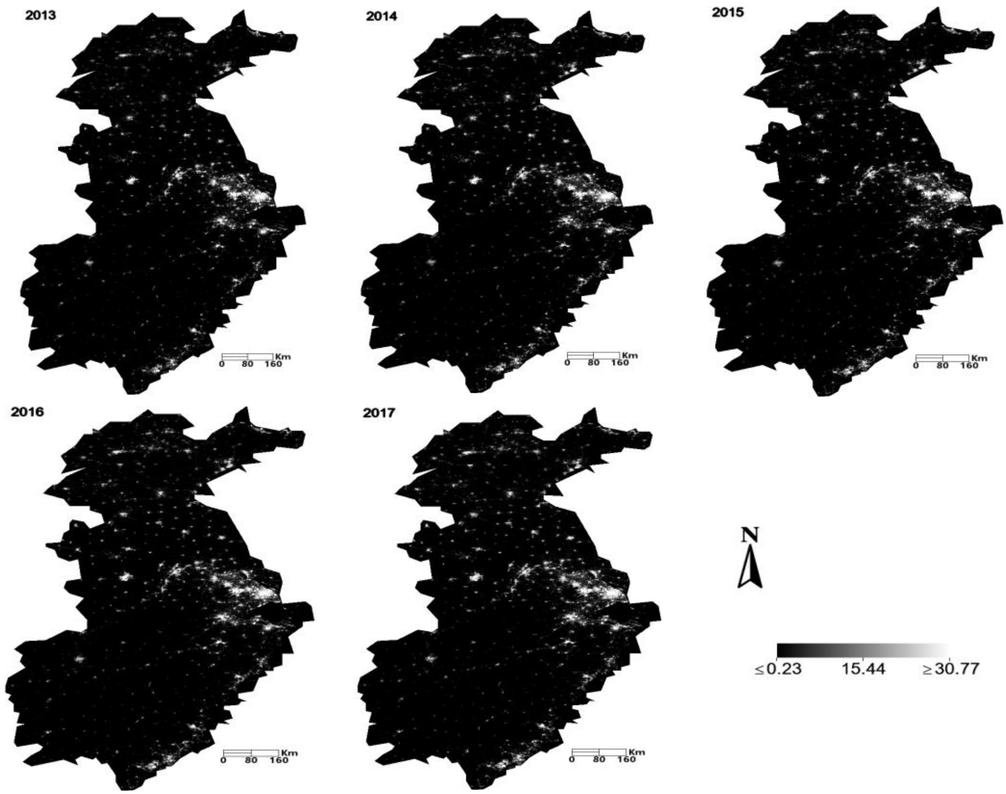

Fig. 2. Nighttime lights brightness images [nW/cm^2/sr]

According to Fig. 2, the brightest lights at night are found in Shanghai and the surrounding area. According to Fig. 3, the PN value of Shanghai has remained the highest from 2013 to 2017, and the PN value of places near Shanghai will be higher than that of places far away from Shanghai. For the five years, Shanghai, Jiangsu, and Zhejiang have remained in the top three.

The raw data for calculating other influencing factors are collected from the *China Statistical Yearbook* in each year. Descriptive statistics for influencing factors are reported in Table 6.

Table 6. Descriptive statistics for influencing factors

Variable	Mean	Std.Dev	Minimum	Maximum
PN	0.015	0.006	0.004	0.025
TS	0.632	0.277	0.186	0.988
TL	6.809	2.677	3.695	13.865
PD	0.273	0.107	0.136	0.482

5. Results and Discussion

5.1. TCERE

According to the super SBM with undesirable outputs model described in Section 3.2, the TCERE is computed. Fig. 4 depicts the spatial distribution of

TCERE in East China from 2013 to 2017. As illustrated in Fig. 4, TCERE decreased almost completely between 2013 and 2017. TCERE in Shanghai has always been at its lowest level, regardless of the year.The statistics for TCERE are shown as box plots in Fig. 5, where we can see that the mean TCERE has been declining from 2013 to 2017, but the trend of decline has got slower, indicating a sign of improvement.

5.2. Influencing Factors Analysis

After calculating the TCERE, this paper also conducts an econometric analysis to study the relationship between TCERE and its influencing factors. Four different econometric models are considered, and the estimation results are reported in Table 7.

As shown in Table 7, the log-likelihood (Log-L) value of OLS_2 is greater than others, and the AIC value is less. Hence, the OLS_2 model seems more suitable to describe the relationship. Turning to estimation results of OLS_2 model in Table 7, the coefficient of PN^2 is positive and statistically significant ($p<0.05$), and the coefficient of PN is negative and also statistically significant ($p<0.05$). It suggests that the relationship between TCERE and economic growth shows an U-shape. Thus, promoting the economic growth is a good way to improve the TCERE.

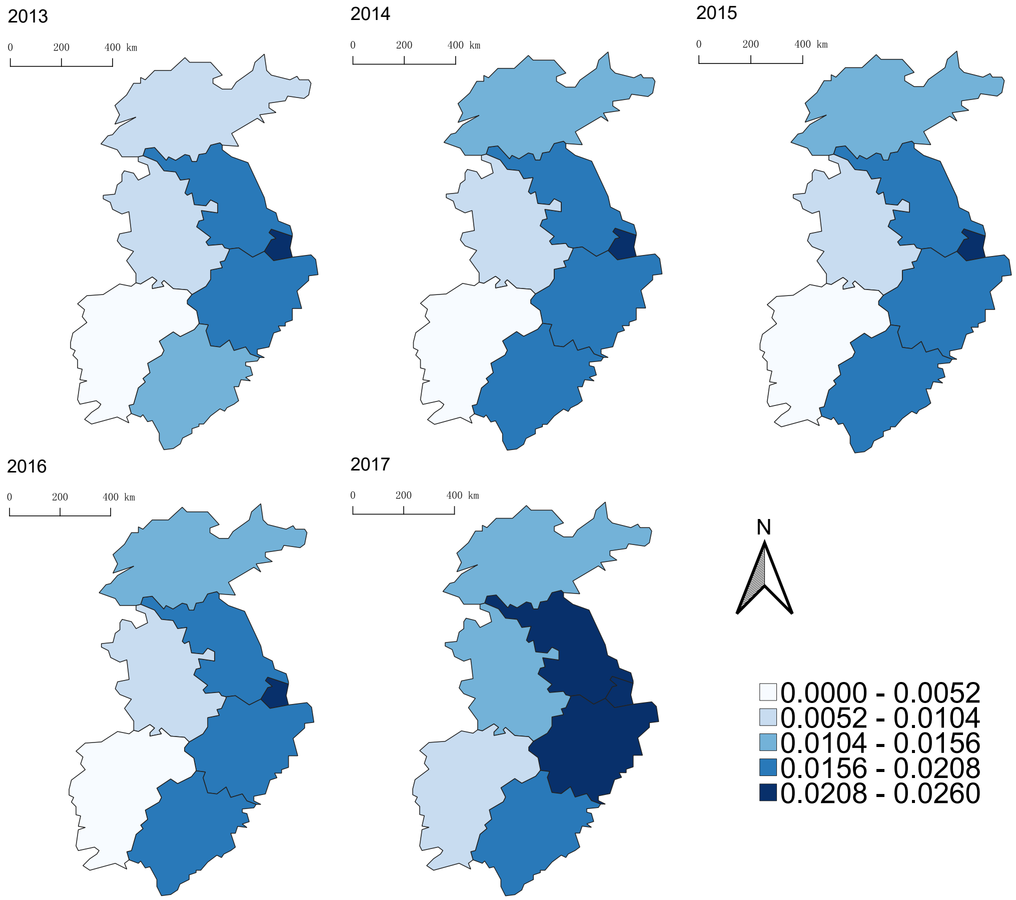

Fig. 3. PN value [$nW/cm^2/sr/person$]

The coefficient of TS is positive and statistically significant, indicating that a better transport structure tends to raise the TCERE. The coefficient of TL is also positive and statistically significant, expressing that a higher technology level lead to an increase in the TCERE. The coefficient of PD is not statistically significant, implying that the population density might not be the main influencing factors of TCERE.

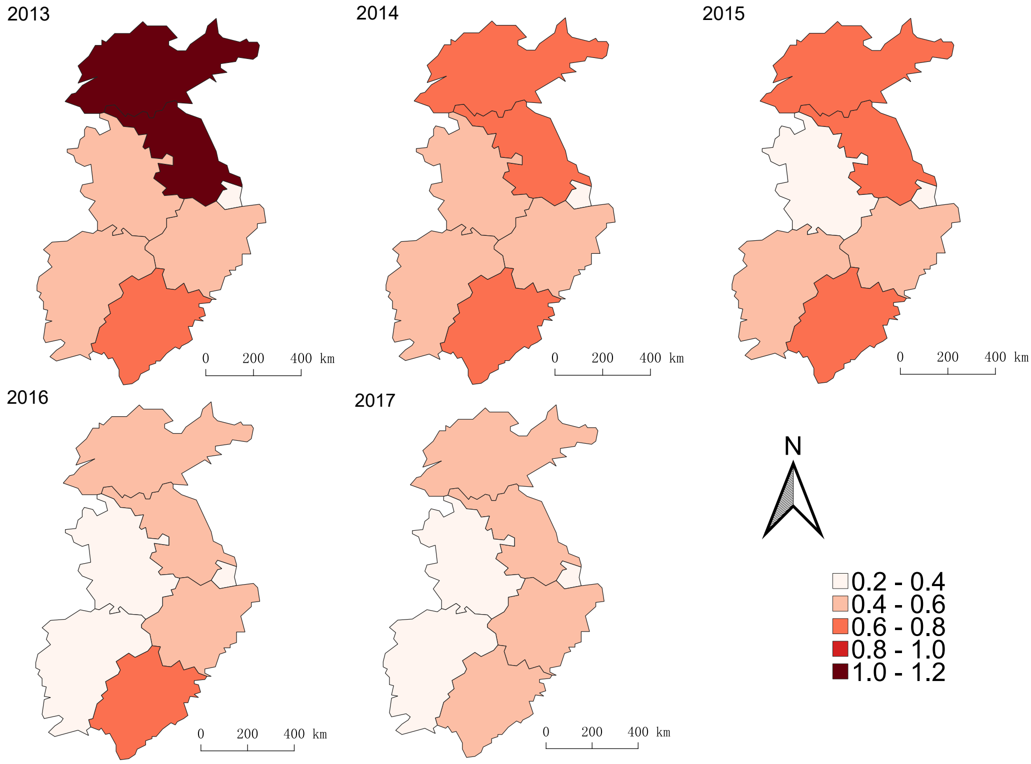

Fig. 4. TCERE [-]

Table 7. Estimation results

Variables	OLS_1	OLS_2	OLS_3	OLS_4
PN^2	1373.412 (1.047)	1846.400** (2.250)	335.983 (0.307)	2107.476* (1.960)
PN	-77.164 (-1.613)	-115.527** (-2.812)	-27.801 (-0.668)	-107.696** (-2.564)
TS	0.747** (2.506)	1.280** (2.648)	0.334 (1.154)	1.724** (2.658)
TL	-0.047*** (-4.457)	0.039** (2.613)	-0.041*** (-4.663)	0.047** (2.444)
PD	-1.340*** (-2.919)	1.322 (0.595)	-0.885** (-2.245)	-4.084 (-1.549)
R^2	0.577	0.857	0.765	0.858
Log-L	24.20	57.87	34.51	43.27
AIC	-36.39285	-95.74795	-49.02432	-62.53118

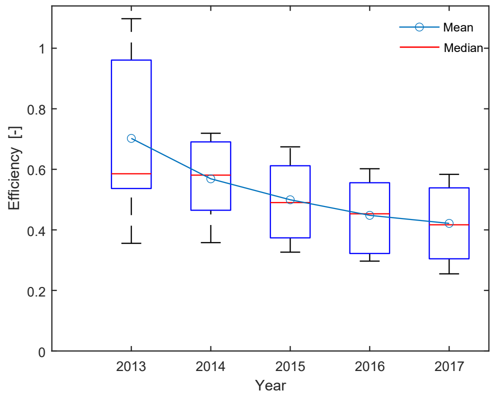

Fig. 5. Box plots of TCERE

6. Conclusion

The transport carbon emissions reduction efficiency (TCERE) is essential for climate change. In order to analyze the TCERE more effectively, this paper has calculated the TCERE based on the model of super SBM with undesirable outputs, and then proposed econometric models to analyze its influencing factors. Previous researchers have hardly studied these influencing factors using nighttime lights images, and that is the main contribution of our work. An empirical study was conducted in East China from 2013 to 2017, and this study has found that the relationship between TCERE and economic growth shows an U-shape. Besides, transport structure and technology level both show a positive impact on TCERE. The implications of our findings are given below.

– The TCERE declines slower in East China, giving us reason to believe that the improvement of TCERE is predictable.
– When economic growth exceeds the turning point, economic growth is conducive to the improvement of TCERE. We could develop the economy boldly and confidently.
– Increased investment in railway and waterway transportation infrastructure projects is needed to strengthen the structure of the railway and waterway transportation systems. Furthermore, the general public and businesses should be encouraged to prefer rail or river transportation.
– Investment in scientific and technological innovation should be enhanced in order to produce more efficient energy-use methods.

The preceding conclusions are also subject to some limitations. For example, we avoid the epidemic factor. More research is needed to better understand how epidemics affect the TCERE. In the future, we could also investigate the practical applications of our research in carbon-reduction activities.

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References

[1] An, C., Muhtar, P., Xiao, Z. (2022). Spatiotemporal Evolution of Tourism Eco-Efficiency in Major Tourist Cities in China. *Sustainability*, 14(20), 13158.
[2] Blesl, M., Das, A., Fahl, U., Remme, U. (2007). Role of energy efficiency standards in reducing CO2 emissions in Germany: An assessment with TIMES. *Energy Policy*, 35(2), 772-785.
[3] Chen, M.g., Zhang, S. (2021). Comparison of regional resident living standards across China: Based on the Global Night-time Lights Data. *Economic Theory and Business Management*, 41(5), 48-67.
[4] Cheng, G. (2014). Data Envelopment Analysis: Methods and MaxDEA Software. Beijing: Intellectual Property Publishing House.
[5] 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. *Annals of Operations Research*, 270, 105-124.
[6] Churchill, S.A., Inekwe, J., Ivanovski, K., Smyth, R. (2018). The Environmental Kuznets Curve in the OECD: 1870-2014. *Energy Economics*, 75, 389-399.
[7] Cooper, W.W., Seiford, L.M., Tone, K. (2007). Data Envelopment Analysis. New York: Springer.
[8] Cui, Q., Li, Y. (2015). An empirical study on the influencing factors of transportation carbon efficiency: Evidences from fifteen countries. *Applied Energy*, 2015, 141, 209-217.
[9] Cullinane, K., Wang, T.F., Song, D.W., Ji, P. (2006). The technical efficiency of container ports: Comparing data envelopment analysis

and stochastic frontier analysis. *Transportation Research Part A: Policy and Practice*, 40(4), 354-374.

[10] Fan, J., Ren, Y., Yu, X. (2017). An analysis of the Mechanism Between Population Urbanization and Regional Green Economic Efficiency Based on Stochastic Frontier Analysis Model. *Journal of Macro-quality Research*, 5(4), 52-65.

[11] Gu, Y., Shao, Z., Huang, X., Cai, B. (2022). GDP Forecasting Model for China Provinces Using Nighttime Light Remote Sensing Data. *Remote Sensing*, 14(15), 3671.

[12] Kang, Y. (2021). China Statistical Yearbook. Beijing: China Statistics Press.

[13] Lan, Z., Zhang, H. (2014). Study on Inter-provincial Difference in Carbon Emissions Efficiency of Traffic and Transportation Industry in China. *Logistics Technology*, 33(4), 132-135.

[14] Park, Y.S., Lim, S.H., Egilmez, G., Szmerekovsky, J. (2018). Environmental efficiency assessment of U.S. transport sector: A slack-based data envelopment analysis approach. *Transportation Research Part D: Transport and Environment*, 61, 152-164.

[15] Qin, M., Liu, X., Li, S. (2019). The Impact of UrbanSprawl on Regional Economic Growth—Empirical Researches Based on DMSP Night-Time Light Data. *China Economic Quarterly*, 18(2), 527-550.

[16] Tan, M., Li, X., Li, S., Xin, L., Wang, X., Li, Q., Li, W., Li, Y., Xiang, W. (2018). Modeling population density based on nighttime light images and land use data in China. *Applied Geography*, 90, 239-247.

[17] Tian, G., Li, J., Miao, C., Du, P. (2022). Urban Green Development Efficiency and Its Influencing Factors in China Based on the Undesirable Outputs. *Economic Geography*, 42(6), 83-91.

[18] Tsolas, I.E. (2022). Assessing Regional Entrepreneurship: A Bootstrapping Approach in Data Envelopment Analysis. *Stats*, 5(4), 1221-1230.

[19] Wang, K., Wei, Y.M., Zhang, X. (2012). A comparative analysis of China's regional energy and emission performance: Which is the better way to deal with undesirable outputs. *Energy Policy*, 46, 574-584.

[20] Wang, K.L., Miao, Z., Zhao, M.S., Miao, C.L., Wang, Q.W. (2019). China's provincial total-factor air pollution emission efficiency evaluation, dynamic evolution and influencing factors. *Ecological Indicators*, 107, 105578.

[21] Wang, X., Wei, Q., Hu, X. (2016). Comprehensive Evaluation of Cities' Green Economy Efficiency and Spatial and Temporal Differentiation in China: Based on the DEA-BCC and Malmquist Model. *Ecological Economy*, 32(3), 40-45.

[22] Wang, Z., Li, M., Jiang, J. (2020). The Impact of Traffic Accessibility on Urban Economic Growth—Spatial Econometric Analysis of DMSP/OLS Nighttime Satellite Lighting Data Based on 283 Cities. *China Economic Studies*, 9(5), 84-97.

[23] Xu, K., Chen, F., Liu, X. (2015). The Truth of China Economic Growth: Evidence from Global Night-time Light Data. *Economic Research Journal*, 50(09), 17-29.

[24] Xu, X., Zhao, T., Liu, N., Kang, J. (2014). Changes of energy-related GHG emissions in China: An empirical analysis from sectoral perspective. *Applied Energy*, 132, 298-307.

[25] Yan, Y., Hu, W. (2020). Does Foreign Direct Investment Affect Tropospheric SO2 Emissions? A Spatial Analysis in Eastern China from 2011 to 2017. *Sustainability*, 12(7), 2878.

[26] Zhang, C., Li, J., Liu, T., Xu, M., Wang, H., Li, X. (2022). The Spatiotemporal Evolution and Influencing Factors of the Chinese Cities Ecological Welfare Performance. International *Journal of Environmental Research and Public Health*, 19(19), 12955.

[27] Zhao, P., Zeng, L., Lu, H., Zhou, Y., Hu, H., Wei, X. (2020). Green economic efficiency and its influencing factors in China from 2008 to 2017: Based on the super-SBM model with undesirable outputs and spatial Dubin model. *Science of the Total Environment*, 741, 140026.

[28] 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.

[29] Zhao, X., Wang, J., Xin Fu., Zheng, W., Li, X., Gao, C. (2022). Spatial-temporal characteristics and regional differences of the freight transport industry's carbon emission efficiency in China. *Environmental Science and Pollution Research*, 29, 75851-75869.

[30] Zhang, Y., Shen, L., Shuai, C., Tan, Y., Ren, Y., Wu, Y. (2019). Is the low-carbon economy efficient in terms of sustainable development? A global perspective. *Sustainable Development*, 27(1), 130-152.