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Regional Differences and Spatial Aggregation of Sustainable Transport Efficiency: A Case Study of China

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Abstract: In the past few decades, traffic congestion, traffic accidents, and air pollution caused by transport become increasingly serious in China, so the issue of sustainable development of transport has attracted much attention. This study explores the development level of provincial sustainable transport in China, measures the level of sustainable development of China's transport from the perspective of transport efficiency, and analyzes the differences and spatial effects of sustainable transport development. The undesired output of the super slacks-based-measurement data envelopment analysis (US-SBM-DEA) model is used to measure the sustainable transport efficiency (*STE*) in different provinces of China, and then the coefficient of variation (*CV*) and Gini coefficient (*GC*) are used to explore the regional differences of *STE*. Finally, we analyze the spatial aggregation of *STE* by the index of Moran's *I*. The results show that the regional mean of *STE* presents a distribution in the order of eastern > western > central > northeastern regions. The *CV* reveals that there is a local σ-convergence in the *STE* differences among the four regions during the study period. The Moran scatter plot of *STE* shows that the provincial *STE*s in China are mainly the aggregations of high–low and low–low with the latter being more obvious. The *GC* basically remained at a relatively stable level during 2007–2015 while quickly decreased in 2016. i.e., the equity of sustainable transport increased dramatically in 2016. These results meet the actual development of the sustainable transport in China's provinces and reflect the level of sustainable transport efficiency more objectively. The results of this study provides theoretical support for the provincial governments to formulate efficient transport policies.

Keywords: sustainable transport efficiency; regional differences; spatial effects; US-SBM-DEA; Moran's *I*

1. Introduction

In September 2015, the General Assembly of the United Nations adopted the agenda "Transforming our World: The 2030 Agenda for Sustainable Development", regarding sustainable development as the major challenge that humanity must face today. The agenda has been widely recognized by the international community [1]. The transport sector occupies an important position in sustainable development and sustainability is also one of the intrinsic requirements for the development of the transport sector [2]. Sustainable transport is a new idea that considers transport as contributing to economic and social development while meeting a long-term dynamic coordination between the transport system and the external environment [3]. At present, developing countries are facing serious transport problems [4] and China is no exception. In the past 30 years in China, traffic congestion, traffic accidents, and air pollution caused by transport become increasingly serious. Therefore, the issue of the sustainable development of China's transport has received much attention.

Some studies have been carried out on the sustainability of transport, such as the concepts of sustainable transport, urban transport sustainability, and sustainability of a single transport mode. First, according to "Sustainable Transport: The Key to Policy Change", published by the World Bank in 1996, sustainable transport is defined as the achievement of economic, ecological, and social sustainability [5]. Subsequently, scholars have reworked the meaning of sustainable transport. Cheba (2013) considered sustainable transport as including the sustainability of the environment, transport systems, and transport processes [6]. Holden (2013) deemed that sustainable passenger transport aims to meet human needs and intra-generational transport fairness [7]. Second, so far, most of the research focuses on the sustainability issues of urban transport. For example, some scholars consider the factors that affect the sustainability of urban transport to include road infrastructure, residents' perceptions, vehicle traffic restrictions, pricing mechanisms, traffic congestion [8,9], accessibility [10], and land usage [11,12]. Meanwhile, other research has put forward some ways to achieve urban sustainable transport. The method of the mixed financing of the construction of urban transport infrastructure helps to improve the financial sustainability of the transport sector [13,14]. In addition, the improvement of the service quality of urban public transport could increase residents' willingness to use sustainable modes of transport such as shared traffic [15]. On the basis of the problems in transport, suggestions and measures for sustainable development have been proposed by scholars. For example, the sustainability of urban transport is measured by using GIS to analyze urban transport networks [16] and logistic systems of goods [17]. Electric vehicles with range extenders [18], intelligent traffic systems (ITS), and bottleneck models can be used to ease traffic congestion in the studied areas [9]. In addition, the intelligent disaster decision support system (IDDSS) also contributes to improving disaster management and increasing the sustainability of transport networks [19]. Third, currently, the sustainability of a single mode transport has been widely explored. For example, Pauli and Yu-Feng (2010) evaluated the sustainability of inland waterways using comprehensive fuzzy evaluation method and explored the influencing factors of sustainable development of inland waterways [20,21]. Railway sustainability in china was evaluated to explore its impact on the development of Chinese society [22]. In summary, on the one hand, the aforementioned research on sustainable transport focused mainly on the sustainability of urban transport. However, the analysis of the sustainability issues of transport was incomplete, which did not include that of rural areas. On the other hand, there have been few studies on the sustainability of integrated transport system including passenger and freight transport with various transport modes [23]. Therefore, this study measures the sustainable transport efficiency of integrated transport systems, which involves passenger and freight transport with various modes such as railways, highways, waterways, and aviation.

Efficiency analysis is an important part of evaluating the sustainability of transport. At present, there are two main kinds of evaluation methods: stochastic frontier analysis (SFA) and data envelopment analysis (DEA). Both methods evaluate transport efficiency on the basis of the distance between the decision unit and the production frontier (the curve or boundary that achieves the best efficiency). SFA was proposed by Aigner and developed by Finn Jorgensen [24,25]. Subsequently, SFA was also used to evaluate the efficiency of transport. For example, it was used to judge the service efficiency of highway management companies and the technical efficiency of 18 road public transport operators, respectively [26,27]. However, the SFA method is a parameter estimation method that requires the evaluated parameters to be independent, but this requirement is very difficult to meet in reality. Therefore, in recent years, the DEA model has become more common in the efficiency evaluation of the transport sector. For example, the energy efficiency and the level of road traffic safety were evaluated by using a generalized DEA model [28,29]. Some scholars have used phased DEA to evaluate the energy and transfer efficiencies of transport [30,31]. Furthermore, a network DEA model was used to evaluate the performance level of India's public transport sector and traffic system [32,33]. However, we find that the DEA method as used by the above-mentioned studies still fails to avoid the truncation drawbacks, i.e., they are impossible to accurately measure the efficiency of the effective evaluation unit of DEA and the input–output redundancy cannot be solved at the same time. The undesired output of the super-slacks-based measurement–data envelopment analysis (US-SBM-DEA) model put forward by Cheng can better solve the problems arising from the above [28–33] efficiency measurement methods. Then this model has been widely used in the efficiency evaluation. For example, the US-SBM-DEA model was used to measure the total carbon emission efficiency [34], the urban ecological efficiency [35] and the cultivated land use efficiency [36]. The US-SBM-DEA model can incorporates the undesired outputs variables into the efficiency evaluation and evaluate the DMUs efficiently [37]. Therefore, we used the US-SBM-DEA model to evaluate the sustainable development efficiency of transport in this study.

In this study, we used sustainable transport efficiency (*STE*) to measure the development level of sustainable transport. First, according to the connotations of sustainable transport as proposed by the World Bank, we selected 11 indicators from economic, ecological and social aspects to evaluate the *STEs* in China's 30 provinces. The indicators include integrated transport modes, such as highways, railways, waterways, and aviation that cover the transport activities of urban and rural areas. Second, we used the coefficient of variation (*CV*) to further analyze *STE* in order to explore the provincial and regional differences of sustainable transport in China. Third, according to the first theorem of geography, we used Moran's *I* to further explore *STE*'s spatial aggregation effect. Finally, we applied the Gini coefficient (*GC*) to analyze the equity of sustainable transport during the period of 2007–2016.

The paper is organized as follows: we first provide the model for calculation, difference measurement, spatial aggregation, and equity analysis of *STE* in Section 2. The evaluation indicators and the data prepared for the calculation of *STE* are described in Section 3. Next, the calculations of *STE* of 30 provinces in China and their regional differences, as well as spatial aggregation characteristics and their equity are presented in Section 4. Finally, the conclusions are discussed in Section 5.

2. Methodology

We used *STE* to describe the sustainable development level of China's transport. According to the *STE* values, the provinces in China are divided into four groups: high efficiency, medium–high efficiency, medium–low efficiency, and low efficiency. The *CV* is used for the analysis of the differences in *STE*, the spatial aggregation effect is explored using the global and local Moran's *I* and the equity of *STE* is presented by *GC* values. On the basis of this, we analyzed the changing law of the sustainable development of transport and its causes in China's provinces. The research framework is shown in Figure 1.

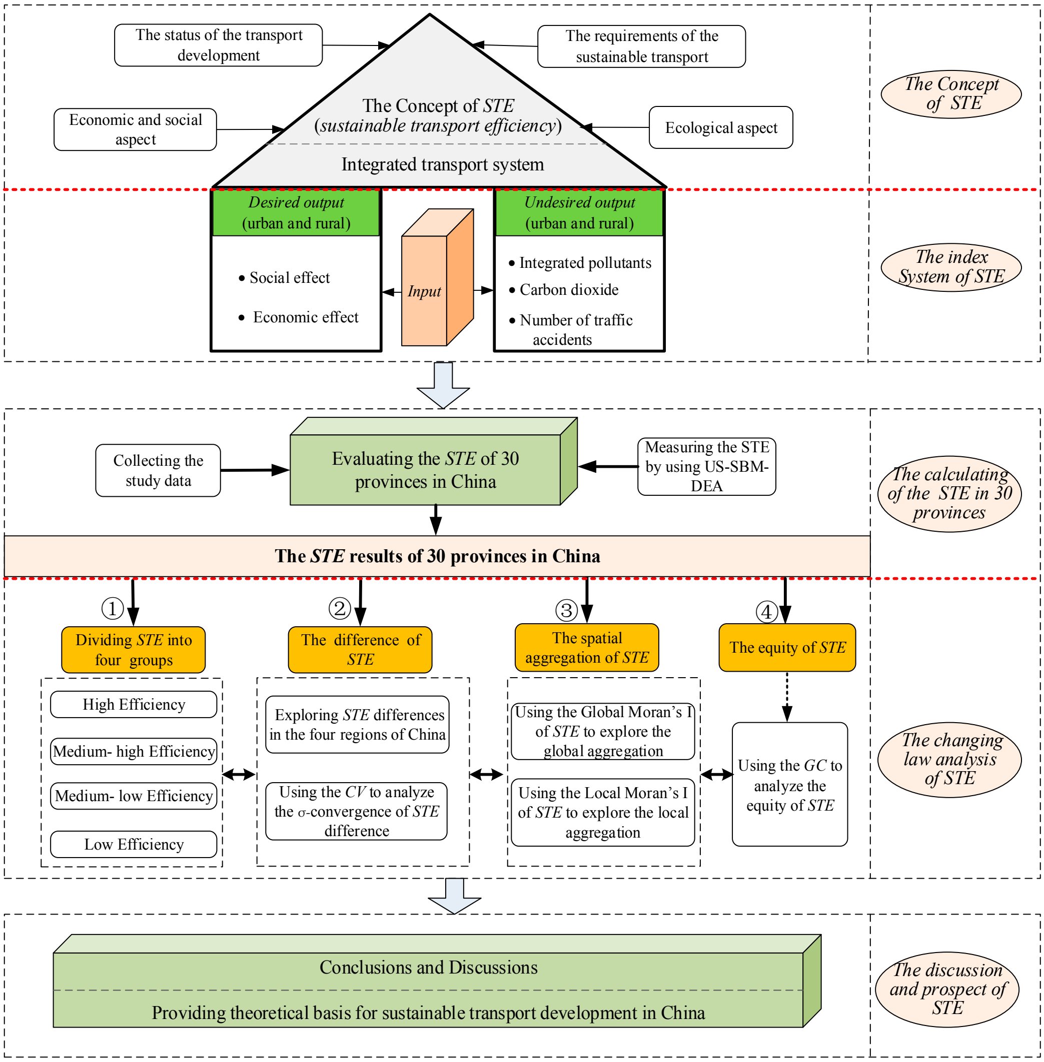


Figure 1. The research framework.

2.1. Efficiency Model of Sustainable Transport Efficiency

The above analysis shows that the *STE* is affected by multiple factors. The most common method for evaluating the *STE* is DEA. Although the DEA method [38] proposed by Charnes et al. can calculate the efficiency values of multiple inputs and outputs without being affected by the metric of the decision unit, they cannot make accurate calculations for effective decision-making units and avoid the radial problems of the input–output variables. Considering the negative effects of transport production and the shortcomings of the traditional DEA model, we introduced the undesired output variables and used the US-SBM-DEA to calculate *STE*.

Suppose there are n decision-making units (DMUs). Each DMU includes the input, desired output and undesired output variables. The US-SBM-DEA model is expressed by Formula (1) [34–37].

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

$$\begin{aligned} s.t.\quad & \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik} \\ & \sum_{j=1, j\neq k}^{n} y_{rj}^{\alpha}\lambda_j + s_r^+ \geq y_{rk}^{\alpha} \\ & \sum_{j=1, j\neq k}^{n} y_{tj}^{\beta}\lambda_j - s_t^- \leq y_{tk}^{\beta} \\ & \lambda, s^+, s^- \geq 0 \\ & i = 1,2,\ldots,m,\quad r = 1,2,\ldots,q_1,\quad t = 1,2,\ldots,q_2,\quad j = 1,2,\ldots,n(j \neq k) \end{aligned} \tag{1}$$

where STE^* is the value of the objective function. The minimum STE^* is the best solution when these variables meet the constraints (see Formula (1)). λ is a weight matrix. s_i^-, s_r^+, and s_t^- are redundant variable for the input, slack variable for the desired output and redundant variable for the undesired output, respectively. m is the number of input variables. q_1 is the number of desired output variables. q_2 is the number of undesired output variables. n is the number of decision units. j represents the jth decision units. x_{ik} represents the ith input of the kth decision unit. y_{rk}^{α} denotes the rth desired output of the kth decision unit. y_{tk}^{β} is the t th undesired output of the kth decision unit. α and β denote the variables of the desired and undesired outputs, respectively.

2.2. Difference Measurement Model for Sustainable Transport Efficiency

To explore the differences in *STE*, we used the coefficient of variation (*CV*) to reflect the differences and performed the σ-convergence test on *STE*. The *CV* of *STE* is the ratio of the standard deviation of *STE* to the mean value of *STE* and can be used to eliminate the influence of the metric. The σ-convergence means that if a region's *CV* decreases over time, there is σ-convergence. Otherwise, there is no σ-convergence.

$$CV_t(STE) = \frac{1}{\overline{STE_t}}\sqrt{\frac{1}{n-1}\left(\sum_{t=1}^{n} STE_{i,t} - \overline{STE_t}\right)^2} \tag{2}$$

where n represents the number of provinces in phase t. $\overline{STE_t}$ is the mean value of *STE* in the 30 provinces in phase t and $STE_{i,t}$ is the *STE* value of province i in the phase t. The smaller the *CV*, the smaller is the difference of *STE*. If $CV_K(STE) < CV_t(STE)$ ($\forall k > t$), there is a global σ-convergence in *STE* during the study period. If $CV_{t+1}(STE) < CV_t(STE)$, there is a local σ-convergence of the *STE* differences for the provinces.

2.3. Global Spatial Autocorrelation Analysis Model for Sustainable Transport Efficiency

Spatial autocorrelation refers to the interdependence of observational data in an area. As Tobler's first theorem of geography points out: everything is related to everything else, but proximate things are more similar than distant things (1970) [39]. However, prior to Tobler, Moran (1948) proposed the Moran's *I*, which is used to reflect the degree of the spatial autocorrelation of unit attribute values in the region [40], as expressed in Formula (3). On this basis, a local spatial autocorrelation analysis method is proposed and described by Anselin (1983, 1995) [41,42]. The index has been widely used by many researchers [43–45]. This study used the global Moran's *I* to verify the overall spatial autocorrelation *STEs* in the Chinese provinces.

$$I_{STE} = \frac{1}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(STE_i - \overline{STE})(STE_j - \overline{STE}) \tag{3}$$

where S^2 is the variance of *STE*, $S^2 = \sum_{i=1}^{n} (STE_i - \overline{STE})^2/n$. $\overline{STE}$ is the average *STE* of *n* spatial units (provinces). w_{ij} is the element of *i* and *j* of the spatial adjacency matrix, which is a first-order Rook matrix of China's 30 provinces (see Formula (4)). I_{STE} is the global Moran's *I*, which measures the *STE* spatial aggregation of the entire spatial sequence (STE_i). I_{STE} ranges between −1 and 1. $I_{STE} > 0$ indicates a positive correlation and a value closer to 1 indicates a more positive spatial correlation. Conversely, $I_{STE} < 0$ denotes a negative correlation and a value closer to –1 indicates a stronger negative correlation. When I_{STE} equals 0, the spatial distribution of *STE* is random and there is no spatial autocorrelation.

$$w_{ij} = w_{ji} = \begin{cases} 1, & wheniandjare\ adjacent \\ 0, & otherwise \end{cases} \tag{4}$$

After calculating I_{STE} from Formula (3), we used a *Z*-test (Formula (5)) to further verify the significance of its spatial correlation.

$$Z(I_{STE}) = \frac{I_{STE} - E(I_{STE})}{\sqrt{Var(I_{STE})}} \tag{5}$$

where $Z(I_{STE})$ is used to test the significance level of *STE* spatial autocorrelation, which is the ratio of the difference (between I_{STE} and its mean value) and the standard deviation of I_{STE}. $Var(I_{STE})$ is the variance of I_{STE}. $E(I_{STE})$ is the expectation of $I(STE)$, i.e., $E(I_{STE}) = -1/(n-1)$. $Z(I_{STE})$ is used to test the significance level of *STE* spatial autocorrelation. When $Z(I_{STE}) > 1.65$, *STE* has a spatial autocorrelation at a 90% confidence level. $Z(I_{STE}) > 1.96$ shows that *STE* has a spatial autocorrelation at a 95% confidence level. $Z(I_{STE}) > 2.58$ shows that *STE* has a spatial autocorrelation at a 99% confidence level.

2.4. Local Spatial Autocorrelation Analysis Model for Sustainable Transport Efficiency

Although $I(STE)$ can explain the spatial aggregation effect of the study area in general, a few local regions may still show the characteristics of spatial aggregation that are completely opposite to the global autocorrelation. Therefore, it is necessary to explore the characteristics of *STE's* local spatial aggregation. In this study, we used local Moran's *I* to measure the local spatial correlation of *STE* as Formula (6)

$$I_i(STE) = \frac{n(STE_i - \overline{STE})}{\sum_{i=1}^{n} (STE_i - \overline{STE})^2} \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(STE_j - \overline{STE}) \tag{6}$$

where $\overline{STE}$ is the mean *STE* of *n* space units. w_{ij} is the space adjacency matrix. $I_i(STE)$ is the Moran's *I* value of the *STE* for province *i*. The range of $I_i(STE)$ is set as −1 to 1. $I_i(STE) < 0$ indicates that there is a negative spatial correlation between STE_i and STE_j. The closer the value to −1, the greater is the difference. $I_i(STE) = 0$ indicates there is no spatial correlation between STE_i and STE_j. $I_i(STE) > 0$ means that there is a positive spatial correlation between STE_i and STE_j. The closer the value to 1, the greater is the positive correlation of *STE*.

2.5. Equity Analysis Model for Sustainable Transport Efficiency

The Gini coefficient (*GC*), proposed by the Italian economist Gini, is an important indicator for measuring the degree of equilibrium in income distribution [46]. The coefficient was later improved upon by many scholars and widely used in the evaluation of industrial development equity. There are many ways to calculate the *GC*. In this study, we used the method proposed by Monti (2007) [47] to calculate the equity of *s*ustainable transport (see Formula (7))

$$GC_t = \frac{1}{2n^2 * \mu} \sum_{i=1}^{n} \sum_{j=1}^{n} \left| STE_i - STE_j \right| = \Delta/2\mu \tag{7}$$

where *n* represents the number of provinces. STE_i and STE_j represent the *STE* values of provinces *i* and *j*, respectively. μ is the mean value of *STE* in different provinces, and Δ is the mean of the absolute value of the *STE* differences between the binary combinations of the units of $n \times n$. $GC \in (0, 1)$ and *GC* below 0.2 represents the absolute average, 0.2–0.3 is relatively average, 0.3–0.4 is relatively reasonable, 0.4–0.5 is a large gap and above 0.5 is a wide gap.

3. Variables Selection and Data Sources

3.1. Variable Selection

As the current environmental problems of transport are becoming much more prominent, scholars are paying more attention to these problems and selecting different inputs and outputs variables to evaluate the impact of transport on the environment (see Table 1).

Table 1. Literature on transport efficiency evaluation.

Authors	Year	Inputs	Outputs
Woo et al. [48]	2015	Labor, capital, energy	Added value, carbon emissions, power generation
Cui et al. [49]	2014	Employees and consumption	CO_2 emissions and added value
X. Guo et al. [50]	2017	Coal and electricity consumption	Gross domestic product
Z. Wei et al. [51]	2012	Energy, capital investment	Intelligent traffic management benefits
L. Yang et al. [52]	2015	Labor, capital, resources	Gross domestic product
Sami Jet al. [27]	2013	Operating expenses, number of employees	Benefits
Xin Xu et al. [53]	2017	Number of employees, capital investment, aviation consumption	Added value
Duygun et al. [54]	2016	Capital, employees, materials	Income

As shown in Table 1, scholars select indicators from different perspectives, which have played a basic role for this study. For example, *TIFA*, *TEC*, *TP*, *PFT*, *AVT*, and *CD* in Table 2 are all from Table 1. In addition, according to the actual situation of serious pollution, increased land occupation, excessive energy consumption and frequent traffic accidents in China's transport development, which greatly affect the development of sustainable transport. Therefore, we have additionally selected some indicators as shown in Table 2.

Table 2. Summary of input and output variables.

Criteria Layer	Element Layer	Indicator Variable	Metric
Input indicators	Production factor input	Transport investment in fixed assets (*TIFA*)	10^8 yuan
		Private car ownership (*PCO*)	10^4 vehicles
		Length of transport line (*LTL*)	10^4 kms
	Energy factor input	Transport energy consumption (*TEC*)	Tons of standard coal
	Labor factor input	Transport practitioners (*TP*)	Person
	Land factor input	Land use of transport (*LUT*)	10^3 hectares
Desired output indicators	Social effect output	Passenger and freight turnover (*PFT*)	10^8 tons km
	Economic effect output	Added value of transport sector (*AVT*)	10^8 yuan
Undesired output indicators	Negative effect output	Integrated pollutants emissions (*IPE*)	Kilogram
		Carbon dioxide (*CD*)	Ton
		Number of traffic accidents (*NTC*)	Case

3.2. Data Sources

This study examines the *STEs* from 2007 to 2016 using the indicators in Table 2. Due to the lack of data, the *STE*s of Tibet, Taiwan, Hong Kong, and Macao are not measured. The data for the transport investments in fixed assets, private car ownership, lengths of transport lines, transport practitioners, land use of transport, added value of the transport sector and the number of traffic accidents are from the National Bureau of Statistics (2007–2016) [55]. The transport energy consumption came from the

"Statistical Yearbooks (2007–2016)" of the 30 provinces [56]. The passenger and freight turnovers are calculated using the conversion factors in Table 3 and Formula (8) [57]. With the statistical data on the energy consumption of the transport sector and the conversion factor of carbon dioxide specified in the Intergovernmental Panel on Climate Change (IPCC), we used Formula (9) to calculate the carbon dioxide emissions.

$$PFT = FT + \sum_{i=1}^{n} PT_i * cpft_i i = 1,2,3,4 \tag{8}$$

where PFT represents passenger and freight turnover (10^8 tons km). FT is the freight turnover (10^8 tons km). PT_i represents passenger turnover in the ith transport mode (10^8 person-kilometers). $cpft_i$ is the conversion factor of the passenger and freight turnover in the ith transport mode.

$$CO_2 = \sum (E_i * scc_i) * ce * 44/12 i = 1,2,3,4,5 \tag{9}$$

where CO_2 (10^4 tons) is the total amount of the carbon dioxide emissions of all kinds of fuel consumed by the transport on highways, railways, waterways, and aviation. E_i is the consumption of the ith energy (coal, gasoline, diesel, natural gas, and electricity) (10^4 tons). scc_i is the conversion factor of standard coal of the ith energy. ce is the CO_2 conversion factor, which is 0.645 (tc/tce) as stipulated by the $IPCC$.

$$IPE = \sum (Gac * pdc_i) + \sum (Doc * pdc_j)/1000 i, j = 1,2,3,4 \tag{10}$$

where IPE is the integrated pollutant emissions (kg). Gac is the gasoline consumption (highways, railways, waterways, and aviation) (L). pdc_i is the emission factor of the ith pollutant of gasoline (g/L). Doc is the diesel consumption (highways, railways, waterways, and aviation) (L). pdc_j is the emission factor of the jth pollutant of diesel (g/L). The quantity of integrated pollutant emissions are calculated with Formula (10) using the fuel consumption by transport sector [58] and the pollutant emission factor given in Table 4.

Table 3. Conversion factor for passenger and freight turnover.

	Highways	Railways	Waterways	Aviations
Conversion Factor of *PFT* ($cpft_i$)	0.1	1	0.33	0.072

Table 4. Pollutant emission factors of transport fuels.

Pollutants	Gasoline as Fuel (g/L)	Diesel as Fuel (g/L)
Lead compounds	2.1	1.56
Sulfur dioxide	0.295	3.24
Carbon monoxide	169	27
Nitrogen oxide	21.1	44.4

Note: the data in Table 4 come from pollutant generation and discharge of industrial products complied by China Environmental Science Press in 1996.

The descriptive statistics of the STE indicators from the above data sources are shown in Table 5. In Table 5, "Min" represents the minimal value of each variable, "Max" indicates the maximal value of each variable, "Mean" denotes the average value of each variable, and "Std. dev" expresses the standard deviation of each variable.

Table 5. Descriptive statistics of the input and output variables.

Variables	Min	Max	Mean	Std. dev
TIFA	48.90	3737.95	962.74	692.66
PCO	7.89	1550.65	286.44	286.67
LTL	1.23	33.95	14.37	7.55
TEC	89.10	3454.97	1035.17	665.73
TP	2383.00	151,764.00	60,327.78	35,708.48
LUT	13.70	228.50	100.45	51.56
PFT	217.77	22,710.34	4864.55	4438.32
AVT	40.59	3209.72	839.13	639.75
IPE	4770.62	274,651.58	72,797.10	54,546.94
CD	218.89	8487.82	2517.01	1622.15
NTC	795.00	46,558.00	7598.31	6806.73

4. Results and Discussion

4.1. Calculations of Sustainable Transport Efficiency

On the basis of the indices shown in Table 2 and Formula (1), the calculation equation for the objective STE was obtained (See Formula (11)). Based on these constraints and objective functions, we used MAXDEA Ultra 7.0 to measure the *STE* value which show the level of sustainable transport development in 30 provinces of China. For instance, using the Formula (11) and the software, the *STE* value of 1 for the Tianjin in 2015 were obtained. All the results of *STEs* are shown in Table 6.

$$\min\ STE^* = \frac{1+\frac{1}{6}\sum_{i=1}^{6} s_i^- x_{ik}}{1-\frac{1}{2+3}\left(\sum_{r=1}^{2} s_r^+ / y_{rk}^{\alpha} + \sum_{t=1}^{3} s_t^- / y_{tk}^{\beta}\right)}$$

$$\begin{cases}
\sum_{j=1, j\neq k}^{30} TIFA_j \lambda_j - s_{TIFA}^- \le TIFA_k \\
\sum_{j=1, j\neq k}^{30} PCO_j \lambda_j - s_{PCO}^- \le PCO_k \\
\sum_{j=1, j\neq k}^{30} LTL_j \lambda_j - s_{LTL}^- \le LTL_k \\
\sum_{j=1, j\neq k}^{30} TEC_j \lambda_j - s_{TEC}^- \le TEC_k \\
\sum_{j=1, j\neq k}^{30} TP_j \lambda_j - s_{TP}^- \le TP_k \\
\sum_{j=1, j\neq k}^{30} LUT_j \lambda_j - s_{LUT}^- \le LUT_k \\
\sum_{j=1, j\neq k}^{30} PFT_j \lambda_j + s_{PFT}^+ \ge PFT_k \\
\sum_{j=1, j\neq k}^{30} AVT_j \lambda_j + s_{AVT}^+ \ge AVT \\
\sum_{j=1, j\neq k}^{30} IPE_j \lambda_j - s_{IPE}^- \le IPE_k \\
\sum_{j=1, j\neq k}^{30} CD_j \lambda_j - s_{CD}^- \le CD_k \\
\sum_{j=1, j\neq k}^{30} NTC_j \lambda_j - s_{NTC}^- \le NTC_k
\end{cases} \tag{11}$$

$$\lambda, s^+, s^- \ge 0$$

$$i = 1, 2, \ldots, m, \quad r = 1, 2, \ldots, q_1, \quad t = 1, 2, \ldots, q_2, \quad j = 1, 2, \ldots, n (j \neq k)$$

where $TIFA_j$, PCO_j, … , NTC_j represent the values of *TIFA*, *PCO*, … *NTC* in the *j*th decision unit, respectively; $\overline{STE}$, $\overline{STE}$ … $\overline{STE}$ represent redundant variables in the *STE* calculation; $\overline{STE}$ and $\overline{STE}$ represent insufficient output variable in the *STE* calculation; $\overline{STE}$, $\overline{STE}$ and $\overline{STE}$ all represent redundant variables in the *STE* calculation; $TIFA_k$, PCO_k, … , NTC_k represent value of the input and output variables of the decision unit *k* evaluated.

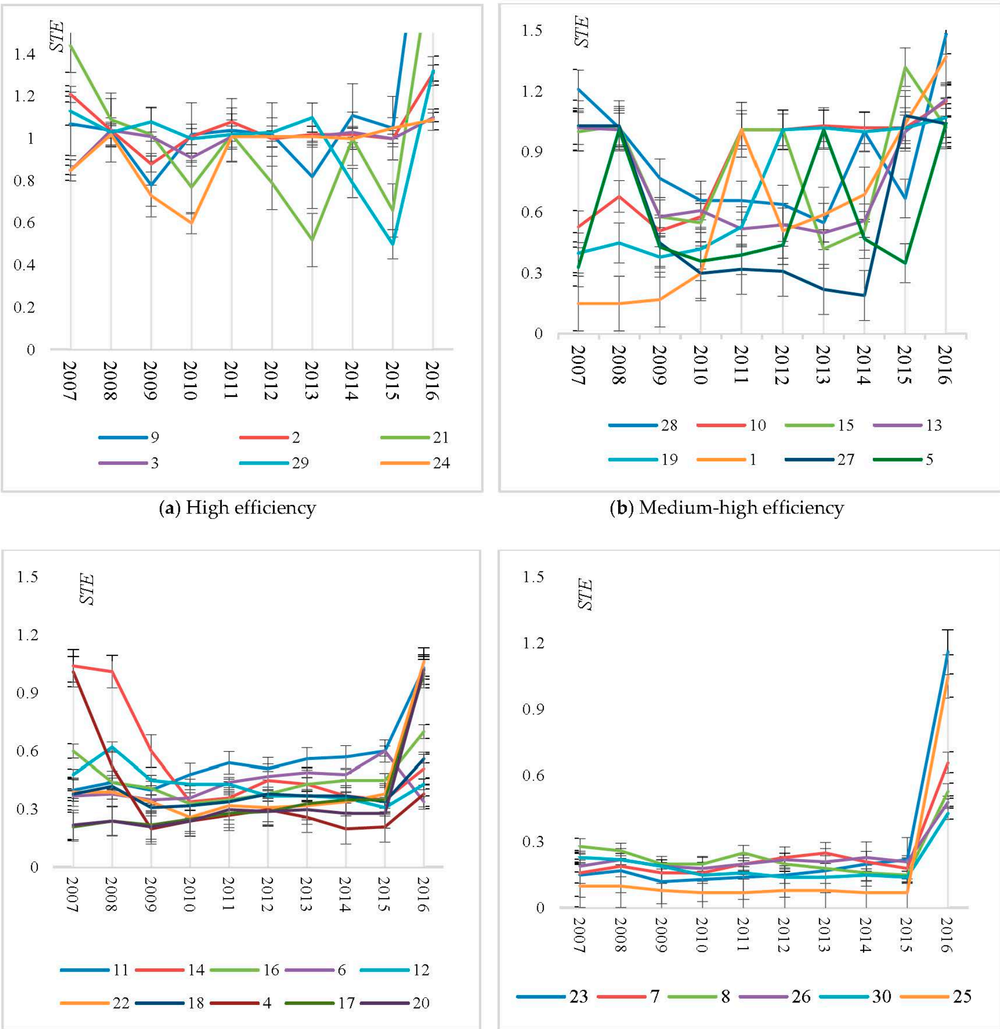
In Table 6, the *STE* values reflect the level of sustainable development of transport in China's provinces objectively. Taking Tianjin as an example, the *STE* values of Tianjin were all around 1 from 2007 to 2016. This is in line with the current level of transport development in Tianjin. Tianjin has formed a complete passenger and freight network, which has greatly enhanced Tianjin's transport efficiency. All the transport infrastructure provides the basic conditions for the sustainable development of transport.

Table 6. Overall *STEs* of 30 provinces in China, 2007–2016

Province No. [a]	*STEs* of 30 Provinces in China during 2007–2016										AVG [b]
	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	
1	0.15	0.15	0.17	0.3	1.01	0.51	0.59	0.69	1.04	1.37	0.60
2	1.21	1.04	0.88	1.01	1.08	1.00	1.02	1.02	1.00	1.31	1.06
3	0.85	1.04	1.01	0.91	1.01	1.01	1.01	1.03	1.00	1.10	1.00
4	1.01	0.52	0.20	0.24	0.27	0.30	0.26	0.2	0.21	0.38	0.36
5	0.33	1.01	0.43	0.36	0.39	0.44	1.01	0.47	0.35	1.04	0.58
6	0.37	0.38	0.35	0.36	0.44	0.47	0.49	0.48	0.60	0.34	0.43
7	0.16	0.19	0.16	0.16	0.20	0.23	0.25	0.21	0.18	0.66	0.24
8	0.28	0.26	0.20	0.20	0.25	0.20	0.18	0.16	0.15	0.53	0.24
9	1.09	1.07	0.78	1.04	1.06	1.04	0.84	1.11	1.06	2.46	1.16
10	0.53	0.68	0.51	0.58	1.01	1.01	1.03	1.02	1.02	1.15	0.85
11	0.40	0.44	0.40	0.48	0.54	0.51	0.56	0.57	0.60	1.03	0.55
12	0.48	0.62	0.45	0.43	0.43	0.37	0.37	0.36	0.31	0.43	0.42
13	1.02	1.01	0.58	0.61	0.52	0.54	0.5	0.56	1.00	1.16	0.75
14	1.04	1.01	0.60	0.34	0.36	0.45	0.43	0.37	0.35	0.51	0.55
15	1.00	1.03	0.58	0.55	1.01	1.01	0.42	0.51	1.32	1.02	0.84
16	0.60	0.44	0.41	0.33	0.35	0.38	0.43	0.45	0.45	0.70	0.45
17	0.21	0.24	0.22	0.25	0.28	0.29	0.33	0.35	0.35	1.00	0.35
18	0.38	0.42	0.31	0.32	0.34	0.38	0.37	0.37	0.34	0.56	0.38
19	0.40	0.45	0.38	0.42	0.53	1.01	1.02	1.00	1.02	1.07	0.73
20	0.22	0.24	0.21	0.24	0.30	0.29	0.30	0.28	0.28	1.02	0.34
21	1.44	1.09	1.02	0.77	1.02	0.79	0.52	1.00	0.66	1.89	1.02
22	0.39	0.39	0.34	0.26	0.32	0.31	0.32	0.34	0.38	1.06	0.41
23	0.15	0.17	0.12	0.13	0.14	0.15	0.17	0.20	0.22	1.16	0.26
24	0.85	1.02	0.73	0.60	1.01	1.01	1.01	1.00	1.05	1.09	0.94
25	0.10	0.10	0.08	0.07	0.07	0.08	0.08	0.07	0.07	1.05	0.18
26	0.19	0.22	0.19	0.18	0.20	0.22	0.21	0.23	0.21	0.48	0.23
27	1.03	1.03	0.45	0.3	0.32	0.31	0.22	0.19	1.08	1.04	0.6
28	1.21	1.02	0.77	0.66	0.66	0.64	0.55	1.00	0.67	1.48	0.87
29	1.13	1.03	1.08	1.00	1.02	1.03	1.10	0.79	0.50	1.32	1.00
30	0.23	0.22	0.19	0.15	0.16	0.14	0.14	0.15	0.14	0.43	0.19

Note: Due to lack of data, efficiency measurements will not include Tibet, Hong Kong, Macao, and Taiwan. [a]: Province no. 1. Beijing 2. Tianjin 3. Hebei 4. Shanxi 5. Inner Mongolia 6. Liaoning 7. Jilin 8. Heilongjiang 9. Shanghai 10. Jiangsu 11. Zhejiang 12. Anhui 13. Fujian 14. Jiangxi 15. Shandong 16. Henan 17. Hubei 18. Hunan 19. Guangdong 20. Guangxi 21. Hainan 22. Chongqing 23. Sichuan 24.Guizhou 25. Yunnan 26. Shaanxi 27. Gansu 28. Ningxia 29. Qinghai 30. Xinjiang; [b]: AVG represents the arithmetic average of *STE* in 30 provinces from 2007–2016.

We can see dramatic changes in the *STE* values of the 30 provinces. For example, the highest average *STE* is in Shanghai (1.16) and is 6.44 times the lowest, which is Yunnan (0.18). The changing trend of the *STE* value of each province is also quite different during 2007–2016. The 30 provinces can be divided into four groups based on the average level of *STE* from 2007 to 2016. The groups correspond to four different *STE* intervals (as shown in Figure 2): (1) high efficiency ($0.9 < \mathrm{AVG}_{STE} \leq 1.16$), indicates that the province's sustainable transport is in a good state of development and ranks as the country's leading position; (2) medium–high efficiency ($0.58 < AVG_{STE} \leq 0.9$), indicates that the province is higher than the national average; (3) medium–low Efficiency ($0.29 < AVG_{STE} \leq 0.58$); and (4) low efficiency ($0 < AVG_{STE} \leq 0.29$), indicates that these provinces are at low levels of sustainable transport development.



(**a**) High efficiency

(**b**) Medium-high efficiency

(**c**) Medium-low efficiency

(**d**) Low efficiency

Figure 2. Changing trend of four groups of *STE* from 2007 to 2016. Note: Province no. 1. Beijing, 2. Tianjin, 3. Hebei, 4. Shanxi, 5. Inner Mongolia, 6. Liaoning, 7. Jilin, 8. Heilongjiang, 9. Shanghai, 10. Jiangsu, 11. Zhejiang, 12. Anhui, 13. Fujian, 14. Jiangxi, 15. Shandong, 16. Henan, 17. Hubei, 18. Hunan, 19. Guangdong, 20. Guangxi, 21. Hainan, 22. Chongqing, 23. Sichuan, 24. Guizhou, 25. Yunnan, 26. Shaanxi, 27. Gansu, 28. Ningxia, 29. Qinghai, 30. Xinjiang.

The provinces of high efficiency (Figure 2a) include Shanghai, Tianjin, Hainan, Ningxia, Hebei, and Guizhou, which show a rising fluctuation trend and the most significant increase in 2016. The *STE* values of Tianjin and Hebei changed the most steadily. In contrast, Hainan, Guizhou, and Qinghai changed much. The *STE* of Hainan fluctuated the most decreasing from 0.77 in 2012 to 0.52 in 2013 and rising to 1.00 in 2014. In general, the sustainable development of transport in these provinces is already at a high level. The provinces of medium–high Efficiency (Figure 2b) are Qinghai, Jiangsu, Shandong, Fujian, Guangdong, Beijing, Gansu, and Inner Mongolia, of which Jiangsu, Guangdong, Beijing, and Inner Mongolia show a trend of rising–falling–rising. While, in Fujian, Qinghai, Shandong, and Gansu, there is a trend of falling–rising. The most obvious performances of the two trends are those of Beijing and Gansu. The *STE* value of Beijing increased from 0.15 in 2007 to 1.01 in 2011, decreased to 0.67 in 2014, then rose to 1.37 in 2016. In Gansu, the *STE* value first fell from 1.03 in 2007 to 0.19 in 2014, and then rose to 1.08. The *STE* fluctuations in the provinces of this group were relatively large and the trends of changes were also quite different during 2007–2016. The provinces of Medium-low Efficiency (Figure 2c) are Zhejiang, Jiangxi, Henan, Liaoning, Anhui, Chongqing, Shanxi, Hunan, Hubei, and Guangxi. The *STE* values of these provinces changed significantly in 2008 and 2015 while the differences were small during the period of the study (2008–2015). Except for the major fluctuations of *STE* that first decreasing then increasing in Jiangxi, Henan and Shanxi, other provinces showed a floating upward trend in the relatively small range of 0.2–0.6. This illustrates that 2008 and 2015 were important turning points in the sustainable development of transport in these provinces. The provinces of Low Efficiency (Figure 2d) are Sichuan, Heilongjiang, Jilin, Shaanxi, Xinjiang, and Yunnan. The *STE* values all show similar characteristics: a steady development trend from 2007 to 2015 and a sharp rise in 2016.

4.2. Difference Analysis for Sustainable Transport Efficiency

Following the analysis of the provincial *STE* results in Section 4.1, we used the *CV* to measure and discuss the differences in *STE* quantitatively, as shown in Figure 3.

In Figure 3, we see that *CVs* of the 30 provinces in 2007–2016 are quite different, indicating that the degree of the *STE* changes are very different. The *CV* of *STE* for Yunnan in Western is 1.64 at the maximum while Hebei in Eastern is at least 0.07, which indicates that Yunnan had the largest difference and Hebei had the smallest difference in 2007–2016. Before 2015, Yunnan was limited by capital investment and the transport organization system was not sound. Yunnan Province had not yet built high-speed rails and nearly half of the province had no railways. However, in 2015, the Yunnan Provincial Government implemented the "Four Transport" strategy proposed by the state, adding 611 km of highway mileage, 4000 km of total mileage by the end of the year and investing 15 billion yuan in rural areas to build transport infrastructure and improve the quality of transport equipment and services. Therefore, the sustainability of Yunnan's transport has improved much since 2015. This is the main reason why the *STE* in Yunnan Province had a large difference during 2007–2016. In contrast, Hebei Province, through which Beijing, the capital city of China, must connect to various provinces, has relatively complete transport networks (metro, light rail, magnetic levitation and tram lines). Therefore, the development of sustainable transport in this province is relatively stable.

According to the economic growth of different regions, the National Bureau of Statistics divides China into the eastern region (Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, and Hainan), central region (Shanxi, Anhui, Henan, Hubei, Hunan, and Jiangxi), western region (Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Ningxia, Qinghai, Xinjiang, and Inner Mongolia), and northeastern region (Liaoning, Jilin, and Heilongjiang), as shown in Figure 4. To explore the distribution characteristics of *STE* in the above four regions, we further calculated the regional *STE* with the mean value of *STE* in the regions (see Figure 5), compared the trends of *STE* in the four regions during 2007–2016 (see Figure 6) and used *CV* to explore the σ-convergence for the differences of the four regions (see Figure 7).

As can be seen from Figure 5, the regional *STE* values are 0.86, 0.42, 0.51, and 0.30 for the eastern, central, western, and northeastern regions, respectively. The size of the *STE* values follows the order of eastern > western > central > northeastern. In general, the *STE* value of the eastern region has the greatest difference with that of northeastern China. The average *STE* of the former is 0.86, which is 2.8 times the latter's value of 0.30. In the eastern region, the provinces with high *STE*s include Shanghai, Tianjin, Hebei, and Hainan. The governments of these provinces proposed the "12th Five-Year Plan (2009–2014)" in 2009 with the transport sector as one of the significant programs. The Eastern Region built modern transport modes, such as high-speed railways and light rails, which kept ahead in carrying out transport management reforms to promote the modernization of transport. Nevertheless, the *STE* values in the central and western regions were extremely low at 0.42 and 0.53, respectively. The permanent resident population of the central and western regions are smaller than that of the eastern region, so the demand for transport in those regions are also significantly smaller, resulting in the insignificant social benefits of their transport sectors. In addition, due to the implementation of the "Rise of Central China" and "Western Development" strategies, the central and western regions are all in an accelerated development stage. The economic benefits of the transport sector were paid more attention but the environmental damage was neglected, resulting in the relatively low STE in the two regions. In addition, the development of sustainable transport in the northeast is the most backward, with an efficiency value of only 0.3. The main reason is that the development of various transport is lagging behind except for railways in the northeast. From the perspective of the interior of each region, the largest difference in *STE*s is in the western region with a difference of 0.82, as compared with the northeastern, which has the smallest difference of only 0.19. As far as the western region is concerned, Ningxia has an *STE* value of 1.0 and Yunnan has a value of 0.18. These two provinces are responsible for the large differences in the western region. In contrast, the *STE* values of Liaoning, Jilin, and Heilongjiang in the northeastern region are 0.43, 0.24, and 0.24, respectively. The *STE* difference among these three provinces is relatively small.

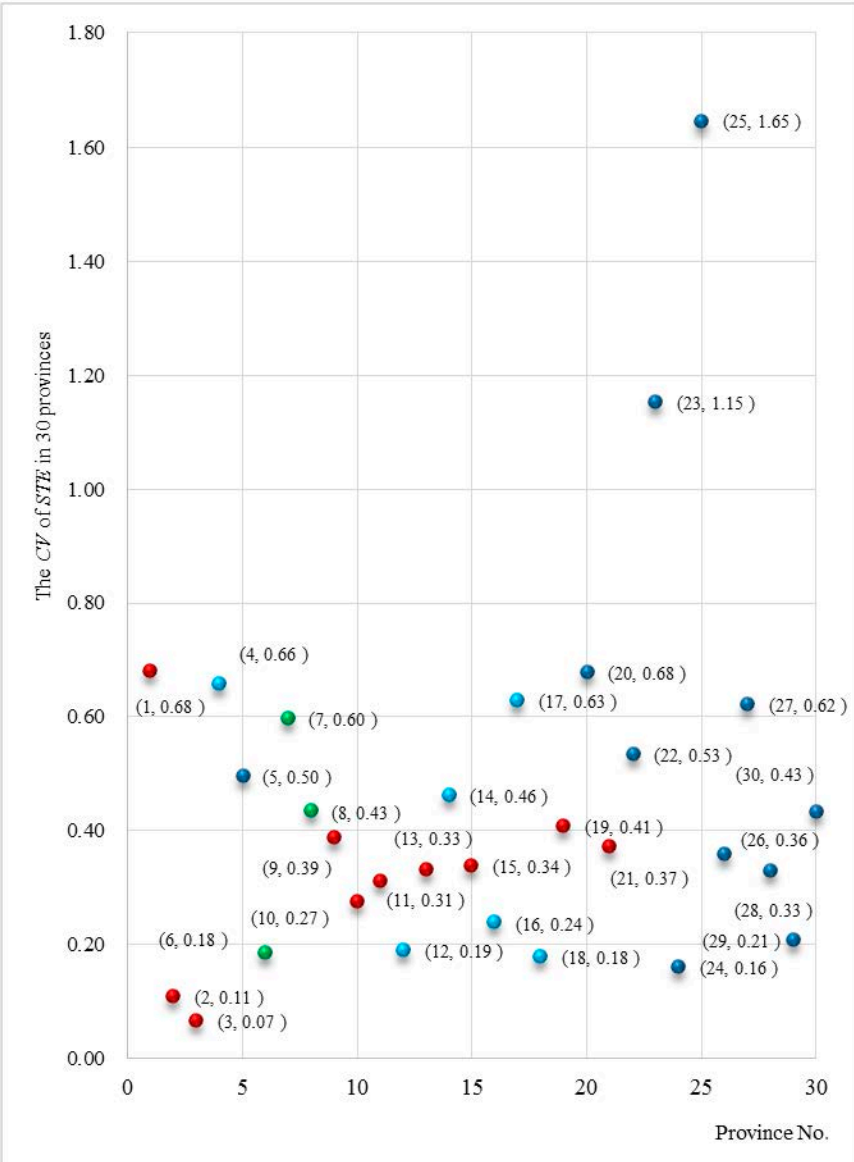


Figure 3. *STE* difference results of 30 provinces. Note: (number, number) represents (province no., CV). Province no. 1. Beijing, 2. Tianjin, 3. Hebei, 4. Shanxi, 5. Inner Mongolia, 6. Liaoning, 7. Jilin, 8. Heilongjiang, 9. Shanghai, 10. Jiangsu, 11. Zhejiang, 12. Anhui, 13. Fujian, 14. Jiangxi, 15. Shandong, 16. Henan, 17. Hubei, 18. Hunan, 19. Guangdong, 20. Guangxi, 21. Hainan, 22. Chongqing, 23. Sichuan, 24.Guizhou, 25. Yunnan, 26. Shaanxi, 27. Gansu, 28. Ningxia, 29. Qinghai, 30. Xinjiang. represent the eastern, central, western, and northeast regions, respectively.

Figure 4. Four regional divisions of mainland China. Note: Province no. 1. Beijing, 2. Tianjin, 3. Hebei, 4. Shanxi, 5. Inner Mongolia, 6. Liaoning, 7. Jilin, 8. Heilongjiang, 9. Shanghai, 10. Jiangsu, 11. Zhejiang, 12. Anhui, 13. Fujian, 14. Jiangxi, 15. Shandong, 16. Henan, 17. Hubei, 18. Hunan, 19. Guangdong, 20. Guangxi, 21. Hainan, 22. Chongqing, 23. Sichuan, 24.Guizhou, 25. Yunnan, 26. Shaanxi, 27. Gansu, 28. Ningxia, 29. Qinghai, 30. Xinjiang.

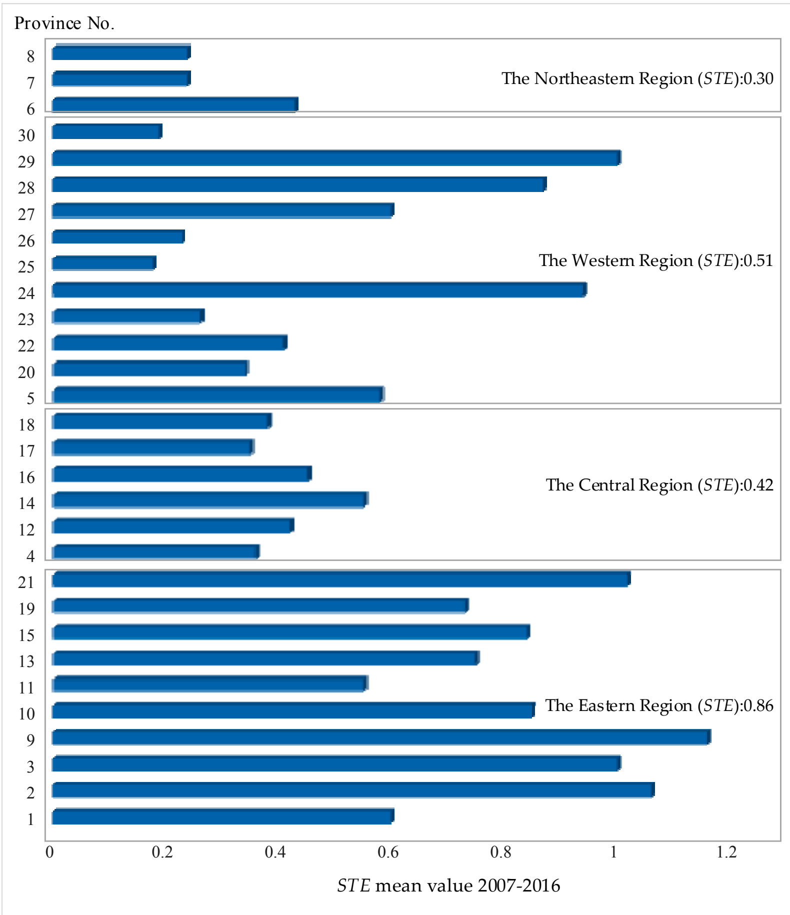


Figure 5. Overall *STE* in China. Note: Province no. 1. Beijing, 2. Tianjin, 3. Hebei, 4. Shanxi, 5. Inner Mongolia, 6. Liaoning, 7. Jilin, 8. Heilongjiang, 9. Shanghai, 10. Jiangsu, 11. Zhejiang, 12. Anhui, 13. Fujian, 14. Jiangxi, 15. Shandong, 16. Henan, 17. Hubei, 18. Hunan, 19. Guangdong, 20. Guangxi, 21. Hainan, 22. Chongqing, 23. Sichuan, 24.Guizhou, 25. Yunnan, 26. Shaanxi, 27. Gansu, 28. Ningxia, 29. Qinghai, 30. Xinjiang.

In Figure 6, from the national point of view, we can see that the *STE* values during 2007–2016 show a 'U' trend (falling and rising) and reached the peak in 2016. The *STE* value was floating at 0.40–0.62 in 2007–2015. The downward trend in 2008–2010 was the most obvious with a drop of 29.09% and increased slightly in 2010, and then there was a gradually rising trend with an increase of 69.5% to 0.99 in 2016. In 2008, affected by the economic crisis, China's economic growth gradually slowed down and the transport sector was no exception. Due to the economic recession, investments in the transport sector were cut, and residents' travel demands dropped sharply. As a result, the revenues of the transport sector, as well as the economy and social sustainability of transport were reduced. In 2010, the Chinese government took more than 20% of the annual funds invested in the transport sector to develop an integrated transport system, spurring technological innovations in transport and improving a road network management system. These investments greatly improved the accessibility, energy efficiency, and safety of transport, which slightly increased the level of sustainable transport in China after 2010. Afterwards, in 2015, under the guidance of the national 'supply-side reforms' (a policy to solve the problems of oversupply and undersupply), China's transport sector gradually made technological innovations to develop intelligent transport and transport quality supervision, as well as increase the construction of safe transport and create new energy-saving and emission-reduction technologies. These measures have significantly promoted the levels of transport sustainability in many provinces in China. From the perspective of regional change, the *STEs* in the eastern region were obviously higher than those in the central, western, and northeastern regions, presenting an upward 'S' trend that was different from that of the whole country in 2007–2016, especially in 2016, which had the most significant increase of 39%. Therefore, sustainable transport development in the eastern region can serve as a model for other regions. The changes in the *STE* values in the central, western, and northeastern regions during 2007–2016 were very similar and showed declines in 2007–2010. For example, in 2009, the *STE*s in the three regions decreased by 34.5, 24.1, and 14.8%, respectively. The changes during 2010–2015 were relatively stable and in slight fluctuation. During this period, the three regions fluctuated around 0.35, 0.45, and 0.30, respectively, but exhibited dramatic growth in 2015–2016 with the western region being the most prominent.

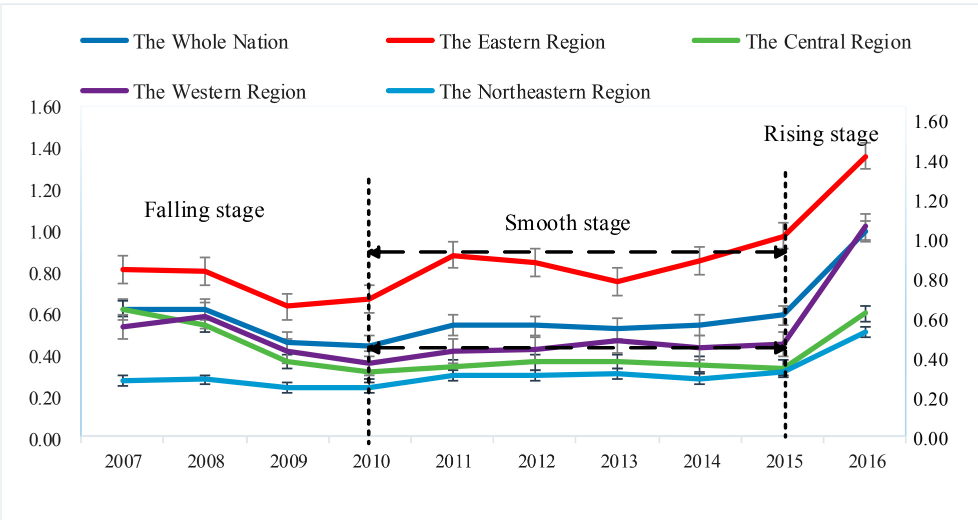


Figure 6. The trend of *STE* in four regions in China from 2007 to 2016.

To explore the trend of changes in the four regions of *STE* more detail, we used the *CV* to measure the differences in the four regions of *STE* and analyzed the changing trends of the regional difference in the four regions and the whole nation during 2007–2016, as shown in Figure 7.

Figure 7 shows the difference degree of *STE* in the regional *STE* in the four regions and the whole nation. On a national scale, the difference in *STE* went through the following stages. In 2007–2008, the *CV* of *STE* in 2008 was lower than in 2007 and there was a σ-convergence. There were diverging trends from 2009 to 2011 and 2012 to 2015. Therefore, the σ-convergences occurred during 2011 to 2012 and 2015 to 2016. These were local but not global σ-convergences. We can also see that the changes in the *CVs* of the eastern and central regions are roughly the opposite of those in the western and northeast regions in 2015–2016. The trends of changes in the western and northeast regions were basically the same as the national trend, but the *CVs* of the eastern and central regions have been diverging since 2015.

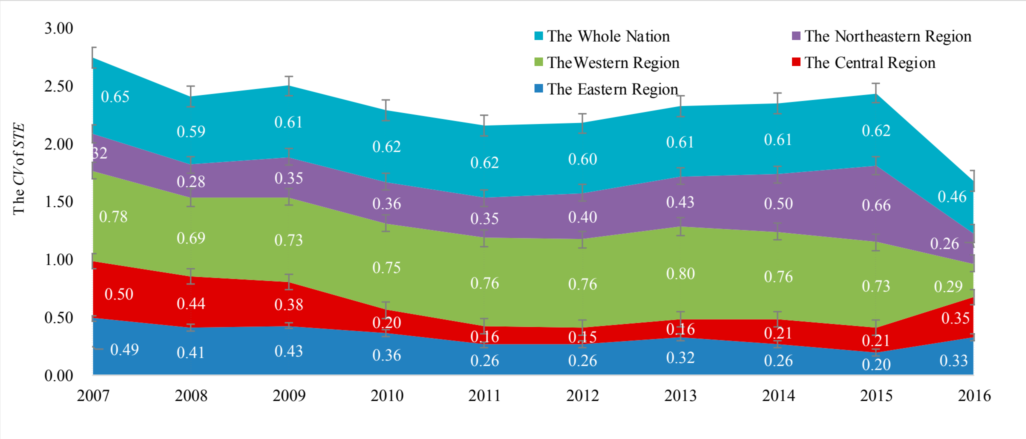


Figure 7. Changes in *STE* difference of the four regions from 2007 to 2016.

4.3. Spatial Aggregation Analysis of Sustainable Transport Efficiency

To further examine whether the provincial *STE* was related to the surrounding provinces, a spatial autocorrelation analysis was conducted on the *STE* from 2007 to 2016. The global Moran's *I* was calculated using Geoda software (Spatial Analysis Laboratory Department of Geography, University of Illinois, Illinois, USA) (see Table 7 and Figure 8). Furthermore, to explore the changes of spatial aggregation of *STE* over time, we choose the four years (2007, 2010, 2013, and 2016) with the same time span to illustrate the spatial aggregation evolution of *STEs* during the whole period. In addition, the values of *STEs* in the four years are very typical. Therefore, we further investigate the local spatial correlation of *STE* in each province by using Moran scatter plots (see Table 8 and Figure 9) and LISA plots for the four years (see Figure 10).

From Table 7 and Figure 8, we can see that in terms of the average *STE* status from 2007 to 2016, the Moran's *I* was 0.172 and passed the 99% significant level test, indicating significantly positive spatial autocorrelation. From the perspective of each year, the global Moran's *I* value of *STE* was more than zero in 2009–2016 and passed the significance test in most years, which means that there was an obvious positive spatial aggregation effect due to the sustainable development of provincial transport. Combined with the trend line of the Moran's *I* from 2007 to 2016, the Moran's *I* of *STE* declined in 2016 but showed an increasing fluctuating trend in 2007–2016. This signifies that the development of provincial sustainable transport is increasingly affected by the surrounding provinces.

Table 7. Global Moran indices for *STE*, 2007–2016

Year	I (*STE*)	E (I)	Z-Value
2007	−0.023	−0.033	0.223
2008	−0.013	−0.033	0.294
2009	0.002	−0.033	0.468
2010	0.138	−0.033	1.959 **
2011	0.341	−0.033	2.931 ***
2012	0.192	−0.033	2.612 ***
2013	0.111	−0.033	1.672 *
2014	0.135	−0.033	1.861 *
2015	0.254	−0.033	2.869 ***
2016	0.071	−0.033	1.317
STE-Avg	0.172	−0.033	2.155 **

Note: * indicates that *STE* has a spatial autocorrelation at a 90% confidence level. ** indicates that *STE* has a spatial autocorrelation at a 95% confidence level. *** indicates that *STE* has spatial autocorrelation at a 99% confidence level. *STE*-Avg: the global Moran's *I* value of the *STE* average for 2007–2016.

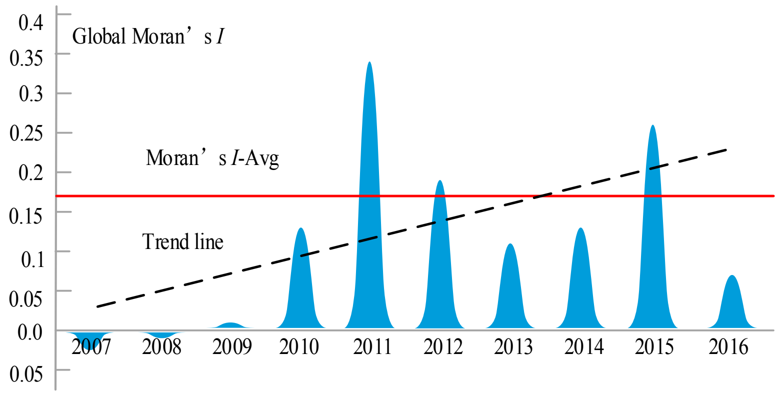


Figure 8. Global Moran's *I*, 2007–2016.

The Moran scatter plot is divided into four quadrants (see Figure 9). The first quadrant (high–high aggregation) indicates that the province's *STE* value and surrounding provincial *STE* values are higher than the national average *STE*. The second quadrant (low–high aggregation) indicates that the *STE* value of the province is lower than the national average *STE* while the *STE* values of the surrounding provinces are higher. The third quadrant (low–low aggregation) indicates the *STE* values of the province and the surrounding provinces are lower than the national average *STE*. The fourth quadrant (high–low aggregation) indicates that the province's *STE* value is higher than the national average *STE* while the surrounding provinces' *STE* values are lower. For the first and third quadrants, the *STE* value of a province and those of its neighbors have positive spatial autocorrelations, whereas the provinces in the second and fourth quadrants have negative spatial autocorrelations. Figure 9 and Table 8 show that the total number of provinces of high–low and low–low aggregation is much larger than two other types of aggregation, with the latter being the most, which means that *STE* has a significant spatial positive correlation, especially those provinces with low *STE* values.

Table 8 shows that the provinces of the *STE* high–high aggregation are mainly distributed in the eastern region in 2007, 2010, 2013, and 2016. The residents of this region have generated large volumes of passenger traffic and freight, which increase the social benefits of transport. In addition, there is a modern and intelligent transport network with wide coverage, which has resulted in lower *TCE*, *LUT*, and *IPE*. These factors have given relatively high levels to the *STE* values of the eastern provinces. The provinces of low–low aggregation are mostly in the central and western regions for the following reasons. On the one hand, the geological conditions are complex and natural disasters occur frequently, so more investments are required to achieve the same output. On the other hand, the technical level of these areas is relatively backward. Under the same inputs, compared with the eastern region, the transport sector has less added value but more consumption and emissions. Those *STE* values represented by the low–high and high–low aggregations indicate that the *STE* values of these provinces are clearly inconsistent with those of the surrounding provinces and are randomly distributed in space.

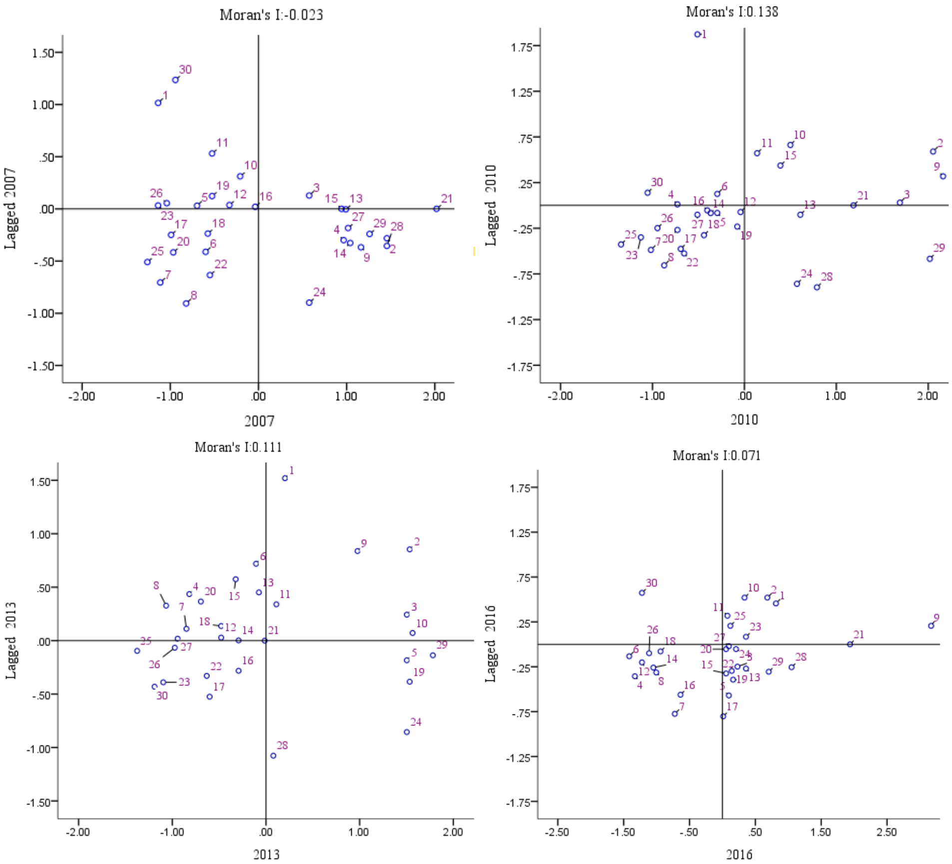


Figure 9. Moran scatter plot of *STE*. Note: Province no. 1. Beijing, 2. Tianjin, 3. Hebei, 4. Shanxi, 5. Inner Mongolia, 6. Liaoning, 7. Jilin, 8. Heilongjiang, 9. Shanghai, 10. Jiangsu, 11. Zhejiang, 12. Anhui, 13. Fujian, 14. Jiangxi, 15. Shandong, 16. Henan, 17. Hubei, 18. Hunan, 19. Guangdong, 20. Guangxi, 21. Hainan, 22. Chongqing, 23. Sichuan, 24.Guizhou, 25. Yunnan, 26. Shaanxi, 27. Gansu, 28. Ningxia, 29. Qinghai, 30. Xinjiang.

Table 8. Moran scatter plot statistics for provinces

Year	Aggregation Characteristics			
	High–High Aggregation	Low–Low Aggregation	Low–High Aggregation	High–Low Aggregation
2007	3, 13, 15	7, 18, 17, 22, 23, 25, 6, 8, 20	1, 12, 10, 11, 6, 19, 26, 30, 5	27, 4, 9, 14, 24, 29, 28, 2
2010	2, 3, 9, 11, 10, 15	5, 7, 8, 14, 17, 20, 22, 23, 25, 26, 27, 30	1, 4,6, 16	12, 13, 19, 24, 29, 28
2013	2, 3, 9, 10, 11, 1	16, 4, 17, 22, 23, 25, 9, 30	6, 15, 13, 8, 27, 24, 7, 12, 18, 14, 20	19, 24, 29, 28, 5
2016	2, 1, 9, 10. 11, 24, 27	6, 12, 14, 8, 26, 30, 7, 16	18, 26	20, 3, 23, 13, 28, 29, 17, 5, 25, 15, 22
Sum	22	37	26	30

Note: Province no. 1. Beijing, 2. Tianjin, 3. Hebei, 4. Shanxi, 5. Inner Mongolia, 6. Liaoning, 7. Jilin, 8. Heilongjiang, 9. Shanghai, 10. Jiangsu, 11. Zhejiang, 12. Anhui, 13. Fujian, 14. Jiangxi, 15. Shandong, 16. Henan, 17. Hubei, 18. Hunan, 19. Guangdong, 20. Guangxi, 21. Hainan, 22. Chongqing, 23. Sichuan, 24.Guizhou, 25. Yunnan, 26. Shaanxi, 27. Gansu, 28. Ningxia, 29. Qinghai, 30. Xinjiang.

The LISA (local index spatial autocorrelation) map is a reflection of the spatial correlation between the *STE* of local sites *i* and surrounding provinces. LISA is not only a way of exploring the local spatial aggregation types of *STE* but also an important indicator for judging whether a spatial aggregation is significant, as shown in Figure 10.

Figure 10 presents the LISA plots of different local spatial aggregations, especially the high–low aggregation of different years. Guizhou showed a spatial aggregation type of high–low in 2007, 2010, and 2013. Qinghai showed a significant high–low aggregation in 2010 and 2013. Inner Mongolia and Hubei showed significant performance in 2016. These provinces had high development levels of sustainable transport but did not promote the progress of sustainable transport in the surrounding provinces or achieve coordinated development with them. In 2007 and 2010, Beijing had a spatial aggregation of low–high but high–high in 2013, which means that under the influence of the sustainable development of transport in the surrounding provinces, the province's *STE* gradually exceeded the national average and the *STE* values of the surrounding provinces. In 2010, Jiangsu showed high–high aggregation, but its performance was not significant in other years. Thereafter, the *STE* values of the province and its surrounding provinces were all at a relatively high level. However, with the decrease of the *STE* value in Jiangsu, this type of aggregation has gradually become insignificant. During the four years depicted in Figure 10, the number of provinces with low–low aggregation was the fewest, of which Xinjiang performed significantly in 2010 and its *STE* value was significantly lower than the national average and the surrounding provinces in 2010.

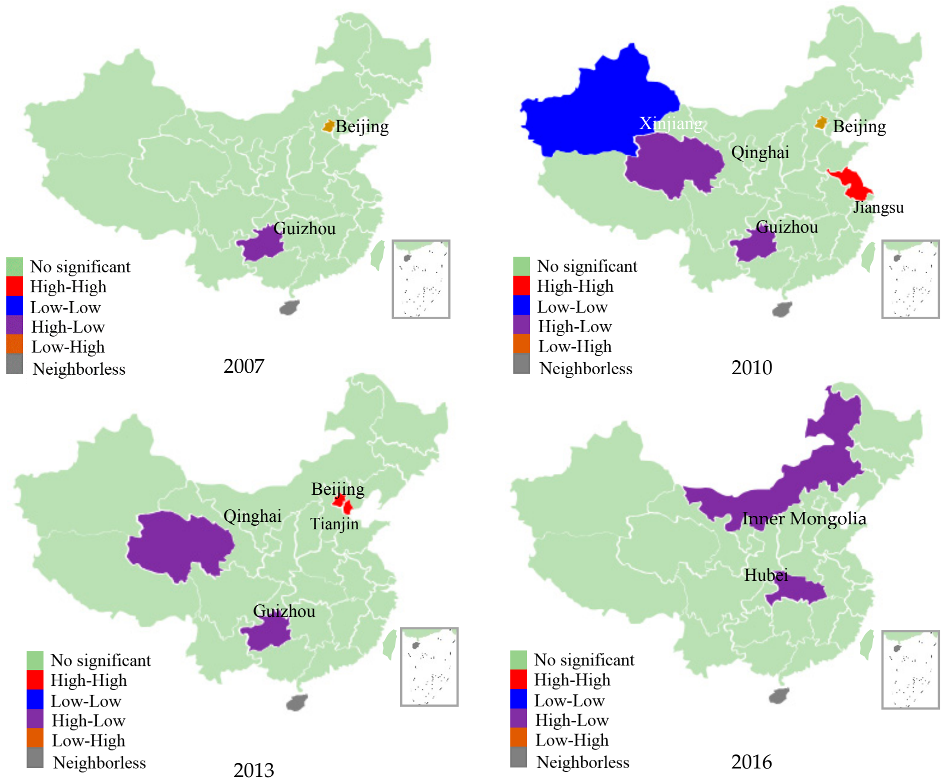


Figure 10. LISA map of *STE*.

4.4. Equity Analysis of Sustainable Transport Efficiency

After the analysis of the STE results (in Section 4.1) and the efficiency difference (in Section 4.2), we obtained the GC (STE) for each year using the STE of each province during 2007–2016 as shown in Table 9, which shows the equity of the development process of STE during 2007–2016.

In Table 9, the *GC* basically remained at a relatively stable level (with a small range of fluctuations around 0.34) from 2007 to 2015, indicating that the *STE* equity in the provinces of China had not changed much in these nine years, i.e., *GC* was between 0.3–0.4 before 2015. However, in 2016, the *GC* quickly decreased to 0.24, which is a drop of 31.4%. The rapid decrease in the inequity of the provincial *STEs* shows that the *STE* in each province tends to have more equity in 2016. Moreover, we find that this result is consistent with the rapid decrease in the *CV* of the national *STE* in 2016, as shown in Figure 7. The main reason for this phenomenon is China's implementation of an unbalanced development strategy in the early years of reform and liberalization. The eastern provinces experienced rapid economic growth through the establishment of special economic zones, economic and technological development zones, and coastal open cities. These changes placed higher requirements on the transport sector to improve transport capacity, service levels, as well as meeting the circulation of people and freight. Thus, the development of transport in the eastern provinces surged ahead of those in other regions. In addition, various production factors were affected by the market economy, shifting to the eastern areas that had high investment returns. As a result, the sustainable development of transport is in a state of more inequity in China. Subsequently, the "Regional Transport Balanced Development New Pattern" project was implemented in 2016 in various provinces of China to establish a long-term mechanism for transport infrastructure investment in the central and western regions. In addition, the Chinese government planned to expand the accessibility and transport services coverage, as well as provided shuttle buses in rural areas for the convenience of the rural resident. The state has vigorously carried out the construction of passenger and freight systems, promoted the standardization of delivery vehicles and transfer equipment, and developed multimodal transport to make transport more efficient. These measures improved the equity and reduced the differences in sustainable transport development in 2016.

Table 9. *STE* equity during 2007–2016 in China

Index	**Changing of *STE* Equity in 2007–2016**									
	2007	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
GC (*STE*)	0.37	0.33	0.34	0.34	0.34	0.33	0.33	0.34	0.35	0.24

5. Conclusions

This study adopted a new model of the US-SBM-DEA to measure the *STE* values of 30 provinces in China during the period of 2007–2016. *GC* and *CV* were first used to analyze the sustainable transport development, and the Moran's *I* was used to explore the spatial correlations of sustainable transport efficiency.

There are large differences in the *STE* values of the 30 provinces in China. The provinces were classed into four groups according to the sizes of their *STE* values: high efficiency, medium–high efficiency, medium–low efficiency, and low efficiency. The trends of these groups of *STE* are also very different. High efficiency shows a rising fluctuation trend. Medium–high efficiency is rising–falling–rising and falling–rising. Medium-low efficiency had small fluctuations during the middle period and large fluctuations in 2007 and 2016, and low efficiency was stable before 2015 but rose sharply in 2016.

There are differences in each province itself and in the whole region. From the provincial perspective, there are large differences in the *STE* values of the provinces. Yunnan had the largest difference and Hebei had the smallest in the past 10 years. From the regional perspective, the magnitudes of the *STE* values of the regions can be ranked as eastern > western > central > northeastern region during 2007–2016. During the study period, the *STE* had an 'S' upward trend in the eastern region and a similar trend of development such as falling–rising in the central, western, and northeastern regions, i.e., *STE* fell in 2007–2010, became stable in 2010–2015 then dramatically rose in 2015–2016. The differences in the development of sustainable transport in the four regions have local σ-convergences but no global σ-convergence.

The development of sustainable transport in one province has a strong relationship with the surrounding provinces. The local spatial aggregation characteristics were also very different among the provinces and had different distribution laws in 2007, 2010, 2013, and 2016. The provinces with high–low and low–low aggregations had the most significant performances. The provinces of high–high aggregation are mostly located in the eastern region while those of low–low aggregation are mainly distributed in the central and western regions during the study period. The inequitable development of sustainable transport had been reduced sharply in 2016.

This study focused on the level of development of sustainable transport and explored the development laws from the perspective of the provinces and regions, as well as the spatial aggregation of sustainable transport efficiency. We aimed to support the formulation of relevant policies and regulations by the relevant departments. For future research, we will integrate the intelligent and sharing transport into a sustainable indices system to provide new theoretical support for sustainable transport development. Due to limited data, the equity in the development of sustainable transport has been covered only up to 2016. We will pay more attention to the development of sustainable transport and put forward efficient measures to improve the equity of transport and shorten the differences of the *STEs* among China's provinces.

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References

1. United Nations U N. *Transforming Our World: The 2030 Agenda for Sustainable Development*; Working Papers; UN Member States: New York, NY, USA, 2015; pp. 1–29.
2. Sakib, N.; Appiotti, F.; Magni, F.; Maragno, D.; Innocenti, A.; Gissi, E.; Musco, F. Addressing the Passenger Transport and Accessibility Enablers for Sustainable Development. *Sustainability* **2018**, *10*, 903. [CrossRef]
3. Zhang, L.; Wei, Y.Y. The Definition and Connotation of the Sustainable Urban Transport. In *Applied Mechanics & Materials*; Trans Tech Publications: Zürich, Switzerland, 2013; pp. 253–255.
4. Boltze, M.; Tuan, V.A. Approaches to Achieve Sustainability in Traffic Management. *Procedia Eng.* **2016**, *142*, 204–211. [CrossRef]
5. Mundial, B. Sustainable Transport: Priorities for Policy Reform. In *Development in Practice*; World Bank: Washington, DC, USA, 1996; pp. 1–131.
6. Cheba, K.; Saniuk, S. Sustainable Urban Transport—The Concept of Measurement in the Field of City Logistics. *Transp. Res. Procedia* **2016**, *16*, 35–45. [CrossRef]
7. Holden, E.; Linnerud, K.; Banister, D. Sustainable passenger transport: Back to Brundtland. *Transp. Res. Part A* **2013**, *54*, 67–77. [CrossRef]
8. Ercan, T.; Kucukvar, M.; Tatari, O.; Al-Deek, H. Congestion Relief Based on Intelligent Transportation Systems in Florida: Analysis of Triple Bottom Line Sustainability Impact. *Transp. Res. Rec.* **2013**, *2380*, 81–89. [CrossRef]
9. Zhang, X.; Zhang, H.M.; Li, L. Analysis of User Equilibrium Traffic Patterns on Bottlenecks with Time-Varying Capacities and their Applications. *Int. J. Sustain. Transp.* **2010**, *4*, 56–74. [CrossRef]
10. Hadiwardoyo, S.P. Impact of traffic composition on accessibility as indicator of transport sustainability. In Proceedings of the IOP Conference Series: Earth and Environmental Science 2017, Krakow, Poland, 20–22 November 2017; IOP Conference Series: Earth and Environmental Science. pp. 12–38.
11. Pojani, D.; Stead, D. Sustainable Urban Transport in the Developing World: Beyond Megacities. *Sustainability* **2015**, *7*, 7784–7805. [CrossRef]
12. Ariffin, R.N.R.; Zahari, R.K. Towards a Sustainable Urban Transport System in the Klang Valley, Malaysia: The Key Challenges. *Procedia Soc. Behav. Sci.* **2013**, *85*, 638–645. [CrossRef]

13. Ardila, A.; Sanchez, A.O. *Sustainable Urban Transport Financing from the Sidewalk to the Subway: Capital, Operations, and Maintenance Financing*; The World Bank: Washington, DC, USA, 2016.
14. Lindholm, M.E.; Blinge, M. Assessing knowledge and awareness of the sustainable urban freight transport among Swedish local authority policy planners. *Transp. Policy* **2014**, *32*, 124–131. [CrossRef]
15. Mugion, R.G.; Toni, M.; Raharjo, H.; Di Pietro, L.; Sebathu, S.P. Does the service quality of urban public transport enhance sustainable mobility? *J. Clean. Prod.* **2018**, *10*, 1566–1587. [CrossRef]
16. Nadi, P.A.; Murad, A. Reviewing the use of Geographic Information System (GIS) to measure Sustainable Urban Transport performance. *J. Geosci. Eng. Environ. Technol.* **2017**, *2*, 171–177. [CrossRef]
17. Havenga, J.H.; Simpson, Z.P. Freight logistics' contribution to sustainability: Systemic measurement facilitates behavioral change. *Transp. Res. Part D Transp. Environ.* **2018**, *58*, 320–331. [CrossRef]
18. Stark, J.; Weiß, C.; Trigui, R.; Franke, T.; Baumann, M.; Jochem, P.; Brethauer, L.; Chlond, B.; Günther, M.; Klementschitz, R.; et al. Electric Vehicles with Range Extenders: Evaluating the Contribution to the Sustainable Development of Metropolitan Regions. *J. Urban Plan. Dev.* **2018**, *144*, 1–11. [CrossRef]
19. Abbas, R.; Thompson, R.G.; Chen, Y. An intelligent disaster decision support system for increasing the sustainability of transport networks. *Nat. Resour. Forum* **2015**, 83–96. [CrossRef]
20. Pauli, G. Sustainable transport: A case study of Rhine navigation. *Nat. Resour. Forum* **2010**, *34*, 236–254. [CrossRef]
21. Li, Y.-F.; Zhou, Y.F. Evaluation Study on Sustainable Development Capacity of Inland Waterway Transport Based on Multilevel Fuzzy Comprehensive Evaluation Method. *Heilongjiang Agric. Sci.* **2010**, *5*, 134–137.
22. Zhou, H.; Hu, H. Sustainability Evaluation of Railways in China Using a Two-Stage Network DEA Model with Undesirable Outputs and Shared Resources. *Sustainability* **2017**, *9*, 150. [CrossRef]
23. Zhang, G.W. Theoretical System of Integrated Transport Development. *J. Transp. Syst. Eng. Inf. Technol.* **2009**, *4*, 1–10.
24. Aigner, D.; Lovell, C.K.; Schmidt, P. Formulation and estimation of Stochastic Frontier Production Function Models. *J. Econometr.* **1977**, *6*, 21–37. [CrossRef]
25. Meeusen, W.; Broeck, J.V.D. Efficiency estimation from Cobb-Douglas production functions with composed error. *Int. Econ. Rev.* **1977**, *18*, 435–444. [CrossRef]
26. Shin, J.S.; Kim, H.J. Efficiency Analysis of Public Service Organizations Using Stochastic Frontier Analysis. *J. Korean Oper. Res. Manag. Sci. Soc.* **2015**, *40*, 117–128. [CrossRef]
27. Sami, J.; Pascal, F.; Younes, B. Public Road Transport Efficiency: A Stochastic Frontier Analysis. *J. Transp. Syst. Eng. Inf. Technol.* **2013**, *13*, 64–71. [CrossRef]
28. Lin, W.; Chen, B.; Pan, L.X.H. Estimating Energy Consumption of Transport Modes in China using DEA. *Sustainability* **2015**, *7*, 4225–4239. [CrossRef]
29. Xu, D.X.; Qing, W.Y.; Hao, W.Z.; Yuanyuan, L.; Chao, L. An Improved Generalized DEA Evaluation Model of Regional Road Traffic Safety. *Transp. Syst. Eng. Inf.* **2016**, *16*, 11–16.
30. Cui, Q.; Li, Y. The evaluation of transportation energy efficiency: An application of three-stage virtual frontier DEA. *Transp. Res. Part D* **2014**, *29*, 1–11. [CrossRef]
31. Sun, L.; Rong, J.; Ren, F.; Yao, L. Evaluation of passenger transfer efficiency of an urban public transportation terminal. In Proceedings of the 2007 IEEE Intelligent Transportation Systems Conference, Seattle, WA, USA, 30 September–3 October 2007; pp. 812–817.
32. Agarwal, S. DEA-neural networks approach to assess the performance of public transport sector of India. *Opsearch* **2016**, *53*, 248–258. [CrossRef]
33. Herrera-Restrepo, O.; Triantis, K.; Trainor, J.; Murray-Tuite, P.; Edara, P. A multi-perspective dynamic network performance efficiency measurement of an evacuation: A dynamic network-DEA approach. *Omega* **2015**, *60*, 45–59. [CrossRef]
34. Yuan, C.; Zhang, S.; Jiao, P.; Wu, D. Temporal and spatial variation and influencing factors research on total factor efficiency for transportation carbon emissions in China. *Resour. Sci.* **2017**, *4*, 687–697.
35. Gai, Z.; Sun, P.; Zhang, J. Cultivated Land Utilization Efficiency and Its Difference with Consideration of Environmental Constraints in Major Grain Producing Area. *Econ. Geogr.* **2017**, *12*, 163–171.
36. Xin, M.A.; Raheel, M.; Xue, T.T.; Wang, J.D. Measurement of China's regional eco-economy input efficiency and its temporal-spatial evolution. *China Popul. Resour. Environ.* **2017**, *3*, 13–21.
37. Cheng, G. *Data Envelopment Analysis: Methods and Max DEA Software*; Intellectual Property Publishing House: Beijing, China, 2014.

38. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *78*, 429–444. [CrossRef]
39. Tobler, W.R. A Computer Movie Simulating Urban Growth in the Detroit Region. *Econ. Geogr.* **1970**, *46*, 234–240. [CrossRef]
40. Moran, P.A. Notes on continuous stochastic phenomena. *Biometrika* **1950**, *37*, 17–23. [CrossRef] [PubMed]
41. Anselin, L. Local Indicators of Spatial Association—LISA. *Geogr. Anal.* **1995**, *27*, 93–115. [CrossRef]
42. Anselin, L. Spatial Processes, Models and Applications. *Economic Geography* **1983**, *59*, 322–325. [CrossRef]
43. Li, Z.; Adamec, D.; Takahashi, T.; Sutherland, S.C. Global autocorrelation scales of the partial pressure of oceanic CO_2. *J. Geophysical Res. Oceans* **2004**, *110*, 1–12. [CrossRef]
44. Wang, W.; Kuang, Y.; Huang, N. Spatial Autocorrelation Analysis on Energy-Related Carbon Emission in Guangdong. *Environ. Sci. Technol.* **2014**, *37*, 180–187.
45. Ma, F.; Wang, W.; Sun, Q.; Liu, F.; Li, D. Ecological pressure of carbon footprint in passenger transport: Spatiotemporal changes and regional disparities. *Sustainability* **2018**, *10*, 1–17.
46. Williams, R.F.; Doessel, D.P. Measuring inequality: Tools and an illustration. *Int. J. Equity Health* **2006**, *5*, 1–8. [CrossRef] [PubMed]
47. Monti, M.G. A Note on the Dagum Decomposition of the Gini Inequality Index. *Soc. Sci. Electron. Publ.* **2007**, *16*, 1–19. [CrossRef]
48. Woo, C.; Chung, Y.; Chun, D.; Seo, H.; Hong, S. The static and dynamic environmental efficiency of renewable energy: A Malmquist index analysis of OECD countries. *Renew. Sustain. Energy Rev.* **2015**, *47*, 367–376. [CrossRef]
49. Cui, Q.; Kuang, H.B.; Wu, C.Y.; Li, Y. The changing trend and influencing factors of energy efficiency: The case of nine countries. *Energy* **2014**, *64*, 1026–1034. [CrossRef]
50. Guo, X.; Zhu, Q.; Lv, L.; Chu, J.; Wu, J. Efficiency evaluation of regional energy saving and emission reduction in China: A modified slacks-based measure approach. *J. Clean. Prod.* **2017**, *140*, 1313–1321. [CrossRef]
51. Wei, Z.; Zhao, P.; Ai, S. Efficiency Evaluation of Beijing Intelligent Traffic Management System Based on super-DEA. *J. Transp. Syst. Eng. Inf. Technol.* **2012**, *12*, 19–23. [CrossRef]
52. Yang, L.; Ouyang, H.; Fang, K.; Ye, L.; Zhang, J. Evaluation of regional environmental efficiencies in China based on super-efficiency-DEA. *Ecol. Indic.* **2015**, *51*, 13–19. [CrossRef]
53. Xu, X.; Cui, Q. Evaluating airline energy efficiency: An integrated approach with Network Epsilon-based Measure and Network Slacks-based Measure. *Energy* **2017**, *122*, 274–286. [CrossRef]
54. Duygun, M.; Prior, D.; Shaban, M.; Tortosa-Ausina, E. Disentangling the European airlines efficiency puzzle: A network data envelopment analysis approach. *Omega* **2016**, *60*, 2–14. [CrossRef]
55. National Bureau of Statistics of the People's Republic of China. Available online: http://www.stats.gov.cn (accessed on 7 December 2017).
56. *China Statistics Yearbook*; National Bureau of Statistics of the People's Republic of China Press: Beijing, China, 2007–2016.
57. Yuan, C.; Zhang, S.; Jiao, P.; Wu, D. Temporal and Spatial Changes of Total Factor Carbon Emission Efficiency and Its Influencing Factors in Chinese Provincial Transportation. *Resour. Sci.* **2017**, *39*, 687–697.
58. *China Energy Statistics Yearbook*; National Bureau of Statistics of the People's Republic of China, Energy Division Press: Beijing, China, 2007–2016.