Research on carbon emission efficiency and spatial-temporal factors in the transportation industry: Evidence from the Yangtze River Economic Belt

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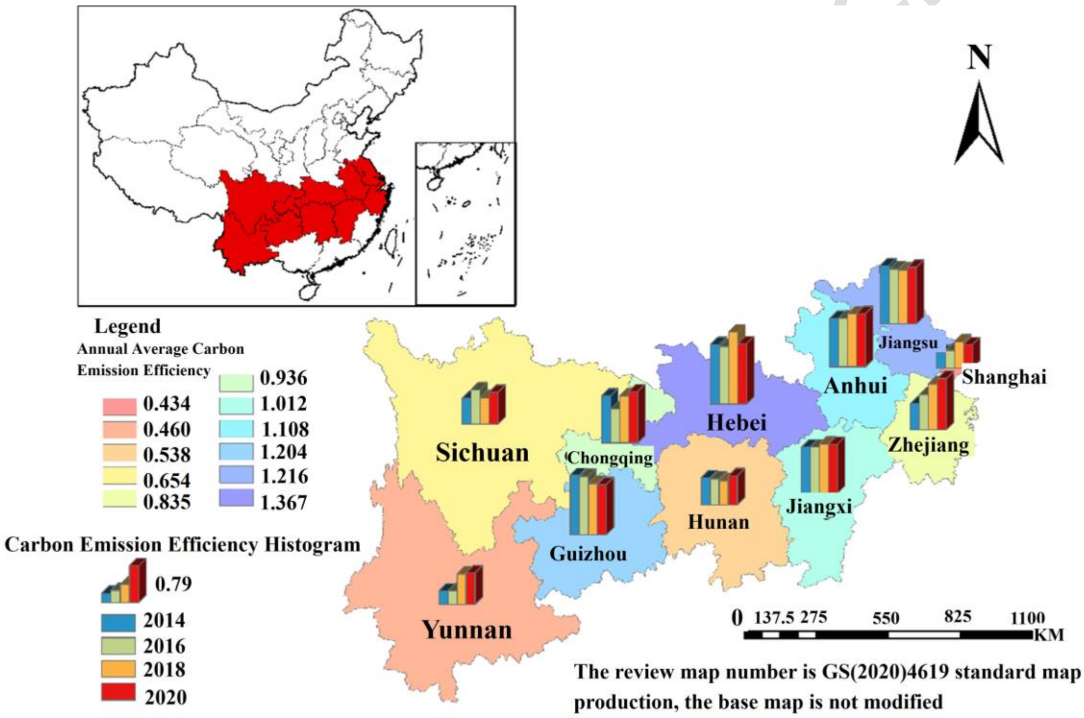
GRAPHICAL ABSTRACT



Abstract: Severe climate problems have forced the Chinese government to put forward the goal of "carbon peak" and "carbon neutrality". The transport sector is a key area for carbon reduction. Based on this background, this paper constructs the Super-SBM model and the Malmquist-Luenberger index model containing the undesirable output. This paper measures the carbon emission efficiency of transport industry in China's Yangtze River Economic Belt from static and dynamic perspectives during 2014-2020. Finally, the GTWR model is constructed to analyze the factors affecting carbon emission efficiency. The results show that: (1) the carbon emission efficiency of provinces in the Yangtze River Economic Belt is characterized by heterogeneity. Hubei was the highest, while Shanghai, Hunan, Sichuan and Yunnan were below average. (2) According to the Malmquist-Luenberger index analysis, the transportation carbon emission efficiency of the Yangtze River Economic Belt has a downward trend. Over the 2014-2020 period, carbon efficiency will decline by an average of 7% per year. (3) Energy consumption structure, industrial upgrading, economic development and population agglomeration have significant effects on carbon emission efficiency.

Keywords: Transportation industry; Carbon emission efficiency; Super-SBM model; Malmquist-Luenberger Index; GTWR model

1. Introduction

Environmental pollution, resource waste, climate change and other issues threaten human survival. The increasing emission of carbon dioxide has led to increasingly serious ecological imbalances. In order to deal with the crisis, the United States, the European Union and other developed countries have introduced a series ofcarbon emission reductionPolicy. The Chinese government also attaches great importance to this work. In 2020, the Chinese government clearly proposed the "dual carbon goal" of "carbon peak in 2030 and carbon neutrality in 2060". The traditional high-energy consumption model of China's economy has led to serious air pollution problems. The transportation industry is one of the main sources of carbon emissions, accounting for about 11% of the country's total. The transportation sector has a large growth rate and a large emission volume of carbon emissions (Zhou, 2014; Tian et al., 2019).

The Yangtze River Economic Belt is a key area of China's regional economy and has made significant contributions to the country's economic growth. In recent years, with the rapid economic development of the Yangtze River Economic Belt, its transportation network has also been increasingly improved (Li et al., 2018), and energy consumption has grown simultaneously (Jiang et al., 2020). Therefore, studying the transportation carbon emissions problem in the Yangtze River Economic Belt has important practical significance. This article will take carbon emission efficiency as the entry point, and through empirical analysis, Analyze carbon emission reductionfeasible strategies.

A certain amount of research has been conducted on carbon emission efficiency at home and abroad. Carbon emission efficiency refers to the economic benefits brought by carbon emissions from various productivity factors that are input into production activities during a certain period of time (Zhou and Hong, 2018). Research methods mainly include static and dynamic measures. In terms of static measures, Teng (2020) et al. constructed a SBM model. Lin et al. (2020) modified the SBM-DEA method. Ma and Dong (2020) used the super-efficiency SBM to compare the differences in carbon emission efficiency among different regions in China.Li et al. (2019)

analyzed theprovincial carbon emissionsThe temporal and spatial characteristics of efficiency. In terms of dynamic efficiency, the Malmquist model is the most widely used. Guo et al. (2020) constructed a DEA-Malmquist indexThe model measures the carbon emission index. Wang (2019) used this model to compare the efficiency differences between different provinces. In addition, some scholars comprehensively used two methods to measure carbon emissions (Hu et al., 2020; Ding and Han, 2022; Shao and Wang, 2020). In recent years, the issue of transportation carbon emissions has attracted attention. Yuan and Lu (2017) used super-SBM to measure the carbon emission efficiency of transportation in the eastern region and made suggestions for emission reduction; Yan et al. (2017) used the CMML model to measure carbon emission efficiency and its decomposition. Hua et al. (2019) used the GML index to dynamically analyze carbon emission efficiency based on panel data from 2005 to 2016.

In addition, some scholars also attach importance to the factors affecting carbon emissions (Li et al., 2021; Lu et al., 2022). The intensity of carbon emissions is mainly affected by the STIRPAT theory. Ding and LU (2020) considered the impact of population, technology, trade freedom, industry proportion, and other factors on residents' energy consumption and carbon emissions based on the STIRPAT theoretical model. Chen and Wu (2021) analyzed the impact of industrial carbon emissions. Energy intensity (Jiang et al., 2022; Li et al., 2017), energy structure (Li and Liu, 2022; Hu and Fang, 2018) are key factors affecting carbon emission efficiency. In existing studies, index decomposition methods such as LMDI are commonly used to study thecovering the provinceAt multiple levels, such as regions (Liu et al., 2021; Liu and Li, 2022), economic zones (Zhang and Su, 2020), or the whole country (Huang and Chang, 2019). In addition, the application of structural decomposition analysis (SAD) is also widespread. For example, Bo and Xuan (2016) used SAD to explore the four main influencing factors of carbon intensity in the food industry. Zhang Cong et al. (2022) used SAD to explore the impact of energy structure effects. When analyzing the factors affecting regional carbon emissions, traditional econometric regression models assume that variables have "co-directional properties" by default, ignoring the temporal and spatial differences in model parameters. Therefore, incorporating temporal and spatial factors into the analysis has become an emerging frontier direction.

The above research provides a foundation for the measurement and analysis of carbon emissions. The main method for measuring carbon emission efficiency is non-parametric modeling, while there are many econometric analysis models for exploring influencing factors. However, there are still some shortcomings in the above research. First, there are not many studies on the analysis of transportation carbon emission efficiency, most of which focus on traditional industrial fields. Second, there are many studies using a single method to analyze efficiency measures or influencing factors. Third, there are not enough achievements based on the new context of the "dual carbon" goal. Therefore, the uniqueness of this study is as follows: (1) Considering the new context of the "dual carbon" goal, analyzing the transportation carbon emission problem in the Yangtze River Economic Belt is innovative. Using the latest panel data to conduct empirical analysis is targeted. (2) In terms of efficiency measurement, a static and dynamic comprehensive analysis model is constructed to improve the depth of research. (3) The GTWR model considering spatial characteristics is introduced to consider the impact of spatial geographical factors on transportation carbon emission efficiency.

2. Materials and Methods

2.1 Construction of a static efficiency model for transportation carbon emissions

According to the mainstream research method, the DEA model is introduced to measure the efficiency of transportation carbon emissions. This model has the advantage of unbiased estimation and can be used to analyze the causes and extent of low efficiency caused by redundant inputs or insufficient outputs in decision-making units, providing information for decision-makers (Luo, 2015). The DEA method was first proposed by the famous operations research scientists Chames, Cooper, and Rod in 1978 and is an important non-parametric method for evaluating productivity (Gong et al., 2017).

The SBM model is a commonly used method in DEA models. The SBM model is a non-angular, non-radial measure of slack variables by Tone (2001). Compared to traditional CCR and BCC models, SBM directly adds slack vectors to the objective function. To solve the problem of comparing effective results, Tone (2002) proposed the Super-SBM model. Therefore, in terms of static efficiency measurement, the article will construct a Super-SBM model for undesirable outputs. The specific method is as follows:

Suppose that the number of decision-making units is n, and the inputs are m, expected output is r_1 and non-expected outputs is r_2 composed of three elements. The vector forms are represented as follows: $x \in R^m, y^d \in R^{r_1}, y^n \in R^{r_2}$; x, Y^d, Y^n represents the coefficient matrix. Among them, $X = [x_1, \ldots, x_2]$, $Y^d = [y_1^d, \ldots, y_n^d] \in R^{r_1 \times n}$ and $Y^u = [y_1^u, \ldots, y_n^n] \in R^{r_2 \times n}$, the SBM model fractional programming is as follows:

$$\min\theta=\frac{1-\frac{1}{m}\sum_{i=1}^{m}(\frac{w_i^-}{w_{ik}})}{1+\frac{1}{r_1+r_2}(\sum_{s=1}^{r_1}\frac{w_s^d}{y_{sk}^d}+\sum_{q=1}^{r_2}\frac{w_q^u}{w_{qk}^u})}$$

$$st.x_{ik}=\sum_{j=1}^{n}x_{ij}\lambda_j+w_i^-,i=1,\dots,\mathrm{m}$$

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$$y_{sk}^d=\sum_{j=1}^{n}y_{sj}^d\lambda_j-w_s^d,s=1,\dots,\mathrm{r}_1$$

$$y_{qk}^d=\sum_{j=1}^{n}y_{qj}^u\lambda_j+w_q^u,q=1,\dots,\mathrm{r}_2$$

$$\lambda_j>0,\ j=1,\dots,\mathrm{n},\ w_i^-\geq 0,i=1,\dots,\mathrm{m}$$

$$w_s^d\geq 0,s=1,\dots,\mathrm{r}_1,w_q^u\geq 0,q=1,\dots,\mathrm{r}_2$$

When and only when, i.e., , is SBM valid. To further construct a Super-SBM model with undesirable outputs, we have the following:

$$\min\rho=\frac{\frac{1}{m}\sum_{i=1}^{m}(\frac{\overline{x}}{x_{ik}})}{\frac{1}{r_1+r_2}(\sum_{s=1}^{r_1}\frac{\overline{y}^d}{y_{sk}^d}+\sum_{q=1}^{r_2}\frac{\overline{y}^u}{y_{qk}^u})}$$

$$st.\overline{x}\geq\sum_{j=1,\neq k}^{n}x_{ij}\lambda_j,i=1,\dots,\mathrm{m}$$

$$\overline{y}^d\leq\sum_{j=1,\neq k}^{n}y_{sj}^d\lambda_j,s=1,\dots,\mathrm{r}_1$$

$$\overline{y}^d\geq\sum_{j=1,\neq k}^{n}y_{qj}^d\lambda_j,q=1,\dots,\mathrm{r}_2$$

$$\lambda_j>0,\ j=1,\dots,\mathrm{n},\overline{x}\geq x_k,i=1,\dots,\mathrm{m}$$

$$\overline{y}^d\leq y_k^d,s=1,\dots,\mathrm{r}_1,\overline{y}^u\leq y_k^u,q=1,\dots,\ \mathrm{r}_2$$

Using the above model, the efficiency of transportation carbon emissions can be calculated. The relationship is as follows:

$$CET_{kt}=\begin{cases}\theta_{kt,}\theta_{kt}<1;\\ \partial_{kt,}\partial_{kt}=1\end{cases}$$

2.2 Construction of dynamic efficiency model for transportation carbon emissions

The Malmquist model was first proposed by Färe. Considering that carbon emissions are non-expected outputs of the economic system, this article constructs a non-expected output SBM model (ML model). Referring to relevant research at home and abroad (Ren et al, 2022), the formula for the ML index model is as follows:

$$ML_t^{t+1}=\left\{\frac{\left[1+D_0^t(x^t,y^t,b^t;g^t)\right]}{\left[1+D_0^t(x^{t+1},y^{t+1},b^{t+1};g^{t+1})\right]}\times\frac{\left[1+D_0^{t+1}(x^t,y^t,b^t;g^t)\right]}{\left[1+D_0^{t+1}(x^{t+1},y^{t+1},b^{t+1};g^{t+1})\right]}\right\}^{\frac{1}{2}}$$

In the above formula, x,y represents the input and output variables of the decision-making unit, b represents the undesirable output, and g represents the slack variables of the factors.

2.3 Construction of the transportation carbon emission efficiency impact model

Due to the focus on the regional carbon emission effect in this article, it is inevitable to consider internal spatial characteristics. Therefore, based on the complex spatial-temporal characteristics, the article will introduce the Spatio-Temporal Geographically Weighted Regression (GTWRL) model. Unlike the classic multiple linear regression model, the GTWRL model fully considers the heterogeneity of geographical factors and constructs a multivariate model including geographical information. Referring to relevant research (Zhang et al.2023), the expression of the GTWRL model is as follows (Rey, 2001):

$$G_i=\alpha_0(\mu_i,\ v_i,\ t_i)+\sum_{k=1}^{z}\alpha_k(\mu_i,\ v_i,\ t_i)H_{ik}+\varepsilon_i, i=1,2,3,\ldots,n$$

Where, G_i represents the explained variable, namely carbon emission efficiency, and H_{ik} is the KTH influencing factor of city i, μ_i,v_i B represent the longitude and latitude coordinates of the research object. $(\mu_i,\ v_i,\ t_i)$ represents the space-time coordinates of the i th sample. Z is the number of influencing factors. $\alpha_0(\mu_i,\ v_i,\ t_i)$ is the intercept term, $\alpha_k(\mu_i,\ v_i,\ t_i)$ is the estimated coefficient of explanatory variable k at province i. The estimation method is as follows (Chen et al., 2020):

$$\hat{\alpha}(u_i,v_i,t_i)=[F^TL(u_i,v_i,t_i)F]^{-1}F^TL(u_i,v_i,t_i)W$$

where $\hat{\alpha}(u_i,v_i,t_i)$ is the estimate of $\alpha_0(\mu_i,\ v_i,\ t_i)$, F^T represents the transposed matrix, W is a matrix of variable coefficients, $L(u_i,v_i,t_i)$ representing the Gaussian function.

2.3 Indicator selection

(1) Selection of input-output indicators for carbon emission efficiency model

The input-output indicators of the efficiency measurement model constructed in this article follow the principles of "scientificity, rationality, and availability". Referring to the practices of relevant research at home and abroad, due to the main inputs of the transportation industry being the consumption of fossil fuels and the investment of capital factors, the input indicators are selected from the two aspects of energy and capital. At the same time, carbon dioxide emissions are the main undesirable output indicators of the transportation industry. Considering the expected output from an economic perspective, the industrial added value is selected to measure it. The indicator system is shown in Table 1:

Table 1 Main Input-Output Indicators

Input/output indicators	Specific indicators	Unit:
Input indicators	Stock of fixed capital	Thousands of people
	energy consumption	10,000 tons of standard coal
Output indicators	Carbon emissions from transportation	Million tons of carbon dioxide
	Added value of transportation industry	RMB100mn

(2) Selection of factors affecting carbon emission efficiency

Carbon emission efficiency is an important indicator that describes the amount of carbon dioxide emitted per unit of GDP. The concept encompasses both carbon emissions and economic development, and better reflects technological progress and economic efficiency. Due to the influence of multiple internal and external factors in the transportation industry, common factors include economic structure, energy structure, economic level, and regional population. The factors affecting carbon emission efficiency in this article are shown in Table 2:

Table 2 Selection of factors affecting carbon emission efficiency

Index name	Index meaning	Selection basis
Economic development	Per capita GDP	The improvement of economic level will trigger changes in production and consumption patterns, which in turn will change the level of carbon emissions.
Industrial upgrading	Added value of the tertiary industry/secondary industry	Industrial structure is an external factor that affects the transportation industry and affects the level of consumption
Energy mix	Coal consumption/energy consumption	The consumption of coal reflects the local low-carbon level and has an external impact on transportation carbon emissions
Population agglomeration	Total population of the city at the end of the year/area of the city	The population density directly affects the transportation volume level of the transportation industry and has a direct impact on carbon emissions

2.4 Data sources

All research data in this article are from national statistical yearbooks, such as the China Environmental Statistics Yearbook, the China Energy Statistics Yearbook, and local statistical yearbooks. Considering the possible missing data in the statistical yearbooks, formissing valueUse linear interpolation to complete.

3. Research results

3.1 Measurement results of static efficiency of transportation carbon emissions

(1) Overall efficiency analysis

This article uses the panel data of 11 provinces on the Yangtze River Economic Belt from 2014 to 2020,and passed through DEA-solver-pro13The software measures the efficiency of carbon emissions in the transportation industry, as shown in Table 4.

Table 4 Average Carbon Emission Efficiency in Different Years

Years	2014	2015	2016	2017	2018	2019	2020
Average efficiency	0.853	0.849	0.850	0.802	0.802	0.956	0.972

As shown in Table 4, the average carbon emission efficiency of the transportation industry in the Yangtze River Economic Belt from 2014 to 2020 is 0.8896, indicating that there is redundancy in carbon emission efficiency and the overall level is not effective. pressure of carbon emission reductionThe average value of carbon emission efficiency is 0.9721 in 2020, with a minimum value of 0.8016 in 2017 and a standard deviation of 0.0617. This indicates that the carbon emission efficiency has a growing trend during the research period, which indicates that under the new context of green development, through environmental governance and pollution control, the Yangtze River Delta has achieved significant progress in carbon emission reduction. Carbon emissions in economic beltThe situation has improved with certain control.

(2) Different provincesDomain transportation carbonComparison of emission efficiency

According to the calculation of DEA-solver-pro13 software, the Yangtze River Economic BeltRegional TransportationThe results of transport carbon emission efficiency are shown in Table 5.

From the results, the carbon emission efficiency of the transportation industry in each province of the Yangtze River Economic Belt was relatively stable before 2017, with a significant increase in 2017, and then tended to be stable, with a range of 0.3328-1.3120. Among them, the carbon emission efficiency of Shanghai, Hunan, Sichuan and Yunnan was lower than the average level during the study period. This indicates that the carbon emission efficiency of the four provinces is below the production frontier. The possible reason is that Shanghai has a rapid economic development, large energy consumption, and excessive carbon emissions in the transportation industry, resulting in low efficiency. Hunan and Sichuan are similar, and Yunnan may be due to insufficient investment leading to low output levels, resulting in low efficiency.

Table 5 Efficiency values of different provinces

Provincial region	2014	2015	2016	2017	2018	2019	2020	Mean value	Ranking
Hubei Province	1.308	1.316	1.258	1.259	1.580	1.527	1.321	1.367	1
Jiangsu	1.281	1.223	1.211	1.188	1.187	1.173	1.248	1.216	2
Guizhou	1.312	1.290	1.277	1.234	1.120	1.102	1.096	1.204	3
Anhui Province	1.067	1.057	1.070	1.058	1.162	1.173	1.169	1.108	4
Jiangxi	1.014	1.023	1.019	0.810	1.081	1.066	1.074	1.012	5
Chongqing	1.032	0.799	0.745	0.750	1.033	1.072	1.124	0.936	6
Zhejiang	0.572	0.611	0.765	0.714	1.003	1.059	1.119	0.835	7
Sichuan	0.563	0.760	0.750	0.662	0.575	0.572	0.695	0.654	8
Hunan Province	0.591	0.575	0.567	0.497	0.528	0.515	0.637	0.558	9
Yunnan Province	0.298	0.314	0.302	0.314	0.667	0.630	0.696	0.460	10
Shanghai	0.342	0.376	0.387	0.333	0.577	0.513	0.514	0.435	11

Furthermore, the spatial distribution of carbon emission efficiency in different provinces is shown in Figure 1. From a horizontal comparison, The efficiency values of Hubei, Jiangsu, Guizhou, Anhui and Jiangxi are greater than 1.0, and the overall efficiency is in the efficient stage. Among them, Hubei's average efficiency value reached 1.3669, making it the province with the highest carbon emission efficiency in the transportation industry on the Yangtze River Economic Belt, mainly due to its relatively low investment cost. Its actual energy consumption is close to the target value, and its variation range is between 0-28.03% during the study period. However, its capital stock investment is too high, and the added value of the transportation industry needs to be improved. This indicates that Hubei's investment in energy consumption for the transportation industry is relatively reasonable. The efficiency value of Shanghai is the lowest, only 0.435, indicating that Shanghai, with a developed transportation industry, has resource investment lower than output due to traffic redundancy and urban disease, and the efficiency of the transportation industry needs to be optimized and improved.

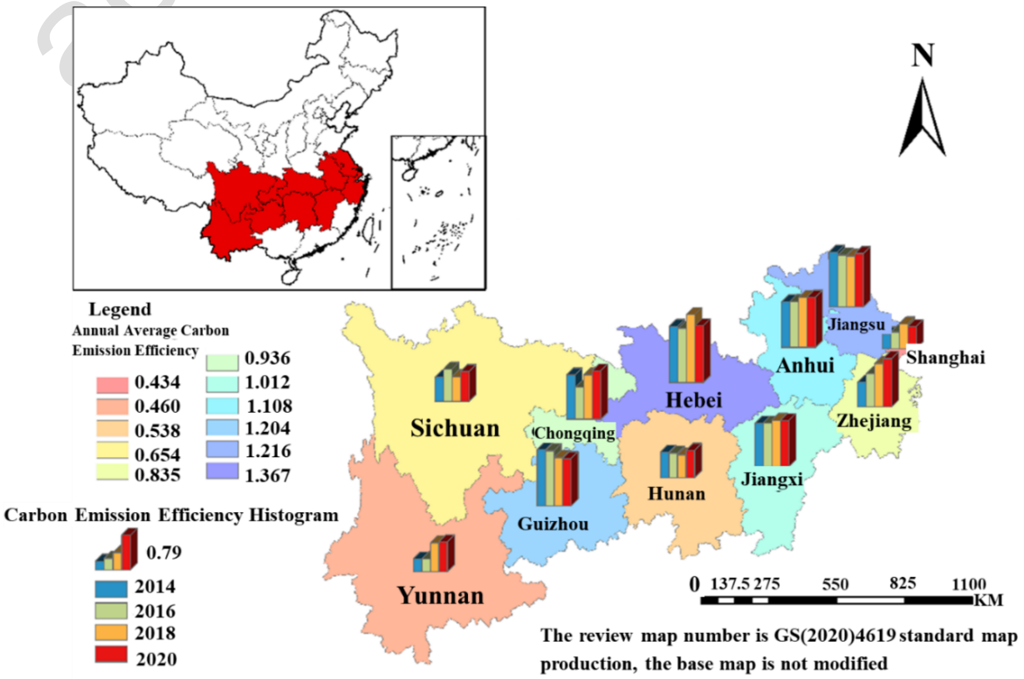


Figure 1 Spatial distribution of carbon emission efficiency in the transportation industry of the Yangtze River Economic Belt

3.2 Measurement results of dynamic efficiency of transportation carbon emissions

（1）Overall efficiency change results

The dynamic efficiency of carbon emissions from transportation in the Yangtze River Economic Belt can be calculated using ML models. The results of changes in different years are shown in Table 6.

According to Table 6, the ML index for the years 2014-2015, 2015-2016, 2016-2017, 2017-2018, 2018-2019, and 2019-2020 were 0.952, 1.562, 0.882, 0.926, 0.914, and 0.583, respectively. Except for the years 2015-2016, the ML index for carbon emissions in the transportation industry in the other years was less than 1, indicating that in these years, the efficiency of carbon emissions in the Yangtze River Economic Belt transportation industry decreased, and there was redundancy in resource input or insufficient output.

Table 6 ML Index of Carbon Emissions from Transportation

Years	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020	Mean value
ML index	0.952	1.562	0.882	0.926	0.914	0.583	0.93

Furthermore, the decomposition of the ML index for transportation carbon emissions is analyzed, as shown in Figure 2. Next, the dispersion of the efficiency values obtained from the ML model is analyzed. From the results, the ML index has the widest distribution, indicating that there is temporal heterogeneity in the distribution of carbon emissions. However, the efficiency values of carbon emissions in most regions are less than 1, and the peak value is around 0.92. This is mainly due to the strong inhibitory effect of technological progress on carbon emissions efficiency, which is reflected in the figure as the efficiency values of technological progress are all less than 1, clustered on the left side of the efficiency value corresponding to the peak of carbon emissions efficiency, and forming two peaks. It can be seen that the Yangtze River Economic Belt needs to strengthen technological innovation to achieve improvement in transportation carbon emissions efficiency.

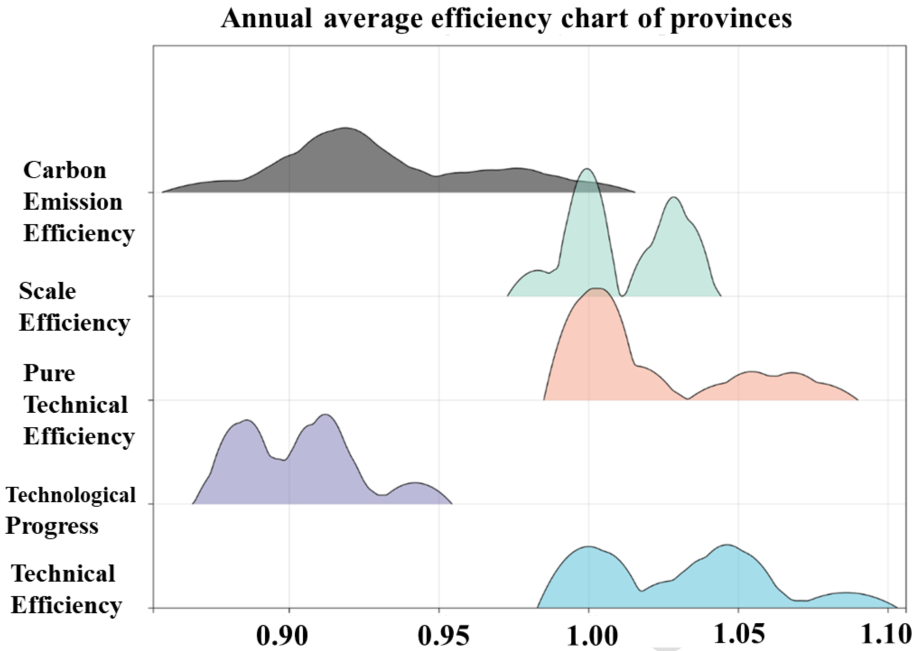


Figure 2 ML Index Distribution of Carbon Emissions from Transportation

（2）Different provincesDomain trafficComparison of Carbon Emission Efficiency in Transportation

In order to further compare the ML index and its decomposition of transportation carbon emissions in different provinces, the results in Table 7 are calculated. From the results, Shanghai, Zhejiang, Jiangsu, and Sichuan ranked first in carbon emissions ML index, which were 0.993, 0.972, 0.963, and 0.937, respectively. Shanghai ranked first in dynamic efficiency, while it ranked last in static efficiency. This indicates that Shanghai has a large amount of transportation carbon emissions and low efficiency. However, under the background of green development, the efficiency has shown a significant upward trend through increased governance efforts. On the contrary, the carbon emissions ML index of Jiangxi, Chongqing, Guizhou, and Hubei were 0.912, 0.908, 0.906, and 0.88, respectively, and the efficiency changes were relatively slow. From the decomposition of ML index, the comprehensive efficiency of the four provinces was mainly affected by technological progress, and their technical efficiency, pure technical efficiency, and scale efficiency were all 1. Therefore, technological progress was the main driving force. Finally, from the overall decomposition of ML index, the average values of technical efficiency, technological progress, pure technical efficiency, and scale efficiency were 1.03, 0.903, 1.019, and 1.011, respectively. Except for technological progress, which was less than 1.0, the other efficiency values were all greater than 1.0, which further indicates that the efficiency of transportation carbon emissions in the Yangtze River Economic Belt is significantly affected by technological progress. This is consistent with the previous analysis results.

Table 7 ML Index and Its Decomposition

Province	Technical efficiency	Technological progress	Pure technical efficiency	Scale efficiency	Carbon emission ML index
Shanghai	1.086	0.914	1.061	1.023	0.993
Jiangsu	1.056	0.920	1.075	0.983	0.972
Zhejiang	1.022	0.942	1.000	1.022	0.963
Anhui Province	1.046	0.896	1.048	0.997	0.937
Jiangxi	1.030	0.903	1.019	1.011	0.930
Hubei Province	1.045	0.886	1.013	1.032	0.926
Hunan Province	1.050	0.881	1.018	1.031	0.925
Chongqing	1.034	0.886	1.000	1.034	0.917
Sichuan	1.000	0.912	1.000	1.000	0.912
Guizhou	1.000	0.908	1.000	1.000	0.908
Yunnan Province	1.000	0.906	1.000	1.000	0.906
Average value	1.000	0.880	1.000	1.000	0.880

3.3 Empirical results of factors affecting transportation carbon emissions

To explore the influencing factors of transportation carbon emissions and build a GTWR model, the Super-SBM model will be used to calculate theofCarbon emission efficiency is taken as the dependent variable, with energy consumption structure, industrial upgrading, economic development, and population agglomeration as explanatory variables. All variables were standardized before calculation, and the relevant parameters of the regression results are shown in the following table:

Table 8 Relevant parameters of spatial-temporal geographically weighted regression

Model parameters	Band width	Sigma is	Residual Squares	AICc	R2	Adjusted R2
The value	0.114 996	0.070264	0.38015	-61.2826	0.955542	0.953073

From the perspective of goodness of fit, both R2 and corrected R2 are higher than 0.95, indicating that the model fits very well and the explanatory variables can explain the explained variables well. In addition, from the statistical results, it can be seen that except for economic development, the regression coefficients of each influencing factor have significant differences.

4. Research and Discussion

4.1 Further discussion on the static efficiency of carbon emissions in transportation

In order to further analyze the carbon emissions from transportation in the Yangtze River Economic Belt, a distribution map is drawn as shown in Figure 3. Figure 3 mainly presents the spatial distribution of carbon emission efficiency in 2014, 2016, 2018, and 2020.

From the results, the efficiency of Hubei, Jiangsu, Anhui and Guizhou reached effective in four years; while Shanghai, Hunan, Sichuan and Yunnan had low carbon emission efficiency. It can be seen that the spatial pattern of carbon emission efficiency of transportation industry in the Yangtze River Economic Belt in China remains basically unchanged. The carbon emission efficiency of Sichuan, Yunnan and Chongqing has rebounded overall with time, while the carbon emission efficiency of Jiangxi, Guizhou and Hunan has declined with time. In contrast, the carbon emission efficiency of Hubei, Jiangsu and Anhui has always been in a dominant position and remained relatively stable during the study period.

The reason is that the transportation industry in some provinces with high carbon emission efficiency is still in the development stage, but the corresponding carbon dioxide emissions are also relatively low, so the overall carbon emission efficiency is relatively high. However, Shanghai has a developed economy, with large energy and capital investment in the transportation industry, large carbon dioxide emissions, and heavy urban traffic congestion and massive investment in transportation facilities, which have led to serious environmental problems, resulting in a decrease in overall efficiency.

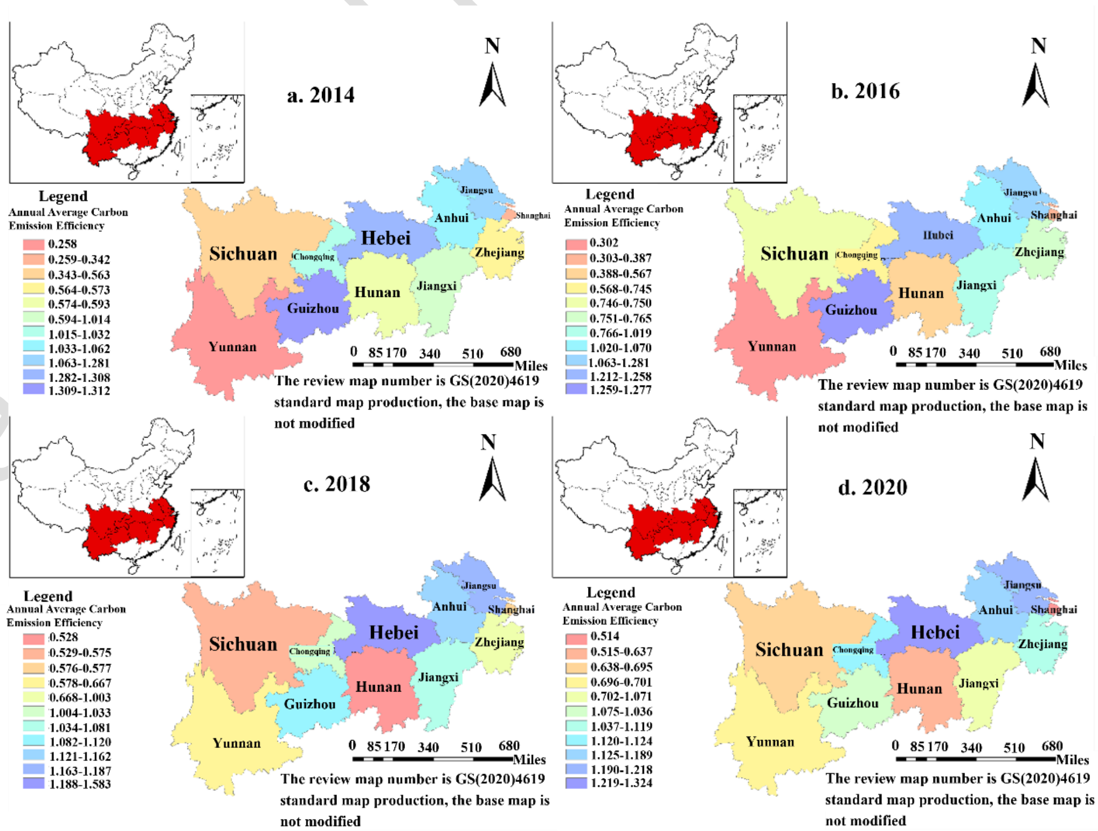


Figure 3 Spatial distribution of transportation carbon emission efficiency in different provinces

4.2 Further comparative analysis of the transport carbon emission ML index

To further analyze the differences between provinces, Domain transportation carbon emission，the changes are plotted in the carbon emission ML index chart shown in Figure 4.

From the results, during the period of 2014-2020, the average annual carbon emission ML index of the transportation industry in the Yangtze River Economic Belt was 0.93, indicating that the Yangtze RiverCarbon emissions in economic beltThe efficiency decreased by 7% annually, with Anhui, Jiangxi, Hubei, Hunan, Chongqing, Guizhou, and Yunnan all below the average of 0.93, but generally distributed around 0.9, all less than 1, showing a downward trend. Among them, Chongqing, Hubei, Guizhou, and Jiangxi had the most significant carbon emission efficiency. Through their decomposition factors, it can be seen that technological progress decreased significantly and technical efficiency did not improve.

Technological progress in other provinces is also in a declining state, but due to the gradual improvement of technological efficiency, theofThe decline in transport carbon emission efficiency has slowed down relatively. It can be seen that technological progress is an important factor driving the improvement of transport carbon emission efficiency.

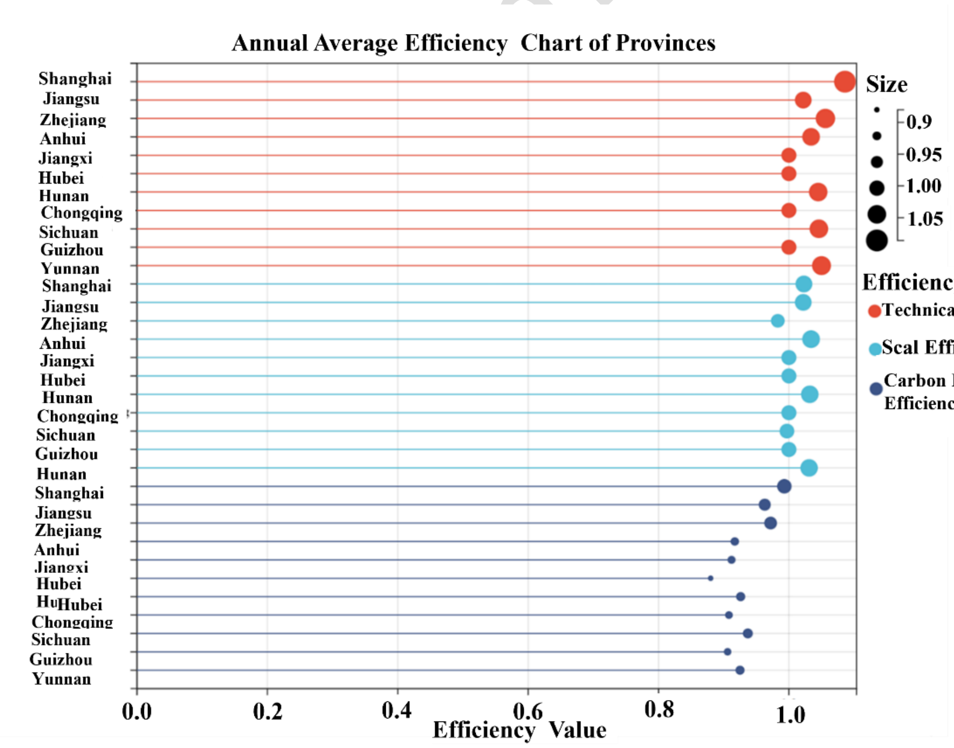


Figure 4 Comparison of ML index values in different provinces

4.3 Further analysis of factors affecting transportation carbon emissions

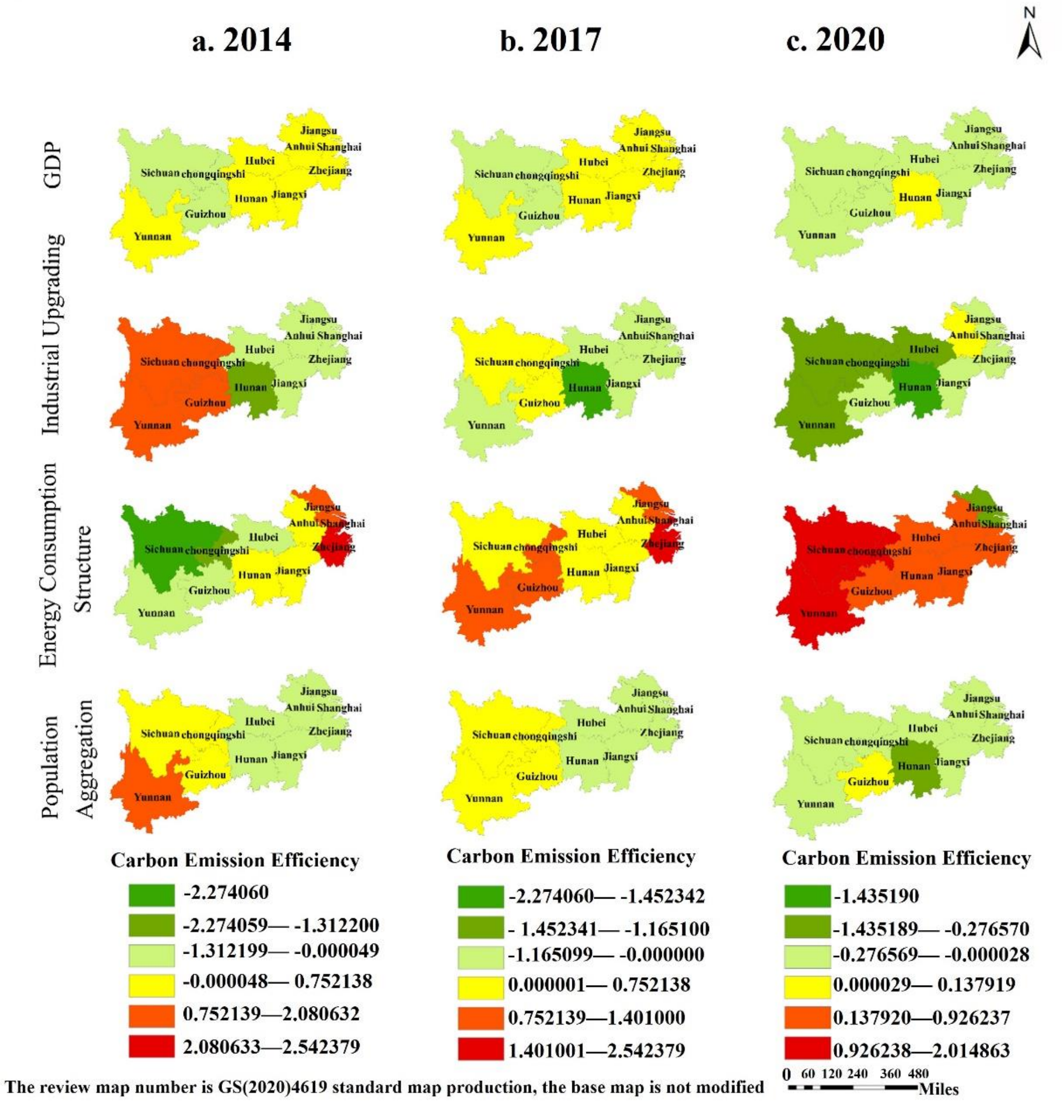
This article further discusses the spatial and temporal differences in various influencing factors in 2014, 2017, and 2020. As shown in Figure 5, the impact of GDP on carbon intensity is becoming smaller, indicating that the economic development of each province is relatively advanced, and the investment in the transportation industry is also relatively sufficient. From the perspective of industrial upgrading, the industrial upgrading in the southwest regions of Sichuan, Yunnan, Chongqing, and Guizhou shows a significant downward trend with the increase of years, while Hunan and Hubei provinces are relatively stable. From the perspective of energy consumption structure, except for Jiangsu, Shanghai, and Zhejiang provinces, the coefficients of other provinces show an upward trend with time, indicating that the energy consumption structure has a negative inhibitory effect on the carbon intensity in Jiangsu, Zhejiang, and Shanghai regions, and will gradually have a positive promoting effect on the carbon emission efficiency of Sichuan, Yunnan, and Chongqing from 2020. From the perspective of population agglomeration, except for

Yunnan in 2014, the population agglomeration in other regions has a negative inhibitory effect on carbon emission efficiency.

Figure 5 Coefficients of factors based on GTWR in different years

5. Conclusions

In the face of severe and complex environmental crises, controlling carbon emissions from transportation has become a key area of environmental governance. This article mainly studies the efficiency and influencing factors of transportation carbon emissions in the Yangtze River Economic Belt in China. Through model construction, empirical analysis, and results discussion, the following conclusions are drawn:



(1) According to the static model results, the Yangtze River Economic Belt provincesDomain transportation carbonThe heterogeneity of emission efficiency is significant. From the calculation results, Hubei, Jiangsu, Guizhou, and Anhui ranked the top four in efficiency, with values of 1.367, 1.216, 1.204, and 1.108, respectively; Sichuan, Hunan, Yunnan, and Shanghai ranked the bottom

four in efficiency, with values of 0.654, 0.558, 0.460, and 0.435, respectively. The maximum value is 1.367 and the minimum value is 0.435, with a difference of 0.932, indicating significant differences.

(2) From the perspective of dynamic efficiency, the Yangtze River Economic Belt's transportation carbon emissions ML index is overall lower than 1.0. From the results, the ML indexes for 2014-2015, 2015-2016, 2016-2017, 2017-2018, 2018-2019, and 2019-2020 were 0.952, 1.562, 0.882, 0.926, 0.914, and 0.583, respectively. Except for 2015-2016, the transportation carbon emissions ML index in the remaining years was less than 1, indicating that in these years, the efficiency of transportation carbon emissions in the Yangtze River Economic Belt decreased, and there was either redundancy in resource input or insufficient output.

(3) From the perspective of dynamic efficiency decomposition, the change in transportation carbon emission efficiency in the Yangtze River Economic Belt is driven by technological progress. From the overall ML index decomposition, the average values of technical efficiency, technological progress, pure technical efficiency, and scale efficiency are 1.030, 0.903, 1.019, and 1.011, respectively. Except for technological progress, which is less than 1.0, the other efficiency values are all greater than 1.0, indicating that the overall transportation carbon emission efficiency in the Yangtze River Economic Belt is significantly affected by technological progress.

(4) From the analysis results of the GTWR model, the transportation carbon emission efficiency in the Yangtze River Economic Belt is significantly affected by energy consumption structure, industrial upgrading, economic development, and population agglomeration.

Finally, in order to achieve the goal of "double carbon" and promote the energy conservation, emission reduction and green development of transportation in the Yangtze River Economic Belt, the following policy suggestions are put forward: First, establish a regional collaborative emission reduction mechanism, and it is necessary to realize energy conservation and emission reduction through ecological compensation for cities studying pollution; Second, increase investment in green technology and vigorously develop low-consumption vehicles such as new energy vehicles; Third, increase the green transformation and upgrading of traditional industries, and drive the emission reduction of transportation through the green transformation of industry and economy.

Competing interests

The authors have no conflicts of interest to declare.

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