Li et al. Energy Informatics (2024) 7:48
https://doi.org/10.1186/s42162-024-00354-y



RESEARCH Open Access

# Effectiveness of spatial measurement model based on SDM-STIRPAT in measuring carbon emissions from transportation facilities

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**Abstract**

To gain a deeper understanding of the carbon emission mechanism from transportation facilities, all system elements affecting carbon emissions from regional transportation facilities are identified and analyzed according to panel data from 30 regions in China. A spatial econometric model for carbon emissions from transportation facilities is constructed using the Spatial Dolbin model from 2004 to 2022 as the research period. From the results, the carbon dioxide emissions from transportation facilities added from 318 million tons in 2004 to 752 million tons in 2022, with an average annual growth rate of 4.9%. The global spatial auto-correlation coefficient was significant at the 5%, with an obvious spatial correlation between carbon dioxide emissions within a geographical range. In addition, through stability testing, the model showed high stability in both spatial lag testing and spatial error testing, demonstrating strong ability to interpret data. The research shows that the carbon emission is affected by independent variables, including population, economy, technology, and transportation, and exhibit significant spatial distribution characteristics in different regions and years, providing a basis for policy formulation and carbon emission management.

**Keywords:** SDM, STIRPAT, Transportation facilities, Energy consumption, Carbon emissions, Relativity

## Introduction

With the acceleration of global economic development and urbanization, urban transportation problems are becoming increasingly prominent. One important influencing factor is the Carbon Emissions (CE) from transportation facilities. CE causes pollution to the environment, posing negative impacts on climate change (Jing et al. 2023). Therefore, measuring and analyzing the CE from transportation facilities is of great significance. At present, the commonly used methods for measuring CE from transportation facilities mainly include energy metering and emission inventory methods (Jiang et al. 2020; Huang et al. 2021). The energy metering method calculates CE by measuring the energy consumption of transportation facilities, but this method requires high technical and economic cost. The emission inventory method lists possible CE based on the type and scale of transportation facilities, but the accuracy is restricted by the completeness and accuracy of transportation facility data and inventory (Li et al. 2020a; Chen et al. 2022).

The study uses 30 provinces, cities, and autonomous regions in China as research samples to conduct auto-correlation tests on spatial data using the Moran index. The Spatial Dolbin Model (SDM) and Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) are combined to construct the SDM-STIRPAT spatial measurement model. The impact of transportation facilities on regional CE is analyzed using the SDM-STIRPAT model. The innovation of the research methodology lies in the spatial econometric model and the dynamic SDM-STIRPAT model, which more accurately consider spatial and temporal effects and provide useful references for future transportation infrastructure construction and carbon emission control.

The paper is mainly divided into four parts. The first part summarizes relevant research. The second part designs the carbon emission analysis method for transportation facilities. The third part analyzes CE from transportation facilities. The fourth part concludes the entire study.

## Related works

With the progress of the economy, the increase in transportation volume and frequency has increased CE and exacerbated climate change. To reduce the CE caused by transportation, it is necessary to promote sustainable transportation development, adopt low-carbon transportation methods, and strengthen the clean energy utilization. Many researchers have conducted extensive research on economic growth, transportation, and CE. Sun et al. investigated the pathways to achieve sustainable development in Malaysia using quantile auto-regressive distribution lag method and Granger causality. The impact of tourism and transportation services on economic growth and CE was observed. The results indicated that the error correction parameters were obvious in the main quantiles, confirming long-term steady-state balance. Meanwhile, the tourism and transportation services industries primarily reduced CE through higher emission quantiles, demonstrating the sustainability of Malaysia's transportation and tourism industries (Sun et al. 2021). Ji et al. used time series data from 1990 to 2016 and applied the visibility graph strategy to evaluate countries. The results showed that the transportation development was an important indicator of a country's modernization, while low-income had relatively low CE (Ji et al. 2022). Liu et al. used 10 sampled cities to examine the urban sustainability level from 1990 to 2018. Shanghai and other places were in a leading position, followed by Wuxi and Nantong. Shanghai and other places had the highest cumulative CE, but per capita CE reached the lowest in 2018. Wuxi and Nantong had relatively low levels. It pointed out that CE in this area mainly came from fossil fuels, while the CE contributed by transportation electricity continued to increase, indicating that electricity may become an important component of energy consumption in this area. Therefore, the study emphasized the urgency of socio-economic adjustment in the Yangtze River Delta from carbonized structure to decarbonized structure (Liu et al. 2020).

The SDM is a sustainable development model used to evaluate and plan the sustainability of projects, policies, or industries, taking into account economic, environmental, and social factors. Zhang and Huang used a hybrid SDM to evaluate the intelligent transportation in 30 provinces from 2001 to 2017. The development of intelligent transportation was gradually improving, and regional differences were narrowing, which had a reducing effect on CE. In addition, economic and technological elements had moderating effects on the impact of intelligent transportation, enhancing its emission reduction effect and providing policy suggestions for intelligent transportation (Zhang and Huang 2022). Lv and Zeng used an ecological footprint strategy to evaluate the sustainable development of the urban agglomeration in the Yangtze River. Meanwhile, complex network models and gravity models were used to characterize the scale, connectivity, and spatial interactions of transportation networks. The ecological footprint slightly decreased from 2010 to 2017, and the spatial impact of transportation networks promoted sustainable development between regions (Lv and Zeng 2022). Atikah et al. used SDM to determine the optimal estimation method to obtain an advertising tax model. The maximum likelihood estimation method was an appropriate method for estimating SDM parameters. All variables had a significant impact on advertising taxation (Atikah et al. 2021). Myovella et al. analyzed the digital gap in sub Saharan Africa based on the inequality in Internet use and broadband subscriptions. 41 geographically closely connected countries were considered, as well as spatial interdependence. Meanwhile, spatial panel analysis was conducted on 451 observations from 2006 to 2016 using SDM specifications. There was a powerful spatial interdependence between sub Saharan Africa, which meant that Internet access and broadband subscriptions in one country were affected another country, probably due to spillover effects (Myovella et al. 2021). Hou et al. used Tapio decoupling elasticity model and environmental Kuznets curve model to analyze the relationship between economic growth and CE in the transportation industry of 30 provinces in China from 2005 to 2020. The long-term energy substitution plan model was used to predict the development of China's transportation industry. The results showed that the CE from the transportation industry in most provinces presented an inverted U-shaped decoupled from economic growth. This decoupling was usually more unstable in provinces with higher levels of economic development (Hou et al. 2023). Aziz and Chowdhury used the STIRPAT model and ridge regression analysis to explore the influencing factors of greenhouse gas emissions in the agricultural sector of Bangladesh, including population trends, energy use, and land use practices. The factors such as total population and rural population, wealth level, urbanization, fertilizer intensity and quantity, carbon and energy intensity, irrigation, rice cultivation, farmland and crop yield all had impacts on greenhouse gas emissions (Aziz and Chowdhury 2023).

In summary, these studies have achieved certain results in the analysis of the relationship between transportation and CE, sustainable development assessment, etc., but there are still limitations. These studies lack in-depth research on CE from transportation facilities. Existing research mostly focuses on single regions or countries, lacking cross regional comparisons. In addition, existing research often uses static models, which lack sufficient characterization for the dynamic process of sustainable development. Therefore, the study adopts the SDM-STIRPAT spatial econometric model to measure CE from transportation facilities, providing scientific basis for carbon emission management of transportation facilities.

## Design of carbon emission analysis methods for transportation facilities

### The impact mechanism of carbon emissions from transportation facilities

This study uses bibliometric methods to determine all systemic factors that affect regional CE from transportation facilities. The construction and expansion of transportation infrastructure have increased transportation activities, directly increasing energy consumption and CE. Simultaneously, it has generated social and economic agglomeration effects, indirectly causing spillover effects on the overall CE of the region. The primary factors affecting regional CE include population, economic, and technological factors. The transportation infrastructure is used as an expansion factor to analyze its impact on regional CE. Environmental, economic, technological, and transportation factors are the four key factors that affect regional sustainable development. Population factor refers to the impact of regional population size and population growth on regional economic development. Economic factors refer to the driving force of the scale, speed, and level of regional economic development on the development of all socio-economic factors, as well as the impact of energy and environmental systems. Technological elements refer to the main objects that the STIRPAT theoretical model expands on, including indicators such as energy intensity, energy structure, and industrialization level. Transportation elements refer to quantifiable indicators during its construction and operation, including investment, network, and transportation service indicators.

The direct impact of transportation infrastructure on regional CE is mainly presented in the construction and operation process, involving energy consumption and greenhouse gas emissions. Based on the construction, operation, and management, energy consumption and CE are the main concerns. The amount and efficiency of energy consumption vary among different transportation modes. The energy consumption rate of land and water transportation is lower, while the air transportation is higher (Patel et al. 2020). The construction and improvement of transportation infrastructure and land use are mutually causal, which improves regional accessibility, drives land prices along the route, and changes the structure, density, and layout of land use. The changes in land use structure also affect transportation demand and transportation system capacity, which is one of the driving forces for improving transportation infrastructure systems. The direct impact of transportation infrastructure on regional CE is shown in Fig. 1. The direct impact on environmental systems is manifested as a one-way negative feedback relationship. This means that transportation activities have a one-way negative impact on

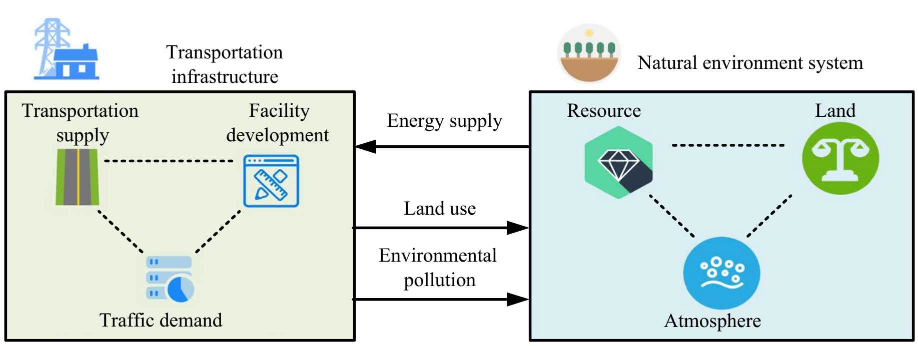


**Fig. 1** The direct impact on regional carbon emissions

regional CE. This one-way negative impact is an important manifestation of the externality of transportation infrastructure environment.

Transportation infrastructure, as the foundation and link of regional socio-economic system development, plays a crucial function in population, economy, and technological factors. The impact of regional economic development on the transportation infrastructure is mainly reflected in two aspects: material guarantee and driving force. The role of population, economy, and technology factors in transportation infrastructure is mainly reflected in three aspects: material support, technological support, and driving force. Transportation infrastructure indirectly affects the uneven development of transportation infrastructure systems in different regions by promoting social and economic activities. There is an obvious spatial distribution effect on the development of socio-economic factors in different regions, which affects the overall balanced development of the socio-economic system (Li et al. 2022). The indirect impact on regional CE is mainly exhibited in promoting socio-economic activities, affecting regional carbon emission levels, and influencing regional carbon emission levels through material support, technological support, and dynamic effects.

## Spatial measurement method for carbon emissions from transportation facilities

### *Data sources and variable descriptions*

The study uses 30 regions as research samples, with a sample time span from 2004 to 2022. The sample data is sourced from publicly available official statistical data, including the China Statistical Yearbook, China Energy Statistical Yearbook, relevant provincial statistical yearbooks, and the Statistical Bulletin on the Development of the Transportation Industry. The data is mainly obtained by collecting and organizing various official statistical yearbooks, which have undergone preliminary screening and cleaning to ensure the accuracy and consistency of the data. However, potential biases in the data still exist, including data quality and statistical caliber. Four factors, including environmental, economic, demographic, and technological factors, are selected to explain China's CE. The chosen dependent variable for the study is carbon dioxide emissions. The four explanatory variables include regional population size, per capita GDP, energy intensity, and transportation capacity. The two control variables include urbanization and industrialization. Regional population size and per capita GDP are key indicators reflecting regional economic activity and population density. These two variables can reflect regional economic development and population agglomeration, thereby affecting the construction and use of transportation facilities. Energy intensity and transportation capacity are key indicators reflecting the operational efficiency and energy consumption of transportation facilities. These two variables can reflect the energy consumption and CE levels of transportation facilities during construction and operation. The urbanization and industrialization are important indicators reflecting the stage of regional socio-economic development and industrial structure. These two variables can affect the demand and use of transportation facilities, thereby further affecting the CE of transportation facilities. All variables can be directly obtained through statistical data, but variables such as carbon dioxide emissions and transportation capacity need to be measured under certain standards (Li et al. 2020b). The carbon dioxide emissions is shown in Fig. 2.

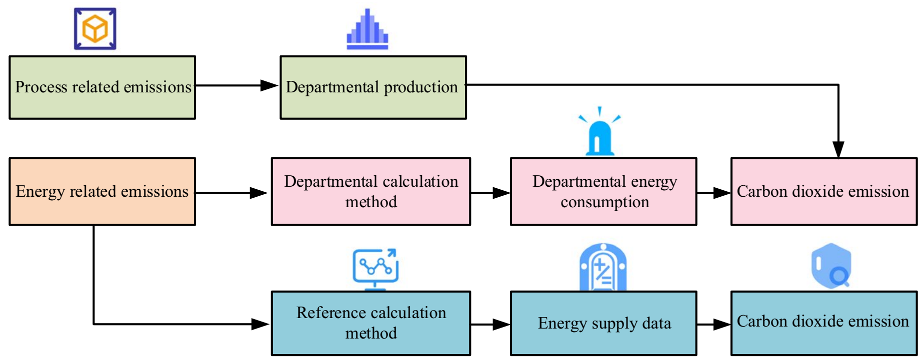


**Fig. 2** Estimation of carbon dioxide emissions

In Fig. 2, the departmental rule is to develop emission standards suitable for different industries based on their production characteristics and energy consumption. The reference rule refers to the emission standards of other similar industries. The CE calculation of the department's production process is shown in Eq. (1).

$$CE_t = AD_t \times EF_t \tag{1}$$

In Eq. (1), within time $t$, the CE of the department's production process is $CE_t$, measured in tons. The department's production data is $AD_t$, measured in tons/year. The production emission factor is $EF_t$. The CE from energy sources in the department is shown in Eq. (2).

$$CE_{ij} = AD_{ij} \times NCV_i \times CC_i \times Q_{ij} \tag{2}$$

In Eq. (2), the CE of department $j$ from the $i$-th energy source is $CE_{ij}$, in tons. The consumption of fossil fuels is $AD_{ij}$, in tons. The unit calorific of the $i$-th fossil fuel is $NCV_i$, in GJ. The corresponding to the CE is $CC_i$, in tons. The oxidation rate of fuel combustion is $Q_{ij}$. The energy CE is shown in Eq. (3).

$$CE_{ref-j} = AD_{ref-j} \times EF_i \tag{3}$$

In Eq. (3), the CE of energy $i$ is $CE_{ref-j}$, in tons. The emission factor corresponding to energy is $AD_{ref-j}$. The total consumption is $EF_i$, in tons. The study uses the conversion turnover method to convert passenger turnover (person/kilometer) into freight turnover (ton/kilometer) through passenger and freight conversion coefficients to reflect the comprehensive capacity of the transportation department's passenger and freight transportation. The conversion turnover calculation is shown in Eq. (4).

$$TCT = \sum_{k=1}^{n} (TFT_k + \beta_k TPT_k) \tag{4}$$

In Eq. (4), the conversion turnover is $TCT$, in tkm. The freight turnover is $TFT$, in tkm. The passenger turnover is $\beta$, in pkm. The conversion coefficient between passenger and freight is $TPT$. The category of transportation modes is represented by $k$. Based on the above variable selection and calculation methods, descriptive statistics of variables are obtained, as shown in Table 1.

**Table 1** Descriptive statistics of variables

| Variable | Explanatory variable | Measure content | Measure unit | Minimum value | Maximum value | Mean value | Variance |
|---|---|---|---|---|---|---|---|
| *I* | Carbon dioxide | Emissions | Million tons | 0.76 | 1673.2 | 231.7 | 211.2 |
| *P* | Population | Total population | Ten thousand people | 513 | 10,987 | 4357.6 | 2541.3 |
| *A* | Economic | Per capita GDP | yuan | 2369 | 108,647 | 25,130.7 | 22,145.7 |
| *T* | Technology | Energy intensity | Tons/10000 yuan | 0.22 | 15.36 | 1.72 | 1.61 |
| *U* | Urbanization | Urbanization rate | % | 15.09 | 90.36 | 46.35 | 17.45 |
| *IN* | Industrialization | Industrialization rate | % | 13.01 | 54.12 | 39.45 | 9.02 |
| *TCT* | Transportation capacity | Conversion turnover | Billion ton kilometers | 82.13 | 20,567.8 | 3315.7 | 3861.4 |

In the spatial distribution of environmental factors, spatial relationships have characteristics such as scale, cognition, hierarchy, uncertainty, and formalization. The study uses Moran's index to perform auto-correlation tests on spatial data. It can reflect the similarity of geographic spatial unit attribute values and explore the impact of transportation infrastructure on regional CE. The global spatial auto-correlation coefficient is shown in Eq. (5).

$$Moran'sI = \frac{\sum_{a=1}^{n}\sum_{b=1}^{n} w_{ab}(Y_a - \overline{Y})(Y_b - \overline{Y})}{S^2 \sum_{a=1}^{n}\sum_{b=1}^{n} w_{ij}} \tag{5}$$

In Eq. (5), the global spatial auto-correlation coefficient is $Moran'sI$. The sample mean is $\overline{Y}$. The observation value for the $a$-th region is $Y_a$. The sample variance is $S^2$. The spatial unit is $n$. The spatial weight matrix is $w_{ab}$. The local spatial auto-correlation is shown in (6).

$$Moran'sI_p = \frac{(Y_a - \overline{Y})}{S^2} \sum_{b=1, b \neq a}^{n} w_{ab}(Y_a - \overline{Y}) \tag{6}$$

In Eq. (6), the local spatial auto-correlation coefficient is $Moran'sI_p$.

#### *SDM-STIRPAT construction*

The scalable environmental impact factor theory model STIRPAT includes population factors, economic factors, and technological factors. The composition of the model $I_c$ is shown in Eq. (7).

$$I_c = \alpha P_c^{\beta_1} \times A_c^{\beta_2} \times T_c^{\beta_3} \varepsilon_c \tag{7}$$

In Eq. (7), the constant term is $\alpha$. The data unit is $c$. The variable coefficient of population factor $P_c$ is $\beta_1$. The variable coefficient of economic factor $A_c$ is $\beta_2$. The variable coefficient of technical element $T_c$ is $\beta_3$. The error term is $\varepsilon_c$. In empirical econometric analysis, variables are usually taken as natural logarithms to eliminate dimensionality, and reduce collinearity and heteroscedasticity, as shown in Eq. (8).

$$\ln I_i = \ln \alpha + \beta_1 \ln P_c + \beta_2 \ln A_c + \beta_3 \ln T_c + \ln \varepsilon_c \tag{8}$$

The STIRPAT theoretical model is extended to an explanatory variable, with traffic variables as the core explanatory variable and other variables as control variables. The variables of urbanization level and industrialization level are also important influencing factors. The extended model is shown in Eq. (9).

$$\begin{aligned}\ln I_{cy} = {} & \ln \alpha + \beta_1 \ln P_{cy} + \beta_2 \ln A_{cy} + \beta_3 \ln T_{cy} + \beta_4 \ln U_{cy} \\ & + \beta_5 \ln IN_{cy} \ + \beta_6 \ln TCT_{cy} + \ln \varepsilon_{cy}\end{aligned} \tag{9}$$

In Eq. (9), the year is represented by $y$. The variable parameter is $\beta$. The carbon emission variable is $I_{cy}$. The population size variable is $P_{cy}$. The per capita GDP variable is $A_{cy}$. The energy intensity variable is $T_{cy}$. The urbanization rate variable is $U_{cy}$. The industrialization rate variable is $IN$. The transportation capacity variable of transportation facilities is $TCT_{cy}$. The spatial measurement model SDM-STIRPAT is used to measure the impact of transportation infrastructure on regional CE. SDM is a hybrid model that includes spatial terms for the dependent and explanatory variables (Zhang et al. 2022). The SDM extended model is shown in Eq. (10).

$$y_{it} = \rho w y_{it} + x_{it}\beta + w\overline{x}_{it}\theta + \mu_{it} + \lambda_{it} + \varepsilon_{it} \tag{10}$$

In Eq. (10), the dependent variable is $y_{it}$. The time is $t$. The geographic space is $i$. The explanatory variable is $x_{it}$. The explanatory variable with spatial effects is $\overline{x}_{it}$. The spatial weight matrix is $w$. The spatial lag coefficient of the dependent variable is $\rho$. The independent variable parameter is $\beta$. The random perturbation term is $\varepsilon_{it}$. The fixed spatial effect parameter is $\mu$. The fixed time effect parameter is $\lambda$. The independent variable parameter of the spatial term is $\theta$. The SDM-STIRPAT is further constructed, as shown in Eq. (11).

$$\begin{aligned}\ln I_{it} = {} & \rho \sum_{i\neq j, j=1}^{n} w_{ij} \ln I_{jt} + \beta_1 \ln P_{it} + \beta_2 \ln A_{it} + \beta_3 \ln T_{it} + \beta_4 \ln U_{it} + \beta_5 \ln IN_{it} \\ & + \beta_6 \ln TCT_{it} + \theta_1 \sum_{i\neq j, j=1}^{n} w_{ij} \ln P_{jt} \ + \theta_2 \sum_{i\neq j, j=1}^{n} w_{ij} \ln A_{jt} + \theta_3 \sum_{i\neq j, j=1}^{n} w_{ij} \ln T_{jt} \\ & + \theta_4 \sum_{i\neq j, j=1}^{n} w_{ij} \ln U_{jt} + \theta_5 \sum_{i\neq j, j=1}^{n} w_{ij} \ln IN_{jt} + \theta_6 \sum_{i\neq j, j=1}^{n} w_{ij} \ln TCT_{jt} + \ln \mu_i \\ & + \ln \lambda_t + \ln \varepsilon_{it}\end{aligned} \tag{11}$$

The dynamic SDM adds first-order lagged variables of the dependent variable and first-order lagged variables with spatial terms on the basis of the static SDM. It is used to test the model estimation results (Finch et al. 2022; Mariscotti 2021). The dynamic SDM is shown in Eq. (12).

$$y_{it} = \tau y_{i,t-1} + \eta w y_{i,t-1} + \rho w y_{it} + x_{it}\beta + w\overline{x}_{it}\theta + u_i + \lambda_t + \varepsilon_{it} \tag{12}$$

In Eq. (12), the dependent variable for time lag is $y_{i,t-1}$. The corresponding variable coefficient is $\tau$. The dependent variable for the time and spatial lag terms is $wy_{i,t-1}$. The corresponding model coefficient is $\eta$. The dynamic SDM-STIRPAT is shown in Eq. (13).

$$\begin{aligned}\ln I_{it} &= \tau \ln I_{i,t-1} + \eta \sum_{i\neq j,j=1}^{n} w_{ij} \ln I_{j,t-1} + \rho \sum_{i\neq j,j=1}^{n} w_{ij} \ln I_{jt} + \beta_1 \ln P_{it} + \beta_2 \ln A_{it} \\ &+ \beta_3 \ln T_{it} + \beta_4 \ln U_{it} + \beta_5 \ln IN_{it} + \beta_6 \ln TCT_{it} + \theta_1 \sum_{i\neq j,j=1}^{n} w_{ij} \ln P_{jt} \\ &+ \theta_2 \sum_{i\neq j,j=1}^{n} w_{ij} \ln A_{jt} + \theta_3 \sum_{i\neq j,j=1}^{n} w_{ij} \ln T_{jt} + \theta_4 \sum_{i\neq j,j=1}^{n} w_{ij} \ln U_{jt} \\ &+ \theta_5 \sum_{i\neq j,j=1}^{n} w_{ij} \ln IN_{jt} + \theta_6 \sum_{i\neq j,j=1}^{n} w_{ij} \ln TCT_{jt} + \ln \mu_i + \ln \lambda_t + \ln \varepsilon_{it}\end{aligned} \tag{13}$$

The study compares the parameter estimation results of non-spatial models and spatial models. Lagrange multiplier test, Wald test, and likelihood ratio test are used to verify the spatial lag and error terms of the spatial model. When considering spatial factors, the maximum likelihood estimation method is applied to estimate parameter. The fixed effects spatial lag model is analyzed and estimated (Wu et al. 2023; Oh 2023). The unit root test is used to test whether time series data has a unit root, that is, whether there is a stable linear trend. Cointegration testing is used to test whether there is a long-term equilibrium relationship between multiple time series. The spatial auto-correlation test is used to analyze whether there is correlation between data at spatial positions. The principles behind these tests are all based on statistical methods, which determine whether the data conforms to a specific pattern or relationship by performing specific processing and calculations on the data. The logarithmic likelihood function of the spatial lag model is shown in Eq. (14).

$$LogL = -\frac{NT}{2}\log(2\pi\sigma^2) + T\log|I_N - \delta W| - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it} - \delta\sum_{j=1}^{N} w_{ij}y_{jt} - x_{it}\beta - \mu_i\right)^2 \tag{14}$$

In Eq. (14), the spatial lag model is $LogL$. The total number of time dimension indicators is $N$. The first-order lagged variable is $\delta$. The spatial correlation coefficient in variables is $W$. The random disturbance is $\sigma$. The main reasons for choosing the SDM-STIRPAT model are as follows. Firstly, the SDM-STIRPAT model is a hybrid model that includes spatial terms for dependent variables and explanatory variables, allowing the model to effectively consider the influence of spatial factors. Secondly, the SDM-STIRPAT model can perform dynamic analysis by incorporating first-order lagged variables of the dependent variable and first-order lagged variables with spatial terms, which helps to test the stability of the model. Finally, the SDM-STIRPAT model can perform parameter estimation through maximum likelihood estimation, estimating fixed effects spatial lag models, which makes the parameter estimation of the model more accurate.

## Analysis results of carbon emissions from transportation facilities

### Carbon emission measurement and correlation analysis

From 2004 to 2022, transportation energy consumption and CE are displayed in Fig. 3. Figure 3a displays the energy consumption from transportation facilities. From 2004 to 2022, the energy consumption form transportation facilities have shown an upward trend. From 173 million tons in 2004 to 636 million tons in 2022, the mean annual growth rate is 7.5%. Figure 3b displays the statistical results of CE from transportation facilities. Similarly, from 2004 to 2023, carbon dioxide emissions from transportation facilities have shown an increasing. The annual growth rate is 4.9%, increasing from 318 million tons in 2004 to 752 million tons in 2022. The data shows that transportation facilities have been continuously increasing in energy consumption and CE over the past decade. This growth may be due to economic and population growth, leading to an increase in transportation demand, thus requiring more transportation facilities and energy to support transportation operations.

The global spatial auto-correlation coefficient of CE from 2004 to 2022 is shown in Fig. 4. The global spatial auto-correlation coefficient fluctuated positively within 0.05 to 0.3, with a significant index at 5% for all years. This indicates a significant spatial correlation of carbon dioxide emissions within a geographical range. Further analysis shows that the global spatial auto-correlation coefficient shows a fluctuating trend during the research time period, with strong spatial correlation years including 2001, 2005, and 2007. The spatial correlation of regional CE is particularly significant in these years. However, after 2010, the spatial correlation showed a significant weakening trend, indicating that the carbon dioxide emissions in a certain region gradually reduced under the influence of neighboring region carbon dioxide emissions.

The local spatial auto-correlation coefficient of CE is displayed in Fig. 5. Figure 5a displays the local spatial auto-correlation coefficient in 2010, with 6 regional observation points located in the first quadrant, corresponding to higher observed CE in the region. 10 regional observation points were located in the third quadrant, corresponding to lower carbon dioxide emissions. Figure 5b shows the local spatial auto-correlation coefficient in 2020, with 8 regional observation points located in the first quadrant, corresponding to higher observed CE in the region. 10 regional observation points were located in the third quadrant, corresponding to lower carbon dioxide emissions in the region. This indicates that the variation of local spatial auto-correlation coefficients is affected by various factors, including the position and year of observation points.

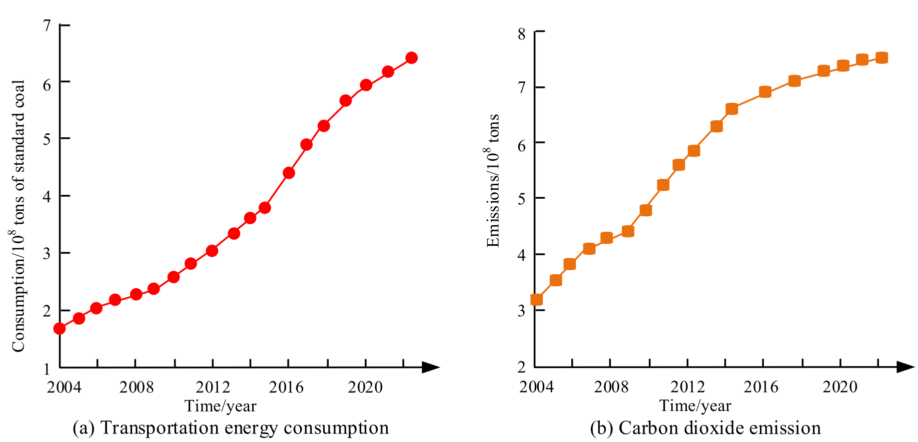


**Fig. 3** Transportation energy consumption and carbon dioxide emissions

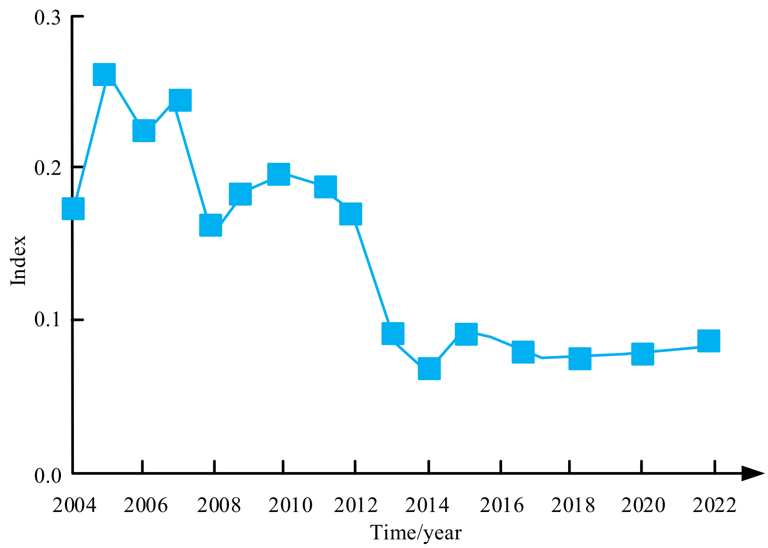


**Fig. 4** Global spatial auto-correlation coefficient of carbon dioxide emissions

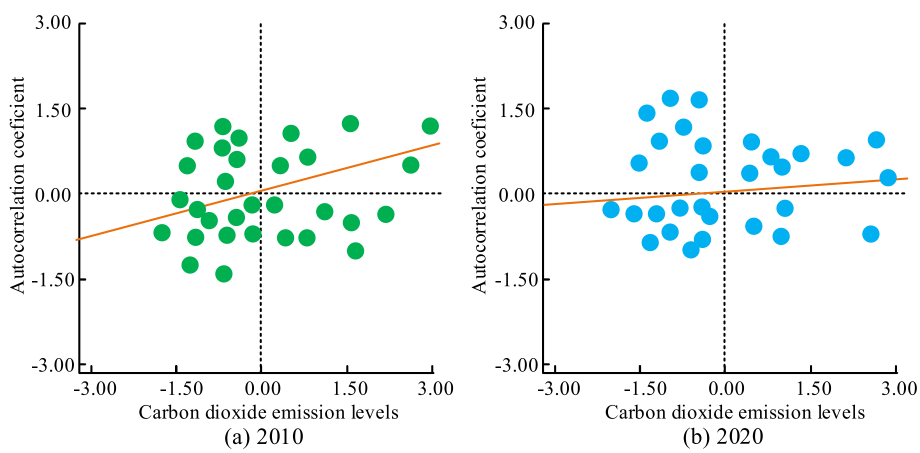


**Fig. 5** Local spatial auto-correlation coefficient of CE

## Analysis of SDM-STIRPAT

In order to determine whether there is a unit root between variables, that is, whether there is a long-term trend, it is necessary to conduct a unit root test. The panel data unit root test results in horizontal order are displayed in Table 2. In Table 2, tests 1–3 represent three testing modes, namely no intercept term, intercept term, and both intercept term and trend term. From the data in Table 2, considering the horizontal order, the unit root test results for each variable were not significant.

The test results under the first-order difference order are shown in Table 3. In a differential order, the test results for all variables with intercept terms were significant, indicating that the variables were the same order and had a monotonic relationship between them. That is, when the value of one variable increased (decreased), the other variable also increased (decreased), and their changes were linear.

The cointegration relationship test results for panel data is displayed in Table 4. It is used to determine whether there is a cointegration relationship between variables, that

**Table 2** Results of horizontal order lower panel

| Variable | Test 1 | Test 2 | Test 3 |
|---|---|---|---|
| ln*I* | 10.1 | − 3.1*** | 3.6 |
| ln*P* | 13.2 | − 11.3*** | − 4.1*** |
| ln*A* | 24.1 | − 10.3*** | 4.3 |
| ln*T* | − 1.3** | 6.7 | − 0.08 |
| ln*U* | 14.7 | − 7.3*** | − 39.8*** |
| ln*IN* | 2.4 | − 1.7* | 0.7 |
| ln*TCT* | 13.5 | − 4.9*** | − 6.32*** |

*, **, and *** represent significance levels of 10%, 5%, and 1%, respectively

**Table 3** Results of unit root test of lower panel data in first-order difference order

| Variable | Test 1 | Test 2 | Test 3 |
|---|---|---|---|
| ln*I* | − 9.5*** | − 4.1*** | − 5.3*** |
| ln*P* | − 6.4*** | − 12.6*** | − 12.7*** |
| ln*A* | − 5.4*** | − 4.87*** | 0.79 |
| ln*T* | − 12.5*** | − 19.2*** | − 19.2*** |
| ln*U* | − 12.3*** | − 14.2*** | − 16.1*** |
| ln*IN* | − 14.6*** | − 9.7*** | − 11.2*** |
| ln*TCT* | − 12.5*** | − 11.7*** | − 20.1*** |

*** represents significance levels of 1%

**Table 4** Panel data cointegration relationship test results

| Statistics | Test 1 | Test 2 | Test 3 |
|---|---|---|---|
| BN | 3.7 | 4.9** | 5.8** |
| HMM | − 3.8*** | − 6.7*** | − 7.8*** |
| ADF | − 5.7*** | − 5.3*** | − 6.7*** |

** and *** represent significance levels of 5%, and 1%, respectively

is, whether their changes are linear. The test results were significant at 1% or 5% confidence, indicating that the null hypothesis that there was no cointegration relationship between variables should be refused. From this, form 2004 to 2022, there was a long-term cointegration relationship in CE under the influence of independent variables such as technology, population, transportation, and economy.

The model results without considering spatial interaction effects are shown in Table 5. Refusing the null hypothesis at 1% or 5% level requires considering both spatial and temporal fixed effects. This indicates that fixed spatial and temporal effects are necessary when constructing models. The likelihood ratio test results indicated that the null hypothesis of joint non significance for two fixed effects should be rejected. It means that a two-way fixed effects model should be constructed. This model can consider both spatial and temporal effects simultaneously, thereby more accurately predicting and interpreting data.

The parameter estimation results of the spatial measurement model are displayed in Table 6. The difference between unbiased and biased spatial econometric models was small, with statistical significance at 1% or 5%. The significance of all variables was

**Table 5** Results of model estimates regardless of spatial interaction effects

| Parameter | Spatial fixed effect | Time fixed effect | Two-way fixation effect |
|---|---|---|---|
| ln*P* | 0.423* | 0.864*** | 0.597** |
| ln*A* | 0.567*** | 0.367*** | 0.735*** |
| ln*T* | − 0.088** | 0.435*** | 0.0897*** |
| ln*TCT* | 0.015* | 0.088** | 0.0512** |
| ln*U* | 0.079 | 0.167 | 0.354*** |
| ln*IN* | 0.634*** | 0.967*** | 0.312** |
| *LogL* | − 213.69 | − 402.16 | − 183.46 |

*, **, and *** represent significance levels of 10%, 5%, and 1%, respectively

**Table 6** Results of the spatial measurement model parameter estimation

| Parameter | No deviation correction | With deviation correction |
|---|---|---|
| ln*P* | 0.621*** | 0.619*** |
| ln*A* | 0.712*** | 0.711*** |
| ln*T* | − 0.021** | − 0.019*** |
| ln*TCT* | 0.153** | 0.152** |
| ln*U* | 0.281** | 0.282** |
| ln*IN* | 0.325*** | 0.324*** |
| *LogL* | − 163.69 | − 163.71 |

** and *** represent significance levels of 5%, and 1%, respectively

consistent. This indicated that the selected model had high accuracy in parameter estimation. In addition, the significance of each variable showed a similar trend in the two modified models, which further strengthened the reliability.

The stability test results of the SDM-STIRPAT are shown in Table 7. The SDM exhibited high stability in both spatial lag and spatial error tests, indicating its strong ability to interpret data. In addition, the dynamic SDM-STIRPAT also had good stability. All explanatory variables significantly affected the dependent variable, with positive or negative coefficients consistent with the estimated results of the original model. The accuracy of SDM selection was further verified through spatial error testing.

## Discussion

From 2004 to 2022, the energy consumption and carbon dioxide emissions of China's transportation facilities showed a significant upward trend. This is mainly due to the rapid development of China's economy and population growth, which has led to a continuous increase in demand for transportation. It requires more transportation facilities and energy to support transportation operations. However, this also reminds relevant personnel to strengthen energy conservation and emission reduction work in the transportation sector while promoting economic development, in order to reduce the impact of transportation facilities on the environment. Secondly, through spatial auto-correlation analysis, the study found that carbon dioxide emissions exhibited significant spatial

**Table 7** Results of the SDM-STIRPAT stability test

| Parameter | SDM-STIRPAT | Dynamic SDM-STIRPAT |
|---|---|---|
| ln*P* | 0.867*** | 0.812** |
| ln*A* | 0.798*** | 0.257*** |
| ln*T* | − 0.083*** | − 0.054** |
| ln*TCT* | 0.0931*** | 0.0712** |
| ln*U* | 0.165*** | 0.186** |
| ln*IN* | 0.312*** | 0.0642 |
| ln*I* | 0.675*** | − 0.127** |
| *LogL* | 295.541 | − 56.542 |
| $\sigma^2$ | 0.018 | 0.051 |
| $R^2$ | 0.957 | 0.945 |
| Corrected $R^2$ | 0.301 | 0.614 |
| Spatial error | 25.678*** | 73.159*** |

** and *** represent significance levels of 5%, and 1%, respectively

correlation within a geographical range. This indicates that carbon dioxide emissions in different regions are greatly influenced by emissions from neighboring regions. Therefore, the spatial correlations between regions need to be considered in policy formulation and implementation. The results of the SDM-STIRPAT spatial econometric model showed that there was a long-term stable synergistic relationship between factors such as technology, population, transportation, and economy and CE. However, the research results also exposed some issues. Firstly, the growth rate of CE from transportation facilities has significantly slowed down since 2010. This may be related to the vigorous promotion of low-carbon environmental protection technologies and the implementation of national policies for energy conservation and emission reduction. By optimizing these factors, it is expected to achieve low-carbon, green, and sustainable development in the transportation sector.

Due to the increasing energy consumption and CE of transportation facilities, improving energy efficiency is an important means to reduce CE. Policy makers should promote the research and application of energy-saving technologies, improve the energy efficiency of transportation facilities, and reduce CE. Developing low-carbon transportation modes such as public transportation, new energy vehicles, bicycles, and walking can reduce dependence on high carbon emission vehicles. The government can encourage citizens to use low-carbon transportation methods and reduce CE from transportation facilities through policies such as subsidies and tax incentives. By optimizing the spatial layout of transportation facilities and reducing unnecessary traffic flow, CE can be reduced. The government should strengthen guidance on transportation facility planning, promote the three-dimensional and diversified development of urban transportation, and improve the operational efficiency of transportation facilities. Due to the global of CE, strengthening international cooperation is crucial. Countries should actively participate in global climate governance, promote the international community to jointly address climate change, and reduce CE. The government should strengthen the supervision of CE from transportation facilities, establish carbon emission monitoring and statistical systems, and strictly control the CE of transportation enterprises. Meanwhile, it is also possible to improve the CE trading system and encourage enterprises to actively reduce CE through market means. Through education and publicity, it is possible to increase public awareness of CE from transportation facilities, guide citizens to establish low-carbon and environmentally friendly travel concepts, and promote social participation in low-carbon transportation construction.

## Conclusion

To address the CE from transportation facilities, the bibliometric method was used to identify all system elements that affect regional CE from transportation facilities. The scalable environmental impact factor theory model STIRPAT was constructed, including population factors, economic factors, and technological factors. The spatial econometric model SDM-STIRPAT for transportation facility CE was constructed using panel data from 30 regions from 2004 to 2022, combined with SDM and other methods. The carbon dioxide emissions from transportation facilities added from 318 million tons in 2004 to 752 million tons in 2022, with a mean annual growth rate of 4.9%. The global spatial auto-correlation coefficient fluctuated positively within the range of 0.05 to 0.3. The index for all years was significant at 5%, and there was a significant spatial correlation between CE in the geographical spatial range. Through the stability test of the SDM-STIRPAT, the model showed high stability in both spatial lag test and spatial error test, indicating strong ability to interpret data. The results indicate that the CE from transportation facilities are affected by independent variables such as population, economy, technology, and transportation, with significant spatial distribution characteristics in different regions and years. The proposed model helps to better understand the carbon emission mechanism from transportation facilities and provides a basis for relevant policy formulation and carbon emission management. The limitation is as follows. It only considers a few key variables, including technology, population, transportation, and economy. Therefore, future research can first consider other variables that affect CE from transportation facilities, such as urban planning, energy policies, etc., on the basis of existing research to improve the predictive accuracy of the model. Secondly, further research can be conducted on CE in different regions and countries, in order to provide more targeted strategies for global carbon emission management. In addition, the model can be further validated and revised by combining field investigations and experimental data to enhance its application value.

**Author contributions**

Guozhi Li, Conceptualization, methodology, funding acquisition, writing-original draft preparation; Yidan Yuan, validation, formal analysis, writing-review and editing; Xunuo Chen, investigation, resources, data curation, writing-review and editing; Dandan Fu, visualization, supervision, investigation; Mengying Jiang, investigation, formal analysis, resources, data curation.

**Funding**

The research is supported by the National Social Science Foundation of China (Project No. 22BJY126); This research is supported by the special project of social science planning of Zhejiang Province "The 20th National Congress of the CPC and the Second Plenary Session of the 15th Zhejiang Provincial Party Committee" (pre approved project).

**Availability of data and materials**

The data are included in the article.

## Declarations

### Ethics approval and consent to participate
Not applicable.

### Consent for publication
Not applicable.

### Competing interests
The author reports that no conflict interests.

Received: 6 May 2024 Accepted: 19 June 2024
Published online: 26 June 2024

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