



The Driving Factors of Carbon Emissions in China's Transportation Sector: A Spatial Analysis

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Studies on the CO₂ emissions from the transportation sector in China are increasing, but their findings are inconclusive. The main reason is that the spatial correlation of CO₂ emissions from the regional transportation sector has been ignored in examinations of the driving factors of CO₂ emissions from this sector. In this paper, new emission factors are adopted to calculate the CO₂ emission levels from the transportation sector in Chinese provinces. By fully considering the spatial correlation of regional CO₂ emissions and based on a two-way Durbin model incorporating both spatial and temporal fixed effects, the driving factors of CO₂ emissions from the transportation sector in China are studied. The CO₂ and spatial regression results for the transportation sector in China suggest the following: 1) Most of the regions with the highest CO₂ emissions from the Chinese transportation sector are located on the east coast; they have gradually expanded over time to include the central and western regions. 2) The CO₂ emissions from the transportation sector are higher in South China than in North China, and the regions with higher CO₂ emissions have gradually shifted from north to south. 3) Transportation activity intensity, urbanization level, technological level, industrial structure and per capita GDP greatly impact CO₂ emissions from the transportation sector in each province of China. Among these factors, transportation activity intensity, urbanization level, and per capita GDP exert not only direct effects but also indirect effects, whereas technological level and industrial structure exert only direct effects.

Keywords: China's transportation sector, CO₂ emissions, driving factors, direct effects, indirect effects

INTRODUCTION

Forty years after the reform and opening up, the economic development of China has achieved world-renowned achievements. The advancement of the transportation industry has played a substantial role in promoting economic development. China has the world's largest transportation infrastructure, including highway and railway networks, which facilitates urbanization and industrialization. However, while the demand for transportation services is strengthening, the CO₂ emissions from the transportation sector are increasing, resulting in increasingly serious environmental pollution. In 2017, China's transportation sector contributed 4.4% of the country's GDP, but its energy consumption accounted for 9.8% of its total energy consumption (Yearbook, 2018). The rapid growth of energy consumption in China's transportation sector over the past forty years has exacerbated its CO₂ emissions, and the CO₂ emissions growth rate of its transportation sector is much higher than that of other industry sectors (Xie et al., 2019).

The high CO₂ emissions and pollution generated by the transportation sector have attracted the attention of scholars in China and abroad. As a major contributor to global CO₂ emissions, the CO₂ emissions from the global transportation sector accounted for 24.34% of the total CO₂ emissions in 2016, increasing by 4.34% from the level in 2012 (IEA, 2018). Although the energy consumption and CO₂ emissions from the transportation sector in China are lower than 10%, with the strong development of China's economy and the continuous improvement of its infrastructure, the demand for services in the transportation sector is growing rapidly, which may exacerbate the energy consumption of this sector and increase the overall CO₂ emission level.

Many scholars have investigated the increasing CO₂ emissions and energy consumption of the transportation sector both worldwide and in China. Applied ridge regression to assess the substitutability of the energy consumption of China's transportation industry. Their results revealed that all energy inputs could be substituted, but they noted that oil and natural gas had a higher possibility of substitution than the other energy inputs (Xie and Hawkes, 2015). Performed scenario analysis and predicted the CO₂ emissions from the Indian transportation sector (Paladugula et al., 2018). Evaluated the impacts of CO₂ emissions-reduction policies or legal regulations on the CO₂ emissions from small- and medium-sized transportation companies in France and found that they had little effect (Touratier-Muller et al., 2019). The above-described studies were focused on the overall CO₂ emissions from the transportation industry. Furthermore, many researchers have conducted in-depth research on CO₂ emissions from subsystems of the transportation sector, such as highway transportation (Yan and Crookes, 2009; Gambhir et al., 2015; Peng et al., 2018; Zuo et al., 2018; Zhang et al., 2019) and water transport and shipping systems (Andreoni and Galmarini, 2012; Chèze et al., 2013; Bo et al., 2019). Furthermore, due to their different organizational systems, the freight and passenger transportation subsectors differ in CO₂ emissions performance. Scholars have analyzed the emissions from both subsectors to identify these differences (He et al., 2013; Hao et al., 2014; Hao et al., 2015; Luo et al., 2016; Wang et al., 2018; Lv et al., 2019).

At the Copenhagen Climate Change Conference in 2009, the Chinese government pledged to reduce its CO₂ intensity by 40–45% from its 2005 level by 2020 (Yang et al., 2019). Facing high pressure to achieve emissions reduction, the Chinese government has implemented a series of environmental and low-carbon policies and measures; however, its overall CO₂ emission levels remain very high. Therefore, it is necessary to formulate specific energy conservation and CO₂ emissions-reduction measures for different industries and analyze the distribution and other characteristics of CO₂ emissions from different industries and the driving factors. Especially in industries with high CO₂ emissions, such as the transportation industry, emissions-reduction measures targeting the transportation sector are of great significance for realizing China's emissions-reduction goals. Many scholars have examined the factors driving CO₂ emissions from the transportation sector by considering the characteristics of CO₂

emissions and the importance of energy conservation and emissions-reduction measures. At present, the main methods used to identify the factors influencing CO₂ emissions in the transportation sector include the following: the logarithmic mean Divisia index (LMDI) method (Wang et al., 2011; Guo et al., 2014; Liu et al., 2015; Zheng et al., 2019), the structural decomposition analysis (SDA) method (Cansino et al., 2016; Dong et al., 2018), and the generalized Divisia index method (GDIM).

Determining the spatial correlation of CO₂ emissions is one focus of research (Li and Li, 2020), and some studies have provided preliminary discussions of the spatial correlation of CO₂ emissions in the transportation sector (Guo et al., 2014; Feng and Wang, 2018). However, analyses of the mechanisms underlying the spatial correlation of CO₂ emissions in the transportation sector are limited and have not been analyzed using econometric methods. CO₂, as a major component of greenhouse gases, has a typical transboundary effect; that is, CO₂ emissions from one region can be transferred to neighboring regions through natural factors such as atmospheric circulation. With the extensive implementation of China's regional integration policy and deepening market integration, China's regional economic development shows strong spatial correlation (Bai et al., 2012). The occurrence of economic activity in a regional system necessarily depends on transportation, and activities such as inter-regional merchandise trade, technology diffusion and factor flow are all realized through transportation. As a result, CO₂ emissions from the transportation sector in one region are transferred to neighboring regions along with economic activity. Furthermore, China is a vast country with widely varying topographic and geographic conditions. The plains areas have a more developed transportation infrastructure, which attracts a greater concentration of transportation activities. Therefore, the spatial correlation of transportation CO₂ emissions is reflected in geographical factors.

Based on the above analysis, it is apparent that the drivers of CO₂ emissions in a local transportation sector may affect the CO₂ emissions of the transportation sector in neighboring regions through spatial correlation and may feedback to the local sector through spatial correlation. Therefore, when using regression methods to analyze the drivers of CO₂ emissions in the transportation sector, ignoring the spatial correlation of the dependent variable is equivalent to omitting variables and can lead to biased model results (Elhorst, 2014a). The spatial econometric model, a new method, has been applied to many areas (Zhang et al., 2018; Bo et al., 2019; Li and Wang, 2019; Yang et al., 2019). Unlike the traditional regression model, the spatial econometric model fully considers regional spatial correlation, which can solve the above problems and thus allows more robust conclusions. Different from the existing literature, this paper adopts new emission factors to measure the CO₂ emissions of China's transportation sector. Based on the full consideration of the spatial correlation of CO₂ emissions in the transportation sector, a geographic distance weight matrix and an economic geospatial weight matrix are constructed. Then, a two-way spatial Durbin model (SDM) is used to explore the CO₂ emission level of China's transportation sector and identify the influencing factors

in the regional transportation sector. This approach can allow scientifically supported and reasonable energy-saving and emission reduction policies to be formulated for the Chinese transportation sector.

The next section introduces the methods, including the CO₂ emissions calculation methods, spatial weight matrix, basic regression model construction and spatial correlation detection methods for the regional transportation sector. Moreover, the data sources are introduced in this section. **Results** presents the results, and **Conclusions and Recommendations** provides the conclusions and recommendations.

METHODS AND DATA SOURCES

CO₂ Emissions of the Transportation Sector

The CO₂ emissions from the transportation sector are calculated based on the combustion of fossil fuels in the sector. Due to limitations in data sources, the smallest basic unit that can be used is the province. The CO₂ emissions from the transportation sector in each province are calculated from the energy consumed for its transportation activities. **Equation 1** describes the specific calculation method (Shan et al., 2018):

$$CE_i = AD_i \times NCV_i \times CC_i \times O_i \quad (1)$$

where CE_i is the CO₂ emissions generated by the different types of fuels in the transportation sector; AD_i is the consumption of the different fuel types in the transportation activities within the province boundary; NCV_i is the net calorific value generated by the combustion of a unit of the different types of fossil fuels; CC_i (the CO₂ content) is the calorific value of a unit of fossil fuels consumed in the transportation activities; O_i is the oxidation efficiency; and i is the oxidation rate of fossil fuels in the combustion process. In addition, because different oxidation rates are used for different industries (Elhorst, 2014a), we mainly refer to the oxidation rate of the transportation industry.

By summing the CO₂ emissions of the different types of fossil fuels in the various transportation activities, **Eq. 2** can be used to obtain the CO₂ emissions from the provincial transportation sector:

$$CE = \sum CE_i \quad (2)$$

The amount of fossil fuel consumed in the provincial transportation sector is derived from the fossil fuel consumed in the transportation, storage, and shipping industries based on the provincial terminal energy consumption in the China Energy Statistics Yearbook; it includes raw coal, cleaned coal, other washed coal, briquettes, gangue, coke, coke oven gas, blast furnace gas, converter gas, other gas, other coking products, crude oil, gasoline, kerosene, diesel, fuel oil, naphtha, lubricants, paraffin waxes and white spirit. (**Supplementary Table S1** lists the fossil fuels consumed by the transportation sector in each province in 2016.)

Although the Intergovernmental Panel on Climate Change (IPCC) and the National Development and Reform Commission

of China (NDRC) have defined specific values of NCV_i and CC_i , most studies currently use default values to study CO₂ emissions. However, analyzed measurements of 602 coal samples from the 100 largest coal-mining areas in China and found that the emissions factors recommended by the IPCC and NDRC frequently were higher than the actual emissions factors in 2012 (Liu et al., 2015; Shan et al., 2016); furthermore, according to Shan et al., the IPCC default emissions factors are approximately 40% higher than Chinese survey values (Shan et al., 2018). It can be seen that the emission factors defined by the IPCC and NDRC are higher than the actual values, which can bias the results and affect the accuracy of the conclusions in this paper. To ensure the accuracy of the results, this paper uses updated NCV_i and CC_i values to estimate the CO₂ emissions from the Chinese transportation sector (Shan et al., 2018). We believe that these new emission factors are more accurate than previous factors. (**Supplementary Table S2** shows the details of the CO₂ emission factors.)

Spatial Weight Matrix

The traditional spatial weight matrix follows the ROOK adjacency rule (that is, the adjacency relationship between two adjacent regions is 1, and the adjacency relationship between two nonadjacent regions is 0), which cannot fully reflect the mutual influence of transportation activities between regions. In addition, the spatial interaction between different areas is not the same. Although the impact of transportation activities in underdeveloped areas on developed areas is weak, the transportation activities in developed areas may spread to neighboring underdeveloped areas. Therefore, based on comprehensive consideration of the spatial distance between regions and economic activity factors, the spatial weight matrix is constructed as follows:

According to the first law of geography, the spatial correlation between units gradually decreases with increasing distance. However, the straight-line distance between provinces in terms of latitude and longitude cannot accurately reflect the traffic correlation between provinces. Therefore, we construct a geographic distance weight matrix with the nearest interprovincial highway mileage using **Eq. 3**:

$$W_{1,ij} = \begin{cases} 1/d_{ij} & i \neq j \\ 0 & i = j \end{cases} \quad (3)$$

where d_{ij} is the nearest highway mileage between the capital city of province i and the capital city of province j .

In addition, because transportation activities may be spatially related through the division of labor in the economic activities of two provinces or may be generated through the internal division of labor in economic activities, geographical factors are not the same as the spatial effects of transportation activities. One factor, such as socioeconomic attributes, can be the cause of the spatial correlation between transportation activities. Therefore, in this paper, an economic geospatial weight matrix combining geographic location and economic connection is constructed using **Eq. 4**:

$$W_{2,ij} = \begin{cases} (\bar{Q}_i \times \bar{Q}_j) / d_{ij}^2 & i \neq j \\ 0 & i = j \end{cases} \quad (4)$$

where \bar{Q}_i and \bar{Q}_j are the real GDPs per capita of provinces i and j , respectively.

Spatial Correlation

In this paper, to accurately identify the spatial correlation between transportation activities, spatial data are analyzed based on the global Moran's I index via exploratory sequential data analysis (ESDA) with two spatial weight matrices, namely, a geographic distance weight matrix and an economic geospatial weight matrix. The calculation equation is as follows:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (5)$$

where I is the global Moran's I index; w_{ij} is the spatial matrix; and x and \bar{x} are the provincial CO₂ emissions and average provincial CO₂ emissions, respectively. The value range of I is $[-1, 1]$. An I higher than 0 would imply a positive correlation between the CO₂ emissions of transportation sectors of different provinces, and an I lower than 0 would indicate that the CO₂ emissions from the transportation sectors of the different provinces are negatively spatially correlated. A global Moran's I index near 0 would mean that the CO₂ emissions from the transportation sectors of the different provinces are randomly distributed in space, with no spatial correlation.

Spatial Econometric Model

The IPAT model proposed by American economists Holdren and Ehrlich in the 1970s is considered the main model used to explain the impacts of human activities on the ecological environment (Holdren and Ehrlich, 1974). They proposed that population size, per capita wealth and technological level are the main factors influencing the ecological environment. The standard IPAT model Eq. 6 is as follows:

$$I = aP_i^b A_i^c T_i^d e_i \quad (6)$$

where I is the impact on the ecological environment; a is a constant; P is population size; A is per capita wealth; T is technical level; and e is a random error term. In this article, to reveal the relationships between transportation activities and CO₂ emissions, Eq. 6 is expanded according to previous scholars (Zhang and Nian, 2013; Li and Wang, 2019; Lv et al., 2019). Specifically, the left side of Eq. 6 is used to represent the CO₂ emissions from the transportation sector, and the right side represents the selected influencing factors and expansion indexes according to the existing literature.

In existing research, the indicators used to explore the driving factors of CO₂ emissions include regional population, regional economic development level, urbanization level, industrial structure changes, transportation activity and the

number of patents in specific regions, etc. (Lakshmanan and Han, 1997; Dong et al., 2018; Li et al., 2019; Ma et al., 2020). However, the number of regionally held patents varies by industry, and it is not clear how they relate to CO₂ emissions from transportation (Albino et al., 2014). Therefore, in this article, the CO₂ emissions stemming from fossil fuel combustion per unit GDP is used to characterize the level of technological progress in the transportation industry (Li et al., 2011). In addition, because CO₂ emissions from road transportation account for the highest proportion of the transportation industry, representing more than 70% (Zhu and Du, 2019), and considering the availability of data, we use road transport turnover to reflect the intensity of transportation activity in each region.

By adding the indicators in Eq. 6, which are selected based on existing research and the above analysis, and taking the natural logarithm of the variables in Eqs. 6, 7 is obtained:

$$\ln CE_{it} = \eta + \alpha_1 \ln TR_{it} + \alpha_2 \ln Pop_{it} + \alpha_3 \ln Urban_{it} + \alpha_4 \ln CE_{it} + \alpha_5 \ln IS_{it} + \alpha_6 \ln PGDP_{it} + \varepsilon_{it} \quad (7)$$

where:

- CE is the CO₂ emissions from each province;
- TR is the intensity of transportation activity in each province, expressed as road transport turnover, where road transport turnover is equal to the sum of road freight turnover and passenger turnover converted by a conversion factor (Song et al., 2015);
- Pop is the population size of the province;
- $Urban$ is the urbanization level of the province, that is, the ratio of the urban population to the total population;
- CEI is the CO₂ emissions stemming from fossil fuel combustion per unit GDP, which measures the level of technological progress, assuming that technological progress reduces the CO₂ emissions per unit of GDP output;
- IS is the industrial structure, namely, the share of the tertiary industry output in the total GDP;
- $PGDP$ is the GDP divided by population size, which represents the level of regional development and prosperity;
- i, t represent time and province respectively; and
- ε is an error term.

Considering the possible spatial correlation of CO₂ emissions from the transportation sector, it is necessary to compile a spatial econometric model reflecting spatial factors. The spatial Durbin model (SDM) is a general model that addresses spatial correlation and can be transformed into a spatial autoregressive model (SAR) and a spatial error model (SEM) under different coefficient settings. Therefore, in this paper, a two-way Durbin model with both fixed space and time effects is chosen to fit the data. The equation is as follows:

$$\begin{cases} \ln CE_{it} = \eta I_N + \delta W_{ij} \ln CE_{it} + \beta X_{it} + \sum \beta X_{it} + \theta W(\beta X_{it} + \sum \beta X_{it}) + a_i + \gamma_t + v_{it} \\ v_{it} = \lambda W_{ij} v_{it} + u_{it} \end{cases} \quad (8)$$

where:

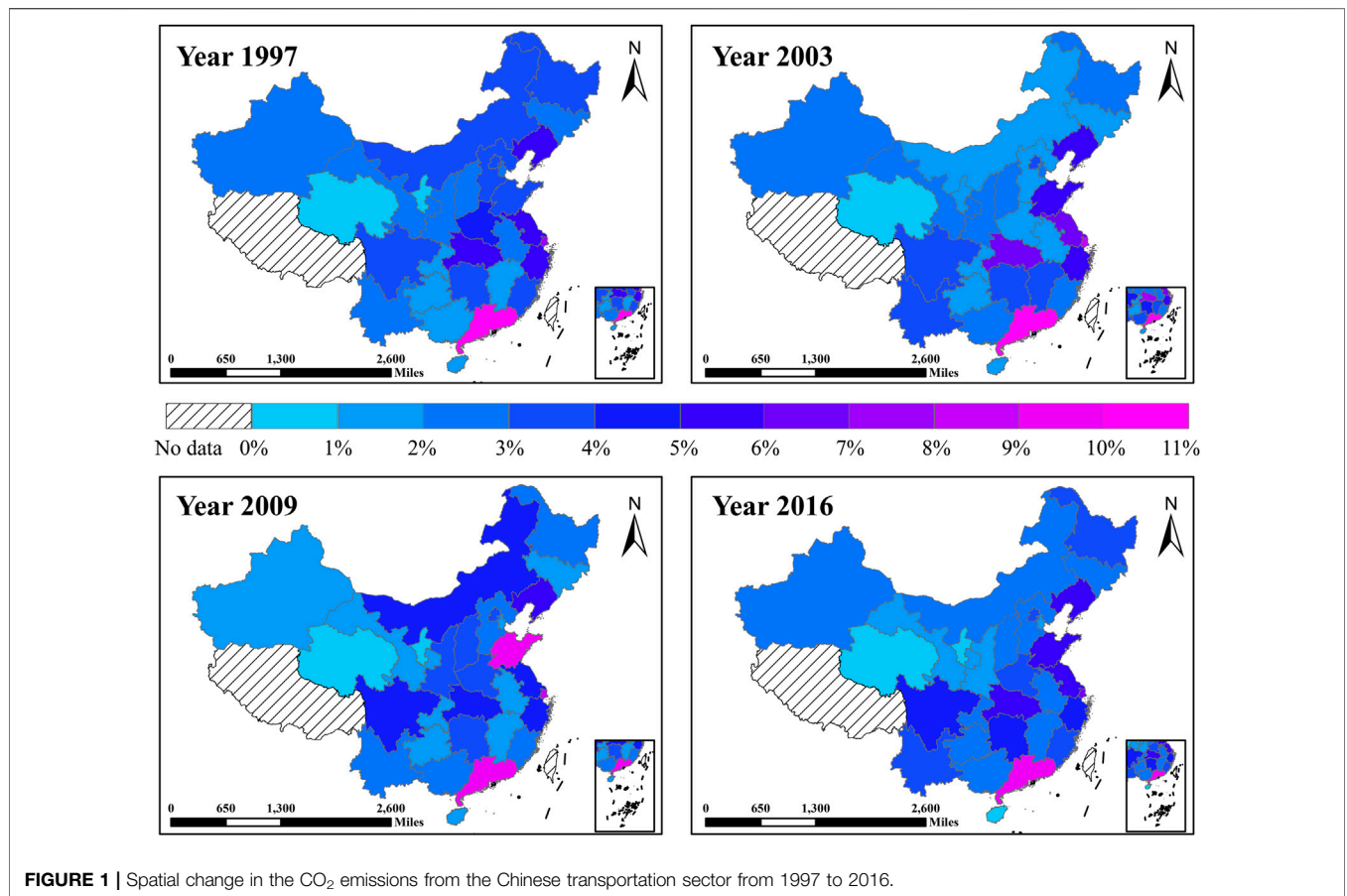


FIGURE 1 | Spatial change in the CO₂ emissions from the Chinese transportation sector from 1997 to 2016.

W_{ij} is a nonnegative spatial weight matrix;
 a_i and γ_t are the spatial and temporal effects, respectively, in the spatial model;
 δ is the spatial autoregressive coefficient;
 λ is the lag term coefficient of the explanatory variable;
 θ is the spatial autocorrelation coefficient; and
 X_{it} is the set of explanatory variables in Eq. 6.

In addition, the results of (Lesage, 2008) revealed that the use of the point estimation method to evaluate whether a spatial spillover effect existed in the spatial regression model would lead to deviations and possibly wrong conclusions. They believed that the direct and indirect effects of variables should be decomposed via partial differentiation. A change in an explanatory variable in a province will affect not only the CO₂ emissions from the transportation sector in that province but also those from nearby provinces, and the effect will be transmitted back to the province via the feedback effect between provinces. Therefore, in this paper, partial differential decomposition of the regression results, including the control variables, is conducted based on the benchmark regression results, and the direct and indirect effects of each explanatory variable are obtained to measure the influence of each influencing factor on each region and its surrounding regions.

All the data on the above explanatory variables are retrieved from the China Statistical Yearbook 1997–2016. Due to the lack of data on Hong Kong, Macao, Taiwan and Tibet in the aforementioned statistical yearbook, the above model does not include any data on these four provinces, leaving only 30 provinces in China.

RESULTS

CO₂ Emissions Calculation

To reveal the CO₂ emissions from the Chinese transportation sector in a more intuitive manner, Figures 1, 2 were constructed, which depict the spatial changes in the CO₂ emissions from the transportation sector of China from 1997 to 2016 and those from the various provincial transportation sectors, respectively. Figure 2 shows that the CO₂ emissions from the provincial transportation sectors in China have generally increased from 1997 to 2016. The transportation sector has high CO₂ emissions, especially in the more economically developed coastal areas, such as Shanghai, Guangdong, and Jiangsu. The high emissions in these coastal areas may be related to the economic development there and the improvement of transportation infrastructure. Internal and external economic activities are more frequent in these regions. Since regional economic exchanges and

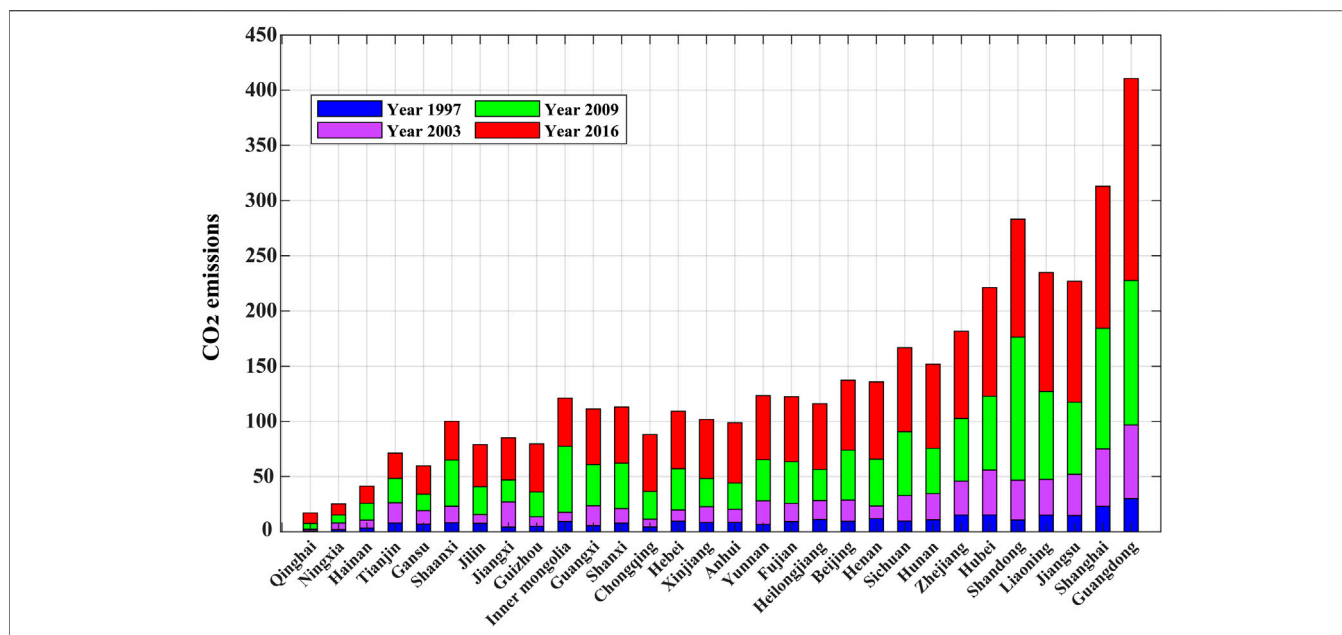


FIGURE 2 | CO₂ emissions from the transportation sector of Chinese provinces in 1997, 2003, 2009, and 2016.

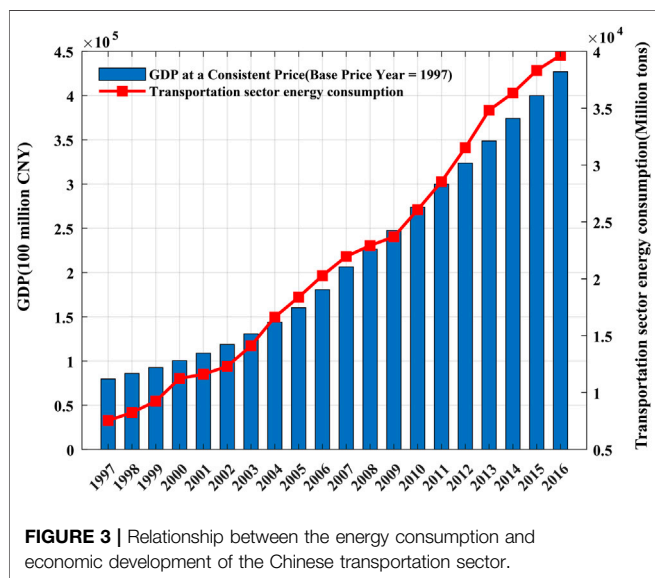


FIGURE 3 | Relationship between the energy consumption and economic development of the Chinese transportation sector.

interactions are intensive in these regions and demand for the transportation sector is higher in these regions than others, their CO₂ emissions are high. **Figure 3** reveals that with the rapid economic and social development, the demand for transportation, the energy consumption of the transportation sector and its CO₂ emissions are all increasing.

Figure 1 shows the spatial changes in the CO₂ emissions from the Chinese transportation sector from 1997 to 2016. The CO₂ emissions from the transportation sector in the provinces of China are generally increasing. Therefore, to more clearly characterize the spatial CO₂ emissions changes, the CO₂

emissions data of each province are normalized and mapped using ArcGIS software. **Figure 1** reveals that among the provinces, those in the coastal areas have the highest CO₂ emissions from the transportation sector; these levels have remained largely stable over time, with high emissions tending to spread inland. **Figure 1** also shows that the overall CO₂ emissions from the transportation sector in China are low. High-emission areas are gradually moving south; i.e., the number of southern areas with high CO₂ emissions from the transportation sector is gradually increasing. Forty years after the reform and opening up, the economic development of the southern provinces has gradually surpassed that of the northern provinces. This rapid economic development has also driven the rapid development of the transportation sector, and its CO₂ emissions have increased. In particular, within the central provinces, Wuhan has consistently had high CO₂ emissions, which may be related to its advantageous geographical location. The CO₂ emissions from the Sichuan transportation sector in the western transport hub province are also high, which may be associated with national major strategies, such as the development of the western region and the implementation of major strategies such as the Belt and Road Initiative. Hence, the demand of the transportation sector has also increased.

Spatial Correlation Test

As shown in **Table 1**, the global Moran's I index is significantly higher than 0 (with values of 0.3149 and 0.3528) at a significance level of 1% (both *p* values = 0) regardless of whether the geographic distance weight matrix *w*₁ or economic geospatial weight matrix *w*₂ is considered. This result indicates that the CO₂ emissions from the Chinese transportation sector are spatially correlated. The impact of the regional CO₂ emissions exhibits a clear positive spatial dependence. Therefore, there is significant

TABLE 1 | Spatial correlation test of the transportation sector carbon emissions.

	Geographic distance weight matrix w_1	Economic geospatial weight matrix w_2
Moran's I index value	0.2837	0.3369
Expected value $E(I)$	-0.0013	-0.0010
$SD(I)$	0.0041	0.0072
Z value	36.1287	42.9514
ρ value	0.0000	0.0000

TABLE 2 | Applicability test of the spatial panel model.

	Geographic distance weight matrix w_1		Economic geospatial weight matrix w_2	
	χ^2	p value	χ^2	p value
From specific to general				
LM-lag	43.667	0.000	56.271	0.000
R-LM-lag	20.172	0.005	49.605	0.008
LM-err	17.601	0.000	17.690	0.000
R-LM-err	18.047	0.000	19.368	0.000
From general to specific				
LR test for SAR	22.071	0.001	95.736	0.000
Wald test for SAR	15.712	0.003	78.450	0.000
LR test for SEM	25.881	0.000	36.263	0.000
Wald test for SEM	19.301	0.000	55.635	0.000
Hausman test	40.572	0.000	51.016	0.000
Joint significance test		LR statistics		p value
Temporal effect		30.074		0.003
Spatial effect		35.763		0.005

spatial correlation between the CO₂ emissions from the transportation sectors of the different Chinese provinces. To accurately reveal the influencing factors of transportation-sector CO₂ emissions, this spatial correlation must be accounted for.

Spatial Econometric Model

Here, we test the applicability of the spatial panel model. According to (Elhorst, 2014b), two dimensions, from specific to general and from general to specific, are adopted to determine the adaptability of the data to the spatial econometric model. We take the forms of Lagrangian multipliers (LM-lag and LM-error) and robust Lagrangian multiplier variants (R-LM-lag and R-LM-error) to test for spatial autocorrelation using the base model that assumes no spatial dependence. The results are listed in Table 2.

As shown in Table 2, the Hausman test results of the geographic distance and economic geospatial weight matrices are both significant at the 1% level, indicating that random effects can be rejected. Thus, a fixed effects model is appropriate. Furthermore, the joint significance test of the time and spatial effects reveals significant likelihood ratio (LR) statistics at the 1% significance level, indicating two-way fixed time and spatial effects.

In the test applying the specific-to-general concept, the model reveals both time and spatial effects. Both the LM and robust LM test results reject the null hypothesis of no spatial lag effect or spatial error effect, which indicates the existence of both spatial lag effect and spatial error characteristics. The LR and Wald tests of the general-to-specific concept yield p values less than 0.05,

indicating that the SDM cannot be simplified into the spatial lag model or the SEM and that the SDM best fits the data.

Based on Eq. 9, the panel data of 30 provinces in China from 1997 to 2016 were analyzed to estimate the maximum likelihood function, and the regression results are summarized in Table 3. The regression results were subjected to partial differential decomposition to obtain the explanatory variables. The direct and indirect effects are listed in Table 4.

As shown in Table 3, the coefficient estimates of the endogenous interaction effect $W^* \ln CO_2$ of both the geographic distance weight matrix and the economic geospatial weight matrix are positive at a significance level of 1%, which indicates that the CO₂ emissions from the provincial transportation sector have a significant positive spatial spillover effect. This is consistent with the conclusions from Table 1. The transmission and diffusion effects of the CO₂ emissions of the regional transportation sector are clear. The robustness of the regression results is evidenced by lack of significant differences in the magnitude, negative sign and significance level of the coefficients of the explanatory variables under the w_1 and w_2 spatial weight matrices. Since the w_2 spatial weight matrix contains both geographic and economic factors, the analysis of the empirical results that follows is based on w_2 .

From the results in Table 4, we can draw the following conclusions:

- (1) The direct and indirect effects of transportation activity intensity on the CO₂ emissions of the transportation sector are both significantly positive. Specifically, in the model, a 1% increase in the intensity of transport

TABLE 3 | Spatial econometric regression results.

Explanatory variable	Geographic distance weight matrix w_1	Economic geospatial weight matrix w_2
W * lnCO ₂	0.403 ^{***} (2.98)	0.496 ^{***} (3.16)
lnTR	0.371 ^{***} (3.68)	0.183 ^{**} (2.01)
lnPop	0.003 (0.64)	0.006 (1.33)
lnUrban	0.084 ^{***} (2.98)	0.070 ^{**} (2.45)
lnCEI	0.321 ^{***} (3.03)	0.208 ^{**} (2.13)
lnIs	-0.069 (-1.13)	-0.0523 ^{***} (-2.88)
lnPGDP	0.763 ^{***} (8.56)	0.639 ^{***} (5.17)
Time effect	including	including
Space effect	including	including
R ²	0.698	0.457
Log-likelihood value	608.654	431.012

Note: The values in parentheses are t statistics; *, **, and *** represent the 10, 5, and 1% significance levels, respectively.

TABLE 4 | Direct and indirect effects obtained via partial differential regression.

Explanatory variable	Geographic distance weight matrix w_1		Economic geospatial weight matrix w_2	
	Direct effect	Indirect effect	Direct effect	Indirect effect
lnTR	0.188 ^{**} (2.43)	0.036 ^{***} (2.87)	0.137* (1.83)	0.031 ^{**} (2.12)
lnPop	0.002 (0.82)	0.001* (1.79)	-0.623 (-1.11)	0.003* (1.98)
lnUrban	0.133* (1.70)	0.986 ^{**} (2.31)	0.254 ^{**} (2.22)	0.930 ^{***} (2.89)
lnCEI	0.583 ^{***} (3.03)	-0.102 (-0.99)	0.207 ^{***} (3.65)	-0.091 (-0.09)
lnIs	-0.071 ^{**} (-2.31)	0.006 (1.39)	-0.318* (-1.76)	0.096 (1.59)
lnPGDP	0.987 ^{***} (8.67)	0.0698 ^{***} (11.22)	0.490 ^{***} (7.04)	0.008 ^{***} (5.59)

Note: The values in parentheses are t statistics; *, **, and *** represent the 10, 5, and 1% significance levels, respectively.

activities corresponds to increases in CO₂ emissions from the transportation sector in the local region and neighboring regions of 0.137 and 0.031%, respectively. This finding indicates that an increase in the intensity of transportation activities will not only increase the level of CO₂ emissions from transportation in the region but also affect the level in neighboring regions through spatial correlation. As inter-regional economic interactions strengthen, inter-regional transportation becomes more frequent. Furthermore, when transportation activities in one region reach a certain level of concentration, they spread out, affecting the CO₂ emissions of neighboring regions.

- (2) A direct effect of population on the CO₂ emissions from the provincial transportation sector is not clear. Neither the geographic distance weight matrix nor the economic geospatial weight matrix provides significant population coefficient estimates. However, the indirect effect of population size is significantly positive at the 10% level, wherein a population increase in a given region is expected to cause the CO₂ emissions from the transportation sector in the adjacent regions to increase by 0.03%. An increase in population increases the demand in the transportation sector, such as demands for travel and energy. Regional travel and energy demands disperse the impact of CO₂ emissions from the transportation sector to neighboring regions.

- (3) The impact of urbanization level on CO₂ emissions from the transportation sector in both local regions and neighboring regions is significantly positive and is stronger in neighboring regions (with coefficients of 0.254 and 0.930%, respectively). A higher urbanization level results in higher car ownership, higher transportation needs, and a more specialized transportation market, which significantly increase transportation-related CO₂ emissions. Furthermore, since regions with high urbanization levels have greater economic development, the spillover effect on neighboring regions is stronger, and traffic-related CO₂ emissions in neighboring regions increase more significantly.
- (4) The impact of changes in technological level on regional transportation sector CO₂ emissions is measured by the composite environmental index (CEI). Clearly, reducing the CO₂ emissions per unit of GDP output and improving the technological level of the transportation sector would significantly reduce the CO₂ emissions from this sector. More precisely, a 1% increase in CEI decreases CO₂ emissions from transportation sector in the local region. Therefore, encouraging technological progress, promoting the technological level of the transportation sector and accelerating the use of new energy in this sector would be effective emissions-reduction measures for the transportation sector in any given region. The

indirect effects of technological level are not significant, indicating that the technological level of a local transportation sector has a limited impact on the CO₂ emissions of this sector in neighboring areas.

- (5) The change in industrial structure is measured by the proportion of the tertiary industry, which has a notable impact on the reduction in CO₂ emissions from the regional transportation sector. The higher the proportion of the tertiary industry is, the lower the CO₂ emissions from the regional transportation sector are. Additionally, among the coefficients of the direct and indirect effects, only the coefficient of the direct effects is significant at the 10% level; according to the model, a 1% increase in the share of the tertiary sector would reduce CO₂ emissions from the transportation sector by 0.318%, which indicates that the industrial structure has a significant impact on the CO₂ emissions from the transportation sector. However, this impact does not include any indirect effects, indicating that changes in the industrial structure will reduce the level of CO₂ emissions from the local transportation sector but have little impact on that of the surrounding areas. A possible reason for this finding is that changes in the regional industrial structure affect CO₂ emissions from the regional transportation sector through industrial agglomeration and industrial spillover effects, but there is no certain way of affecting the surrounding areas.
- (6) The impact of the level of regional development and affluence, represented by the GDP per capita, on the level of CO₂ emissions from the regional transportation sector is significantly positive for both the direct and indirect effects. Specifically, a 1% increase in GDP per capita can be expected to increase CO₂ emissions from the transportation sector in the local region and neighboring regions by 0.490 and 0.008%, respectively. In economically developed areas, regional economic and population transportation activities are more frequent, transportation needs are higher, and CO₂ emissions from the transportation section are higher. Furthermore, due to the economic exchanges between regions, the transportation activities in developed areas spread to and thus affect less developed areas; i.e., the CO₂ emissions generated by the transportation activities in a specific area will affect the surrounding areas.

In summary, the above results reveal that the spatial effect is of great significance for understanding the level of CO₂ emissions of the transportation sector at the regional level and the influencing factors. The similarity of the spatial regression results between the geographic distance weight matrix w_1 and the economic geospatial weight matrix w_2 indicates that the estimated coefficients of the factors influencing the CO₂ emissions from the regional transportation sector are robust.

CONCLUSIONS AND RECOMMENDATIONS

In this paper, we implement new CO₂ emission factors to calculate CO₂ emissions from the transportation sector in each province of China and explore the factors influencing CO₂ emissions from this sector based on a two-way Durbin model. The conclusions are as follows:

- (1) The CO₂ emissions of China's transportation sector exhibit strong positive spatial correlation. Most of the regions with the highest CO₂ emissions from the transportation sector are located on the eastern coast of China; these regions have gradually spread to include central and western regions. The CO₂ emissions of transportation sector in the south have gradually exceeded those in the north, and the regions with high CO₂ emissions are spreading from the north into the south.
- (2) The intensity of transportation activities, urbanization level, technology level, industrial structure, and GDP per capita have strong influences on the CO₂ emissions from the transportation sector in each province of China. The intensity of transportation activities, urbanization level, and GDP per capita have not only direct effects but also indirect effects. Technological level and industrial structure only have direct effects.

Based on the above findings, we can formulate some policies to reduce the level of CO₂ emissions from the Chinese transportation sector. First, while the level of urbanization continues to increase, we should continue to improve the policies related to transportation and maintain a governmental role in energy conservation and emission reduction in the transportation sector, engaging in measures such as accelerating the development of rail transit and integrating road use. Formulating corresponding policies and measures can achieve a win-win scenario for transportation and environmental protection by optimizing the transportation structure.

Second, we should fully utilize the role of the government in promoting new technologies, formulating policies related to active taxation and other new technologies and improving the New Energy Vehicle Subsidy Policy to promote and apply new energy technologies in the automotive industry. When new technologies are widely applied in a province, they must also be actively promoted and implemented in the surrounding provinces where conditions permit, and the scale and spillover effects resulting from the improvement of the technological level should be fully taken advantage of to promote the coordinated development of the economy and society.

Third, we should take advantage of regional comparative advantages, vigorously develop the tertiary industry, promote the transformation of regional industrial structures, and reduce the level of the CO₂ emissions from the regional transportation sector. Finally, considering the spatial correlation of CO₂ emissions from transportation, regional governments should strengthen the joint management of CO₂ emissions from the transportation sector and form a regional emission-reduction linkage mechanism by formulating collaborative standards and policies. Furthermore, within urban regions, residents should be encouraged to choose public transport,

such as public buses and subways, to reduce travel by private cars as much as possible. Outside urban regions, the transformation of long-distance transportation from highways to railways as well as regional traffic and transportation structures should be actively promoted to reduce the overall level of CO₂ emissions.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

HX contributed to conception and design of the study. XX organized the database, performed the statistical analysis, and

wrote the first draft of the manuscript. XX and HX wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fenrg.2021.664046/full#supplementary-material>

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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