Analysing Regional Disparities and Shifting Trends in Transportation Carbon Emissions in China

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***Abstract*— This study examines the regional data in transportation carbon emissions across China and investigates the shifting trends of the carbon emission centroid over time. Using the IPCC (2006) carbon emission calculation formula, emissions data from 30 provinces for the years 2005, 2010, 2015, and 2020 were analyzed using an Exploratory Spatial Data Analysis (ESDA) model. The Economic Centroid Model and standard deviation ellipse were applied to assess the movement of the carbon emission centroid, which was consistently located in Henan Province. Further analysis using the Kaya model identifies the key factors influencing transportation carbon emissions in Henan from 2005 to 2020. The findings offer insights into regional carbon reduction strategies and the challenges in achieving China's dual carbon goals.**

Keywords*— *carbon emissions, transportation sector, ridge regression

I. Introduction

With the ongoing deterioration of the global climate and environment, extreme weather events are becoming increasingly frequent worldwide. It is becoming clear that sacrificing the environment for economic growth is not sustainable. Consequently, more countries and regions are now pursuing green and sustainable development. As the world's second-largest economy and the largest emitter of carbon dioxide, China has set ambitious goals to peak carbon emissions by 2030 and achieve carbon neutrality by 2060. In 2021, carbon emissions from the transportation sector accounted for approximately 10% of China's total emissions. These dual carbon goals present significant challenges to the development of China's transportation sector. The International Energy Agency (IEA) has emphasised that reducing carbon emissions in transportation is crucial for achieving global emissions reductions in the near term. The "Action Plan for Peaking Carbon Emissions by 2030," issued by the State Council in 2021, highlights the need to accelerate the development of green and low-carbon transportation methods to ensure that carbon emission growth in this sector remains within reasonable limits. Research on regional differences in carbon emissions is essential for implementing precise carbon reduction measures. Like the regional disparities in economic development, carbon emissions also show significant regional variations. Due to the uneven economic development, resource distribution, and differences in transportation infrastructure across China, there are substantial variations in transportation carbon emissions among different regions. Therefore, in our rapidly changing world, it is crucial to continuously monitor the shifting national transportation carbon emission centroid, analyse the key factors influencing transportation carbon emissions, and make predictions to help achieve these dual carbon goals.

To comprehensively examine carbon emissions in China's regional transportation and logistics sectors, this study will adopt a multifaceted analytical approach, beginning with the application of the carbon emission calculation formula as proposed by the Intergovernmental Panel on Climate Change (IPCC) in 2006. This well-established methodology will be used to accurately compute carbon emissions across various provinces, providing a detailed and standardized measure of transportation-related emissions. The first phase of the study involves the collection of relevant data across China's transportation sector, spanning the years 2005, 2010, 2015, and 2020. This data will be gathered from authoritative sources, including governmental databases, transportation records, and environmental reports. The IPCC (2006) carbon emission calculation formula will be employed to convert this data into quantifiable carbon emissions. This formula considers factors such as fuel consumption, vehicle type, and emission coefficients, ensuring a robust and reliable estimate of emissions for each province. Following the computation of carbon emissions, the study will implement an Exploratory Spatial Data Analysis (ESDA) model to investigate the spatial distribution of these emissions across the selected provinces. This analysis will reveal regional data differences in transportation sector carbon emissions, highlighting areas with significantly high or low emissions, and providing insights into the underlying geographic, economic, and infrastructural factors. To capture the dynamic nature of carbon emissions over time, the study will utilize the Economic Centroid Model and the standard deviation ellipse technique. The Economic Centroid Model will calculate the centroid's position based on emission data, while the standard deviation ellipse will illustrate the dispersion and directional trends of emissions relative to this trend. By applying this model to Henan Province, the study will identify and quantify the relative contributions of these factors to the region’s transportation carbon emissions from 2005 to 2020. This analysis will provide valuable insights into the socioeconomic and technological factors driving emissions in Henan, offering a nuanced understanding of the challenges and opportunities for carbon reduction in this pivotal region.

The rest of paper is organized as follows. Section II provides a brief introduction to the relevant background and context, outlining the importance of carbon emissions reduction in China's transportation sector and setting the stage for the subsequent analysis. Section III presents the methodology used in the study, detailing the carbon emission calculation formula based on IPCC (2006), the application of the Exploratory Spatial Data Analysis (ESDA) model, the Economic Centroid Model, and the standard deviation ellipse. Section VI reports the results of the analysis, including the spatial distribution of transportation carbon emissions across the provinces, the shifting trends of the carbon emission centroid over time, and the key factors influencing emissions in Henan Province as identified by the Kaya model. Section V concludes the paper by summarizing the key insights and contributions of the study and suggesting directions for future research to further explore the dynamics of transportation-related carbon emissions in China.

II. Literature Review

Currently, scholars have systematically analysed the spatiotemporal evolution of transportation carbon emissions at various spatial scales, making significant advances in understanding their spatial characteristics. For example, Zhao et al. [1] used the geographic detector method to explore the spatial differentiation and driving factors of transportation carbon emissions across provinces involved in the Belt and Road Initiative (BRI). Similarly, Lv et al. [2] employed the Geographically and Temporally Weighted Regression (GTWR) model to examine the influence of transportation carbon emission efficiency and its spatiotemporal heterogeneity. Further, Li et al. [3] and Xu et al. [4] utilised methods such as map visualisation and kernel density estimation to study the spatiotemporal evolution of urban carbon emission intensity. In recent years, many scholars have adopted Exploratory Spatial Data Analysis (ESDA) methods to investigate the spatial distribution patterns and differences in carbon emissions across China. For instance, Zeng et al. [5] applied ESDA to analyse the spatiotemporal distribution of transportation emissions, while Zhang et al. [6] and Yuan et al. [7] used ESDA along with spatial connectivity and super-efficiency SBM models to measure carbon emission efficiency. Other researchers like Zhao et al. [8], Song et al. [9], and Gao et al. [10] have also focused on the spatiotemporal evolution of China's energy consumption carbon emissions using the ESDA method. From the above literature, it is evident that different scholars have used various methods to study the spatial distribution of transportation sector carbon emissions. Among these, the ESDA method offers a comprehensive analytical framework, considering spatial distribution patterns, correlations, and spatiotemporal evolution characteristics. Given its comprehensive nature, this study will also employ the ESDA method to analyse the spatial distribution of carbon emissions in China's transportation sector.

The theory of economic centroids has been widely applied in studying regional development differences across different industries. For example, Xie et al. [11] used the theory of centroid displacement to calculate the movement trajectories of three economic attributes' centroids—ecosystem service value, urbanisation rate, per capita GDP, and per capita fiscal budget expenditure—in Sichuan Province for the years 2000, 2010, and 2020. Their results indicated that from 2000 to 2020, Sichuan Province's ecological value centroid shifted towards the southeast, while the economic centroid moved towards the northeast. Similarly, Li et al. [12] used the centroid model to study the migration characteristics of population and economic centroids in the Beijing-Tianjin-Hebei region between 2006 and 2017, revealing that both centroids deviated from the geometric centroid, showing a significant trend. Chen et al. [13] also employed the economic centroid model to analyse the migration characteristics and equilibrium of China's economic centroid from 2003 to 2012, identifying a semi-equilibrium trend in the migration of the country's economic centroid. Given that this theory effectively reveals the spatial distribution and migration trends of economic activities, helping researchers and policymakers understand dynamic changes in regional economic development, this study introduces the economic centroid theory to examine carbon emissions in the transportation sector. This approach will quantify the spatial dynamic evolution of transportation carbon emissions. In the analysis of carbon emission influencing factors, many domestic and international scholars have researched the factors affecting transportation carbon emissions using various models and methods. For instance, Shi [14] analysed the impact of population pressure on global carbon emissions using the STIRPAT model, while Wang [16] applied the same model to study the factors influencing energy-related CO2 emissions in Guangdong Province, China. Martínez-Zarzoso et al. [17] examined the effect of urbanisation on carbon emissions in developing countries using the STIRPAT model. Lv et al. [19] explored how factors like population, per capita GDP, the added value of the tertiary industry, and urbanisation levels influenced carbon emissions from automobile transportation in the Beijing-Tianjin-Hebei region, using the STIRPAT and spatial econometric models. Solaymani [20] analysed transportation-related carbon emissions in seven countries using the LMDI method, finding that economic growth and energy structure were the main drivers. Zhang et al. [21] used the Kaya identity to assess the impact of various factors on the carbon footprint of Xi'an, while Tang [22], using the Kaya model, compared the carbon emission peaking process among OECD and non-OECD economies, including China. Compared to the LMDI method and the STIRPAT model, the Kaya identity is more intuitive, as it decomposes carbon emissions into four factors—population, GDP, energy intensity, and carbon intensity—making it easier to understand each factor's contribution to emissions. Therefore, this study extends the Kaya identity to analyse the driving factors influencing transportation carbon emissions in Henan Province.

III. Research Methodology

A. *Calculation Methods for Transportation Carbon Emissions*

Currently, two commonly used methods for calculating carbon emissions in China are the activity-based approach and the emission factor approach. The activity-based approach relies on measured physical consumption quantities, while the emission factor approach uses emission factors to convert energy consumption into standard coal heat equivalents for

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statistical purposes. Due to the lack of clear monitoring data on carbon emissions from the transportation sector in China, this study estimates carbon emissions in each province based on energy consumption in the transportation sector using the IPCC emission factor approach. The model for calculating carbon emissions is represented by Equation (1):

$$\mathrm{CF} = \sum_{i=1}^{n} E_i \times F_i \times O_i \quad (i=1, 2, \ldots, 7) \tag{1}$$

Where CF represents the total carbon emissions from fossil fuel combustion, E_i denotes energy consumption, F_i signifies the adjusted carbon emission coefficient, and O_i stands for the emission factor. With advancements in technology, most fuel combustion processes now exhibit high efficiency, with an oxidation rate typically reaching 100%. Consequently, this value is assumed to be 1 by default. The variable i represents various energy sources, including seven types of fossil fuels: raw coal, gasoline, kerosene, diesel, fuel oil, natural gas, and liquefied petroleum gas. Although the IPCC provides comprehensive guidelines for calculating national greenhouse gas emission inventories, variations in energy statistics across different countries and regions often lead to the adoption of diverse operational methods based on these guidelines. These differences necessitate adjustments to ensure the accuracy and comparability of emission calculations. In this study, we will utilize the carbon emission coefficients from the IPCC (2006) guidelines, as detailed in Table I, along with standardized coal consumption data to compute carbon emissions for China's transportation and logistics sector. The carbon emission coefficients provided by the IPCC represent the amount of carbon dioxide emitted per unit of energy consumed, and they are tailored to different types of fuels and energy sources. By applying these coefficients to the energy consumption data—specifically, the standardized coal equivalent—we can accurately estimate the carbon emissions for each province. Furthermore, the use of standardized coal, which serves as a common energy unit to compare different fuels, allows for the integration of various energy sources into a single metric. This standardization is crucial for accurately assessing carbon emissions across provinces with diverse energy mixes and consumption patterns. These calculated emissions will then serve as the foundation for further spatial and temporal analysis, including the exploration of regional disparities in transportation sector emissions and the investigation of shifting trends in the carbon emission centroid.

TABLE I. CARBON EMISSION COEFFICIENTS OF VARIOUS ENERGY SOURCES IN CHINA

Energy Type	Emission Factor	Energy Type	Emission Factor
Raw Coal	0.5399（t CO2/t standard coal）	Fuel Oil	0.8836（t CO2/t fuel oil）
Gasoline	0.8149（t CO2/t gasoline）	Natural Gas	0.5447（t CO2/thousand m³）
Kerosene	0.8408（t CO2/t kerosene）	Liquefied Petroleum Gas	0.8644（t CO2/t liquefied petroleum gas）
Diesel	0.8627（(t CO2/t diesel）		

B. Exploratory Spatial Data Analysis (ESDA)

In Exploratory Spatial Data Analysis (ESDA), global Moran's I and hotspot analysis are key methods used to examine the global spatial autocorrelation and clustering characteristics of spatial data. This study uses the ESDA model to analyse the spatial distribution of carbon emissions in China's transportation industry. Global spatial autocorrelation is typically measured using Moran's I statistic, which assesses whether a particular feature exhibits significant clustering or dispersion across a geographic area. In this study, Moran's I statistic is used to measure the global autocorrelation of transportation carbon emissions. The index ranges from -1 to 1. When the Z value passes a significance test and Moran's I is positive, it indicates that transportation carbon emissions exhibit clustering, meaning that neighbouring areas in space have similar observations. A negative Moran's suggests dispersion of transportation carbon emissions, while a value of 0 indicates a random distribution. The closer the absolute value is to 1, the more pronounced the trend. Hotspot analysis (Getis-Ord Gi*) is another important method used in ESDA. It calculates the z-value and p-value for each feature in the data to identify clusters of high or low values in space. The formula used for this analysis are:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}w_{i,j}}{S\sqrt{\frac{[n\sum_{j=1}^{n} w_{i,j}^2 - (\sum_{j=1}^{n} w_{i,j})^2]}{n-1}}} \tag{2}$$

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{3}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \tag{4}$$

$$G_i^* = Z(G_i^*) = \frac{G_i^* - E(G_i^*)}{\sqrt{Var(G_i^*)}} \tag{5}$$

In this study, the z-value of transportation carbon emissions for each province is calculated annually and then categorised into four emission levels: high-value cluster area, moderately high-value cluster area, moderately low-value cluster area, and low-value cluster area, based on the natural breaks method. A higher and significant z-value indicates a high-value cluster area for transportation carbon emissions, while a lower and negative z-value indicates a low-value cluster area.

C. Dynamic Evolution of Carbon Emissions in the Chinese Transportation Industry

To further investigate the dynamic evolution of carbon emissions in China's transportation industry, this study introduces the theory of the economic gravity centre to analyse the trajectory of carbon emissions within this sector. Additionally, the standard deviation ellipse (SDE) is utilised to reveal the directional characteristics of the spatial distribution of economic geographical elements.

In this study, the "centre" is defined as the weighted average point of the geographical locations and carbon emissions from the transportation industry across various provinces in China. This approach aims to quantify and visualise the geographical distribution characteristics of carbon emissions. By combining carbon emission data with the geographical locations of each province, the weighted average centre of carbon emissions in the transportation industry is calculated. This point represents the "centre of gravity" or the average concentration of carbon emissions relative to geographical locations in space. The model for the coordinates of the centre of gravity is as follows:

$$X = \frac{\sum_{i=1}^{n} x_i \times C_i}{\sum_{i=1}^{n} C_i} \tag{6}$$

$$Y = \frac{\sum_{i=1}^{n} y_i \times C_i}{\sum_{i=1}^{n} C_i} \tag{7}$$

The standard deviation ellipse (SDE) method is then employed to intricately characterise and explore the trajectory and dispersion trend of the centre of mass migration of inter-provincial transportation carbon emissions in China over four selected years (2005, 2010, 2015, 2020) during the sample period. The relevant formulae are as follows:

$$\overline{X} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}, \overline{Y} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i}; S = \pi \sigma_x \sigma_y \tag{8}$$

$$\tan\theta = \frac{(\sum_{i=1}^{n} w_i^2 x_i^2 - \sum_{i=1}^{n} w_i^2 y_i^2) + \sqrt{(\sum_{i=1}^{n} w_i^2 x_i^2 - \sum_{i=1}^{n} w_i^2 y_i^2)^2 + 4(\sum_{i=1}^{n} w_i^2 x_i y_i)^2}}{\sum_{i=1}^{n} 2 w_i^2 x_i y_i} \tag{9}$$

$$\sigma_x = \sqrt{\frac{2\sum_{i=1}^{n} (w_i x_i \cos\theta - w_i y_i \sin\theta)^2}{\sum_{i=1}^{n} w_i^2}} \tag{10}$$

$$\sigma_y = \sqrt{\frac{2\sum_{i=1}^{n} (w_i x_i \sin\theta + w_i y_i \cos\theta)^2}{\sum_{i=1}^{n} w_i^2}} \tag{11}$$

Where, $(\overline{X}, \overline{Y})$ represents the geographic coordinates of the centroid of the ellipse, where (x_i, y_i) denotes the spatial weight of city *i*, representing the carbon emissions from transportation in different provinces. (x_i, y_i) represents the geographic coordinates of the centroid point of city *i*, indicating the difference between these coordinates and the centroid. σx and σy represent the standard deviations of the ellipse's x (major) and y (minor) axes, respectively. The angle θ denotes the directional angle of the spatial distribution pattern (with the major axis as the reference, where 0° represents north, and rotation is clockwise). *S* denotes the area of the ellipse.

D. Kaya Identity

In 1989, Japanese scholar Kaya proposed the Kaya Identity, which identifies the driving factors of carbon emissions as the carbon emission coefficient, energy intensity, per capita GDP, and population size. The principle behind the Kaya Identity is to break down carbon emissions into the product of several variables and analyse the contribution of each variable to carbon emissions. The general form of the Kaya Identity is expressed as:

$$C = \frac{C}{E} \times \frac{E}{X} \times \frac{X}{Z} \times \frac{Z}{P} \times P \tag{12}$$

Where C represents carbon emissions from the transportation sector, E represents total energy consumption in the transportation sector, X represents the GDP of the transportation sector, Z represents the GDP of a specific province, and P represents the population size of the province. According to Equation (12), the driving factors of carbon emissions in the transportation sector can be broken down into five explanatory variables: carbon intensity of energy consumption in the transportation sector $\frac{C}{E}$, energy intensity of the transportation sector $\frac{E}{X}$, economic share of the transportation sector $\frac{X}{Z}$, per capita GDP ($\frac{Z}{P}$), and population size (P). To address the inconsistency in the units of the explanatory variables, both sides of Equation (13) are logarithmised. The model can then be expressed as:

$$\ln C = \beta_1 \ln ES + \beta_2 \ln EF + \beta_3 \ln L + \beta_4 \ln PG + \beta_5 \ln P + \varepsilon \tag{13}$$

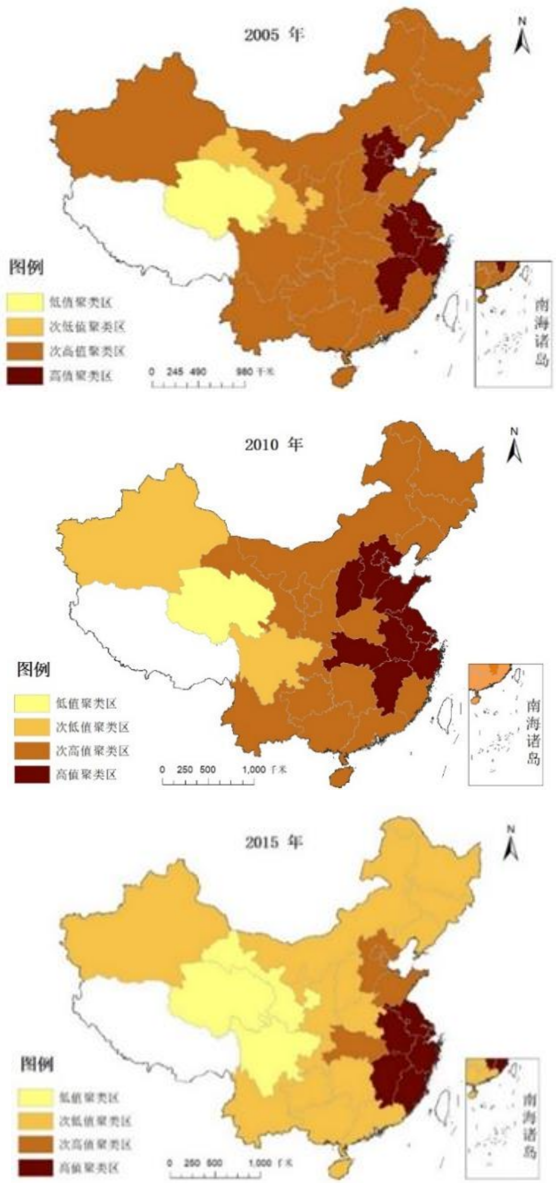
In this model, C denotes carbon emissions from a specific province's transportation sector; ES represents energy consumption carbon intensity in the transportation sector; EF denotes energy intensity of the transportation sector; L represents the industrial structure of the transportation sector; PG denotes per capita GDP; and P represents population size.

IV. RESULTS ANALYSIS

This paper uses data from Henan Province for the years 2005-2020 as the research dataset. The data for energy consumption in the transportation sector, GDP of the transportation industry, provincial GDP, per capita GDP, population size, and urbanisation rate were sourced from the "China Statistical Yearbook," "China Energy Statistical Yearbook," provincial greenhouse gas inventory guidelines, and the "Henan Statistical Yearbook" for the years 2005-2020. Some of the data were derived through calculations. Currently, the statistical yearbooks do not provide separate data for energy consumption and GDP specifically for the transportation sector; instead, they combine data for transportation, warehousing, and postal services. Since the warehousing and postal sectors account for a smaller share, this paper uses the combined energy consumption and GDP of transportation, warehousing, and postal services to represent the energy consumption and GDP of the transportation sector.

A. Spatiotemporal Distribution of Carbon Emissions in the Transportation Sector

Using the Jenks natural breaks method, the Z values derived from Equation (5) were categorized into four distinct clusters: low cluster area, lower-middle cluster area, upper-middle cluster area, and high cluster area. Given that carbon emissions from transportation logistics tend to be relatively stable over short periods, the years 2005, 2010, 2015, and 2020 were selected at regular intervals for cluster analysis. The results of this analysis are illustrated in Figure 1. It shows that overall carbon emissions from transportation in China are higher in the east and lower in the west, decreasing progressively from the eastern coastal areas to the west. In 2005, Beijing, Tianjin, Hebei, Jiangsu, Zhejiang, Anhui, and Jiangxi were all in the high cluster area. By 2010, Shanxi, Shandong, and Hubei had also shifted from the upper-middle to the high cluster area, regions which are largely the focus of the nation's emission reduction strategies. However, after 2015, transportation carbon emissions in the Beijing-Tianjin-Hebei area dropped to the upper-middle cluster area, indicating to some extent that the government's emission reduction policies for high-emission areas were effective. Qinghai remained in the low cluster area throughout these years, while Gansu was in the lower-middle emission area in 2005 but then rose to the upper-middle emission area, and by 2015, along with Ningxia, it became a low emission area. Notably, in 2015, carbon emissions from transportation logistics in most provinces decreased. However, in 2020, there was a "rebound" in this



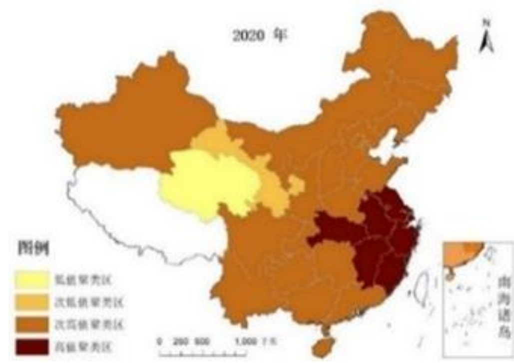


Figure 1 the spatial evolution of transportation carbon emissions from 2005 to 2020

trend, with the emission pattern resembling that of 2010, but with high cluster areas becoming more concentrated. Additionally, Xinjiang's carbon emissions from transportation

Figure 3 the distribution direction and path transition of carbon emission in Transportation Sector from 2005 to 2020

shifted from the lower-middle to the upper-middle area, while Gansu moved from the upper-middle to the lower-middle area.

The overall trend shows a decrease in transportation carbon emissions across most provinces from 2005 to 2015, which aligns with the emission reduction efforts. However, the rebound observed in 2020 indicates that some regions experienced increased emissions again, with a more pronounced concentration in high-emission areas. Moreover, the persistent low emissions in Qinghai and the shifting emission levels in Gansu and Xinjiang highlight the dynamic nature of regional emission patterns and the varying effectiveness of emission reduction policies across different provinces. These findings highlight the regional disparities in transportation carbon emissions and the effects of emission reduction strategies over time. The analysis indicates both progress in reducing emissions in some areas and challenges in managing the rebound effect in others.

B. Spatiotemporal Shift and Dispersion Trend of the Carbon Emission Centroid

The analysis of the carbon emission centroid provides insights into the spatial distribution and intensity of transportation carbon emissions across China. The carbon emission centroid represents areas with the highest concentration of emissions, while the standard deviation ellipse illustrates the spatial dispersion of carbon intensity across different provinces. The analysis tracks the migration and dispersion trends of the carbon emission centroid at four key time points: 2005, 2010, 2015, and 2020. According to Figure 2, The carbon emission centroid for transportation consistently remains in Henan Province across all four time points, fluctuating within the coordinates of 113.756-114.243°E and 33.300-33.683°N. This centroid is positioned southeast of China's geometric center (103°E, 36°N), indicating a higher overall intensity of transportation carbon emissions in the eastern and southern regions compared to the western and northern regions. The migration trajectory shows that in 2005, the centroid was located at the junction of Luohe and Zhoukou cities (114.243°E, 33.683°N). By 2010, it shifted 0.08 km southwest to Luohe, then moved 1.80 km northwest to Zhoukou in 2015, and finally settled 2.35 km southwest in Zhumadian. Overall, from 2005 to 2020, the centroid has shifted approximately 2.43 km southwest and 1.80 km northwest, indicating a predominant southward and westward movement of transportation carbon emissions. Furthermore, the standard deviation ellipse, which reflects the spatial dispersion of transportation carbon intensity, predominantly covers the southern and northern regions of China, with a noticeable southward movement over the period analyzed. The ellipse displayed a "northeast-southwest" distribution pattern. The area of the ellipse increased by 6% in 2015 compared to 2005, but decreased by 3.3% in 2020. This trend signifies a shift from a more dispersed to a more concentrated pattern of transportation carbon intensity over the 15-year period. The angle of the ellipse remained relatively stable, ranging from 18.78° to 21.26°, indicating minimal change in the directional distribution. The major axis of the ellipse extended from 833.15 km to 885.54 km, reflecting increased concentration of emissions along the north-south direction. Conversely, the minor axis shortened from 1087.33 km to 1053.34 km, indicating a broader dispersion in the east-west direction. These findings highlight a general trend of increasing concentration of transportation carbon emissions along the north-south axis while maintaining broader dispersion across the east-west axis. The centroid's migration towards the southwest and the changes in the standard deviation ellipse reflect dynamic shifts in transportation carbon emission patterns across China.

C. Study on the Factors Affecting Transportation Carbon Emissions

This study employs SPSS software to conduct a multiple regression analysis to identify the factors affecting transportation carbon emissions in China from 2005 to 2020. The analysis includes variables such as the carbon intensity of energy consumption, energy intensity, output structure, per capita GDP, and population size. The results, presented in Table II, reveal that the Variance Inflation Factor (VIF) values for industrial structure and population size are significantly greater than 10, indicating issues with multicollinearity. Additionally, the R^2 value equals 1, suggesting potential overfitting. These issues render the coefficients from the ordinary least squares (OLS) regression unreliable for inferential purposes. To address these challenges, ridge regression analysis was performed using SPSS. Ridge regression is a technique that provides biased estimates to counteract multicollinearity, improving the reliability of the regression coefficients. The ridge regression analysis, conducted with a ridge parameter K=0.15K = 0.15K=0.15, shows that the ridge trace stabilizes, and the F-test yields a significance level (P-value) of 0.000, which indicates statistical significance and supports the regression relationship between the independent and dependent variables. The model demonstrates excellent performance with a goodness of fit (R^2) of 0.984. The parameters and indicators from the ridge regression are detailed in Table II. The resulting regression equation is as follows:

$$lnC = -59.617 + 1.658lnES + 0.844lnS + 0.168lnL + 0.594lnG + 9.049lnP \quad (14)$$

The results indicate that transportation energy intensity, per capita GDP, and population size significantly impact the carbon emissions of the transportation sector in Henan province. Firstly, transportation energy carbon intensity is a major contributor to emissions. Specifically, a 1% increase in transportation energy carbon intensity results in a 1.658% increase in total transportation carbon emissions. This underscores how the carbon intensity of the energy used in transportation directly impacts overall emissions levels. Similarly, a 1% rise in transportation energy intensity leads to a 0.844% increase in total carbon emissions. This indicates that the efficiency of energy use in transportation also plays a crucial role in determining emission levels. The economic share of the transportation sector is another significant factor. A 1% increase in this share results in a 0.168% rise in total carbon emissions. This suggests that a larger economic contribution from the transportation sector is associated with higher emissions. Moreover, changes in the industrial structure affect emissions as well. A 1% increase in industrial structure corresponds to a 0.594% rise in total transportation carbon emissions. This reflects how shifts in industrial activities influence transportation-related emissions. The most substantial effect comes from population size. A 1% increase in population size leads to a significant 9.049% increase in total transportation carbon emissions. This highlights the strong relationship between population growth and increased transportation demand, which drives up emissions. These model coefficients provide a detailed understanding of how various factors drive transportation carbon emissions in Henan province. The findings emphasize the importance of addressing energy carbon intensity, energy efficiency, economic contributions of the transportation sector, industrial structure, and population growth to effectively manage and reduce transportation emissions. By focusing on these areas, Henan can develop targeted strategies to mitigate the impact of these factors on overall carbon emissions from transportation.

TABLE II. CARBON EMISSIONS OF THE TRANSPORTATION SECTOR IN CHINA

K=0.15	Unstandardized Coefficients		Standardized Coefficients	t	P	R^2	Adjusted R^2	F
	B	Standard Error	Beta					
Constant	-59.617	31.186	-	-1.912	0.085*	0.984	0.976	122.843(0.000***)
lnES	1.658	3.219	0.022	0.515	0.618			
lnS	0.844	0.081	0.439	10.368	0.000***			
lnG	0.168	0.259	0.028	0.65	0.530			
lnL	0.594	0.04	0.454	14.808	0.000***			
lnP	9.049	0.993	0.287	9.114	0.000***			
Dependent Variable:lnC								
Note: ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively.								

From the regression results, it is evident that: Firstly, the most significant factor driving the increase in transportation carbon emissions is the growth in population size and density. As the population rises, the demand for travel and energy intensifies, leading to higher energy consumption and, consequently, increased carbon emissions. To address this, Henan should implement targeted energy-saving and emission-reduction strategies that account for population growth. Secondly, energy consumption carbon intensity and energy intensity are the second and third major factors affecting Henan's transportation carbon emissions, respectively. This is due to the rapid development of the transportation sector without widespread adoption of new and clean energy sources and without an increase in energy utilization efficiency. Hence, accelerating energy transition and enhancing energy utilization efficiency are crucial for constructing a transportation energy-saving and emission-reduction system. Thirdly, Per capita GDP is also a major factor affecting transportation carbon emissions. Adjustments in the industrial structure to develop the tertiary sector, which consumes less transportation energy, can reduce transportation carbon emissions while maintaining stable economic growth. Lastly, the economic share of the transportation sector also has a strong carbon emission effect, primarily because freight turnover in Henan province relies heavily on rail and road transport, both of which are high-energy-consuming modes of transportation. Therefore, adjusting the freight modal mix in Henan is one of the important ways to accelerate carbon emission reduction in the transportation sector.

V. CONCLUSION AND RECOMMENDATIONS

This study employed the Exploratory Spatial Data Analysis (ESDA) model to investigate the regional distribution of transportation carbon emissions across 30 Chinese provinces from 2005 to 2020, with findings indicating that Henan Province consistently serves as a central hub of emissions. The use of ridge regression analysis further identified key factors driving these emissions, notably transportation energy intensity, per capita GDP, and population size. To achieve meaningful emission reductions in Henan, the study recommends focusing on several strategies: promoting clean energy, accelerating the transition to more sustainable energy sources, and encouraging the widespread adoption of electric vehicles. Despite these robust findings, the study acknowledges several limitations. For instance, the analysis did not include detailed energy consumption data, which could provide a more nuanced understanding of the emission drivers. Additionally, external factors such as global economic fluctuations were not considered, which might influence the transportation sector's carbon emissions. Looking ahead, future research will aim to develop a hybrid forecasting model to predict carbon emissions in Henan Province's transportation sector over the coming years. This model will incorporate a broader range of variables and expand the sample size to improve the accuracy and applicability of the predictions, ensuring that the research can better inform policy decisions and contribute to the ongoing efforts to reduce carbon emissions.

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