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*Original Research*

# Research on the Spatial Heterogeneity of Carbon Intensity at the Provincial Level in China and Its Driving Factors

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## Abstract

To effectively and expeditiously address emission reduction, a comprehensive understanding of the current status of carbon intensity and the spatial interactions of carbon intensity in China is necessary. This paper utilizes GIS technology, the Moran Index, and combines traditional Markov chain, spatial Markov chain, and social network analysis (SNA) methods to investigate various features of carbon intensity at the provincial level in China. The study yields the following findings: (1) The center of China's carbon intensity has shifted towards the northwest, whereas the center of economic development has moved towards the south. This indicates a significant spatial divergence in China's low-carbon development level. (2) The distribution pattern of carbon emission intensity in China is dominated by the proximity of high carbon emission intensity provinces to other high carbon emission intensity provinces and low carbon emission intensity provinces to other low carbon emission intensity provinces. (3) Carbon emission intensity exhibits significant spatial spillover effects, with positive spillover effects being more pronounced in regions with low carbon emission intensity. (4) The trend toward the development of China's overall carbon intensity is positive, but the spatial connectivity network of carbon intensity demonstrates a tendency to be entrenched, and leading provinces in low-carbon development have yet to fully realize their positive driving role.

**Keywords:** carbon intensity, spatial spillover effect, spatial Markov chain, SNA, spatial Durbin model (SDM)

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## Introduction

China's rapid economic development and expansion of production activities have led to an alarming surge in carbon dioxide emissions. In 2005, China surpassed the United States as the world's largest carbon emitter, accounting for 29 percent of the world's total carbon emissions in 2016, according to the World Bank. Coal and oil constitute about 80 percent of China's primary energy consumption, thereby serving as the primary source of carbon dioxide emissions, as stated in the China Power Media Energy Information and Research Center's China Energy Big Data Report for 2016-2020. However, the increasing global climate change, which is a result of carbon emissions, is becoming more and more severe, leading to severe impacts on both nature and humans [1]. Therefore, the reduction of carbon emissions has been prioritized by many countries, where measures are being taken to address this pressing issue [2, 3]. As a response, the Chinese government has taken several measures to reduce its carbon footprint and committed to reaching peak carbon emissions by 2030 at the Paris Climate Conference [4, 5].

Research on carbon emissions has extended to various levels and industries. For instance, Sun et al. [6] utilized Theil's index, GIS techniques, and Moran's I index to explain the spatio-temporal evolution of carbon emissions and analyzed its influencing factors using the SDM in the construction industry. Their research revealed that factors such as size, economic level, technological innovation, government support, foreign trade, environmental regulation, and financial development affect China's economic growth.

In another study, Zhao et al. [7] devised a framework to explore carbon emission trajectories by using a log-mean zonal index approach to expound on the driving forces. They found that building size and demand structure are the primary drivers of the growth of China's building energy efficiency index, which is significantly reduced by the decline in energy consumption. Jiang et al. [8] analyzed the decomposition of the driving effects of carbon emissions from the construction industry in Jiangsu Province by employing a logarithmic mean Divisia index (LMDI) model. Their research showed that energy intensity, population density, energy structure, and new building area accounted for 114.13%, 36.13%, 26.83%, and 20.31%, respectively, while the contribution of new energy-efficient building area and the economic level of the construction industry were -5.13% and -92.26%, respectively.

Other researchers, such as Zheng et al. [9], used a super-SBM model to analyze carbon emission efficiency in the transportation sector. They employed the log-mean partitioning approach to explain the drivers of carbon emissions and found that population size and level of economic development promote carbon emissions, with the latter having the most significant effect. Energy efficiency had the greatest inhibiting effect on carbon emissions, but the structure of energy consumption played a minimal role in increasing carbon emissions. Liu et al. [10] designed an LSTM carbon emission model based on carbon emission forecasts for the transportation sector under low-carbon, baseline, and high-carbon scenarios. Their research showed that the peak carbon emission years for the low-carbon, baseline, and high-carbon scenarios were 2033, 2035, and 2038, respectively.

In the power sector, Zuo et al. [11] calculated the MCE of the sector and determined the carbon emission intensity, which provides a basis for policy formulation. Wang et al. [12] created an elasticity relationship-based carbon emission prediction model for Shanghai's power and energy, as well as a carbon emission prediction model based on different scenarios. Their research showed that the model effectively assesses future carbon emissions from the power sector in Shanghai. Lv et al. [13] studied the effect of smart manufacturing on industrial $CO_2$ emissions and found that smart manufacturing significantly reduces $CO_2$ emissions in the industrial sector. Smart manufacturing achieves industrial emission reductions primarily by reducing the consumption of fossil energy in the production process and improving the efficiency of energy utilization. Additionally, Lin et al. [14] utilized structural path analysis to compare and analyze supply-driven and demand-driven chain structures. Their research revealed that the more optimized the industry chain structure, the more economic benefits are generated per unit of carbon dioxide emissions, resulting in higher economic connectivity and lower carbon emission linkages. It is noteworthy that researchers have accomplished substantial progress in studying carbon emissions across different industries.

In recent years, several studies have explored the linkages between carbon emission intensity in diverse regions. For instance, Zhang et al. [15] employed SNA and exploratory spatial data analysis to analyze the spatial correlation of carbon emissions sinks in the Beijing-Tianjin-Hebei region at the county level. Their research also produced a county-level zoning carbon balance zone, presenting a way forward for the carbon balance zones' division. In another study, Li et al. [16] used static and dynamic SDMs to explore the spatial effects and mechanisms of the impact of green finance on carbon emissions. Their results showed that economic development positively influences the reduction of carbon emissions by green finance. They also found that green finance can promote industrial upgrading and reduce carbon emissions, but its inhibitory effect varies from region to region.

Other researchers, such as Li et al. [17], utilized various models such as kernel density estimation, standardized partial ellipse, and geographically and temporally weighted regression (GTWR) models to study the spatio-temporal evolution and path migration of carbon emission intensity in Chinese cities. Their research discovered that carbon-intensive energy consumption positively contributes to carbon emission intensity while economic development, industrial upgrading, population agglomeration, foreign investment intensity, and technological research and development negatively inhibit it. In another study, Gao et al. [18] analyzed the spatial correlation network and formation mechanism of carbon emission efficiency in China's construction industry using the global super-efficiency EBM model, SNA, and QAP model. They found that regional economic differences and urbanization differences positively impacted the formation of spatially relevant networks, while industrial agglomeration disparity had a negative impact.

Moreover, Wang et al. [19] estimated the carbon emission efficiency in China using the DDF model and unveiled the spatial clustering characteristics of carbon emission efficiency using the Moran index. Although some scholars have examined the factors affecting carbon emissions while controlling for spatial spillover effects, there is currently no consideration of the impact of geographic proximity on carbon emissions [20-25]. However, several studies have investigated the spatial correlation of carbon emission efficiency. Finally, given the complexity of the various spatial linkages of carbon emission intensity, further research in this field is required.

Existing research has explored the issue of the impact of China's industrial transfer on carbon emissions, including spatial transfer, hidden carbon emissions, and carbon leakage, through input-output modeling. However, the compilation of China's input-output table is a long and discontinuous process, which limits the currentness of this research. Furthermore, input-output tables assembled based on industrial sectors lead to high errors due to the homogenization of industries, which affects the study's accuracy. Another approach is to use spatial measurement to examine the impact factors associated with carbon emissions while considering their spatial spillover. This approach shifts the research hypothesis from single geographical segregation to a more reasonable geographical correlation, producing more accurate and credible research results. However, most existing research studies the geographical heterogeneity and spillover effect of carbon emissions only from the perspective of geographically proximate regions, which doesn't truly reflect the multidimensional spatial dependence of carbon emissions across different regions of China. Therefore, both research methods inadequately describe the multidimensional spatial correlation effect of carbon emissions and do not enable the effective identification of its internal mechanisms. Consequently, they cannot provide a scientific basis for decision-making in solving the issue of resource scarcity in the context of carbon trading in China.

To address these limitations, SNA has been increasingly utilized to investigate carbon emissions [26, 27]. SNA has been well-established in various fields, including sociology and economics [28]. The approach primarily investigates interrelationships and structural evolution laws among factors within a region [29, 30]. It is also capable of addressing the limitations of qualitative research, particularly the lack of objective quantitative indicators. Consequently, the model is highly advantageous in evaluating low-carbon synergies between regions [31].

Provinces and regions are essential economic units in implementing carbon emission reduction in China and play a key role in regulating total national carbon emissions [32]. The carbon emission intensity of a province depends not only on its economic development and energy consumption but also on the development of its neighboring areas. Thus, analyzing changes in carbon emission intensity at the provincial level and uncovering the potential driving mechanisms behind them is crucial for achieving the national goal of "peak carbon" and promoting sustainable economic and social development. This study employs the Moran index to measure the spatial correlation of carbon emission intensity (per unit of carbon dioxide emission) at the provincial level. Additionally, a spatial lag term is included based on traditional Markov chains to examine the spillover effect of carbon emission intensity utilizing a spatial Markov chain. Most spatial econometric models typically consider geographic proximity, which cannot accurately reflect carbon emission intensity relationships between non-adjacent regions [33]. Therefore, this study applies SNA to evaluate spatial correlation between non-adjacent regions. Finally, the SDM is employed to analyze the drivers behind carbon emission intensity.

## Material and Methods

### Standard Deviation Ellipse

The standard deviation ellipse method is a classical technique utilized to evaluate the directional characteristics of spatial distributions. This method quantitatively explains the centrality, discretization, orientation, and overall spatial pattern of economic factors from both a global and spatial perspective.

### Moran's Index

The Moran index is a critical and frequently used metric for studying spatial autocorrelation [34, 35]. It comprises both global and local measures - the global Moran's index assesses clustering or outliers in spatial data. If global autocorrelation is detected, local autocorrelation is then conducted to locate where clusters or outliers occur [36]. The correlation formula is as follows:

$$I = \frac{n}{S_o} \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^{2}} \tag{1}$$

$$S_o = \sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{i,j} \tag{2}$$

$$I_i = \frac{Z_i}{\sum_{i=1}^{n} z_i^2}\sum_{j}^{n}\omega_{i,j}Z_i \tag{3}$$

where $z_i$ indicates the difference in carbon emission intensity of province $i$ from its mean value, $\omega_{ij}$ is the spatial weight between provinces $i$ and $j$, and $n$ represents the total number of provinces, while $S_o$ is the summation of all spatial weights.

### Spatial Markov Chain

Spatial Markov chains effectively examine interactions between provinces by incorporating spatial lag terms [37, 38]. This compensates for traditional Markov chains' deficiency in accounting for spatial correlation effects of interregional carbon emission intensities. By conditioning the spatial lag type of carbon emission intensity in the current year at the provincial level in China, this study classifies it into N-type. It then decomposes the N×N transfer probability matrix into N conditional transfer probability matrices with an N×N size. The calculation formula is:

$$Lag_i = \sum_{j=1}^{n} Y_j W_{ij} \tag{4}$$

where $Y_j$ stands for the carbon emission intensity of province $j$, $n$ represents the total number of provinces, and $W_{ij}$ represents the spatial adjacency relationship between provinces $i$ and $j$. A value of 1 denotes neighboring regions, while a value of 0 indicates non-neighboring regions.

### Social Network Analysis

The SNA method is primarily used to assess the relational structure and attributes of social networks. Its significance resides in accurately quantifying relationships, thereby providing a quantitative tool for constructing intermediate theories and empirically testing propositions. Widely applied in various disciplines such as management, sociology, and economics [39], it requires the identification of network relationships to facilitate their analysis. Hence, this study applies a gravity model suitable for cross-sectional data to investigate the provincial carbon intensity spatial correlation network's dynamic evolution characteristics. The correlation formula is as follows:

$$x_{ij} = k_{ij}\frac{\sqrt[3]{p_i C_i G_i}\sqrt[3]{p_i C_i G_i}}{D_{ij}^2} \tag{5}$$

$$k_{ij} = \frac{C_i}{C_i + C_j} \tag{6}$$

$$D_{ij} = \frac{d_{ij}}{g_i - g_j} \tag{7}$$

where $x_{ij}$ represents the level of association of provinces $i$ with $j$, and $k_{ij}$ represents the contribution rate of province $i$ to the spatial correlation of carbon emission intensity between provinces $i$ and $j$; $C$, $p$, $G$, and $g$ refer to carbon emission intensity, population, GDP, and GDP per capita, respectively; $d_{ij}$ denotes the geographical distance between provinces $i$ and $j$, which is measured using the latitude and longitude distance in this study.

### Spatial Durbin Model

In economics, spatial dependence in regional activities is widely observed [40]. The SDM aims to investigate these spatial relationships, enhancing our understanding of social object relationships. The specific model is as follows:

$$y_{it} = \rho\sum_{j=1}^{n} W_{ij} y_{jt} + \partial x_{it} + \theta\sum_{j=1}^{n} W_{ij} x_{jt} + \varepsilon_{it} \tag{8}$$

where $y$ represents carbon emission intensity and $x$ represents explanatory variables; $\rho$ and $\theta$ are spatial autocorrelation coefficients for carbon emission intensity and explanatory variables, respectively; $W$ is a spatial weight matrix, $\partial$ is the regression coefficient for explanatory variables, and $\varepsilon$ is the random error term; $i$ and $j$ represent provinces, $t$ represents time, and $n$ is the total number of provinces.

### Data Sources

This study utilizes carbon emission data from the Multi-resolution Emission Inventory for China, which has been managed and developed by Tsinghua University since 2010. The data sources comprise the China Statistical Yearbook (population, foreign investment, GDP per capita, and urbanization rate), the China Energy Statistical Yearbook (electricity consumption per capita), and the China Statistical Yearbook of Science and Technology (technology market transactions).

## Results and Discussion

### Analysis of Spatial Evolution of Carbon Emission Intensity

Based on the accessible data, this study omitted provinces with missing data and examined the carbon emission intensity of 30 provinces in China from 2004 to 2020. To illustrate the spatial disparities in carbon emission intensity more effectively, ArcGIS was employed to visualize the data at four time points: 2004, 2009, 2014, and 2020. The spatial migration trajectory of carbon emission intensity in China was delineated using standard deviation ellipses, as depicted in Fig. 1.

In 2004, the carbon emission intensity of eight provinces exceeded 40,000 tons per 100 million yuan, with Shanxi, Ningxia, Guizhou, and Inner Mongolia reaching 85,370 tons, 90,110 tons, 79,230 tons, and 71,820 tons per 100 million yuan, respectively. By 2009, the carbon emission intensity of four provinces surpassed 40,000 tons per 100 million yuan, with Ningxia at 60,540 tons per 100 million yuan. Both in 2014 and 2020, Ningxia's carbon emission intensity remained above 40,000 tons per 100 million, reaching 50,290 and 53,640 tons per 100 million, respectively. Overall, China's carbon emission intensity has decreased steadily over the years, mainly due to adjustments in China's energy structure and technological advancements. China has shifted from a coal-dominated energy structure to a more diverse one, fostering research and innovation in energy consumption. Ningxia's high carbon emission intensity is attributed to its reliance on coal-based energy. With rapid economic growth, the demand for energy has risen sharply. Ningxia, being less developed, still relies heavily on high-carbon industries, particularly chemical production, which significantly impacts economic development and employment in the region.

As depicted in Fig. 1, the number of provinces with low carbon emission intensity in China significantly increased from 2004 to 2020, while most provinces experiencing a rise in high carbon emission intensity are situated in the southern region. The shifting center position of the standard deviation ellipse indicates a movement of the carbon emission intensity center towards the northwest. However, China's overall economic development center is shifting towards the southeast [41], indicating a misalignment between economic development direction and carbon emission intensity, consistent with the findings of Liu et al. [42].

## Spatial Correlation Analysis

### *Global Moran's Index Analysis*

In this study, the global Moran index of China's provincial carbon emission intensity from 2004 to 2020

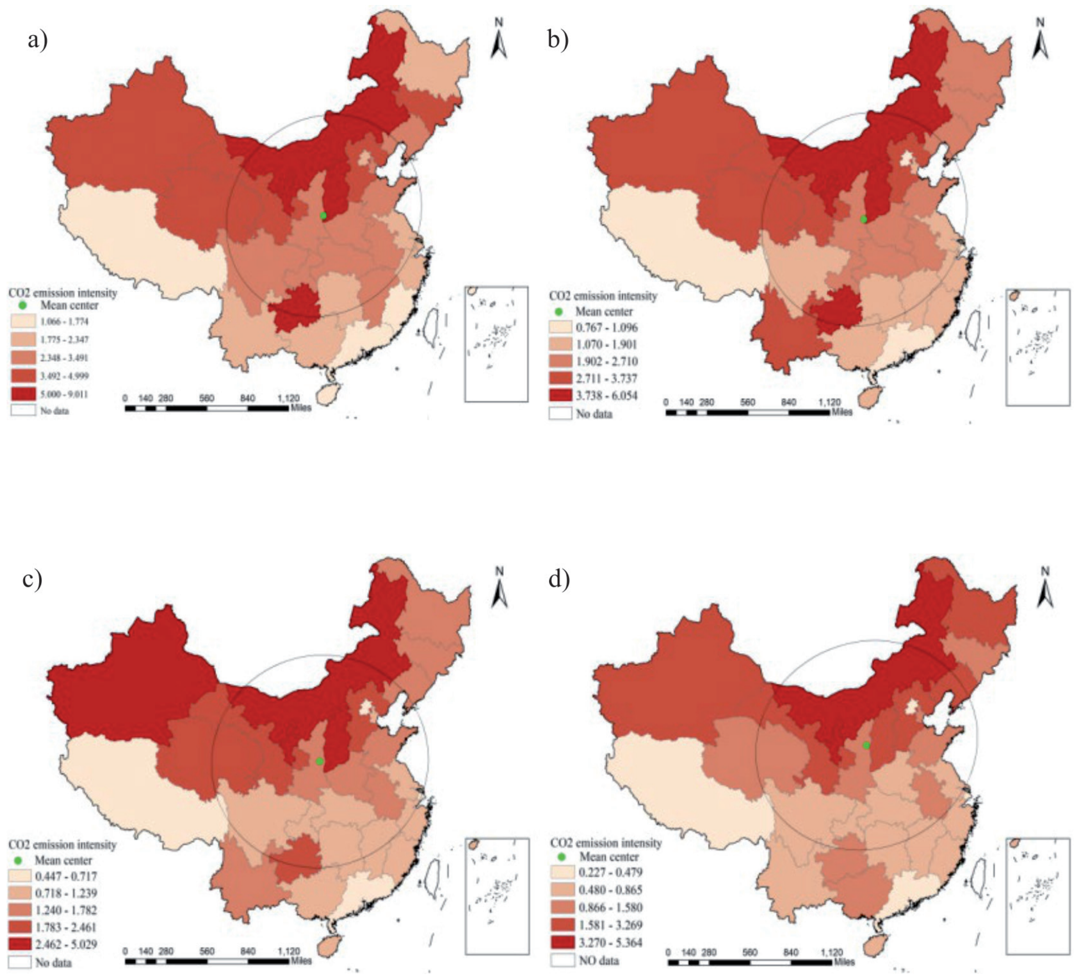


Fig. 1. Spatial Evolution of Carbon Emission Intensity in 2004, 2009, 2014, and 2020.
a) In the year 2004, b) In the year 2009, c) In the year 2014, d) In the year 2020.

Table 1. Global Moran's Index of provincial carbon emission intensity in China from 2004 to 2020.

| Year | I | Sd(I) | z | P-value* | Year | I | Sd(I) | z | P-value* |
|---|---|---|---|---|---|---|---|---|---|
| 2004 | 0.253 | 0.119 | 2.411 | 0.016 | 2013 | 0.309 | 0.116 | 2.958 | 0.003 |
| 2005 | 0.257 | 0.119 | 2.443 | 0.015 | 2014 | 0.327 | 0.117 | 3.100 | 0.002 |
| 2006 | 0.219 | 0.119 | 2.142 | 0.032 | 2015 | 0.351 | 0.117 | 3.296 | 0.001 |
| 2007 | 0.253 | 0.118 | 2.434 | 0.015 | 2016 | 0.384 | 0.120 | 3.495 | 0.000 |
| 2008 | 0.313 | 0.120 | 2.894 | 0.004 | 2017 | 0.360 | 0.115 | 3.422 | 0.001 |
| 2009 | 0.297 | 0.120 | 2.759 | 0.006 | 2018 | 0.365 | 0.116 | 3.434 | 0.001 |
| 2010 | 0.328 | 0.119 | 3.045 | 0.002 | 2019 | 0.406 | 0.115 | 3.827 | 0.000 |
| 2011 | 0.303 | 0.113 | 2.995 | 0.003 | 2020 | 0.412 | 0.114 | 3.904 | 0.000 |
| 2012 | 0.329 | 0.116 | 3.136 | 0.002 | | | | | |

was computed using the relevant formula, as presented in Table 1.

As observed in Table 1, the Moran index of China's provincial carbon emission intensity from 2004 to 2020 is positive, with all $p$-values below 0.05. This suggests a significant positive spatial correlation of carbon emission intensity. Furthermore, the global Moran index rose from 0.253 in 2004 to 0.412 in 2020, while the $p$-value declined from 0.016 to 0.000. These findings indicate an increasing spatial correlation of carbon emission intensity over time.

### *Local Moran's Index Analysis*

To gain a clearer understanding of the spatial distribution of carbon emission intensity among provinces, this study further computed the local Moran's index and presented a scatterplot to analyze the clustering effect of carbon emission intensity more intuitively.

As depicted in Fig. 2, most provinces are situated in the first and third quadrants. The first quadrant signifies that a province and its neighboring provinces exhibit higher carbon emission intensity, while the third quadrant indicates lower carbon emission intensity for a province and its neighboring samples. This phenomenon primarily arises from increased cooperation among major industries in neighboring provinces during the study period, fostering economic and technological exchanges and resulting in a higher spatial agglomeration rate of carbon emission intensity.

Several provinces are situated in the second quadrant, with only a few located in the fourth quadrant. The second quadrant signifies that a province has low carbon intensity on its own, while its neighboring provinces exhibit high carbon intensity. The fourth quadrant, on the other hand, indicates provinces with high carbon intensity and neighboring provinces with low carbon intensity.

For instance, Beijing, being the capital city, was bordering the second and third quadrants in 2004. In 2009, 2014, and 2020, it remained in the second quadrant. The principal reason for this is the city's strong "siphon effect," drawing in talent and investment from neighboring provinces and beyond. Consequently, Beijing ranks first in nationwide comprehensive science and technology innovation and provides strong support for green research and development technologies. Beijing also exports carbon emission sources and gradually relocates heavily polluting and high-emission enterprises out of the city. For instance, the Shougang Group relocated from Shougang Park in Beijing to Tangshan City in Hebei Province successfully within five years.

### *Analysis of Spillover Effects*

According to the Moran index analysis, there is a significant positive spatial correlation and clustering phenomenon in provincial carbon emission intensity across China. This study uses panel data analysis with Markov and spatial Markov chains to explore the spatial evolution patterns of provincial carbon emission intensity and the interactions between neighboring provinces. Carbon emission intensity is classified into four categories: very low (VL), low (L), medium (M), and high (H). The findings are summarized in Tables 2 and 3.

The main diagonal values in Table 2 are all above 0.808, indicating at least an 80.8% probability of maintaining the original carbon intensity. The highest value on the main diagonal is 0.994 for the VL state, suggesting its high stability. Other values indicate the probability of transitioning to a different state in the next period. The transition probabilities from the L state to the VL and M states are 12.4% and 1.7%, respectively. Transitions from the M state to the L and H states occur at rates of 16.3% and 2.7%, respectively, suggesting a downward trend in carbon emission intensity and a positive overall trend in China's carbon emissions.

With the inclusion of the spatial lag term, the transition probabilities between different carbon

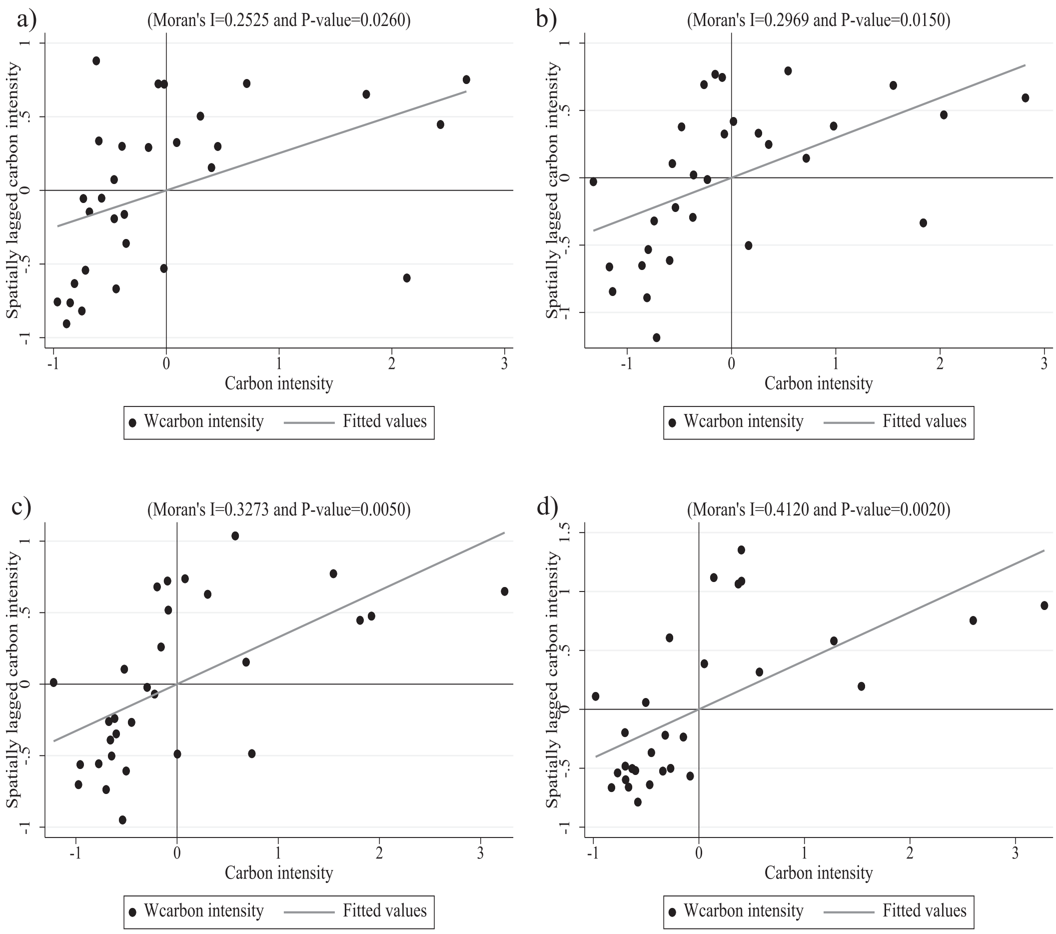


Fig. 2. Local Moran scatter plot for the years 2004, 2009, 2014, and 2020.
a) In the year 2004, b) In the year 2009, c) In the year 2014, d) In the year 2020.

intensity states change significantly. The VL state region maintains its original state at 99.4%, and when surrounded by VL, L, or M states, the probabilities are 100%, 98.3%, and 100%, respectively. This stability is attributed to the high economic and technological levels and comprehensive low-carbon development models in VL state regions, making them less susceptible to neighboring influences. This also explains the occurrence of low-high agglomeration. In M-state regions, the probability of evolution is 16.4% and regression is 2.7%. When surrounded by VL, L, M, and H states, the evolution probabilities are 100%, 8.3%, 23.1%, and 20%, while the regression probabilities are 0%, 2.8%, 3.8%, and 0%. This suggests that regions with lower carbon emission intensity experience more pronounced positive spillover effects from neighboring regions.

### *Spatial Network Analysis of Carbon Emission Intensity*

This paper employs the SNA method to examine the spatial correlation network of provincial carbon emission intensity in China, owing to the difficulty in representing the multidirectional spatial dependence between regional carbon emissions using spatial indicators [43]. To this end, a square gravity matrix of order 30 based on the gravity formula was established. A threshold value,

Table 2. Traditional Markov transition probability matrix.

| | VL | L | M | H |
|---|---|---|---|---|
| VL | 0.994444444 | 0.005555556 | 0 | 0 |
| L | 0.124293785 | 0.858757062 | 0.016949153 | 0 |
| M | 0 | 0.164383562 | 0.808219178 | 0.02739726 |
| H | 0 | 0 | 0.16 | 0.84 |

Table 3. Spatial Markov transition probability matrix.

| Space lag | | VL | L | M | H |
|---|---|---|---|---|---|
| VL | VL | 1 | 0 | 0 | 0 |
| | L | 0.2 | 0.8 | 0 | 0 |
| | M | 0 | 1 | 0 | 0 |
| | H | 0 | 0 | 0 | 0 |
| L | VL | 0.982758621 | 0.017241379 | 0 | 0 |
| | L | 0.163636364 | 0.836363636 | 0 | 0 |
| | M | 0 | 0.083333333 | 0.888888889 | 0.027777778 |
| | H | 0 | 0 | 0.125 | 0.875 |
| M | VL | 1 | 0 | 0 | 0 |
| | L | 0.023255814 | 0.930232558 | 0.046511628 | 0 |
| | M | 0 | 0.230769231 | 0.730769231 | 0.038461538 |
| | H | 0 | 0 | 0.2 | 0.8 |
| H | VL | 0 | 0 | 0 | 0 |
| | L | 0 | 0.8889 | 0.1111 | 0 |
| | M | 0 | 0.2000 | 0.8000 | 0 |
| | H | 0 | 0 | 0.1429 | 0.8571 |

as the average value of each row in the gravity matrix, was set, according to previous research [44]. A value greater than or equal to the threshold is defined as 1 denoting spatial correlation between the corresponding regions in terms of carbon emission intensity. Conversely, a value less than the threshold is defined as 0, indicating no such correlation exists. Ultimately, a spatial correlation network matrix on carbon emission intensity is created, and the corresponding network diagram is presented in Fig. 3.

In Fig. 3, the carbon emission intensity of each province is not only correlated with neighboring provinces but also exhibits spatial correlation with non-neighboring provinces, surpassing the limitations of geographic proximity. Shandong, Guangdong, Jiangsu, Shanghai, Henan, and Hebei are provinces with a strong spatial correlation of carbon emission intensity. Among them, Shandong, Guangdong, Jiangsu, and Shanghai are all situated in the coastal region, characterized by robust economic and technological levels, favorable geographic locations, and relatively mature green development models. Consequently, they exhibit stronger correlations with other provinces. However, although Henan and Hebei are active in the spatial correlation network, this does not necessarily imply that the green development of these provinces is at a high level. The main reason is that they are recipients of carbon emissions. For instance, Henan's incomes in 2004, 2009, 2014, and 2020 are 11, 10, 14, and 12 respectively, and its outgoings are 4, 3, 2, and 3, respectively.

To further explore the spatial correlation network of carbon emission intensity in China, this study calculates four statistical metrics: edge counts, graph density, average degree, and average clustering coefficient, with the results reported in Fig. 4. Edges signify the connections between provinces, while the graph density is the ratio of the maximum potential edges to the actual ones. Meanwhile, the average degree is the proportion of the sum of outgoing and incoming degrees and the number of nodes, and the average clustering coefficient indicates the degree of interaction between the provinces regarding the carbon intensity correlation network. As evident in Fig. 4, the number of edges in the spatial correlation network reduces from 118 in 2004 to 99 in 2020, and the average degree of edges decreases from 3.933 to 3, implying that the spatial connectivity among provinces in carbon emission intensity has declined. The figure density indicates that the growth of the spatially correlated network of carbon emission intensities between provinces is unsatisfactory, with many expected connections yet to occur. Out of four statistical measures, the only one displaying an overall increase is the average clustering coefficient, which rises from 0.518 to 0.538. This suggests that nodes form more triangles with neighboring nodes, indicating higher correlation and aggregation. A trend toward coagulation of spatial connections of carbon emission intensity between regions in China is inferred from the changes in the four statistical indicators. Nonetheless, disparities in green development levels exist among regions, with the majority of southern regions, the southeastern coastal

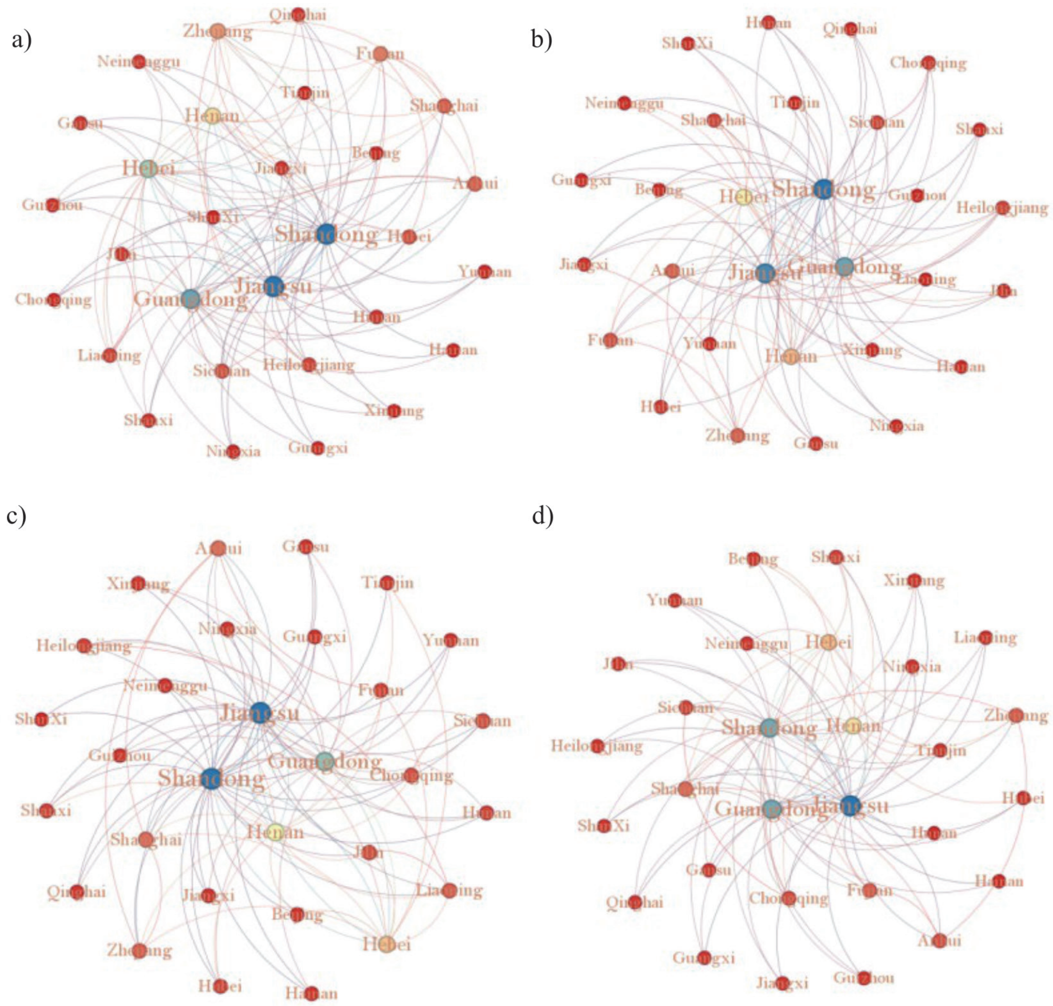


Fig. 3. Spatial Correlation Networks of Carbon Emission Intensity in 2004, 2009, 2014, and 2020.
a) In the year 2004, b) In the year 2009, c) In the year 2014, d) In the year 2020.

region, and the Beijing-Tianjin region displaying higher green development levels compared to other areas.

## Analysis of Driving Factors for Carbon Emission Intensity

### *Selection of Spatial Econometric Model*

To explore the drivers of carbon emission intensity at the provincial level in China, this study employs the SDM to investigate the effects of economy, technology, foreign exchange, and energy consumption on carbon emission intensity. The independent variables include population (X1), GDP per capita (X2), urbanization rate (X3), technology market transactions (X4), foreign investment (X5), and electricity consumption per capita (X6), while the dependent variable is the carbon emission intensity of each province. Various tests were conducted on this data.

Both the LM test and Robust-LM test statistics exceed 0, and the *p*-value is less than 0.05, indicating significant results. Therefore, the SDM model is deemed appropriate. The Wald test, Hausmann test, and LR test were also conducted. The statistics for all three tests exceed 0, and the *p*-values are less than 0.05, indicating significant results. Consequently, based on the Wald test, the SDM model does not degenerate into the SLM model or the SEM model. According to the Hausman test, the SDM model should use fixed effects. The LR test suggests the utilization of double fixed effects.

### *Result Analysis*

In this study, the double fixed-effects SDM is employed to investigate the determinants of changes in carbon emission intensity at the provincial level in China. Table 4 presents the outcomes of the effect decomposition.

The SDM dissects the influencers of carbon emission intensity into direct, indirect, and total effects. The direct effect delineates the impact of explanatory variables within a region on the carbon emission

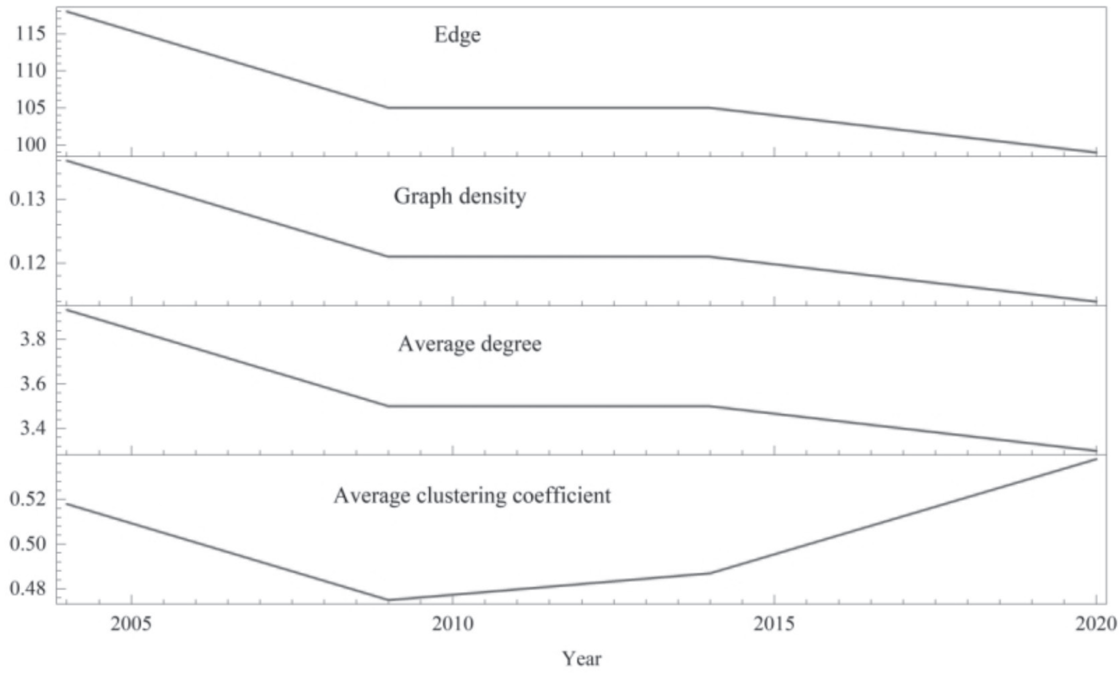


Fig. 4. Statistical Measures of Spatial Correlation Network.

Table 4. Decomposition results of driving factors of carbon emission intensity changes.

| *y* | Coefficient | Std.err. | z | P>\|z\| |
|---|---|---|---|---|
| LR_Direct | | | | |
| X1 | 0.0004282 | 0.0001067 | 4.01 | 0.000 |
| X2 | -0.0311374 | 0.0294429 | -1.06 | 0.290 |
| X3 | -0.033163 | 0.0091285 | -3.63 | 0.000 |
| X4 | 2..48e-08 | 6.55e-09 | 3.79 | 0.000 |
| X5 | -0.0000123 | 0.0000137 | -0.90 | 0.367 |
| X6 | 0.3182505 | 0.2030169 | 1.57 | 0.117 |
| LR_Indirect | | | | |
| X1 | 0.0003068 | 0.0001688 | 1.82 | 0.069 |
| X2 | -0.2077138 | 0.0534768 | -3.88 | 0.000 |
| X3 | -0.0763069 | 0.0154265 | -4.95 | 0.000 |
| X4 | 4.46e-08 | 1.30e-08 | 3.44 | 0.001 |
| X5 | 0.0000249 | 0.0000303 | 0.82 | 0.411 |
| X6 | 1.328678 | 0.4355616 | 3.05 | 0.002 |
| LR_Total | | | | |
| X1 | 0.0007349 | 0.0002233 | 3.29 | 0.001 |
| X2 | -0.2388513 | 0.0516022 | -4.63 | 0.000 |
| X3 | -0.1094700 | 0.0124531 | -8.79 | 0.000 |
| X4 | 6.94e-08 | 1.57e-08 | 4.43 | 0.000 |
| X5 | 0.0000126 | 0.0000326 | 0.39 | 0.700 |
| X6 | 1.6469290 | 0.4631061 | 3.56 | 0.000 |

intensity within the same region. Meanwhile, the indirect effect comprises two facets: the influence of explanatory variables within neighboring regions on the carbon emission intensity within the focal region, and the impact of explanatory variables within the focal region on its own carbon emission intensity via a network of feedback loops.

As indicated in Table 4, the *p*-values associated with GDP per capita, foreign direct investment, and electricity consumption per capita – direct determinants of carbon emission intensity – are all above 0.05, indicating insignificance. Furthermore, both the direct and indirect effects of population, urbanization rate, and technology market turnover rate on carbon emission intensity exhibit similar patterns of change, demonstrating facilitating, inhibiting, and facilitating effects, respectively.

Population growth stimulates various energy demands, such as those arising from the expansion of the construction sector, where numerous buildings consume substantial energy and materials, consequently resulting in increased carbon emissions. Additionally, rapid population growth fosters population mobility, which in turn influences carbon emissions in adjacent regions [45].

Early stages of urbanization were characterized by heightened energy consumption and carbon emissions. Nevertheless, with the progression of urbanization, there emerges a rationalization of technological and industrial structures, leading to more efficient resource utilization and diminished carbon emissions. Consequently, the nation's level of urbanization has experienced significant growth.

The rapid advancement of science and technology is anticipated to trigger an upsurge in energy utilization. Technological innovations can enhance energy efficiency, optimize the energy mix, and propel the adoption of green energy, thereby mitigating carbon emissions. However, improvements in energy efficiency may inadvertently result in increased energy consumption, consequently leading to higher carbon dioxide emissions.

GDP per capita exhibits no significant direct impact but exerts a moderating influence on carbon emissions through indirect effects. This phenomenon is primarily attributed to the dual impact of economic growth on carbon emission intensity. On one hand, it enhances consumption quality, thereby reducing carbon emissions; on the other hand, it stimulates consumption, leading to increased carbon emissions. Consequently, the effect of GDP per capita on carbon emission intensity remains uncertain. Previous studies have revealed an "N"-shaped relationship between GDP per capita and per capita carbon dioxide emissions, with the strength of these effects contingent upon the stage of economic development.

The relationship between foreign direct investment (FDI) and per capita electricity consumption on carbon intensity is not characterized by a simple linear association. While FDI fosters economic growth, it may also introduce carbon emission sources from abroad into China. Moreover, the correlation between per capita electricity consumption and carbon emission intensity is influenced by the level of economic and technological advancement. Some regions exhibit high per capita electricity consumption coupled with low energy utilization efficiency, resulting in elevated carbon emission intensity, whereas others demonstrate high per capita electricity consumption alongside high energy utilization efficiency, leading to reduced carbon emission intensity.

In conclusion, based on the findings derived from the SDM model, it can be inferred that, at China's current developmental stage, the overall impacts of population, GDP per capita, urbanization rate, technology market transactions, total FDI, and per capita electricity consumption on carbon emission intensity are facilitating, inhibiting, mitigating, facilitating, facilitating, and promoting, respectively. However, the influence of FDI was found to be statistically insignificant.

## Conclusion

This study utilizes GIS technology and the Moran index to explore the spatial dynamics and aggregation effect of carbon emission intensity in China. It integrates traditional Markov chain, spatial Markov chain, and SNA methods to examine the spatial interaction of carbon emission intensity between adjoining and non-adjoining provinces. Additionally, the factors driving carbon emission intensity were analyzed using the SDM. Based on the findings, the following conclusions can be drawn:

(1) The shifting of China's carbon emission intensity towards the northwest while the economic center is moving southwards indicates noticeable spatial disparities in the level of low-carbon development across China. This phenomenon can be attributed to factors such as regional economic development, energy resource distribution, policy support, technological innovation capacity, geographic environment, and climatic conditions.

(2) China's carbon emission intensity distribution is predominantly characterized by high carbon emission intensity regions adjacent to other high carbon emission intensity regions and low carbon emission intensity provinces adjacent to other low carbon emission intensity provinces. Carbon emission intensity exhibits evident spatial spillover effects, with the positive spillover effects being more pronounced in regions with low carbon emission intensity. Regions with higher levels of low-carbon development can foster low-carbon development in surrounding areas through technological, policy, capital, and market influences. Similarly, regions with lower levels of low-carbon development can gradually close the low-carbon development gap and attain comprehensive low-carbon transformation

by learning, referencing, and engaging in win-win cooperation.

(3) While the overall trend for China's carbon intensity development is positive, the spatial connectivity network of carbon intensity is embedded, and the leading provinces in low-carbon development have not fully utilized their positive driving role. The lack of effective cooperation mechanisms between the leading provinces and the surrounding regions leads to poor information-sharing and difficulty in policy coordination, impeding the formation of good synergies and restricting the overall advancement of low-carbon development. While the leading provinces may lead in low-carbon technology research and development, the spillover of technology to the surrounding areas is limited, thus restraining the driving effect of low-carbon development. Furthermore, while the leading provinces may have attracted ample resources and talents, the surrounding areas may face inadequate and unappealing resource allocation, insufficient incentives for low-carbon development, and the inability to form a desirable development pattern.

(4) At China's current level of development, population, GDP per capita, urbanization rate, technology market turnover, total foreign investment, and per capita consumption of electric energy cumulatively facilitate, inhibit, inhibit, facilitate, facilitate, and facilitate carbon emission intensity, respectively. The impact of foreign investment has no significant effect.

Based on the above-mentioned conclusions, this paper proposes several recommendations. Under the prevailing conditions of carbon emission intensity and economic development imbalance, the positive spillover effect of highly developed low-carbon regions on neighboring regions needs to be further utilized. Carbon exchanges between non-neighboring regions must be promoted. The government should leverage regulatory tools to direct low-carbon technology exchange between advanced and relatively backward regions, encourage low-carbon technology circulation, and minimize carbon emissions in economically less-developed regions. Investment in environmental protection should be augmented, and capital investment in areas such as clean energy, pollution reduction, and carbon emissions should be enhanced at the national level. A well-developed carbon market mechanism or carbon emissions trading system should be established to prompt regions and enterprises to independently diminish carbon emissions and guide enterprises through economic incentives to reduce carbon emissions.

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## Conflict of Interest

The authors declare that there is no conflict of interest.

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