Academic Journal of Mathematical Sciences
ISSN 2616-5805 Vol. 4, Issue 5: 31-41, DOI: 10.25236/AJMS.2023.040505

Research on Spatial Effects of Regional Carbon Emission Intensity in China

Maosen Xia[1], Linlin Dong[1], Huiting Wang[1,*]

[1]*School of Applied Mathematics and Statistics, Anhui University of Finance and Economics, Bengbu, 233000, China*
[*]*Corresponding author: 1908390305@qq.com*

Abstract: *The results indicate that there is a significant spatial effect on carbon emission intensity between regions in China; Economic level, population density, and foreign investment intensity have a positive spatial direct effect on carbon emission intensity, while industrial structure, energy structure, scientific research investment, and urbanization level have a negative spatial direct effect on carbon emission intensity. The economic level, industrial structure, energy structure, and urbanization level have a negative spatial spillover effect on carbon emission intensity, while population density has a positive spatial spillover effect on carbon emission intensity. The spatial spillover effect of scientific research investment and foreign investment intensity on carbon emission intensity is not significant. Economic growth, industrial structure, and urbanization level are important factors that affect the intensity of carbon emissions.*

Keywords: *carbon emission intensity, spatial autocorrelation, spatial Durbin model, spatial effect*

1. Introduction

Climate change is a major challenge facing humanity today, and addressing it has become a global consensus. Since the implementation of the reform and opening up policy, while China's economy has flourished, it has also brought serious negative impacts on the environment. China has become the second largest economy in the world, but it is also the world's largest energy consumer and carbon emitting country, accounting for about one-third of the global total carbon emissions. Therefore, it faces enormous pressure to reduce emissions internationally. In this context, China proposed at the 75th United Nations General Assembly in 2020 the goal of striving to achieve peak carbon emissions by 2030 and striving to achieve carbon neutrality by 2060. Carbon emission intensity is an indicator used to measure the relationship between economic activities and carbon dioxide emissions in a country or region, and is also an important indicator for evaluating carbon reduction efforts. Low carbon emission intensity means that economic activities generate less carbon dioxide emissions. On the contrary, high carbon emission intensity means that the creation of the same wealth requires more energy consumption, which is not conducive to sustainable development. Energy conservation and emission reduction policies based on carbon emission intensity can help promote China's economic transformation and form a mechanism for long-term effects. [1-4].

This article explores the regional differences in carbon emission intensity caused by the imbalance in regional economic development and energy utilization in China. At the same time, considering the geographical relationship between different regions in China, there are geographical connections between neighboring regions, which promotes the connection between regional economies and results in significant spatial effects. Based on this background, this study provides a reference for measuring the level of green and low-carbon development in different regions by analyzing the spatial effects of carbon emission intensity in China.

2. Literature Review

The significant increase in total carbon emissions leads to environmental problems, posing many risks to human health and socio-economic development [5,6,7]. Because how to reduce total carbon emissions has become a focus of research for scholars both domestically and internationally, with the development of econometrics, scholars have begun to use spatial econometric models to analyze the influencing factors of changes in total carbon emissions, per capita carbon emissions, and carbon emission intensity [8,9].

ISSN 2616-5805 Vol. 4, Issue 5: 31-41, DOI: 10.25236/AJMS.2023.040505

Among them, the research on carbon emission intensity is the most extensive. By constructing a spatial econometric model of carbon emission intensity, it was found that the gradient distribution of carbon emission intensity in China has a strengthening effect on the spatial agglomeration of carbon emission intensity between regions [10,11]. Further adopting the theories and methods of spatial econometrics, the evolution mechanism of the spatiotemporal pattern of carbon emission reduction in China's provinces was revealed.

Research results on factors affecting carbon emission intensity: Yu Yihua et al. found a "N" shaped relationship between economic development level and carbon emission intensity using the generalized least squares panel model, while industrial structure has a significant positive impact on carbon emission intensity [12]. Yao Yi et al. used provincial panel data and dynamic panel models to study and found that foreign direct investment technology spillovers effectively reduced China's carbon emission intensity [13]. Fu Yunpeng et al. studied the influencing factors of carbon emission intensity in 30 provinces and cities in China from 2000 to 2012 using a spatial lag model. The results showed that population structure, energy intensity, energy structure, and industrial structure are the main influencing factors of carbon emission intensity in China [14]. The research by Ibrahim M. H et al. shows that in highly developed regions, financial development is beneficial for reducing carbon emission intensity [15]. Liang S et al. constructed a spatial panel model from the perspective of innovation driven, combined with innovative technology and scale factors, and found that innovative technology, foreign direct investment, and GDP have a significant negative impact on carbon emission intensity [16].

In addition, Ma Yanyan et al.'s research revealed that technological progress has significantly promoted the reduction of carbon emission intensity in the province, and there is a positive spatial spillover effect; The role of industrial structure in reducing carbon emission intensity in this province is not significant, but there is a negative spatial spillover effect [17]. Wang S et al. analyzed the spatial spillover effect of carbon emission intensity in 283 cities in China and found that there is a spatial spillover effect of carbon emission intensity in Chinese cities, and there is heterogeneity of spillover effects in different regional environments [18]. Thursday's study by Jun and Jiang Qiuchi used a dynamic spatial Durbin model to study the influencing factors of inter provincial carbon emission intensity in China. The results showed that economic growth and technology investment have a negative spatial direct effect on carbon emission intensity, while industrial structure, energy intensity, and energy consumption structure have a positive spatial direct effect on carbon emission intensity, and technology investment has a negative spatial spillover effect, Energy intensity has a positive spatial spillover effect [19]. Zhao Guimei et al. combined the STIRPAT model with the EKC model to examine the spatial spillover characteristics of factors affecting carbon emission intensity in China [20].

In summary, existing research has provided us with valuable references, but there are still some shortcomings. In terms of research methods, the static spatial Durbin model is currently mainly used to analyze the spatial effects of carbon emission intensity, with less consideration given to dynamic effects, which limits the in-depth analysis and explanation of the spatial effects of carbon emission intensity. Therefore, this article will construct a dynamic spatial Durbin model to study the spatial effects of regional carbon emission intensity, including spatial direct effects and spatial spillover effects, and provide countermeasures and suggestions for reducing regional carbon emission intensity.

3. Model Building

3.1 Selection and Explanation of Influencing Factors

Due to the lack of authoritative official institutions in China that directly release carbon dioxide emission data, conducting carbon emission intensity research requires first verifying and calculating carbon dioxide emissions. This article uses the exponential decomposition method to calculate carbon dioxide emissions, and calculates the total carbon dioxide emissions of a region or industry by multiplying and accumulating the consumption of different types of fossil fuels and carbon emission factors [21, 22, 23].

Based on literature review and theoretical analysis, with reference to the studies of Zhang Cuiju et al. [24, 25, 26], the research focuses on the impact of economic level, population density, industrial structure, energy structure, scientific research investment, urbanization level, and foreign investment intensity on carbon emission intensity. The following factors were selected for analysis, and the dependent variable was Y, the total carbon emission intensity, which is the ratio of carbon emissions to regional gross domestic product.

ISSN 2616-5805 Vol. 4, Issue 5: 31-41, DOI: 10.25236/AJMS.2023.040505

The data of 30 provinces, cities and autonomous regions in China from 2000 to 2021 (data on Hong Kong, Macao, Taiwan and Xizang are temporarily unavailable) were selected for research. The data is sourced from the "China Statistical Yearbook", "China Energy Statistical Yearbook", "China Urban Statistical Yearbook", as well as the statistical yearbooks of various provinces and cities, as well as the "National Economic and Social Development Statistical Bulletin". To ensure the consistency, completeness, and accuracy of the data, moving average and trend prediction methods are used for imputation of individual missing data. In addition, in order to eliminate the influence of price factors, the actual amount of foreign investment used is first converted from US dollars to RMB using the average exchange rate of the current year. All design price variables are adjusted using the GDP deflator of each city's province to the actual variables based on the initial 2000 years of the sample. To reduce the absolute difference between the data and avoid the impact of individual extreme values, the original indicator data is logarithmized. The descriptive statistics are shown in Table 1.

Table 1: Descriptive Statistics of Variables

Variable	Mean	Std.Dev.	Min	Max	Obs
lnY	0.931	0.729	-1.143	2.950	660
lnX_1	9.185	0.522	7.887	10.78	660
lnX_2	5.432	1.271	1.967	8.275	660
lnX_3	-0.0296	0.389	-0.704	1.667	660
lnX_4	-3.629	0.694	-5.878	-2.210	660
lnX_5	-4.508	0.694	-6.493	-2.729	660
lnX_6	-0.711	0.327	-1.974	-0.110	660
lnX_7	-4.195	1.117	-9.210	-1.921	660

3.2 Structural modeling

According to existing research, China's economic development shows a strong spatial correlation, and the process of economic development cannot be separated from energy consumption, which generates a large amount of carbon dioxide. It can be seen that carbon emission levels also have a significant correlation in geographical space. Therefore, this article uses a spatial econometric model based on spatial correlation. Currently, widely used econometric models include Spatial Lag Model (SLM), Spatial Error Model (SEM), and Durbin Spatial Model (SDM). The Spatial Durbin Model (SDM) is an econometric model that combines the characteristics of SLM and SEM. It introduces the spatial lag term of explanatory variables and explanatory variables to better evaluate the spatial effects measured from panel data and better handle spatial interdependence and geographical dependencies, and can provide more accurate prediction results. The Spatial Durbin Model (SDM) has certain advantages in solving spatial effects problems, but specific applications need to be selected and adjusted according to different research problems.

3.2.1 Spatial weight matrix

Geographical location can reflect the degree of mutual relationship between regions. This article constructs a geographic distance weight matrix based on the geographical connections of each province and the actual geographic distance. The element W_{ij} is the reciprocal of the nearest road distance between region i and region j, and the element d_{ij} is the nearest road distance between region i and region j. The matrix is:

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}} & ,i \neq j \\ 0 & ,i = j, \end{cases} \tag{1}$$

3.2.2 Spatial autocorrelation analysis

Moran’s I index is mainly used to reflect the similarity of attribute values between a certain spatial unit and adjacent spatial units, in order to analyze the overall spatial distribution and spatial correlation of the region:

ISSN 2616-5805 Vol. 4, Issue 5: 31-41, DOI: 10.25236/AJMS.2023.040505

$$I=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(x_i-\bar{x})(x_j-\bar{x})}{(\sum_{i=1}^{n}\sum_{j=1}^{nn}\omega_{ij})\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{2}$$

In the formula, the Moran index I represents the overall correlation of various regional indicators in China, n represents 30 provinces in Chinese Mainland, ω_{ij} is the spatial weight matrix, x_i and $\bar{x}$ are independent variables and mean values, respectively. The Moran index mainly ranges from -1 to+1. When the Moran index is positive, it indicates a positive relationship between provinces and cities, and the larger the value, the stronger the correlation.

3.2.3 Panel data regression analysis

Stata's unofficial command xsmle provides MLE estimation methods for spatial panel models. This command has a wide range of applications and can be used to estimate various types of spatial panel models. Therefore, for researchers who need to estimate spatial panel models, xsmle is a very useful tool. Its model can be represented as:

$$\begin{cases} y_{it}=\tau y_{i,t-1}+\rho w_i' y_t+x_{it}'\beta+d_i' X_t\delta+u_i+\gamma_t+\varepsilon_{it} \\ \varepsilon_{it}=\lambda m_i'\varepsilon_t+\nu_{it} \end{cases} \tag{3}$$

Among them, $y_{i,t-1}$ represents the first-order lag of the dependent variable y_{it} (if the research object does not have temporal characteristics, it can be set as $\tau=0$), which is the value of the previous time point; $d_i' X_t \delta$ represents the spatial lag of the explanatory variable, which considers spatial correlation through spatial weight D, d_i' is the i-th row of the corresponding spatial weight matrix D; γ_t represents the time effect, usually using time dummy variables to control the time trend; If m_i' represents the i-th row of the perturbation space weight matrix M, it is usually necessary to consider the impact of unobserved factors on the model. By using these parameters, it is possible to more accurately analyze the spatiotemporal correlation and spatial spillover effects of variables.

Another method for modeling spatial effects is to assume that the dependency of the explained variable y_i in region i is influenced by the independent variables of its neighbors:

$$y=X\beta+WX\delta+\varepsilon \tag{4}$$

Among them, $WX\delta$ Represents the influence from the neighbor independent variable, while δ Is the corresponding coefficient vector. This model is called the Spatial Durbin Model (SDM), as equation (3) does not have endogeneity, it can be directly used for OLS estimation; It should only be noted that there may be multicollinearity between the explanatory variables X and WX. If $\delta=0$, then equation (3) can be simplified as a general linear regression model. In order to further consider spatial correlation, the spatial lag model can be combined with the spatial error model to form the spatial Durbin model. The Durbin model allows for a more comprehensive analysis of the relationship between the dependent variable and the independent variable, while considering the impact of spatial spillover effects. The combined spatial Durbin model is:

$$y=\lambda Wy+X\beta+WX\delta+\varepsilon \tag{5}$$

4. Empirical analysis results

4.1 Analysis of the current situation of regional carbon emissions

Based on Figure 1, describe and analyze the temporal changes in carbon emissions and carbon emission intensity in China from 2008 to 2021. Overall, China's carbon emissions have shown a continuous upward trend without a significant downward turning point. The national carbon emission intensity shows a continuous linear downward trend. The increase in carbon emissions is related to various factors, but the decrease in carbon emission intensity indicators indicates that China is increasingly focusing on environmental protection and sustainable development while achieving economic development, and the energy utilization efficiency of various regions is becoming higher. Therefore, by monitoring and controlling carbon emission intensity when controlling carbon emissions, it can effectively guide the formulation and implementation of policies in various regions, promote

ISSN 2616-5805 Vol. 4, Issue 5: 31-41, DOI: 10.25236/AJMS.2023.040505

economic transformation and upgrading, and sustainable development. At the same time, it is also conducive to protecting and improving environmental quality.

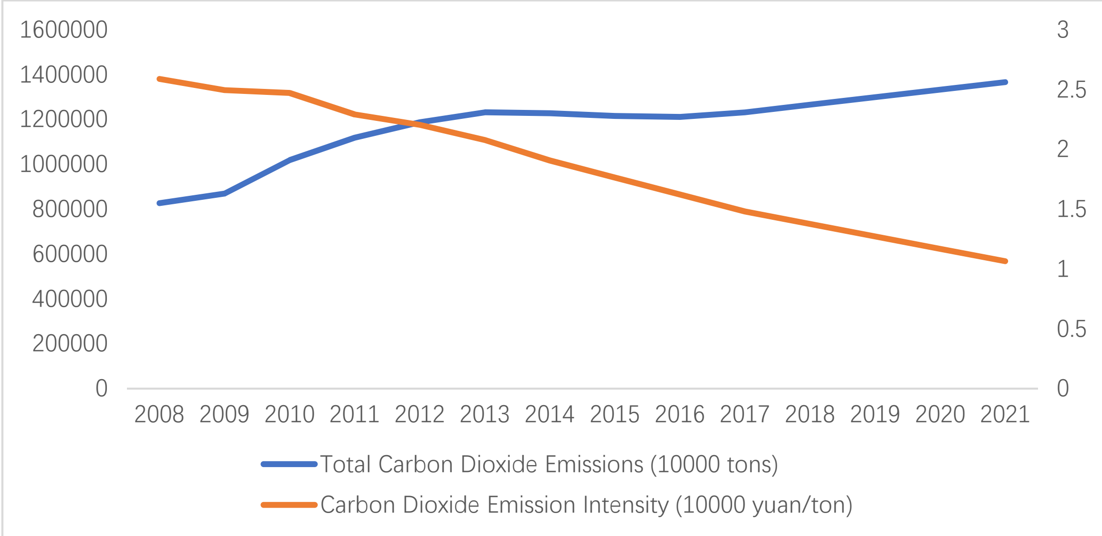


Figure 1: Trends in China's Carbon Emissions from 2008 to 2021

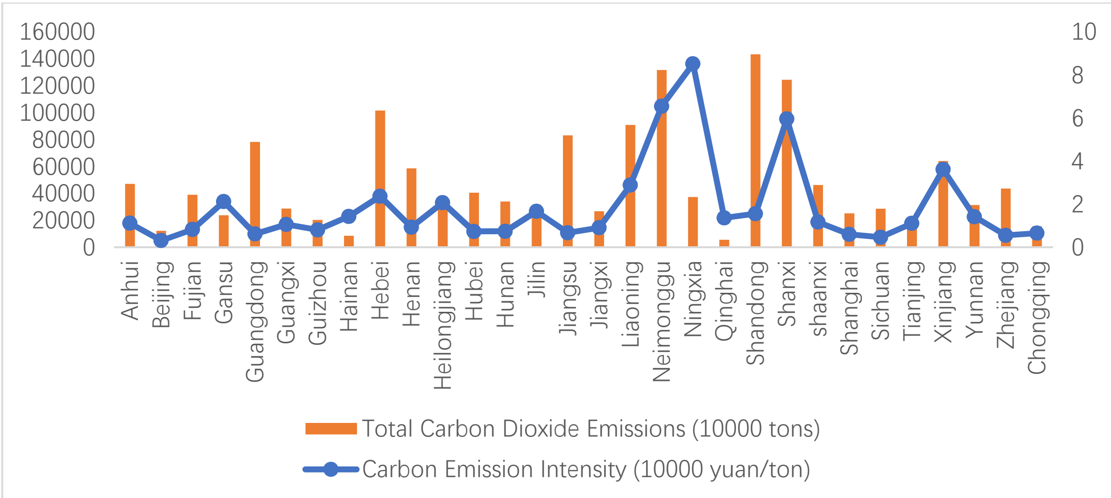


Figure 2: Distribution of Total Regional Carbon Emissions and Regional Carbon Emission Intensity in 2022

From Fig. 2, we can see that there are significant differences in the spatial distribution of carbon emissions among 30 provinces (including cities and autonomous regions) in China. The specific manifestations are as follows:

(1) Among the differences in total carbon emissions between provinces in China, it can be observed that there are significant differences in carbon emissions between provinces. Firstly, Shandong, Inner Mongolia, Shanxi, Hebei, Liaoning, and Jiangsu are among the top six industrial provinces, with total carbon emissions exceeding 900 million tons. The industrial structure of these provinces leans towards heavy industry, the energy structure is relatively single, and they lean towards coal, so they can provide a large number of high energy products for other regions. On the contrary, the six provinces ranked lower are Qinghai, Hainan, Beijing, Chongqing, Guizhou, and Tianjin.

(2) Some significant differences can be observed in China's carbon emission intensity. According to data, the top six provinces are Ningxia, Inner Mongolia, Shanxi, Xinjiang, Liaoning, and Hebei, which have higher carbon emission intensity. The energy structure of these provinces is mainly based on coal, so in the process of economic development, carbon emissions are relatively large. On the contrary, among the six lower ranked provinces, Beijing, Sichuan, Zhejiang, Shanghai, Guangzhou, and Chongqing have relatively low carbon emission intensity. The energy structure of these provinces is mainly focused on clean energy, and the achievements of their economic transformation and green development are gradually emerging.

ISSN 2616-5805 Vol. 4, Issue 5: 31-41, DOI: 10.25236/AJMS.2023.040505

Overall, due to certain differences in carbon emissions and intensity among different provinces in China, there are also differences in the pressure of controlling carbon emissions among different provinces in China. Some provinces with high carbon emissions and intensity, such as Hebei Province, Inner Mongolia Province, and Shanxi Province, face significant pressure in controlling carbon emissions due to their high carbon emissions and intensity. On the contrary, some provinces with low total and intensity, such as Beijing and Shanghai, which mainly focus on the service industry, have relatively low total and intensity carbon emissions, so the pressure to control carbon emissions is relatively small. However, some provinces with higher total emissions but relatively lower intensity, such as Jiangsu and Guangdong, also face certain challenges in controlling carbon emissions due to their large emissions. Therefore, each province in China needs to take different measures based on its own situation to control carbon emissions and achieve emission reduction targets.

4.2 Analysis of spatial autocorrelation results

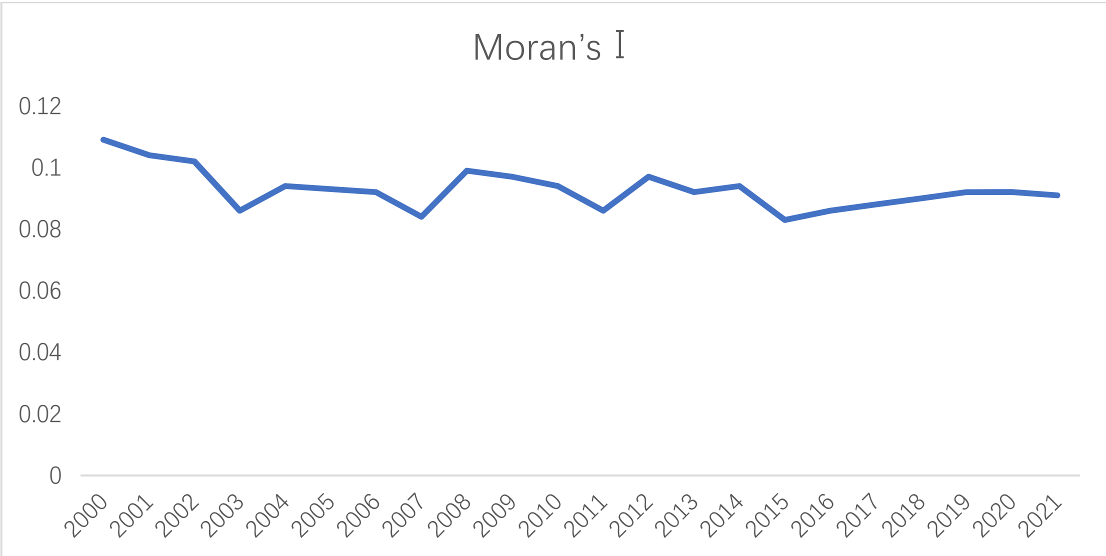
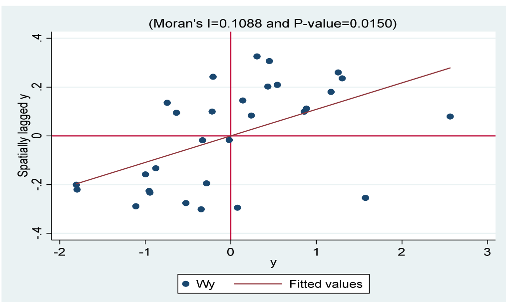
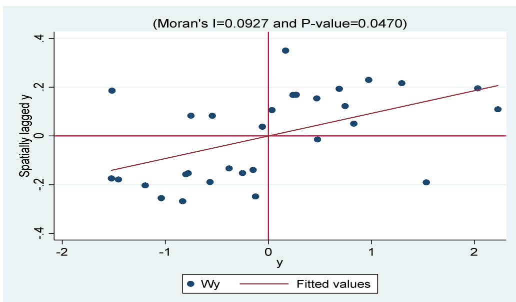


Figure 3: Global Moran Index Test Results

Using Stata software to calculate the global Moran's I index of carbon emission intensity in different regions of China from 2000 to 2021, we can see the temporal trend of regional development in China. From the test results in Figure 3, it can be seen that the Moran's I index is all positive and significant at the 5% level, indicating that various regions in China have shown significant positive spatial effects in each year. Therefore, spatial econometric analysis can be conducted. The positive relationship between various regions in our country fluctuates normally over time, which is also corresponding to the government's policies. With the growth of our country's economy, policies have increased economic and environmental exchanges in each province. In the foreseeable future, the people of various regions in China will definitely be able to closely unite and integrate talent resources, in order to better and faster achieve the goal of dual carbon.

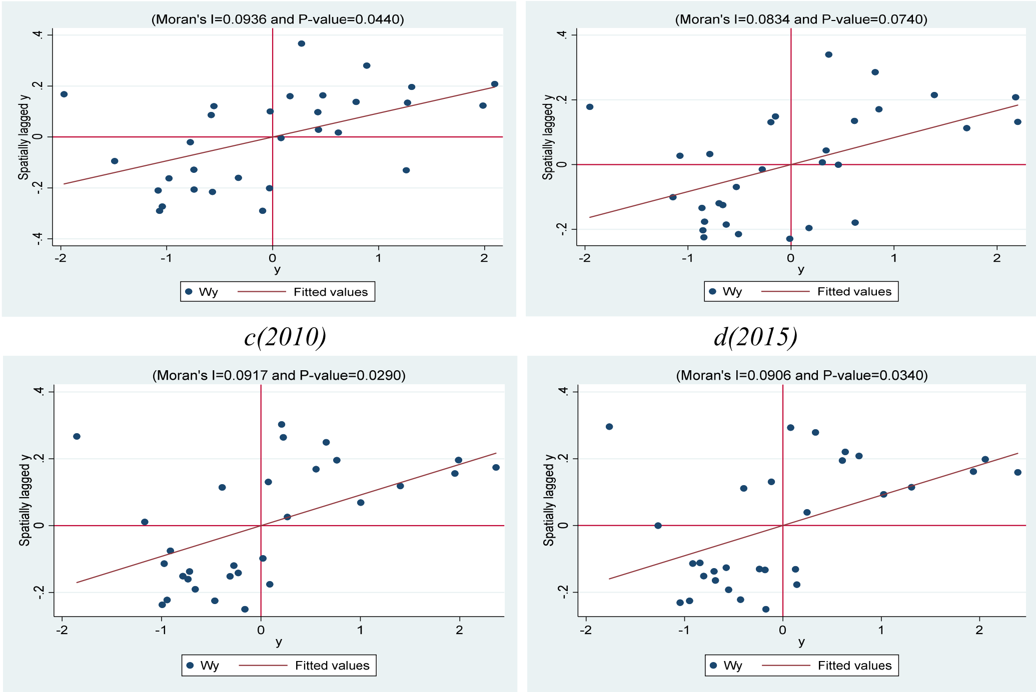


a(2000)



b(2005)

ISSN 2616-5805 Vol. 4, Issue 5: 31-41, DOI: 10.25236/AJMS.2023.040505



c(2010) *d(2015)*

e(2021) *f(2022)*

Figure 4: Scatter plot of local Moran's I index for regional carbon emission intensity

Use Stata software to calculate the local Moran's I index of carbon emission intensity in different regions of China from 2000 to 2021, and draw Moran scatter plots with the years 2000, 2005, 2010, 2015, 2020, and 2021. The Moran index scatter plot has the following four types of spatial connections. The first type is the first quadrant (H-H), and the H-H type exhibits a spatial positive correlation, which is the aggregation of high-level provinces and high-level provinces; The second type is the second quadrant (L-H), where the L-H type exhibits a spatial negative correlation, which is the aggregation of low-level and high-level provinces; The third type is the Third Quadrant (L-L), which exhibits a spatial positive correlation and is the aggregation of low-level provinces and regions; The fourth category is the fourth quadrant (H-L), where the H-L type exhibits a negative spatial correlation, which is the aggregation of high-level and low-level provinces; Based on the analysis in Figure 4, we can see that the number of provinces in high value and low value clusters accounts for about 5/6 of the total number of provinces in the study area, indicating that high value and low value clusters dominate, and carbon emission intensity has a significant positive spatial autocorrelation and strong spatial agglomeration.

4.3 Comprehensive analysis of elements based on spatial econometric models

Table 2: Test Results for Model Selection

Testing Method	Test statistic results	p-value
LM-Lag	165.345	0.000
Robust LM-Lag	61.382	0.000
LM-Error	107.088	0.000
Robust LM-Error	3.124	0.077
LR-SDM-SEM	74.7	0.000
LR-SDM-SAR	80.57	0.000
LR-both-time	942.75	0.000
LR-both-ind	60.06	0.000
Hausman	46.53	0.000
Wald-SAR	87.06	0.000
Wald-SEM	80.88	0.000

The data used in Table 2 below have all passed the correlation and collinearity tests, and a spatial effect measurement model has been selected based on the Moran's I test. Firstly, the LM test results indicate that both spatial error and spatial lag models are significant at a 1% significance level, and a spatial econometric model can be chosen for empirical research. Then, the LR likelihood ratio test

ISSN 2616-5805 Vol. 4, Issue 5: 31-41, DOI: 10.25236/AJMS.2023.040505

statistical data also passed the test at the significance level of 1%, and there were individual and time effects. Meanwhile, the Hausman test results indicate that the fixed effects model is superior to the random effects model. Finally, the Wald test showed that choosing the SDM model was more optimal compared to SEM and SAR models. The inspection results are shown in Table 2:

In summary, the fixed effects and bidirectional fixed effects models of the optimal spatial Durbin model (SDM) were selected for spatial econometric analysis in this article.

Table 3: Spatial Durbin Model Results

	lny	Coef.	Std. Err.	z	P>|z|
main					
	x1	0.0000976	0.0000281	-3.48	0.001
	x2	0.0010393	0.0006109	1.70	0.089
	x3	-0.5749901	0.223949	-2.57	0.010
	x4	-1.476275	0.643455	-2.29	0.022
	x5	-4.415052	1.141393	-3.87	0.000
	x6	-16.85263	2.957997	-5.70	0.000
	x7	70.42455	17.37333	4.05	0.000
Wu					
	x1	-0.0004681	0.0001368	-3.42	0.001
	x2	0.011808	0.0044915	2.63	0.009
	x3	-5.734985	1.227154	-4.67	0.000
	x4	-8.450599	4.57296	-1.85	0.065
	x5	4.581935	5.56275	0.82	0.410
	x6	-76.89355	20.43119	-3.76	0.000
	x7	156.2589	98.84851	1.58	0.114
Spatial					
	rho	-0.8033607	0.1778935	-4.52	0.000

The Durbin model, which uses the natural logarithm of carbon emission intensity as the dependent variable, reveals the effects of various factors on carbon emission intensity in Table 3. The research results indicate that the p-value of the spatial autoregressive coefficient is 0.000, which is significant at the 1% level, and its coefficient is -0.8034, which is negative, indicating that the explanatory variable y, i.e. carbon emission intensity, has a negative spatial spillover effect. From the statistical P-values of spatial direct effects, x1, x5, x6, and x7 reached a significance level of 1%, with coefficients of 0.0001, -4.415, -0.357, and -0.08, respectively. X3 and x4 reached a significance level of 5%, with coefficients of -0.575 and -1.4763, respectively. The significance of x2 reaches a 10% level. From the coefficient, it can be seen that economic growth, population density, and foreign investment intensity have a promoting effect on carbon emission intensity, while industrial structure, energy structure, scientific research investment, and urbanization level have a restraining effect on carbon emission intensity.

The spatial spillover effect term is more indicative of spatial conduction effects than the coefficient of spatial direct effects. Wx1, Wx2, Wx3, Wx4, and Wx6 are significant at the 10% level, with coefficients of -0.0005, 0.0118, -5.735, -8.4506, -76.8936, respectively. A negative x2 coefficient indicates that population density has a positive spatial spillover effect, and an increase in population density has a positive conduction effect on nearby carbon emission intensity. The coefficients of x1, x3, x4, and x6 are negative, indicating a negative spatial spillover effect on economic growth, industrial structure, energy structure, and urbanization level. The adjustment of economic growth, industrial structure, energy structure, and urbanization level has a negative transmission effect on adjacent carbon emission intensity. The estimated coefficients of X5 and x7 are positive, but not significant, indicating that an increase in scientific research investment and foreign investment intensity will promote an increase in carbon emission intensity in adjacent regions, resulting in a spatial spillover effect of carbon emissions, but the effect is not significant.

The above results demonstrate the complexity, diversity, and diversity of regional socio-economic development in China. Factors such as economic structure, industrial characteristics, and capital flow in different regions will have different impacts on carbon emissions. Therefore, when formulating emission reduction policies, it is necessary to consider the characteristics of different regions and adopt differentiated emission reduction measures to achieve the goal of carbon reduction. In addition, this also reminds us to pay more attention to the balance between economic development and environmental protection, adopt a sustainable development path, and achieve coordinated development of the economy, society, and environment.

ISSN 2616-5805 Vol. 4, Issue 5: 31-41, DOI: 10.25236/AJMS.2023.040505

Table 4: Decomposition effects of spatial spillover effects

		Coef.	Std. Err.	z	P>|z|
Direct effect					
	x1	-.0000844	.000029	-2.90	0.004
	x2	.0006609	.0005569	1.19	0.235
	x3	-.3892321	.2159132	-1.80	0.071
	x4	-1.227778	.6261699	-1.96	0.050
	x5	-4.683299	1.19732	-3.91	0.000
	x6	-14.66199	2.849353	-5.15	0.000
	x7	67.6089	18.345	3.69	0.000
Indirect effect					
	x1	-.0002303	.0000792	-2.91	0.004
	x2	.0065644	.0024651	2.66	0.008
	x3	-3.079052	.6939933	-4.44	0.000
	x4	-4.394959	2.58002	-1.70	0.088
	x5	5.165467	3.549339	1.46	0.146
	x6	-37.92019	12.08783	-3.14	0.002
	x7	56.2079	56.84591	0.99	0.323
Total effect					
	x1	-0.0003146	.0000792	-3.97	0.000
	x2	0.0072253	.0025842	2.80	0.005
	x3	-3.468284	.7029876	-4.93	0.000
	x4	-5.622738	2.595208	-2.17	0.030
	x5	0.4821676	3.223613	0.15	0.881
	x6	-52.58218	12.44226	-4.23	0.000
	x7	123.8168	53.69814	2.31	0.021

From the results in Table 4, it can be seen that x1, x3, and x6 (economic growth, industrial structure, and urbanization level) are very significant in terms of direct effects, indirect effects, and overall effects. This indicates that an increase of one unit in economic growth, industrial structure, and urbanization level will lead to a change of -0.0001, -0.3892, and -14.662 units in the carbon emission intensity of the region, respectively. In the indirect effect, an increase of one unit in economic growth, industrial structure, and urbanization level can lead to a change of -0.0002, -3.079, and -37.9202 units in the carbon emission intensity of neighboring regions, respectively. In the total effect, the economic growth, industrial structure, and urbanization level changes in all regions can have an impact of -0.0003, -3.4683, and -52.5822 units on the carbon emission intensity of the region.

5. Conclusion

This article analyzes the influencing factors of regional carbon emission intensity in China from 2000 to 2021 using the spatial econometric Durbin model method using Stata15.0 and conducts correlation tests. Analyzing the current situation and influencing factors of carbon emissions spatial differences in 30 provinces (cities, autonomous regions) in China will contribute to the achievement of China's "dual carbon" goals. After analysis, the following conclusions can be drawn:

(1) The carbon emission intensity between regions in China has a significant spatial effect. In terms of the overall spatial pattern, the regional carbon emission intensity shows a significant positive spatial autocorrelation, with good continuity and spatial self-organization. This means that neighboring provinces have similar performance in terms of carbon emission intensity. Local spatial autocorrelation shows a spatiotemporal distribution feature of agglomeration and differentiation in regional carbon emission intensity, with certain spatial locking or path dependence characteristics.

(2) The test results of the spatial Durbin model indicate that economic level, population density, and foreign investment intensity have a positive spatial direct effect on regional carbon emission intensity; The industrial structure, energy structure, scientific research investment, and urbanization level have a negative spatial direct effect on the intensity of regional carbon emissions. The economic level, industrial structure, energy structure, and urbanization level have a negative spatial spillover effect on carbon emission intensity; Population density has a positive spatial spillover effect on carbon emission intensity; The spatial spillover effect of research investment and foreign investment intensity on carbon emission intensity is not significant.

ISSN 2616-5805 Vol. 4, Issue 5: 31-41, DOI: 10.25236/AJMS.2023.040505

(3) The impact of various factors on carbon emission intensity has significant spatial heterogeneity, and the same factor has different impacts in different regions. Economic growth, industrial structure, and urbanization level are important factors that affect the intensity of carbon emissions. Therefore, in order to better control carbon emissions, China needs to take different emission reduction measures tailored to the characteristics of different provinces while considering overall development, in order to achieve the goal of carbon reduction.

Overall, controlling carbon emissions is a complex and systematic issue. The country, province, and region must fully implement the measure of reducing emissions and controlling carbon emissions, and formulate production transformation plans and goals based on the actual situation of the country and the local area. Local governments must strengthen regional exchanges and cooperation, and jointly manage carbon dioxide emissions between regions. Abandoning the misconception of 'pollution before treatment' to promote the transformation, upgrading, and sustainable development of China's economy. Enterprises need to actively respond to national policies, strengthen technological innovation, actively develop new energy technologies, gradually phase out high energy consumption and high pollution technologies, establish a new industrial structure, and gradually reduce the share of the secondary industry. All citizens in society should strengthen their awareness of environmental protection, implement a low-carbon lifestyle, reduce unnecessary energy consumption and waste, and jointly create a good social atmosphere of energy conservation and environmental protection. China needs to actively participate in international climate change negotiations, strengthen cooperation with other countries, and jointly address the challenges of global climate change. Through the joint efforts of the government, enterprises, the whole society, and international cooperation, we believe that China's goal of "carbon peaking and carbon neutrality" will be achieved.

References

[1] He J, Liu B. Analysis of carbon emission intensity as a measure of greenhouse gas emissions. Journal of Tsinghua University (Science and Technology). 2004, No. 6, p. 740-743.

[2] Pan J H, Huang C L, Li M. Systematically grasping the basic strategy of ecological civilization construction in the new era: Interpretation of the spirit of ecological civilization construction in the report of the 19th National Congress of the Communist Party of China. Environmental Economy. 2017, No. 20, p. 66-71.

[3] Wang C, Wang F. China can lead on climate change. Science. Vol. 357 (2017) No 6353, p. 764-764.

[4] Xiao H, Yang J H, Jiang X M. Analysis of the complete carbon emission intensity changes and influencing factors of final demand. China Population. Resources and Environment. Vol. 24 (2014) No 10, P. 48-56.

[5] Dong L, Liang H. Spatial analysis on China's regional air pollutants and CO2 emissions: emission pattern and regional disparity. Atmospheric Environment. Vol. 92 (2014), p. 280-291.

[6] Dobes L, Jotzo F, Stern D I. The economics of global climate change: a historical literature review. Review of Economics. Vol. 65 (2014) No. 3, p. 281-320.

[7] Wang S, Chu C, Chen G, et al. Efficiency and reduction cost of carbon emissions in China: a non-radial directional distance function method. Journal of Cleaner Production. Vol. 113 (2016), p. 624-634.

[8] Zhang Y G. Influence of changes in economic development mode on carbon emission intensity in China. Economic Research. Vol. 45 (2010) No. 04, p. 120-133.

[9] Zhao G M, Chen L Z, Sun H P. Research on the decoupling effect of carbon emission intensity based on heterogeneity convergence. East China Economic Management. Vol. 31 (2017) No. 04, p. 97-103.

[10] Aguiar A P D, Ometto J P, Nobre C, et al. Modeling the spatial and temporal heterogeneity of deforestation-driven carbon emissions: the INPE-EM framework applied to the Brazilian Amazon. Global Change Biology. Vol. 18 (2012) No. 11, p. 3346-3366.

[11] Feng Z X, Wang K Y. Spatial statistical analysis of carbon intensity clusters in China. Resources Science. Vol. 36 (2014) No. 07, p. 1462-1468.

[12] Yu Y H, Zheng X Y, Zhang L. Economic development level, industrial structure, and carbon emission intensity: panel data analysis of Chinese provinces. Economic Theory and Economic Management. 2011, No. 03, p. 72-81.

[13] Yao Y, Ni Q. The impact of foreign direct investment on carbon intensity: an empirical study based on dynamic provincial panel data in China. Mathematical Statistics and Management. Vol. 32 (2013) No. 1, p. 113-122.

[14] Fu Y P, Ma S C, Song Q. Spatial econometric analysis of China's regional carbon emission intensity. Statistical Research. Vol. 32 (2015) No. 6, p. 67-73.

[15] Ibrahim M H. Trade-finance complementarity and carbon emission intensity: panel evidence from

ISSN 2616-5805 Vol. 4, Issue 5: 31-41, DOI: 10.25236/AJMS.2023.040505

middle-income countries. Environmental Systems and Decisions. Vol. 38 (2018) No. 04, p. 489-500.
[16] Liang S, Zhao J, He S, et al. Spatial econometric analysis of carbon emission intensity in Chinese provinces from the perspective of innovation-driven. Environmental Science and Pollution Research. Vol. 26 (2019) No. 14, p. 13878-13895.
[17] Ma Y Y, Lu Y W, Sun Y T. Technological progress, structural adjustment, and carbon emission intensity: empirical study based on spatial panel data model at provincial level in China. Research and Development Management. Vol. 28 (2016) No. 5, p. 23-33.
[18] Wang S, Huang Y, Zhou Y. Spatial spillover effect and driving forces of carbon emission intensity at the city level in China. Journal of Geographical Sciences. Vol. 29 (2019) No. 2, p. 231-252.
[19] Zhou S J, Jiang Q C. Research on the spatial effect of carbon emission intensity based on dynamic SDM in China. Journal of Hunan University (Social Sciences Edition). Vol. 34 (2020) No. 01 p. 40-48.
[20] Zhao G M, Geng Y, Sun H P, Zhao G Q. Research on the spatial effect and transmission mechanism of inter-provincial carbon emission intensity in China. China Population, Resources and Environment. Vol. 30 (2020) No. 03, p. 49-55.
[21] IPCC, 2007, Intergovernmental Panel for Climate Change Fourth Assessment Report. Cambridge: Cambridge University Press.
[22] Lin B Q, Mao D X. Study on the stage characteristics of China's carbon emission intensity decline. Financial Research. 2014, No. 8, p. 101-117.
[23] Wang K, Tang X H, Gan C, Liu H L. Spatial-temporal pattern and influencing factors of carbon emission intensity in China's service industry. China Population, Resources and Environment. Vol. 31 (2021) No. 08, p. 23-31.
[24] Zhang C J, Bai Q, Zhang W A. Research on influencing factors and spatial spillover effect of China's regional carbon emission intensity based on spatial Durbin model. Systems Engineering. Vol. 35 (2017) No. 10, p. 70-78.
[25] Zhang Z Q, Zhang T, Feng D F. Research on regional differences, dynamic evolution, and convergence of carbon emission intensity in China. Journal of Mathematical Economics and Technical Economics. Vol. 39 (2022) N0. 04, p. 70-78.
[26] Wang S J, Huang Y Y. Spatial spillover effects and driving factors of urban carbon emission intensity in China. Acta Geographica Sinica. Vol. 74 (2019) No. 06, p. 1131-1148.