Carbon emission intensity measurement and spatial effect of high energy consuming industries: evidence from China

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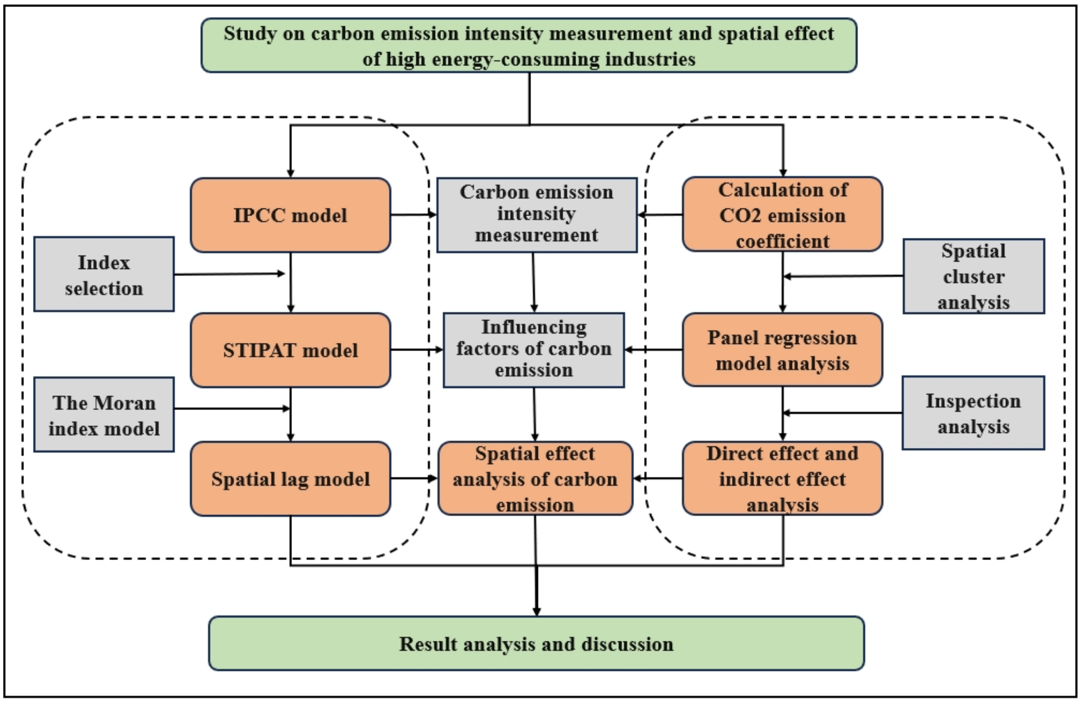
Graphical Abstract



Abstract: high energy consumption industry is an important source of carbon dioxide emissions, and reducing pollution and carbon is an important measure for China to achieve the goal of "2030 carbon peak 2060 carbon neutral". Based on the improvement of the traditional calculation method of IPCC carbon emission intensity, this paper measures the carbon emission intensity, selects the data of high energy consuming industries in 30 provinces in China from 1997 to 2022 as samples, uses the stipat model and Moran index to analyze the correlation of the influencing factors of carbon emission, and uses the spatial measurement model to study the spatial effect of carbon emission intensity. The results show that: first, the overall carbon emission intensity of high energy consuming industries shows a downward trend, with typical spatial heterogeneity. During the sample period, the carbon emission intensity of high energy consuming industries in 30 provinces in China was calculated based on the IPPC method, with the overall decline. Second, the carbon emission intensity of high energy consuming industries has significant spatial autocorrelation characteristics. According to the global Moran index, the center of gravity moves from east to West as a whole. Third, the carbon emission intensity of high energy consuming industries is affected by multiple environmental factors. Industrial structure (INS), regional gross domestic product (GDP) and regional economic development (ECO) have a significant impact. Fourth, the carbon emission intensity of high energy consuming industries has a significant spatial spillover effect. According to the regression results of spatial Dobbin model with double fixed effects, the direct and indirect effects of carbon emission intensity of high energy consuming industries are significant.

Key words: High energy consumption industry; Carbon emissions; Influencing factors; Spatial effect

1. Introduction

Since the 21st century, environmental pollution and climate change caused by carbon emissions have attracted global attention. The potential problems caused by global climate change are considered to cause unpredictable "catastrophic" risks. According to the statistical prediction, the emission of greenhouse gases will lead to the increase of global temperature from 2030 to 2050 or will reach 1.5 ℃. If climate change exceeds the upper limit of global temperature control, it will cause immeasurable damage to human society and ecology. The Chinese government attaches great importance to the issue of carbon emissions, and clearly puts forward the strategic goal of "2030 carbon peak and 2060 carbon neutrality" in 2019. In 2022, the Chinese government issued the implementation plan for carbon peaking in the industrial sector, which proposed that by 2025, the energy consumption per unit of added value of China's industry would be reduced by 13.5% compared with 2020. Building materials industry, steel industry, chemical industry and other industries are considered to be high energy consuming industries. High energy consuming industries are one of the main sources of carbon emissions in China, and carbon emissions from high energy consuming industries have typical regional differences. Research on the difference of carbon emission intensity of high energy consuming industries is conducive to regional emission reduction and the realization of double carbon goals.

Revealing the temporal and spatial characteristics of carbon emission intensity of high energy consuming industries and analyzing the carbon emission trend of high energy consuming industries have increasingly become the hot spot of carbon emission management and decision-making. Scholars at home and abroad have carried out fruitful research on the characteristics of carbon emissions, carbon emissions measurement, influencing factors of carbon emissions and carbon emission reduction path. In terms of carbon emission characteristics, Wei et al. (2024) used panel data to analyze the spatial characteristics of carbon emissions of major urban agglomerations in China based on spatial econometric model, and proposed that collaborative management among different cities would help promote the sustainable development of regional urban agglomerations. Xu et al. (2023) analyzed the characteristics of urban residents' living carbon emissions through the spatial Markov chain model, and believed that the dynamic change of residents' carbon emissions was significantly affected by the geospatial spillover effect. Yue et al. (2024) constructed a super SBM model to measure energy efficiency, and used GIS spatial analysis method to describe its spatial pattern. It was found that the comprehensive energy efficiency of cities in the Yellow River Basin remained basically stable, but had a downward trend . These studies have important contributions to reveal the spatial characteristics of carbon emissions, and become an important basis for this study.

In the calculation of carbon emission intensity, most scholars measure it based on IPCC method. Li et al. (2024) used the IPCC inventory method to calculate the ratio of the total urban carbon emissions to the GDP of the corresponding region as the carbon emission intensity index . Cui et al. (2024) used IPCC carbon accounting method to calculate the total amount and intensity of China's agricultural carbon emissions from 2010 to 2021. Tian et al. (2024) calculated the carbon emission intensity factor of electric power with reference to the IPCC method [6]. Zhao and Xu (2023) calculated the energy carbon emissions of 17 primary energy sources in 47 sectors based on the IPCC method. Li et al. (2023) used IPCC method to quickly calculate China's carbon emission intensity. Therefore, it can be seen that the calculation model of carbon emission intensity using IPCC method has formed a relatively broad consensus (Wang et al., 2022; Ren et al., 2022; Li et al., 2022; Zhu et al., 2022; Wu et al., 2024; Jiang et al., 2024).

The analysis of influencing factors of carbon emissions is also the focus of scholars at home and abroad. Common analysis methods include spatial autocorrelation, nuclear density estimation, Theil index and dagum Gini coefficient (Sun, et al, 2023; Ahn, et al, 2022; Hoang, et al, 2023; gharaei, et al, 2023). Peng et al (2024) estimated the spatial characteristics of agricultural carbon emissions based on the standard deviation ellipse method, and used the LMDI model to decompose the influencing factors of carbon emissions. Liu et al (2024) revised the gravity model to analyze the characteristics of urban carbon emission network, and analyzed the influencing factors of carbon emission based on social network and secondary assignment procedure method. Li et al (2024) studied the characteristics of carbon emissions in the Yangtze River Delta by using spatial autocorrelation analysis and Markov chain model, and analyzed the influencing factors of carbon emissions by using GTWR influencing factors analysis, and most of them use the model of parameter estimation to analyze. In addition, Li and Huang(2024) took the influencing factors of carbon emissions as samples, introduced lasso variable selection method and BP neural network model to predict the peak value of carbon emissions, and proposed control measures. Shi et al (2024) used the bivariate spatial correlation analysis method to analyze the relationship between traffic informatization and carbon emissions, and used geographical detectors to explore the temporal and spatial characteristics of carbon emissions. Li et al (2024) analyzed the driving factors of the synergistic effect of urban pollution and carbon reduction by using the coupling coordination degree model and the convergence coefficient model. These studies pay attention to the application of spatial geographical model in the method, and at the same time, improve the traditional model to consider the influence factors of real situation on carbon emissions.

To sum up, the research on carbon emission measurement, spatial characteristics and influencing factors is the current hot spot, which has aroused widespread concern. However, there are still some deficiencies in the current research: ① most studies focus on the carbon emissions of urban agglomerations, mainly from the regional perspective, such as the Yangtze River Delta, the Yellow River Basin, Guangdong, Hong Kong and Macao Bay area, and less on the analysis of high energy consumption industries. High energy consumption industry is one of the key areas of carbon emissions, so it is necessary to deepen the research on this industry and put forward targeted countermeasures. ② In terms of research methods, traditional models are mostly used to analyze the carbon emission intensity and influencing factors of high energy consuming industries, and the research on the integration of spatial correlation analysis and STIRPAT model is insufficient. This paper will improve the above deficiencies, take high energy consuming industries as the object, and comprehensively use the combination model to study the carbon emission intensity measurement and spatial effect of high energy consuming industries. The idea of this study is shown in Figure 1:

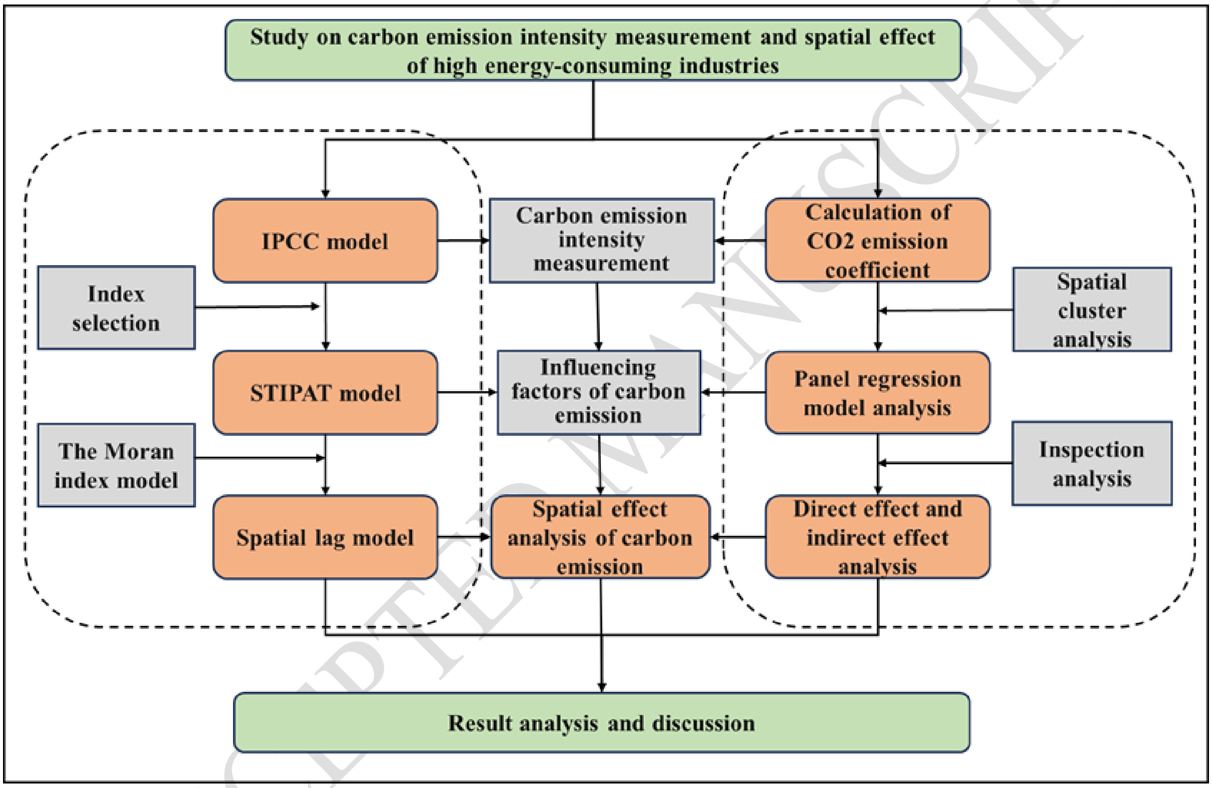


Fig. 1 the train of thought of this paper

2. Research methods and data sources

2.1. Construction of carbon emission intensity calculation model

The waste gas of high energy consuming industries mainly comes from fossil fuels. Referring to the research ideas of Cai, et al. (2021), and combining with the specific reality, this paper assumes that the carbon in the supply of three major fossil fuels is equal to the carbon contained in the total consumption of 17 fossil fuels.

In the calculation of carbon emissions, the calculation method used in this paper refers to Shan(Yuli, et al. 2018)According to their research, IPCC default value of greenhouse gas emission inventory was optimized, 47 departments consistent with those used in China's national accounts were used in the energy statistics system, and emission factors were updated. Therefore, the calculation formula of emissions from different industries is as follows:

$$CE_n = \sum_{m=1}^{17} (AD_{nm} \times NCV_m \times EF_m \times O_{nm}) \quad \textbf{(1)}$$

Including:

CE_n represents CO_2 emissions from fossil fuel combustion in industry n;

AD_{nm} represents the average low calorific value of the m energy of the n industry;

NCV_m represents the average low calorific value of different fossil fuels;

EF_mrepresents the CO_2 emission coefficient of the m energy after renewal;

$O_{nm}$is the oxidation efficiency of the m energy in the n industry.

Table 1 CO_2 emission coefficient of different energy sources

Energy fuel type	*raw coal*	*Clean coal*	*other Coal washing*	*Coal brick*	*coke*	*coke coal gas*	*other Gas*	*Other coking products*	*crude oil*
NCV_m	0.21	0.26	0.15	0.18	0.28	1.61	0.83	0.28	0.43
CC_n	26.32	26.32	26.32	26.32	31.38	21.49	21.49	27.45	20.08

EF_m	0.087	0.087	0.087	0.087	0.104	0.071	0.071	0.091	0.073
O_{nm}	0.94	0.98	0.90	0.90	0.93	0.99	0.99	——	0.98

Energy fuel type	gasoline	kerosene	diesel oil	fuel oil	Other oil product	liquefied petroleum gas	Refinery natural gas	natural gas
NCV_m	0.44	0.44	0.43	0.43	0.51	0.47	0.43	3.89
CC_n	18.9	19.6	20.2	21.1	17.2	20	20.2	15.32
EF_m	0.069	0.072	0.074	0.077	0.063	0.073	0.074	0.056
O_{nm}	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.99

The carbon emissions of high energy consuming industries can be obtained through the above methods. $HECCI$ represents the carbon emission intensity of high-energy-consuming industries; GRO_j is the total industrial output value of industry j; CE_j is the CO2 emission of industry j, The specific calculation formula is as follows:

$$\mathrm{HECCI} = \frac{\sum_{j=1}^{n} CE_j}{\sum_{j=1}^{n} GRO_j} \quad \textbf{(2)}$$

2.2. Analysis of influencing factors of carbon emissions based on stipat model

When considering the influence factors of carbon emissions, the classical model of IPAT equation was first used in history. However, the model has some limitations, that is, the model is too simple in theory, structure and other aspects. When analyzing, it is considered that all the possible related influencing factors considered in the model are the same. Therefore, in the later history, many scholars at home and abroad invested a lot of energy in the study of the optimization model of environmental impact, so the stochastic environmental impact assessment model (STIRPAT model) came into being.

STIRPAT model is an improved version of the model, which has been upgraded and improved on the basis of IPAT, and the influencing factors can be flexibly changed according to the needs of researchers. This paper will describe the influencing factors of carbon emission intensity of high energy consuming industries based on STIRPAT model.

Referring to the research of Lian Yanqiong et al. (2024) [26], the general expression of STIRPAT model is as follows:

$$F = \alpha \times Q^{b} \times P^{c} \times T^{d} \times e$$

Where F represents carbon emissions, Q is the population size, P stands for economic level, T is for technological level. The specific values of the model parameters can be estimated by taking the derivative of both sides of the equation.

2.3. Correlation analysis of carbon emission factors based on global Moran index

3.4.2 Setting of spatial weight matrix

There are generally two types of spatial weight matrices: geographical adjacency spatial weight matrix based on binary algorithm and spatial distance matrix based on linear Euclidean distance. Since the number of regions is small and the degree of compactness is large, this paper uses the formula to build the spatial weight matrix according to the geographical adjacency between regions

$$W_{ij}^{n}=\begin{cases}1, & i \text{ and } j \text{ are adjacent}\\ 0, & else\end{cases} \tag{3}$$

3.4.3 Moran index model

Spatial autocorrelation is the prerequisite for building a spatial econometric model. Through spatial autocorrelation analysis, we can verify whether there is a spatial correlation between the carbon emission intensity of high energy consuming industries in various regions, so as to correctly build a spatial econometric model of the national carbon emission intensity. Moran index is a commonly used indicator for global spatial autocorrelation analysis. It explores the spatial relationship between regions in the whole space and measures the spatial aggregation degree of carbon emissions from high energy consuming industries. Its theoretical formula is as follows:

$$\text{Moran's I}=\frac{\sum_{x=1}^{n}\sum_{y=1}^{n}\omega_{xy}\left(a_x-\bar{a}\right)\left(a_y-\bar{a}\right)}{C^2\sum_{x=1}^{n}\sum_{y=1}^{n}W_{xy}} \tag{4}$$

$$C^2=\frac{\sum_{x=1}^{n}\left(a_x-\bar{a}\right)}{n} \tag{5}$$

In the above formula, n represents the total number of study areas, and w_{xy} is a spatial weight matrix; The geographical adjacency space weight matrix constructed by the binary algorithm in this study is obtained by nesting the geographical matrix and the economic matrix, where the value range of I is [-1,1]. A larger absolute value indicates a higher degree of agglomeration or dispersion, that is, a region with a high or low value is adjacent to a region with a low or high value. I = 0 indicates that the industry is randomly distributed in space. In practical application, the spatial distribution characteristics of the industry in a region are generally judged by significance test under a given significance level.

2.4. Construction of spatial effect model of carbon emission intensity

At present, there are three commonly used spatial econometric models in the field of spatial research of carbon emission intensity: spatial Durbin model (SDM), spatial lag model (SLM), and spatial error model (SEM)**Error! Reference source not found.** As shown in:

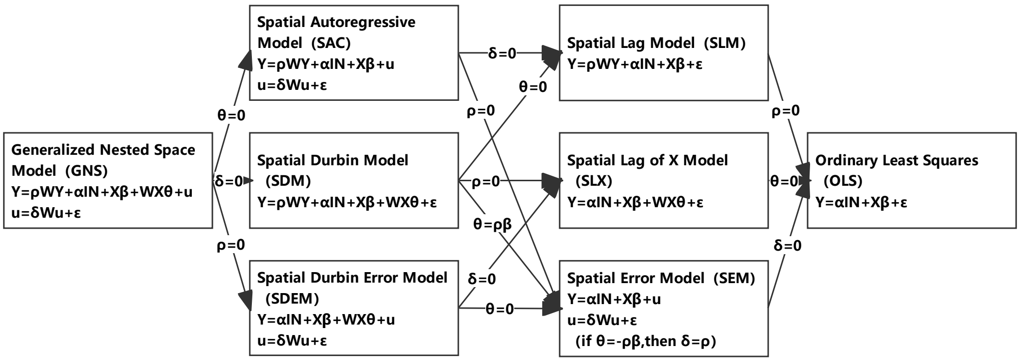


Figure 2 classification diagram of spatial model

SLM: when the research variable is affected by the variables of adjacent units, it is necessary to introduce the lag term of the research variable based on the spatial panel data, indicating that the research variable not only has spatial autocorrelation, but also is affected by the variable in other spaces. As shown is in:

$$\begin{aligned} Y &= \rho WY + \alpha I_N + X\beta + WX\theta + u \\ u &= \delta Wu + \varepsilon \end{aligned} \quad \textbf{(6)}$$

SEM: when the spatial disturbance term of the research variable affects this variable or other spaces, it is necessary to introduce the research variable error term based on the spatial panel data, indicating that the disturbance of one space will affect other spaces. The general expression is as follows:

$$Y = X\beta + \lambda W\varepsilon + u, u \sim N(0, \sigma^2 I) \quad \textbf{(7)}$$

The spatial Durbin model (SDM) is a combination of SLM and SEM by introducing an error term into SLM. The general expression is as follows:

$$Y = \rho WY + X\beta + WX\theta + \varepsilon, \varepsilon \sim N(0, \sigma^2 I) \quad \textbf{(8)}$$

Four tests are required to select the model for spatial research on carbon emission intensity. First, the panel data model is regressed by using the ordinary least squares (OLS) method. The common methods for further test are as follows:

First, the residual test is performed on the regression data to determine whether the local Moran index under SLM and SEM models is significant. If both are significant, the second step robustness test is performed. If R-lmerror is significant, SEM is selected. If R-lmlag is significant, SLM is selected. If both are significant, the spatial Durbin model (SDM) is preliminarily determined. After that, Hausmann test is required to determine whether the fixed effect or random effect is used. Then, LR test is used to determine which fixed effect is used and whether SDM will degenerate into SLM or SEM.

2.5. Data sources

The data about carbon emissions in this paper is from China carbon accounting database (CEADs). The indicators for measuring the influencing factors of traffic carbon emissions come from the yearbooks of national and local statistical bureaus such as China Industrial Statistics Yearbook, China Statistics Yearbook, China Energy Statistics Yearbook, and the statistical bulletin of social development. The study area includes 30 provinces and cities across the country (Tibet, Hong Kong, Macao and Taiwan are not included in the missing data).

This paper describes the panel data of 30 provinces with a time span of 1997-2022 and a spatial span. According to the common practice in academia, some missing data are completed by linear interpolation or trend extrapolation.

3. Result analysis

3.1 Analysis of carbon emission intensity measurement results

This paper first calculates the carbon emission intensity of China's 30 provincial high energy consuming industries based on IPPC method, which spans the period from 1997 to 2022. The relevant results are shown in Figure 3 and table 2.

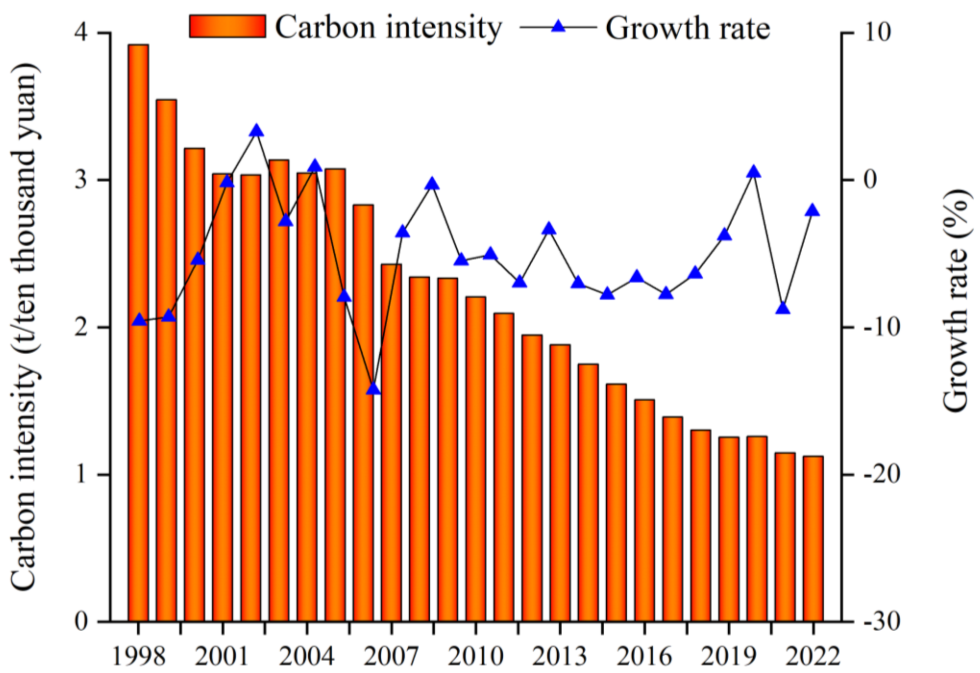


Fig. 3 time variation trend of carbon emission intensity

Table 2 carbon emission intensity results of high energy consuming industries in different regions

region	Carbon emission intensity				region	Carbon emission intensity			
	2007	2012	2017	2022		2007	2012	2017	2022
Beijing	0.77	0.50	0.23	0.17	Henan	2.66	1.88	1.24	0.59
Tianjin	2.16	1.58	1.06	0.83	Hubei	2.24	1.39	0.72	0.66
Hebei	3.74	2.78	1.77	1.39	Hunan	2.18	1.30	0.82	0.49
Shanxi	4.01	7.32	10.50	7.21	Guangdong	1.03	0.85	0.58	0.47
Inner Mongolia	6.37	7.53	5.14	5.69	Guangxi	1.64	1.71	1.09	1.06
Liaoning	3.99	3.04	2.38	2.87	Hainan	2.77	1.94	1.35	1.07
Jilin	3.97	3.06	1.96	1.60	Chongqing	1.92	1.29	0.64	0.45
Heilongjiang	3.63	3.57	2.89	2.19	Sichuan	1.97	1.21	0.61	0.60
Shanghai	1.02	0.79	0.48	0.41	Guizhou	5.60	4.26	2.50	1.40

Jiangsu	1.68	1.15	0.75	0.50	Yunnan	2.71	1.76	1.07	0.25
Zhejiang	1.75	1.12	0.77	0.61	Shaanxi	4.12	2.86	2.97	2.19
Anhui	2.49	1.94	1.34	0.93	Gansu	4.41	3.22	2.37	1.73
Fujian	1.38	1.03	0.69	0.64	Qinghai	3.47	3.83	1.97	0.94
Jiangxi	1.86	1.14	0.89	0.61	Ningxia	11.20	8.85	7.07	5.91
Shandong	3.37	2.35	1.75	1.51	Xinjiang	4.36	4.50	4.05	3.58

Overall, the carbon emission intensity of high energy consuming industries showed a downward trend during the sample period. The carbon emission intensity in 1997 was as high as 4.35 tons/10000 yuan, which was due to the fact that China's industrialization was at an early stage of vigorous development, China's high energy consumption industry was running well, the production of coal, electricity, oil and other energy was growing rapidly, and fossil energy such as coal was rapidly consumed. As China continues to promote the adjustment of industrial structure and energy structure, and promote the green revolution and technological innovation, the carbon emission intensity of China's high energy consuming industries has been significantly reduced. By 2022, the intensity has been adjusted to 1.12 tons/10000 yuan, about a quarter of that in 1997, and the carbon emission intensity of high energy consuming industries in most cities has been reduced to less than 1 ton/10000 yuan.

According to the natural discontinuity method, the carbon emission intensity of high energy consuming industries is divided into five levels: ultra-high intensity, high intensity, medium intensity, low intensity and ultra-low intensity. Further, the spatial clustering analysis of carbon emission intensity of high energy consuming industries is carried out. As shown in Figure 4.

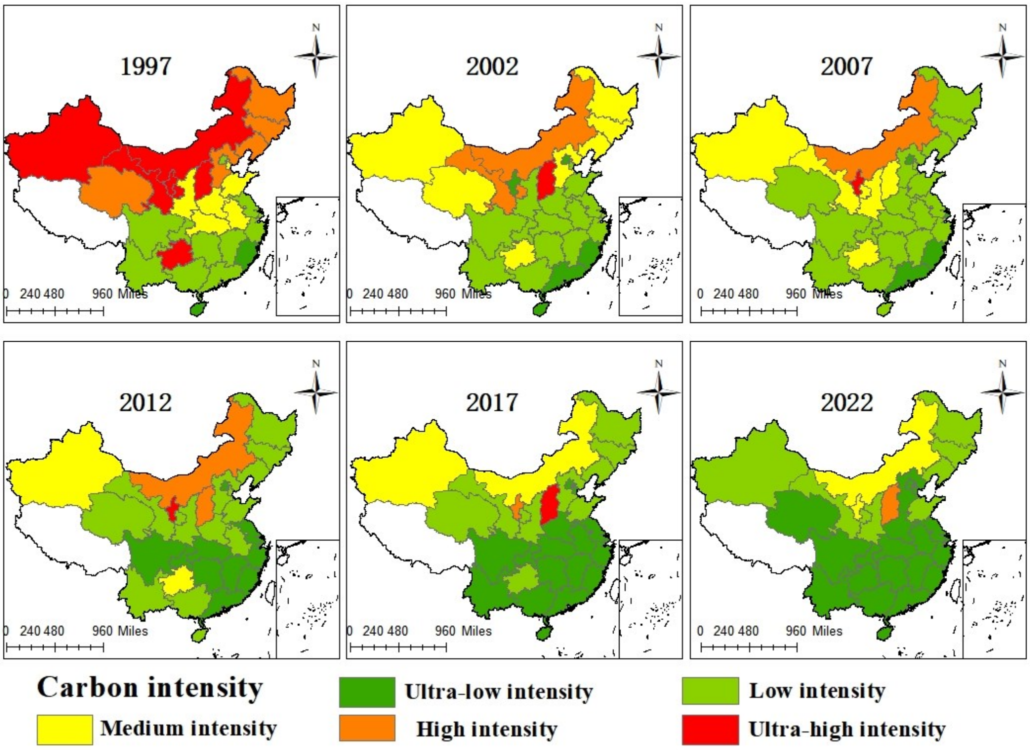


Fig. 4 spatial clustering results of carbon emission intensity in different regions

Locally, in 1997, the carbon emission intensity of high energy consuming industries in Shanxi reached 15.65 tons/10000 yuan, which is due to the problems of high energy consumption, serious environmental pollution and low resource utilization rate in its high energy consuming industries. With the integration and upgrading of the coal industry, the transformation of the coal industry to an efficient and clean direction has been promoted. By 2022, the carbon emission intensity of high energy consuming industries in Shanxi has decreased significantly, to 7.21 tons/10000 yuan. In 1997, there were six ultra-high intensity regions, namely Shanxi, Inner Mongolia, Guizhou, Gansu, Ningxia and Xinjiang, all of which were located in the western region except Shanxi; There are five high intensity regions, namely Hebei, Liaoning, Jilin, Heilongjiang and Qinghai. Hebei is located in the eastern region, Qinghai is located in the western region, and the rest are located in the northeast region; There are six areas of medium intensity type, namely Tianjin, Anhui, Shandong, Henan, Hubei and Shaanxi. Among them, Tianjin and Shandong are located in the eastern region, Shaanxi is located in the western region, and the rest are located in the central region. In 2022, the high intensity and medium intensity regions are mostly located in the central and western regions, and the eastern regions are mainly low intensity and ultra-low intensity regions. From 1997 to 2022, the ultra-high intensity areas were located in northern provinces except Guizhou, and the medium high intensity areas were located in northern provinces.

At the regional level, the carbon emission intensity is basically "high in the West and low in the East" and "low in the South and high in the north", and the spatial difference in the north-south direction is greater than that in the east-west direction. As shown in Figure 5, from the perspective of the differences among the three regions in China, in 1997, the carbon emission intensity of high energy consuming industries in the eastern, central and western regions showed significant regional differences, with values of 3.15 tons/10000 yuan, 5.07 tons/10000 yuan and 4.88 tons/10000 yuan, respectively. The carbon emission intensity in the central and western regions was much higher than that in the eastern regions, and was 1.61 times and 1.55 times higher than that in the eastern regions, respectively. In 2022, the carbon emission intensity of high energy consuming industries in the eastern, central and western regions will be significantly adjusted, with values of 0.76 T/10000 yuan, 1.28 T/10000 yuan and 1.50 T/10000 yuan, respectively. The central and western regions are 1.68 times and 1.97 times that of the eastern regions, respectively.

Therefore, this paper points out that there are significant differences in energy efficiency among the eastern, central and western regions, and the relative gap has not narrowed over time. In view of the differences in the north-south direction, in order to facilitate the investigation of the differences in the carbon emission intensity of high energy consuming industries between the northern provinces and other provinces, this paper takes Xinjiang, Gansu, Inner Mongolia, Ningxia, Shaanxi, Shanxi, Hebei, Liaoning, Jilin and Heilongjiang as a whole. In 1997, the carbon emission intensity of northern provinces and other provinces was 8.02 tons/10000 yuan and 3.28 tons/10000 yuan, respectively, and the former was about 2.45 times that of the latter; In 2022, the value will be adjusted to 3.24 tons/10000 yuan and 0.66 tons/10000 yuan respectively, and the former is about 4.90 times that of the latter. Therefore, the carbon emission intensity of China's high energy consuming industries shows a significant trend of "high in the West and low in the East", "low in the South and high in the north", and the spatial difference in the north-south direction is greater than that in the east-west direction.

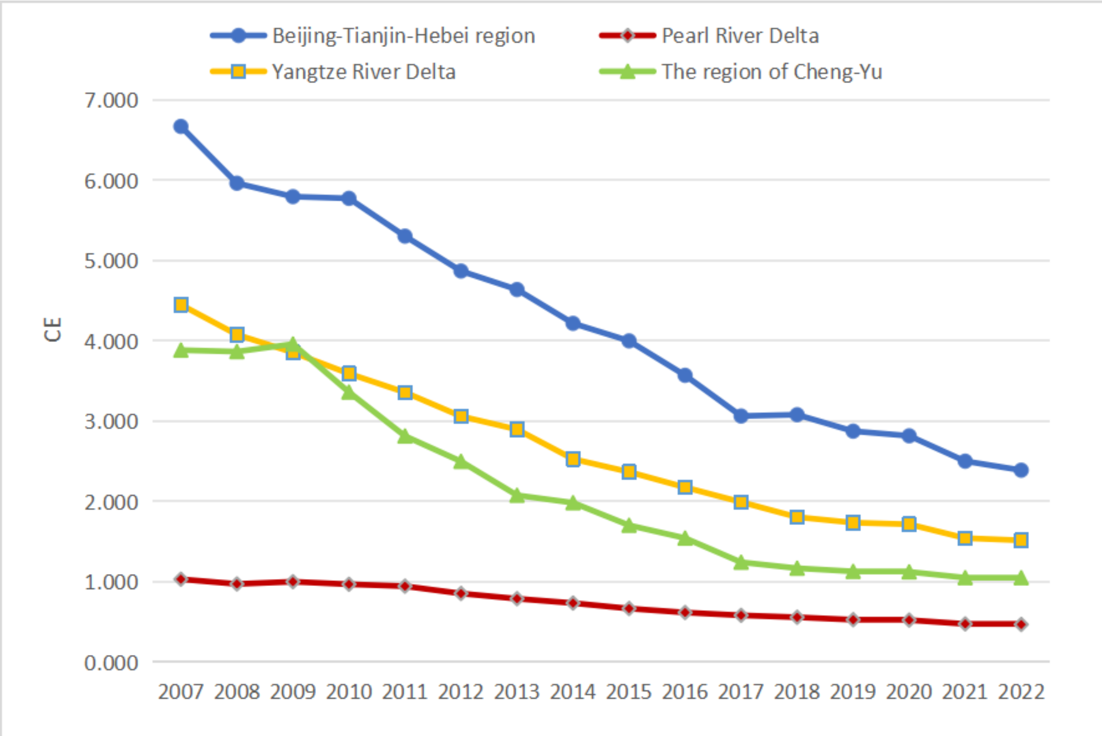


Fig. 5 time variation trend of carbon emission intensity in different regions

3.2 Analysis of the impact of carbon emission intensity based on stipat model

Referring to the literature on the influencing factors of carbon emissions at home and abroad, and based on the availability of data, the following eight factors are finally considered as the influencing factors of carbon emission intensity, which are distributed as follows: industrial structure, energy structure, regional economic development level, urbanization rate, technological innovation, foreign trade, industrial agglomeration and enterprise scale.

According to STIRPAT model, when constructing the equation, it is necessary to first determine the explained variable a on the left side of the equation and the explanatory variables on the right side of the equation, such as B, C, D, etc., as shown in the following formula.

$$\ln A = \ln a + b \ln B + c \ln C + d \ln D + \ln e \tag{9}$$

The ordinary panel data regression model of influencing factors of carbon emission intensity of high energy consuming industries in various regions of the country can be obtained, and the equation constructed is as follows:

$$\begin{aligned} \ln CE_{mn} &= a_{mn} + b_1 \ln INS_{mn} + b_2 \ln GDP_{mn} + b_3 \ln ECO_{mn} + b_4 \ln URB_{mn} \\ &+ b_5 \ln TRA_{mn} + b_6 \ln INA_{mn} + c_{mn} \end{aligned} \tag{10}$$

Where ln represents the natural logarithm; m stands for 30 provincial districts, $1 \le m \le 30 (m \in N)$; n indicates the time range, $1 \le n \le 26 (n \in N)$; x_{mn}, y_{mn}, z_{mn} are expressed as fixed effects, elastic coefficients of explanatory variables and random error terms of Chinese provinces, respectively.

Table 3 basic information of various variables

variable	symbol	unit	definition
Carbon emissions Carbon intensity in high-energy intensive industry	CE	Million tons	Carbon emission intensity of 30 provinces and cities in China
industrial structure Industrial structure	INS	100 million yuan	Industrial added value
Regional GDP per capita Gross Domestic Product	GDP	100 million yuan	GDP of 30 provinces and cities in China
Regional economic development level Economic level	ECO	100 million yuan	Per capita GDP
Urbanization rate Urbanization level	URB	%	Proportion of urban population in total population
Foreign trade	TRA	%	Proportion of total import and export trade in GDP

Industrial Agglomeration	INA	%	Average number of employees in high energy consuming industries

3.3 Correlation analysis of carbon emission factors based on global Moran index

In order to ensure the scientific and reliable results, Stata, geoda and MATLAB were used for statistical calculation, and the results showed amazing consistency, such as Table 4 global Moran index results **Error! Reference source not found.** As shown in.

Table 4 global Moran index results

Year	2007	2012	2017	2022
Moran's I	0.1086	0.1467	0.1104	0.0815
z	1.8790	2.2604	1.9423	1.5284
p-value	0.0602	0.0238	0.0521	0.1264

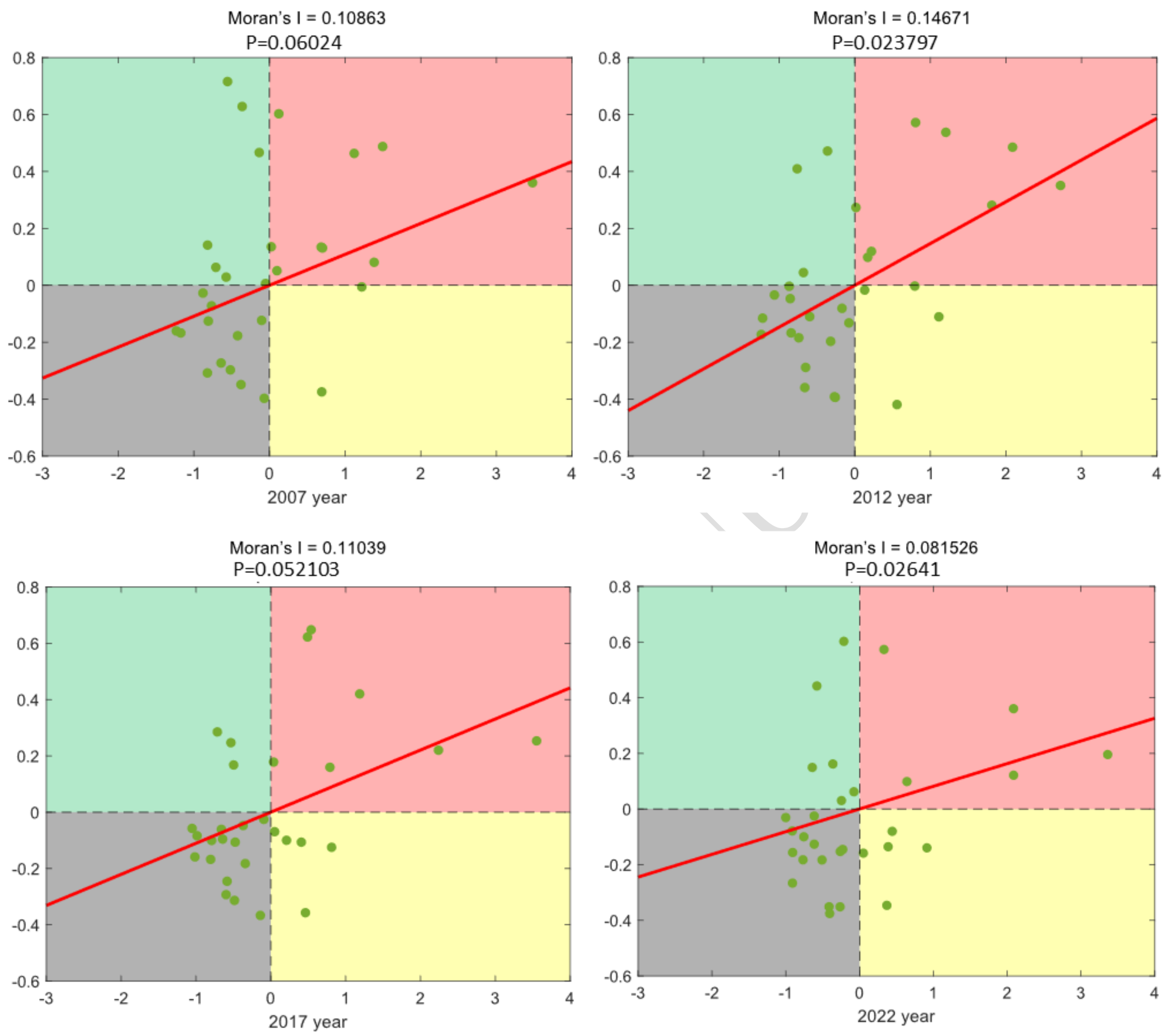


Figure 6 Moran scatter diagram of characteristic years

dUsing formula (4) to test the carbon emission intensity of China's provincial high energy consuming industries in the four characteristic years of 2007, 2012 and 20172022, the vertical coordinate is the global moran's I, and the horizontal coordinate is the spatial lag term of moran's I. taking the origin of the two coordinate axes as the center, the spatial region is divided into four quadrants. The lower quadrants are L-L and H-L from left to right, and the upper quadrants are L-H and H-H from left to right.

According to the test results in the above table and the significance level test, at the 10% confidence level, $0<\text{moran's } I<1$, $Z\geq 1.69$，$P\leq 0.1$， It shows that the overall carbon emissions of high-carbon manufacturing industry have spatial autocorrelation. Among them, the number of "H-H" (high-high) regions and provinces increased from 7 in 2007 (Figure ce-2007) to 9 in 2012 and 2017 (Figure ce-2012, ce-2017), and finally changed to 7 in 2022 (Figure ce-2022) in 2017, while the number of "L-L" (low-low) regions and provinces increased from 9 to 11 and finally changed to 12, which also showed that the carbon emissions of high energy consuming industries were becoming closer, and the spatial spillover effect of carbon emissions among provinces showed a deepening trend.

3.1. Analysis on the results of spatial effect model of carbon emission intensity

3.3.1 LM inspection results

Lagrange and robust Lagrange test (LM Test) are used to judge whether there is spatial relationship between variables and the type of spatial relationship, and to judge the robustness of SDM model and SEM model.

The LM test results are shown in Table 5. The p-value values of the spatial error model and the spatial lag model are less than 0.05, that is, both models are applicable at the 95% confidence level, and their robustness has passed the test. Therefore, the spatial Dobbin model should be selected to describe the spatial characteristics of the national carbon emission intensity.

Table 5 LM inspection results

Test	Statistic	df	p-value
Spatial error:			
Moran's I	8.995	1	0.000
Lagrange multiplier	76.094	1	0.000
Robust Lagrange multiplier	5.629	1	0.018
Spatial lag:			
Lagrange multiplier	79.946	1	0.000
Robust Lagrange multiplier	6.482	1	0.011

3.3.2 Hausmann test results

Hausmann test is to judge whether the original hypothesis is tenable according to the significance of the results under the condition that the explanatory variable and individual effect are not relevant. When p value<0.05, it indicates that fixed effect can be used.

The Hausmann test result (chi2 (3)=280.06, which was calculated by Stata, Prob > chi2 = 0.0000）， Therefore, the original hypothesis can be rejected in the 95% confidence interval, so the fixed effect should be used.

3.4.3 Wald test and LR test results

Wald test and LR test are conducted to determine whether SDM will degenerate into SAR or SEM model and further select which fixed effect should be used for SDM.

There are two test criteria for LR test: the hypothesis of "two-way" and "individual" and the hypothesis of "time" and "two-way". When the current one is significant but the latter is not significant, the individual fixed effect is selected; when the latter is significant but the former is not significant, the time fixed effect is selected; when both are significant, the double fixed effect is selected.

Wald test results (chi2 (4)=99.24, prob>chi2=0.0000; chi2 (5)=156.04, Prob > chi2 = 0.0000）， It is easy to know that SDM will not degenerate into SAR or SEM models at 95% confidence level.

LR test results (SEM nested within SDM: lr chi2 (5)=123.63, prob>chi2=0.0000; SAR nested within SDM: lr chi2 (5)=178.66, prob>chi2=0.0000) (ind nested within both: lr chi2 (12)=72.87, prob>chi2=0.0000, time nested within both: lr chi2 (12)=649.52, Prob > chi2 = 0.0000）。

Yi Zhi can refuse to use time fixed effect and individual fixed effect at 95% confidence level, so double fixed effect should be selected.

To sum up, this paper selects the SDM model with double fixed effects to study the temporal and spatial differences of carbon emission intensity of high energy consuming industries in China.

3.5 Regression results of SDM model with double fixed effects

Based on the double fixed SDM model, the regression results of different variables are obtained by bringing in relevant data, as shown in the table. The coefficient of interactive terms represents that the core explanatory variables in the surrounding areas can promote (positive coefficient)/inhibit (negative coefficient) the promotion of the explained variables in the region.

ρ value of the spatial autocorrelation coefficient (which must be significant, $p<0.1$) indicates that there is a negative (coefficient is negative)/positive (coefficient is positive) spatial spillover effect of the explained variable in the local region. Here, the positive and negative directions represent whether the promoting or inhibiting directions are the same, the same is positive, and the different is negative.

Table 6 regression results of SDM model

Explanatory variable	regression coefficient	Z-statistics	P	Interactive item	regression coefficient	Z-statistics	P
INS	.0510768	9.12	0.000	WxINS	.2481082	2.92	0.004
GDP	-.013449	-6.25	0.000	WxGDP	-.0190093	-0.62	0.538
URB	-63.83334	-0.65	0.516	WxURB	-3110.934	-2.77	0.006
ECO	-.0027053	-4.51	0.000	WxECO	-.0539931	-6.95	0.000
TRA	80.6649	1.72	0.085	WxTRA	955.5775	1.81	0.070
				$\rho \times CE$	-.8956155	-3.54	0.000

It can be seen from the results that foreign trade (TRA) and urbanization rate (urb) failed to pass the significance test of 95% confidence level. The three explanatory variables of industrial structure (INS), regional gross domestic product (GDP) and regional economic development level (ECO) all passed the significance test.

The regression coefficient of industrial structure is positive, indicating that industrial structure has a positive impact on carbon emission intensity. It indicates that CE will increase by 0.051% for every 1% increase in industrial added value of high energy consuming industries nationwide. The regional GDP and the level of regional economic development have a negative impact on carbon emission intensity, indicating that for every 1% increase in regional GDP and per capita GDP, CE will decrease by 0.013% and 0.003%.

The spatial autocorrelation coefficient is significantly negative, indicating that the carbon emission intensity of high energy consuming industries across the country has obvious spatial spillover effect. For every 1% change in the carbon emission intensity of adjacent areas, the carbon emission intensity of high energy consuming industries in the city will change by 0.9% in the opposite direction, which is the so-called "siphon effect".ρ

The spatial interaction coefficient of industrial structure is significantly positive, indicating that the gross industrial output value of high energy consuming industries in adjacent cities is 1%, and CE in this region increases by 0.25%, which has a significant promoting effect.

3.6 Analysis of direct and indirect effects

Further Using Stata software, the direct and indirect effects of carbon emissions can be calculated. The relevant results are shown in Table 7:

Table 7 direct and indirect effects of explanatory variables

Explanatory variable	Direct effect			Indirect effect		
	regression coefficient	Z-statistics	P	regression coefficient	Z-statistics	P
INS	.0467449	8.82	0.000	.1162225	2.21	0.027
GDP	-.0133488	-6.69	0.000	-.004778	-0.28	0.778
URB	13.63158	0.16	0.876	-1709.622	-2.68	0.007
ECO	-.0015748	-2.73	0.006	-.0288478	-3.70	0.000
TRA	60.45676	1.43	0.153	506.7319	1.74	0.081

The first type of explanatory variable has both direct and indirect effects. Industrial structure (INS) and regional economic development level (ECO) belong to this type of explanatory variable, as shown in table 46. The direct effect and indirect effect of regional economic development level (ECO) are significantly positive, indicating that the industrial added value of high energy consuming industries has a significant impact on the local carbon emission intensity in the same direction, and will also have the same impact on the surrounding areas.-

The direct and indirect effects of regional economic development level (ECO) are significantly negative, indicating that every 1% increase in per capita GDP in each region will reduce CE by 0.002% and 0.029% in itself and adjacent cities, respectively. This result shows that with the improvement of economic level, the investment in environmental governance and carbon emission control will increase, which will lead to the reduction of carbon emission intensity.

The second type of explanatory variable has only direct effect, but no indirect effect. Only the direct effect of regional gross domestic product (GDP) is significantly negative, and the indirect effect is not significant, indicating that every 1% increase in regional GDP can only reduce the city's carbon emission intensity by 0.013%. It can be seen that the increase of the level of economic development has an inhibitory effect on carbon emissions. When developing the economy, the increase of local fiscal revenue is conducive to optimizing the industrial structure and reducing energy consumption.

The third type of explanatory variable is the variable with indirect effect and no direct effect. Only the urbanization rate (urb) belongs to this type of variable, indicating that the higher the proportion of urban population in the total population in the region, the greater the impact on the reduction of carbon emissions in the surrounding areas.

The fourth type of explanatory variable is that there is neither direct effect nor indirect effect, and the impact of foreign trade (TRA) on carbon emissions in the region and surrounding areas is not significant.

4. Conclusion

Based on the panel data of 30 high energy consuming industries in China from 1997 to 2022, this paper measures the carbon emission intensity of 30 high energy consuming industries, constructs stipat model and spatial econometric model, and analyzes the spatial spillover effect and spatial heterogeneity combined with their spatial correlation. The main conclusions are as follows:

First, the carbon emission intensity of high energy consuming industries is declining as a whole, with typical spatial heterogeneity. During the sample period, the carbon emission intensity of high energy consuming industries in 30 provinces in China was calculated based on the IPPC method, with the overall decline. At the same time, from the perspective of regional distribution, there are significant differences in carbon emission intensity among the eastern, central and western regions, which are basically high in the West and low in the East, high in the north and low in the south, and the spatial difference in the north-south direction is greater than that in the east-west direction.

Second, the carbon emission intensity of high energy consuming industries has significant spatial autocorrelation characteristics. According to the calculation of global Moran index, its center of gravity is roughly distributed in the border zone between Shanxi and Shandong, and is generally located in the regional zone of 907.6494 ° -1094.336 ° E and 3906.624 ° -3958.002 ° n, moving from east to West as a whole.

Third, the carbon emission intensity of high energy consuming industries is affected by multiple environmental factors. With the higher level of regional development, the optimization of industrial structure, technological progress and other factors affecting carbon emission intensity are restrained. CE will increase by 0.051% for every 1% increase in industrial added value of high energy consuming industries nationwide. For every 1% increase in regional GDP and per capita GDP, CE will be reduced by 0.013% and 0.003%, respectively. For every 1% increase in per capita GDP in each region, CE in itself and adjacent cities will be reduced by 0.002% and 0.029%, respectively.

Fourth, the carbon emission intensity of high energy consuming industries has a significant spatial spillover effect. According to the regression results of spatial Dobbin model with double fixed effects, the carbon emission intensity of high energy consuming industries in the city will change by 0.9% in the opposite direction for every 1% change in the carbon emission intensity of high energy consuming industries in adjacent provinces.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

Not applicable.

Competing interests

The authors have no conflicts of interest to declare.

Funding

This research was funded by 2023 National Foreign Experts Project of the Ministry of Science and Technology of China (No. DL2023202002L), by General project of Natural Science of the Central University Fund in 2024 (3122024034).

Acknowledgements

Not applicable.

Authors' information (optional)

Not applicable.

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