Research on Driving Factors and Spatial Effects of Electricity Carbon Emissions in China

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Abstract. For the past 25 years, China's power system has maintained rapid growth and can face a huge transformation, and many of the advantages of the past have become resistance to the transformation from such a large-scale centralized, fossil-fuel-based power system to a zero-carbon power system. From a full life cycle perspective, this paper recalculates the carbon emissions(CE) of the power industry, and measures global Moran's I values, which reveals that there is a positive spatial effect of CE from power industry in some provinces of China, but the spatial aggregation effect is gradually weakening. This paper establishes a spatial error model to study the impact of different drivers on CE in each province, and the spatial panel results show that the proportion of thermal power generation, total installed capacity, per capita electricity consumption, and the average utilization hours of thermal power all contribute significantly to the CE of the power sector. Therefore, it is necessary to consider various aspects to reduce thermal power generation, optimize the structure of electricity supply, consider the spatial effect of neighboring provinces and cities, strengthen the synergistic control of carbon emission reduction among provinces, and promote the synergistic and optimal development of the power system in a green and low-carbon manner.

Keywords: Electricity carbon emissions; Full life cycle; Spatial effect; Spatial spillover effects; Driving factors

1 Introduction

China's rapid economic and social development has led to significant energy consumption and carbon dioxide emissions, making green, low-carbon, and sustainable development crucial for addressing global climate change. In 2022, China's total carbon emissions (CE) reached 11 billion tons, with 5.1 billion tons (46.37%) coming from the

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power sector. The heavy reliance on coal for electricity generation and the manufacturing-dominated end demand are key drivers of emissions. However, uncertainties in primary data and emission coefficients have led to discrepancies between estimated and actual emissions.

China's natural endowments and regional economic conditions differ, with electricity production concentrated in the western regions and consumption in the east, creating a clear spatial imbalance[1]. Cities like Beijing and Shanghai, with service-oriented economies, have lower emissions, while industrial provinces such as Jiangsu and energy-rich provinces like Xinjiang experience higher emissions, though these vary significantly across regions. To address environmental degradation, China has launched initiatives like developing a new energy system and reforming the power industry to reduce carbon emissions.

In view of the above problems, this paper's main contributions are as follows: First, this paper recalculates the CE from the perspective of the full life cycle, which makes the estimation of CE more accurate. Second, the spatial aggregation effect of CE is analyzed by constructing a geographic adjacency matrix and a comparative GDM. Third, this paper establishes a spatial error model to analyze the spatial effects of electricity CE in various regions, focusing on the heterogeneity of electricity CE in different regions.

2 Related Works

In recent years, global research on CE has increased with the increasing number of CE, especially in developing countries [2]. Since the 1970s, China's CE have grown at 5.34%, 3.5% higher than the world average. In the field of CE measurement research, the focus of academics is mainly on the industry, agriculture, tourism and transportation sectors [3]. Therefore, this paper re-measures the CE of electricity through the Data and Methods of the World Nuclear Energy Association. Thermal coal-fired power plants are the largest source of CO2 in the power system. CE from the power sector are typically the largest source of CE of any sector in a country [4]. Therefore, the study of CE from a power perspective has broad prospects.

Even if the electricity demand continues to increase, the associated increase in CE can be decoupled from an increase in electricity demand if appropriate measures are taken. In the context of green, low-carbon sustainable development and related energy policies, it is essential to understand the drivers of CE growth in the power sector [5]. Some studies have used the Logarithmic Mean Divisor Index to analysis the influencing factors of electric CE[6]. This paper summarizes previous studies and finds that population size, economic development, and green innovation contribute positively, while energy composition and energy use intensity have a negative contribution [7].

There is significant spatial heterogeneity in CE between regions in China, mainly due to differences in the degree of electrification development between regions [8]. Some of the literature analyzes the factors influencing CE and whether they are spatially correlated through some kind of spatial modeling [9]studied the renewable electricity penetration of spatial heterogeneity and dynamic evolution using EU panel data from 2001 to 2017. The application of instrumental variables approach and spatial econometric modeling to address the heterogeneity of CE from electricity is a common methodology used in studies [10], some literatures also decomposed the spatial effects to study the spillover effects of CE [11].

Most studies on carbon reduction in the power sector have focused on macro-level drivers. However, these studies often overlook micro-level differences and their impact on CE. This paper, therefore, measures the CE of the electric power industry across provinces from a life-cycle perspective, investigates the driving factors of CE, and analyzes them using spatial econometrics, aiming to provide insights for reducing power sector carbon emissions.

3 Methodology

3.1 Electricity CE Accounting

This paper adopts the World Nuclear Association's detailed accounting method of full life-cycle CE from electricity to estimate power-side CE as much as possible [12].Because of the different technical equipment and operating conditions, different power generation methods will produce different CE.

Transmission-side CE are mainly generated by transmission line laying and transmission process losses. Transmission loss is the loss incurred by the grid company in the process of delivering power to users through the distribution network. The amount of CE from transmission lines during the material manufacturing, transportation and construction, and end-of-life recycling phases can be derived from existing studies The results are shown in Table 1.

Table 1. CE at each stage of the transmission side

Stage	CO_2 emissions($kg \cdot km^{-1}$)
Material manufacturing	23900
Construction transportation	1195
Scrap recycling	-4460

3.2 Spatial Correlation Index

This paper describes the possible relevant spatial characteristics of CE in terms of the Global Moran Index(GMI) and the Local Moran Index(LMI), respectively. These two indices are commonly used spatial correlation indicators, which are mostly used for spatial heterogeneity and cluster analysis [13,14].

The GMI index is used to measure whether the values of the attributes of the variable are spatially correlated in neighboring areas throughout the region, and the range of values is [-1,1]. If it is significantly positive, it means that the attribute values of the variables in each region are spatially positively correlated; if it is negative, it means that the attribute values of the variables in each region are opposite to each other, i.e., they are spatially negatively correlated; if it is zero, it means that the variables are spatially distributed randomly in each region. The index changes dynamically over time and also decays with increasing distance. The expression is:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{1}$$

Where S^2 is the sample variance, n is the number of subjects, w_{ij} is the (i, j) element of the spatial weight matrix, x_i is the electricity CE in the region i, and $\overline{x}$ is the sample mean.

The LMI measures the specific type of spatial correlation of attribute values of variables in different provinces, which can be expressed as:

$$I_i = \frac{\left(x_i - \overline{x}\right)}{S^2}\sum_{j=1}^{n} w_{ij}\left(x_j - \overline{x}\right) \tag{2}$$

If the value of LMI is significantly positive, it means that the value of the attribute of CE in the province is consistent with the value of the attribute of CE in the neighboring provinces, it shows low-low aggregation or high-high aggregation; if the value of the index is significantly negative, it means that the CE attribute value of the province is opposite to the surrounding provinces, it shows low-high aggregation or high-low aggregation; if the LMI takes the value 0, it shows that the spatial distribution is randomized.

3.3 Spatial Weight Matrix

Before calculating the Moran index, it is first necessary to determine which spatial weight matrix to use and the geographic relationship between regions. The commonly used spatial weight matrices mainly include the Geographic Adjacency Matrix (GAM-W1) and GDM (GDM-W2).

The GAM is the most used spatial weight matrix in spatial econometrics. Determine whether the spatial regions are adjacent to each other;if the two regions have a common boundary, then take 1; otherwise, take 0. The matrix elements are determined as follows.

$$W_1 = \begin{cases} 1 & adjacent \\ 0 & nonadjacent \end{cases} \tag{3}$$

The GDM is derived by calculating the distance the actual geographic coordinates of the capital city of each province and municipalit, representing the distance in the geographical space, and the closer it is, the greater the weight. The formula is as follows. Here D_{ij} indicates distance between Provinces i and j.

$$W_2 = \begin{cases} \dfrac{1/D_{ij}}{\sum_{j=1}^{n}\left(1/D_{ij}\right)} & i \neq j \\ 0 & i = j \end{cases} \tag{4}$$

4 Data Sources and Variable Selection

4.1 Variable Selections

The electricity CE were selected as the dependent variable to test the spatial correlation. In addition, economic development, installed capacity, per capita electricity consumption, and power generation structure all have certain spatial effects. Taking into account the possible estimation deviations and inconsistencies in the data observations. In this paper, the spatial econometric analysis of power CE is carried out by using spatial panel model. The spatial panel model of electricity CE can be expressed as follows.

$$\ln carbon_{it} = \gamma PTPG + \beta X_{it} + \rho \sum_{j=1}^{n} W_{ij} \ln carbon_{it} + \theta \sum_{j=1}^{n} W_{ij} X_{it} + \alpha_i + \xi_t + \mu_{it} \tag{5}$$

$$\mu_{it} = \lambda \sum_{j=1}^{n} W_{it} \mu_{it} + \varepsilon_{it} \tag{6}$$

Where $carbon_{it}$ refers to the CE from electricity in the year t of the province i; $PTPG$ is the share of thermal power generation; W_{ij} is the spatial weight matrix of the interconnection between provinces i and j; γ represents the spatial regression coefficient of core variables; ρ represents the spatial lag autoregressive coefficient; θ represents the spatial regression coefficients for control variables; λ is the spatial error autoregressive coefficient; α_i represents the solid effect; ξ_i represents the time effect; μ_{it}, ε_{it} are independent and uniformly distributed random disturbance items; X_{it} is the relevant control variable that affects how much carbon is emitted by the power sector. X_{it} includes the following factors.

$$X_{it} = \{PGDP_{it}, PCEC_{it}, TIC_{it}, AUHT_{it}, LTL_{it}, PIEC_{it}\} \tag{7}$$

Where the controlled variables $PGDP_{it}, PCEC_{it}, TIC_{it}$ $AUHT_{it}, LTL_{it}, PIEC_{it}$ refer to GDP per capita, electricity consumption per capita, total installed capacity, average utilization hours of thermal power equipment, length of transmission lines, the proportion of industrial electricity consumption, the details are as follows.

(1) Per capita GDP (PGDP). Human economic activities contribute significantly to the world's economic growth but have also brought a lot of CE. Regional economic development is expected to affect CE to a large extent.

(2) Per capita electricity consumption (PCEC). In recent years, The power sector is facing the arduous task of reaching its peak, and there is huge potential for electricity substitution. Per capita electricity consumption is expected to rise steadily, at the same time, to produce more CE.

(3) Total installed capacity (TIC). Newly-added installed capacity is the main route to increase CE in the power sector. China's installed power generation capacity has consistently ranked first in the world, and installed capacity has shown a clear positive effect on CE.

(4) Average utilization hours of thermal power equipment (AUHT).The rapid increase in installed capacity will cause a mismatch with the electricity demand due to the rapid increase, making part of the installed capacity inefficiently utilized, resulting in a waste of resources. The large-scale access to clean energy generation in China has also led to a gradual reduction in reliance on thermal power, with the effective utilization hours of thermal power decreasing continuously.

(5) Length of transmission lines (LTL). The construction of transmission lines can produce CE directly or indirectly through building materials and electrical equipment. Studies have verified that the construction of transmission lines will generate significant CE.

(6) Proportion of industrial electricity consumption (PIEC). Industrial electricity consumption accounts for nearly 70%, and the manufacturing, power and heating sectors account for about 94% of emissions. In addition, the popularization and application of electricity substitution technology in the industrial sector has led to the rapid growth of substitution electricity, which has become the main driving force for new electricity consumption.

The above variables are the main factors affecting CE from electricity, and Table 2 shows the relevant statistics.

Table 2. Summary variable statistics

Variable	Definition	Min	Mean	Max
Carbon	Total CE from electricity(10000 tons)	2.27	12203.29	55957.93
PTPG	The proportion of thermal power generation(%)	0.07	73.94	100.00
PGDP	GDP per capita (Yuan)	3240.55	39102.60	187508.45
PCEC	Electricity consumption per capita(kWh)	136.55	3840.54	16487.50
TIC	Total installed capacity(10000 kw)	36.33	3864.67	17334
AUHT	Average utilization hours of thermal power equipment(hour)	100.00	4486.28	7559.00
LTL	Length of transmission lines(km)	1010	45211	128927
PIEC	Proportion of industrial electricity consumption(%)	11.61	68.14	94.40

4.2 Data Sources

The panel data for this paper include 31 provinces in China from 2002 to 2021.The power generation data comes from the National Bureau of Statistics, Other data from the "China Electric Power Yearbook" and the "China Electric Power Statistical Yearbook 2022". In addition, the panel analysis is only available for 31 provinces, excluding Taiwan, Macau, and Hong Kong. To minimize the impact of differences in data units and nature on the regression results, reduce the impact of data fluctuation differences, and increase the interpretability and accuracy of the results, some data are processed by natural logarithms.

5 Result

5.1 Analysis of Spatial Evolution Characteristics

Combining the GAM (W1) and the GDM (W2) constructed in the previous article, the GMI values corresponding to CE from 2002 to 2021 is calculated. The results are shown in Table 3.

Table 3. GMI for each year under W1 and W2

	W1		W2	
	I	Z-value	I	Z-value
2002	0.220***	3.073	0.123*	1.424
2003	0.229***	3.129	0.119*	1.360
2004	0.241***	3.232	0.119*	1.341
2005	0.240***	3.272	0.121*	1.385
2006	0.226***	3.160	0.112*	1.324
2007	0.230***	3.200	0.110*	1.305
2008	0.234***	3.257	0.118*	1.386
2009	0.259***	3.305	0.144*	1.508
2010	0.288***	3.442	0.151*	1.487
2011	0.283***	3.391	0.146*	1.444
2012	0.274***	3.299	0.157*	1.530
2013	0.258***	3.077	0.158*	1.518
2014	0.237***	2.950	0.146*	1.474
2015	0.237***	2.979	0.142*	1.447
2016	0.251***	3.067	0.168*	1.635
2017	0.238***	2.971	0.148*	1.488
2018	0.246***	3.040	0.139*	1.409
2019	0.236***	2.928	0.134*	1.370
2020	0.223***	2.704	0.132*	1.308
2021	0.192***	2.478	0.118	1.245

Notes: ***, **and * refer to significant at 1%, 5% and 10% confidence level, respectively. The same is below.

From Table 4, the GMI values of China's electricity CE are all greater than 0 and more significant under the geographic neighbor matrix, indicating that electricity CE show a certain spatial positive correlation under both matrices, with strong spatial correlation for electricity CE from neighboring provinces, and weaker spatial effects for electricity CE from more distant provinces. Under the GDM, the GMI value shows a decreasing trend from 2010 onwards, indicating that the spatial aggregation effect of electricity CE in each province is in a weakening trend.Fig.1 shows that China's electricity CE show obvious aggregation effects.

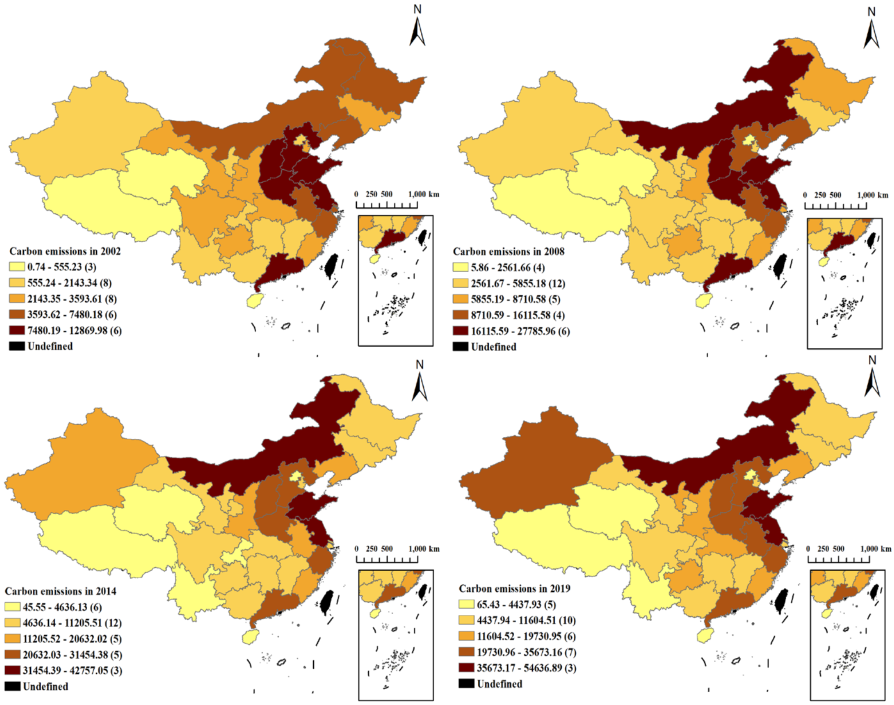

Fig. 1. Spatial distribution of CE from electricity in China

Fig.1 shows that China's electricity CE show obvious aggregation effects. Fig.2 and Fig.3 are the LISA cluster maps under different spatial weights. The LISA clustering map categorizes areas into four segments of Low-Low, High-High, Low-High, and High-Low. The first two categories indicate that electricity CE are positively correlated in space, and the latter two are negatively correlated. The L-L areas are mostly located in nouthwestern China, and the H-H areas are mostly located in North China, indicating that electricity CE have a certain relationship with China's traditional geographical divisions. This is consistent with the high dependence of north China thermal power cluster on surrounding abundant coal resources. By comparing the GMI value with the LISA maps, the spatial aggregation effect has been significantly weakened.

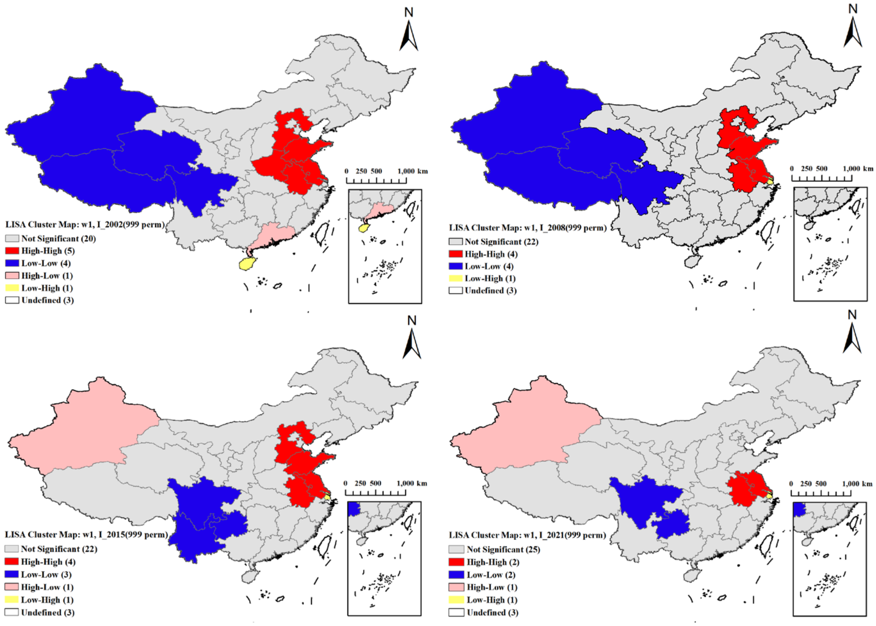

Fig. 2. Lisa map of CE under W1

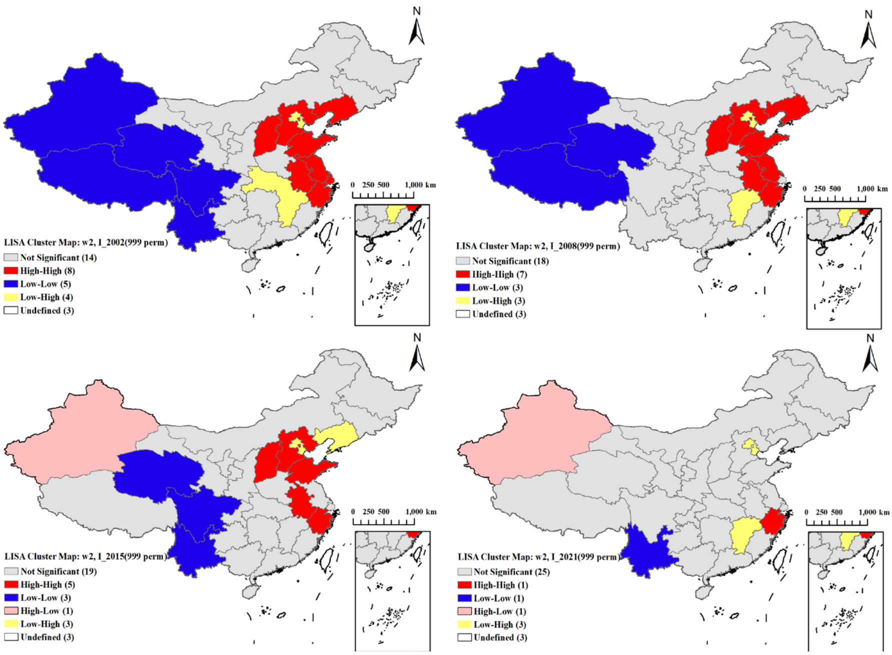

Fig. 3. Lisa map of CE under W2

5.2 Verification and Selection of Spatial Econometric Models

To further study the spatial effects of CE from electricity, a spatial model needs to be established for parameter analysis. This paper selects three models by LM test, Hausman test and LR test, and The results of the test in Table 4 show that it is appropriate to use the spatial error model with double fixed effects.

Table 4. Results of LM test

Test	Statistic(W1)	Statistic(W2)
Spatial lag:		
Lagrange multiplier	0.111	1.845
Robust Lagrange multiplier	0.054	1.107
Spatial error:		
Moran's I	3.630***	1.5e+05***
Lagrange multiplier	203.984***	79.453***
Robust Lagrange multiplier	203.927***	78.715***
Hausman test	110.28***	76.66***
LR TEST(Assumption: sem_ind nested in sem_both)	50.20***	52.11***
LR TEST(Assumption: sem_time nested in sem_both)	871.41***	863.73***

5.3 Spatial Panel Analysis Results

Table 5 shows that the spatial error coefficients under the two spatial matrices are significantly positive, indicating that there is a positive spatial correlation, and that CE in a region are affected by CE from neighboring regions in the same direction, and there is a certain spatial spillover effect.

Table 5. Results of spatial panel data regression

Variable	W1	W2
	Model 1	Model 2
	SEM	SEM
PTPG	0.401***	0.401***
	(0.0189)	(0.0191)
PGDP	-0.0286	-0.0152
	(0.0452)	(0.0451)
PCEC	0.637***	0.622***
	(0.0479)	(0.0489)
TIC	0.469***	0.464***
	(0.0325)	(0.0323)
AUHT	0.142***	0.142***
	(0.0345)	(0.0350)
TLL	-0.0115	-0.0123

Variable	W1	W2
	Model 1	Model 2
	SEM	SEM
	(0.0306)	(0.0313)
PIPC	-0.0843	-0.0619
	(0.0555)	(0.0553)
Spatial lambda	0.219***	0.168***
	(0.0555)	(0.0771)
Variance sigma2_e	0.00895***	0.00915***
	(0.000511)	(0.000521)
N	620	620
R-squared	0.852	0.852
AIC	-1139.86	-1129.822
BIC	-1099.993	-1089.955

The results of the significance estimation of each variable are completely consistent. Among them, PTPG, PCEC, TIC and AUHT all have positive effect. It indicates that PTPG is significantly and positively correlated with CE from electricity, which is further evidence that PTPG should be reduced and the mix of cleaner power generation should be increased. With the in-depth implementation of electricity substitution, the level of electrification of end-use energy continues to increase, and electricity consumption also continues to grow, and per capita electricity consumption will also gradually increase. TIC and AUHT also have a positive impact, indicating that power emission reduction should mainly start from these two parts, increase application of clean energy generation and change the power structure. For the analysis of regression results of other control variables, such as GDP per capita is negative and non-significant, indicating that GDP per capital has a negative and insufficiently significant impact on regional CE, and that more resources need to be invested in controlling CE. The modeling results for the length of transmission lines and the share of industrial electricity consumption are not significant, indicating that there is no significant spatial correlation between their effects on regional CE. Therefore, it is imperative to build a diversified clean energy system in the field of power supply, actively promote the application of clean energy, enhance the efficiency of coal power utilization and the level of clean and low-carbon, continue to enhance the level of electrification of the whole society, strengthen the research of cutting-edge green and low-carbon technologies.

6 Discussion

6.1 Comparisons to Other Studies

The finding of significant spatial heterogeneity in CE aligns with other studies that have highlighted regional disparities in emissions. This study's use of spatial econometrics provides a more nuanced understanding of these disparities and their drivers. The positive contributions of population size, economic development, and green innovation to CE are consistent with global trends where urbanization and economic growth are linked to increased emissions. However, this study also identifies the negative impact of energy composition and energy use intensity, emphasizing the need for a shift towards cleaner energy sources.What’s more,The observation of spatial positive correlations in CE is supported by other studies that have used spatial modeling to analyze emissions. This study's detailed analysis of spatial effects using various matrices adds depth to the understanding of spatial spillover effects.

6.2 Limitations of the Current Study

The study relies on panel data from 2002 to 2021, which may not fully capture the recent changes in China's energy landscape, especially with the rapid development of renewable energy sources. What’s more,the spatial error model used in this study assumes that unobserved heterogeneity is randomly distributed, which may not hold in all cases. Future studies could explore more complex models that account for potential endogeneity and omitted variable bias.

7 Conclusions

In this paper, the spatial measurement method is firstly used to test whether the electric power carbon emission has certain spatial correlation. Then the spatial error model is used to analyze the driving factors of electric power CE and analyze the influence of each factor on electric power CE. Based on the research results, the following conclusions and recommendations are drawn.

Spatial autocorrelation test results indicated that electricity CE have obvious spatial positive correlations in geographically adjacent areas, with characteristics of low-low aggregation and high-high aggregation, but this aggregation effect is weakening and the gap between neighbouring regions is narrowing. The results show that PTPG, TIC, PCEC, and AUHT all have a significant positive impact on electricity CE. Therefore, the following initiatives could be taken:

First, strengthen the development of carbon emission reduction technology innovation. On the premise of ensuring stable and rapid economic development, promote carbon reduction-related technologies such as carbon capture, utilization and storage and bioenergy combined with carbon capture and storage, and increase research on carbon adsorption materials, so as to fundamentally control CE.

Secondly, establishment of regional joint prevention and control mechanisms. Utilize the government's macro-control to strengthen regional linkages and exchanges. Taking into full consideration the positive spatial spillover effect of CE, each province should fully study the emission reduction policies of neighboring regions, share information, technology overflow and exchange talents on the basis of mutual cooperation, and realize the synergistic development of the electric power industry.

Finally, Optimizing the power structure and developing clean energy. Thermal power generation is still the mainstay, so as to optimize the power supply structure under the premise of guaranteeing supply, gradually increase the proportion of electricity generated from other clean energy sources.

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