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How Renewable Energy Expansion Affects Carbon Emissions from the Perspective of Spatial Correlation—Evidence in China

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Abstract

The proportion of renewable energy has increased in the context of zero-carbon targets, highlighting the need to explore its role in carbon emission reduction. This study first calculated Moran's I to assess the existence of spatial autocorrelation in carbon emissions. Next, the geographical detector method was employed to evaluate the contributions of six factors to the temporal-spatial dynamics of carbon emissions. Finally, the role of these factors in driving carbon emissions was assessed using the Spatial Durbin Model (SDM). The results indicate that carbon emissions exhibit significant spatial autocorrelation characteristics. The analysis revealed that private car ownership ($q = 0.2993$) emerged as the dominant driving force influencing the evolution of carbon emission patterns. Additionally, the interaction detector identified interaction links between pairs of factors as either enhanced and bivariate (EB) or enhanced and nonlinear (EN). The findings from the Spatial Durbin Model revealed an inverse U-shaped relationship between the expansion of renewable energy and carbon emission outcomes.

Keywords Renewable energy expansion · Carbon emission · Spatial statistic model · China

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Introduction

As the largest carbon-emitting nation, China continues to experience rising carbon emissions (Wu et al., 2022). Consequently, carbon mitigation has become a pressing issue that requires urgent attention from scholars both domestically and internationally. In response to global warming and to engage in international climate governance, China has set forth its"3060"goal (Song et al., 2024). The country's carbon-intensive energy mix is the primary driver of its increasing carbon emission levels (Yu et al., 2020). To achieve this goal, it is essential to enhance energy efficiency and drive technological transformation while significantly expanding the use of renewable energy and fundamentally reshaping the energy system (Gao et al., 2023; Wu et al., 2024ab). From 2000 to 2022, China's cumulative installed capacity and renewable energy electricity generation surged from 82 million kWh and 0.24 trillion kWh to 1.213 billion kWh and 2.7 trillion kWh, respectively (Ke et al., 2023). The implementation of various regional and spatial development strategies has strengthened the spatial autocorrelations and interactions among cities (Wu, 2023). The spatial dynamics of carbon emissions are not confined by administrative or geographical boundaries; emissions can spread to neighboring cities due to atmospheric conditions and the exchange of production factors, such as population shifts (Dong et al., 2021). These spatial linkages have significantly influenced carbon emission levels within urban areas, ultimately transforming the regional spatial pattern of carbon emissions (Radmehr et al., 2021).

Developing effective strategies to manage elevated carbon emissions necessitates a thorough understanding of the factors contributing to these emissions and their interactions (Wu et al., 2020). This paper focuses on renewable energy as a primary factor of concern. However, carbon emissions are also influenced by other elements, such as industrial production and motor vehicle usage. Few studies have examined the interactions among these factors, making it essential to explore how one contributing element can modulate the impact of others on the evolution of carbon emissions. Decomposition analysis is a well-established research method for investigating the driving forces behind changes in various indicators. Recently, the spatial geographical detector approach has emerged as a valuable tool for addressing similar issues, offering distinct advantages in evaluating the interactive effects between factors compared to traditional methods like Indicator Decomposition Analysis (IDA) and Spatial Decomposition Analysis (SDA).

The spatial linkage of carbon emissions has often been overlooked in traditional econometric approaches (Wu et al., 2021). To address this gap, spatial models have been increasingly applied, offering greater accuracy compared to conventional methods (He et al., 2022). Various techniques, such as Moran's I and Geary's C, have been utilized to measure spatial linkages. The geographical detector approach is a spatial statistics-based method that reveals the driving mechanisms behind spatial heterogeneity (Wu et al., 2020). Known for its mathematical rigor and clear physical interpretation, this approach has been employed in numerous research domains. For instance, Chen et al. (2020) used the geographical detector framework to investigate the pattern properties and underlying drivers of certain phenomena. Similarly, Sun et al. (2021) applied the geographical detector approach to identify the driving factors influencing water-use efficiency (WUE) in China, subsequently proposing policies to enhance efficiency. Wang et al. (2017) also leveraged this method to identify determinants of housing prices, providing a robust scientific basis for housing policy formulation. Furthermore, the geographical detector approach has been employed in public health research to measure the relationships between various factors and the morbidity of hand, foot, and mouth disease (HFMD), uncovering the interaction links among these variables. Its application in environmental research is well-established, including studies that identify determinants of PM2.5 concentration. In this paper, we use the geographical detector model to study the impact of per capita GDP, urbanization rate, per capita consumption, industrial structure, and private car density ownership per unit area and renewable energy development on the driving forces of carbon emission changes and their interactions.

The paper is structured as follows: Sect."Literature review"provides an in-depth review of previous investigations related to each driving element. Sect."Methodology and data"outlines the theoretical foundations of Moran's I, the geographical detector approach, and the spatial econometric model. Sect."Results"focuses on detailing the outcomes derived from the data analysis. Finally, Sect."Conclusion and Policy Implications"concludes with a summary of the key propositions and their regulatory implications.

Literature Review

Existing literature on carbon-driving elements primarily focuses on single-factor analyses. Research has examined how the deployment of renewable energy influences carbon emission patterns, utilizing panel data from various national contexts (Chopra et al., 2024). Some scholars argue that expanding renewable energy will reduce the consumption of coal, oil, and gas, ultimately leading to lower carbon emissions. For instance, Beltrami et al. (2021) evaluated the financial value of the carbon emissions reductions achieved through renewable energy generation in the Italian electricity sector, finding that approximately 22 million tons of emissions were curtailed, valued at 348 million euros. Sun et al. (2022) assessed the impact of renewable energy expansion on carbon emissions in North African economies, positing that renewable energy consumption is an effective strategy for offsetting emissions. This view is supported by Acheampong et al. (2019), who also highlight the benefits of renewable energy in reducing emissions. Conversely, some researchers contend that the expansion of renewable energy may have negligible effects or even exacerbate carbon emissions. Saidi and Omri (2020) found no general correlation between carbon emissions and renewable energy growth in their study of 15 leading renewable energy-utilizing nations. Nguyen and Kakinaka (2019) suggest that in low-income economies, increased use of renewable energy sources can lead to higher carbon emissions. Additionally, Abbasi et al. (2021) indicated that while renewable energy had a statistically significant negative impact on carbon emissions in Thailand, this effect was only temporary.

Existing research has predominantly focused on understanding how financial performance influences carbon emissions. Numerous studies highlight the strong correlation between economic factors and carbon emissions. For instance, Sun et al. (2020) conducted an empirical analysis that identified financial performance as the primary driver of carbon emissions. The prevailing scholarly consensus is that the relationship between financial performance dynamics and carbon emissions is nonlinear (Radmehr et al., 2021). However, there remains a lack of consensus on the finer details of this relationship. The concept of an inverse U-shaped relationship, known as the Environmental Kuznets Curve (EKC), has been proposed to describe the connection between financial performance and carbon emissions (Rahman et al., 2021).

As the economy grows, carbon emissions initially rise before eventually declining, reflecting a nuanced relationship often described by the environmental Kuznets curve (EKC). Subsequent research has identified a'U-shaped trend, where emissions decrease initially and then rise with economic growth. Shan et al. (2021) proposed an'N'-shaped relationship, delineating three distinct stages: carbon emissions first decrease, then increase, and finally decrease again as economic activity progresses. Additionally, discussions surrounding urbanization reveal two contrasting perspectives (Liu et al., 2024). One view posits that urbanization leads to increased infrastructure development, heightening demand for energy-intensive and polluting materials like cement, coal, and steel, thereby exacerbating carbon emissions (Zhao & Wu, 2024). Conversely, another perspective argues that urbanization fosters technological advancement, improves energy structures, and creates agglomeration effects, which can also lead to increased carbon emissions (Wang et al., 2021). Furthermore, as socioeconomic levels rise, so do people's material need and consumption levels, which are linked to pollution due to increased energy use. Household consumption alone accounts for nearly 30% of total pollution emissions. Wackernagel and Rees (1997) emphasized that unsustainable consumption patterns must change to achieve sustainable development. Recent studies have corroborated that rising consumption levels contribute significantly to environmental pollution (Wu et al., 2024a).

The proliferation of private cars has become a significant driver of carbon emissions, as car emissions include carbon monoxide and hydrocarbons, which are key components of overall carbon output. Hurmekoski et al. (2020) report that nearly 80% of car emissions originate from private vehicles. If no control measures are implemented, the number of private cars is expected to continue rising, thereby increasing carbon emissions over time. Consequently, it is crucial to address this issue. Current research indicates that the underlying industrial structure is another critical factor influencing carbon emission trends (Ehigiamusoe and Dogan, 2022). It is widely recognized that a larger share of the secondary sector contributes to higher carbon emissions, as secondary industries typically generate greater amounts of soot and gaseous pollutants. However, rational adjustments to the industrial structure can effectively improve pollution conditions. In summary, considering industrial structure is of great significance. Moreover, the interaction effects of various factors are important; for instance, Ehigiamusoe and Dogan's (2022) study on impoverished nations found that the use of renewable energy has a carbon-reducing effect and that the adoption of renewable energy and increases in real income levels complement each other in lowering carbon emissions.

Previous literature on the topic has rarely accounted for the spatial linkages and dependencies inherent in carbon emission patterns. The interplay between the driving factors has also been largely neglected in prior studies. The highlights of this paper are: (1) Investigate and compare the explanatory power of factors such as renewable energy expansion, financial performance, urbanization rate, industrial structure, resident consumption level, and private car ownership on the evolution of carbon emissions. (2) The analysis extends to explore interactions between two factors, which reveals synergistic effects that are frequently missing from existing studies. (3) Rigorously examine and articulate the influence of each variable on carbon emissions, which provides a comprehensive view of spatial dependencies and interactions.

Methodology and Data

Date Description

Six driving elements are selected as the study subject regarding related literature: renewable energy expansion (Zhu et al., 2024), financial performance (Hou et al., 2024), urbanization rate (Tian et al., 2024), industrial structure (Feng et al., 2024), resident consumption level (Lin & Li, 2024), and private car ownership (Cai et al., 2024). The data selected starts from the year 2004 and ends in 2020. The study focuses on 30 provinces as examples, as the remaining areas like Taiwan, Xizang, and Macao have incomplete data available. The data of explanatory variables, renewable energy development, come from the China Electricity Statistical Yearbook and Electricity Data Statistical Compilation. The energy data in the carbon emission calculation process are derived from the China Energy Statistical Yearbook. Aligning with the recommendations of the Intergovernmental Panel on Climate Change (IPCC), the carbon emission accounting method employed in this analysis includes all direct carbon emissions from human socio-economic activities within the city administrative limits. It is noteworthy that the access of fossil fuel emission factor is based on the investigation result from more than 4000 state-owned coal mines. The data on per capita GDP, urbanization rate, per capita consumption, industrial structure, and private car ownership density per unit area in this study are from the China Statistical Yearbook.

Table 1 displays the descriptive statistics for the examined sets. The highest degree of volatility, as indicated by the standard deviation, minimum, and maximum values, is observed in the carbon emission, gross domestic product per person, and individual-oriented consumption data. This volatility can be attributed to notable regional disparities among provinces. Building on the work of Yu et al. (2020), this study employs renewable energy generation as an explanatory parameter to capture the tangible link between renewable electric output on overall energy output. Per capita GDP is the metric that captures the stage of financial performance. Meanwhile, real GDP measured at constant 2000 prices is the variable employed to reflect economic growth, thereby excluding the impacts of inflation.

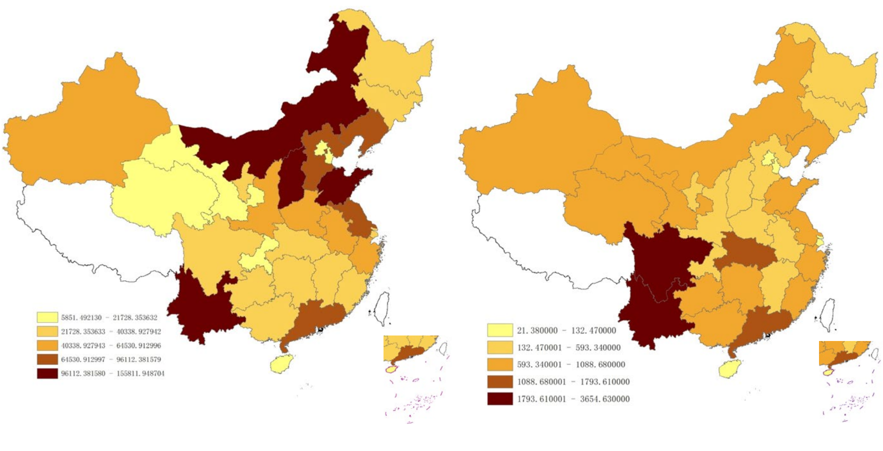
Table 1 Exploratory statistics for the independent model variables

Notation	Signification	Unit	Mean	St. dev	Minimum	Maximum
CE	Carbon emission	10,000 ton	37,656.269	28,168.488	1626.049	1.56e+05
RE	Renewable energy expansion	TWh	404.381	559.837	0.000	3654.630
PGDP	Per capita GDP	Yuan	27,714.220	17,802.799	3806.232	1.09e+05
UR	Urbanization rate	%	54.216	14.416	13.890	89.600
PC	Per capita consume	Yuan	12,620.720	7665.980	2674.000	45,605.000
IS	Industrial structure	%	0.428	0.083	0.160	0.620
PCP	Private car density ownership per unit area	10,000/km^2	39.604	72.545	0.068	551.730

Using ArcGIS software, we created spatial distribution maps for two variables in 2020. Each variable is categorized into five classes based on data size, with darker colors representing higher index values. Figures 1-a through 1-b illustrate that each variable exhibits significant regional differences across provinces. Regarding carbon emission, Inner Mongolia, Shandong, Shanxi, and Yunnan provinces show notably higher emissions compared to other provinces. Additionally, each variable demonstrates spatial dependence characteristics, highlighting the necessity of considering spatial factors in the research.

Spatial Linkage Analysis

To investigate the spatial distribution of carbon emission, the Global Moran's I value first worked. The relevant formulas are defined as follows: Formula (1) is



(a) Carbon emission (b) Renewable energy

Fig. 1 Regional distribution of variables in 2020 utilized to compute the Global Moran's I solution, while Formula (2) defines the method for determining the Local Moran's I. A Local Moran's I below 0 denotes those areas with high carbon emissions are proximate to other areas with analogously high carbon emissions. The Moran's I parameter is constrained to the interval [−1, 1]. Conversely, a Local Moran's I less than 0 signifies those areas with high carbon emission are abutting areas with low carbon emission.

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

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

where ω_{ij} indicates the spatial weight array, x_i represents the carbon emission in the i th province, $\overline{and\ x} = \frac{1}{\sum_{i=1}^{n} x_i}$ represents the average value of the data. $S^2 = \frac{\sum_{i=1}^{n} (x_i - \overline{x})^2}{n}$, denoting data's numerical measure of volatility.

Geographical detector approach

Geographical-based statistical analysis through the geographical detector approach is derived from spatial interdependence theory. It suggests that a stronger link exists between driving elements and carbon emission when their spatial distributions are more similar. This model's capability to accommodate heterogeneous data sources without restrictions is a praiseworthy advantage. Other data types, like the sequence or ratio quantity, can also be studied by discretizing. Another highlight is embodied in the interaction detector. Adding a cross term in the regression Formula is the most typical approach to explore the interaction link among factors. However, not always a multiplication link among factors. The geographical detector approach overcomes the defect that the existing model cannot describe the superimposed influence of the two factors. Moreover, the model can explore not only linear links but also nonlinear links. The geodetector framework is built upon four distinct detectors: factor, interaction, ecological, and risk detectors, but the current paper only makes use of the results from the first two detectors. This paper has employed factor detectors and interaction detection to find solutions to the problems at hand. The geographic raster data used in the ODIAC (Open-Data Inventory for Anthropogenic Carbon Dioxide) geography model facilitates the delivery of global fossil fuel CO2 emission values at a 1 km by 1 km spatial scale. Since this data is continuous monthly, we first process it into annual data using ArcGIS tools.

The focus of this study is the spatial correlation of carbon emissions. First, geographical proximity is the main reason for the spatial correlation of carbon emissions, therefore we used the inverse distance spatial matrix (W). The matrix is based on the fundamental principle of the first law of geography, which states that everything is connected to everything around it and that closer things are more connected than things that are far away. The inverse distance spatial matrix values are organized and defined in an array format, as shown in Eq. (3):

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}}, i \neq j \\ 0, i = j \end{cases} \tag{3}$$

where d_{ij} represents the geographical separation of provinces i and j, obtained based on their latitudes and longitudes.

Factor detector

Through the application of the factor detector, the contribution of factor X to the spatial arrangement of the explanatory parameter Y can be assessed, with the strength of this link denoted by the q value. The equation representing the q value is:

$$q = 1 - \frac{\sum_{h=1}^{L} N_k \sigma_k^2}{N\sigma^2} = 1 - \frac{SSW}{SST} \tag{4}$$

$$SSW = \sum_{h=1}^{L} N_k \sigma_k^2 \tag{5}$$

$$SST = N\sigma^2 \tag{6}$$

where q indicates the impact of factor x_i on explained variable Y; h represents the different layers or categories that make up the element Y or element X; N_k indicates the value or scale of the explained parameter Y or X within the specific slice or section h, while N signifies the overall value or scale across the entire area. SSW expresses the cumulative squared differences between the records and their group-specific means, while SST captures the cumulative squared differences between the records and the global average. σ_k^2 refers to the average squared distance between each explained parameter Y value and its group mean within the subset or partition h, while σ^2 indicates the average squared distance between each explained parameter Y value and the grand mean across the whole sample. The index q, confined to the range [0, 1], suggests the level to which the explanatory parameter X is successful in capturing or representing the systematic variations observed in the explained parameter. The closer q is to 1, the closer the link or the greater the contribution of the explanatory parameter X in describing the changes in the explained parameter Y. If the value is 0, show no link between variable X and explained parameter Y.

Interaction detector

Utilizing the interaction evaluation procedure, researchers can establish if the joint impact of the explanatory parameters X_1 and X_2 enhances or weakens the model's capacity to elucidate variations in the explained parameter. To begin with, the q values corresponding to the explanatory parameters X_1 and X_2 must be obtained separately.

Secondly, to calculate the interaction value $q(X_1 \cap X_2)$. Finally, compare the value of $q(X_1)$, $q(X_2)$ and $q(X_1 \cap X_2)$. Following the comparison results shown in Table 2, the data can be subdivided and allocated across five categories.

Spatial quantitative model

The geographic detector model can only compare the driving degree of each influencing factor but cannot judge whether this effect promotes or inhibits carbon emission. To investigate the impact of these factors more comprehensively, the spatial Durbin model is employed to figure it out. This model assumes that the explained variable in the province i depends on the explanatory parameters of adjacent provinces. In this paper, establish the formula can be established as follows:

$$\begin{aligned} CE_{it} &= \rho \sum_{j=1}^{n} w_{ij}C_{it} + \alpha + \beta_1 RE_{it} + \beta_2 (RE_{it})^2 + \beta_3 PGDP_{it} + \beta_4 UR_{it} + \beta_5 PC_{it} + \beta_6 IS_{it} + \beta_7 PCP_{it} \\ &+ \theta_1 \sum_{j=1}^{n} w_{ij}RE_{it} + \theta_2 \sum_{j=1}^{n} w_{ij}(RE_{it} + \theta_3 \sum_{j=1}^{n} w_{ij}PGDP_{it} + \theta_4 \sum_{j=1}^{n} w_{ij}UR_{it} + \theta_5 \sum_{j=1}^{n} w_{ij}PC_{it} \\ &+ \theta_6 \sum_{j=1}^{n} w_{ij}IS_{it} + \theta_6 \sum_{j=1}^{n} w_{ij}PCP_{it} + \mu_i + \gamma_t + \xi_{it}\xi_{it} = \lambda \sum_{j=1}^{n} w_{ij}\xi_{it} + \varepsilon_{it} \end{aligned} \tag{7}$$

where notation i is applied to designate the province, w_{ij} indicates the spatial weighting array, CE denotes the carbon emission, RE indicates renewable energy expansion, PGDP is GDP per capita, UR represents urban rate, PC refers to residential consumption level, IS denotes industrial structure, PCP indicates private car ownership. β is the parameter to be estimated, ρ refers to the spatial autoregression parameter, θ represents the spatial hysteresis parameter of the explanatory parameter. μ_i is the individual fixed effect, γ_t is the time-fixed effect, t represents the year, and the quantity λ is used to quantify the degree of spatial linkage.

Table 2 Interaction categories

Criterion	Interpretation
$q(X_1 \cap X_2) < Min(q(X_1), q(X_2))$	Weaken and nonlinear (WN)
$Min(q(X_1), q(X_2)) < q(X_1 \cap X_2) < Max(q(X_1), q(X_2))$	Weaken and univariate (WU)
$q(X_1 \cap X_2) > Max(q(X_1), q(X_2))$	Enhance and bivariate (EB)
$q(X_1 \cap X_2) = q(X_1) + q(X_2)$	Independent (ID)
$q(X_1 \cap X_2) > q(X_1) + q(X_2)$	Enhance and nonlinear (EN)

Results

Spatial covariance of carbon discharge

In this section, local and global spatial autocorrelation tests are conducted to investigate the spatial autocorrelation character of carbon emission. Applying the Global Moran's I technique allows for an exploration of the spatial organization and interdependence exhibited by carbon emission values. Global Moran's I fluctuate between 0 and 1, and a value surpassing 0 denotes the presence of positive spatial dependence. A Moran's I measure less than 0 signifies negative spatial interdependence, whereas a value near 0 reflects a random spatial arrangement, lacking any spatial linkage. Table 3 showcased Moran's I index values over the years from 2004 to 2020. The analysis of Moran's I over the 2004 to 2020 period showed statistical significance at the 1% level, suggesting a positive spatial autocorrelation for carbon emission across the provincial areas. In conclusion, carbon emissions present spatial autocorrelation, and spatial factors are necessary to be considered.

The local spatial autocorrelation of variables can be reflected by the Local Moran's I scatter chart. Therefore, the Local Moran's I scatter chart is drawn for 2004, 2011, 2015, and 2019 with inverse distance spatial matrix W. The 2020 COVID-19 crisis is anticipated to bring about changes and deviations in the underlying laws that dictate carbon emission dynamics. Therefore, the spatial autocorrelation for 2020 is not discussed. The scatter plots in Fig. 2 show the standardized carbon emission values on the x-axis and the corresponding spatial lag on the y-axis. The grouping of data points in the top-right and bottom-left quadrants implies a positive spatial linkage. Where provinces with high carbon emissions are associated with other high-emission areas, and low-emission provinces are grouped.

Figure 3 presents the clustering map of carbon emissions across provinces from 2004 to 2020. It reveals that provinces such as Shanxi, Liaoning, Inner Mongolia, and Jiangsu exhibit high-high clustering, indicating that these provinces have relatively high levels of carbon emissions, and the surrounding provinces also exhibit elevated emissions. In contrast, Guangdong and Yunnan demonstrate high-low clustering, suggesting that these provinces have high carbon emissions levels while being surrounded by areas with lower emissions.

Table 3 The Moran's I index over the 2004 to 2020 period

Year	I	Z	P
2004	0.059	2.604	0.005
2007	0.055	2.507	0.006
2010	0.051	2.419	0.008
2013	0.050	2.364	0.009
2016	0.045	2.306	0.011
2019	0.045	2.255	0.012
2020	0.007	1.171	0.121

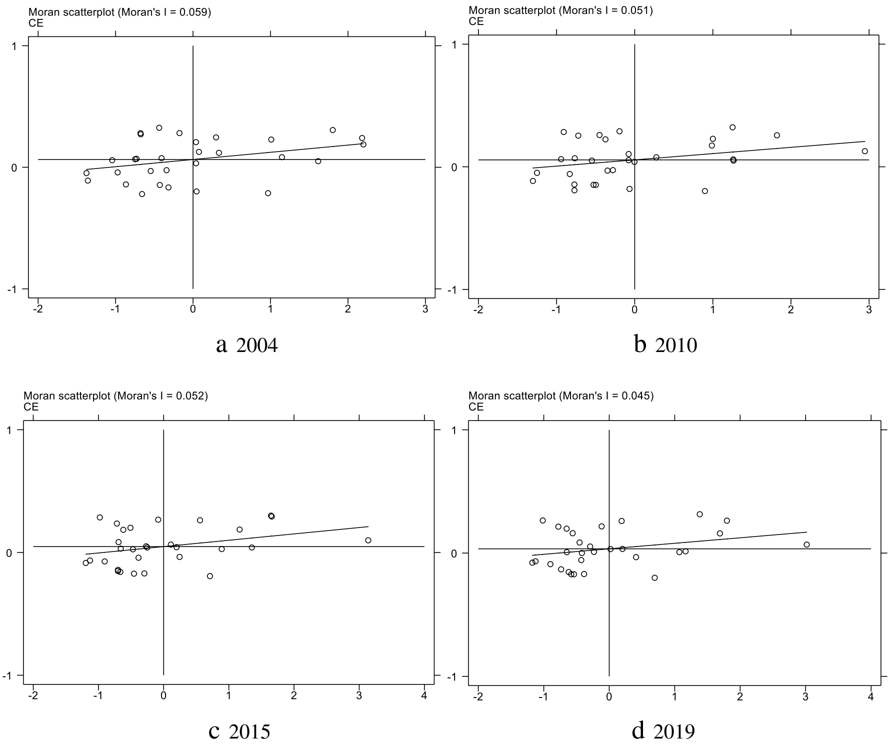


Fig. 2 Scatter charts of Local Moran's I from 2004 to 2020

Factor detector

This paper thoroughly examined the explanatory power of seven distinct factors in the evolution of carbon emissions from 2004 to 2020. The key insights from the analysis are captured in Table 4, which showcases the outcomes of the factor detector functionality within the Geodetector model. According to these results, private car ownership stands out with the highest average q-value among the driving elements considered. This demonstrates that the prevalence of private vehicle ownership was a key explanatory factor behind the changes in carbon emission observed across the studied timeframe. Other important factors identified include industrial structure, renewable energy expansion, urbanization, per capita GDP, and resident consumption.

The findings of this analysis reveal several key insights into the factors influencing carbon emissions, particularly the dominant role of private car ownership. The high average q-value associated with private vehicles indicates that as ownership increases, so too do carbon emissions. This trend can be attributed to increased vehicle miles traveled; as more individuals own private cars, the total distance driven tends to rise, leading to higher emissions from fuel combustion. Economic growth also plays a significant role, as rising per capita GDP often correlates with increased living levels, enabling more people to afford electrical appliances. This relationship highlights the

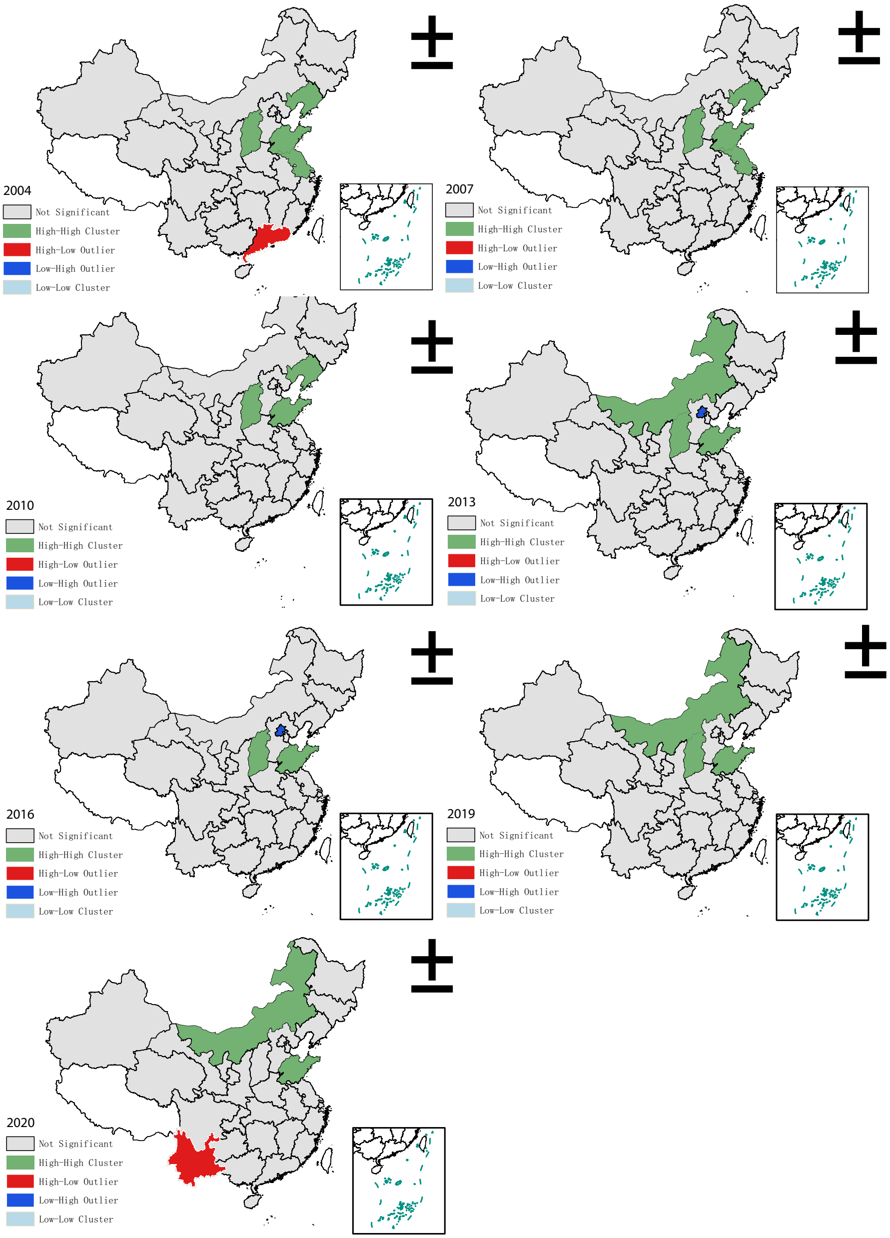


Fig. 3 Lisa aggregation map

interplay between economic development and environmental impact. Furthermore, the presence of other significant factors, such as industrial structure, renewable energy expansion, and urbanization, suggests that a multifaceted approach is necessary for

Table 4 Factor detector results

Year	RE	PGDP	UR	PC	IS	PCP
2004	0.0428	0.1214	0.0237	0.0752	0.1722	0.3030
2007	0.0830	0.0976	0.1018	0.0451	0.1342	0.2799
2010	0.0912	0.0992	0.1022	0.0367	0.1581	0.2861
2013	0.0802	0.0409	0.1064	0.0377	0.1255	0.2956
2015	0.1962	0.0451	0.1064	0.1033	0.1175	0.3168
2017	0.1030	0.0970	0.1124	0.1028	0.0860	0.3068
2019	0.0912	0.0816	0.1338	0.0828	0.1149	0.3066
Average	0.0982	0.0833	0.0981	0.0691	0.1298	0.2993

effective carbon management. The industrial sector's emissions indicate that transitioning to cleaner technologies and practices is crucial. While renewable energy expansion is a positive trend, its effectiveness in reducing emissions may be limited by concurrent increases in other factors, such as urbanization, which can lead to higher energy demands. To mitigate the impact of private car ownership on carbon emissions, there is a need to promote public transportation and incentivize the development of efficient transit systems. Sustainable urban planning is essential, with a focus on integrating mixed-use developments that reduce travel distances and promote walking or cycling. Encouraging the adoption of electric vehicles through subsidies and expanding charging infrastructure can also help decrease emissions from the transportation sector. Additionally, regulating emissions from industries that contribute significantly to carbon outputs is crucial, alongside continued investment in renewable energy sources to ensure they can effectively offset emissions from other sectors.

Figure 4 presents radar charts depicting the *q*-values of six different factors influencing carbon emission. These charts illustrate how the driving forces of these factors have evolved. As depicted in Fig. 4-a, the contribution of renewable energy expansion to carbon emission displayed a continuous upward trajectory from 2004 to 2015, followed by a gradual decrease after 2015. Conversely, Fig. 4-b demonstrates that the driving force of GDP per capita follows an inverted"N"pattern over the study period. In Fig. 4-c, the driving force of urbanization level shows a consistent upward trend, indicating a steady increase in its influence on carbon emission. Figure 4-d reveals that the trend of household consumption level mirrors the pattern observed for per capita GDP, showing similar fluctuations. Figure 4-e highlights that the driving force of the industrial structure exhibits a fluctuating pattern, indicating variable impact over time. Lastly, Fig. 4-f shows that the influence of private car ownership on carbon emission changes most smoothly, suggesting a relatively stable impact throughout the study period.

Interactor detector results

The interaction between driving elements from 2004 to 2020 is detailed in Table 5 −1 through 5-7. Due to spatial constraints, Tables A.1 through A.6 are included in Appendix A. The analysis has determined that the interaction effect between any two explanatory variables is limited to either the Enhanced and Bivariate (EB) or the Enhanced

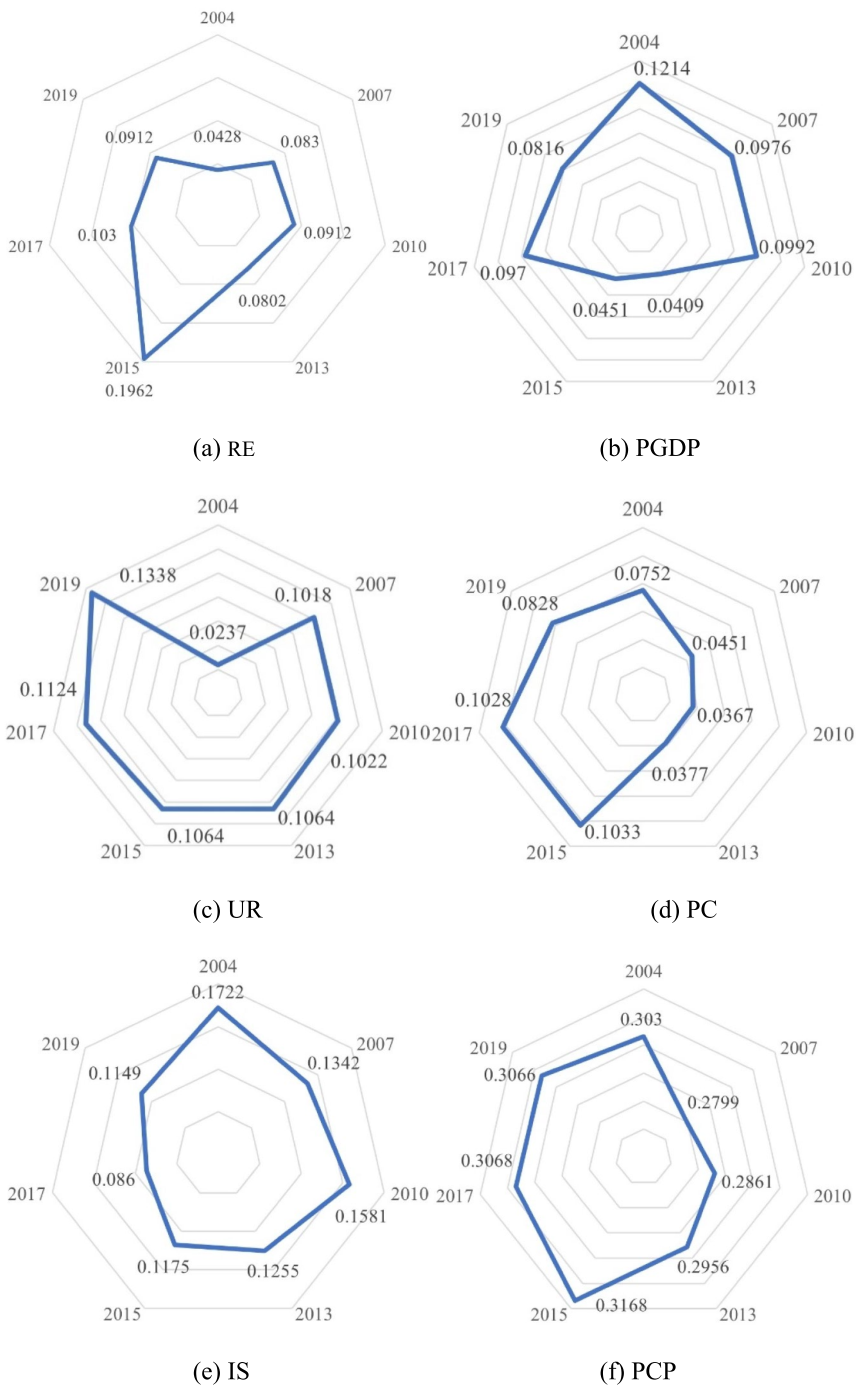


Fig. 4 Evolution trend of driving elements' explanatory power from 2014 to 2020

Table 5 –1 Interaction in 2019

	RE	PGDP	UR	PC	IS	PCP
RE	0.0912					
PGDP	0.2757 EN	0.0816				
UR	0.2477 EN	0.1904 EB	0.1338			
PC	0.2491 EN	0.1185 EB	0.1882 EB	0.0828		
IS	0.3354 EN	0.2214 EN	0.2479 EB	0.2306	0.1149	
PCP	0.3638 EB	0.3475 EB	0.3315 EB	0.3373 EB	0.3488 EB	0.3066

and Nonlinear (EN) category. The results underscore the complex interactions among various driving factors influencing carbon emissions from 2004 to 2020. The classification of these interactions into Enhanced and Bivariate (EB) or Enhanced and Nonlinear (EN) categories indicates that the combined effect of two explanatory variables significantly enhances the understanding of carbon emission trends, suggesting that these relationships are not merely additive but interact in ways that amplify their impact on emissions. Many examined variables, such as economic growth, urbanization, and private car ownership, are intrinsically interconnected; for example, economic expansion often leads to increased urbanization, resulting in heightened demand for transportation and more private vehicles. This interconnectedness means that changes in one factor can trigger cascading effects on others, creating a complex web of influences that collectively shape carbon emissions. Additionally, traditional analyses that treat these factors in isolation may overlook critical dynamics emerging from their interactions, such as the relationship between renewable energy adoption and industrial structure, which reveals how shifts in energy sources affect emissions based on industrial activity levels. From a policy perspective, these insights highlight the need for integrated approaches to carbon management; policymakers should consider the interactions among various driving factors when formulating strategies to reduce emissions. For instance, promoting renewable energy should not only emphasize production but also address its implications for industrial practices and urban planning. Similarly, policies aimed at reducing private car ownership, such as enhancing public transportation and encouraging carpooling, should be coupled with initiatives that address economic growth and urbanization patterns. A holistic framework that acknowledges the interdependencies among these factors will be more effective in achieving significant reductions in carbon emissions, fostering sustainable urban environments, and ultimately contributing to climate goals.

Empirical Results and Discussions

Within the context of a spatial econometric framework, spatial autocorrelation may arise from the dependent factor, independent factor, or disturbance term. This study

Table 6 The result of the LM test, LR test, and Wald test

Variable	Statistic	P-value
LM_lag	96.257	0.000
LM_err	120.994	0.000
Robust_LM_lag	8.511	0.004
Robust_LM_err	33.248	0.000
LR_lag	81.55	0.000
LR_err	77.51	0.000
Wald_lag	86.61	0.000
Wald_err	79.27	0.000

begins with a Lagrange multiplier (LM) test to guide the model selection process. Underlying the LM test is a null proposition that rules out the existence of spatial lag effects and spatial error effects. Table 6 provides sufficient evidence to dismiss the null assumption at a 1% significance standard, indicating that the model incorporates spatial lag effects and spatial error effects. Combined with the analysis of Moran's I value, this result further confirms the existence of spatial autocorrelation in carbon emission. Therefore, incorporating spatial factors into the model analysis is both necessary and appropriate. The Likelihood Ratio (LR) test and the Wald test results also show that the Spatial Durbin Model (SDM) cannot be simplified to either the Spatial Lag Model (SLM) or the Spatial Error Model (SEM). Consequently, the Spatial Durbin Model is considered the most appropriate choice for this research, as it effectively reflects the complexity of spatial dependencies in the data.

Table 7 presents the regression analysis, the regression results are structured as follows: models (1) and (2) contain the OLS regression outputs, and models (3) and (4) contain the regression outputs using the spatial weight array W. The data indicates that the link between renewable energy growth and carbon emission follows an inverted U-shaped dynamic. The foundational phases of renewable energy advancement reveal a correspondence with amplified carbon emission, yet as renewable energy systems become more established, they will work to offset carbon emissions. When renewable energy was first introduced, the renewable energy fraction was relatively insignificant, and fossil-based energy sources continued to be the predominant energy source. Moreover, some renewable energy equipment manufacturing will also involve certain carbon emissions, such as wind power generation equipment.

It is the transformation of the prevailing energy structure that acts as a primary driver for the development of renewable energy to curb carbon emissions in the later stage. Renewable energy alternatives are preferable due to their capacity to reduce carbon emissions considerably. On the other hand, the burning of conventional fossil-based energy resources including coal, oil, and natural gas produces significant amounts of carbon dioxide and other greenhouse gases. The preference for energy sources with high carbon intensity can be addressed by transitioning to renewable energy sources, ultimately leading to a decline in carbon emissions. (2) Increasing energy efficiency. Renewable energy expansion is habitually accompanied by concurrent energy efficiency gains. An illustration of technology that is continuously

Table 7 Spatial quantitative model results

Variable	(1)	(2)	(3)	(4)
	OLS	OLS	SDM	SDM
RE	49.57***	23.37***	25.19***	16.92***
	(2.945)	(4.326)	(3.857)	(3.972)
RE2	−0.0112***	−0.00569***	−0.00577***	−0.00401***
	(0.000902)	(0.00108)	(0.000970)	(0.000967)
PGDP		0.581***		0.201***
		(0.163)		(0.145)
UR		382.7***		302.6***
		(91.52)		(91.71)
PC		−0.545***		−2.079***
		(0.330)		(0.409)
IS		−7901.3**		−4464.2**
		(12,005.4)		(13,843.6)
PCP		35.39**		30.70***
		(18.13)		(20.09)
WRE			−129.1***	−92.98**
			(27.59)	(33.78)
WRE2			0.0217**	0.00595***
			(0.00754)	(0.00835)
WPGDP				−5.765***
				(1.064)
WUR				1903.5**
				(587.1)
WPC				6.166*
				(2.774)
WIS				3156.3
				(79,373.7)
WPCP				463.1**
				(145.4)
Province FE	Yes	Yes	Yes	Yes
Year FE	Ye	Yes	Yes	Yes
Log-L			−5289.8153	−5252.5529
R^2	0.406	0.490	0.132	0.143
N	510	510	510	510

The symbols *, **, and *** correspond to p-values below the 0.1, 0.05, and 0.01. The figures in parameter brackets are the standard errors of the reported values

advancing can be found in solar and wind power generation systems, increasing energy conversion efficiency. Correspondingly, the growth of renewable energy technology facilitates the enhancement and automation of the energy system, curbing energy waste and dissipation, and eventually leading to a reduction in carbon emission; (3) Clean transportation and electrification transition. The expansion of renewable energy is driving the transformation towards clean transportation and electrification. The advancement of renewable energy is catalyzing the heightened adoption of electric and hybrid vehicles. The substitution of traditional fuel-based vehicles for new energy vehicles has contributed to reduced carbon emissions in the transportation segment. (4) Energy diversification and decentralization. Renewable energy expansions foster energy diversification and decentralization, lessening the dependence on conventional energy sources. By decentralizing energy production and supply, such as distributed solar power generation systems and personal wind generators, energy loss and carbon emissions are reduced during energy transmission and distribution. (5) Technological progress and innovation. Continuing technological advancements and innovations in renewable energy have driven improvements in energy efficiency. With the maturity and large-scale application of technology, renewable energy has gradually become an economically viable option, and more countries and enterprises choose to invest in and adopt renewable energy, thereby reducing overall carbon emissions.

Given the linkage between per capita GDP and carbon emissions, the former's ascent will probably significantly drive the latter. Because economic growth brings more demand for fossil fuel consumption, resulting in more carbon emissions. The increasing urbanization of the population is a major impetus for the augmentation of carbon emissions. Many buildings and infrastructure construction require energy supply, such as heating, air conditioning, and electricity, in the process of urbanization. Energy demands are typically greater in urban buildings than in rural areas, and energy-intensive activities involve escalated electricity and fuel consumption, ultimately driving up carbon emissions. The regression results reveal a significantly negative link between the resident consumption level and the explained parameter. As residents' consumption levels rise, their environmental consciousness tends to increase, and they are more likely to acquire and utilize living equipment with superior energy efficiency. The regression outputs reveal that the industrial structure has a markedly adverse impact, driven by the shift away from energy-intensive industries towards more sustainable and low-emission operations. The strategic management of industrial transitions—from high-carbon to low-carbon activities—has resulted in a decline in the aggregate level of carbon emission. A significant boost in carbon emission levels

Table 8 Direct, indirect, and total effects

	RE	RE2	PGDP	UR	PC	IS	PCP
Direct effect	18.32***	−0.00416***	0.288*	279.4**	−2.185***	−4046.1**	24.82
	(4.116)	(0.00100)	(0.142)	(89.93)	(0.393)	(13,082.6)	(19.69)
Indirect effect	−79.70**	0.00609	−4.640***	1449.0**	5.491*	1133.3*	358.2**
	(26.26)	(0.00629)	(1.008)	(532.4)	(2.291)	(67,080.7)	(132.2)
Total effect	−61.38*	0.00193	−4.352***	1728.3**	3.307**	−2912.8**	383.0**
	(26.33)	(0.00623)	(1.030)	(546.3)	(2.291)	(73,649.8)	(134.8)

The symbols *, **, and *** correspond to p-values below the 0.1, 0.05, and 0.01. The figures in parameter brackets are the standard errors of the reported values is anticipated to accompany the increase in private car ownership. Vehicular exhaust is a widely accepted and critical component in the overall landscape of carbon emission.

It is apparent from Table 8 that the regression parameter for the proximate linkage of SDM is divergent from the regression parameter of the corresponding variable in Table 7, owing to the presence of response effects. The concept of response effects describes the process whereby alterations in the explanatory variables of an area elicit responses in neighboring areas, which subsequently propagate back to the initial area via spatial spillover. Data from the direct impact study indicates the linear regression parameter tied to renewable energy expansion is optimistic and satisfies the demanding 1% significance threshold, and the quadratic regression parameter is negative and statistically significant at the 1% level, suggesting the existence of a contribution of renewable energy expansion on carbon emission. The data suggests an inverted U-shaped function, where renewable energy expansion initially contributes to increased carbon emission, but then shifts towards decreasing carbon emission. Furthermore, we observed that the proliferation of renewable energy in adjacent areas can help reduce carbon emissions within the focal area. The cumulative impact embodies the totality of the direct and indirect consequences. The parameter for renewable energy expansion is notably negative, the increasing adoption of renewable energy has a pronounced dampening impact on carbon outputs.

Discussions

The findings of this study align closely with those of Zhu et al. (2024), who believe that renewable energy systems can reduce carbon emissions by 10% to 50%. This range highlights the variability in effectiveness based on specific implementation strategies and local contexts. Furthermore, Wu et al., (2024a, 2024b) explored the role of carbon pricing in shaping renewable energy development in China, revealing that higher carbon prices significantly decrease coal consumption, which in turn promotes an increase in the share of renewable energy. This relationship underscores the critical role of economic incentives in facilitating the transition to cleaner energy sources, suggesting that policy frameworks incorporating carbon pricing are essential for achieving emission reduction targets. Wu et al. also identified significant regional disparities in renewable energy development, advocating for targeted emission reduction initiatives in East China to ensure that climate action is both effective and equitable. Reinforcing these themes, Qing et al. (2024) demonstrated the importance of renewable energy investment in achieving carbon neutrality goals through an empirical study approach in Asia, emphasizing that financial commitment to renewable technologies is crucial for long-term sustainability. In summary, these studies illustrate a result: renewable energy systems, supported by appropriate economic policies and localized strategies, can play a pivotal role in reducing carbon emissions and advancing global climate objectives. Future research should continue to investigate the interplay between economic incentives, regional policies, and renewable energy adoption to further elucidate pathways toward a sustainable energy future.

Conclusion and Policy Implications

The purpose of this paper is to check the link between the implementation of renewable energy and carbon emission via a detailed multi-step process. The spatial autocorrelation of carbon emission is initially confirmed by computing Moran's I statistic, which checks out spatial reliance. Subsequently, by applying the geographic detector model, the driving forces of two key predictor variables on changes in carbon emissions were studied, and insights into their relative importance were provided. Lastly, the Spatial Durbin Model (SDM) is employed to employ a comprehensive analysis and characterization of the impact of each variable on carbon emission, facilitating a detailed understanding of both spatial and non-spatial influences. The research indicates several key findings: From 2004 to 2020, carbon emissions data for China's 30 provinces reveal significant spatial interdependence and clustering patterns, with notable high-high and low-low aggregation, indicating regional disparities in carbon output. The geographic detector model highlights private car ownership as the primary driver of carbon emission variations, followed by industrial structure, renewable energy expansion, urbanization, per capita GDP, and resident consumption levels. Additionally, the spatial Durbin model shows an inverse U-shaped relationship between renewable energy growth and carbon emissions, suggesting that while initial growth can reduce emissions, further development may lead to increases. Furthermore, per capita GDP, urbanization, and private car ownership are positively linked to higher carbon emissions, whereas changes in industrial composition and improved consumption patterns can contribute to reductions, underscoring the importance of transitioning to cleaner and more sustainable industrial practices. Drawing from the findings, the following policy recommendation is proposed:

(1) Provinces such as Shanxi, Inner Mongolia, and Liaoning exhibit significantly higher carbon emissions compared to their neighboring regions; therefore, more targeted, and region-specific mitigation strategies are needed. In these coal-dependent regions, efforts should focus on accelerating the transition from fossil fuels to renewable energy sources—such as wind, solar, and biomass—by providing financial incentives, including subsidies for renewable energy projects and tax reductions for green investments. In parallel, introducing retraining programs for workers in traditional coal industries can help facilitate a just transition.

(2) The transportation sector is a major contributor to carbon emissions, making it essential to accelerate the shift toward low-carbon mobility. While expanding charging infrastructure is a critical step toward promoting electric vehicle (EV) adoption, its effectiveness depends on accompanying policy support. For instance, offering purchase subsidies for EVs, implementing carbon pricing or fuel taxes, and providing tax incentives for clean vehicle manufacturers can directly influence consumer behavior and industry development.

(3) Renewable energy holds great potential in reducing carbon emissions, especially in developing countries that are still undergoing industrialization. To maximize its impact, a multi-pronged policy approach is needed. This includes promoting R\&D investment to drive technological breakthroughs and reduce production costs, as well as implementing feed-in tariffs, green certificates, or carbon trading schemes to ensure

that renewable energy sources receive fair market treatment. Furthermore, establishing regional power trading platforms and inter-regional grid integration can help balance energy supply and demand more efficiently.

This study mainly focuses on 30 provinces in China, and the results may not apply to carbon emission patterns and renewable energy implementation in other countries or regions. Although multiple driving factors were explored, some important variables affecting carbon emissions, such as policy changes and technological progress, may still have been omitted. Moreover, while the geographical detector method performs well in identifying spatial heterogeneity and capturing interaction effects among variables, it is relatively weak in inferring causal relationships.

Appendix A

Table 9 Interaction in 2004

	RE	PGDP	UR	PC	IS	PCP
RE	0.0428					
PGDP	0.1981 EN	0.1214				
UR	0.1698 EN	0.2644 EN	0.0237			
PC	0.2137 EN	0.1751 EB	0.1188 EN	0.0752		
IS	0.2193 EN	0.2951 EN	0.2370 EN	0.2376 EB	0.1722	
PCP	0.3713 EN	0.3181 EB	0.3393 EN	0.3296 EB	0.3583 EB	0.3030

Table 10 Interaction in 2007

	RE	PGDP	UR	PC	IS	PCP
RE	0.0830					
PGDP	0.2113 EN	0.0976				
UR	0.2702 EN	0.1858 EB	0.1018			
PC	0.1991 EN	0.1991 EN	0.2154 EN	0.0451		
IS	0.2729 EN	0.2335 EN	0.2733 EN	0.2252 EN	0.1342	
PCP	0.3685 EN	0.3582 EB	0.3550 EB	0.3119 EB	0.3749 EB	0.2799

Table 11 Interaction in 2010

	RE	PGDP	UR	PC	IS	PCP
RE	0.0912 EN					
PGDP	0.3102 EN	0.0992				
UR	0.3034 EN	0.2764 EN	0.1022			
PC	0.3055 EN	0.1857 EN	0.1499 EN	0.0367		
IS	0.2490 EB	0.3502 EN	0.3379 EN	0.3151 EN	0.1581	
PCP	0.3851 EN	0.3061 EB	0.3430 EB	0.3009 EB	0.4204 EB	0.2861

Table 12 Interaction in 2013

	RE	PGDP	UR	PC	IS	PCP
RE	0.0802					
PGDP	0.2175 EN	0.0409				
UR	0.2038 EN	0.1241 EB	0.1064			
PC	0.2178 EN	0.0741 EB	0.1387 EB	0.0377		
IS	0.2816 EN	0.1737 EN	0.2511 EN	0.2459 EN	0.1255	
PCP	0.3608 EB	0.3322 EB	0.3238 EB	0.3389 EN	0.3618 EB	0.2956

Table 13 Interaction in 2015

	RE	PGDP	UR	PC	IS	PCP
RE	0.1962					
PGDP	0.3333 EN	0.0451				
UR	0.2754 EN	0.1297 EB	0.1064			
PC	0.3258 EN	0.1667 EN	0.1994 EB	0.1033		
IS	0.2983 EB	0.2033 EN	0.2629 EN	0.2497 EN		
PCP	0.3597 EB	0.3481 EB	0.3603 EB	0.3422 EB	0.3653 EB	0.3168

Table 14 Interaction in 2017

	RE	PGDP	UR	PC	IS	PCP
RE	0.1030					
PGDP	0.2802 EN	0.0970				
UR	0.2314 EN	0.1669 EB	0.1124			
PC	0.2614 EN	0.1539 EB	0.2015 EB	0.1028		
IS	0.1368 EB	0.2321 EN	0.2440 EN	0.2567 EN	0.0860	
PCP	0.3617 EB	0.3339 EB	0.3427 EB	0.3337 EB	0.3533 EB	0.3068

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Data Availability The datasets generated during and analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethical Approval This work does not require any ethical approval.

Consent to Participate Not applicable.

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References

Abbasi, K. R., Adedoyin, F. F., Abbas, J., & Hussain, K. (2021). The impact of energy depletion and renewable energy on CO2 emissions in Thailand: Fresh evidence from the novel dynamic ARDL simulation. *Renewable Energy, 180*, 1439–1450.

Acheampong, A. O., Adams, S., & Boateng, E. (2019). Do globalization and renewable energy contribute to carbon emissions mitigation in Sub-Saharan Africa? *Science of the Total Environment, 677*, 436–446.

Alhasnawi, B. N., Almutoki, S. M. M., Hussain, F. F. K., Harrison, A., Bazooyar, B., Zanker, M., & Bureš, V. (2024). A new methodology for reducing carbon emissions using multi-renewable energy systems and artificial intelligence. *Sustainable Cities and Society, 114*, 105721.

Beltrami, F., Fontini, F., & Grossi, L. (2021). The value of carbon emission reduction induced by Renewable Energy Sources in the Italian power market. *Ecological Economics, 189*, 107149.

Cai, J., Zhao, Z., Zhou, Z., & Wang, Y. (2024). Predicting the carbon emission reduction potential of shared electric bicycle travel. *Transportation Research Part d: Transport and Environment., 129*, 104107.

CESY (China Energy Statistical Yearbook), 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021. National Bureau of Statistics of China, National Development and Reform Commission.

Chen, J., Wang, B., Huang, S., & Song, M. (2020). The influence of increased population density in China on air pollution. *Science of the Total Environment, 735*, 139456.

China Electricity Statistical Yearbook, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021. National Bureau of Statistics of China, National Development and Reform Commission.

Chopra, R., Rehman, M. A., Yadav, A., & Bhardwaj, S. (2024). Revisiting the EKC framework concerning COP-28 carbon neutrality management: Evidence from Top-5 carbon embittering countries. *Journal of Environmental Management, 356*, 120690.

CSY (China Statistical Yearbook), 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021. National Bureau of Statistics of China, National Development and Reform Commission.

Dong, C., Zhou, R., & Li, J. (2021). Rushing for subsidies: The impact of feed-in tariffs on solar photovoltaic capacity development in China. *Applied Energy, 281*, 116007.

Feng, T., Liu, B., Wei, Y., Xu, Y., Zheng, H., Ni, Z., Zhu, Y., Fan, X., & Zhou, Z. (2024). Research on the low-carbon path of regional industrial structure optimization. *Energy Strateg Rev., 54*, 101485.

Fingleton, B., & Le Gallo, J. (2008). Estimating spatial models with endogenous variables, a spatial lag and spatially dependent disturbances: Finite sample properties. *Papers in Regional Science, 87*, 319–340.

Gao, F., Wu, J., Xiao, J., Li, X., Liao, S., & Chen, W. (2023). Spatially explicit carbon emissions by remote sensing and social sensing. *Environmental Research, 221*, 115257.

García, G. A., Badillo, E. R., & Aristizábal, J. M. (2024). Housing Informality and Labor Informality in Space. In Search of the Missing Links. *Applied Spatial Analysis and Policy, 17*, 923–949.

He, Z., Cao, C., & Wang, J. (2022). Spatial Impact of Industrial Agglomeration and Environmental Regulation on Environmental Pollution—Evidence from Pollution-Intensive Industries in China. *Applied Spatial Analysis and Policy, 15*, 1525–1555.

Hou, A., Liu, A., & Chai, L. (2024). Does reducing income inequality promote the decoupling of economic growth from carbon footprint? *World Development, 173*, 106423.

Hurmekoski, E., Myllyviita, T., Seppälä, J., Heinonen, T., Kilpeläinen, A., Pukkala, T., Mattila, T., Hetemäki, L., Asikainen, A., & Peltola, H. (2020). Impact of structural changes in wood-using industries on net carbon emissions in Finland. *Journal of Industrial Ecology, 24*, 899–912.

IPCC. 2006 IPCC Guidelines for national greenhouse gas inventories. Intergovernmental Panel on Climate Change, 2006

Ke, N., Lu, X., Kuang, B., & Zhang, X. (2023). Regional disparities and evolution trend of city-level carbon emission intensity in China. *Sustainable Cities and Society, 88*, 104288.

Lin, C., & Li, X. (2024). Carbon peak prediction and emission reduction pathways exploration for provincial residential buildings: Evidence from Fujian Province. *Sustainable Cities and Society, 102*, 105239.

Liu, X., You, C., Cifuentes-Faura, J., & Peng, X. (2024). Bigger cities and less carbon? Government-driven urbanization and carbon emissions in China. *Journal of Cleaner Production, 467*, 142808.

Nguyen, K. H., & Kakinaka, M. (2019). Renewable energy consumption, carbon emissions, and development stages: Some evidence from panel cointegration analysis. *Renewable Energy, 132*, 1049–1057.

Qing, L., Abbas, J., Najam, H., Ma, X., & Dagestani, A. A. (2024). Investment in renewable energy and green financing and their role in achieving carbon-neutrality and economic sustainability: Insights from Asian region. *Renewable Energy, 221*, 119830.

Radmehr, R., Henneberry, S. R., & Shayanmehr, S. (2021). Renewable Energy Consumption, CO2 Emissions, and Economic Growth Nexus: A Simultaneity Spatial Modeling Analysis of EU Countries. *Structural Change and Economic Dynamics, 57*, 13–27.

Rahman, M. M., Nepal, R., & Alam, K. (2021). Impacts of human capital, exports, economic growth and energy consumption on CO2 emissions of a cross-sectionally dependent panel: Evidence from the newly industrialized countries (NICs). *Environmental Science & Policy, 121*, 24–36.

Saidi, K., & Omri, A. (2020). The impact of renewable energy on carbon emissions and economic growth in 15 major renewable energy-consuming countries. *Environmental Research, 186*, 109567.

Shan, Y., Fang, S., Cai, B., Zhou, Y., Li, D., Feng, K., & Hubacek, K. (2021). Chinese cities exhibit varying degrees of decoupling of economic growth and CO2 emissions between 2005 and 2015. *One Earth., 4*, 124–134.

Song, J., Liu, Z., & Leng, X. (2024). The Impact of the Digital Economy on Provincial Carbon Emissions in China. *Applied Spatial Analysis and Policy, 17*, 1209–1235.

Sun, H., Samuel, C. A., Kofi Amissah, J. C., Taghizadeh-Hesary, F., & Mensah, I. A. (2020). Non-linear nexus between CO2 emissions and economic growth: A comparison of OECD and B&R countries. *Energy (Oxf)., 212*, 118637.

Sun, H., Bai, Y., Lu, M., Wang, J., Tuo, Y., Yan, D., & Zhang, W. (2021). Drivers of the water use efficiency changes in China during 1982–2015. *Science of the Total Environment, 799*, 149145.

Sun, Y., Li, H., Andlib, Z., & Genie, M. G. (2022). How do renewable energy and urbanization cause carbon emissions? Evidence from advanced panel estimation techniques. *Renewable Energy, 185*, 996–1005.

Tian, Y., Zuo, S., Ju, J., Dai, S., Ren, Y., & Dou, P. (2024). Local carbon emission zone construction in the highly urbanized regions: Application of residential and transport CO2 emissions in Shanghai. *China. Build Environ., 247*, 111007.

Wackernagel, M., & Rees, W. E. (1997). Perceptual and structural barriers to investing in natural capital: Economics from an ecological footprint perspective. *Ecological Economics, 20*, 3–24.

Wang, Y., Wang, S., Li, G., Zhang, H., Jin, L., Su, Y., & Wu, K. (2017). Identifying the determinants of housing prices in China using spatial regression and the geographical detector technique. *Applied Geography, 79*, 26–36.

Wang, W., Liu, L., Liao, H., & Wei, Y. (2021). Impacts of urbanization on carbon emissions: An empirical analysis from OECD countries. *Energy Policy, 151*, 112171.

Wu, W. (2023). Is air pollution joint prevention and control effective in China—evidence from "Air Pollution Prevention and Control Action Plan." *Environmental Science and Pollution Research International, 30*, 122405–122419.

Wu, W., Zhang, M., & Ding, Y. (2020). Exploring the effect of economic and environment factors on PM2.5 concentration: A case study of the Beijing-Tianjin-Hebei region. *Journal of Environmental Management, 268*, 110703.

Wu, W., Huang, M., Lv, H., Wang, W., & Zhang, M. (2021). Does the air pollution joint prevention and control policy possess the Porter effect in China -evidence from two perspectives. *Environmental Impact Assessment Review, 91*, 106678.

Wu, W., Wang, W., & Zhang, M. (2022). Does internet public participation slow down environmental pollution? *Environmental Science & Policy, 137*, 22–31.

Wu, H., Yang, H., Hu, X., Zheng, L., Li, J., Li, Y., Wang, X., Ge, W., Zhou, Y., Liu, Y., Liu, J., Wang, Y., Ma, J., & Tao, S. (2024a). Complementing carbon tax with renewable energy investment to decarbonize the energy system in China. *Renewable and Sustainable Energy Reviews., 189*, 113997.

Wu, W., Zhang, M., Jin, D., Ma, P., Wu, W., & Zhang, X. (2024b). Decision-making analysis of electric vehicle battery recycling under different recycling models and deposit-refund scheme. *Computers & Industrial Engineering, 191*, 110109.

Wu, W., Li, M., Zhang, M., Wang, Y., Wang, L., You, Y., 2024ab. Electric vehicle battery closed-loop supply chain pricing and carbon reduction decisions under the carbon cap-and-trade and reward-penalty policies. Process Saf Environ Prot. 192, 1467–82.

Yu, S., Hu, X., Li, L., & Chen, H. (2020). Does the development of renewable energy promote carbon reduction? Evidence from Chinese provinces. *Journal of Environmental Management, 268*, 110634.

Zhao, K., & Wu, L. (2024). Spatial disturbance grey model of nonlinear impact on carbon emissions under urbanization policies. *Applied Mathematical Modelling, 129*, 48–69.

Zhu, Y., Wu, S., Li, J., Jia, Q., Zhang, T., Zhang, X., Han, D., & Tan, Y. (2024). Towards a carbon-neutral community: Integrated renewable energy systems (IRES)–sources, storage, optimization, challenges, strategies and opportunities. *J Energy Storage., 83*, 110663.