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# Study on the spatio-temporal evolution characteristics and driving mechanism of China's carbon emissions

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The present study aims to explore the spatial and temporal changes and drivers of carbon emission patterns in China, with the aim of encouraging county-level carbon reduction policies in pursuit of sustainable development. To this end, we have studied the spatial disparities, spatio-temporal patterns, and evolution characteristics of carbon emissions using county-level carbon emissions data from China between 2002 and 2017. Additionally, we have comprehensively considered the dynamic impacts of both county-level and city-level environmental factors on carbon emissions based on an optimized hierarchical random forest model. The results show that the carbon emissions of China's counties have generally followed an upward trend before stabilizing. Notable characteristics include elevated carbon emissions in the northern regions and reduced carbon emissions in the southern areas. Additionally, there are higher carbon emissions in the eastern regions compared to lower emissions in the western and inland areas, with discernible local clustering patterns. These findings underscore the importance of tailoring the government's emission reduction strategy to address the phased variations in carbon emissions across different districts and counties. It is essential to emphasize the key role of major urban agglomerations and metropolitan areas in carbon emission reduction, while also addressing potential emission sources in the resource-rich, yet technologically disadvantaged, northwest region. Furthermore, improving energy efficiency through technological innovation should be the primary means of carbon emission reduction at the county level.

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## Introduction

With the massive consumption of fossil energy, global climate change has become one of the most concerning environmental challenges in the 21st century. Climate change is easy to trigger climate disasters, especially climate warming, which leads to the rise of sea levels, forest fires, an increase of extreme climate events (such as drought, flood, and dust storm), and the re-emergence of prehistoric viruses, posing a serious threat to low-lying areas and biodiversity, and the risk of global epidemic panic (Mora et al. 2018; Trisos et al. 2020; Xia and Zhang 2022). Greenhouse gas emissions are a major contributor to climate warming. Therefore, since the Kyoto Agreement came into effect, reducing greenhouse gas emissions and promoting a low-carbon economic development model have gradually attracted the attention of all countries. At the Conference of Parties (COP26) held in 2021, 137 countries signed the UN climate Convention and committed to achieving net zero emissions by 2050, accounting for more than 80% of global greenhouse gas emissions (Fuss et al. 2020).

As the world's largest emitter and the second-largest economy, China's urbanization and rapid industrial development are often accompanied by a large amount of energy consumption and $CO_2$ emissions. According to statistics, in 2018, China's $CO_2$ emissions reached 9.4Gt, accounting for 27.8% of the global total (British Petroleum 2019). This high dependence on energy consumption for economic growth is bound to put enormous pressure on the environment and eventually slow down China's urbanization process. Therefore, to address the challenges related to climate change and achieve sustainable economic development, China has set a series of $CO_2$ emission reduction targets. The National Climate Change Plan (2014–2020) issued in 2014 clearly states that by 2020, carbon dioxide emissions per unit GDP will decrease by 40–45% compared with 2005, and the proportion of non-fossil energy in primary energy consumption will increase by about 15% (Xu et al. 2016). Meanwhile, the Chinese government made a commitment in 2019 to peak carbon emissions by 2030 and strive to achieve carbon neutrality by 2060 (Cui et al. 2019). However, the realization of these goals requires not only the optimization of the overall energy structure and industrial transformation and upgrading at the national level, but also energy conservation and emission reduction measures and pollution control by governments at all levels.

A review of previous studies reveals that the spatial distribution of carbon emissions in China exhibits significant non-equilibrium and agglomeration effects. Carbon emissions and per capita carbon emissions in the eastern region, especially the eastern coastal cities, are significantly higher than those in the central and western regions. These cities are the center of energy consumption and transportation carbon emissions (Zheng and Tang 2023). An analysis of regional differences in China's carbon intensity across the west, central, east, and northeast regions indicates that spatial disparities primarily stem from within-region variations, with the central region contributing the most to overall differences and the western region's influence gradually increasing (Shen et al. 2023). In addition, Major cities such as Beijing, Shanghai, Tianjin, Chongqing, Chengdu and Suzhou have substantially higher carbon emissions than other cities, with obvious spatial spillover effect on the surrounding areas, and the changes among neighboring cities will have mutual influence (Liu et al. 2022; Liu et al. 2021).

To understand the reasons for spatial heterogeneity or aggregation of carbon emissions, evaluate the environmental impact, clarify carbon reduction paths, and develop low-carbon targets, studying the factors that affect carbon emissions has become an important research direction. Wang et al. (2022) established datasets of influencing factors such as resident population, GDP, the proportion of output value of secondary industry in GDP, the scale of construction land, and investment in fixed assets in 1042 counties of the Yangtze River Economic Belt in China. Based on these datasets, they thoroughly considered the spatial correlation between each influencing factor and carbon emissions. Using a geographical weighted regression model, they found that the population size is the key determinant of energy consumption in the study area, with population expansion being the leading contributor to carbon emission increases. Qi et al. (2022) took the county unit of Zhejiang Province as the research object and employed the spatial error STIRPAT model to reveal that the increase of per capita GDP and the proportion of secondary industry had positive and negative effects on the increase of carbon emissions, respectively. They also showed that the socio-economic factors affecting the carbon emissions of counties are spatially correlated. Qin et al. (2022) concluded that the imbalance of energy intensity, resource allocation and labor force are the main drivers of the imbalance of carbon emission distribution among provinces and regions in China, as determined through a spatio-temporal decomposition method. Liu et al. (2022) took 283 prefecture-level cities in China as samples and found that digital technology could have a positive impact on carbon emission reduction through "spillover effect" and reduce carbon emissions in local and surrounding cities. Summarizing the above studies, the environmental factors affecting carbon emissions can be decomposed into four aspects: population size, economic model, energy structure and means of reducing carbon emissions.

Considering the vast territory of China, there are significant differences in resource endowment, industrial structure, economic development model, and environmental carrying capacity among different cities. It is necessary to clarify the spatial heterogeneity, evolution trend, and driving mechanism of carbon emissions in different regions, so as to formulate industrial, energy, and environmental protection policies according to local conditions. At present, the research on carbon emission generally takes "unitized" or "modular" regions as the target, most of them take the country, province, and city as the division unit, and a few are oriented to the county-level scale. The exploration of the spatio-temporal distribution pattern of carbon emissions in county units and the proposal of systematic emission reduction measures are not only the extension of the existing research on carbon emissions at a finer granularity but also lay the foundation for further clarifying the spatial relationship between economic, energy, population and other social factors and carbon emissions. At the same time, because it is difficult to refine the night light data and energy consumption data to the county scale, the research on the driving mechanism of carbon emission spatial differentiation cannot cover all the influencing factors, and thus cannot provide help for the development of carbon emission policies at the county level.

In this context, we took the total carbon emissions of 2877 county units and 371 city units in China as the research object. Based on spatial autocorrelation analysis and standard deviation ellipse, we refined the spatial and temporal distribution pattern and evolution trend of carbon emissions at the county scale. To further collect the county-level or city-level influencing factor data of population, economic model, economic model, energy structure and carbon reduction means, the multi-level random forest (RF) model is used to quantify the nonlinear impact of environmental factors on carbon emissions and reveal the driving mechanism of carbon emissions spatial differentiation. Relevant studies have enriched the understanding of the differences in China's carbon emissions under the demand of multi-spatial scale analysis, and provided regionally targeted scientific energy conservation and emission reduction measures and pollution control means for the realization of the "double carbon" goal.

**Table 1 Descriptive statistics and correlation explanation of potential influencing factors of carbon emissions (multi-year average value).**

| Influencing factors | | Min | Max | Mean | Std | Pearson correlation |
|---|---|---|---|---|---|---|
| county-level | TP ($10^5$) | 1 | 371.09 | 48.03 | 34.17 | 0.40[a] |
| | AVPI ($10^8$ ¥) | 0.01 | 75.53 | 12.54 | 12.87 | 0.23[a] |
| | AVSI ($10^8$ ¥) | 0.22 | 2548.38 | 58.67 | 100.44 | 0.54[a] |
| | EC (GWh) | 7.20 | 34609.86 | 1208.91 | 1557.09 | 0.74[a] |
| | NL (nW/cm2/sr) | 0 | 63.01 | 8.96 | 13.94 | 0.29[a] |
| | CSTV (MT) | 0 | 116.99 | 3.91 | 5.48 | −0.07[a] |
| city-level | NIES | 0 | 11523.50 | 628.62 | 1096.23 | 0.74[a] |
| | EC (GWh) | 12.63 | 67992.01 | 9374.77 | 9821.54 | 0.80[a] |
| | NL (nW/cm2/sr) | 0 | 56.71 | 5.06 | 7.54 | 0.43[a] |
| | TISIE | 0 | 100 | 39.62 | 31.83 | 0.53[a] |

[a]means 1% significance level.

This paper is organized as follows: Section 2 presents the methods and data collection techniques employed in the research. In Section 3, we delve into the results, highlighting the spatial disparities, spatio-temporal patterns, and evolution characteristics of carbon emissions. Section 4 provides a discussion on the implications of our findings, particularly summarizing the key takeaways and suggesting directions for future research.

## Data and methodology

**Data**. Previous studies have relied on published energy use data to calculate county-level carbon dioxide, but because county-level energy use information is often missing, estimated carbon dioxide emissions are limited by study area and study duration. Based on the above considerations, this paper adopts the carbon emission data at the county and city levels in the CEADs database (www.ceads.net). The database, jointly established by Chinese, British, American and European research institutes, presents the latest research results of China's multi-scale energy, carbon emissions and socio-economic accounting inventory, including sub-databases such as energy inventory, carbon dioxide inventory, industrial process carbon inventory, emission factors and input-output tables (Chen et al. 2020). Multi-scale and long time series (1997–2015) of national, provincial and urban energy and $CO_2$ emission data are provided.

Summarizing previous studies (Liu et al. 2022; Qi et al. 2022; Qin et al. 2022; Wang et al. 2022), the potential influencing factors of carbon emissions are selected based on the following four aspects: population size (total population (TP)), economic model (added value of primary industry(AVPI), added value of secondary industry (AVSI), the number of industrial enterprises above the scale (NIES), Energy structure (electricity consumption (EC)), average value of nighttime light data (NL) and means of reducing carbon emissions (carbon sequestration value of terrestrial vegetation (CSTV), the total index score of innovation and entrepreneurship (TISIE).

Among them, County-level impact indicators include CSTV, EC, NL, AVPI, AVSI, and TP, while city-level impact indicators encompass NIES, EC, NL, and TISIE. It is noteworthy that, CSTV is also obtained from CEADs database; TISIE is obtained from Enterprise Big Data Research Center of Peking University (https://www.cer.pku.edu.cn/); EC (Chen et al. 2022) and NL data (Y Wu et al. 2022) are obtained by summarizing the original 1 km*1 km resolution raster data according to county-level and city-level administrative units; Additionally, AVPI, AVSI, TP, and NIES are all obtained from China Statistical Yearbook. Table 1 shows the descriptive statistics and correlation analysis results of the multi-year average values of the potential influencing factors of carbon emissions from 2002 to 2017.

**Research method**. To comprehensively examine the geographical differences and trends of carbon emissions in China, we utilize spatial autocorrelation to describe the overall spatial distribution pattern and local clustering of carbon emissions. Subsequently, the standard deviation ellipse characterizes the spatial features of China's carbon emissions, including the trend of center of gravity migration, dispersion, and directional trends. Finally, we capture the complex nonlinear relationship between carbon emissions and county-level and city-level influences through an improved hierarchical RF model.

Spatial autocorrelation reflects the correlation degree between an attribute value on a unit in the study area and the same attribute value on the adjacent unit, which can be divided into global spatial autocorrelation and local spatial autocorrelation. Global spatial autocorrelation reflects the aggregation of a phenomenon based on the overall spatial distribution. Global Moran's $I$ is used to measure global spatial autocorrelation, and the formula is as follows:

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

where, $n$ represents the number of spatial units; $x_i$ and $x_j$ represents the attribute values of spatial objects $i$ and $j$ respectively; $W_{ij}$ is the spatial weight matrix; represents the adjacency relationship between spatial objects $i$ and $j$.

Local spatial autocorrelation is used to analyze the correlation degree between a spatial element and its neighbors, and to determine the spatial hot areas or high incidence areas of the attribute values of spatial objects. The calculation formula is as follows:

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

Where, $x_i$ and $x_j$ respectively represent the attribute values of the unit $i$ and $j$, and $W_{ij}$ is the spatial weight matrices. When the attribute value of a spatial unit is similar to that of its neighbors, the corresponding value $I_i$ is positive; when the attribute value of a spatial unit is different from that of its neighbors, the corresponding value $I_i$ is negative.

Standard deviation ellipse is a common spatial statistical technique to measure the distribution form of geographic elements, which can reflect the overall dominant distribution direction of spatial elements and the dispersion degree of each direction (Gao et al. 2022). By applying the standard deviation ellipse, we can identify the concentration and direction of carbon emissions, which aids in understanding regional disparities and informing targeted policy interventions. The center of standard deviation ellipse can be expressed as below:

$$\bar{x} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}; \bar{y} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \quad (3)$$

Where $\bar{x}$ and $\bar{y}$ are longitude and latitude coordinates of the incidence center of lung cancer in Henan; $n$ is the total number of districts and counties; $x_i$ and $y_i$ are the central longitude and latitude coordinates of the counties $i$; and $w_i$ is the incidence rate of lung cancer in space unit $i$.

We capture the complex nonlinear relationship between carbon emissions and various factors at different spatial scales (i.e., county and city levels) through the Hierarchy RF Model. The hierarchical structure of the model accounts for the nested nature of the data, which enables us to simultaneously analyze the effects of factors at multiple levels. The model has been improved based on the hierarchical linear model (HLM), which is a model that considers the interaction between data within a group. It not only takes into account the influence of micro independent variables on dependent variables, but also considers the interaction between macro independent variables and dependent variables, overcoming the tendency of homogeneity within a group among nested data. The HLM formula adopted in this study is as follows:

The first layer:

$$y\_carbon = \varepsilon_1 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 \quad (4)$$

The second layer:

$$\beta_2 = f_7 x_7 + \varepsilon_2 \quad (5)$$

$$\beta_3 = f_8 x_8 + f_9 x_9 + \varepsilon_3 \quad (6)$$

$$\beta_5 = f_{10} x_{10} + \varepsilon_4 \quad (7)$$

The factorization is as follows:

$$\begin{aligned} y\_carbon = {} & \varepsilon_1 + \beta_1 x_1 + f_7 x_7 x_2 + \varepsilon_2 x_2 + f_8 x_8 x_3 + f_9 x_9 x_3 + \varepsilon_3 x_3 \\ & + \beta_4 x_4 + f_{10} x_{10} x_5 + + \varepsilon_4 x_5 + \beta_6 x_6 \end{aligned} \quad (8)$$

Where $y\_carbon$ represents the county-level carbon emissions, $\beta_i$ represents the regression coefficient of the $i$ th independent variable of the first layer, $\varepsilon_1$ represents the regression constant of the first layer, $f_i$ represents the regression coefficient of the $i$ th independent variable of the second layer, and $\varepsilon_2$ and $\varepsilon_3$ are the regression constants of the second layer.

In general, linear models can capture the linear relationship between variables, but if there is some nonlinear functional relationship between variables, or there is a strong hierarchical relationship between independent variables and dependent variables, it is difficult to use linear models to achieve effective data fitting. At the same time, the HLM model can judge the positive and negative effects of each independent variable on carbon emissions, but it cannot quantify the impact degree of each variable on carbon emissions. Based on the above two considerations, this paper uses RF to improve HLM. RF is a set model based on decision trees. In regression experiments, RF integrates the results of multiple different decision trees by "bagging" method, which not only achieves the purpose of nonlinear modeling but also weakens the influence of overfitting of a single decision tree. In addition, the increment of mean square error can be used to calculate the importance degree of self-variables.

## Results

**Spatial distribution pattern and spatial-temporal evolution of carbon emissions at the county level**. From 2002 to 2017, the total carbon emissions of all districts and counties in China showed an overall upward trend (Fig. 1), and the spatial distribution gradually became stable, with obvious characteristics of higher carbon emissions in the east and lower carbon emissions in the west, higher carbon emissions in the north and lower carbon emissions in the south, higher carbon emissions in the coastal areas and lower carbon emissions in the inland areas, and local agglomeration. Northern distribution with many industries in China, such as the three northeastern provinces, Inner Mongolia, Hebei, and Shandong provinces, the city industrial development mainly depends on the resources superiority, energy consumption is given priority to coal, urban development is highly dependent on carbon-intensive industries, this kind of resource-oriented extensive economic development mode led to the northern city of carbon emissions is generally on the high side.

When faced with the problem of resource depletion, an economic downturn will occur, which is the main reason why the increase of carbon emissions in Northeast China, a traditional industrial base, has decreased in recent years. In addition to the agglomerations in coastal urban clusters and industrial bases such as the Beijing-Tianjin-Hebei region, Shandong Peninsula urban cluster, Yangtze River Delta region, and Pearl River Delta region, the carbon emissions of provincial capital cities and their adjacent counties are also significantly higher than those of other regions in the province, indicating a clear "core-edge" pattern in the distribution of carbon emissions within each province. Therefore, accelerating industrial transformation and low-carbon development in economically developed areas is of great significance to achieve China's overall emission reduction target and drive the green and sustainable development of surrounding cities.

To further realize the quantitative evaluation of carbon emissions in China, we describe the overall spatial distribution of carbon emissions and the clustering or dispersion of local spatial distribution based on global Moran's $I$ and local LISA clustering graphs, so as to reflect the spatial clustering characteristics of carbon emissions distribution. The global Moran's I and corresponding significance test results of China's carbon emissions in 2002, 2007, 2012, and 2017 are shown in Table 2. The Moran's $I$ of carbon emissions in China's counties were all greater than 2, and the $Z$ value was greater than 1.96, indicating that they passed the significance test at the level of 99% and were statistically significant. The overall distribution of carbon emissions in geographical space showed significant spatial aggregation rather than random dispersion. At the same time, Moran's $I$ showed an inverted "U" -shaped trend, increasing from 0.299 in 2002 to 0.338 in 2007, and then continuously decreasing to 0.322 in 2017. This indicates that the agglomeration level of carbon emissions in China's counties increased first and then decreased, and gradually became stable in the later stage.

Based on the global spatial autocorrelation analysis, the LISA diagram was further used to analyze the local spatial agglomeration and dispersion of carbon emissions in counties (Fig. 2), and it was found that there were obvious aggregation areas in the whole study period. On the whole, the spatial clustering pattern of carbon emissions in counties was dominated by high clustering and low clustering, and the number of districts and counties with high clustering gradually increased, while the number of districts and counties with low and low clustering constantly decreased. In 2002, the high cluster areas were mainly distributed in the Bohai Rim economic circle (Beijing-Tianjin-Hebei region, central and southern Liaoning region and Shandong Peninsula urban agglomeration), Yangtze River Delta region, Pearl River Delta region, and Changchun - Shenyang region, all of which are important light or heavy industry bases in China, with typical characteristics of high energy consumption, high emissions, and clustering of workers.

As time went by, especially under the influence of the decline of the pillar industrial industry in Northeast China and the rise of

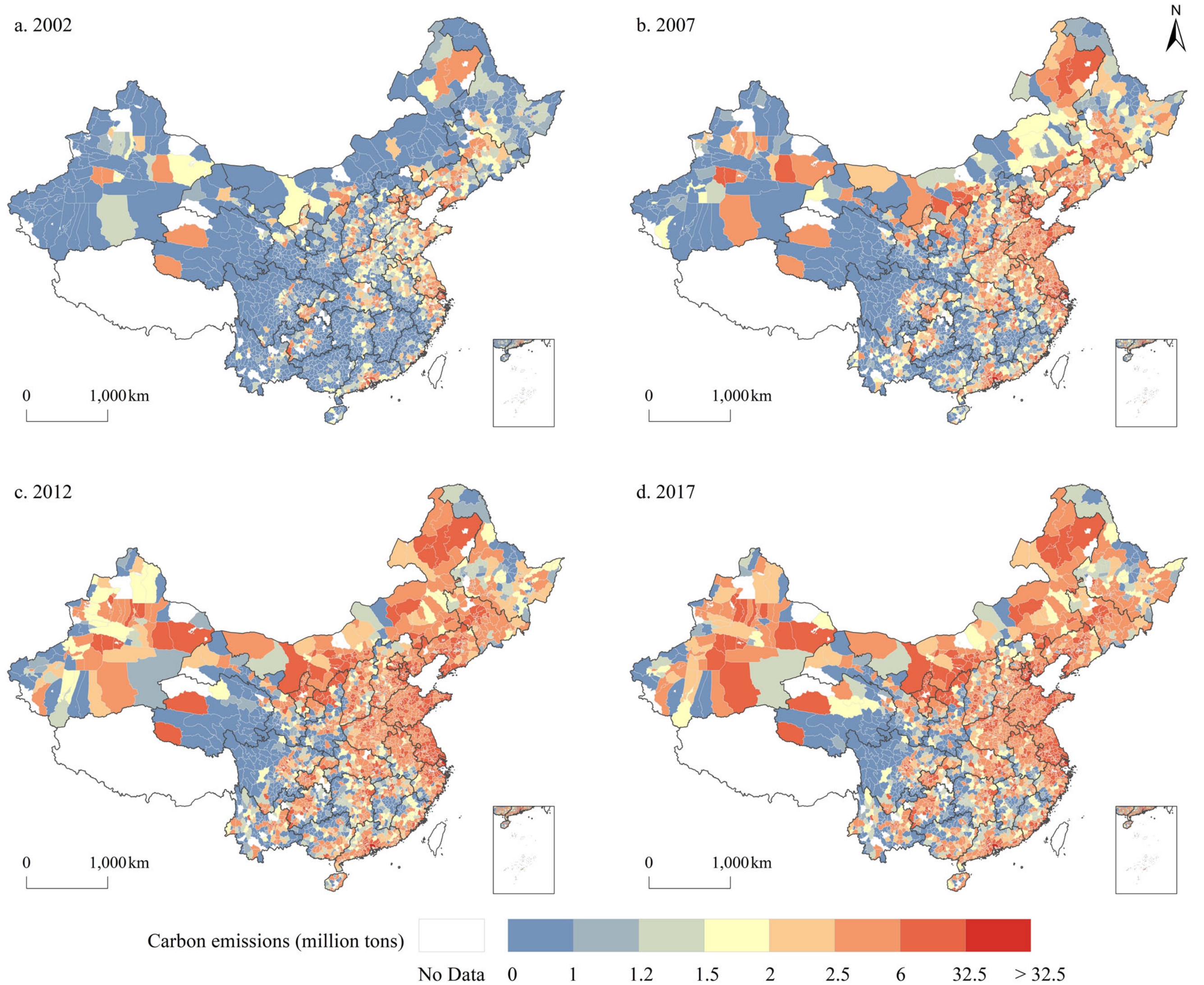


**Fig. 1 Spatial and temporal patterns of carbon emissions at the county level in China for the years.** **a** 2002, **b** 2007, **c** 2012, and **d** 2017.

**Table 2 Moran's I analysis results of China's global carbon emissions from 2002 to 2017.**

| Year | Moran's I | Z | P | Spatial pattern |
|---|---|---|---|---|
| 2002 | 0.299 | 27.751 | 0.01 | Cluster |
| 2007 | 0.338 | 32.423 | 0.01 | Cluster |
| 2012 | 0.326 | 31.545 | 0.01 | Cluster |
| 2017 | 0.322 | 29.446 | 0.01 | Cluster |

the industry in Northwest China, the original high-altitude agglomeration areas in the central and southern Liao, Changchun and Shenyang disappeared, and the new high-altitude agglomeration areas in the northern and central Inner Mongolia, Ningxia, and southern Xinjiang began to appear in the later period. The high-concentration area has an obvious tendency to move to the west. The low-concentration areas were relatively concentrated in Sichuan, Chongqing, Hunan, and Jiangxi during the study period. The low and low-concentration areas in the west of China gradually disappeared with the increase of high-concentration areas nearby. It is foreseeable that the energy consumption level in Northwest China increases synchronously with the urban development level, but the energy utilization and carbon reduction measures have a lag compared with the developed coastal cities, and it may become a major carbon emission province in China for a long time in the future.

Based on the preliminary identification of the spatial and temporal distribution characteristics of carbon emissions in China, it is of great significance to scientifically identify the evolution characteristics, change trend, and development law of the spatial pattern of carbon emissions, so as to clarify the focus of the next step of emission reduction work for relevant departments and cooperate with local governments to formulate scientific strategies for energy conservation and sustainable development. To this end, we used the barycentric standard deviation ellipse to quantitatively explain the centrality, directionality, and dispersion of the spatial and temporal distribution of carbon emissions in China's counties (Fig. 3). From 2002 to 2017, the standard deviation ellipses were basically distributed in central and eastern China, showing a "northeast to southwest" spatial distribution pattern. Huaiyang, Taikang, Yanling, and Weidu counties were found in the Huaiyang, Huaiyang, Taikang, Yanling, and Weidu counties. During the 15 years, the center of gravity generally moved to the northwest, and the distances moved were 25.79 km, 66.90 km, and 46.09 km every five years. From 2002 to 2007, it moved to the north obviously, and from 2007 to 2017, it mainly moved to the west.

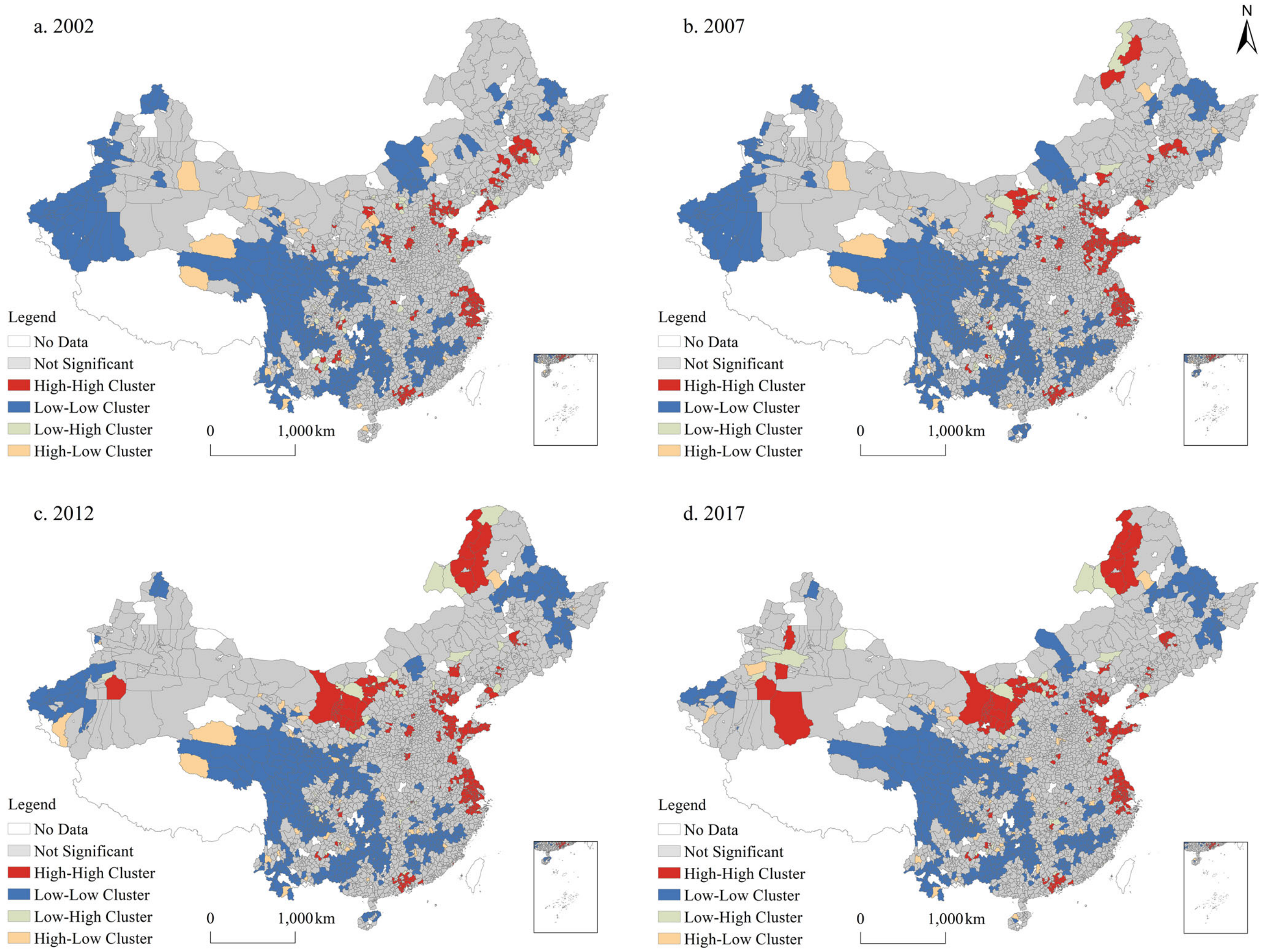


**Fig. 2 LISA agglomeration of carbon emissions at the county level in China for the years. a** 2002, **b** 2007, **c** 2012, and **d** 2017.

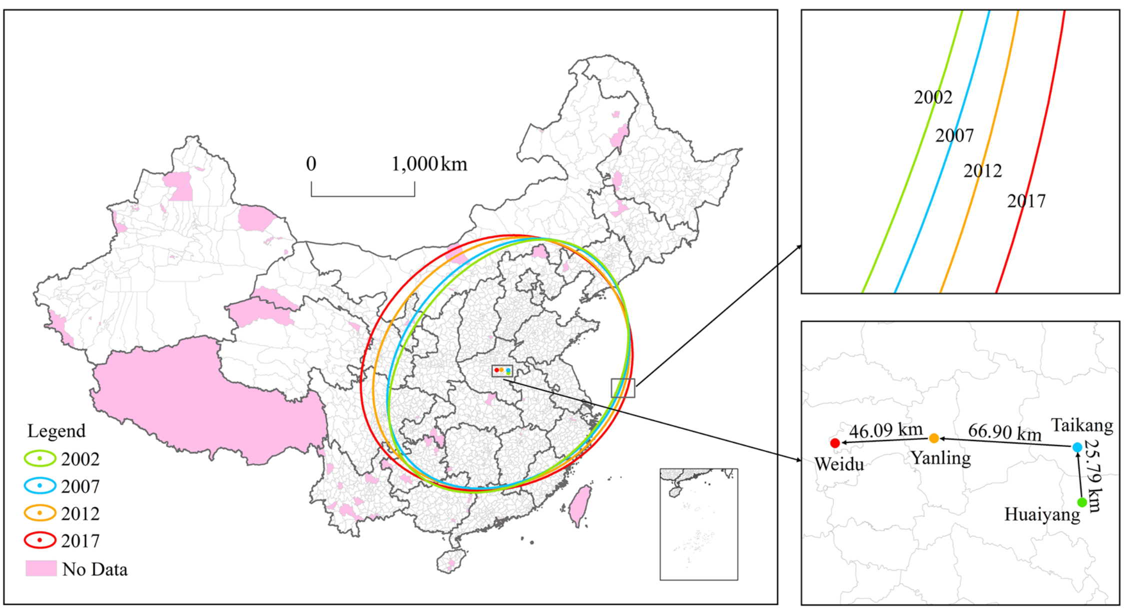


**Fig. 3** Gravity center and directional distribution of carbon emissions at the county level in China from 2002 to 2017.


**Fig. 4** Contribution rate and evaluation index of environmental factors to carbon emission.

This spatial distribution and moving trend of carbon emission centers at the county level in China may be related to the following reasons. First of all, effective control measures have been taken in areas with high carbon emissions, such as industrial restructuring and environmental pollution control in the Beijing-Tianjin-Hebei region. Secondly, relying on the regional advantages of linking east and west, the central region began to implement the strategy of the rise of the central region. The local government and enterprises actively developed industries and promoted industrial undertakings. In recent years, energy consumption and economic growth maintained a relatively high level, which greatly promoted the growth of carbon emissions. Finally, in the northeast old industrial base - gradually withdrawn from the historical stage, Xinjiang and Inner Mongolia as coal resources, China has to solve the problem of traffic inconvenience, as the coal chemical industry devastated the steady progress of the project, has become China's main coal production and coal chemical industry, carbon emission levels increased rapidly in recent years. All these conclusions indicate that while focusing on pollution control and emission reduction in developed cities, China should also pay more attention to the new energy-consuming provinces in northwest China, strive to promote the optimization of local industrial structure, and actively promote the clean production and low-carbon and efficient utilization of coal with the focus on reducing energy intensity.

**Impact of environmental factors on carbon emissions in China**. To further clarify the differences in the impact of environmental variables on carbon emissions with the change of time, we conducted a regression screening of county carbon emissions and environmental variables based on an improved hierarchical RF model, taking into account the interaction between city and county level independent variables (macro and micro, respectively). Due to the correlation between explanatory variables, the estimation of the regression model will be distorted or difficult to estimate accurately. Therefore, it is necessary to diagnose the collinearity of variables before using the model to avoid serious multicollinearity. Here, the variance inflation factor (VIF) was used to test the collinearity among variables. When VIF > 10, the variable was considered to have a strong collinearity relationship with other variables and was eliminated. The test results show that the VIF of all variables is less than five, that is, there is no multicollinearity among variables, which can be input into the model as explanatory variables. The results are shown in Fig. 4 and Table 2. Among them, the smaller RMSE, MAPE, and $R^2$ of the model are, the closer the predicted value of the model is to the real value, and the more accurately it can describe the mapping relationship between independent variables and dependent variables. Figure 4 shows that the range values of RMSE, MAPE, and $R^2$ are 0.47–1.87, 29.39–37.14%, and 0.71–0.85, respectively, with mean values of 1.11, 32.75%, and 0.79, respectively, indicating a high degree of accuracy of the model.

**Table 3 Average contribution rate of environmental factors to carbon emissions.**

| Environmental factor | Mean contribution rate |
|---|---|
| Total population | 0.074 |
| Night light | 0.107 |
| Power consumption | 0.157 |
| Added value of primary industry | 0.066 |
| Added value of secondary industry | 0.173 |
| Total index score | −0.064 |
| Carbon sequestration of vegetation | −0.009 |

From 2002 to 2017, the impact degree and direction of environmental factors affecting China's carbon emissions were different and in constant change. By analyzing the average contribution rate of environmental factors to carbon emissions (Table 3), total population, night light, power consumption, AVPI and AVSI drive carbon emissions. total index score and carbon sequestration of vegetation play a role in inhibiting carbon emissions. From the perspective of impact degree, AVSI has the highest contribution rate, followed by power consumption and night light, indicating that energy consumption and industrial structure are the main factors for the increase of carbon emissions in China. Considering the population size, energy consumption, industrial structure and carbon reduction means, the main conclusions are as follows.

(1) Population size effect. At present, there are two main views in the research focusing on the environmental impact of population aggregation. According to one view, excessive population concentration, while bringing high productivity, will accelerate resource consumption and produce a large amount of household waste, thereby destroying the self-purification capacity of the ecosystem and increasing environmental pollution and carbon emissions (Zhang et al. 2017). Another argument is that by accelerating industry transformation, and promoting technological innovation, increasing the proportion of service industry to form the development of the green energy-efficient model, and the high density and compact city spatial structure to some extent reduced the demand for private cars, there are population agglomeration increases with the environmental quality improvement of a win-win situation (Hong 2017). In this regard, Yi et al. conducted case studies and found that carbon emissions first increased and then decreased with the growth of the permanent population in big cities, showing an "inverted U-shaped" change trend (Zhou et al. 2022).

On the basis of these studies, we provide a developmental, global perspective on the impact of population size on carbon emissions. Affected by different levels of urban development, the driving ways of population aggregation on carbon emissions may also be different, but the contribution rate is always positive, indicating that the overall promoting effect is still dominant. In addition, the contribution rate fluctuates and decreases year by year, which means that with the improvement of urbanization level, especially the development of green technology innovation and public transportation, most Chinese cities have entered a benign development mode, and the positive feedback of population aggregation on carbon emission reduction is increasingly obvious.

(2) Energy consumption effect. From 1978 to 2021, China's total primary energy consumption increased by 9.18 times from 571 million tons of standard coal to 5.24 billion tons of standard coal. Among them, the proportion of non-renewable fuels (such as coal and oil) in energy consumption has been kept above 80% (NBSC 2021). Fossil energy consumption is the main source of carbon emissions. Previous studies to estimate $CO_2$ emissions at the county level usually rely on published primary energy use data (Chen et al. 2020), but rarely consider the relationship between secondary energy and carbon emissions. As a clean and efficient secondary energy source, electrification has always been considered the key to the low-carbon development of all industries and even the whole of society in the future (X Wu et al. 2022). However, EC plays a stable role in promoting carbon emissions (Fig. 4), and the carbon emissions related to electricity account for more than 40% of China's total carbon emissions (Wang and Xie 2015). The reason for this is related to the fact that the main form of power generation in China is thermal power. Therefore, the transformation and development of traditional thermal power are related to national energy security and people's livelihood, and it is also the obstacle of new energy consumption and energy storage that must be overcome to promote the rapid development of renewable energy under the "double carbon" goal.

(3) Economic structure effect. The economic structure is a complex system influenced by the labor force, capital, and technology under the geographical background of the regional system, resources, and culture. Therefore, the economic structure is characterized by similarities within regions and differences between regions, which is the main reason for the spatial heterogeneity of carbon emissions. There are differences in carbon emissions in different industries, and there is a long-term equilibrium relationship between economic (industrial) structure and carbon emissions, which is often regarded as the largest source of carbon emissions (Feng et al. 2018; Yu et al. 2018). Since the added value of the tertiary industry has a relatively weak impact on carbon intensity (Liu et al. 2018), and there is serious collinearity with the added value of the secondary industry, we only study the impact of the added value of the primary industry and the secondary industry on carbon emissions.

The primary industry includes agriculture, forestry, animal husbandry, and fishery. The contribution rate curve shows that the added value of the primary industry plays a role in promoting carbon emissions, but the contribution rate is decreasing. However, how to improve carbon emission efficiency without reducing crop yield and develop low-carbon crop production is still an effective means to mitigate global warming (H Wu et al. 2022). In the past, work on carbon emission nucleic acids from crop production has been carried out (Hillier et al. 2009). On this basis, the proposed measures such as tillage and irrigated farmland management (Lal 2004), fertilizer and pesticide upgrading (Zhang and Fang (2013)), and banning straw burning (Linquist et al. 2012) have strongly promoted the transition to low-carbon crop production.

The secondary industry consumes a large amount of energy for a long time and has low utilization efficiency of resources, resulting in a large number of pollutants (Yu and Liu 2020). In particular, regions rich in natural resources tend to give priority to the development of resource-based industries. While attracting more investment in physical and human capital, they further show a "crowding out effect" on industries with low energy consumption and a "lock-in effect" on industries with high energy consumption (Zheng et al. 2023). Such resource dependence will not only hinder industrial diversification but also affect the effect of industrial structure transformation on carbon emission reduction. Therefore, in the future, the transformation from heavy industry with high energy consumption to the light industry with low energy consumption, getting rid of resource-dependent industries, and the adjustment of internal industrial structure can reduce the energy consumption of the national economy.

(4) Carbon reduction means. At present, we believe that there are two main carbon emission reduction methods: one is to

promote industrial structure transformation and resource utilization efficiency through technological innovation; the other is to give full play to the carbon sequestration effect of vegetation through afforestation. The aggregate index score is an important index to evaluate the quality of innovation and entrepreneurship in a region by comprehensively considering the multi-dimensional data such as R&D funds, patents, and enterprise registrations. It has a significant inhibitory effect on carbon emissions in a region. With the development of technology, the traditional resource-dependent industries are gradually eliminated, and the leading industries begin to change from labor-intensive to technology-intensive and capital-intensive. Under the guidance of this trend, the demand structure and supply structure change, thus indirectly improving the region's energy structure and energy efficiency, and reducing carbon emissions.

Carbon sequestration by vegetation means that plants absorb large amounts of carbon dioxide and release oxygen during photosynthesis. Therefore, some people have suggested alleviating the pressure of carbon emission in cities by improving the natural photosynthetic rate, the carbon storage capacity of the soil, and the utilization rate of biological building materials, and putting the theory into practice, achieving an ideal emission reduction effect (Kuittinen et al. 2023). However, some people also believe that quantifying plant carbon sequestration is not important because the carbon absorbed by plants, especially crops, will decompose and return to the atmosphere after being eaten by humans and animals (Li et al. 2019). Although our study found that carbon sequestration by vegetation does not always show an obvious effect of inhibiting carbon emissions, increasing the urban green area is still a positive measure to optimize the living environment and curb carbon emissions.

## Conclusions and policy recommendations

Guided by the goals of carbon peaking and carbon neutrality, we analyzed the spatial and temporal distribution patterns of carbon emissions in China and their evolutionary trends and quantified the driving mechanisms of four environmental factors on the development of carbon emissions, namely, population size, energy structure, economic model and means of carbon reduction, based on a hierarchical RF model. The main findings are as follows:

(1) From 2002 to 2017, carbon emissions at the county level in China showed an upward trend, with obvious spatial differentiation. Overall, carbon emissions in northern counties were higher than those in southern counties, and carbon emissions in eastern coastal cities were higher than those in western and central cities. The carbon emission at the county level has a significant spatial agglomeration feature, and the carbon emission center of each province is concentrated in the provincial capital cities and the surrounding areas, showing a "core-periphery" distribution pattern. Spatial autocorrelation analysis showed that the aggregation level increased first and then decreased, and gradually tended to a strong aggregation state in the later stage. The high cluster is mainly distributed in the Bohai Economic circle, Yangtze River Delta, Pearl River Delta, and Changchun - Shenyang area, which are all important light or heavy industry bases in China, and the role of these regions in China's current and future carbon emission reduction cannot be ignored.

There are obvious spatial differences in China's carbon emissions. Therefore, the carbon emission reduction strategy must be adapted to local conditions, and under the premise of considering the unique characteristics and needs of different regions in China. Tailor-made, reasonable and efficient regional carbon emission reduction action plans should be developed. For example, the population and economy in the eastern coastal areas are highly concentrated, and the carbon trading system should be further improved and implemented, thereby promoting the green transformation of the economic model. As the main production base of grain and industrial raw materials in China, the central region should focus its carbon emission reduction on promoting concentrated and efficient use of land and solving the problem of extensive waste in land use. The western region should avoid the extensive development of industries with high carbon emissions such as oil and coal, and start from the adjustment of industrial structure and the optimization of energy utilization efficiency. In addition, due to the spatial spillover effect of carbon emissions, special attention should be paid to reducing the carbon emissions of provincial capital cities so that their carbon emissions can have a driving effect on surrounding areas. For industrial urban agglomerations with concentrated carbon emissions, a regional joint prevention and control working group should be established to coordinate and coordinate the implementation plan of carbon emission reduction in the region.

(2) Based on the preliminary identification of the spatial and temporal distribution characteristics of carbon emissions in China, we used standard deviation ellipses to explain the center of gravity and direction of the spatial and temporal evolution of carbon emissions in China's counties. From 2002 to 2017, the center of the standard deviation ellipse was always distributed in Henan Province and generally moved northwest. The main reasons for this phenomenon include the decline or transformation of the old industrial base, the rising strategy of central China, and the steady advancement of the project of the coal chemical industry moving west. Compared with existing studies focusing on high carbon emission areas such as northern China and eastern coastal urban agglomerations, we found that northwest China has gradually become a new energy-consuming province and may become the main source of carbon emissions in China in the future through the study of carbon emission center shift at the county level. Therefore, how to actively promote the optimization of local industrial structure and technological progress, and improve energy utilization efficiency is the hot direction of future emission reduction work.

To realize the low-carbon energy revolution in Northwest China, the key lies in two points. On the one hand, focus on breakthroughs in key traditional energy technology bottlenecks such as low-carbon, energy-saving, intelligence, and energy storage. The specific plan includes the promotion of clean and efficient utilization of coal technology, and the overall promotion of the flexibility improvement, ultra-low emission, heating and energy-saving transformation of existing coal-fired power units. As well as improving coal railway transportation capacity, accelerating the construction of national trunk oil and gas pipelines, intensively deploying and orderly promoting the optimization of coal production capacity structure, and continuously improving the quality of supply. On the other hand, it is necessary to continuously improve the utilization level of clean energy. The key measures focus on building a multi-energy and complementary clean energy base, and developing new clean energy such as geothermal energy and biomass energy according to local conditions. For example, focus on deserts, Gobi, and desert areas to accelerate the construction of large-scale wind power and photovoltaic bases, and orderly promote the construction of hydrogen energy infrastructure.

(3) Total index score and carbon sequestration of vegetation help curb carbon emissions at the county level, total population, night light, power consumption, AVPI, and AVSI have a significant positive relationship with carbon emissions. Among them, AVSI, power consumption, and night light have a much higher impact on carbon emissions than other factors. Considering the population scale, energy consumption, economic model and carbon reduction means, the reasonableness of energy consumption intensity and industrial structure is the key to

determine the carbon emission of a certain region. In addition, the formulation and implementation of carbon emission reduction policies should consider the phased differences in county development, and scientific and technological progress and the adjustment of socio-economic development structure are the keys to achieve overall carbon emission reduction.

Future priorities should include the following. First, scientifically and reasonably promoting population agglomeration in cities and towns, vigorously developing urban public transport, and increasing government public financial input to improve the greening rate can effectively promote the green and low-carbon development of districts and counties with high carbon emission levels. Second, strengthen the energy-saving transformation of thermal power facilities, control the scale of coal-fired power generation, rationally coordinate power production and economic development, and give full play to the effect of the power supply structure in limiting carbon emissions. Third, we should reduce the proportion of high-consumption and high-emission industries through technological innovation, optimize the energy consumption structure and other means to promote the transformation of resource-dependent areas and counties, and realize sustainable low-carbon development.

## Data availability

Data are available from the authors upon reasonable request.

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## Author contributions

Conceptualization, YX and YL; methodology, YL, RC and YM; formal analysis, YM, KL and CF; writing (original draft preparation), YL, RC, YM and YX; writing (review and editing), KL and YX; visualization, YL, RC and CF; supervision, YX and CF. All authors have read and agreed to the published version of the manuscript.

## Competing interests

The authors declare no competing interests.

## Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors. Ethical approval is not required.

## Informed Consent

This article does not contain any studies with human participants or animals performed by any of the authors. Informed consent is not applicable.

## Additional information

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