



Spatial–temporal evolution of the allometric growth between economic scale and carbon emissions in China’s cities and its driving mechanism

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Abstract

Exploring the relationship between economic development and carbon emissions is a hot issue of concern to academia. Taking Chinese cities as the research object, this study constructed an allometric growth model of economic scale and carbon emissions to analyze the spatial–temporal evolution of their allometric growth from 2000 to 2017. Additionally, the geographical detector model was used to reveal the driving mechanism of allometric growth. The findings were as follows. (1) The spatial–temporal patterns of economic scale and carbon emissions were dominated by hot spots. Additionally, their size distribution was in an equilibrium stage. (2) The gap between the economic growth rate of Chinese cities and the growth rate of carbon emissions grew, reflecting the remarkable achievements in carbon emission reduction in Chinese cities as a whole. The scaling exponent declined from east to the west during 2000–2008, but showed the opposite trend during 2009–2017. The proportion of cities with negative allometric growth in the sample cities increased from 76.49 to 97.86%. (3) The influence of city investment intensity, energy utilization efficiency, technological development level, social consumption level, fiscal investment level and economic development level on allometric growth gradually decreases. These factors were also the main factors affecting the spatial–temporal heterogeneity of allometric growth. (4) The impact of various factors had a synergetic enhancement effect. These factors can be classified as economic factors, environmental factors and a combination of them. Under the nonlinear coupling of multiple factors, a spatially differentiated pattern of allometric growth was formed.

Keywords Economic scale · Carbon emissions · Allometric growth · Nonlinear coupling · China

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1 Introduction

Since the beginning of the twenty-first century, China's economy has been developing rapidly. By 2010, China overtook Japan to become the world's second largest economy. As early as 2006, China's carbon emissions surpassed the USA to become the world's largest carbon emitter (Yang et al., 2019; Zhang et al., 2020). In 2020, China's gross domestic product (GDP) accounted for approximately 17.4% of the world's GDP, but its carbon emissions accounted for 30.7% of the world's GDP (BP, 2021), reflecting that China's carbon emissions per unit of GDP are much higher than the world average. At the Seventy-Fifth Session of the United Nations General Assembly in September 2020, China proposed to have a CO₂ emissions peak before 2030 and achieve carbon neutrality before 2060 (The Chinese Foreign Ministry, 2020). Additionally, at the Global Climate Ambition Summit in December 2020, China set a goal of reducing CO₂ emissions per unit of GDP by more than 65% in 2030 compared with 2005 (Jiang et al., 2022; Sun et al., 2022). As China's economy enters a stage of high-quality development, how to reduce the growth rate of carbon emissions and even total carbon emissions while maintaining sustained economic growth is a serious issue facing the future. It may affect the sustainable economic and social development of China during the 14th Five-Year Plan period and beyond. Therefore, clarifying the relationship between economic development and carbon emissions of Chinese cities can provide a basis for formulating scientific and reasonable emission reduction policies, as well as theoretical and practical guidance for achieving carbon peaks and carbon neutrality. Therefore, taking China's city economic scale and carbon emissions as the research object, this study attempted to construct an allometric growth model and reveal the driving mechanism of allometric growth. Scientifically and accurately analyzing the temporal and spatial changes in the relationship between economic development and carbon emissions in different regions is the key to formulating carbon emission reduction regulation policies in line with the region's own development stage and reasonably promoting the process of carbon emission reduction in each region to provide a reference for other countries and regions.

The relationship between economic development and environmental protection is an important focus of regional economics, environmental economics and economic geography (Kube et al., 2018; Moutinho et al., 2017; Tang et al., 2022; Wang et al., 2022). International research on the relationship between economic growth and environmental pollution began in the 1990s. Investigating space pollutants and regional income levels, scholars find that economic growth and pollution levels exhibit an inverted U-shaped relationship (Grossman & Krueger, 1991, 1995). Panyotou (1993) defines such a relationship as the "environmental Kuznets curve" (EKC). Since then, the EKC has gradually become a classic theory to study the relationship between economic development and environmental quality, which has led many scholars to conduct a large number of empirical studies. With the intensification of global changes, greenhouse gas emissions represented by CO₂ have gradually become a hot issue of global concern. The academic community has also turned the research on environmental pollution to carbon emissions. Relevant studies have focused on the estimation and accounting of total carbon emissions (Tuesta et al., 2020; Wegener et al., 2019), the spatial differentiation of carbon emission efficiency (Fan et al., 2016; Gregg et al., 2009), the factors influencing carbon emissions and mechanisms (Bai et al., 2020; Zhang & Zhao, 2018), and carbon emission reduction strategies and policy simulations (Eichner & Pethig, 2009; Khastar et al., 2020; Khan et al., 2022).

With sustained and rapid economic development, the world's energy consumption has risen sharply, and carbon emissions have also exhibited a rapid upward trend. In this

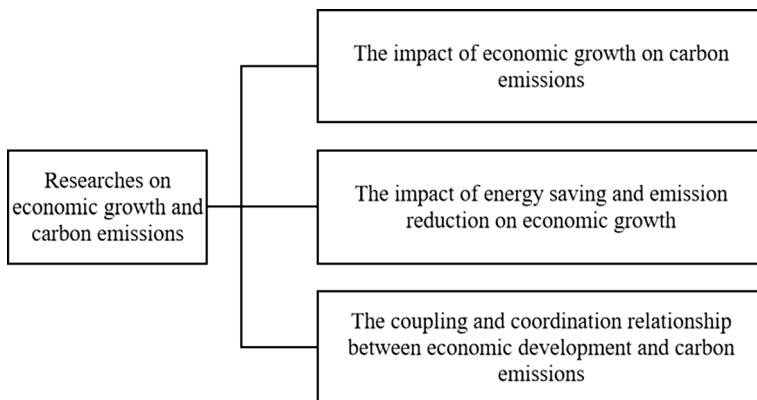


Fig. 1 Main research contents of the relationship between economic growth and carbon emissions

context, many governments have signed the *Kyoto Protocol*, which aims to curb the global warming process through joint efforts of the world. The contradiction between rapid economic development and the continuous growth of carbon emissions has become increasingly prominent and the main bottleneck restricting the sustainable development of the economy and society. Current studies on economic growth and carbon emissions mainly focus on the following (Fig. 1). (1) The impact of economic growth on carbon emissions (Alam et al., 2016; Lu, 2018). Several indicators need to be selected to measure the regional economic growth mode, then construct econometric models of the economic growth mode and carbon emissions, and finally analyze the impact of each indicator on regional carbon emissions. For example, Zhang et al. (2022) used panel quantile regression to reveal the impact of information and communication technology on carbon emissions in developing countries. (2) The impact of energy saving and emission reduction on economic growth (Feichtinger et al., 2005; Dietz & Venmans, 2019). Most researchers recognize that carbon emissions are an important factor affecting economic growth. Therefore, relevant studies often use general equilibrium models, regression models, data envelopment analysis (DEA) and other methods to measure the impact of carbon emission reduction target constraints on economic growth. For example, Li and Wang (2022) use nonlinear analysis methods such as the spatial Dubin model (SDM) and panel threshold model (PTM) to reveal the impact of China's prefecture-level digital economy on carbon emission reduction. (3) The coupling and coordination relationship between economic development and carbon emissions (Song et al., 2018; Zhao et al., 2015). Regarding economic development and carbon emissions as two relatively independent aspects and constructing the EKC model, logarithmic mean divisia index (LMDI) model, decoupling model and the coupling coordination degree model, researchers revealed the relationship and interaction mechanism between economic development and carbon emissions. For example, Liu (2020) uses the EKC model to examine the relationship between carbon dioxide emissions and regional economic growth.

The above-mentioned studies provide rich viewpoints and diversified perspectives for the scientific understanding of the relationship between economic development and carbon emissions, but there are still some shortcomings that can be further expanded. For instance, (1) only the relationship between economic development and carbon emissions is analyzed by establishing models, ignoring the relationship between their growth rates

and rarely investigating the impact mechanism of the relationship between them; (2) the EKC, LMDI and other models are mainly used to examine the single effect of economic development on carbon emissions, focusing on analyzing the time series data, but lacking the consideration of the impact of carbon emissions on economic development and ignoring the spatial characteristics of the relationship between them; and (3) in terms of research scale, most start from the levels of provinces, urban agglomerations and specific regions. However, research from the city scale is insufficient.

Allometric growth originated from biology and gradually expanded to other fields, such as physics, computer science, geography, economics and sociology (Batty et al., 2008; Lee, 1989). The allometric relationship is usually defined as the constant proportional relationship between the local relative growth rate of the system and the whole system or another local relative growth rate of the system (Chen, 2016; Marshall, 2007). Allometric growth can integrate spatial distribution, hierarchical structure and dynamic evolution, providing new ideas and methods for urban and regional research. Based on the above analysis, we considered the economic scale and carbon emissions of Chinese cities as the research object. The relevant data of Chinese cities from 2000 to 2017 were used to construct an allometric growth model of economic scale and carbon emissions to analyze the spatial–temporal evolution characteristics of their allometric growth. We found that the economic scale–carbon emissions allometric growth of Chinese cities was generally in a stage in which the growth rate of carbon emissions was lower than the economic growth rate, and most cities are about to enter the stage of carbon emissions contraction. Additionally, the geographical detector model is employed to examine the driving mechanism of allometric growth. We found that city investment intensity, energy utilization efficiency, technological development level, social consumption level, fiscal investment level and economic development level were the main factors that affect the spatial heterogeneity of allometric growth, and the effects of each factor have a synergistic enhancement effect.

The academic contributions of this article and the expansion of existing research were mainly reflected in the following. First, the law of allometric growth is one of the basic laws of city geography. The relative growth relationship between economic scale and carbon emissions is explored by constructing an allometric growth model herein, which organically links the spatial distribution, hierarchical structure and dynamic evolution, so that we make a deeper understanding of the growth relationship between economic scale and carbon emissions. This provides a new perspective for related research on the carbon emissions of cities. Second, China, the country with the most carbon emissions in the world, is selected as the research area. The economic scale and carbon emissions of 285 cities in China from 2000 to 2017 are taken as the main research objects. This has a certain degree of representativeness and can more comprehensively explore the development relationship between economic scale and carbon emissions. Third, because there are many factors that affect the allometric growth relationship between economic scale and carbon emissions and there may be interactions between these factors, the geographical detector model was employed to analyze the influencing factors. It can detect not only the influence of a single factor, but also the interactive influence of multiple factors, which greatly enriches the research content of the relationship between economic scale and carbon emissions.

The rest of the article is organized as follows. Section 2 describes the data sources and research methods. Section 3 analyzes the evolutionary distribution characteristics of economic scale and carbon emissions. Section 4 investigates the allometric growth characteristics of economic scale and carbon emissions. Section 5 explores the factors influencing the allometric growth of economic scale and carbon emissions. Section 6 summarizes the

influencing mechanism of allometric growth. Section 7 is the discussion, and Sect. 8 summarizes the paper.

2 Data sources and research methods

2.1 Data sources

This article takes a city as a basic research unit and defines the scope of a city by the administrative boundaries of the city. The administrative division was based on 2017 (see “Appendix Fig. 7”), and then, the data are merged accordingly. Due to the lack of relevant data of some cities, 285 cities were selected, including 4 municipalities directly under the central government and 281 prefecture-level cities.¹ The study period was 2000–2017. In 2017, the 285 cities had a total population of 1.287 billion, accounting for 92.58% of the total population in mainland China. Among them, 13 cities had a population of over 10 million, and 88 had a population of over 5 million. The economic scale of a city is represented by the GDP of the city. The carbon emission data are derived from the study by Chen et al. (2020a). Cities’ socioeconomic data were derived from the 2001–2018 provincial and municipal statistical yearbooks, *China City Statistical Yearbook (2001–2018)* (NBSC, 2001–2018a), *China Statistical Yearbook for Regional Economy (2001–2018)* (NBSC, 2001–2018b) and *China Urban Construction Statistical Yearbook (2001–2018)* (MHURDC, 2001–2018).

2.2 Selection of driving factors

According to the relevant theories of regional economics and urban geography and combined with the existing research on allometric growth and urbanization levels (Moussiopoulos et al., 2010; Lang et al., 2019; Alix-Garcia & Sellars, 2020), this article selects 12 indicators, i.e., the economic development level, industrial development level, fiscal investment level, city investment intensity, social consumption level, technological development level, urban development level, land use level, transportation development level, opening up level, urban greening level and energy utilization efficiency, to construct the driving factor system for the allometric growth coefficient of the economic scale and carbon emissions of China’s cities (see Table 1).

2.3 Research methods

Starting from the distribution characteristics of economic scale and carbon emissions, this study used spatial–temporal hot spot analysis to reveal their local spatial characteristics and the rank-scale rule to analyze their overall distribution characteristics. Additionally, an allometric growth model was established to explore their allometric growth characteristics, and finally, the driving factors affecting allometric growth are investigated with a geographical detector (Fig. 2).

¹ 12 prefecture-level cities established after 2000 are removed. Additionally, due to the lack of carbon emission data in Lhasa, it is also removed.

Table 1 Driving factors of the allometric growth coefficient

Driving factor	Expressed by	Unit
Economic development level (X1)	GDP/permanent population	Yuan/person
Industrial development level (X2)	Industrial added value/GDP	%
Fiscal investment level (X3)	Local fiscal expenditure/GDP	%
City investment intensity (X4)	Fixed-asset investment/GDP	%
Social consumption level (X5)	Total retail sales of consumer goods/permanent population	Yuan/person
Technological development level (X6)	Total number of patents granted/permanent population	Piece/10000 persons
Urban development level (X7)	Urban population/permanent population	%
Land use level (X8)	Urban built-up area/Urban area	%
Transportation development level (X9)	Number of private car ownership/permanent population	Set/1000 persons
Opening up level (X10)	(Imports + exports)/GDP	%
Urban greening level (X11)	Urban green coverage/Urban built-up area	%
Energy utilization efficiency (X12)	Total electricity consumption/GDP	Kilowatt-hour/10000 yuan

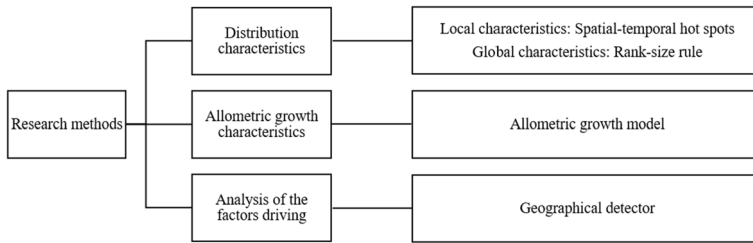


Fig. 2 Main research methods of the paper

2.3.1 Analysis of spatial–temporal hot spots

Space time pattern mining was introduced to identify the spatial–temporal evolution pattern of the economic scale and carbon emissions. It primarily included the creation of space–time cubes and the analysis of emerging spatial–temporal hot spots. The former was used to obtain point datasets and build a multidimensional cube data structure (NetCDF) for analysis. The latter can calculate the Getis–Ord G_i^* statistics of each cube bin through the neighborhood distance and time step parameter values. Then, the Mann–Kendall trend test was adopted to evaluate the trends of the hot and cold spots. Finally, the hot and cold spot patterns can be classified (Huang et al., 2015; Mo et al., 2020).

2.3.2 Rank-size rule

The rank-size rule was used to examine the rank-size distribution of specific factors in a region based on the factor scale and factor scale rank (Tan, 2017). It is the most extensive and classic method of studying the rank system (Modica, 2017). Currently, it has been widely applied to research on the size structure and difference of the floating population, tourist flow, traffic flow and resource flow. Therefore, we introduced the rank-size rule and fractal theory to explore the rank-size distribution and fractal characteristics of the economic scale and carbon emissions of China’s cities. The basic form of the rank-size distribution and its logarithmic form are as follows (Reggiani & Nijkamp, 2015):

$$P_i = P_1 \times R_i^{-q} \quad (1)$$

$$\ln P_i = \ln P_1 - q \ln R_i \quad (2)$$

where P_i is the economic scale or carbon emissions of city i ; P_1 is the economic scale or carbon emissions of the largest city; R_i is the rank of city i ; and q is the Zipf exponent. The Zipf exponent is the reciprocal of the Hausdorff exponent. When $q = 1$, the ratio of the economic scale or carbon emissions of the largest city to the smallest city is just the total number of cities in the region. Carroll (1982) calls this pattern a constrained sequence-scale distribution. The Zipf exponent can reflect the spatial distribution and hierarchical structure changes of the regional economic scale and carbon emissions. When $q = 1$, $q < 1$ and $q > 1$, the hierarchical distribution of regional economic scale and carbon emissions is in the optimal distribution, normal distribution (equalization) and Pareto distribution (centralization) pattern, respectively, under the natural state.

2.3.3 Allometric growth model

Allometric growth is the most classic scale concept in biology and ecology, reflecting the geometric measurement relationship between the part and the whole of the organism (Beckmann, 1958). In 1936, biologists Huxley and Tessier studied tide crabs and found that the size of their claws and body follow a power-law dependence relationship (Shingleton, 2010); i.e., the original meaning of allometric growth is “differences in proportions associated with changes in absolute size of the whole organism” (Gould, 1966). Similar to biological phenomena, this relationship also exists in urban geographical systems, which was introduced from the field of biology to the field of geography by Naroll and Bertalanffy in 1956 (Naroll et al., 1956). Beckmann (1958) proposed the allometric equation of the urban system to describe the relative ratio of the population of the largest city to the total population of all cities in the urban system. In this paper, a city is regarded as a whole. Economic scale and carbon emissions are two important attributes of a city. They are also two subsystems of a city. This study explored the relative development relationship between the two subsystems. Allometric growth can be divided into vertical allometric and horizontal allometric growth. The former explores the allometric growth relationship of different spatial units at a certain time, while the latter analyzes the allometric growth relationship of a certain spatial unit during a time period. The allometric growth model is as follows (Chen et al., 2020b):

$$C_t = aE_t^b \quad (3)$$

Taking the logarithms of both sides of Formula (3), we can obtain:

$$\ln C_t = \ln a + b \ln E_t \quad (4)$$

where C_t is a city's carbon emissions at time t ; E_t is a city's economic scale at time t ; a is the proportional coefficient; and b is the scaling exponent, also named the allometric growth coefficient. When $b=1$, economy and carbon emissions are growing at the same rate; when $b>1$, the growth rate of economy is slower than that of carbon emissions, i.e., positive allometric growth; when $b<1$, the growth rate of economy is faster than that of carbon emissions, i.e., negative allometric growth. The positive allometric growth was divided into two levels, and the negative allometric growth is divided into four levels, for a total of six levels. Table 2 reports the classification criteria and characteristics of each allometric growth level.

2.3.4 Geographical detector

Geographical detector is a statistical analysis method used to identify geographical spatial differentiation and reveal the driving factors behind it (Wang et al., 2010). It can effectively and independently detect the spatial distribution consistency and causality of two variables (Wang et al., 2017). Specifically, the relevant factors that affect the change in the allometric growth coefficient are spatially heterogeneous. If the strength of a certain factor and the allometric growth coefficient are significantly consistent or similar in spatial distribution, it can be explained that this factor has a decisive effect on the allometric growth coefficient. The geographical detector model is as follows (Song et al., 2020):

Table 2 Classification of the allometric growth of economic scale and carbon emissions

Type of allometric growth	Level	Criteria	Type of allometric growth relationship	Characteristics
Positive allometric growth	Positive allometric level 2	$3 < b$	Strong carbon emissions expansion	The growth rate of carbon emissions is much higher than that of economy, and carbon emissions per unit of GDP rise sharply
	Positive allometric level 1	$1 < b < 3$	Weak carbon emissions expansion	The growth rate of carbon emissions is higher than that of economy, and carbon emissions per unit of GDP increase slightly
Negative allometric growth	Negative allometric level 1	$0.85 < b < 1$	Basic coordination of economy and carbon emissions	The growth rate of carbon emissions is slightly higher than that of economy
	Negative allometric level 2	$0.5 < b < 0.85$	Weak economic expansion	The growth rate of carbon emissions is slower than that of economy, and the carbon emissions per unit of GDP decline slightly
	Negative allometric level 3	$0 < b < 0.5$	Strong economic expansion	The growth rate of carbon emissions is much slower than that of economy, and carbon emissions per unit of GDP drop significantly
	Negative allometric level 4	$b < 0$	Reduction in economy and carbon emissions	One or both of carbon emissions and economic scale are reduced

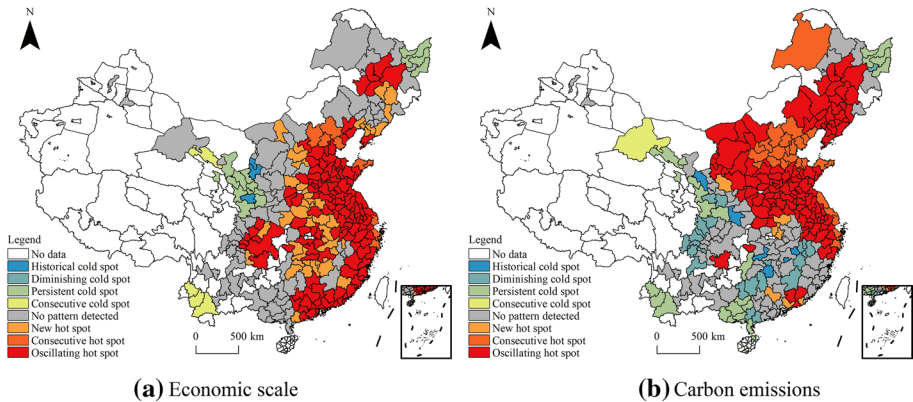


Fig. 3 Spatiotemporal hot spot analysis of the economic scale and carbon emissions of Chinese cities during 2000–2018

$$q_{D,U} = 1 - \frac{1}{n\sigma_U^2} \sum_{i=1}^m n_{D,i} \sigma_{U_{D,i}}^2 \quad (5)$$

where $q_{D,U}$ denotes the explanatory power of the influencing factor D to the allometric growth coefficient; n is the number of cities in the study area; m is the number of types of influencing factors; $n_{D,i}$ is the number of cities within type i of the influencing factor D ; σ_U^2 is the variance of the allometric growth coefficient of all cities in the study area; and $\sigma_{U_{D,i}}^2$ is the variance of the allometric growth coefficient of cities within type i . $q_{D,U}$ ranges from 0 to 1. A larger $q_{D,U}$ means a higher explanatory power of the factor D to the spatial distribution of the allometric growth coefficient.

3 The evolution and distribution characteristics of the economic scale and carbon emissions from China's cities

3.1 Spatiotemporal evolution characteristics

The ArcGIS spatiotemporal pattern mining tool was adopted to explore the spatial agglomeration evolution characteristics of the economic scale and carbon emissions for China's cities from 2000 to 2017 (see Fig. 3). The cold and hot spot patterns of the economic scale and carbon emissions of cities have strong regional characteristics (see “Appendix Table 6” for details). In terms of economic scale, the study area was mainly classified into oscillating hot spots and new hot spot patterns. In terms of carbon emissions, the study areas were mainly classified into the following spatiotemporal patterns: oscillating hot spots, consecutive hot spots, consecutive cold spots and diminishing cold spots.

In terms of the spatiotemporal evolution of the economic scale, a total of 184 cities showed a spatiotemporal trend of hot spots, accounting for 64.56% of the whole study area. Specifically, 129 oscillating hot spots are mainly distributed in the eastern coastal provinces, as well as Anhui, Hubei and Chongqing. Forty-five new hot spots are mainly

concentrated in the central region surrounding the oscillating hot spots, such as Henan, Hunan, Jiangxi and Shanxi; and 10 consecutive hot spots are distributed in Beijing–Tianjin–Hebei, the Yangtze River Delta and Shandong Peninsula. Additionally, the number of cold spots was relatively small. A total of 22 cities showed a trend of cold spots, accounting for 7.72% of the whole study area. Specifically, 14 persistent cold spots were mainly distributed in Gansu, southern Ningxia and northeastern Heilongjiang; 5 consecutive cold spots were distributed in central Gansu and southwestern Yunnan; and there were only 3 historical cold spot cities, namely Tianshui, Yinchuan and Wuzhong. Additionally, 79 cities do not show a significant spatiotemporal trend, accounting for 27.72% of the whole study area. They are mainly distributed in Guangxi, Sichuan, Shaanxi, Inner Mongolia and other regions in the west.

In terms of the spatiotemporal evolution of carbon emissions, 148 cities showed a spatiotemporal trend of hot spots, accounting for 51.93% of the whole study area. Specifically, the number of oscillating hot spots is the largest, 114 in total. They were mainly distributed in Zhejiang, Jiangsu, Anhui, Shandong, Henan, Liaoning, Jilin, southwestern Shanxi, central Inner Mongolia, etc.; 27 consecutive hot spots were mainly distributed in Beijing–Tianjin–Hebei, the coast of the Yangtze River Delta, the coast of the Shandong Peninsula, northwestern Shanxi, etc.; and 7 new hot spots are scattered in Guangdong, Hubei, Henan and Gansu. Fifty-six cities show a trend of cold spots, accounting for 19.65% of the whole study area. Specifically, 26 persistent cold spots are mainly distributed in Hainan, southwestern Guangxi, southwestern Yunnan, Gansu, etc.; 23 diminishing cold spots were mainly distributed in eastern Jiangxi, central Sichuan, northeastern Guangxi, etc. Six historical cold spots were distributed in Jiangxi, Hunan, Shaanxi and Gansu, and there is only 1 consecutive cold spot city, namely Jiuquan. Finally, 81 cities did not show a significant spatiotemporal trend, accounting for 28.42% of the whole study area, and were mainly distributed in Fujian, Chongqing, central and eastern Guangdong, central and eastern Hubei, eastern Sichuan, eastern Hunan and other regions.

In general, the spatiotemporal evolution pattern of economic scale and carbon emissions is dominated by hot spots. The hot spots were distributed in a concentrated and contiguous manner, while cold spots were more scattered. The distribution of cold and hot spots in terms of economic scale and carbon emissions was somewhat similar in space. Compared with the economic scale, the evolution pattern of carbon emissions shows fewer hot spots and more cold spots, which reflects the continuous improvement of the economic development of China's cities. Although the carbon emissions pattern is dominated by hot spots as a whole, the growth rate of carbon emissions gradually declines, and cold spots may continue to increase.

3.2 Distribution characteristics of economic scale and carbon emissions

The rank-size rule is a common model used to study the distribution of scale levels, which lays the foundation for the following research on the allometric growth relationship. Through the double logarithmic linear fitting of the economic scale and carbon emission data of China's cities versus their corresponding ranks, the relevant parameters of the fitting equation are shown in Table 3. From 2000 to 2017, the *R*-squared values of the fitting equations for the economic scale were all above 0.87, and the *R*-squared values of the fitting equations for the carbon emissions were all above 0.82, indicating that the goodness of fit of the fitting equations in each year was relatively high. That is, the rank-size rule can

Table 3 Scaling index of rank-size distribution of economic scale and carbon emissions in Chinese cities during 2000–2017

Year	Economic scale		Carbon emissions	
	Zipf exponent	R^2	Zipf exponent	R^2
2000	0.8978	0.8737	0.7305	0.8314
2001	0.9051	0.8789	0.7397	0.8276
2002	0.9075	0.8838	0.7325	0.8344
2003	0.9158	0.8904	0.7353	0.8344
2004	0.9117	0.8925	0.7398	0.8319
2005	0.9122	0.9084	0.7510	0.8310
2006	0.9127	0.9101	0.7519	0.8320
2007	0.9057	0.9088	0.7535	0.8345
2008	0.8979	0.9040	0.7522	0.8355
2009	0.8962	0.9095	0.7455	0.8360
2010	0.8867	0.9053	0.7394	0.8386
2011	0.8756	0.9029	0.7236	0.8398
2012	0.8681	0.9059	0.7211	0.8415
2013	0.8686	0.9039	0.6995	0.8395
2014	0.8766	0.9011	0.6979	0.8383
2015	0.8883	0.8994	0.7052	0.8377
2016	0.9041	0.8977	0.7053	0.8373
2017	0.9158	0.8995	0.6970	0.8399

better express the scale distribution characteristics of the economic scale and carbon emissions of China's cities.

In terms of economic scale, its Zipf exponent ranged from 0.8681 to 0.9158 during 2000–2017, showing an overall "N"-shaped trend. That is, it showed an inverted "V"-shaped trend from 2000 to 2008 and a "V"-shaped trend from 2009 to 2017. Specifically, from 2000 to 2003, it gradually increased from 0.8978 to 0.9158; from 2004 to 2006, it was relatively stable and remained at approximately 0.9122; from 2007 to 2012, it gradually declined from 0.9057 to 0.8681; and from 2013 to 2017, it increased from 0.8686 to 0.9158. In summary, it exhibited a fluctuating trend of "increasing–declining–increasing," with a value below 1. This indicated that the economic scale during the study period was balanced. In other words, the primacy of Chinese cities is obviously insufficient, the middle-ranking cities occupy the dominant position, and the distribution of economic scale tends to be concentrated. Additionally, due to the rapid economic development of low- and middle-ranking cities, their economic scale grows faster than that of high-ranking cities.

In terms of carbon emissions, its Zipf exponent ranged from 0.6970 to 0.7535, showing an overall declining trend during 2000–2017. Specifically, from 2000 to 2007, it gradually increased from 0.7305 to 0.7535; from 2008 to 2013, it decreased from 0.7522 to 0.6995; and from 2014 to 2017, it showed an inverted U-shaped trend, i.e., it rose first and then fell. Overall, it was lower than 1 during 2000–2017, indicating that the carbon emissions in the study period were in a balanced distribution pattern. That is, the differences in carbon emissions among cities are relatively small, and the primacy ratio of carbon emissions in China's cities was low with a downward trend.

In summary, the economic scale and carbon emissions of China's cities were in a balanced distribution pattern during 2000–2017. The Zipf exponent of economic scale showed a fluctuating upward trend, while the Zipf exponent of carbon emissions

Table 4 Allometric growth fitting model of economic scale and carbon emissions in Chinese cities during 2000–2017

Year	Fitting model	Scaling exponent	R^2	Allometric growth level
2000	$\ln C = -2.8462 + 0.6518 \ln E$	0.6518	0.6107	Negative allometric level 2
2001	$\ln C = -3.1547 + 0.6691 \ln E$	0.6691	0.6311	Negative allometric level 2
2002	$\ln C = -3.1623 + 0.6707 \ln E$	0.6707	0.6520	Negative allometric level 2
2003	$\ln C = -3.2812 + 0.6835 \ln E$	0.6835	0.6781	Negative allometric level 2
2004	$\ln C = -3.5256 + 0.6981 \ln E$	0.6981	0.6898	Negative allometric level 2
2005	$\ln C = -3.8422 + 0.7224 \ln E$	0.7224	0.7044	Negative allometric level 2
2006	$\ln C = -3.9022 + 0.7266 \ln E$	0.7266	0.7112	Negative allometric level 2
2007	$\ln C = -4.0888 + 0.7341 \ln E$	0.7341	0.7149	Negative allometric level 2
2008	$\ln C = -4.2146 + 0.7377 \ln E$	0.7377	0.7168	Negative allometric level 2
2009	$\ln C = -4.1983 + 0.7365 \ln E$	0.7365	0.7206	Negative allometric level 2
2010	$\ln C = -4.1485 + 0.7307 \ln E$	0.7307	0.7110	Negative allometric level 2
2011	$\ln C = -3.9040 + 0.7142 \ln E$	0.7142	0.6946	Negative allometric level 2
2012	$\ln C = -4.0572 + 0.7198 \ln E$	0.7198	0.6977	Negative allometric level 2
2013	$\ln C = -3.5202 + 0.6842 \ln E$	0.6842	0.6703	Negative allometric level 2
2014	$\ln C = -3.2463 + 0.6662 \ln E$	0.6662	0.6515	Negative allometric level 2
2015	$\ln C = -3.1607 + 0.6557 \ln E$	0.6557	0.6354	Negative allometric level 2
2016	$\ln C = -2.7868 + 0.6330 \ln E$	0.6330	0.6141	Negative allometric level 2
2017	$\ln C = -2.3173 + 0.6034 \ln E$	0.6034	0.5870	Negative allometric level 2

showed a fluctuating downward trend. Additionally, the Zipf exponent of economic scale was far higher than that of carbon emissions, indicating that the primacy of economic scale distribution has been improved or would change to a centralized distribution pattern. The primacy ratio of carbon emissions was decreasing, which would maintain a balanced distribution pattern for a long time.

4 Allometric growth characteristics of the economic scale and carbon emissions in Chinese cities

4.1 Vertical allometric growth characteristics

An allometric growth model of economic scale and carbon emissions was constructed, and double logarithmic linear fitting is performed; therefore, a fitting model of the allometric growth of economic scale and carbon emissions of Chinese cities was obtained (see Table 4). The R -squared of the fitting model in each year from 2000 to 2017 was above 0.58; i.e., the fitting effect was good. The scaling exponent of each year varied in the range of 0.6034 to 0.7377, basically showing an inverted U-shaped trend. Specifically, it increased from 0.6518 in 2000 to 0.7377 in 2008 and then decreased from 0.7365 in 2009 to 0.6034 in 2017. The allometric growth of economic scale and carbon

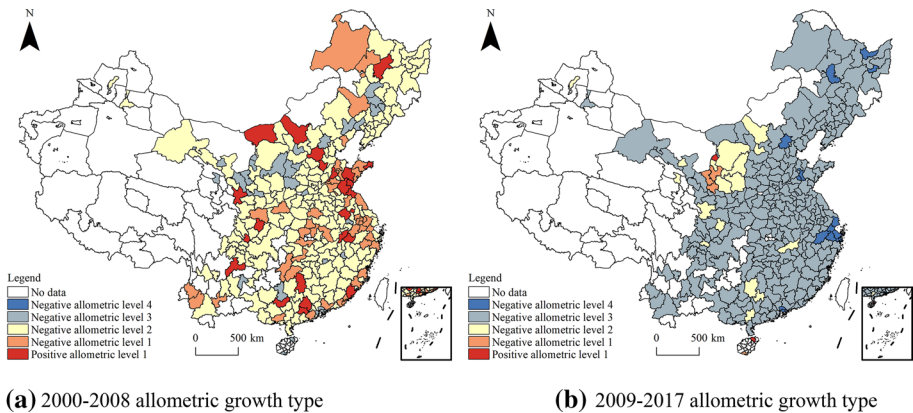


Fig. 4 Distribution of allometric growth types of economic scale and carbon emissions in China's cities during 2000–2017

emissions in China's cities is all at an economic weak expansion stage where the economic growth rate was relatively higher than that of carbon emissions. The growth rate of carbon emissions increased from 2000 to 2008 and then declined from 2009 to 2017.

4.2 Horizontal allometric growth characteristics

Industry is an important emitter of carbon emissions. From 2000 to 2008, the proportion of China's industrial added value in GDP showed an overall upward trend, but a downward trend from 2009 to 2017. That is, with the remarkable achievements in the green and low-carbon transformation of China's industrial structure and production methods, the growth rate of total carbon emissions slowed down, so the vertical allometric growth coefficient tended to decline after 2008. Therefore, to further explore the allometric growth relationship between economic scale and carbon emissions in different regions, the study period was divided into 2000–2008 and 2009–2017. The allometric growth model was employed to construct the fitting model of the horizontal allometric growth of the economic scale and carbon emissions in different regions during the two periods. Figure 4 depicts the spatial distribution of the scaling exponent type.

From 2000 to 2008, the allometric growth type of the economic scale and carbon emissions of China's cities was dominated by negative allometric growth. There were 262 negative allometric growth cities, accounting for 91.93% of the study area. They are widely distributed. Among them, 44 cities were negative allometric level 1, mainly distributed in the Yangtze River Delta, Shandong, eastern Fujian, eastern Guangdong, eastern Hubei and western Hunan. A total of 187 cities were negative allometric level 2, accounting for 71.37% of the negative allometric growth cities. They are also the largest in all types of allometric growth, mainly distributed in Jiangxi, Anhui and Henan in the central region, Chongqing, Sichuan, Guangxi and Shaanxi in the western region, and Liaoning and Heilongjiang in the northeastern region. Thirty-one cities were negative allometric level 3,

Table 5 Detection results of driving factors of the allometric growth coefficient

Driving factors	2000–2008			2009–2017		
	$q_{D,U}$	<i>P</i> value	Sorting of $q_{D,U}$	$q_{D,U}$	<i>P</i> value	Sorting of $q_{D,U}$
X1	0.0407**	0.0252	6	0.0589***	0.0031	6
X2	0.0742***	0.0000	3	0.0157	0.3604	11
X3	0.0459**	0.0139	4	0.0582***	0.0033	7
X4	0.0850***	0.0000	2	0.0953***	0.0000	2
X5	0.0263	0.1228	10	0.1049***	0.0000	1
X6	0.0371**	0.0375	7	0.0941***	0.0000	3
X7	0.0255	0.1338	11	0.0461**	0.0136	9
X8	0.0289*	0.0931	8	0.0499***	0.0087	8
X9	0.0423**	0.0210	5	0.0156	0.3625	12
X10	0.0076	0.7105	12	0.0789***	0.0000	5
X11	0.0272	0.1112	9	0.0265	0.1203	10
X12	0.0916***	0.0000	1	0.0794***	0.0000	4

***, ** and * represent significance at the 1%, 5% and 10% levels, respectively

mainly distributed in Hainan, southern Guangdong, western Shanxi, Ningxia, Liaoning and Jilin. Additionally, there were 23 positive allometric growth cities, accounting for 8.07% of the study sample. They were all positive allometric level 1 and were mainly distributed in central Shandong, central Hebei, southern Anhui and western Guangdong. In terms of goodness of fit, the *R*-squared of each city was above 0.6, and the average *R*-squared is 0.9470, which indicated that the fitting effect of each city in this stage was good.

From 2009 to 2017, the allometric growth type of the economic scale and carbon emissions of China's cities was still dominated by negative allometric growth. The number of negative allometric growth cities increases to 283, accounting for 99.30% of the study area. Among them, 4 cities are negative allometric level 1, specifically, Wuzhong, Guyuan and Zhongwei in Ningxia as well as Sanya in Hainan. Seventeen cities are negative allometric level 2, mainly distributed in western China, such as eastern Guangxi, northern Shaanxi, central and western Inner Mongolia; 249 cities are negative allometric level 3, accounting for 87.99% of the negative allometric growth cities. They were widely distributed in many areas of China, and 13 cities were negative allometric level 4, mainly distributed in Beijing, Shanghai, northern Zhejiang and southern Guangdong. Furthermore, there are only 2 positive allometric growth cities. They were positive allometric level 1, namely Haikou in Hainan and Shizuishan in Ningxia. Although the *R*-squared has a decline compared with the previous stage, the *R*-squared of each city was above 0.4, and the average *R*-squared was 0.6232, which means that the fitting effect of each city was also good at this stage.

In summary, the relative growth rate of carbon emissions was mostly lower than that of the economy between 2000–2008 and 2009–2017. Additionally, the growth gap between carbon emissions and the economy was growing. It can be predicted that with the continuous reduction of carbon emissions and steady economic growth in China, most cities will be transformed into negative allometric level 4 in the future; i.e., most cities will realize carbon emission reduction after the carbon peak and sustained economic growth in the near future.

5 Analysis of the factors driving allometric growth

5.1 Factor detection results

On the basis of the two periods of 2000–2008 and 2009–2017 divided in the analysis of the horizontal allometric growth, the geographical detector model was used to analyze the impact of various factors on the spatial differentiation of the allometric growth of economic scale and carbon emissions of China's cities in the two periods (see Table 5).

From 2000 to 2008, the explanatory power ($q_{D,U}$) of energy utilization efficiency, city investment intensity, industrial development level, fiscal investment level, transportation development level, economic development level, technological development level and land use level to the allometric growth coefficient decreased successively, and all of them passed the significance tests. Additionally, from 2009 to 2017, the explanatory power ($q_{D,U}$) of the social consumption level, city investment intensity, technological development level, energy utilization efficiency, opening up level, economic development level, fiscal investment level, land use level and urban development level to the allometric growth coefficient decreased successively, and all of them also passed the significance tests. Comparing the changes in the explanatory power of the driving factors in the two time periods, we found that the explanatory power of the social consumption level, opening up level and technological development level greatly increases, and the explanatory power of the land use level, urban development level, economic development level, fiscal investment level and city investment intensity slightly increases. However, the explanatory power of the industrial development level and transportation development level decreases significantly, and the explanatory power of the energy utilization efficiency and urban greening level decreases slightly.

In summary, city investment intensity, energy utilization efficiency, technological development level, social consumption level, fiscal investment level and economic development level were the dominant driving factors that affect the allometric growth relationship between economic scale and carbon emissions in Chinese cities.

5.2 Interactive detection results

The study period was divided into two periods, 2000–2008 and 2009–2017, in the horizontal allometric growth analysis. Next, the interactive detector tool in the geographical detector was employed to measure the effect of the driving factors on the spatial differentiation of the allometric growth coefficient during the two periods (see Fig. 5). During the two periods, the explanatory power of the interaction between driving factors was higher than the explanatory power of a single factor. The interaction types between driving factors were classified into nonlinear enhancement types and binary enhancement types. Additionally, the former dominates. This indicated that the interaction between any two driving factors increased the explanatory power for the spatial differentiation of the allometric growth coefficient.

From 2000 to 2008, the interaction between driving factors has 65 items of nonlinear enhancement, accounting for 98.48% of the total, and only one item of two-factor enhancement. The explanatory power of the interaction between the industrial development level and other factors is the strongest, with an average value of 0.1951. Additionally, the explanatory power of the interaction between city investment intensity, energy utilization

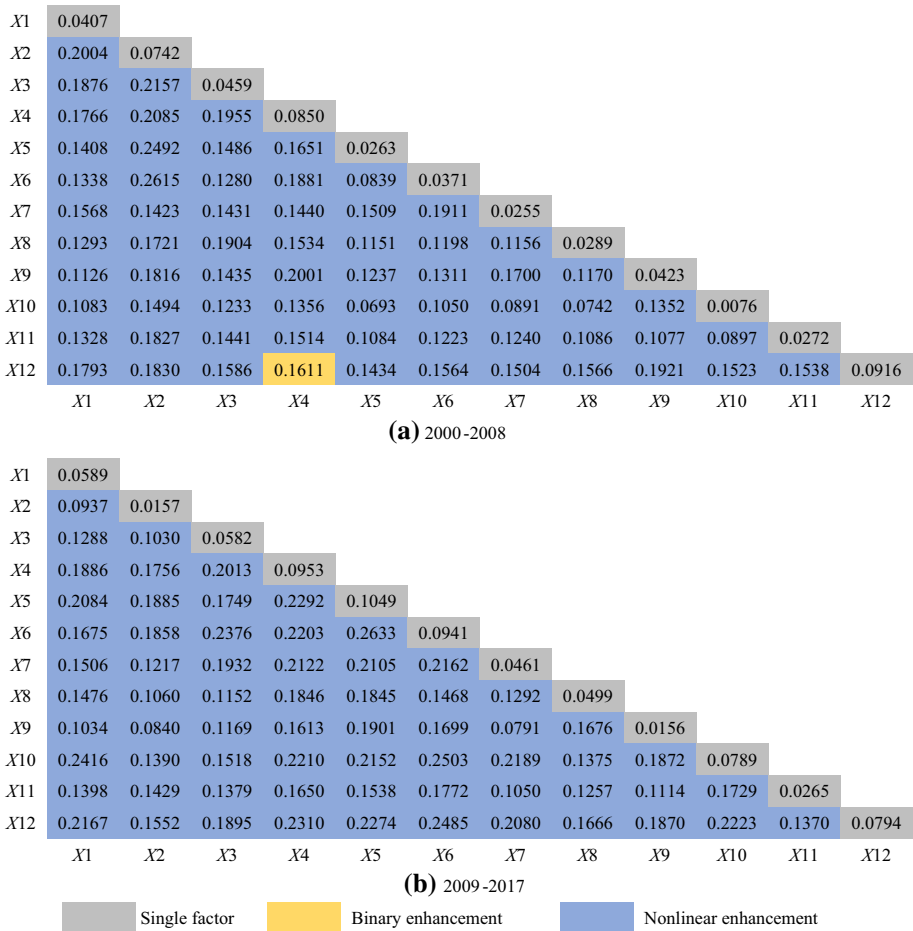


Fig. 5 Interaction between driving factors of allometric growth coefficient

efficiency, fiscal investment level, economic development level and other factors is also high, with an average value above 0.15. The increase in the explanatory power of the interaction between the urban development level, opening up level and other factors ranks in the top two, and their interactive explanatory power increases by more than 115%. The explanatory power of the interaction between the social consumption level, urban greening level, fiscal investment level, technological development level, land use level, economic development level and other factors increases by more than 80%.

From 2009 to 2017, the interaction types of the driving factors were all nonlinear enhancement. The average explanatory power of the interaction between technological development level, social consumption level and other factors ranks among the top two, reaching 0.2076 and 0.2042, respectively. The average explanatory power of the interaction between city investment intensity, energy utilization efficiency, opening up level, urban development level, economic development, fiscal investment level and other factors is above 0.15, which is strong for the spatial differentiation of allometric growth. The increase in the explanatory power of the interaction between the transportation development level,

industrial development level and other factors ranks among the top two. Their explanatory power increases by more than 80%. The explanatory power of the interaction between the urban greening level, urban development level, energy utilization efficiency, opening up level, land use level and other factors also increases significantly, with an increase rate of more than 40%.

Comparing the interactive detection results of the two periods, the explanatory power of the interaction between urban investment intensity, energy utilization efficiency, technological development level, social consumption level, fiscal investment level, economic development level and other factors has always been at the forefront. We know that they are the key driving factors that affect the allometric growth between economic scale and carbon emissions in China's cities. The increase in the interaction between the urban development level, urban greening level, opening up level, transportation development level, industrial development level, land use level and other factors is more obvious. That is, the explanatory power of the interaction between these factors on the spatial differentiation of the allometric growth coefficient is more significant than that of a single factor. After all factors interact with other factors, the average explanatory power has improved to varying degrees, indicating that the influence of the driving factors is not independent of each other, but synergistically enhances. That is, the allometric growth between economic scale and carbon emissions is the result of multifactor nonlinear coupling.

6 Driving mechanism of allometric growth

The evolution of the allometric growth between economic scale and carbon emissions in China's cities is a relatively complex process involving the economy, the environment and their dual impact. Combined with the detection of changes in the influence of various factors by geographical detectors, the driving mechanism on allometric growth is explored as follows.

6.1 The impact of economy

Factors such as the economic development level, fiscal investment level, city investment intensity and opening up level mainly affect the economic scale. The explanatory power of these factors on allometric growth is on the rise. Among them, the economic development level, fiscal investment level and city investment intensity are the leading driving factors. The economic development level is an important indicator that reflects the state of regional economic development, and the increase in per capita GDP is self-evident to the economic scale. Local fiscal expenditures characterize the redistribution of fiscal funds by local governments to meet the common needs of society. Its purpose is to promote the development of social productivity, maintain social stability and create a good social environment for economic development. Investment in fixed assets is the main means for the reproduction of social fixed assets. Through the construction and purchase of fixed assets, cities continue to adopt advanced technology and equipment, thereby further adjusting and optimizing the economic structure and enhancing the strength of city economic development. The proportion of total imports and exports to GDP represents a city's dependence on foreign trade. It is an important indicator to measure the degree of openness to the outside world. As the opening up level continues to increase, the impact of economic globalization on China is getting deeper. The explanatory power of the four economic-dominant factors

for allometric growth increases to varying degrees, indicating that economic factors are becoming increasingly important for the allometric growth of economic scale and carbon emissions. Wang et al. (2019) investigated the impact mechanism of carbon emissions in Hebei Province, China. They found that economic level, population, industrial structure, urbanization level, energy structure and technology are important factors affecting carbon emissions, of which economic factors are the most important factors. This study also found that economic factors such as city investment intensity, fiscal investment level and economic development level are important factors affecting the allometric growth of economic scale and carbon emissions.

6.2 The impact of environment

The urban greening level and energy utilization efficiency mainly affect the environment. The explanatory power of the two factors on the allometric growth is in a downward trend, and the latter is the dominant driving factor. The urban greening level can not only meet people's needs for a beautiful ecological environment, but also have the functions of maintaining ecological balance, regulating climate and preventing disasters and floods. A green area is an important carbon storage place and an important part of the construction of an ecological civilization and beautiful China. Currently, the development of China's economy mainly relies on resource-consuming production, which consumes a large amount of energy such as electricity. A large amount of energy consumption also brings about serious environmental pollution (such as water pollution, air pollution, soil pollution, etc.) and a large amount of carbon emissions. Zhang et al. (2021) studied the influencing factors of carbon emissions in China's logistics industry and found that energy intensity, that is, energy consumption per unit of output, had a significant inhibitory effect on carbon emissions, but its factor contribution rate was small. In this paper, the energy utilization efficiency has a greater impact. The possible reason is that the logistics industry has large carbon emissions, its energy consumption per unit output is high, and the decline is small, so the impact of energy intensity on the carbon emissions of the logistics industry is small. The gradual increase in the urban greening level keeps its impact on allometric growth in a relatively stable state, and the gradual increase in energy efficiency (i.e., gradual decline in electricity consumption per unit of GDP) means a decline in carbon emission intensity. As the improvement of energy efficiency declines, its explanatory power for the allometric growth of economic scale and carbon emissions also shows a downward trend.

6.3 The dual impact of economy and environment

The industrial development level, social consumption level, technological development level, urban development level, land use level and transportation development level all have a certain impact on the economic scale and environmental pollution. Specifically, the explanatory power of the industrial development level and transportation development level for allometric growth shows a downward trend, while the explanatory power of the social consumption level, technological development level, urban development level and land use level shows an upward trend. Additionally, the former two are the leading driving factors.

The industrial development level is an important factor not only affecting economic growth, but also causing environmental pollution and carbon emissions. During the study period, the

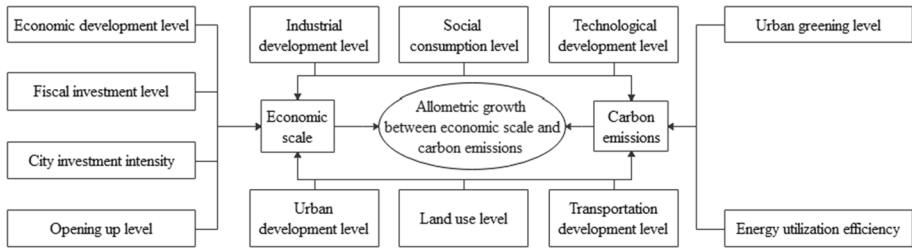


Fig. 6 Driving mechanism of allometric growth between economic scale and carbon emissions

proportion of China's industrial added value in GDP showed an overall upward trend and then a downward trend. By 2012, the proportion of tertiary industry's added value surpassed that of the secondary industry; i.e., the increase in economic scale gradually reduced its dependence on the secondary industry and turned to rely increasingly more on the tertiary industry. Therefore, the explanatory power of the industrial development level for allometric growth declines. As the main driving force of economic growth, the promotion of the social consumption level also means an increase in resource consumption, thereby intensifying environmental pollution and carbon emissions. As the world economy continues to decline and trade tensions intensify, expanding domestic demand has become the basic driving force for China's economic development. The increase in the social consumption level and the expansion of its influence have significantly improved its explanatory power for allometric growth. The enhancement of the technological development level injects a new impetus into economic development, thereby promoting the transformation of the economic development mode, the transformation of economic growth momentum and the optimization of the economic structure, as well as innovating the development of low-carbon technologies. It can also better promote green development, protect and restore ecosystems, and reduce carbon emissions, thereby speeding up the construction of ecological civilization. Research on carbon emissions in China's manufacturing industry by Liu et al. (2022) also showed that the innovation input carbon intensity is the main factor inhibiting the enhancement of carbon emissions, which is similar to the results of this paper.

Urbanization is another important driving force for China's economic development. The urban development level and land use level are important indicators of population urbanization and land urbanization, respectively. Urbanization and industrialization are accompanied and developed together. The agglomeration effect produced by urbanization promotes industrial development, which in turn drives economic development. Additionally, the rapid progress of urbanization also increases the rigid demand for energy, resulting in an increase in carbon emissions. The increase in car ownership reflects the rapid development of the automobile industry and the increase in the income level of residents and explains the rapid development of China's economy from the side. However, carbon emissions from automobile exhaust aggravate the deterioration of regional air quality and damage the ecological environment. With the increase in vehicle fuel utilization and the gradual promotion of new energy vehicles, the explanatory power of the transportation development level on the allometric growth has gradually decreased.

In summary, the allometric growth of economic scale and carbon emissions in China's cities is the result of a combination of multiple factors. Among them, the economic development level, fiscal investment level, city investment intensity and opening up level mainly affect the economic scale. The urban greening level and energy utilization efficiency mainly affect carbon emissions. The industrial development level, social consumption level, technological development level, urban development level, land use level and transportation development level all affect the economic scale and carbon emissions (see Fig. 6).

7 Discussions

Under the severe situation of global carbon peaking and carbon neutrality, it is urgent to reasonably evaluate the impact of economic growth on carbon emissions. As an effective method to identify the carbon emission pressure of economic growth, the allometric growth model can not only quantitatively measure the coupling coordination degree of economic scale and carbon emissions, but also capture the interactive response law of economic scale and carbon emissions to provide a reliable basis for implementing targeted carbon emission reduction strategies. Allometric growth can also link urban studies such as regional development laws, regional coordination relationships, and scale and structure analysis to form a relatively complete theoretical and research framework, injecting new vitality into urban and regional related research. Under the background of profound changes in the spatial structure of global economic development, China's economic development is facing new opportunities and challenges. By studying the allometric growth relationship between economic scale and carbon emissions, we will explore new development models for urban and regional growth to further achieve higher-quality regional development.

The analysis results of the study are of great significance for realizing carbon emission reduction and carbon peaking. Specifically, the following suggestions are made: (1) Due to the impact of city investment intensity, energy utilization efficiency and technological development level at the forefront, the investment structure should be adjusted and optimized, and the focus of investment should be tilted toward pollution control and ecological construction. Energy efficiency should be improved in all aspects, the energy consumption structure adjusted, and a diversified and clean energy supply system built. Additionally, governments should improve independent innovation capabilities, promote industrial technological progress, increase investment in energy science and technology, and encourage R&D and the application of energy-saving technologies. (2) Based on the overall economic and social development, all provinces should speed up the formulation of carbon emission reduction plans and policies, thereby systematically coordinating the carbon emission reduction work of all regions and industries and establishing and improving carbon emission monitoring, reporting and accounting systems. Additionally, carbon emission policies and accounting systems should be linked up. (3) Since the relative growth rate of carbon emissions has already been lower than the relative growth rate of the economy, the relationship between economic development and the carbon peak and carbon neutrality goals should be coordinated. In the context of the global pandemic of the new crown pneumonia (COVID-19), the world economy is facing huge uncertainty, and the possibility of economic recession is rising sharply. Achieving a carbon peak and carbon neutrality is of great significance and far-reaching impact, which requires the joint cooperation of the international community.

It is true that there are still some deficiencies in the research of this paper: First, the allometric growth coefficient of economic scale and carbon emissions calculated in different time periods have large fluctuations; second, we comparatively analyzed all cities at different administrative levels and do not separately consider the differences in the influencing factors of positive allometric and negative allometric cities; finally, due to the difficulty of data acquisition, this study only explored the allometric relationship between economic scale and carbon emissions from the municipal scale. With the development of big data technology and the improvement of analysis technology, it is possible to obtain data at the county level or even smaller scales. In the future, we can further reveal the spatiotemporal evolution process of allometric growth at the county level or smaller scales to explore the allometric growth law in detail and provide a theoretical basis for coordinated regional

development. In addition, we can also predict the future development trend of allometric growth between the economic scale and carbon emissions with the help of the gray prediction model, neural network model, system dynamics model and other methods and make timely adjustments to the development of regional economic and environmental systems.

8 Conclusions

Taking China's 285 cities as the research object, this study explored the allometric growth of economic scale and carbon emissions in these cities from 2000 to 2017. Then, the geographical detector model was employed to analyze the driving mechanism of allometric growth. We obtained the following conclusions:

- (1) The spatiotemporal evolution pattern of the economic scale and carbon emissions of Chinese cities was dominated by hot spots. The hot spots tended to weaken from the eastern coastal regions to the western inland regions as a whole. They were concentrated and contiguous. Cold spots were relatively scattered in space. The economic scale and carbon emission system are relatively well developed in a stage of balanced distribution. Among them, the primacy ratio of economic scale increased. Alternatively, the economic scale was transformed into a centralized mode. The primacy ratio of carbon emissions continued to decrease.
- (2) The allometric growth of economic scale and carbon emissions in China's cities is generally in a stage of economic expansion, where the relative growth rate of carbon emissions is lower than the relative growth rate of the economy. In terms of vertical allometric growth, the gap between the growth rate of carbon emissions and the growth rate of the economy showed a trend of narrowing first and then widening. In terms of horizontal allometric growth, the scaling exponent decreased from east to the west as a whole from 2000 to 2008, but showed an opposite trend from 2009 to 2017.
- (3) City investment intensity, energy utilization efficiency, technological development level, social consumption level, fiscal investment level and economic development level were the main factors affecting the spatiotemporal heterogeneity of the allometric growth of economic scale and carbon emissions in China's cities. Additionally, the explanatory power of city investment intensity, technological development level, social consumption level, fiscal investment level and economic development level is on the rise, and the explanatory power of energy utilization efficiency was on the decline. The explanatory power of the two-factor interaction is higher than that of a single factor, and most of the interactions were nonlinear enhancement types. The influence of factors had a synergistic enhancement effect. Economic factors, environmental factors and the combined effect of the two have formed a spatially differentiated pattern of the allometric growth of economic scale and carbon emissions in China's cities.

Appendix

See Fig. 7, Table 6.



Fig. 7 Map of China with administrative divisions

Table 6 Distribution of spatiotemporal hot spot types and allometric growth types in Chinese cities

Code	Province	City	Spatiotemporal hot spot type		Allometric growth type	
			ES	CE	2000–2008	2009–2017
1	Beijing	Beijing	7	7	-3	-4
2	Tianjin	Tianjin	8	7	-2	-3
3	Hebei	Shijiazhuang	8	7	-2	-3
4	Hebei	Tangshan	7	7	-2	-3
5	Hebei	Qinhuangdao	8	7	-1	-3
6	Hebei	Handan	8	8	-2	-4
7	Hebei	Xingtai	8	8	-2	-3
8	Hebei	Baoding	8	7	+1	-3
9	Hebei	Zhangjiakou	7	7	-2	-3
10	Hebei	Chengde	7	7	-2	-3
11	Hebei	Cangzhou	8	7	-2	-3
12	Hebei	Langfang	8	7	-2	-3
13	Hebei	Hengshui	8	7	+1	-3
14	Shanxi	Taiyuan	6	7	-3	-3
15	Shanxi	Datong	8	7	-2	-3
16	Shanxi	Yangquan	6	8	-2	-3
17	Shanxi	Changzhi	8	8	-2	-3
18	Shanxi	Jincheng	6	8	-2	-3
19	Shanxi	Shuozhou	6	7	-3	-2
20	Shanxi	Jinzhong	5	8	-2	-3
21	Shanxi	Yuncheng	8	8	-2	-3
22	Shanxi	Xinzhou	6	7	-2	-3
23	Shanxi	Linfen	6	8	-3	-3
24	Shanxi	Luliang	5	8	-3	-3
25	Inner Mongolia	Hohhot	5	8	-2	-3
26	Inner Mongolia	Baotou	6	8	-2	-3
27	Inner Mongolia	Wuhai	5	8	-2	-3
28	Inner Mongolia	Chifeng	5	8	-2	-3
29	Inner Mongolia	Tongliao	5	8	-1	-3
30	Inner Mongolia	Ordos	5	8	-2	-2
31	Inner Mongolia	Hulunbuir	5	7	-1	-3
32	Inner Mongolia	Bayannur	5	8	+1	-3
33	Inner Mongolia	Ulaan Chab	5	8	+1	-2
34	Liaoning	Shenyang	5	8	-2	-3
35	Liaoning	Dalian	8	8	-2	-3
36	Liaoning	Anshan	6	8	-2	-3
37	Liaoning	Fushun	5	8	-2	-3
38	Liaoning	Benxi	5	8	-2	-3
39	Liaoning	Dandong	6	8	-2	-3
40	Liaoning	Jinzhou	6	8	-3	-3
41	Liaoning	Yingkou	6	8	-2	-3
42	Liaoning	Fuxin	5	8	-2	-3

Table 6 (continued)

Code	Province	City	Spatiotemporal hot spot type		Allometric growth type	
			ES	CE	2000–2008	2009–2017
43	Liaoning	Liaoyang	5	8	-2	-3
44	Liaoning	Panjin	6	8	-2	-3
45	Liaoning	Tieling	5	8	-3	-3
46	Liaoning	Chaoyang	8	8	-3	-3
47	Liaoning	Huludao	8	7	-2	-3
48	Jilin	Changchun	6	8	-2	-3
49	Jilin	Jilin	6	8	-2	-3
50	Jilin	Siping	5	8	-3	-3
51	Jilin	Liaoyuan	5	8	-3	-3
52	Jilin	Tonghua	6	8	-2	-3
53	Jilin	Baishan	5	5	-2	-3
54	Jilin	Songyuan	8	8	-3	-3
55	Jilin	Baicheng	8	8	-2	-3
56	Heilongjiang	Harbin	8	8	-2	-3
57	Heilongjiang	Qiqihar	5	5	-1	-3
58	Heilongjiang	Jixi	3	3	-2	-3
59	Heilongjiang	Hegang	3	3	-2	-4
60	Heilongjiang	Shuangyashan	3	3	-2	-3
61	Heilongjiang	Daqing	8	8	-2	-4
62	Heilongjiang	Yichun	5	5	-2	-3
63	Heilongjiang	Jiamusi	3	3	-2	-3
64	Heilongjiang	Qitaihe	5	2	-2	-4
65	Heilongjiang	Mudanjiang	5	5	-2	-3
66	Heilongjiang	Heihe	5	5	-2	-3
67	Heilongjiang	Suihua	8	8	+1	-3
68	Shanghai	Shanghai	7	7	-2	-4
69	Jiangsu	Nanjing	8	8	-2	-3
70	Jiangsu	Wuxi	8	8	-1	-3
71	Jiangsu	Xuzhou	8	8	-2	-3
72	Jiangsu	Changzhou	8	8	-1	-3
73	Jiangsu	Suzhou	8	8	-1	-3
74	Jiangsu	Nantong	8	7	-2	-3
75	Jiangsu	Lianyungang	8	8	+1	-3
76	Jiangsu	Huai'an	8	8	-2	-3
77	Jiangsu	Yancheng	8	7	-1	-3
78	Jiangsu	Yangzhou	8	8	-2	-3
79	Jiangsu	Zhenjiang	8	8	-1	-3
80	Jiangsu	Taizhou	8	8	-2	-3
81	Jiangsu	Suqian	8	8	-1	-3
82	Zhejiang	Hangzhou	8	8	-2	-4
83	Zhejiang	Ningbo	7	7	-2	-4
84	Zhejiang	Wenzhou	8	8	-2	-3

Table 6 (continued)

Code	Province	City	Spatiotemporal hot spot type		Allometric growth type	
			ES	CE	2000–2008	2009–2017
85	Zhejiang	Jiaxing	8	8	-1	-4
86	Zhejiang	Huzhou	8	8	-1	-3
87	Zhejiang	Shaoxing	8	8	-1	-4
88	Zhejiang	Jinhua	8	8	-1	-3
89	Zhejiang	Quzhou	8	5	-2	-3
90	Zhejiang	Zhoushan	7	7	-2	-3
91	Zhejiang	Taizhou	7	7	-1	-3
92	Zhejiang	Lishui	8	8	-2	-3
93	Anhui	Hefei	8	8	-2	-3
94	Anhui	Wuhu	8	8	-2	-3
95	Anhui	Bengbu	8	8	-2	-3
96	Anhui	Huainan	8	8	-2	-3
97	Anhui	Ma'anshan	8	8	-3	-3
98	Anhui	Huaibei	8	8	-2	-3
99	Anhui	Tongling	8	8	-2	-3
100	Anhui	Anqing	8	5	-2	-3
101	Anhui	Huangshan	8	8	+1	-3
102	Anhui	Chuzhou	8	8	+1	-3
103	Anhui	Fuyang	8	8	-2	-3
104	Anhui	Suzhou	8	8	-2	-3
105	Anhui	Lu'an	6	5	-2	-3
106	Anhui	Bozhou	8	8	-2	-3
107	Anhui	Chizhou	8	8	+1	-3
108	Anhui	Xuancheng	8	8	-1	-3
109	Fujian	Fuzhou	8	5	-1	-3
110	Fujian	Xiamen	8	5	-2	-3
111	Fujian	Putian	8	5	-2	-3
112	Fujian	Sanming	8	5	-2	-3
113	Fujian	Quanzhou	8	5	-1	-3
114	Fujian	Zhangzhou	8	5	+1	-3
115	Fujian	Nanping	8	5	-2	-3
116	Fujian	Longyan	6	5	-2	-3
117	Fujian	Ningde	8	5	-2	-3
118	Jiangxi	Nanchang	6	1	-2	-3
119	Jiangxi	Jingdezhen	6	2	-2	-3
120	Jiangxi	Pingxiang	6	5	-2	-3
121	Jiangxi	Jiujiang	6	5	-2	-2
122	Jiangxi	Xinyu	6	1	-3	-3
123	Jiangxi	Yingtian	5	2	-3	-3
124	Jiangxi	Ganzhou	5	2	-2	-3
125	Jiangxi	Ji'an	6	5	-2	-3
126	Jiangxi	Yichun	8	5	-2	-3

Table 6 (continued)

Code	Province	City	Spatiotemporal hot spot type		Allometric growth type	
			ES	CE	2000–2008	2009–2017
127	Jiangxi	Fuzhou	5	2	-2	-3
128	Jiangxi	Shangrao	5	2	-2	-3
129	Shandong	Jinan	8	8	+1	-3
130	Shandong	Qingdao	8	8	-1	-3
131	Shandong	Zibo	8	8	-1	-4
132	Shandong	Zaozhuang	8	8	-2	-3
133	Shandong	Dongying	8	7	-2	-3
134	Shandong	Yantai	7	7	-1	-3
135	Shandong	Weifang	8	8	+1	-3
136	Shandong	Jining	8	8	-1	-3
137	Shandong	Tai'an	8	8	-1	-3
138	Shandong	Weihai	7	7	+1	-3
139	Shandong	Rizhao	8	8	+1	-3
140	Shandong	Laiwu	8	8	-2	-4
141	Shandong	Linyi	8	8	+1	-3
142	Shandong	Dezhou	8	8	-2	-3
143	Shandong	Liaocheng	8	8	-2	-3
144	Shandong	Binzhou	8	7	-1	-3
145	Shandong	Heze	8	8	-2	-3
146	Henan	Zhengzhou	6	8	-2	-3
147	Henan	Kaifeng	8	8	-2	-3
148	Henan	Luoyang	8	8	-2	-3
149	Henan	Pingdingshan	6	8	-2	-3
150	Henan	Anyang	8	8	-2	-3
151	Henan	Hebi	8	8	-2	-3
152	Henan	Xinxiang	8	8	-2	-3
153	Henan	Jiaozuo	6	8	-3	-3
154	Henan	Puyang	8	8	-2	-3
155	Henan	Xuchang	6	8	-2	-3
156	Henan	Luohe	6	8	-2	-3
157	Henan	Sanmenxia	8	8	-2	-3
158	Henan	Nanyang	6	8	-2	-3
159	Henan	Shangqiu	8	8	-2	-3
160	Henan	Xinyang	6	6	-2	-3
161	Henan	Zhoukou	6	8	-2	-3
162	Henan	Zhumadian	8	8	-1	-3
163	Hubei	Wuhan	8	6	-2	-3
164	Hubei	Huangshi	6	5	-2	-3
165	Hubei	Shiyan	6	5	-2	-3
166	Hubei	Yichang	5	5	-2	-3
167	Hubei	Xiangyang	8	8	-2	-3
168	Hubei	Ezhou	8	5	-2	-3

Table 6 (continued)

Code	Province	City	Spatiotemporal hot spot type		Allometric growth type	
			ES	CE	2000–2008	2009–2017
169	Hubei	Jingmen	8	5	-1	-3
170	Hubei	Xiaogan	8	6	-1	-3
171	Hubei	Jingzhou	8	5	-1	-3
172	Hubei	Huanggang	6	5	-1	-3
173	Hubei	Xianning	8	5	-2	-3
174	Hubei	Suizhou Shi	6	8	-1	-3
175	Hunan	Changsha	8	5	-2	-3
176	Hunan	Zhuzhou	6	5	-2	-3
177	Hunan	Xiangtan	6	2	-2	-3
178	Hunan	Hengyang	6	1	-2	-3
179	Hunan	Shaoyang	6	5	-1	-3
180	Hunan	Yueyang	8	5	-2	-3
181	Hunan	Changde	6	5	-2	-3
182	Hunan	Zhangjiajie	8	8	-2	-3
183	Hunan	Yiyang	6	1	-1	-3
184	Hunan	Chenzhou	8	5	-2	-3
185	Hunan	Yongzhou	5	2	+1	-3
186	Hunan	Huaihua	5	3	-1	-3
187	Hunan	Loudi	6	5	-2	-3
188	Guangdong	Guangzhou	8	5	-2	-3
189	Guangdong	Shaoguan	8	5	-2	-3
190	Guangdong	Shenzhen	8	5	-3	-4
191	Guangdong	Zhuhai	8	5	-2	-3
192	Guangdong	Shantou	8	5	-1	-3
193	Guangdong	Foshan	8	5	-2	-3
194	Guangdong	Jiangmen	8	5	-1	-3
195	Guangdong	Zhanjiang	5	3	-2	-3
196	Guangdong	Maoming	6	2	-2	-3
197	Guangdong	Zhaoqing	8	5	+1	-3
198	Guangdong	Huizhou	8	6	-1	-3
199	Guangdong	Meizhou	8	8	-2	-3
200	Guangdong	Shanwei	8	8	-2	-3
201	Guangdong	Heyuan	8	8	-2	-3
202	Guangdong	Yangjiang	8	5	-2	-3
203	Guangdong	Qingyuan	8	6	-2	-3
204	Guangdong	Dongguan	8	5	-3	-4
205	Guangdong	Zhongshan	8	5	-3	-3
206	Guangdong	Chaozhou	8	5	-1	-3
207	Guangdong	Jieyang	8	6	-1	-3
208	Guangdong	Yunfu	8	5	+1	-3
209	Guangxi	Nanning	5	3	-2	-3
210	Guangxi	Liuzhou	5	2	-3	-3

Table 6 (continued)

Code	Province	City	Spatiotemporal hot spot type		Allometric growth type	
			ES	CE	2000–2008	2009–2017
211	Guangxi	Guilin	5	2	-2	-2
212	Guangxi	Wuzhou	8	5	-2	-3
213	Guangxi	Beihai	5	3	-2	-3
214	Guangxi	Fangchenggang	5	3	-2	-3
215	Guangxi	Qinzhou	5	3	-1	-3
216	Guangxi	Guigang	5	3	-2	-3
217	Guangxi	Yulin	5	2	-2	-2
218	Guangxi	Baise	5	5	-2	-3
219	Guangxi	Hezhou	8	5	-2	-2
220	Guangxi	Hechi	5	5	-2	-3
221	Guangxi	Laibin	5	3	+1	-3
222	Guangxi	Chongzuo	5	3	-2	-3
223	Hainan	Haikou	5	3	-3	+1
224	Hainan	Sanya	5	3	-3	-1
225	Chongqing	Chongqing	8	5	-2	-3
226	Sichuan	Chengdu	5	2	-2	-3
227	Sichuan	Zigong	5	2	-2	-3
228	Sichuan	Panzhihua	5	5	-2	-3
229	Sichuan	Luzhou	6	5	-2	-3
230	Sichuan	Deyang	5	2	-2	-3
231	Sichuan	Mianyang	5	2	-2	-3
232	Sichuan	Guangyuan	5	2	-2	-3
233	Sichuan	Suining	8	5	+1	-3
234	Sichuan	Neijiang	8	5	-2	-3
235	Sichuan	Leshan	5	2	-2	-3
236	Sichuan	Nanchong	8	5	-2	-3
237	Sichuan	Meishan	5	2	-2	-3
238	Sichuan	Yibin	5	5	-2	-3
239	Sichuan	Guang'an	8	5	-2	-3
240	Sichuan	Dazhou	6	5	-2	-3
241	Sichuan	Ya'an	5	2	-2	-3
242	Sichuan	Bazhong	8	5	+1	-2
243	Sichuan	Ziyang	8	5	-2	-2
244	Guizhou	Guiyang	5	5	-2	-3
245	Guizhou	Liupanshui	5	5	-3	-3
246	Guizhou	Zunyi	8	8	-2	-3
247	Guizhou	Anshun	5	5	-2	-3
248	Yunnan	Kunming	5	5	-2	-3
249	Yunnan	Qijing	5	5	-2	-3
250	Yunnan	Yuxi	5	5	-1	-3
251	Yunnan	Baoshan	4	3	-1	-3
252	Yunnan	Zhaotong	5	2	+1	-3

Table 6 (continued)

Code	Province	City	Spatiotemporal hot spot type		Allometric growth type	
			ES	CE	2000–2008	2009–2017
253	Yunnan	Lijiang	5	5	-2	-3
254	Yunnan	Pu'er	4	3	-2	-3
255	Yunnan	Lincang	4	3	-1	-3
256	Shaanxi	Xi'an	5	5	-2	-3
257	Shaanxi	Tongchuan	5	5	-2	-3
258	Shaanxi	Baoji	3	2	-2	-3
259	Shaanxi	Xianyang	5	5	-2	-3
260	Shaanxi	Weinan	5	8	-2	-3
261	Shaanxi	Yan'an	5	8	-2	-2
262	Shaanxi	Hanzhong	5	3	-1	-3
263	Shaanxi	Yulin	5	8	-3	-2
264	Shaanxi	Ankang	5	1	-2	-3
265	Shaanxi	Shangluo	5	5	-1	-3
266	Gansu	Lanzhou	3	3	-2	-3
267	Gansu	Jiayuguan	4	3	-3	-3
268	Gansu	Jinchang	5	3	-3	-2
269	Gansu	Baiyin	3	1	-3	-3
270	Gansu	Tianshui	1	2	-2	-3
271	Gansu	Wuwei	3	5	-2	-3
272	Gansu	Zhangye	4	3	-2	-3
273	Gansu	Pingliang	3	5	-3	-3
274	Gansu	Jiuquan	5	4	-2	-3
275	Gansu	Qingyang	5	6	-2	-2
276	Gansu	Dingxi	3	3	+1	-3
277	Gansu	Longnan	3	3	-2	-2
278	Qinghai	Xining	3	3	-3	-2
279	Ningxia	Yinchuan	1	8	-3	-2
280	Ningxia	Shizuishan	5	8	-3	+1
281	Ningxia	Wuzhong	1	8	-2	-1
282	Ningxia	Guyuān@@	3	5	-2	-1
283	Ningxia	Zhongwei	3	5	-3	-1
284	Xinjiang	Urumqi	5	5	-2	-3
285	Xinjiang	Karamay	5	5	-2	-2

In the spatiotemporal hot spot type, ES is the abbreviation for economic scale (Fig. 1a), CE is the abbreviation for carbon emissions (Fig. 1b); numbers 1, 2, 3, 4, 5, 6, 7 and 8 represent historical cold spots, diminishing cold spots, persistent cold spots, consecutive cold spots, no pattern detected, new hot spots, consecutive hot spots and oscillating hot spots, respectively. In the allometric growth type, numbers -4, -3, -2, -1 and +1 represent negative allometric level 4, negative allometric level 3, negative allometric level 2, negative allometric level 1 and positive allometric level 1, respectively

Author contributions CB conceived the ideas and designed the research framework. SY performed the literature research. SY and WX performed the data collection and result calculation. SY, CB and WX led the writing of the manuscript. CB led the revising of the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no competing interests.

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