Spatiotemporal Evolution and Influencing Factors of China’ s Per Capita Carbon Footprint Based on the MGWR Model

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Abstract

Scientifically measuring and analyzing the per capita carbon footprint and its influencing factors provides a scientific basis for China to advance coordinated regional carbon-emission governance from the dual dimensions of emission reduction and carbon sequestration. This study employs a net primary productivity model to measure the per capita carbon footprint of 30 provinces (regions) in China from 2009 to 2022 (excluding Tibet, Hong Kong, Macao, and Taiwan) and of each province (region), and explores the spatiotemporal pattern of per capita carbon footprint through exploratory spatial data analysis. Furthermore, from a multidimensional "economy-energy-ecology" perspective, the multiscale geographically weighted regression (MGWR) model is used to analyze the spatially heterogeneous mechanisms through which influencing factors affect the per capita carbon footprint. The results show that: (1) From 2009 to 2022, the per capita carbon footprint of China' s 30 provinces (regions) and of each province (region) exhibited a significant upward trend, with the growth rate peaking at 10.56% in 2011. The spatial distribution of per capita carbon footprint showed a pattern of "higher in the north and lower in the south" ; hot spots and sub-hot spots were highly concentrated in Inner Mongolia and neighboring provinces (regions), while sub-cold spots were scattered across southern regions. (2) During the study period, the center of gravity of the per capita carbon footprint shifted northwestward, and the main axis of spatial agglomeration followed a "southwest-northeast" orientation. (3) In terms of influencing factors, the level of economic development, as the core driving factor, and the proportion of cultivated land use had both positive and negative bidirectional effects on the per capita carbon footprint; population density, energy intensity, and energy flows were positive driving factors, while the urbanization rate and the proportion of newly added forest land were negative inhibitory factors. The findings provide theoretical support for formulating targeted and differentiated regional dual-carbon policies.

Full Text

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Abstract: Scientifically measuring and analyzing the per capita carbon footprint and its influencing factors provides a scientific basis for China to advance coordinated regional carbon-emission governance from the dual dimensions of emission reduction and carbon sequestration. Using the net primary productivity model, this study measures the per capita carbon footprints of 30 provinces (autonomous regions and municipalities) in China (excluding Tibet, Hong Kong, Macao, and Taiwan) and of each province (autonomous region) from 2009 to 2022. Exploratory spatial data analysis is then used to investigate the spatiotemporal pattern of the per capita carbon footprint. Further, from the multidimensional perspective of "economy–energy–ecology," the multiscale geographically weighted regression (MGWR) model is employed to analyze the spatial heterogeneity mechanism of the factors influencing the per capita carbon footprint. The results show that: (1) From 2009 to 2022, the per capita carbon footprint of China' s 30 provinces (autonomous regions and municipalities) and of each province (autonomous region) showed a significant growth trend, with the growth rate reaching a peak of 10.56% in 2011. The spatial distribution of the per capita carbon footprint exhibited the characteristic of "high in the north and low in the south" ; hot spots and sub-hot spots were highly concentrated in Inner Mongolia and neighboring provinces (autonomous regions), while sub-cold spots were dispersed in southern regions. (2) During the study period, the center of gravity of the per capita carbon footprint shifted toward the northwest, and the main axis of spatial agglomeration showed a "southwest–northeast" orientation. (3) In terms of influencing factors, the level of economic development, as the core driving factor, had a positive and negative "bidirectional" effect on the per capita carbon footprint through its ratio to cultivated-land use; population density, energy intensity, and energy flow were positive driving factors, while the urbanization rate and the proportion of newly added forest land were negative inhibiting factors. The research results provide theoretical support for formulating "precision-oriented and differentiated" regional dual-carbon policies.

Keywords: per capita carbon footprint; spatial heterogeneity; influencing factors; multiscale geographically weighted regression (MGWR) model

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With the rapid expansion of the global industrial economy, the excessive consumption of fossil energy has led to a continuous rise in total carbon emissions, triggering a series of ecological crises such as climate change and biodiversity loss[^1]. In response to this global challenge, China explicitly proposed in the *Report to the 20th National Congress of the Communist Party of China* to "accelerate the establishment of a dual-control system for carbon emissions, with intensity control as the primary approach and total-amount control as a supplement," providing an institutional framework for achieving the "dual carbon" goals. From the perspective of total carbon emissions, China currently ranks first in the world. In 2022, its carbon emissions accounted for 26% of the global total, with the United States following at 11.5% (about 44% of China' s emissions)[^2]. However, from a per capita perspective, the United States ranks first in the world in per capita carbon emissions, with a value nearly twice that of China[^2]. This comparison reveals the difference between total-volume accounting and per capita responsibility. Compared with aggregate indicators, per capita carbon emissions can better reflect the true efficiency and fairness of regional carbon emissions. Based on this, this study combines China' s regional energy endowments with the distribution characteristics of the resident population, constructs an indicator of the per capita carbon footprint, and establishes an association mechanism between per capita carbon emissions and the regional ecological carrying capacity[^3]. Analyzing the dynamic impact mechanisms of factors such as the economy, ecology, and resources from a spatial perspective can provide scientific guidance for optimizing carbon-emission reduction pathways and advancing the construction of ecological civilization.

Carbon emission reduction is currently a core issue in the field of global environmental science. Research in this area mainly focuses on three aspects: carbon footprint accounting, spatial distribution, and its influencing factors. Carbon-footprint studies have covered multiple industries (construction[^4], agriculture[^5], electricity[^6], etc.) and multiple scales (national[^7], provincial[^8], urban agglomeration[^9], watershed[^10], etc.), but they mostly focus on emission-reduction pathways while neglecting carbon sequestration capacity and spatial heterogeneity. Spatial analysis has shifted from early methods such as Moran' s I to spatial econometric models[^8-^9], focusing on interpreting the spatial dependence and agglomeration patterns of carbon footprints[^7]. Regarding influencing factors, scholars have introduced spatial econometric models and geographically weighted regression (GWR) models and, by integrating the spatial attributes of influencing factors, have analyzed the spatial heterogeneity characteristics of influencing factors from both temporal and spatial dimensions[^11-^12]. Existing studies show that economic development[^13], population structure (including aging)[^14], and industrial …

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structure[^14], energy structure[^15], and other socioeconomic factors not only act directly on the local carbon footprint, but also generate spillover effects in surrounding regions through spatial transmission mechanisms[^16-^17]. Therefore, under the background of the "dual-carbon" goals, relying solely on the control of carbon-emission increments faces practical challenges; it is necessary to shift toward the coordinated promotion of the dual pathways of emission reduction and sink enhancement (carbon sequestration). Accordingly, research on the driving mechanisms of ecological carbon-sequestration potential and energy-use efficiency has equally important theoretical significance and practical value.

In summary, although significant progress has been made in the field of carbon-footprint research, the following research gaps remain to be filled: (1) studies that systematically interpret China' s low-carbon transition mechanism from the perspective of per capita carbon footprint still need to be deepened; (2) existing studies mostly focus on exploring emission-reduction pathways, while systematic pathway research on enhancing carbon-sequestration capacity remains insufficient. In view of this, by introducing net primary productivity (NPP), this study links carbon emissions with the carbon-sequestration capacity of ecosystems, and redefines the per capita carbon footprint as "the ratio of carbon emissions to regional ecological carbon-sink capacity and population size," forming a two-dimensional "emission–absorption" evaluation framework to identify the core contradictions of regional carbon balance, thereby remedying the shortcomings of traditional indicators that ignore ecological carrying capacity and lack policy targeting. On this basis, the per capita carbon footprints of China and its provinces (regions) from 2009 to 2022 are measured, and their spatiotemporal dynamic evolution characteristics are revealed, providing scientific support for the formulation of differentiated regional carbon-emission-reduction policies and coordinated ecological-environment governance[^11]. Furthermore, exploratory spatial data analysis and the multiscale geographically weighted regression (MGWR) model are applied. On the basis of the core factors covered by the Environmental Pressure Driving Decomposition (IPAT) model—such as population size, economic development level, and technological level—energy-flow conversion and ecological carbon-sequestration elements are expanded and incorporated, so as to explore the impacts of the above multidimensional factors on the spatial heterogeneity of the per capita carbon footprint, realize an expansion from a single emission-reduction orientation to a multidimensional collaborative evaluation perspective of "emission reduction–carbon sequestration–governance," and ultimately provide decision-making support for the optimization and efficient utilization of regional energy structure.

1 Data and Methods

1.1 Data Sources

This paper takes 30 provinces (regions) in China (excluding Tibet, Hong Kong, Macao, and Taiwan) as the research objects. Data for nine types of fossil fuels (raw coal, coke, crude oil, gasoline, diesel, kerosene, natural gas, fuel oil, and electricity), including unit heat value carbon content, average low calorific value, and carbon oxidation rate, are obtained from the *Guidelines for the Compilation of Provincial Greenhouse Gas Inventories* and the national energy balance sheets for 2009–2022 (updated to 2022). The selected nine fuels constitute the main body of China' s energy-consumption structure and are highly representative: first, they cover the energy types with the most complete statistics and the highest data quality at the provincial level; second, strict adherence to official statistical standards, together with the authority and consistency of their classification system, further ensures the comparability of accounting results. Land-use data, economic data, industrial pollution-control funds, and industrial value-added data are from the *China Statistical Yearbook* and the official website of the Ministry of Natural Resources.

1.2 Research Methods

1.2.1 Calculation model for per capita carbon footprint based on net primary productivity

According to the carbon-absorption capacity of each province' s (region' s) ecological land types and the corresponding land area, the average NPP of each province (region) is expressed by calculating the ratio of the sum of total net primary productivity within the region to the regional area[^18]. The formula is as follows:

$$\overline{\mathrm{NPP}} = \frac{\sum_{i=1}^{n}(A_i \times \mathrm{NPP}_i)}{\sum_{i=1}^{n} A_i} \qquad (1)$$

where: $\overline{\mathrm{NPP}}$ is the regional average net primary productivity; n is the number of ecosystem types; A_i is the regional area of the i-th ecosystem type; and NPP_i is the net primary productivity corresponding to the i-th ecosystem type. The NPP data for various ecosystems adopt the research results of Fang et al.[^18] (Table 1).

Table 1 Global average net primary productivity (NPP) of ecosystems
Tab. 1 Global average net primary productivity (NPP) of ecosystems

Indicator	Cultivated land	Garden land	Forest land	Grassland	Construction land	Water area
NPP/t C · hm^{-2} · a^{-1}	4.243	5.415	6.583	4.835	0.997	5.344

The per capita carbon footprint is the ratio of the carbon emissions of each province (region) to its regional average NPP and permanent population. The calculation formula is as follows:

$$C_r = \frac{\sum_{j}^{m}(Q_j \times V_j \times R_j \times F_j \times 3.67)}{\overline{\mathrm{NPP}} \times P_t} \qquad (2)$$

where: C_r is the per capita carbon footprint of province r; m is the number of energy types; Q_j is the consumption of the j-th energy type; V_j is the average low calorific value of the j-th energy type (Table 2); and R_j is the carbon content per unit heat value of the j-th energy type.

Table 2 Energy types and carbon emission coefficients
Tab. 2 Energy types and carbon emission coefficients

Energy type	Average low calorific value / 10^{-6} TJ · t^{-1}	Carbon content per unit heat value / t C · TJ^{-1}	Carbon oxidation rate / %
Raw coal	20.91	26.37	94
Coke	28.44	29.42	93
Crude oil	41.82	20.08	98
Gasoline	43.07	18.90	98
Kerosene	43.07	19.60	98
Diesel	42.65	20.20	98
Fuel oil	41.82	21.10	98
Natural gas	38.93	15.32	99
Electricity	1 kWh of electricity = 0.1721 kg raw coal; according to this conversion relationship, the electricity footprint is converted into a raw-coal footprint for calculation		

amount; F_j is the carbon oxidation rate of the jth energy source; 3.67 is the relative molecular mass ratio of CO_2 to C; P_i is the resident population of province i.

1.2.2 Exploratory Spatial Data Analysis

With the aid of the spatial exploratory analysis techniques of the ArcGIS 10.8 software platform, this study analyzes and identifies the distribution characteristics, dynamic change trends, and spatial dependence relationships of spatial cross-sectional data. The specific analytical methods include global Moran' s I, local Moran' s I, hot-cold spot analysis, and standard deviational ellipse analysis. The detailed calculation procedures follow the study by Yang Di et al.[14].

1.2.3 Multiscale Geographically Weighted Regression Model

The MGWR model considers the influence of spatial characteristics on global regression analysis. It uses its own optimal bandwidth to conduct regression analysis for each independent variable[19], explores the spatial heterogeneity of influencing factors, and is calculated as follows:

$$Y_i = \sum_{j=1}^{k} \beta_{bj} x_j + \varepsilon \qquad (3)$$

where Y_i is the dependent variable; k is the number of explanatory variables; β_{bj} is the jth regression coefficient with bandwidth b; x_j is the jth covariate; and ε is the regression residual.

2 Results and Analysis

2.1 Temporal Characteristics of Per Capita Carbon Footprint

2.1.1 Overall Evolution Characteristics From 2009 to 2022, China' s per capita carbon footprint showed a significant growth trend (Fig. 1). The years 2009–2011 were a period of economy-driven growth, with the average annual GDP growth rate reaching 9.60%, and industry and construction serving as the core driving forces. The share of coal consumption remained above 68%, driving a rapid rise in the national per capita carbon footprint; in 2011, it increased by as much as 10.56% compared with 2009. The years 2012–2015 were a turning period of policy regulation and control. As environmental pressure from economic development intensified, the state implemented energy-conservation and emission-reduction policies and promoted the transformation and upgrading of high-energy-consuming enterprises. The growth of the national per capita carbon footprint slowed markedly, and in 2015 negative growth of −0.40% appeared for the first time, indicating the initial effectiveness of policies. The years 2016–2020 were a green transition period. During the "13th Five-Year Plan" period, China incorporated "carbon intensity" into local government assessments through the *Work Plan for Controlling Greenhouse Gas Emissions*. Coupled with the decline in industrial capacity in 2019–2020, the growth of the national per capita carbon footprint was effectively controlled, and the five-year average growth rate fell to 0.80% (a decrease of 2.10% compared with 2012–2015). The years 2021–2022 were a rebound-and-challenge period. Capacity utilization in high-energy-consuming industries such as steel and cement rose back to over 90%, and in 2022 the national per capita carbon footprint increased by 4.62% compared with 2020.

2.1.2 Regional Evolution Characteristics From 2009 to 2022, the per capita carbon footprint of most Chinese provinces (regions) showed an increasing trend (Fig. 2). Major energy provinces (Shaanxi, Xinjiang, Inner Mongolia, etc.) had per capita carbon-footprint increases exceeding 100% (Shanxi

Fig. 1 Per capita carbon footprint in China and its growth rate changes

Figure 1: Fig. 1 Per capita carbon footprint in China and its growth rate changes

Fig. 2 Temporal changes in per capita carbon footprint across provincial-level regions in China

Figure 2: Fig. 2 Temporal changes in per capita carbon footprint across provincial-level regions in China

had the highest increase, 224.30%), all displaying the characteristic of "high coal consumption and heavy industry." Relying on their energy reserves, these provinces (regions) vigorously developed high-energy-consuming heavy industry, while also undertaking the mission of transmitting energy southward, playing an important role in balancing regional energy disparities in China. Beijing, Henan, and Chongqing showed a trend of rising first and then falling, decreasing in 2022 by 45.24%, 3.59%, and 5.64%, respectively, compared with 2009. The reason is that Beijing withdrew more than 1,800 high-energy-consuming enterprises from 2014 to 2022, and the share of the tertiary industry rose rapidly. As a major grain-producing area, Henan reduced carbon emissions per unit of grain output through technologies such as straw return to fields and soil-testing-based formulated fertilization. Chongqing replaced traditional heavy industry with electronics manufacturing and energy-saving and environmental-protection industries, and its energy consumption per unit of GDP in 2022 decreased by 26.30% compared with 2012. The above regional differences led to a widening gap in per capita carbon footprint between the north and the south: the north supports electricity demand for industry in the south through "transporting coal from north to south" and "transmitting electricity from west to east" (in Shanxi and Inner Mongolia, coal outflows in 2022 exceeded 50% of production), while all southern provinces except Guizhou are energy-importing areas. The process of energy transfer has intensified ecological pressure in northern regions; land after mining requires long-term restoration, thereby increasing the cost of regional environmental governance.

Fig. 1 Per capita carbon footprint in China and its growth rate changes

Fig. 2 Temporal changes in per capita carbon footprint across provincial-level regions in China

However, in input regions such as Guangdong, local carbon emissions are reduced through purchases of electricity from outside the region, causing the actual per capita carbon footprint to be underestimated and forming a pattern in which "the north bears the emissions, while the south enjoys the benefits," further widening the disparity in per capita carbon footprints among provinces (regions).

2.2 Exploratory spatial data analysis of per capita carbon footprint

2.2.1 Spatial distribution characteristics

From 2009 to 2022, China' s per capita carbon footprint showed significant positive spatial autocorrelation (Table 3). The global Moran' s I values were all positive (with a peak of 0.341 in 2012), and gradually weakened after 2012, fluctuating around 0.279, indicating that the spatial correlation of China' s per capita carbon footprint was slowly decreasing.

Table 3 Global autocorrelation analysis results of per capita carbon footprint in China

Year	Global Moran' s I	Z value	P value
2009	0.339	3.136	0.002
2012	0.341	3.230	0.001
2015	0.279	2.753	0.006
2018	0.272	2.692	0.007
2022	0.279	3.030	0.002

Note: Moran's I is Moran's index; the Z value indicates the strength of deviation from randomness ($|Z| > 1.96$ is significant); the P value indicates the probability of randomness ($P < 0.05$ is significant).

According to the local Moran's I results, China's per capita carbon footprint can be divided into high-high, low-high, and low-low clustered spatial patterns (Fig. 3). The evolution of local spatial clustering from 2009 to 2022 shows that the northern high-high and low-high clusters expanded from a "mixed distribution" [3 provinces (regions) in 2009] to energy-supply provinces (regions) centered on "Shaanxi-Inner Mongolia-Hebei-Gansu" [4 provinces (regions) in 2022], whereas the southern low-low cluster consisted of nine neighboring provinces (regions), including Guangdong, Guangxi, and Jiangxi. This differentiation is essentially a spatial mismatch between "responsibility for energy production" and "benefits from consumption-based emission reduction." Therefore, exploring the influencing factors of per capita carbon footprints among provinces (regions) is not only of great significance for regional environmental co-governance, but can also provide an effective basis for assigning carbon-emission responsibilities among provinces (regions).

2.2.2 Hot- and cold-spot analysis

From 2009 to 2022, the distribution of hot and cold spots of China' s per capita carbon footprint was divided into hot spots, sub-hot spots, sub-cold spots, and cold-spot areas (Fig. 4). Hot-spot areas (99% confidence): the number decreased from two in 2009 (Inner Mongolia and Hebei) and two in 2012 (Inner

Mongolia and Ningxia) to one after 2015 (Inner Mongolia), forming a "single-core lock-in" pattern. Sub-hot-spot areas (90%-95% confidence): the number increased from three (Shanxi, Ningxia, and Liaoning in 2009) to five (Shanxi, Hebei, Ningxia, Gansu, and Shaanxi in 2022). Hebei and Ningxia shifted from hot-spot areas to sub-hot-spot areas, spatially forming an "annular radiation belt" around Inner Mongolia.

Because Inner Mongolia continuously exports energy, the per capita carbon footprint is highly active there and has a significant radiating effect on adjacent provinces (regions), producing high carbon emissions in energy production and consumption that pull sub-hot-spot areas. Neighboring provinces (regions) such as Shanxi, Hebei, and Ningxia were mostly located in sub-hot-spot areas. Inner Mongolia, together with Shanxi and Shaanxi, formed a coal "production-transportation-consumption" chain, creating the "Shanxi-Shaanxi-Inner Mongolia (Shanxi, Shaanxi, Inner Mongolia)" collaborative spatial network. The number of sub-cold-spot areas decreased from nine to two (Guizhou and Hunan), a contraction of more than 77%; Guangdong, Hubei, and other regions withdrew from the sub-cold-spot areas because of the expansion of electronic manufacturing, rising population density, and industrial transfer out of the Yangtze River Economic Belt. Although Guizhou is a core area for west-to-east electricity transmission, coal-fired power still accounted for 58% in 2022; the transformation of its energy structure was relatively delayed, and therefore its per capita carbon footprint increased by 19.50% compared with 2009, making it the only remaining sub-cold-spot boundary in the south.

(a) 2009 (b) 2012 (c) 2015

Review map number: GS(2025)6204
Legend Clustering type
National boundary Not significant
Undetermined boundary High-High
Provincial boundary Low-High
Coastline Low-Low
Non-study area

(d) 2018 (e) 2022

Review map number: GS(2025)6204
Legend Clustering type
National boundary Not significant
Undetermined boundary High-High
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Coastline Low-Low
Non-study area

Fig. 3 Spatial clustering results of per capita carbon footprint in China

green area. Overall, in 2022, the area north of the Qinling-Huaihe Line was the clustering area of hotspots and secondary hotspots of per capita carbon footprint, while the south was the clustering area of secondary cold spots, forming a significant "Hu Huanyong Line" mirror image of energy consumption, reflecting the fundamental differences in industrial structure and resource endowment between northern and southern China.

2.3 Standard deviational ellipse analysis

From 2009 to 2022, the barycenter of China' s per capita carbon footprint was located in Shanxi (Fig. 5) and showed a trend of moving northwestward (from 35.92°N to 36.61°N, and from 112.89°E to 111.48°E). This was mainly attributable to the continuous rise in per capita carbon footprint in provinces (regions) of northwestern China, which pulled the barycenter to shift. During the study period, the flatness of the standard deviational ellipse continued to increase, indicating that the direction of change in the high-value area became increasingly significant and moved regularly; the azimuth angle increased from 80.90° to 88.44°, confirming that the dense range of the high-value area expanded westward, with the southwest-northeast dispersion feature being the most prominent, consistent with the pattern of barycenter shift[^20]. Combined with the direction of offset and trend prediction, high-value areas in the future will continue to cluster toward the northwest, and emphasis should be placed on controlling energy consumption and carbon emissions in northwestern China. By comparison, the per capita carbon footprints of southern provinces are stable and have small increases, so their influence on the barycenter can be ignored.

2.4 Analysis of influencing factors of per capita carbon footprint

2.4.1 Variable selection and model testing Alleviating carbon pollution is the primary task for China' s future development. With the goal of ecological and environmental protection, exploring the spatial influence pathways of economic development, environmental protection, and resource conservation on the per capita carbon footprint is of great significance for China' s sustainable development. Based on the IPAT model analytical framework and the multidimensional perspective of "economy-energy-ecology," this paper identifies, from three core levels—affluence level (economic dimension), population size and urbanization rate (social dimension), and technological level and energy flow transition (energy dimension)—the factors influencing the environmental pressure of China' s per capita carbon footprint.

(a) 2009
Map approval number: GS(2025)6204

Legend
National boundary; Undetermined national boundary; Provincial boundary; Coastline
Cold/hot spot analysis
Sub-cold spot (95% confidence); Sub-cold spot (90% confidence); Not signifi-

cant; Sub-hot spot (90% confidence); Sub-hot spot (95% confidence); Hot spot (99% confidence); Non-study area
0 500 km

(b) 2012
Map approval number: GS(2025)6204

Legend
National boundary; Undetermined national boundary; Provincial boundary; Coastline
Cold/hot spot analysis
Sub-cold spot (95% confidence); Sub-cold spot (90% confidence); Not significant; Sub-hot spot (90% confidence); Sub-hot spot (95% confidence); Hot spot (99% confidence); Non-study area
0 500 km

(c) 2015
Map approval number: GS(2025)6204

Legend
National boundary; Undetermined national boundary; Provincial boundary; Coastline
Cold/hot spot analysis
Sub-cold spot (95% confidence); Sub-cold spot (90% confidence); Not significant; Sub-hot spot (90% confidence); Sub-hot spot (95% confidence); Hot spot (99% confidence); Non-study area
0 500 km

(d) 2018
Map approval number: GS(2025)6204

Legend
National boundary; Undetermined national boundary; Provincial boundary; Coastline
Cold/hot spot analysis
Sub-cold spot (95% confidence); Sub-cold spot (90% confidence); Not significant; Sub-hot spot (90% confidence); Sub-hot spot (95% confidence); Hot spot (99% confidence); Non-study area
0 500 km

(e) 2022
Map approval number: GS(2025)6204

Legend
National boundary; Undetermined national boundary; Provincial boundary; Coastline
Cold/hot spot analysis
Sub-cold spot (95% confidence); Sub-cold spot (90% confidence); Not significant; Sub-hot spot (90% confidence); Sub-hot spot (95% confidence); Hot spot

Fig. 5 Standard deviational ellipse analysis of per capita carbon footprint in China

Figure 3: Fig. 5 Standard deviational ellipse analysis of per capita carbon footprint in China

(99% confidence); Non-study area
0 500 km

Fig. 4 Cold and hot spot analysis of per capita carbon footprint in China

Key driving factors (Table 4) were also incorporated into the ecological carbon-sink dimension to quantify ecological carbon-sequestration potential, thereby providing the analytical basis for constructing the MGWR model. This paper selects per capita GDP as the core proxy indicator for measuring the level of economic development. This indicator can accurately characterize the "per capita level of economic activity" indicated by the affluence component in the IPAT model, and thus reveal the dynamic driving relationship between the economic system and the environmental pressure of carbon emissions. Population size reflects pressure on the resource environment; in essence, it represents the dynamic coupling between the intensity of population activity and spatial carrying capacity. Using population density to characterize population size can accurately reflect the spatial agglomeration characteristics of population, directly link per capita resource endowment with the concentration of pollutant emissions, and reveal the localized pressure exerted by population concentration on regional resources, thereby compensating for the limitation that total population ignores differences in spatial distribution[^21-22]. At the same time, as the core indicator of the level of urbanization, the urbanization rate can effectively characterize the urban–rural spatial distribution structure of the population, and is significantly associated with patterns of energy consumption and the intensity of economic activity[^23]. As an intermediary variable connecting economic development, population mobility, and technological progress, it can more clearly reveal differences in the structural characteristics of the population[^24-25]. Therefore, a joint analysis of population size and the level of urbanization can, compared with a single total-population indicator, more accurately capture the spatial heterogeneity of the impact of population on the per capita carbon footprint. At the technological level, energy intensity and energy-flow conversion efficiency, as jointly quantified indicators, can directly

Figure legend: national boundary; undetermined national boundary; provincial boundary; coastline; study area; non-study area; center of gravity (2009, 2012, 2015, 2018, 2022); standard deviational ellipse (2009, 2012, 2015, 2018, 2022). Map approval number: GS(2025)6204.

Fig. 5 Standard deviational ellipse analysis of per capita carbon footprint in China

Table 4 Key variables and descriptive statistics of MGWR model

Tab. 4 Key variables and descriptive statistics of MGWR model

Explanatory variable	Calculation equation
Level of economic development	Per capita GDP (standardized)
Population density	Total regional population / total regional land area (standardized)
Urbanization rate	Ratio of the regional urban permanent population to the total regional permanent population / %
Energy intensity	Total energy consumption / regional gross domestic product (standardized)
Energy flow rate	Ratio of net inflow of coal and oil products to terminal consumption of coal and oil products / %
Proportion of newly added forest land	Ratio of the annual newly added forest-land area to the total forest-land area / %
Proportion of cultivated-land use	Ratio of cultivated-land area to total land-use area / %

This characterizes the driving effect of technology on the per capita carbon footprint. Energy intensity quantifies the energy-use efficiency of the economic system through "energy consumption per unit GDP." The energy flow rate focuses on the circulation and recycling level of the energy system; by quantifying the spatial mismatch between "production-side emissions and consumption-side benefits," it can not only reveal the inequality of regional carbon-emission responsibility, but also characterize the positive correlation between the ecological pressure of output areas and the scale of flows, further distinguishing regional heterogeneity in energy consumption and accurately identifying a low-carbon consumption model of "high input–low emissions." The combination of the two can directly reveal the intrinsic logic through which technology affects the per capita carbon footprint and then acts on the sustainable development of ecology and resources. When analyzing the driving factors of the carbon footprint, traditional studies[21-22] focus on emission-reduction technologies at the carbon-source end and do not incorporate the improvement of carbon-sink capacity (the carbon-sink-side sink-enhancement path) into the regulatory scope, resulting in limitations in analyses of solid-carbon enhancement. Therefore, this paper introduces the proportion of forest land and the proportion of cultivated-land use as proxy variables for quantifying ecological solid-carbon potential at the provincial scale. They directly reflect the association between ecological functions and the carbon-sink mechanism, so as to systematically characterize their pathways of influence on the per capita carbon footprint. At the same time, the two are highly consistent with China' s policies such as the "red line for cultivated-land protection" and "returning cultivated land to forest," and can accurately capture regional differences in the ecological background, ultimately providing direct support for the design of cross-regional ecological compensation mechanisms.

To avoid the influence of correlations among variables on the model-analysis results, before MGWR modeling, ordinary least squares (OLS) regression analysis[26] was conducted for the per capita carbon footprint, and multicollinearity tests were performed. In comparison, the MGWR model has better fitting performance in terms of goodness of fit (R^2), adjusted R^2, and corrected Akaike information criterion (AICc)[26] than the GWR model and the OLS model (Table 5). Thus, the MGWR model is a better choice for analyzing the factors influencing changes in the per capita carbon footprint.

Table 5 Comparison of fitting results of OLS, GWR and MGWR models

Tab. 5 Comparison of fitting results of OLS, GWR and MGWR models

Model	Residual sum of squares	AICc	R^2	Adjusted R^2
OLS	19.776	99.635	0.341	0.131
GWR	19.133	99.616	0.362	0.110
MGWR	8.915	96.212	0.703	0.499

Note: OLS is ordinary least squares; GWR is geographically weighted regression; MGWR is multiscale geographically weighted regression; AICc is the corrected Akaike information criterion; R^2 is goodness of fit; adjusted R^2 is a statistic that guards against overfitting.

2.4.2 Analysis of influencing factors

Overall, the effects and significance levels of different influencing factors on the per capita carbon footprint in China show spatiotemporal differences (Fig. 6). The influence of the level of economic development on the per capita carbon footprint exhibits significant regional heterogeneity, with a core spatial pattern of "positive in the east and negative in the west." In the eastern region (such as Beijing–Tianjin–Hebei and Shandong), the level of economic development is much higher than in the west, industrial development is already mature, and the regional consumption level is relatively high, producing a significant positive driving effect on the per capita carbon footprint. In the central and western regions, however, the effect is negative. Although economic development is relatively lagging and there is a heavy-industry foundation, these regions have promoted industrial restructuring through "low-carbon adjustments"; the shares of agriculture, ecological service industries (such as ecological tourism in Qinghai and the health-care industry in Yunnan), and distinctive low-carbon industries (such as the electronic-information industry in Sichuan) have continued to increase. Coupled with the rigid constraints imposed on high-energy-consuming industries by national policies such as "Western Development" and "ecological protection of the Yellow River Basin," this has decoupled economic development from the growth rate of carbon emissions, effectively curbing the increase in the per capita carbon footprint. Population density has a significant positive effect on the per capita carbon footprint, most prominently in North China and Northeast China (such as Inner Mongolia and Heilongjiang). In these regions, a heavy-industry-dominated industrial structure is highly coupled with population density, and population concentration directly expands the scale of industrial production.

(a) Economic development level

Legend
National boundary
Undetermined national boundary
Provincial boundary
Coastline
Regression coefficient
−0.8793–−0.6605
−0.6605–−0.3084
−0.3084–0.1226
0.1226–0.4313
0.4313–0.7966
Non-study area
Map approval No.: GS(2025)6204

(b) Population density

Legend
National boundary
Undetermined national boundary
Provincial boundary
Coastline
Regression coefficient
0.1749–0.1755
0.1755–0.1762
0.1762–0.1768
0.1768–0.1775
0.1775–0.1791
Non-study area
Map approval No.: GS(2025)6204

(c) Urbanization rate

Legend
National boundary
Undetermined national boundary

Provincial boundary
Coastline
Regression coefficient
−0.0651-−0.0644
−0.0644-−0.0638
−0.0638-−0.0632
−0.0632-−0.0622
−0.0622-−0.0613
Non-study area
Map approval No.: GS(2025)6204

(d) Energy intensity

Legend
National boundary
Undetermined national boundary
Provincial boundary
Coastline
Regression coefficient
0.5025-0.5027
0.5027-0.5031
0.5031-0.5041
0.5041-0.5055
0.5055-0.5069
Non-study area
Map approval No.: GS(2025)6204

(e) Energy conversion rate

Legend
National boundary
Undetermined national boundary
Provincial boundary
Coastline
Regression coefficient
0.1519-0.1520
0.1520-0.1521
0.1521-0.1523
0.1523-0.1524
0.1524-0.1527
Non-study area
Map approval No.: GS(2025)6204

(f) Proportion of newly added forest land

Legend
National boundary
Undetermined national boundary
Provincial boundary

Coastline
Regression coefficient
–0.1320––0.1319
–0.1319––0.1316
–0.1316––0.1315
–0.1315––0.1314
–0.1314––0.1312
Non-study area
Map approval No.: GS(2025)6204

(g) Proportion of cultivated-land use

Legend
National boundary
Undetermined national boundary
Provincial boundary
Coastline
Regression coefficient
–0.3573––0.3560
–0.3560––0.3550
–0.3550––0.3546
–0.3546––0.3541
–0.3541––0.3532
Non-study area
Map approval No.: GS(2025)6204

Fig. 6 Spatial distributions of regression coefficients of influencing factors of per capita carbon footprint in China

drives the growth of the carbon footprint; the rigid demand for centralized heating in northern regions further strengthens this effect, causing carbon emissions from domestic energy use in densely populated cities to increase with rising population density. By comparison, southern regions (such as Guangdong, Guangxi, etc.) are dominated by low-energy-consuming industries, and population agglomeration

sharing of infrastructure generated by agglomeration (such as public transport networks) and improvements in energy-use efficiency, thereby effectively weakening its positive driving effect. The negative impact of the urbanization rate on the per capita carbon footprint is relatively weak, and the degree of influence in western China is slightly higher than in eastern China. Compared with the later, stable stage of urbanization in the east, urbanization in the west (such as Xinjiang, Qinghai, and other places) is in a mid-term accelerated stage: the marginal effect of population concentration in cities and towns is stronger, and the rural low-efficiency energy-use model is being transformed toward shared infrastructure such as centralized urban heating and public transportation, which can substantially reduce per capita energy consumption; centralized energy supply in parks also improves energy-use efficiency, jointly strengthening the negative driving effect. Energy intensity has a significant positive effect on the per capita carbon footprint, and its influence shows a "high in the west and low in the east" stepped pattern. In western regions (such as Xinjiang, Gansu, and other places), because industries are highly dependent on energy and the R&D and application of energy-saving technologies lag behind, its positive driving effect is significant; in the eastern region, the energy-efficiency improvements brought about by an industrial structure dominated by high-tech manufacturing and modern services, high utilization of clean energy, and technological innovation effectively weaken its positive driving effect. The positive effect of the energy conversion rate shows a spatial distribution of "high in the north and low in the south," with the northwest performing most prominently. Energy conversion raises the per capita carbon footprint in the northwest through a spatial mismatch of "production-side emissions—consumer-side benefits" ; in southern coastal provinces, because carbon-emission accounting focuses on the consumption side and the industrial structure is dominated by low-energy-consuming industries, its marginal impact is significantly lower than in the northwest. The north–south regional differences further highlight the regional imbalance of the per capita carbon footprint in the "production–consumption" spatial mismatch. The negative effect of the proportion of newly added forestland on the per capita carbon footprint shows regional differences characterized by "prominent in North China and Northeast China, weakened in western China." North China and Northeast China rely on ecological projects centered on high-carbon-sequestration arbor forests, such as the "Three-North Shelterbelt Forest Program" ; the governance targets are mostly low-carbon-sequestration land such as farmland and degraded wetlands, and carbon-sequestration density has increased markedly, producing prominent carbon-sink gains. In the western region, ecological projects focus mainly on desertification control; most newly added forestland consists of shrubland, whose carbon-sequestration capacity is far lower than that of arbor forests, resulting in a negative impact significantly weaker than that in North China and Northeast China. The proportion of cultivated land has a negative impact on the northwest and the Central Plains, while it shows a positive impact on the southeast. The major grain-producing areas of the Central Plains are centered on large-scale farmland ecosystems, and cultivated land is an important "sink" in the regional carbon cycle; in the northwest, cultivated-land expansion suppresses desertification, and the carbon-sequestration rate of irrigated cultivated land is higher than that of deserts. All of the above regions need to optimize cultivated-land layout to balance ecological protection and food security. In the eastern and southern coastal areas, because the urbanization rate is high, the proportion of cultivated land is relatively low, and cash crops predominate, the impact of cultivated-land carbon-sink effects is positive; this difference reflects the coupling relationship between cultivated-land carbon-sink effects and land-use structure, among which the inhibitory effect of cultivated-land protection and expansion on the per capita carbon footprint is more prominent in ecologically fragile areas.

3 Discussion

By innovatively introducing the regional NPP parameter, this paper establishes the per capita carbon footprint as the core indicator for carbon-emission assessment, thereby remedying the key shortcoming of previous studies[^14-15], which emphasized only total carbon emissions while neglecting the absorptive capacity of ecosystems, and significantly improving the scientific validity and rationality of environmental impact assessment. The spatial distribution of the per capita carbon footprint across China' s provinces (regions) shows a pattern of "high in the north and low in the south," and during the study period the center of gravity continued to move toward the northwest. This pattern is highly similar to the results of previous studies on per capita carbon emissions[^2,27-28], both showing the characteristic that the Hu Huanyong Line forms a boundary and northern provinces have higher values than southern regions. However, by integrating carbon-cycle capacity, the per capita carbon footprint constructs a more comprehensive assessment framework for regional carbon-emission pressure. Its advantage is especially evident in refined analysis at subregional and provincial scales. Traditional per capita carbon-emission analysis reflects only spatial differences in emissions (for example, the east is higher than the national average, the central region is lower than the national average, and the west has a rapid growth rate, with hotspots concentrated in Inner Mongolia, Xinjiang, and Qinghai)[^2,27-28], but it does not link these differences to the regional ecological background. In contrast, the spatial distribution of the per capita carbon footprint better conforms to the synergistic characteristics of industrial structure and ecological carbon sinks: low-value areas are distributed in eastern and southern provinces (regions) (such as Jiangxi and Guangxi), which are dominated by agriculture and coastal light industry and have high vegetation coverage, strong carbon-absorption capacity, and faster "carbon-neutralization" processes; high-value areas are concentrated in western and northern provinces (regions) (such as Inner Mongolia and Shanxi), corresponding to energy production bases and heavy-industry clusters. Because such regions have high carbon emissions, fragile ecosystems, and limited carbon-absorption capacity, they form the dual pressure of "high emissions–low absorption." This is precisely the key information that per capita carbon-emission analysis cannot identify[^29-30]. In the evolution of hotspot and cold-spot areas, hotspots of per capita carbon emissions are concentrated in Inner Mongolia and Hebei and form a range-like isolated arc[^2], while secondary cold spots are widely distributed in South China with blurred boundaries; by contrast, hotspots of the per capita carbon footprint radiate outward from Inner Mongolia as the center and form outward-extending high-value areas in Northeast China and North China, while secondary cold spots gradually contract from South China to the agricultural and light-industrial core areas of Guizhou and Hunan. By integrating the two dimensions of "emissions–absorption," the per capita carbon footprint accurately identifies key governance areas and remedies the regional governance bias of traditional per capita carbon-emission analysis.

This study further breaks through the limitations of the traditional single economic or energy perspective and constructs a three-dimensional "economy-energy-ecology" impact-analysis framework. In terms of the economic driving mechanism, this study finds that there is "east-west" heterogeneity in the per capita carbon footprint: economic development in eastern China is positively associated with the per capita carbon footprint[^31], whereas western China shows a negative association. This finding challenges the linear assumption that "economic growth inevitably intensifies carbon emissions" [^9,14] and provides new scientific evidence for differentiated regional policy formulation. At the level of population and urbanization driving mechanisms, population-density change in this study has a positive driving effect on the per capita carbon footprint, which is consistent with existing research[^25]. However, the effect of the urbanization rate shows differentiated characteristics: existing studies indicate that the urbanization rate overall has a positive effect on carbon emissions[^24], but the conclusion that it has a negative effect in the agricultural sector[^23] is consistent with this study.

The results are consistent, because agricultural carbon-emission accounting has already been incorporated into ecological land-use factors; by integrating the two dimensions of carbon sources and carbon sinks, the per capita carbon-footprint indicator constructed in this paper can reveal more comprehensively and accurately the mechanism by which the urbanization rate affects provincial carbon emissions.

Existing studies[^31] have confirmed that energy intensity has a significant spatial effect on the per capita carbon footprint of Chinese provinces (autonomous regions and municipalities). However, because energy cross-regional transfer analysis was not incorporated, there has been insufficient empirical explanation for the phenomenon that "the carbon footprint of exporting provinces (autonomous regions and municipalities) is relatively high." This study, for the first time, incorporates energy transfer into the analytical framework and constructs a carbon-emission tracing system. Its mechanism of spatial influence on the per capita carbon footprint is as follows: the transport losses and additional carbon emissions from processing and conversion in cross-regional energy transfer are borne by the exporting provinces (autonomous regions and municipalities), and energy extraction and transport directly induce ecological land degradation and weaken the ecological carrying capacity of exporting provinces (autonomous regions and municipalities). At the same time, the impact of energy transfer on the per capita carbon footprint is uncertain, rooted in differences among energy types in physical properties, transport costs, and industrial compatibility. First, differences in carbon-emission intensity lead to accounting bias. The carbon-emission intensity of coal transport is significantly higher than that of petroleum pipeline transport. Although electricity, as a secondary energy source, is transmitted through power grids, it is constrained by coverage and entails line losses. Aggregate statistics may obscure the differential impacts of clean energy and fossil energy on the per capita carbon footprint of exporting regions. Second, differences in industrial compatibility intensify uncertainty. In the north, coal transfer mainly serves local heavy industry; in the south, coal inputs are combined with clean energy, diluting carbon-emission intensity and creating a pattern of "similar energy—heterogeneous utilization," which causes a north–south differentiation in coal-transfer coefficients. The failure to refine petroleum categories will obscure the differentiated contributions of different transportation modes. Existing indicators (such as the share of coal carbon emissions and the petroleum transfer rate), although revealing driving mechanisms from the dimensions of structural attributes and spatial flows, have limited representativeness because they are affected by differences in energy types. Future research should refine energy classification and incorporate parameters such as transport losses and processing-conversion efficiency, so as to improve the accuracy of results and their policy relevance. In studies of the driving mechanism of ecological carbon sequestration, previous literature[^19,^32–^33] has confirmed the spatial spillover effect of land-use change on carbon emissions. This study further reveals that the spatial coefficients of the share of newly added forest land and the share of cultivated land exhibit a gradient of "high in the east and low in the west, shifting from negative to positive from northwest to southeast," demonstrating regional differentiation in the mechanism of ecological carbon-sequestration drivers. However, the north–south vegetation types, climatic conditions, and statistical heterogeneity of data cause regional bias in model estimates of carbon-sink capacity. Specifically, first, regional vegetation types differ significantly in carbon-sequestration efficiency. The north is dominated by natural forests and grasslands; carbon sinks are relatively stable, but ecosystems are fragile and interannual NPP fluctuations are relatively large. The south is dominated by plantations and economic forests, with shorter growth cycles and weaker carbon-sink functions. Second, climatic and soil conditions are highly heterogeneous. The high-temperature and high-humidity environment in the south accelerates organic-matter decomposition, and soil carbon-storage capacity is lower than in the north, resulting in regional differences in the carbon-sequestration efficiency of cultivated land. Third, the land-use classification system does not cover carbon-sink types such as wetlands, deserts, and bare land; this may underestimate their carbon-sequestration potential. In addition, failure to distinguish forest types may overestimate the carbon-sequestration contribution of newly added forest land in provinces (autonomous regions and municipalities). Future research should refine ecosystem classification and introduce dynamic NPP parameters to reduce estimation uncertainty.

4 Conclusions and Recommendations

4.1 Conclusions

(1) From 2009 to 2022, China' s per capita carbon footprint showed a linear growth trend, with a stable pattern of "high in the north and low in the south."Based on local spatial autocorrelation analysis, high–high clustering hot spots were concentrated in North China (Inner Mongolia and Hebei)

and the northwest region (Shaanxi), displaying a "spatially contiguous" distribution. Low-low clustering cold spots were located in the middle and lower reaches of the Yangtze River and in South China (Hubei, Jiangxi, Guangdong, etc.), showing a "multi-center dispersed" pattern. Low-high clustering transition zones were scattered across Gansu, Hebei, Liaoning, and other provinces, manifesting spatial heterogeneity in which "local high values are surrounded by low values."

(2) During the study period, the center of gravity of China' s per capita carbon footprint remained within Shanxi Province and exhibited a slow migration toward the northwest. The spatial clustering of high per capita carbon-footprint values showed a trend of dispersion along the southwest-northeast direction. The spatial pulling effects of the Shanxi-Inner Mongolia energy base and the emerging Xinjiang-Ningxia industrial cluster caused the clustering center of gravity to expand toward both ends along this axis, with the diffusion rate in the northwestern segment (Inner Mongolia-Ningxia) higher than that in the southwestern segment (Shanxi-Shaanxi).

(3) From the perspective of spatial heterogeneity among influencing factors, the level of economic development is a key factor in the growth of the per capita carbon footprint. Together with the proportion of cultivated land use, it exhibits a "positive-negative" bidirectional effect on the per capita carbon footprint. The regional effects of population density and urbanization rate differ significantly: they respectively show a positive driving effect and a negative inhibitory effect on the per capita carbon footprint. Energy intensity and the energy transfer rate have significant positive driving effects on the per capita carbon footprint, whereas the share of newly added forest land shows a negative inhibitory effect.

4.2 Recommendations

(1) It is recommended that per capita carbon-footprint hot-spot areas such as North China and Northwest China accelerate the formation of a new supply model characterized by "renewable energy as the mainstay, fossil energy as the safeguard, and support from energy storage and the power grid." Cold-spot areas such as the middle and lower reaches of the Yangtze River and South China should place emphasis on demand-side guidance, reduce demand for high-energy-consuming products through green procurement policies, and inversely curb carbon emissions at upstream production ends.

(2) In response to the trend of high-value areas dispersing along the southwest-northeast axis, it is recommended to establish a collaborative emission-reduction alliance of "Shanxi-Inner Mongolia-Shaanxi-Ningxia-Xinjiang (Shanxi, Inner Mongolia, Shaanxi, Ningxia, Xinjiang)," and unify access standards for high-energy-consuming industries. The north should opti-

mize industrial structure (strictly control high-energy-consuming production capacity), the south should strengthen governance investment (promote green consumption), and the northwest should supplement governance funds (establish special funds), while ecological buffer zones should be arranged around high-value areas to form a collaborative mechanism of "production-side emission reduction—ecological-side restoration."

(3) Establish a carbon-emission responsibility-sharing mechanism. Energy-output regions should levy an "ecological compensation tax" on energy products, while energy-input regions should pay a "carbon-sink compensation fund" according to consumption, so as to balance regional emission-reduction responsibilities[^34]. At the same time, carbon-sink indicators for cultivated land and forest land should be incorporated into the "dual-carbon" assessment system, forming a closed-loop pathway of "energy decarbonization—fund governance—ecological carbon-sink enhancement."

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Spatiotemporal evolution and influencing factors of per capita carbon footprint in China based on the MGWR model

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Abstract: To quantitatively assess the per capita carbon footprint and its driving factors in China, this study provides a scientific basis for promoting coordinated regional carbon emission governance from both emission reduction and carbon sequestration perspectives. Using the net primary productivity model, the per capita carbon footprint in China and its provincial-level regions from 2009 to 2022 was estimated. The spatiotemporal patterns of the per capita carbon footprint were explored via exploratory spatial data analysis. Furthermore, from the multidimensional perspective of the economy–energy–ecology nexus, the spatial heterogeneity of factors influencing the per capita carbon footprint was analyzed using the multiscale geographically weighted regression model. The results show that: (1) From 2009 to 2022, the per capita carbon footprint in China and its provincial-level regions exhibited a significant upward trend, with the annual growth rate peaking at 10.56% in 2011. The spatial distribution of the per capita carbon footprint presented a pattern of being higher in the north and lower in the south. Hotspots and sub-hotspots were highly concentrated in Inner Mongolia and its neighboring provinces, whereas sub-coldspots were scattered across southern China. (2) During the study period, the spatial center of gravity of the per capita carbon footprint shifted northwestward, while the main axis of spatial agglomeration showed a southwest–northeast trend. (3) In terms of influencing factors, economic development level serves as a core driving force, exerting a "bidirectional" positive-and-negative effect on per capita carbon footprint in conjunction with the proportion of cultivated land use. Population density, energy intensity, and energy flow act as positive driving factors, while urbanization rate and the proportion of newly increased forestland serve as negative inhibiting factors. The results provide theoretical support for formulation of precision-oriented and differentiated regional policies aimed at achieving carbon peaking and carbon neutrality.

Keywords: per capita carbon footprint; spatial heterogeneity; influencing factors; multiscale geographically weighted regression (MGWR) model

Note: Figure translations are in progress. See original paper for figures.