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Research on the spatiotemporal evolution and non-stationarity effect of urban carbon balance: Evidence from representative cities in China

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ABSTRACT

Accelerating the attainment of carbon balance in Chinese cities has become pivotal in addressing global climate change and promoting green, low-carbon development. This study, encompassing 277 prefecture-level and above cities from 2007 to 2020, reveals a positive overall trend in China's urban carbon balance index. The evolution unfolds in two stages, demonstrating a distinct "tiered development" pattern across the eastern, central and western regions. Moreover, significant spatial agglomeration characteristics characterize China's carbon balance hot and cold spots throughout the study period, with their spatial agglomeration degree remaining stable. The standard deviation ellipse analysis confirms these hot and cold spots' alignment with China's economic development level and population distribution. The GTWR test results highlight the pronounced non-stationary characteristics of different driving factors in space and time, exhibiting variations in strength and direction among regions. Consequently, enhancing China's urban carbon balance requires tailored measures based on different areas' unique conditions and development characteristics, emphasizing a hierarchical and classified approach to leverage distinct driving factors and foster a green development system in China.

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1. Introduction

Urbanization accelerates economic growth, and high-level urbanization supports regional development on a large scale(Liang and Yang, 2019). Fast urbanization has strained the environment, especially carbon emissions(Tan et al., 2016). Urban infrastructure construction and industrial production have released much carbon dioxide that cannot be handled(Gür, 2022). This causes massive impacts on the ecological environment and residents' health(Mahmood et al., 2020). China is the world's largest developing country, the primary energy consumer and carbon emitter (Tan et al., 2023). From 2010 to 2012, nearly three-quarters (73%) of global carbon emissions growth occurred in China (Green and Stern, 2016). In 2019, China's carbon emissions accounted for 28% of global carbon emissions, exceeding the total emissions of the United States and Europe(Liu et al., 2021). To control carbon dioxide emissions, slow down global warming trends, and promote sustainable human development, the Chinese government has implemented several carbon reduction strategies (Zhao et al., 2022) and signed the Paris Agreement, promising to achieve peak carbon emissions by 2030 and carbon neutrality by 2060(Liu et al., 2023). In addition, by 2030, the carbon dioxide emissions per unit of Gross Domestic Product (GDP) must be reduced by 60%–65% (Wang and Wang, 2017; Wei et al., 2020; Yang et al., 2020). In past 35 years, China's urbanization rate has increased from 19.39% in 1980 to 63.89% in 2020, much faster than in the United States and the United Kingdom (Bai et al., 2023). While urbanization has promoted industrialization and rapid economic growth in China, it has also significantly increased its energy consumption and carbon emissions. According to the CEIC database 2013, there are currently 31 cities with populations ranging from 20 to 40 million and 14 cities with populations exceeding 40 million. Based on the "Green Book of Small and Medium-sized Cities" released in 2010, cities with a population of 30–100 million are defined as megacities. Due to their high concentration of industrial output and rapid urban population growth, these megacities have always been areas where human activities, resources, and environmental pollution are most concentrated (Liang and Gong, 2020). Moreover, most cities have exceeded their

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environmental carrying capacity for carbon emissions (Hu et al., 2023c). Specifically, in 2020, China's 337 cities experienced a cumulative total of 345 days with severe pollution and 1152 days with heavy pollution, and the proportion of cities with acid rain reached 34%, while areas with poor ecological quality accounted for 31.3% of the country's total area (Wu et al., 2024). Several negative factors indicate that the current issue of carbon emissions poses a severe challenge to China's ecological environment and residents' health, necessitating research on carbon balance. Can the urban environmental environment's carbon-carrying capacity equal the city's carbon emissions and achieve carbon neutrality? How has the urban carbon balance changed recently? What are the factors influencing urban carbon balance development? This essay researches these challenges to support urban environmental development.

Urban carbon balance represents carbon emissions and environmental carbon absorption. The primary sources of urban carbon emissions are transportation, energy generation, construction, and garbage disposal (Sadorsky, 2014). Although these activities are closely related to urban residents' lives, the ever-expanding construction land contrasts with the shrinking vegetation area, tilting the balance between urban carbon emissions and environmental absorption capacity (Feng et al., 2023). Some Chinese cities use "emission mitigation" and "sink enhancement" to balance carbon emissions and absorption, reducing climate change and ecological damage from carbon surplus (Tobin et al., 2018). Research suggests that clean production, energy efficiency, and a carbon emissions trading platform drive urban "emission mitigation"(-Shi et al., 2022; Wu et al., 2021). "Sink enhancement" means increasing green space, forest covering, green infrastructure, and sustainable land management to improve the metropolitan environment's carbon-carrying capacity (Cui et al., 2022). These strategies may work better in practice due to city-specific geography, climate change, and economic development. Considering their integration, urban carbon balancing is a "blind spot" in the present study, this paper attempts to explore the spatial differences in carbon balance and its driving factors in Chinese cities during rapid urbanization. It aims to provide practical ways to improve air quality, protect public health, and reduce the negative impacts of air pollution on human health. Additionally, the paper offers references for developing more targeted carbon balance plans to mitigate global warming, achieve sustainable urban development, enhance economic development quality, and improve the quality of life for citizens.

The innovative contribution of this paper is mainly reflected in the following aspects:

Firstly, it addresses the problem of existing studies that calculate environmental elements such as carbon emission equivalents, economic effects of carbon emissions, or terrestrial carbon sinks in isolation, and lack a comprehensive assessment of multiple carbon-related factors (Guenther, 2002; Piao et al., 2009). This study combines urban carbon emissions with carbon sinks and provides scientific measurements of urban carbon balance through a complete and rigorous calculation method. This helps government to understanding the current environmental status accurately. Notably, our research not only examines China's overall urban carbon balance but also focuses on the differences in carbon balance among cities in various geographical locations within China, highlighting the differentiated effects of industrial policies on carbon emission reduction and carbon sink enhancement.

Secondly, compared to previous studies, this paper places greater emphasis on the dynamic trends of urban carbon balance during the examination period. Although earlier studies have conducted preliminary analyses of changes in urban carbon balance, the processes of these changes remain relatively unclear (Huang et al., 2024). Our research visualizes the spatial distribution of urban carbon balance, emphasizing the dynamic process of its distributional changes and providing a more detailed analysis of its patterns. These findings are significant for government policy-making to improve environmental governance effectiveness. In particular, we use hotspot distribution and standard deviation ellipse to analyze the overall trajectory of carbon balance changes, revealing that economic development is the main driving force affecting the distribution of urban carbon balance. This offers important insights for developing countries aiming to enhance economic growth while controlling environmental pollution.

Thirdly, as one of the first studies to employ the GTWR model to test urban carbon balance, our research holds special significance for advancing carbon governance. Against the backdrop of global warming and climate crisis, green and low-carbon development has become the core goal of environmental governance. There is a gap in the analysis of spatiotemporal variations in the existing research on the influencing factors of urban carbon balance. This paper fills the gap and provides a new perspective for urban environmental research. Different from existing views, our study finds that besides social factors such as economy, population, and trade which negatively impact urban carbon balance, government intervention and environmental regulation as policy factors also influence urban carbon balance. Therefore, we believe that the government can play a significant role in environmental governance. This conclusion reinforces the interaction between government efficacy and environmental regulation, contributing to the simultaneous development of the environment and the economy. This paper uses NASA Earth observation system data and socio-economic data to calculate the carbon balance level of Chinese cities and quantitatively analyzes its spatial distribution, local correlation characteristics, and space transfer. In addition, the geographical and temporal weighted regression (GTWR) model is used to consider the spatiotemporal heterogeneity of the drivers in terms of both social development and natural environment, and to explore way to promote carbon balance in China. Overall, this study examines the spatiotemporal evolution and non-stationarity effects of urban carbon balance in Chinese cities, aiming to provide insights for informed policy-making and sustainable development.

2. Literature review

Carbon emission reduction is crucial for preventing global warming and achieving carbon neutrality. Consequently, international research on carbon neutrality has predominantly focused on strategies related to energy conservation and emission reduction(Liu et al., 2021). The relevant environmental economics theories encompass environmental externalities, sustainable development, and low-carbon economics (Zhang et al., 2013). Additionally, research has explored carbon emission intensity and efficiency measurement (Yu and Zhang, 2021), evaluation of low-carbon economic development (Duan et al., 2016), carbon emission decoupling effects(Pan et al., 2022), and underlying driving mechanisms.

However, it is imperative to note that the existing literature concentrates solely on carbon dioxide emissions from fossil fuel combustion during economic activities, often overlooking carbon absorption (Sreedhar et al., 2017). This study focuses on the "receipt-expense" balance of regional carbon emissions to address this gap, adopting a comprehensive carbon-neutral, low-carbon sustainable development model. The aim is to provide a more nuanced understanding of carbon balance by considering both emissions and absorption through vegetation (Ma et al., 2022).

The current state of research can be categorized into four main themes.

1. **Carbon balance calculation:** Early research centered on ecological compensation and environmental carrying capacity, expressed predominantly through carbon budget accounting (Yu et al., 2022). Building on a regional carbon budget system, the study applies the carbon budget approach to quantify carbon sources and sink enhancement (Lahn, 2020). This approach facilitates tailored heterogeneous carbon compensation programs for each region, offering

an operational basis for determining the carbon balance coefficient (Fu et al., 2022; Rong et al., 2020).

2. **Nature's impact on carbon balance:** The study of natural carbon balance, rooted in ecology and geography, explores ecosystems such as forests, lakes, wetlands, and grasslands to comprehend their role in carbon balance (Zhao et al., 2021). Climate change, considered a significant factor, induces alterations in regional carbon balance through phenomena such as droughts, fires, and other biological calamities (Mekonnen et al., 2021).
3. **Artificial carbon balancing factors:** Carbon offsetting research increasingly focuses on human influence. The traditional LMDI model decomposes carbon emissions, attributing the rise in emissions to factors like extensive industrial development, energy consumption intensity, population agglomeration, and urban land expansion (Ding and Li, 2017; Zhang et al., 2016).
4. **The carbon balance path:** A holistic view acknowledges that a single factor does not determine carbon balance and goal achievement. Coordinated or trade-off relationships between components may result in heterogeneous impacts at various regional and temporal scales (Gu et al., 2023). Studies have explored the co-evolution of urbanization construction and carbon emission balancing, developed composite indicator allocation methods for carbon quotas, and assessed current carbon balance status using dynamic land ecosystem models (Ma et al., 2022; Tian et al., 2022).

In summarizing the literature, it is evident that while carbon balancing studies are abundant, growth opportunities exist. Specifically, there is a need for (1) Further development of traditional index measurement, theoretical discussion, and viewpoint argumentation for carbon balance measurement and (2) Expanded research focusing on prefecture-level city development and geographic distribution, considering spatial-temporal non-stationary changes in economic activity and locational endowments of different cities. The introduction of the geographical and temporal weighted regression (GTWR) model, which incorporates time characteristics, offers a compelling analysis method for studying China's urban carbon balance's "space-time" non-stationarity (Li et al., 2022).

Based on this, this paper selects 277 cities at and above the prefecture level in China from 2007 to 2020 as the research unit. It comprehensively considers the natural and socio-economic factors affecting carbon balance and examines the spatiotemporal evolution and spatial driving factors of China's carbon balance. The analysis is conducted using exploratory spatial analysis, standard deviation ellipse and the geographical and temporal weighted regression (GTWR) and other models. The models calculate the carbon balance index to achieve a comprehensive low-carbon green development model and contribute to the goal of 'carbon neutrality' for Chinese cities. The findings provide empirical experience and decision-making references.

3. Research methods and data sources

3.1. Research methods

3.1.1. Carbon balance index

The explained variable in this article is the carbon balance index. Carbon balance refers to the ratio of energy consumption carbon emissions (*CE*) to vegetation carbon sink (*CA*) (Piao et al., 2009). Compared with carbon emissions, it can reflect the regional carbon neutrality process. Based on the level of anthropogenic energy consumption, carbon emissions, and vegetation carbon sequestration, the carbon balance index (*CBI*) expression is set as follows (Ma et al., 2022):

$$CBI_{i,t} = \frac{CA_{i,t}}{CE_{i,t}} \tag{1}$$

In the formula, $CA_{i,t}$ represents the amount of vegetation carbon sequestration in the *i*-th year *t*; $CE_{i,t}$ represents the carbon dioxide emissions caused by energy consumption in the *i*-th year t. The carbon balance index can be divided into three states: when $CBI_{i,t} = 1$, it indicates that the regional carbon emissions and carbon absorption are in equilibrium, representing carbon balance; when $CBI_{i,t} < 1$, it indicates that the regional carbon emissions are too high and the vegetation has insufficient carbon sequestration capacity, showing a carbon deficit; when $CBI_{i,t} > 1$, it indicates that regional carbon emissions are within the tolerance of the ecosystem, which is a carbon surplus. In addition, carbon emissions and carbon sinks are calculated and measured as follows.

(1) Carbon Emissions (*CE*)

Considering that urban carbon sources mainly come from energy consumption, the greenhouse gas inventory method, as outlined by Schievelbein and Lee (1999), is employed for measurement. Among them, industrial energy consumption is the primary unit of urban energy consumption and can reflect the overall trend of urban energy consumption. Industrial enterprises above the designated size are selected to measure energy carbon emissions. The formula is as follows:

$$CE_i = \sum_{i=1}^{9} E_i \times C_i \tag{2}$$

In the formula, E_i represents the *i-th* energy consumption (measured in 10,000 tons of standard coal), including coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, natural gas, electricity, and heat; C_i represents the *i-th* energy carbon emission coefficient.

(2) Carbon Sink (CA)

The carbon sink data relies on the NASA Earth Observation System, specifically the MOD17A3 dataset, which provides information on China's vegetation surface primary productivity, or NPP. Some scholars have applied it to the study of vegetation carbon fixation. For example, Chen et al. used the NPP data system to measure the amount of carbon sequestration by vegetation at the county level in China (Chen et al., 2020). Based on this, this paper matches NPP data to the Chinese city level as a vegetation carbon sink (CA) measurement indicator.

3.1.2. Exploring spatial data analysis (ESDA)

Two global and local tools dominate ESDA. The first instrument is the global Moran's l index, which is used to determine if there is a spatial connection between a geographical unit and nearby locations within the research region (Hu et al., 2023a). The geographical distribution in the area is frequently studied using attribute value correlation (Liu et al., 2022). Here is the calculation:

$$Moran's\ I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}\left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right)}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}} \tag{3}$$

Among these variables: I is Moran's I index, y_i is the observed value in region i, $\overline{Y}$ is the arithmetic mean of energy eco-efficiency of all cities, n is the number of cities, and W_{ij} is the spatial adjacency matrix of study city i and city j. The value range of Moran's I index is $[-1,1]$, where $I >$ 0 means positive spatial correlation, $I = 0$ means no spatial correlation, and $I < 0$ means negative spatial correlation.

Getis-Ord Gi* method is a statistical technique used to identify statistically significant spatial clusters of high and low values. It calculates the z-score and p-value for each feature in the input feature class and generate a new output feature class (Songchitruksa and Zeng, 2010). The calculation is as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \overline{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \quad (4)$$

Among these variables: x_j is the attribute value of element j; $w_{i,j}$ is the spatial weight between elements i, and j; n is the total number of elements.

3.1.3. Standard deviation ellipse

The center of gravity-standard deviation ellipse utilizes parameters including the center of gravity, azimuth angle, central axis standard deviation, and minor axis standard deviation to analyze and describe the spatial evolution characteristics of the object (Liu et al., 2023). The formula is as follows:

$$\text{Center of gravity}: (X, Y) = \left(\frac{\sum_{i=1}^{n} w_i \times x_i}{\sum_{i=1}^{n} w_i}, \frac{\sum_{i=1}^{n} w_i \times y_i}{\sum_{i=1}^{n} w_i}\right) \quad (5)$$

In the formula, (X, Y) represents the coordinates of the center of gravity, (x_i, y_i)represents the center mass point of each city's administrative district, and w_i represents the weight and carbon balance index of each city.

$$\text{azimuth angle}: \tan\theta = \frac{\left(\sum_{i=1}^{n} w_i^2\widetilde{x}_i^2 - \sum_{i=1}^{n} w_i^2\widetilde{y}_i^2\right) + \sqrt{\left(\sum_{i=1}^{n} w_i^2\widetilde{x}_i^2 - \sum_{i=1}^{n} w_i^2\widetilde{y}_i^2\right)^2 + 4\sum_{i=1}^{n} w_i^2\widetilde{x}_i^2\widetilde{y}_i^2}}{2w_i^2\widetilde{x}_i\widetilde{y}_i} \quad (6)$$

$$\text{major axis standard deviation}: \sigma_x = \sqrt{\frac{\sum_{i=1}^{n}(w_i\widetilde{x}_i\cos\theta - w_i\widetilde{y}_i\sin\theta)^2}{\sum_{i=1}^{n} w_i^2}} \quad (7)$$

$$\text{minor axis standard deviation}: \sigma_y = \sqrt{\frac{\sum_{i=1}^{n}(w_i\widetilde{x}_i\sin\theta - w_i\widetilde{y}_i\cos\theta)^2}{\sum_{i=1}^{n} w_i^2}} \quad (8)$$

In the formula, θ represents the azimuth angle, (x_i, y_i) represents the spatial location of city i, $(\widetilde{x}_i, \widetilde{y}_i)$ represents the coordinate deviation from the location of study city i to the center of the ellipse, and w_i represents the weight.

3.1.4. Geographically and Temporally Weighted Regression

GTWR (Geographically and Temporally Weighted Regression), an extension of the GWR (geographically weighted regression) model, introduces the time dimension based on the traditional geographically weighted regression mode. It enables spatial regression analysis using panel data to deal with regional "time-space" non-stationary. The model provides new tools, and the calculation formula is as follows:

$$Y_t = \beta_0(\mu_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i)Z_{ik} + \varepsilon_i \quad (9)$$

In the formula: Y_i is the sample value; β_0 represents the constant term in the model; μ_i; v_i, represents the longitude and latitude of the i-th sample point; (u_i, v_i, t_i) represents the spatial-temporal coordinates of the i-th sample point; t_i represents the time series; β_k (u_i, v_i, t_i) represents the regression parameter of the independent variable k at the i-th sample point; ε_i represents the model residual.

Similar to the GWR model, the focus of GTWR is the selection of bandwidth and spatial-temporal weight matrix. Specifically, the method provides the regression parameters of β_k (μ_i, v_i, t_i) for each sample i and independent variable k. The calculation formula is as follows:

$$\widehat{\beta}(u_i, v_i, t_i) = [Z^t W(u_i, v_i, t_i)Z]^{-1} Z^t W(u_i, v_i, t_i)Y \quad (10)$$

In the formula: $\widehat{\beta}$ (u_i, v_i, t_i) represents the estimated value of β_0 (u_i, v_i, t_i); Z represents the matrix composed of independent variables; Z^t represents the transpose of the matrix; Y represents the matrix composed of sample points; W (u_i, v_i, t_i) is the spatial-temporal weight matrix. To avoid measurement errors caused by data discretization, a finite Gaussian function is selected as the space-time weight matrix, that is, a bi-square space weight function:

$$d_{i,j} = \sqrt{\left[(u_i + u_i)^2 + (v_i + v_i)^2 + \mu(t_i + t_i)^2\right]} \quad (11)$$

In the formula, $d_{i,j}$ represents the spatio-temporal distance between point i and j. It should be noted that the bandwidth will affect the establishment of the spatial weight matrix, so this article chooses the AIC_C criterion, which stands for adaptive bandwidth.

3.2. Driving factors selection

The carbon balance index of different cities in China is comprehensively affected by economic, social, ecological, and other factors. Therefore, this article follows the comprehensive, systematic, and hierarchical principles when selecting driving factors and picks from the economic, social, and natural environment levels.

Economic and social level.

① Energy consumption structure (*es*). Fossil energy, such as coal, releases a large amount of greenhouse gases during the combustion process, reducing the quality of the atmospheric environment, increasing carbon emissions, and weakening the carbon balance. Energy consumption is the "primary source" of greenhouse gases. To reflect its impact on China's carbon balance, the total energy consumption data of prefecture-level cities is selected as a proxy variable (Hu et al., 2023b).

② Degree of opening up (*fdi*). Due to the existence of "pollution paradise" and technology diffusion effects, the degree of opening up is also an important factor affecting China's carbon balance. As China' expands its engagement with the global world, the competitive pressure of industrial enterprises in the global value chain increases, which can encourage innovation in corporate management models, thereby reducing carbon emissions and helping to achieve carbon balance. We measure the degree of openness by considering the total amount of foreign capital used in each region.

③ Level of economic development (*pgdp*). On the one hand, economic development intensifies energy consumption and leads to the increase in carbon balance. On the other hand, the economically developed regions show higher public enthusiasm for participating in environmental protection activities and higher environmental awareness, therefore reaching the "turning point of the environmental Kuznitz curve". This promotes the decoupling of economic development and carbon emissions and achieves carbon balance. Therefore, per capita GDP was selected as an economic measure for empirical testing (Hu and Zhang, 2023).

④ Government intervention (*gov*). Local government intervention in carbon balance is reflected in raising the entry threshold for enterprises to restrict the entry of polluting enterprises and promoting the realization of carbon balance through policy support and financial allocation. This paper selects the proportion of local fiscal expenditure to GDP at the end of the year as the proxy variable for government intervention (Xiang et al., 2023).

⑤ Intensity of environmental regulation (*er*). The "Porter Hypothesis" believes that environmental regulation is the driving force for industrial innovation, and "innovation compensation" can be used to offset input costs, gain "first-mover advantage," and promote the simultaneous improvement of energy consumption and ecological quality. There are currently two main categories of measurement for environmental regulations. The first is measured by the proportion of pollution control investment and pollution charges to total industrial output value. The second type is measured by constructing a comprehensive index based on pollution control investment or undesired environmental output. This paper chooses the second method to use the comprehensive emission index of various undesirable outputs (industrial wastewater, industrial waste gas, industrial smoke (powder) dust, and industrial waste solids) as the proxy variable for environmental regulation (Wu et al., 2020). For the methods of measuring environmental regulation, see Appendix A.

(2) Natural environment level:

① Precipitation (*pre*): Changes in precipitation will directly affect vegetation growth and the carbon cycle process. Abundant precipitation is beneficial to plant growth and promotes the formation of carbon sinks. At the same time, plants absorb carbon dioxide through photosynthesis and store it as organic carbon, all contributing to the realization of carbon balance. On the contrary, dry climate conditions will slow plant growth, increase carbon emissions, and affect the carbon balance process. In addition, the difference in precipitation in different regions will also affect the regional carbon balance, and we choose the average annual precipitation of cities to measure it(Jia et al., 2017).

② Sunlight level (*sun*): Sufficient sunshine can promote the photosynthesis of plants, increase carbon dioxide absorption, and convert it into organic carbon. At the same time, higher sunshine conditions can help increase vegetation growth rate, thereby increasing carbon sinks and achieving carbon balance. On the contrary, lack of sunshine may lead to limited plant growth, reduced carbon absorption, and delayed regional carbon balance. This article selects the average annual sunshine hours in cities for measurement(Ampratwum and Dorvlo, 1999).

To avoid spurious regression in the GTWR model, multicollinearity testing was performed with the help of stata 15.0. The results showed that the *VIF* expansion index of all variables was less than 3. There was no multicollinearity problem among the variables. The selection of variables met the regression requirements. The description and test of carbon balance driving factors are shown in Table 1.

3.3. Data sources

The data used in the article is divided into two parts: geographical information data and socio-economic data. The time range selected for this study, spanning from 2007 to 2020, is a critical aspect that warrants clarification. The choice of this specific timeframe is rooted in the evolution of available data and the transformative shifts in China's environmental policies during this period. In 2007, the Chinese government introduced the concept of building an ecological civilization, signaling a heightened emphasis on environmental protection. Notably, before 2007, comprehensive and reliable urban carbon emission data in China were notably incomplete or unavailable. The significance of 2007 lies in the subsequent availability of robust and comprehensive urban carbon emission data, aligning with the nation's commitment to environmental objectives. This improved dataset, covering the period from 2007 to 2020, is a foundation for rigorous research and analysis in understanding the spatiotemporal evolution and non-stationarity effects of urban carbon balance across 277 prefecture-level and above cities. During this timeframe, 3878 observational data points from these cities were meticulously selected as research objects, ensuring comprehensive coverage of the rapid development stage of China's urbanization process. This selection strikes a balance between inclusivity and avoiding excessive remoteness, which may impede capturing the latest policy changes and trends.

In summary, the chosen period of 2007–2020 is strategically grounded in the availability of more robust data post-2007, aligning with China's environmental policy shifts and ensuring comprehensive coverage of relevant urbanization stages. This provides a solid foundation for the study's objectives. In terms of geographical information data, the carbon emission coefficients of major consumed energy sources come from the IPCC National Greenhouse Gas Emission Inventory. The coefficients of conversion of various energy sources into standard coal are taken from the "General Principles for Comprehensive Energy Consumption Calculation" (GB/T2589-2008). MODIS-ND▪VI data comes from NASA (https://www.nasa.gov, satellite MOD13A2), and meteorological data comes from the China Meteorological Data Network. The vegetation type data is based on the Chinese subset of global land cover data (GLC2000) of SPOT4 remote sensing data. Social and economic data mainly come from the statistical yearbooks of each city in the corresponding year, the "China Cities Statistical Yearbook" from 2008 to 2021, and the statistical bulletins of each city's national economic and social development.

4. Results

4.1. Analysis on the spatial-temporal evolution of China's carbon balance

4.1.1. Time series characteristics of China's carbon balance

Based on formula (1), the industrial ecological efficiency of 277 Chinese cities is estimated. The National Bureau of Statistics divides China into east, middle, and west areas. Fig. 1 illustrates the 2007–2020 carbon balance index settlement findings and trends for China, the

Table 1
Description of driving factors for carbon balance in Chinese cities.

Variables	Symbol	Indicators	Unit	Literature source	*VIF*
Energy consumption structure	*es*	Total energy consumption	10,000 tons	Hu et al. (2023b)	1.91
The degree of openness	*fdi*	Number of foreign investments	ten thousand $	Zhu et al. (2024)	1.80
Economic Development	*pgdp*	Regional GDP/Population	ten thousand RMB	Hu and Zhang (2023)	2.37
Government Intervention	*gov*	Fiscal spending/Reginal GDP	%	Xiang et al. (2023)	2.27
Environmental regulation	*er*	Comprehensive emission index of various pollutants	–	Wu et al. (2020)	1.12
Precipitation	*pre*	Annual average precipitation	mm	Jia et al. (2017)	2.37
Sunlight level	*sun*	Annual average sunshine hours	h	Ampratwum and Dorvlo (1999)	1.90

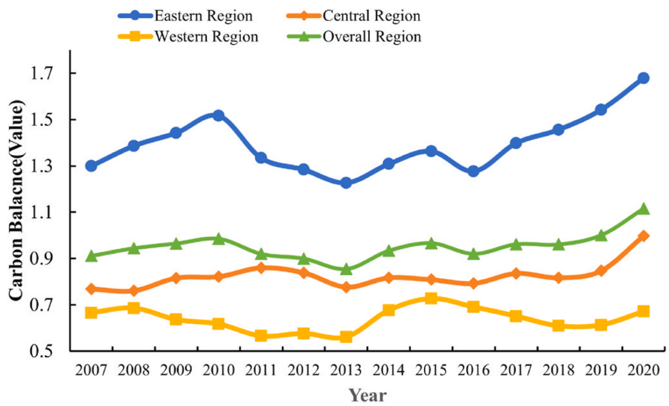

Fig. 1. Changing trends of carbon balance in Chinese cities from 2007 to 2020.

eastern, central, and western regions. From 2007 to 2020, the national carbon balance index exhibited a "two-stage" development pattern, characterized by a decline from 2007 to 2013 and an increase from 2014 to 2020, with significant overall fluctuations. However, with the total index ranging between 0.855 and 1.11, China's overall carbon balance index fluctuates around 1, demonstrating a carbon surplus in 2020 and environmental resilience related to energy consumption. This is owing to China's industrial reorganization, energy efficiency improvements, and environmental protection policies during inspection. The government has gradually eliminated high-carbon industries and restored forests and land (Chen et al., 2023). These approaches have reduced carbon emissions and supported carbon balance. Carbon balance decreased from 2007 to 2013, with 2013 being the lowest value. Energy demand has increased due to fast industrialization and economic growth in China. China uses a lot of coal to supply this need, increasing carbon emissions (Bi et al., 2023). Subsequently, the carbon balance index tended to stabilize from 2014 to 2020. With production technology innovation, China has made technological breakthroughs in energy production and usage, including more efficient power generation and industrial production process improvements to cut carbon emission (Cai et al., 2023). China is one of the world's most significant carbon emitters, even though it had a carbon balance surplus during the evaluation period. China must boost emission reduction efforts, improve carbon emission reduction technology, promote sustainable development, and participate in international climate negotiations to address climate change.

This study also analyzes the development trends of carbon balance in China's three major regions, understands their characteristics, and proposes targeted carbon emission reduction strategies to achieve sustainable development and address climate change. Firstly, the carbon balance in China's eastern region has been in a state of surplus for a long time, and showed a trend of "first decreasing then increasing" during the study period. As the leading area of China's economy, the eastern region relied on heavy industries and high-energy-consuming industries in its early stages of development. With the enhancement of environmental awareness and the implementation of sustainable development strategy, this region may have adjusted its industrial structure to reduce the proportion of high-carbon emission industries and increase the use of low-carbon and clean energy, thus effectively reducing carbon emissions.

Second, the central region's carbon balance index rose steadily in 2018 after inconsistent growth. The balancing index has proliferated as the main area has upgraded and transformed its industrial structure, eliminating high-carbon-emitting industries and growing cleaner production and service industries. The essay concludes with the western carbon balance index. Its development declined from 2007 to 2013. The carbon balance index fell 18.22% from 0.686 to 0.561. Meanwhile, from 2014 to 2020, the carbon balance index in the western region began to increase and reached its peak value of 0.727 in 2015. Roads, bridges, urban growth, and other large-scale infrastructure projects consume significant energy and materials, leading to increased carbon emissions. The western region's carbon balance index is still substantially lower than China's overall and eastern and central regions. Therefore, the government in the western region should increase forest covering, improve land management, and protect natural ecosystems (Li et al., 2023), in order to enhance its carbon absorption capacity and improve the carbon balance index.

In conclusion, due to environmental awareness and sustainable development strategy in the eastern region, the industrial structure has gone through continuous adjustment. In addition, because of technological innovations that have improved energy efficiency and developed new energy technologies, carbon emissions have been effectively reduced and the carbon balance index has been in a long-term surplus state. The central region, experiencing a steady rise in carbon balance index from 2018, showcases successful transformations in industrial structure. The phased elimination of high-carbon-emitting industries and the growth of cleaner production and service sectors have been instrumental in achieving a positive carbon balance. This highlights the importance of targeted industrial policies in mitigating carbon emissions. Contrastingly, despite an incline in carbon balance index development, the western region still maintains a substantial carbon deficit compared to the national average. The increase in the index is attributed to large-scale infrastructure projects such as roads, bridges, and urban growth, which intensify energy and material consumption, leading to increased carbon emissions. Therefore, to improve carbon uptake capacity, the western region should strengthen efforts in enhancing forest coverage, improving land management and protecting natural ecosystems.

4.1.2. *Spatial analysis of carbon balance in Chinese cities*

Next, this study used ArcGIS 10.2 software to spatially visualize China's carbon balance index in 2007 and 2020 to reflect its spatial differences and evolution characteristics, as shown in Fig. 2. Blue to red represents the carbon balance from low to high, evaluation criteria are shown in Table 2.

According to Table 2, we can find that in 2007, there were 192 cities in China with a carbon balance in the Low Balance range, accounting for 69.31% of the total sample size in this study. In 2015, 182 cities accounted for 65.70% of the full sample size. In 2020, there were 179 cities, accounting for 64.62% of the full sample size. As shown in Fig. 1, the urban carbon balance index is above 1, indicating a carbon surplus. However, Fig. 1 represents the regional average, and it is difficult to distinguish the carbon balance levels of different cities. Therefore, further analysis is needed in combination with Fig. 2.

According to Fig. 2, China's northern areas have been in a low carbon balance area for a long time. The regions mentioned above have better economic development, a better industrial base, and a huge population, so the industrial production and residents' lives will produce a large amount of CO_2. In addition, the urbanization level is high, the ecological damage is severe and the carbon sink capacity is weak, which are the main reasons for the substantial carbon emissions in China (Wang et al., 2023).

China exhibits significant geographical variations in carbon balance intensity. Overall, from 2007 to 2020, the northern regions showed an upward trend in carbon balance intensity, while the southern areas exhibited a downward trend. With the development of clean energy technologies, the northern region is actively promoting the transformation of its energy structure by increasing the use of new energy sources such as wind and solar energy, thereby reducing its dependence on traditional fossil fuels such as coal. Simultaneously, the government has introduced a series of policies and measures for energy conservation and emission reduction, encouraging enterprises and individuals to adopt energy-saving technologies, improve energy efficiency, and reduce carbon emissions. On the other hand, the southern regions may

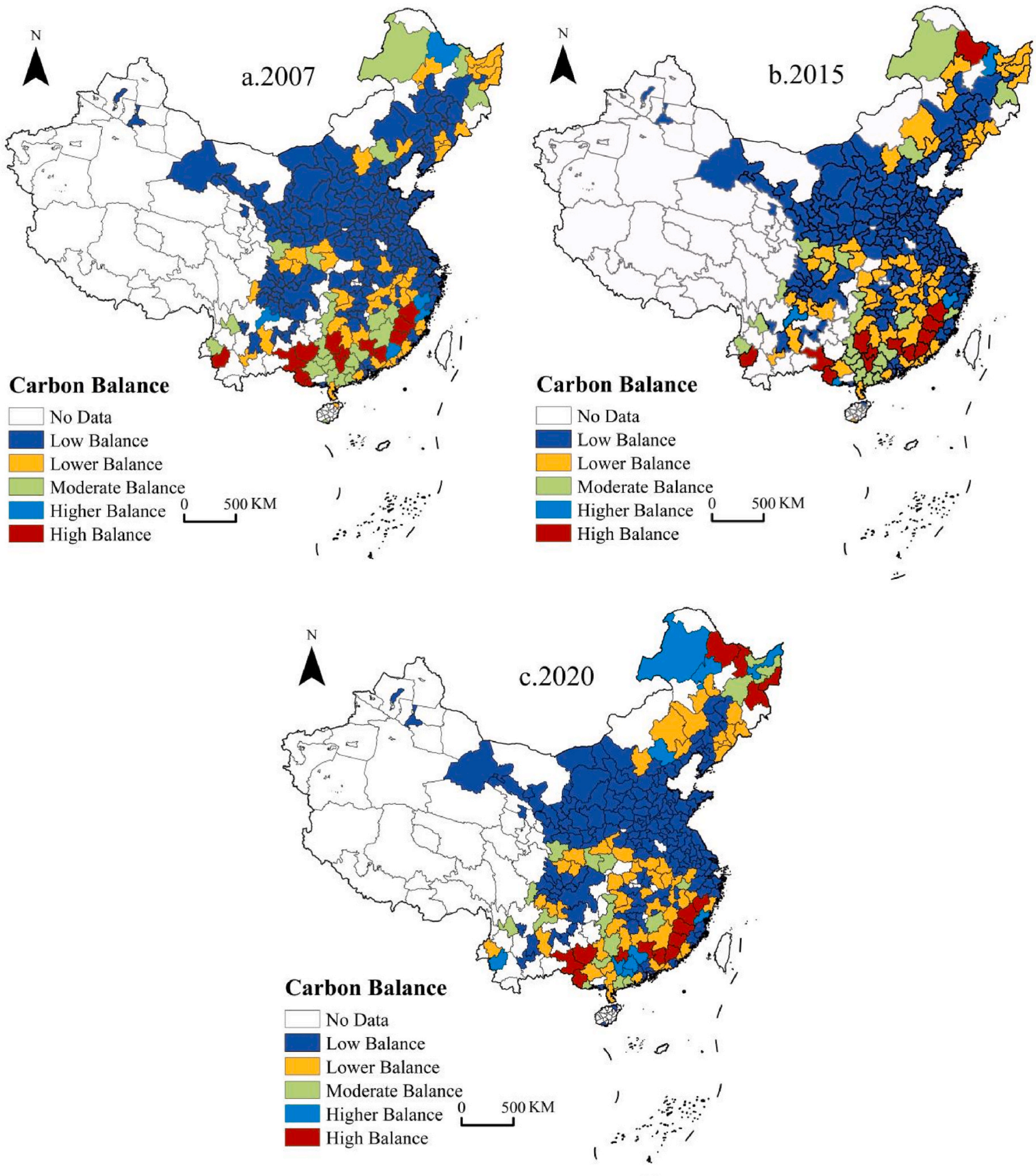

Fig. 2. Spatial distribution of carbon balance in Chinese cities in 2007 and 2020.

face issues with an immature carbon market and lack sufficient incentive measures to reduce carbon emissions (Permana et al., 2023), leading to an decrease in the carbon balance index.

Specifically, in 2007, 13 cities with high carbon balance, concentrated in southern China. In 2015, Fangchenggang City and Hechi City withdrew from the list of high-carbon balance areas, while Heihe City and Meizhou City joined the list. By the end of the study period in 2020, the number of high carbon balance regions in China reached 15. Guilin City, Wuzhou City, and Lincang City dropped out of the high-carbon balance category, while Jixi City, Hegang City, Mudanjiang City, Lishui City, and Hechi City entered. This indicates an overall decline in the carbon balance index in southern China, while a continuous rise in northern China further highlights the significant spatial differences in carbon balance within China.

Additionally, regions with similar carbon balance levels tend to exhibit spatial proximity. As shown in Fig. 2, regions with similar carbon balance levels are distributed in clusters in space. For example, in 2007, Jiujiang City, Yichun City, and Shangrao City, which had carbon balance levels 1.36, were spatially proximate. In addition, in the visual map for 2020, it can be observed that certain areas in northern Shaanxi, northern Henan, and western Shandong also exhibited clustered distribution. The reasons for spatial clustering can be summarized as follows: Firstly, geographical location, to some extent, determines the distribution of natural resources in a region, including renewable energy sources, forest coverage, and land use(Ali et al., 2023). Adjacent regions often share similar natural resource characteristics, which may influence similarity in carbon balance levels. Secondly, neighboring areas may have similar economic and industrial structures (Zhang et al., 2019). This means they

Table 2
Carbon balance evaluation criteria and change.

(1) Value range	(2) Grade	(3) Cities Number in 2007	(4) Cities Number in 2015	(5) Cities Number in 2020
$0.01 < \rho \leq 1.00$	Low Balance	192	182	179
$1.01 < \rho \leq 2.50$	Lower Balance	43	55	54
$2.51 < \rho \leq 4.00$	Moderate Balance	24	22	19
$4.01 < \rho \leq 5.00$	Higher Balance	5	4	10
$\rho > 5.01$	High Balance	13	13	15

Note: ρ represents the carbon balance value.

Table 3
Global Moran index of carbon balance in Chinese cities.

Year	Moran's *I*	*Z*	*P*-value	Year	Moran's *I*	*Z*	*P*-value
2007	0.086***	17.833	0.000	2014	0.087***	17.809	0.000
2008	0.086***	17.819	0.000	2015	0.090***	18.560	0.000
2009	0.088***	18.124	0.000	2016	0.088***	18.085	0.000
2010	0.091***	18.714	0.000	2017	0.086***	17.708	0.000
2011	0.088***	18.151	0.000	2018	0.078***	16.115	0.000
2012	0.086***	17.736	0.000	2019	0.077***	15.996	0.000
2013	0.088***	18.085	0.000	2020	0.077***	16.227	0.000

Note: ***, **, * indicate that the estimated coefficient is significant at the 1%, 5%, and 10% levels, respectively.

may face similar production activities, energy demands, and sources of carbon emissions, resulting in similar carbon balance levels. Thirdly, human factors such as lifestyles, consumption habits, and social values may also influence neighboring regions.

4.2. Spatial autocorrelation analysis

4.2.1. Global spatial autocorrelation

Given the apparent "block" characteristics of carbon balance in Chinese cities, it is speculated that there are spatial correlation characteristics. According to equation (3), an inverse distance matrix is selected, and Moran's I index is used to estimate the spatial effect of carbon balance in China from 2007 to 2020. The results (Table 3) show that the carbon balance index of Chinese cities all passed the significance test at the 1% level, and it can be considered that the carbon balance of Chinese cities has a spatial correlation on the whole, which can be further analyzed.

4.2.2. Local spatial autocorrelation

Using the Getis-Ord G*i statistic method, it is possible to identify which cities are hot spots for carbon balance or cold spots for carbon sinks. This paper describes the local correlation characteristics of the carbon balance of Chinese cities by classifying them into cold spots, sub-cold spots, non-significant areas (randomly distributed regions), sub-hotspots, and hotspots. It effectively recognizes the carbon balance situation of each city and its neighboring cities, thereby determining whether there are spatial clusters of high or low values. Additionally, this method takes into account factors such as geographical neighborhoods, regions, and connectivity, making the Getis-Ord G*i statistic an important tool for analyzing spatial autocorrelation and heterogeneity. From 2007 to 2020, China's carbon balance showed apparent agglomeration features of cold and hot places, with cold spots remaining steady while hot spots moved. The span of randomly distributed zones expanded while southern hot spots shrank. Hot areas in the north are growing. According to Fig. 3, the northern part of Heilongjiang, the central part of Hunan, and some areas in Yunnan transitioned from non-significant regions to sub-hot spots between 2007 and 2015. Additionally, the eastern part of Inner Mongolia and Heilongjiang became hot spots by 2020, while Guizhou province degraded from hot spots to non-hot spots. This indicates that China's carbon balance has a significant northward trend during the observation period, with cities in northern regions gradually moving towards a green transformation for carbon reduction.

The results above provide a better understanding and analysis of the spatial distribution characteristics of carbon balance in Chinese cities. This, in turn, offers a scientific basis for policy formulation to promote balanced development of urban carbon emissions and environmental protection.

4.3. Standard deviation ellipse

The Standard Deviation Ellipse can demonstrate the spatial distribution trends of data, including the central location, direction and shape of the distribution, which aids in identifying the geographical concentration tendencies and directionality of urban carbon emissions or sinks. Moreover, by comparing Standard Deviation Ellipses at different time points, the spatial transition patterns of urban carbon balance can be observed. The spatial distribution direction of China's urban carbon balance index in the investigation period was "northeast-southwest," which matches the "Hu Huanyong Line" and the level of economic development and population distribution. China's urban carbon balance in 2007 was centered in Huaihua City, Hunan Province. During the period, China's urban carbon balance shifted north and finally to Yichang, Hubei, in 2020 (see Fig. 4). The reasons for the shift are as follows:

Firstly, the Chinese government has continuously emphasized environmental protection and sustainable development in recent years. With the growing prominence of environmental issues, the government has intensified pollution control and energy conservation efforts (Khanam et al., 2023). Since 2012, the country has implemented the "Green Development Legal Guarantee Strategy for Central China" plan, aiming to establish a legal structure for green growth that is friendly to the market economy, which has changed the spatial distribution of carbon balance. Then, in 2016, the State Council issued the "13th Five-Year Plan for Ecological Environment Protection and Sustainable Development," further strengthening biodiversity conservation efforts, enhancing the protection and utilization of natural ecosystems such as forests and oceans, and improving vegetation carbon sequestration capacity.

Secondly, the transformation and upgrading of China's economic structure is also an essential reason for the northward shift in China's urban carbon balance index. Over the past few decades, China's economy has developed rapidly, but it has also faced issues such as high resource consumption and severe environmental pollution (Usman et al., 2022). To achieve sustainable economic development, the Chinese government has actively promoted financial restructuring, intensified efforts to phase out high-energy-consuming and high-polluting industries, and encouraged the development of low-carbon and environmentally friendly industries (Chen and Lin, 2021). This adjustment in the economic structure has gradually reduced carbon emissions in Chinese cities, thereby promoting the northward shift of the carbon balance index.

Thirdly, changes in urban planning and construction concepts have also positively impacted the northward shift of China's urban carbon balance index. In the past, Chinese urban construction often focused on scale expansion and functional improvement neglecting the importance of environmental protection and ecological construction (Jung et al., 2005). However, with increasing public awareness of environmental protection and the popularization of sustainable development concepts in cities, more and more cities have begun to focus on protecting and improving the ecological environment (Shen et al., 2021). Through measures such as promoting green buildings, developing public

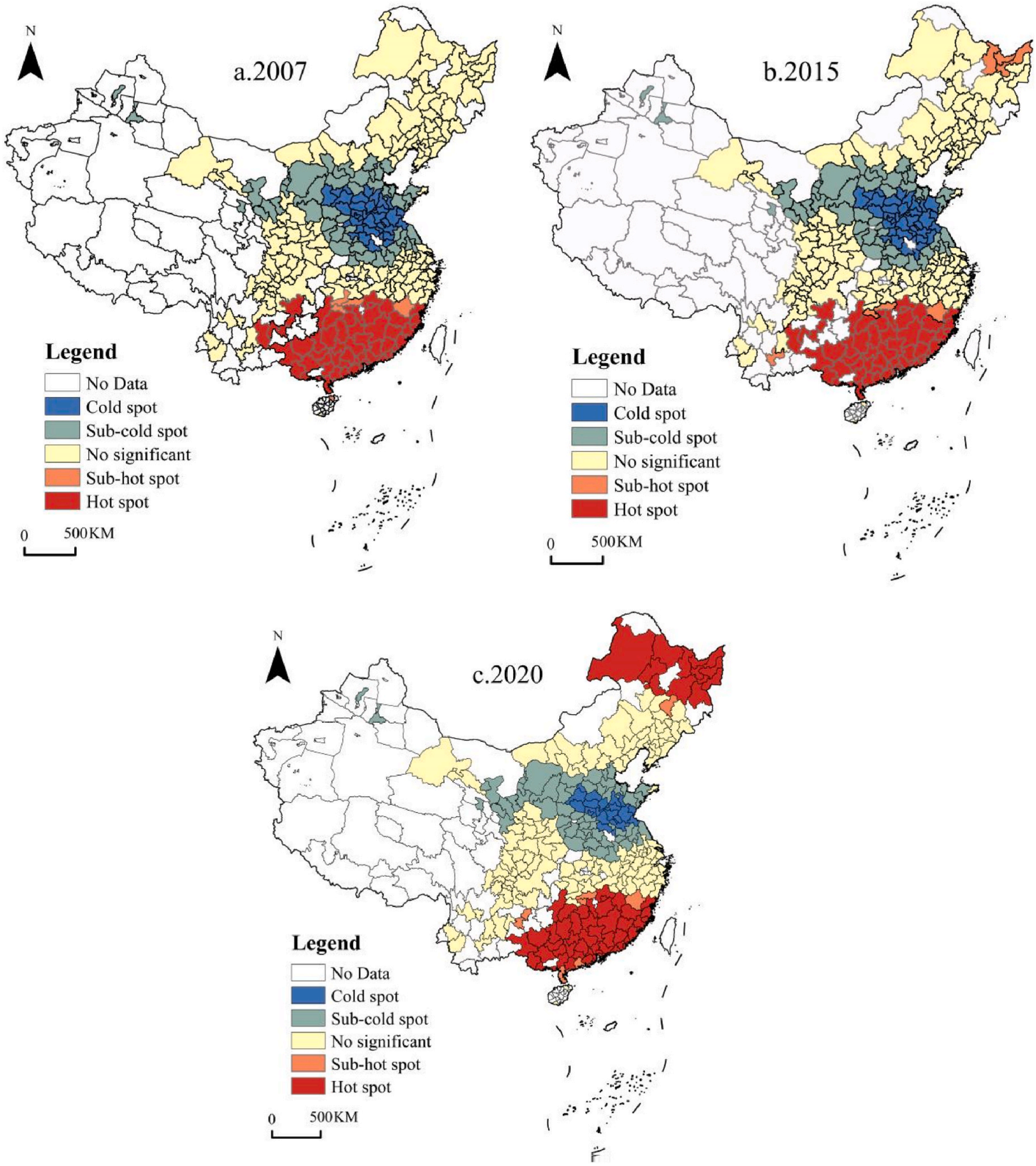

Fig. 3. Distribution of hot and cold spots of carbon balance in Chinese cities in 2007 and 2020.

transportation, and increasing green spaces, carbon emissions in Chinese cities have been effectively controlled, further enabling the northward shift of the carbon balance index.

Finally, international cooperation and experience sharing have also played a positive role in the northward shift of China's urban carbon balance index. China actively participates in global climate change negotiations and cooperation mechanisms, sharing experiences and technologies with other countries to address climate change challenges jointly (Seo, 2017). At the same time, China learns from the experiences of developed countries, drawing lessons from their advanced low-carbon technologies and management practices, accelerating its low-carbon transformation process. This international cooperation and experience sharing strongly support the northward shift of China's urban carbon balance index.

The results indicate that utilizing the Standard Deviation Ellipse method is conducive to a deeper understanding of the spatial distribution characteristics and evolutionary trends of China's urban carbon balance, providing a scientific basis for policy making and environmental management.

4.4. Multi-scale analysis of driving factors

The advantage of the GTWR (Geographical and Temporal Weighted Regression) method in studying China's urban carbon balance lies in its ability to account for spatial non-stationarity, which assumes that the relationships between data can vary with geographical location. This allows GTWR to reveal local spatial relationships and regional differences, providing more refined analytical results that can more accurately simulate and predict the carbon emission and absorption capacities of different cities or regions. Moreover, by assigning different weights to different geographical locations, GTWR can effectively

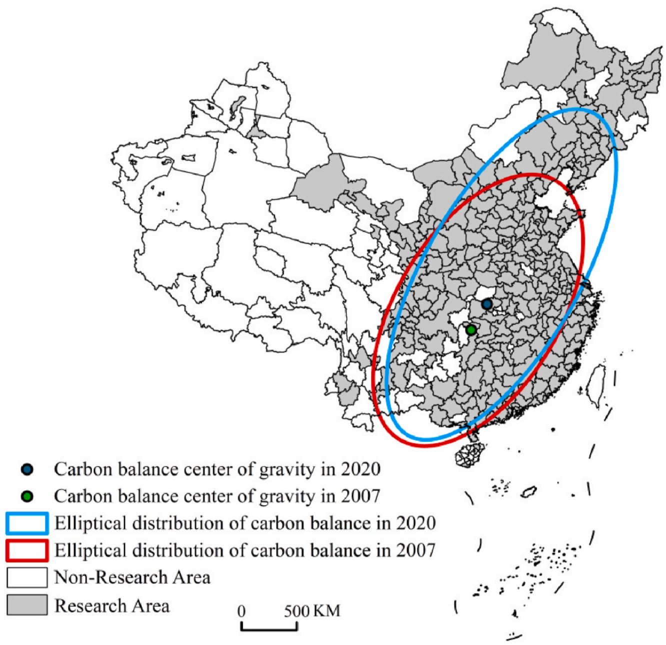

Fig. 4. Changes in standard deviation ellipse of spatial kernel density of carbon balance in Chinese cities.

capture spatial heterogeneity and spatial dependence, which is of great significance for formulating targeted urban planning and environmental policies. Therefore, the GTWR is adopted to estimate the regression of explanatory variables for each city's carbon balance from 2011 to 2020 and to analyze the "spatial and temporal" impact of different driving factors on China's carbon balance.

4.4.1. Data inspection and model selection

Multi-scale geographically weighted regression analysis and calculation were performed using ArcGIS 10.2 software. The spatial-temporal distance parameter ratio was set to 1, the bandwidth was optimized automatically, and OLS and GWR regressions were executed to enhance the contrast of model results. Meanwhile, the *AICc* criterion and goodness of modified R^2 were selected as confidence evaluation indicators, and the results are shown in Table 4. The GTWR model had an *AICc* criterion of −651.459, lower than the OLS regression of 217.8462 and the GWR model of −269.801. The goodness of fit R^2 was 0.518, higher than the OLS regression of 0.379 and the GWR model of 0.419. Therefore, the GTWR model had a better fitting effect and should be selected for local estimation of driving factors of carbon balance in Chinese cities.

4.4.2. Temporal evolution of driving factors

The GTWR model was used to perform regression analysis on the driving elements of carbon balance in Chinese cities throughout time, determining their contributions at distinct geographical and temporal locations. A box plot was created to examine their temporal development (Fig. 5).

Energy consumption structure (*es*) was detrimental to Chinese cities' carbon balance throughout the study, and its intensity grew over time.

Table 4
Comparison of overall fitting status based on OLS, GWR, and GTWR models.

Model parameters	OLS	GWR	GTWR
Bandwidth	–	103.427	93.000
RSS	–	60.855	110.028
AICc	217.8462	−269.801	−651.459
Modified R^2	0.379	0.419	0.518
R^2	0.393	0.470	0.603

High-input, high-pollution industrial companies consume many coal resources to promote economic expansion, and the "three wastes" and carbon emissions produce considerable output, hindering carbon balance. Meanwhile, the energy consumption structure influence coefficient on carbon emissions fluctuated later and was constant early on. The gap between cities narrowed and widened, showing that coal-dominated energy consumption structure's carbon balance inhibitory impact still exists and is spreading. Traditional energy use hinders carbon balance in Chinese cities.

The degree of openness (*fdi*) has a relatively stable influence on the carbon balance of Chinese cities. In most cities, it promotes carbon balance, indicating that FDI will produce technology spillover and form a "pollution halo" effect that encourages carbon balance. Foreign-invested companies follow local environmental norms and policies to ensure their production process meets ecological requirements. Foreign-funded firms also cooperate and exchange talent with local enterprises to strengthen their technical and management skills and minimize industrial chain carbon emissions. Further study demonstrates that foreign investment does not affect carbon balance and coefficient fluctuation. Foreign investment has a single industrial structure and few low-carbon industries, making a complete carbon balance scheme difficult. Foreign investment is unevenly distributed in cities and mostly in coastal and economically prosperous areas. However, technology spillover in inland and less developed areas has little impact on carbon balance.

The carbon balance of Chinese cities is positively correlated with *pgdp* at the start of the study. A positive association exists between economic development and carbon balance because carbon emissions are gradually regulated as economic development, environmental consciousness, and policy regulation increase. After economic growth and urbanization accelerate, high per capita GDP is related to higher energy reliance, larger building scale, and higher industrial production, which increases carbon emissions. Economic growth also reduces resource consumption efficiency, worsening the carbon balancing issue.

Government intervention (*gov*) had a positive promoting effect on carbon balance during the study period, but its coefficient fluctuated wildly. By reducing the "three-high" layout and increasing subsidies for scientific and technological innovation, the government reduced pollution emissions and energy consumption, promoted economic growth from "extensive" to "intensive," and improved carbon balance at the start of the study. The market's response to government intervention varied during the study due to variances in its method and intensity, resulting in considerable fluctuations in its impact on carbon balance. The effectiveness of policy implementation and market participant expectations will also affect government intervention.

The regression coefficient of the impact of environmental regulation (*er*) on carbon balance has a slight change range during the study period. In most cities, it shows an inhibitory effect on the carbon balance coefficient. Environmental regulation eventually limits market carbon emissions and diminish regression coefficient variation. It also influences market players' expectations and behaviors, stabilizing the regression coefficient. Environmental constraint hinders carbon balancing in most cities. Moreover, it urges companies to decrease carbon emissions or use greener production methods, lowering their carbon balance coefficient. However, the restriction may raise business production costs and slow the growth of carbon balance coefficient (Shelton, 2021).

The influence of precipitation (*pre*) on the carbon balance of Chinese cities fluctuates around the coefficient 0, and the dispersion degree of the regression coefficient shows a trend of first expanding and then decreasing over time. Increased precipitation boosts plant growth, soil moisture, photosynthesis, and urban carbon sink. Industrial activity, energy use, and other factors have a greater impact on carbon balance in most regions, resulting in a smaller regression coefficient of precipitation variation range.

Like government action, sunlight level (*sun*) continued to positively affect carbon balance during the study period, demonstrating that

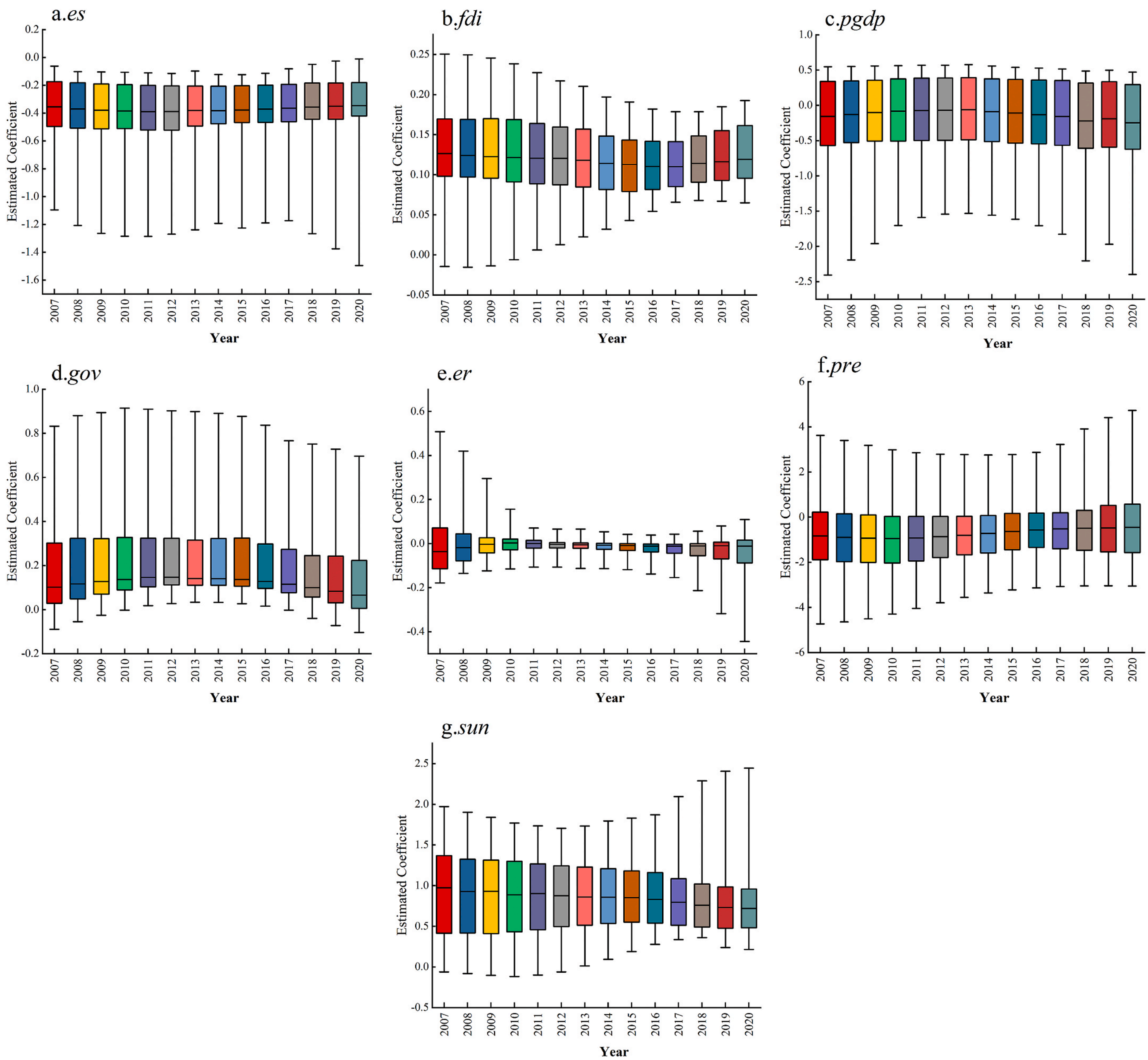

Fig. 5. Time series trend of driving factors from 2007 to 2020.

average annual sunshine hours can enhance carbon balance. Plants need sunlight to photosynthesize and transform carbon dioxide into organic matter. Plants' response to sunlight is nonlinear, and as sunlight increases, plants' photosynthetic efficiency may hit saturation and cannot be improved. Various cities have various climates, land uses, and flora kinds (Singh et al., 2018). Hence, sunshine degree has a modest effect on carbon balance.

4.4.3. Non-stationary evolution of driving factor space

The regression coefficients measured by GTWR were visualized using ArcGIS10.2 to obtain their spatial distribution pattern (as shown in Fig. 6), and the spatial heterogeneity of each driving factor on China's urban carbon balance was explored.

Energy consumption structure factor (*es*). In China, energy structure has been found to have an inhibitory effect on urban carbon balance, and the inhibitory effect is largest in northeast China, where a 1% increase in coal consumption will result in a −1.325%~-1.026% reduction in local urban carbon balance. The developed heavy industry in Northeast China drives coal use, which emits greenhouse gases. While maintaining indoor temperature, the Northeast has a long, cold winter requiring many heating units. The carbon balance will improve when coal burning increases since it is the predominant heating fuel. Low inhibitory effect locations occur in southern Shandong, Anhui, Hunan, and Jiangxi provinces, with regression coefficients between −0.212 and 0.018. These areas have relatively diversified economic structures, with a greater emphasis on developing emerging industries like the service and high-tech sectors, while also implementing measures to control polluting enterprises. This focus on industrial upgrading and green development helps to limit high-energy and high-pollution businesses, reducing coal dependence and leading to carbon emission balance.

The degree of opening up (*fdi*). The effect of opening up on carbon balance is highest in Beijing and most of northern China and lowest in most of Hunan and Guangxi, indicating a "high in the north and low in the south" trend. As significant global gateways, Beijing and most of

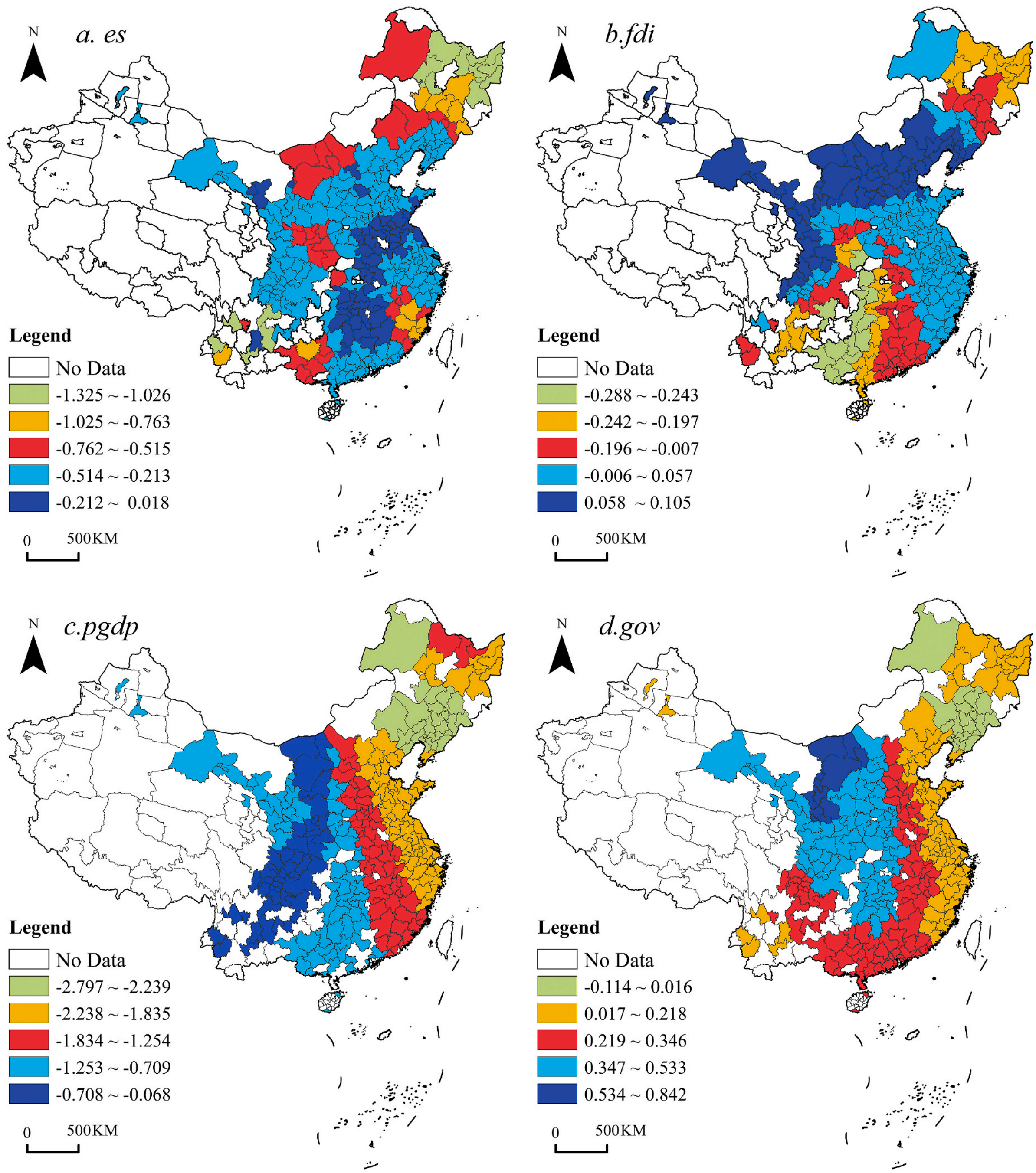

Fig. 6. (a) Spatial distribution of regression coefficients for driving factor es, (b) Spatial distribution of regression coefficients for driving factor fdi, (c) Spatial distribution of regression coefficients for driving factor pgdp, (d) Spatial distribution of regression coefficints for driving factor gov, (e) Spatial distribution of regression coefficients for driving factor er, (f) Spatial distribution of regression coefficients for driving factor pre, (g) Spatial distribution of regression coefficients for driving factor sun

northern China have attracted foreign investment and trade. Foreign direct investment has increased energy consumption and carbon emissions, but technology spillover from foreign enterprises has improved green technology and pollution control in the region and controlled carbon emissions. The local government in these areas is actively promoting green development, emphasizing ecological building, protecting forest resources and wetlands, enhancing carbon sinking capacity, and striving to improve carbon balance. In contrast, due to the simple local economic structure, low-value places rely heavily on agriculture and resource-based businesses, which consume much energy and emit carbon. Although climate in these areas is wet and rainy, they are prone to natural disasters like flooding, geological disasters, soil erosion, and deforestation, which negatively impact the local ecological environment (da Silva Junior et al., 2018). These factors weaken carbon sink capability, lowering carbon balance.

Economic development factor (*pgdp*). Economic development level affects Chinese cities' carbon balance "stepwise"—higher in the West and lower in the East. The rise in per capita GDP corresponds to increased income and consumption power, accelerating the local clean energy economy and reducing dependence on high-carbon energy. Increased per capita GDP will also raise local environmental awareness and encourage citizens to take more action to achieve carbon balance.

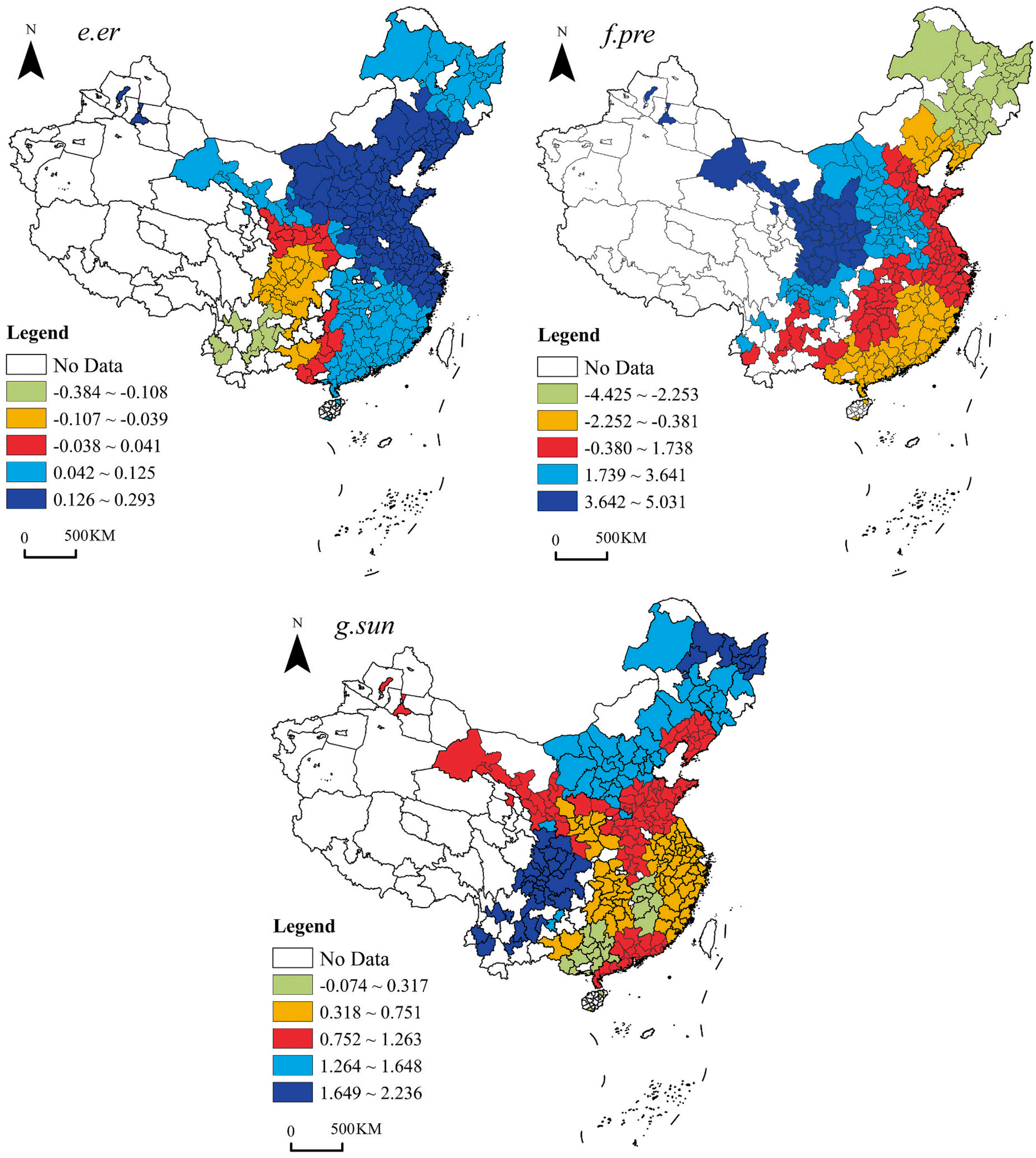

Fig. 6. (*continued*).

The low-value area in Northeast China decreases carbon balance by 0.068% for every 1% increase in per capita GDP. Population expansion and urbanization will raise resource consumption and environmental pressure as per capita GDP rises. Meanwhile, the local energy structure relies on fossil fuels, increasing industrial emissions and air pollution, thus hindering carbon balance.

Government intervention factor (*gov*). The regression coefficient of government fiscal expenditure on urban carbon balance in China promotes the entire country, with higher values in the middle and lower values on the four edges. The high-value areas are mostly in northern Inner Mongolia and Shaanxi Province. The government can reduce fossil fuel dependence, accelerate carbon emission reduction technology research and development, support related industry innovation and development, and reduce carbon emissions by investing more in clean energy and renewable energy. The government can also spend more on forests, wetlands, and grasslands to improve carbon sink capacity and promote carbon balance. The low-value area is mainly in the northeast, where foreign trade and investment introduction capability is weak, limiting the market size and the government's ability to boost fiscal expenditure to achieve the carbon balancing aim (Ren et al., 2020).

Environmental regulation factor (*er*). Environmental regulations negatively affect carbon balance nationwide. Environmental legislation strongly inhibits carbon balancing in northern China, Hubei, and other regions. Heavy industry with high energy consumption and pollution emits many greenhouse gases like carbon dioxide, which, combined with the increased demand for coal-fired heating and low vegetation coverage, reduces the carbon balance. The southwest region is predominantly characterized by low-value carbon balance. Complicated topography and a vast number of mountains and hills prevent pollutant diffusion and dilution, causing pollution to accumulate near the surface and obstruct carbon balance. Second, Southwest China's humid, rainy climate with enough water vapor promotes plant growth and increases vegetation's carbon absorption capacity. However, it also became the region with the lowest coefficient value due to the increased accumulation of pollutants in the soil, which inhibits carbon balance.

Precipitation factor (*pre*). Carbon balance is positively affected by precipitation in most locations and negatively affected in northeast China. The regression coefficient absolute values follow the pattern of West > Middle > East > Northeast. Shaanxi, Ningxia, and Gansu are in China's arid and semi-arid regions, where scant rainfall, low soil water content, limited plant growth, and delayed organic matter breakdown enhance soil carbon storage. The land is primarily used for animal husbandry or agriculture, with little human activity and natural solid recovery. Maintaining soil fertility and carbon cycle stability results in a 3.642%–5.031% gain in local carbon balance with a 1% increase in precipitation. However, rising precipitation would hinder Northeast China's improvement in carbon balance. Northeast China has a cold, dry environment with minimal precipitation, which lowers soil water content and hinders plant growth and nutrient absorption, falling carbon sink levels. The region's lengthy winter, low temperature, and soil freezing period inhibit microbial activity and soil organic matter decomposition. It reduces soil organic matter and carbon release, inhibiting carbon balance improvement.

Sunlight level factor (*sun*). Most areas of China positively influence yearly sunshine hours on carbon balance, although a few regions in northeast and southwest China have high values. The overall distribution is "two-level" with high values on both sides and low values in the middle. The low-value area is primarily in southern China, where a 1% increase in sunshine hours will enhance the carbon balance by −0.074%–0.317%, and the effect is minimal. The soil's carbon fixation potential is inadequate due to low vegetation covering, especially forest vegetation coverage, and human activities greatly impact land use and resource development. It destroys ecosystems and degrades land quality, affecting the carbon cycle and weakly improving carbon balance. The high-value locations are primarily in Northeast China, Sichuan Province, and Yunnan Province, and sunshine length improves carbon balance. Northeast China has a cold, dry environment with less precipitation and more extended sunshine, which boosts plant photosynthesis and carbon dioxide fixation. Sunshine helps decompose organic matter and release carbon in the soil, which has the most significant impact on the region's carbon balance.

5. Conclusions, policy recommendations, and discussion

5.1. Conclusions

This study, encompassing a sample of 277 Chinese prefecture-level cities, employed exploratory spatial data analysis and the standard deviation ellipse method to analyze the temporal change, spatial distribution, and evolution direction of carbon balance in China from 2007 to 2020. The investigation into the "time-space" non-stationarity of carbon-balancing driving elements, conducted using the spatial-temporal weighted regression model, yielded the following key findings:

First, the evolution of time series demonstrated a "two-stage" change in the national carbon balance index from 2007 to 2020 and a fluctuation drop from 2007 to 2013. The carbon balance index shows an "oscillation period" from 2007 to 2013, declining from 2013 to 2020. The 2014–2020 was the "increasing period," and the carbon balance index remained steady. The 2007–2020 Chinese urban carbon balance shows a "gradient development" from eastern to central to western regions.

Second, the urban carbon balance index in China throughout the study period had significant geographic disequilibrium, with high and low divisions. Compared to 2007, the 2020 carbon balance index and high-value regions have increased dramatically. As urban agglomerations strengthen regional collaboration, the carbon balance index displays "diffusion" and "polarization." The apparent change in carbon balance intensity between cities and the "contiguous" distribution of regions with similar carbon balance levels reflect it.

Third, agglomeration of China's carbon balance chilly hot areas was evident from a spatial evolution standpoint during the study period. Cold spots remained steady, hot places moved, and random distribution zones expanded. The standard deviation ellipse shows that the spatial distribution direction of the carbon balance index during the study period was "northeast-southwest," which is consistent with the Hu Huanyong line and economic development and population distribution.

Finally, the estimation results underscore the non-stationarity of driving variables in both time and space, exhibiting variations in intensity and direction across different areas. Specifically, the following six points are included: first, the impact of energy structure on China's urban carbon balance is consistently negative, and the strength of its inhibitory effect increases significantly over time. Second, the degree of openness to foreign trade positively promotes carbon balance in most cities, with the "pollution halo" effect generated by technological spillovers conducive to achieving carbon balance. Third, economic development initially shows a positive driving force but has a negative impact at the end of the study period. Fourth, government intervention consistently promotes carbon balance throughout the study period. In terms of geographical space, the coefficients show the distribution of higher value in the central region and lower value in the marginal region. Fifth, environmental regulation has mostly inhibited the carbon balance coefficients in many cities, with regression coefficients showing a converging trend. Sixth, precipitation and average annual sunshine have a positive impact on most regions of the country, effectively contributing to carbon balance.

5.2. Policy recommendations

In light of the study's conclusions, the following targeted and specific policy recommendations are proposed:

Firstly, the government is encouraged to bolster the development and utilization of clean energy and to promote the increase of renewable energy. Additionally, targeted regional policies should be formulated based on the observed gradient of carbon balance in Chinese cities in order to achieve the overall goal of a national carbon balance.

Furthermore, intensified efforts are needed for carbon emission reduction, involving optimizing energy structures and enhancing energy efficiency. This focus aims to propel low-value regions towards carbon neutrality. Strengthened cooperation and coordination among different areas are crucial for facilitating the "diffusion" of the carbon balance index, establishing cooperative mechanisms with "contiguous" distribution, and jointly advancing the realization of carbon balance.

Moreover, the government should enhance carbon emission reduction initiatives in hot spot regions by optimizing energy structures and improving energy efficiency, thereby facilitating the achievement of carbon balance goals. Concurrently, support and guidance should be provided to cold spot regions to encourage the enhancement of their carbon balance levels and prevent them from becoming new hot spots. Attention must also be given to the impact of economic development and population distribution on the carbon balance index, necessitating strengthened cooperation and coordination among regions.

Lastly, considering the unique circumstances of each region, the government should comprehensively analyze the main factors influencing local carbon balance. This involves clear policy focus, continuous optimization of energy structures, encouragement of international collaboration and technology overflow, and developing differentiated policies to address economic changes. Strengthening government intervention and environmental regulation, along with the rational utilization of precipitation and average annual sunshine hours through diverse approaches, will improve local carbon balance levels.

5.3. Discussion

This paper calculates the carbon balance index of Chinese cities, shows its spatial and temporal evolution characteristics, spatial distribution density, and direction, and introduces time characteristics based on the geographically weighted regression model to conduct regression analysis of each driving factor affecting carbon balance from natural conditions and social economy. Clearing up the "time-space" non-stationary features of each driving factor's force and direction on carbon balance is new and gives cities a policy focus to enhance carbon balance. However, given this topic, there is still the possibility of further deepening, mainly in (1) Exploring more factors affecting urban carbon balance, such as urban planning, transportation, industrial structure, to have a more comprehensive understanding and (2) Introducing more spatial statistical methods and technologies, and combining new technological means like big data and artificial intelligence.

CRediT authorship contribution statement

Jiansheng You: Writing – original draft, Validation, Software, Resources, Methodology, Data curation. **Zheming Dong:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis. **Hengyan Jiang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Not applicable.

Appendix A

Environmental regulations will be calculated as follows:
First, standardize unit pollution output:

$$CY^s_{i,j} = \frac{[CY_{i,j} - \min(CY_j)]}{[\max(CY_j) - \min(CY_j)]}$$

Among them, CY_{ij} represents the actual emission of the *j-th* pollutant in the *i-th* city, max(CY_j) and min(CY_j) represent the maximum and minimum unit pollution emissions of each city, respectively, and $CY^s_{i,j}$ represents the standardized value.

Use the adjustment coefficient to adjust the proportion of different pollution output and pollution intensity in each city to clarify the pollution differences between other cities:

$$W_j = \frac{CY_{i,j}}{\overline{CY_{i,j}}}$$

Among them, $\overline{CY_{i,j}}$ represents the average unit emission of the *j-th* pollutant in the *i-th* city during the study period.

Calculate the environmental regulation intensity emission index:

$$ER_i = \frac{1}{4}\sum\nolimits_{j=1}^{4} W_j CY^s_{i,j}$$

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