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Evolution Model, Mechanism, and Performance of Urban Park Green Areas in the Grand Canal of China

Zihan Cai [1,*], Sidong Zhao [2], Mengshi Huang [1] and Congguo Zhang [3,*]

1 School of Architecture & Art Design, Hebei University of Technology, Tianjin 300401, China; 2019098@hebut.edu.cn
2 School of Architecture, Southeast University, Nanjing 210096, China; 230189013@seu.edu.cn
3 Spatial Planning Center, Yangtze Delta Region Institute of Tsinghua University, Zhejiang, Jiaxing 314006, China
* Correspondence: 2020108@hebut.edu.cn (Z.C.); zcg96@163.com (C.Z.)

Abstract: Urban park green areas are part of territorial space planning, shouldering the mission of providing residents with high-quality ecological products and public space. Using a combination of several measurement models such as the BCG (Boston Consulting Group) matrix, ESDA (Exploratory Spatial Data Analysis), MLR (Machine Learning Regression), GWR (Geographically Weighted Regression), and GeoDetector, this paper presents an empirical study on the changes in Urban Park Green Areas (UPGAs) in the Grand Canal of China. By quantitatively measuring the spatio–temporal evolution patterns of UPGAs, this study reveals the driving mechanisms behind them and proposes policy recommendations for planning and management based on performance evaluation. The spatio–temporal evolution of UPGAs and their performance in China's Grand Canal are characterized by significant spatial heterogeneity and correlation, with diversified development patterns such as HH (High-scale–High-growth), HL (High-scale–Low-growth), LH (Low-scale–High-growth), and LL (Low-scale–Low-growth) emerging. The evolution performance is dominated by positive oversupply and positive equilibrium, where undersupply coexists with oversupply. Therefore, this paper recommends the implementation of a zoning strategy in the future spatial planning of ecological green areas, urban parks, and green infrastructure. It is also recommended to design differentiated construction strategies and management policies for each zoning area, while promoting inter-city mutual cooperation in the joint preparation and implementation of integrated symbiosis planning. Furthermore, the spatio–temporal evolution of the UPGAs in the Grand Canal of China is influenced by many factors with very complex dynamic mechanisms, and there are significant differences in the nature, intensity, spatial effects, and interaction effects between different factors. Therefore, in the future management of ecological green areas, urban parks, and green infrastructure, it is necessary to interconnect policies to enhance their synergies in population, aging, industry and economy, and ecological civilization to maximize the policy performance.

Keywords: urban park; evolution mode; driving mechanism; spatial planning; grand canal; China

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1. Introduction

1.1. Background

In the national spatial planning system, the planning for urban green areas is one of the most important projects, aimed at providing high-quality ecosystem services and public spaces for residents in China. Scientific planning of the quantity, quality, and spatial structure of the supply of urban green areas, especially Urban Park Green Areas (UPGAs), will significantly foster a more sustainable and livable urban environment [1,2]. In addition, as the construction of the Yangtze River Economic Belt, the protection and utilization of the Grand Canal and the construction of its cultural belt, and the ecological protection and high-quality development of the Yellow River Basin have been successively upgraded to national strategies, watershed spatial governance has become a key task of territorial spatial planning and a hotspot in academic research [3]. Therefore, quantitatively analyzing the spatio–temporal evolution patterns and driving mechanisms of UPGAs from a regional holistic perspective and evaluating the performance of land supply and demand will provide a basis for green infrastructure planning practice in watersheds and will help establish a technological system adapted to territorial spatial planning in these areas.

1.2. Literature Review

1.2.1. Urban Green Areas and Parkland

Current research on urban green areas mainly deals with planning methods and management policies [4,5], accessibility and satisfaction assessment [6,7], spatio–temporal dynamics and their influencing factors [8,9], value for ecosystem services and health [10,11], and other areas [12], while research on urban parkland focuses on areas such as spatial siting and configuration [13,14], needs assessment [15], planning methods [16], and willingness to pay [17]. Overall, there has been a large body of research on urban green areas and parkland, but still less attention has been paid to UPGAs [18]. For example, given that the unbalanced distribution of UPGAs has a significant impact on the well-being of residents, Li [19] and Xu [20] proposed an optimal spatial division plan for the service levels of UPGAs from the perspective of opportunity equity and spatial scale, based on the case studies of Taiyuan and Xuchang. Doll [21] assessed the greenness of UPGAs in Australia from the perspective of landscape preference and water consumption. Wang [22] quantitatively measured the equity of UPGAs in the central city of Beijing, analyzing the space to reveal a serious mismatch between the supply and demand of green areas. Yin [23] quantitatively examined the retention capacity of 176 urban park green areas within the Fifth Ring Road of Beijing for PM2.5 and endeavored to provide a basis for the design and construction of UPGAs to improve air quality. Biernacka [24] mapped and analyzed the dynamics of UPGAs in Poland, and they suggested the inclusion of informal green areas in urban planning. Engstrom [25] analyzed the advantages and disadvantages of using a hedonic price approach to capture the values of UPGAs in urban planning, and Ayele [26] studied the management model of UPGAs in Addis Ababa during rapid urbanization in Ethiopia.

1.2.2. Basin Planning and the Grand Canal

As Molle [27] and Antwi [28] put it, watershed planning has its origins in regional water resource management, but the embeddedness of other natural and ecological resource management systems has contributed to its gradual transformation into a new concept of socio–political life and spatial governance systems. Suhardiman [29] argued that watershed planning has evolved in Nepal as an arena for power operations and struggles, with its cross administrative boundaries jointly created by different government agencies. Essentially, watershed planning is a debate between multiple interests on development opportunities around the two perspectives of conservation and utilization, during which a large number of integrated modeling methods [30,31] and planning tools are created [32]. At present, the study of artificially excavated canals plays an important role in watershed planning, especially in China, the United States, Egypt, and India [33]. For the Grand Canal of China, the current research mainly focuses on the fields of cultural heritage, heritage and ecological protection, tourism development, land use, urban and rural spatial changes, and human habitat analysis. It has moved beyond the construction of water facilities and the development of cultural belts to green belts and economic belts [34] (Table 1).

Table 1. Literature review of the Grand Canal of China.

Areas	Viewpoints
Cultural Heritage and Ecological Protection	I. Study the distribution, characteristics, and influencing factors of historical relics and intangible cultural heritage along the canal [35,36] and further propose strategies for protection and utilization [37]. II. Assess the value of cultural heritage and relics along the canal and determine the adaptive landscape development methods [38–40]. III. Emphasize the evaluation of canal habitat quality [41], ecological functions [42], and pollution risks [43] and analyze their impact on ecosystem services [44].
Tourism development	I. Value the construction of tourism destinations and the construction of the tourism industry system, including the image perception of tourism destinations and its impact on tourism loyalty [45,46], tourism value assessment and resource utilization [47,48], tourism spatial development models [49], and regional tourism openness and cooperation [50]. II. Analyze the coupling relationship between tourism and ecology, heritage, and climate, including the impact of climate change on the development of canal tourism [51], the collaboration between tourism and ecosystems and their development obstacles [52], and the correlation between the spatio–temporal distribution of cultural heritage and tourism response [53].
Land use and Urban-rural changes	I. Analyze the level of sustainable and healthy land use along the canal [54] and land use/cover changes [55] and their impact on regional development [56]. II. Analyze the rise and fall of cities along the canal and spatial pattern and structural changes and their influencing factors, especially the role of canal logistics and flooding [57,58]. III. Analyze the geographical evolution of rural spatial settlements along the canal and its influencing factors, especially traditional villages and historical and cultural ancient villages [59–61].
Sustainable Development	I. Assess the spatial sustainable development of the canal basin [62] and its contribution to regional development [63]. II. Analyze the spatio–temporal characteristics of urbanization and the socio–economic benefits of canal land using the coupled coordination degree model to identify the synergistic development model of water–economy–innovation [64].

1.2.3. Research Gaps and Questions

There are three shortcomings in the current research. First, there is a wealth of research on urban green areas separated from parkland, but fewer studies combining the two, and such studies mainly focus on single-city case studies, lacking an analysis of the whole area and not matching the needs of watershed planning. Second, studies on the Grand Canal are mainly concerned with culture, ecological protection, and tourism development. Few scholars have focused on land use and change, except for Xia [65], who analyzed the impact of green areas on the well-being of residents in the Hangzhou section of the Grand Canal. Third, the Grand Canal is essentially a regional cultural, economic, and green belt, but current research lacks spatial correlation analysis from a regional perspective, and discussion of the driving mechanism ignores the influence of spatial and interactive effects.

To address the aforementioned shortcomings, this paper introduces a combination of spatial measurement models to study the whole area of the Grand Canal and analyze the spatio–temporal evolution patterns of UPGAs to reveal the driving mechanisms behind them, and it proposes suggestions and strategies for green areas or green infrastructure planning based on the change performance evaluation. This study aims to (1) quantitatively measure the evolutionary patterns of the UPGAs in the Grand Canal and reveal their spatial effects through the BCG (Boston Consulting Group) matrix and ESDA (Exploratory Spatial Data Analysis) in both temporal and spatial dimensions; (2) quantitatively measure the direct influence of different influencing factors on their spatio–temporal evolution patterns, as well as the spatial and interactive effects of the influencing factors using the MLR (Machine Learning Regression) method, the GWR (Geographically Weighted Regression) method, and GeoDetector; (3) evaluate the performance of their changes according to the indicators defined in the United Nations Sustainable Development Agenda, which dynamically analyzed the match between land supply and population demand; and (4) provide suggestions for their management policy and planning design based on the analysis results.

2. Materials and Methods

2.1. Study Area

The Grand Canal of China, with a history of more than 1000 years and spanning thousands of kilometers from north to south, crosses a number of water systems from north to south, such as the Haihe River, the Yellow River, the Huaihe River, the Yangtze River, Taihu Lake, and the Qiantang River, and has served as an important water transportation channel as well as an artery for the economic and cultural exchanges between the north and south of China since ancient times. The Grand Canal of China, consisting of the Beijing–Hangzhou Grand Canal, the Sui–Tangshan Grand Canal, and the Zhedong Canal, was officially approved by UNESCO on 22 June 2014 for inclusion in the World Heritage List. The State Council issued the Outline of the Plan for the Protection, Inheritance, and Utilization of the Grand Canal Culture in February 2019, which defines the spatial scope of the Grand Canal basin as the two municipalities of Beijing and Tianjin and the six provinces of Hebei, Shandong, Jiangsu, Zhejiang, Henan, and Anhui, comprising a total of 86 cities. The study area in this paper is the same as the planned scope, covering all 86 cities (Figure 1).

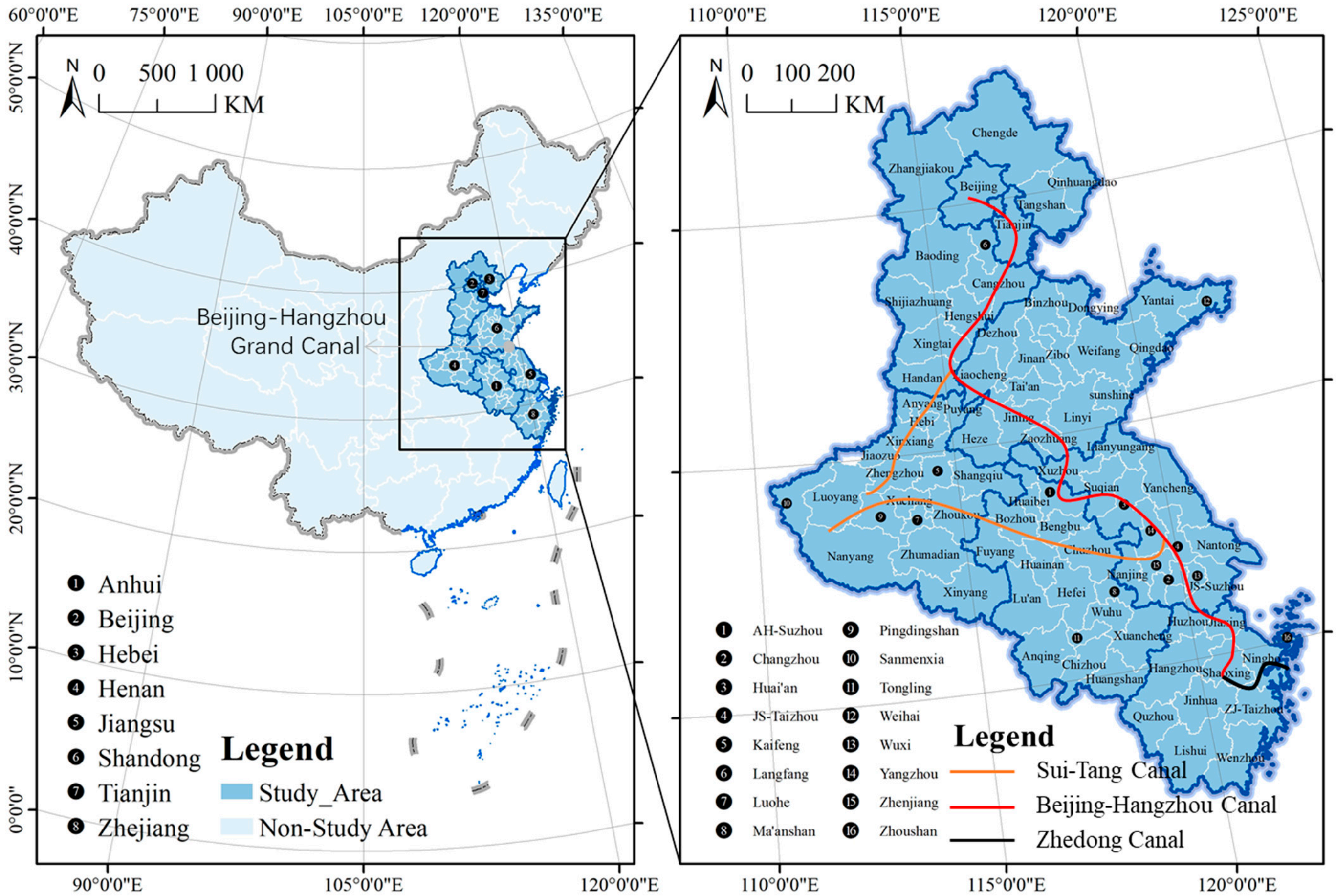

Figure 1. The Grand Canal and its location in China.

2.2. Research Steps and Technical Route

This study is based on a variety of measurement models, and it is performed in four steps (Figure 2):

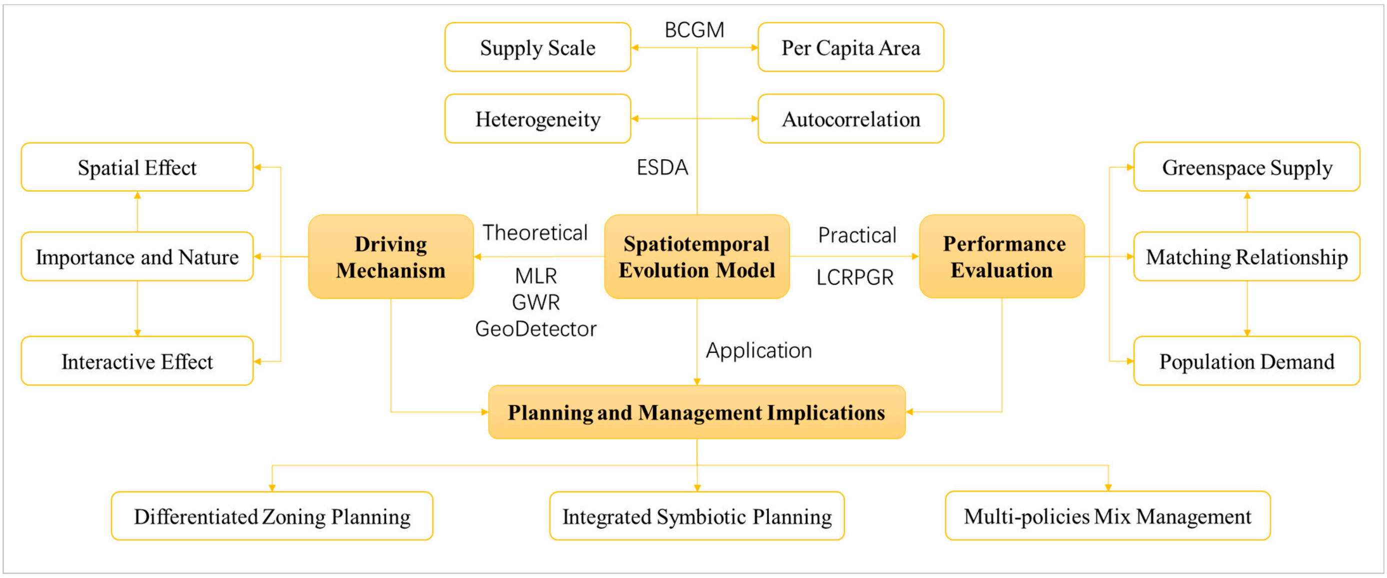

Figure 2. Technical route for the study of urban park green areas within the Grand Canal.

The first step is to analyze the spatio–temporal evolution patterns of the supply scale and per-capita area of UPGAs in the Grand Canal using the BCG (Boston Consulting Group) matrix, and to analyze their spatial heterogeneity and autocorrelation through ESDA (Exploratory Spatial Data Analysis).

The second step is to quantitatively analyze the driving mechanisms of changes in the scale of their supply and per-capita area, including the importance of factors, spatial effects, and interaction effects, based on a combination of MLR (Machine Learning Regression), GWR (Geographically Weighted Regression), and GeoDetector.

The third step is to analyze the match between their supply and demand from the perspective of sustainable development based on the LCRPGR (Ratio of Land Consumption Rate to Population Growth Rate).

The fourth step is to propose planning and management suggestions as guidance and a basis for green area planning and green infrastructure policy design based on the analysis results of the first three steps.

2.3. Research Methods and Indicator Selection

2.3.1. Boston Consulting Group (BCG) Matrix

The BCG matrix is often used in enterprise strategy management to classify the development status of businesses or products into four types, Star, Question, Cow, and Dog, and propose differentiated development strategies based on the combined analysis of the relative market share and growth rate of business departments or products. A development strategy is needed for Star products, and further investment is required to support their rapid expansion in the market and to make them the leading products of the enterprise. Cow products require a profit strategy, but the core of future development strategies is not to increase business investment, enterprise output, or market supply, but rsther to quickly recover funds through high product profits to support the development of Star products. For Question products, more research is needed and flexible strategies should be developed according to the actuality. Specifically, it is necessary to, based on the survey and research results, select some potential subcategories for key investments, while abandoning others. Dog products should be stopped, either by abandonment or recycling, in order to decisively stop loss, as they are the products that have been in a period of decline, unable to create more earnings for the enterprise.

In this paper, a concept is introduced to analyze the spatio–temporal evolutionary patterns of UPGAs in the Grand Canal of China, where Relative Share (RS) and Growth Rate (GR) represent the regional status in the spatial dimension and the growth capacity in the temporal dimension, respectively. With their median as the threshold, the spatio–temporal evolutionary patterns of UPGAs of the 86 cities in the study area can be categorized into four quadrants—HH (High-scale–High-growth), HL (High-scale–Low-growth), LH (Low-scale–High-growth), LL (Low-scale–Low-growth)—by the Cartesian coordinate system. With UPG_i and UPG_i' as the indicators for UPGAs in the i-th city in 2020 and 2010, respectively, and UPG_{max} as the maximum value for 86 cities in the study area, RS and GR are calculated as follows [66]:

$$RS = \frac{UPG_i}{UPG_{max}} \times 100\% \tag{1}$$

$$GR = \left(\frac{UPG_i - UPG_i'}{UPG_i'} - 1 \right) \times 100\% \tag{2}$$

2.3.2. Exploratory Spatial Data Analysis (ESDA)

This paper employs ESDA to quantitatively judge and visualize the spatial features of UPGAs, including spatial autocorrelation and spatial heterogeneity. Moran's I index is used to measure the overall strength of spatial autocorrelation, and a value greater or less than zero represents the positive or negative spatial autocorrelation in the spatial distribution of UPGAs, respectively, otherwise it represents a random distribution [67,68]. To further measure the localized characteristics of spatial associations, the Getis–Ord G_i^* index is introduced to classify the cities in the study area into four types: hot, sub-hot, sub-cold, and cold. To measure regional differences in UPGAs, coefficient of variation and spatial clustering methods are introduced to represent and visually demonstrate spatial heterogeneity. A larger coefficient of variation indicates a greater regional difference in UPGAs, with 0.36 and 0.16 being the thresholds to determine high and low levels of spatial heterogeneity [69]. With $\overline{UPG}$ being the mean of UPGA metrics, S being their standard deviation, and W_{ij} being the spatial weight, Moran's I, Getis–Ord G_i^*, and CV are calculated as follows [70]:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(UPG_i - \overline{UPG}\right)\left(UPG_j - \overline{UPG}\right)}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\right)\sum_{i=1}^{n}\left(UPG_i - \overline{UPG}\right)^2} \tag{3}$$

$$G_i^* = \frac{\sum_{j=1}^{n} W_{ij} UPG_i - \overline{UPG}\sum_{j=1}^{n} W_{ij}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} W_{ij}^2 - \left(\sum_{j=1}^{n} W_{ij}\right)^2\right]}{n-1}}} \tag{4}$$

$$CV = S/\overline{UPG}, \quad S = \sqrt{\frac{\sum_{i=1}^{n}\left(UPG_i - \frac{\sum_{i=1}^{n} UPG_i}{n}\right)^2}{n}}, \quad \overline{UPG}\frac{\sum_{i=1}^{n} UPG_i}{n} \tag{5}$$

2.3.3. Machine Learning Regression (MLR)

Given the nonlinear characteristics of distribution planning for UPGAs and machine learning regression methods that do not rely on a priori subjective human experience, a non-linear econometric model is adopted to analyze the importance of influencing factors [71]. In this paper, the decision tree, random forest, adaboost, and ExtraTrees algorithms in machine learning regression models are used to analyze the influence of different factors on the spatio–temporal evolution patterns of UPGAs. Decision tree, a tree-like structure, tests the data sample from the root node, divides the data sample into different data sample subsets according to different results, and calculates the data through a series of rules [72]. Random forest is a supervised machine learning algorithm constructed by integrating decision tree-based learners, which introduces randomness into the training process of decision tree to make it excellent in overfitting and noise resistance [73]. The AdaBoost model is an iterative algorithm that adds a new weak classifier in each round until a predetermined sufficiently small error rate is reached [74]. Extra-trees are derived from the traditional decision tree algorithm, characterized by the direct use of random features and thresholds in the node division of the decision tree, resulting in a larger and more random shape and difference in each decision tree [75]. The purpose of introducing machine learning regression in this paper is to measure the importance of factors, not to make predictions. Therefore, all data are included in the calculation, and the final result is determined according to goodness of fit and the comparative analysis of different algorithms.

Dependent variables include the supply scale of UPGAs and per-capita area of UPGAs, labeled with Y_1 and Y_2, respectively. For independent variables, the combined influence of social, economic, and natural factors should be considered (Table 2). For social factors, population density represents the overall impact of a population aged 60 and above, and the proportion of population aged 60 and above represents the impact of special aging groups [76]. Outflow population indicates the impact of a semi-urbanized, transient population [77]. Of the economic factors, GDP represents the impact of the size of the economy [78]. Per-capita GDP represents the impact of the stage and quality of economic development [79,80] and fiscal self-sufficiency rate represents the government's ability to intervene in the economy [81,82]. In terms of natural factors, topography represents the impact of topographic complexity [83], average temperature represents the impact of climate change, especially the urban heat island effect [84], and ventilation coefficient represents the impact of regional wind environment and urban air quality [85,86]. According to the measurement of covariance between factors using the least squares linear regression model, the maximum value of VIF for per-capita GDP among the nine independent variables reaches 8.25, but is still less than 10, indicating that the covariance of the independent variables is weak and can be almost ignored. The dependent variable data came from the China Urban Construction Statistical Yearbook; the population data came from the population census; the economic data came from the China City Statistical Yearbook and the statistical yearbooks of eight provinces/municipalities directly under the central government; the topographic relief data come from the Relief Degree of Land Surface Dataset of China (1 km) [87,88]; the average temperature data came from data.cma.cn; and ventilation coefficients were calculated from ECMWF re-analysis-interim data by the methods of Broner [89], Hering [90], and Chen [91]. Equations (6) and (7) are used for the positive and negative indicators in the standardization of dependent and independent variables, where $D_i^{+/-}$ is a standardized value, D_i is the original value, and D_{Max} and D_{Min} are the maximum and minimum values of the original data, respectively.

$$D_i^{+} = \frac{D_i - D_{Min}}{D_{Max} - D_{Min}} + 0.001 \tag{6}$$

$$D_i^{-} = \frac{D_{Max} - D_i}{D_{Max} - D_{Min}} + 0.001 \tag{7}$$

Table 2. Indicator selection of independent variables.

Indicator		Code	VIF
Supply scale of UPGAs		Y_1	--
Per-capita area of UPGAs		Y_2	--
Society	Population density	X_1	1.14
	Proportion of population aged 60 and above	X_2	1.93
	Outflow population	X_3	3.49
Economic	GDP	X_4	2.84
	Per-capita GDP	X_5	8.25
	Fiscal self-sufficiency rate	X_6	5.41
Natural	Topography	X_7	1.27
	Average temperature	X_8	1.58
	Ventilation coefficient	X_9	1.63

2.3.4. Geographically Weighted Regression (GWR)

In this study, GWR is used to analyze the impact of each factor on the spatio–temporal evolution patterns of UPGAs. GWR improves the computational accuracy of the regression model by creating localized regression equations for each city and incorporating the spatial autocorrelation and heterogeneity of UPGA changes into the regression process [92]. With Y_i representing the spatio–temporal evolution pattern of UPGAs of the i-th city (HH, HL, LH, LL are assigned values of 4, 3, 2, and 1, respectively, in the calculation), X_{ik} being the k-th independent variable (influencing factor), β_0 being a constant term, (μ_i, v_i) being the spatial location of the i-th city (geographic center of gravity coordinate), $\beta_{k_{(\mu_i, v_i)}}$ being the correlation between the variables of the i-th city, and ϵ_i being the error of the regression equation, GWR is calculated as follows [93]:

$$Y_i = \beta_{0_{(\mu_i,\ v_i)}} + \sum_k \beta_{k_{(\mu_i,\ v_i)}} X_{ik} + \epsilon_i \tag{8}$$

2.3.5. GeoDetector

In this study, GeoDetector is used to measure the interaction between different factors. Different factors interact with each other when they act together in the UPGA planning, and GeoDetector measures the interaction effect of factor pairs using the q-index. It calculates the spatial pattern of the dependent variable Y_i and the similarity of independent variables X_{ik} and X_{il} to obtain the single-factor and dual-factor influences q (X_i), q (X_j), and q $(X_i \cap X_j)$; furthermore, it compares q $(X_i \cap X_j)$ and other parameters to select and identify the final result—nonlinear weaken (q $(X_i \cap X_j)$ < Min q (X_i), q (X_j)), single weaken (Min (q (X_i), q (X_j) < q $(X_i \cap X_j)$ < Max q (X_i), q (X_j)), double enhance (q $(X_i \cap X_j)$ > Max q (X_i), q (X_j)), independent (q $(X_i \cap X_j)$ = q (X_i) + q (X_j)), and nonlinear enhance (q $(X_i \cap X_j)$ > q (X_i) + q (X_j)) [94,95]. With h = 1, 2, 3, . . . l, where l is the number of partitions of spatial clustering, σ^2 is the total variance of dependent variables, σ_h^2 is the variance of dependent variables of the h-th partition, and SSW and SST are the sums of variances within the partition and the study area, the index q is calculated as follows [96]:

$$q = 1 - \frac{\sum_{h=1}^{l} n_h \sigma_h^2}{n\sigma^2} = 1 - \frac{SSW}{SST},\quad SSW = \sum_{h=1}^{l} n_h \sigma_h^2,\ SST = n\sigma^2 \tag{9}$$

2.3.6. Ratio of Land Consumption Rate to Population Growth Rate (LCRPGR)

The *Transforming Our World—the 2030 Agenda for Sustainable Development* proposes 17 SDGs (sustainable development goals). Indicator SDG 11.3.1 is defined as the ratio of the Land Consumption Rate (LCR) to the Population Growth Rate (PGR) and is used to represent the relationship between urban expansion and population change [97]. This study chooses to use this method to evaluate the performance of UPGAs from a sustainable development perspective. LCR is a reflection of the growth rate of land used for urban park purposes and represents the efficiency of changes in the supply of urban green areas. PGR reflects the change rate of urban population and is used to measure the change rate of the green area demand of the population in an area over a period of time. LCRPGR measures the relationship between the change rates of two variables, LCR and PGR, and is used to represent the match between supply and demand in UPGAs. Theoretically, an LCRPGR equal to 1 is the most desirable result, and in view of the elasticity in practice development, 0.75 and 1.25 are set as thresholds to classify the analysis results into eight categories (Table 3). LCRPGR is calculated as follows [98]:

$$LCRPGR = \frac{LCR}{PGR} = \frac{\frac{\ln\left(UPG_i/UPG_i'\right)}{n}}{\frac{\ln\left(PD_i/PD_i'\right)}{n}} \tag{10}$$

Table 3. Matching relationship between urban park green space supply and population demand based on LCRPGR measurements.

Type	LCR	PGR	LCRPGR
Super oversupply	>0	<0	<0
Super undersupply	<0	>0	<0
Negative oversupply	<0	<0	>0 and <0.75
Negative undersupply	<0	<0	≥1.25
Negative equilibrium	<0	<0	>0.75 and <1.25
Positive oversupply	>0	>0	≥1.25
Positive undersupply	>0	>0	>0.75 and <1.25
Positive equilibrium	>0	>0	>0 and <0.75

3. Results

3.1. Spatiotemporal Evolution Model

3.1.1. Supply Scale

According to the relative share of supply scale of UPGAs, the coefficient of variation and Moran's I are 1.47 and 0.05, respectively ($Z = 1.90$, $p < 0.05$), indicating huge inter-city differences and significant positive spatial autocorrelation. Most of the high-value cities are concentrated in Shandong, Beijing, Tianjin, and provincial capital metropolitan areas such as Zhengzhou, Hefei, Hangzhou, Shijiazhuang, and Nanjing. The Nanjing metropolitan area extends to cover the region of Southern Jiangsu (Suzhou, Wuxi, Changzhou, etc.). In addition, Ningbo, Linyi, Yantai, Wuxi, Nantong, Luoyang, and Zibo also have a leading edge, with a relative share of over 10%. Most of the low-value cities are concentrated in the north and south of Hebei and Henan and in the west of Anhui and Zhejiang, especially Zhoushan, Jinhua, Hengshui, Tongling, Lu'an, Xuchang, Xinxiang, Anyang, Xinyang, Puyang, Suzhou, Zhumadian, Hebi, Cangzhou, Sanmenxia, Zhoukou, Bozhou, Quzhou, Xuancheng, Huangshan, Chizhou, and Lishui, and have a large disadvantage, with a relative share of not more than 3%. The hotspots are concentrated in Beijing, Tianjin, and the north of Hebei Province; the sub-hotspots are in the Shandong Peninsula and the densely populated urban areas of Southern Jiangsu; and most of the coldspots are located in the border areas of Henan, Anhui, Shandong, and Jiangsu Provinces (Figure 3).

According to the growth of UPGA supply scale, the CV and Moran's I are 0.70 and 0.01 ($Z = 0.61$, $p > 0.05$), respectively, indicating that neither the inter-urban differences nor the spatial correlations are significant. High-value cities are not spatially clustered geographically, and include Nantong, Fuyang, Zhengzhou, Wenzhou, Jining, Kaifeng, Ningbo, Chuzhou, Shangqiu, Yancheng, Taizhou, Qingdao, Suqian, and Liaocheng. Most of the low-value areas are clustered in northern Hebei and southeastern Shandong, with Pingdingshan, Luohe, Xinxiang, Qinhuangdao, Rizhao, Huaibei, Wuxi, Handan, Chizhou, Zhenjiang, Zhangjiakou, and Tangshan lagging behind in development, and Chengde in particular showing negative growth. The hotspot cities are mainly in the border areas of Henan, Anhui, and Shandong Provinces and extend to central Jiangsu. The sub-hotspot cities are distributed in the periphery of the hotspot cities in a "center-edge" structure. In southeastern Zhejiang, a small "center-edge" structure is developing. The coldspots are concentrated in Beijing, Tianjin, northern Hebei Province, central Shandong Province, and the border areas of Anhui and Zhejiang Provinces.

According to the spatiotemporal evolution model of the scale of UPGA supply, the median relative share and growth rates are 4.66% and 68.92%, respectively. A high proportion is found in HH and LL cities, both at approximately 30%. HH cities are scattered in distribution and are only in western Shandong; coastal Jiangsu; and the provincial capital metropolitan areas of Henan, Anhui, and Zhejiang, including Beijing, Tianjin, Xingtai, Changzhou, and others. LL cities are relatively clustered in the north of Hebei, the south of Anhui, the west of Zhejiang, and the northeast corner of Henan, including Zhangjiakou, Chengde, Cangzhou, Langfang, Zhenjiang, Jiaxing, Jinhua, Quzhou, Zhoushan, Lishui, Ma'anshan, Huaibei, Huangshan, Lu'an, Chizhou, Xuancheng, Zaozhuang, Rizhao, Binzhou, Pingdingshan, Anyang, Hebi, Xinxiang, Puyang, Luohe, and Xinyang. Most of the HL cities are concentrated in Shandong, Hebei, and Jiangsu, including Shijiazhuang, Tangshan, Qinhuangdao, Handan, Baoding, Nanjing, Wuxi, Xuzhou, Suzhou, Yangzhou, Huzhou, Taizhou, Huainan, Zibo, Yantai, Weifang, and Linyi. Most LH cities are concentrated in Henan and Anhui, especially in the border areas of the two provinces, including Hengshui, Taizhou, Suqian, Bengbu, Tongling, Anqing, Chuzhou, Suzhou, Bozhou, Heze, Kaifeng, Jiaozuo, Xuchang, Sanmenxia, Shangqiu, Zhoukou, and Zhumadian. Overall, most of the hotspot cities are clustered in the west of Shandong and extend to Jiangsu and Hebei, while most of the coldspot cities are in the central part of Henan and the border area of Anhui and Zhejiang, both geographically distributed in a band (Figure 4).

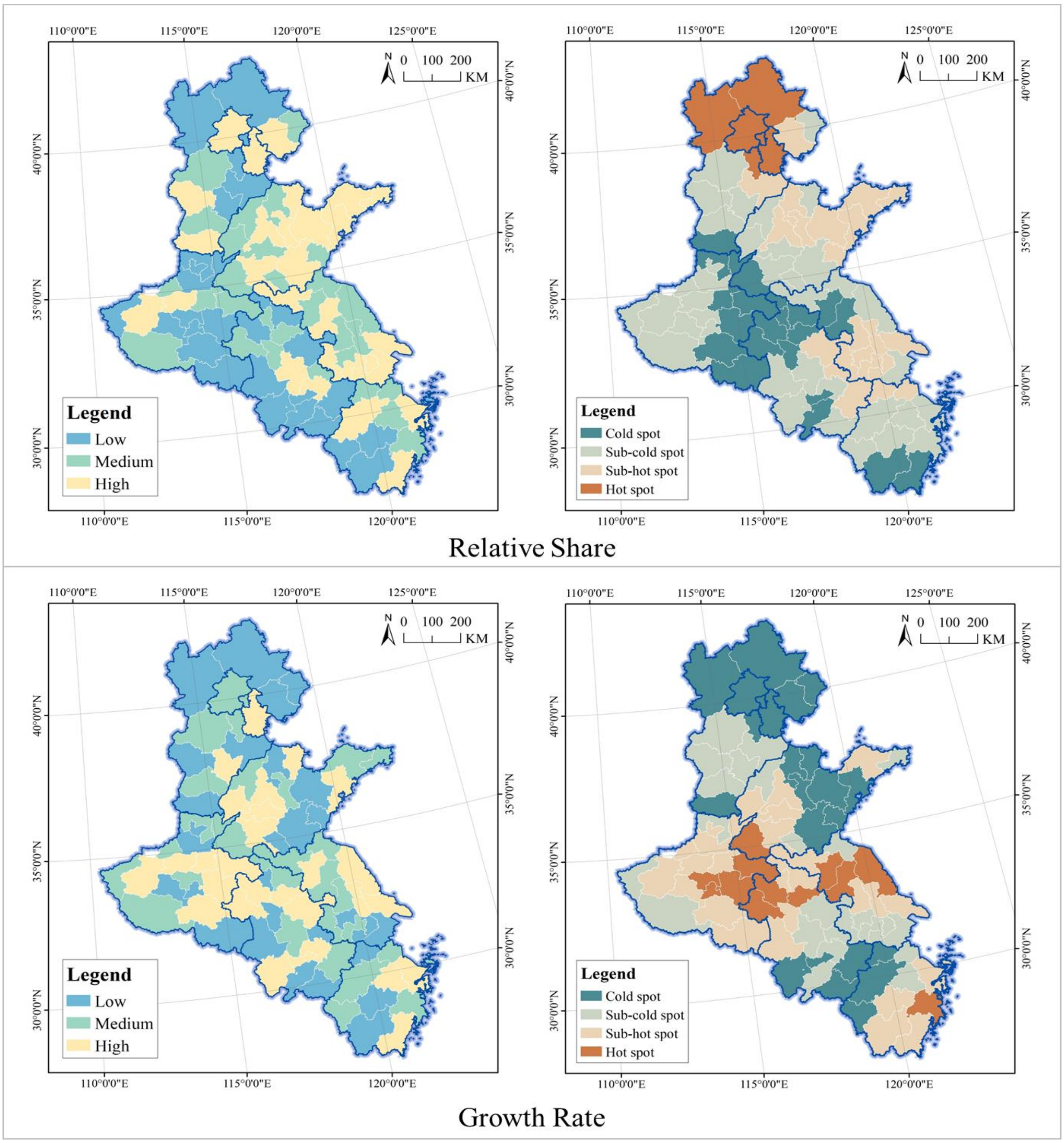

Figure 3. Relative share and growth rate spatial analysis of the supply scale of UPGAs in the Grand Canal of China.

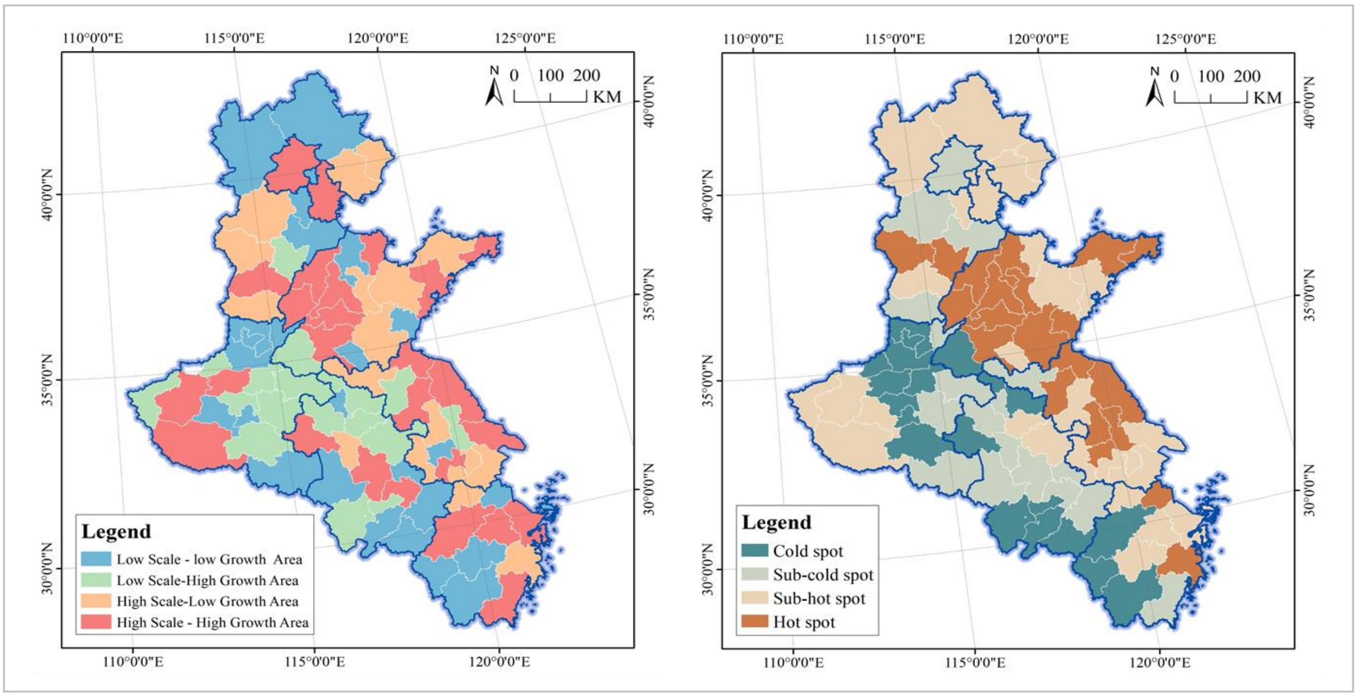

Figure 4. Spatiotemporal evolution model of the supply scale of urban park green areas on the Grand Canal of China.

3.1.2. Per-Capita Area

According to the relative share of the per-capita area of UPGAs, the CV and Moran's I are 0.19 and 0.17, respectively ($Z = 3.93$, $p < 0.01$), indicating moderate inter-city differences but significant positive spatial autocorrelation. Most of the high-value cities are concentrated in Shandong, with a few in the northern end of Hebei and southern Anhui. In addition, Chuzhou, Bozhou, Fuyang, Nantong, Yangzhou, and other cities also have a leading edge, with a relative share close to 70%. Most of the low-value cities are concentrated in Zhejiang, the western part of Hebei, the border area of Henan and Shandong, and the central part of Anhui, especially Taizhou, Wuhu, Pingdingshan, Hefei, Anyang, Suzhou, Jinhua, Hangzhou, Xinxiang, Jinan, Lishui, Cangzhou, Zhangjiakou, and Tianjin, and they have a significant disadvantage, with a relative share of less than 50%. The hotspot cities are all clustered in Shandong and the sub-hotspot cities are in its periphery and extend to Hebei and Jiangsu, forming a "center-edge" structure. There are three clusters of coldspot cities in Zhejiang (except Hangzhou), Beijing–Tianjin, and the east of Henan, while all other cities are sub-hotspots (Figure 5).

According to the growth rate of the per-capita area of UPGAs, the CV and Moran's I are 1.17 and 0.20 ($Z = 4.53$, $p < 0.01$), respectively, indicating significant spatial heterogeneity and spatial autocorrelation. Most of the high-value cities are concentrated in Henan and extend in a continuous belt towards Anhui and a necklace (stepping stone) towards Shandong. Low-value cities are clustered in northern Hebei, central Zhejiang, Shandong, and southern Jiangsu, with Zhangjiakou, Shaoxing, Hefei, Qinhuangdao, Yantai, Handan, Rizhao, Hangzhou, Chengde, and Suzhou in particular showing negative growth. The hotspot cities are mainly concentrated in the border area of Henan and Anhui Provinces, while the sub-hotspot cities are in its periphery, forming a "center-edge" structure. There are three coldspot urban clusters in northern Zhejiang, the peninsula and south of Shandong, and the eastern part of the Beijing–Tianjin–Hebei metropolitan area (Beijing–Tangshan–Qinhuangdao region).

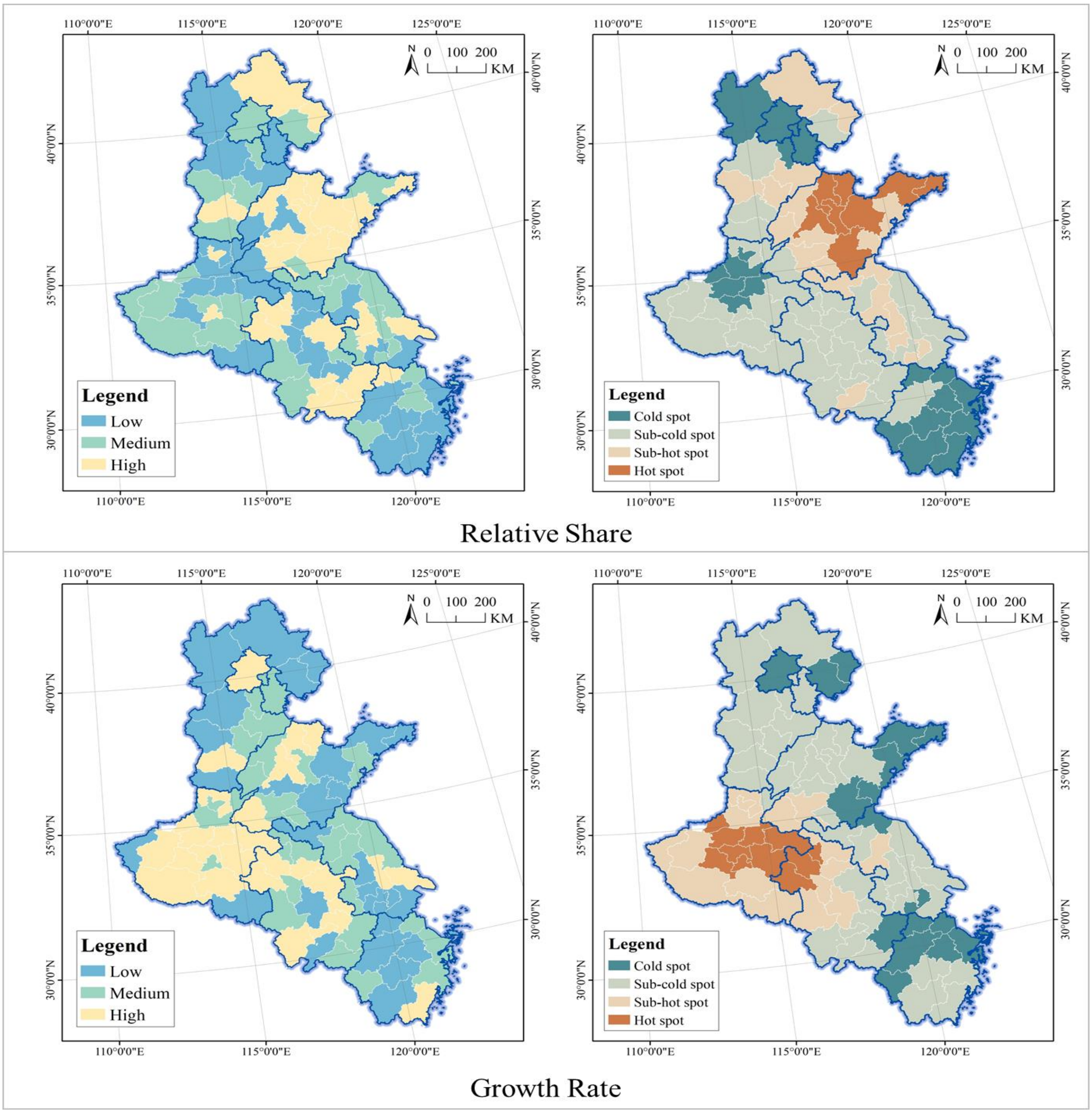

Figure 5. Relative share and growth rate spatial analysis of the per-capita area of UPGAs in the Grand Canal of China.

According to the spatiotemporal evolution model of per-capita area of UPGAs, the median relative share and growth rate are 59.33% and 22.86%, respectively. A high proportion is found in HL and LH cities, both at approximately 25%. HH cities are dispersed in a geographical distribution, including Xingtai, Langfang, Nantong, Taizhou, Suqian, Quzhou, Huaibei, Tongling, Chuzhou, Fuyang, Lu’an, Bozhou, Qingdao, Beijing, Zibo, Dongying, Jining, Binzhou, Luoyang, and Xuchang. Most of the LL cities are concentrated in Hebei and Zhejiang, a small number are located in the densely populated urban areas of southern Jiangsu, and very few are randomly distributed. LL cities include Tianjin, Shijiazhuang, Baoding, Zhangjiakou, Cangzhou, Wuxi, Changzhou, Suzhou, Hangzhou, Jiaxing, Shaoxing, Jinhua, Taizhou, Lishui, Hefei, Huainan, Zaozhuang, Liaocheng, Puyang, and Xinyang. Most of the HL cities are concentrated in Shandong, and there are two small clusters in the southern end of Anhui and the northeast corner of Hebei. These include Tangshan, Qinhuangdao, Handan, Chengde, Nanjing, Xuzhou, Yangzhou, Zhenjiang, Huzhou, Zhoushan, Huangshan, Chizhou, Xuancheng, Yantai, Weifang, Tai'an, Weihai, Rizhao, Linyi, Dezhou, Hebi, Luohe, and Sanmenxia. Most of the LH cities are concentrated in Henan and extend to northern Anhui and northern Jiangsu, including Hengshui, Lianyungang, Huai'an, Yancheng, Ningbo, Wenzhou, Wuhu, Bengbu, Ma'anshan, Anqing, Suzhou, Jinan, Heze, Zhengzhou, Kaifeng, Pingdingshan, Anyang, Xinxiang, Jiaozuo, Nanyang, Shangqiu, Zhoukou, and Zhumadian. Overall, most of the hotspot cities are clustered in Shandong; sub-hotspot cities are mostly found in Henan, Anhui, Jiangsu, Hebei, Beijing, and Tianjin; most of the coldspot cities are in Zhejiang; and most of the sub-coldspot cities are in the border areas of Hebei, Henan, and Shandong, showing significant clustering characteristics (Figure 6).

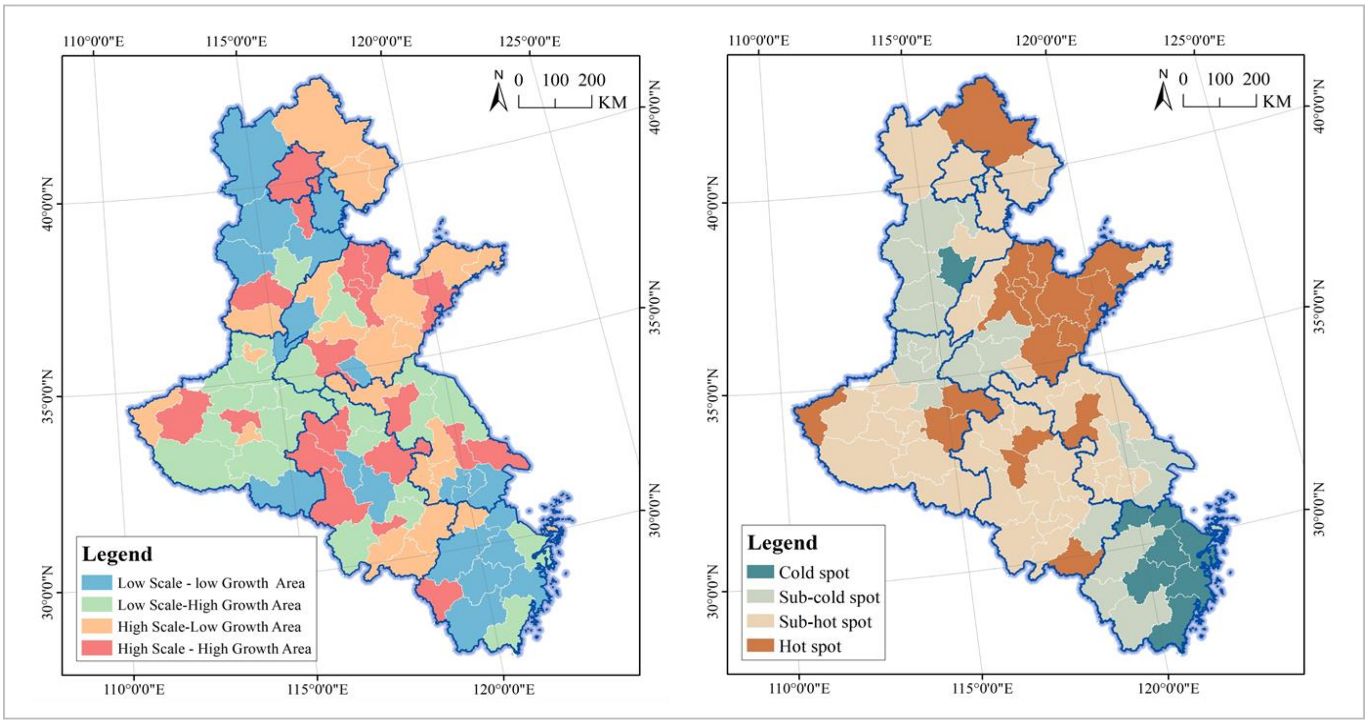

Figure 6. Spatiotemporal evolution model of the Ppr-capita area of urban park green areas on the Grand Canal of China.

The comparative analysis in the above two dimensions shows that Anyang, Pingdingshan, Puyang, Shangqiu, Xinyang, and Zhengzhou are always at a low level in the supply and per-capita area of urban green areas, with the construction of urban green infrastructure far behind that of other cities along the Grand Canal. Therefore, more investment and support are needed in future planning, construction, and management. On the contrary, Qingdao, Linyi, Nantong, Zibo, Weifang, Jining, Weihai, and Dongying are consistently at a high level, with the urban green infrastructure development ahead of the other cities in the Grand Canal, making them of exemplary value in the region. It should be noted that historical and cultural cities and livable cities such as Hangzhou, Beijing, Nanjing, Tianjin, and Suzhou are regional leaders in the scale of urban green areas supply, but they have no competitive advantage per capita. They should attach special attention and focus to green infrastructure planning, construction, and management in the future.

3.2. Driving Mechanism

3.2.1. Importance and Nature of Factors

The analysis results from the machine learning regression algorithms show a high goodness, generally greater than 0.85, with decision tree being optimal in both schemes. The results of the four algorithms are in general similar. Although there are differences in the coefficients of factors with higher and lower importance, their ranking remains relatively stable (Table 4). To provide full play to the advantages of all algorithms and eliminate the defects of a single algorithm, this paper uses the average values of four algorithms to determine the importance of factors. For the supply scale of UPGAs, topography, outflow population, and population density have much higher importance than other factors, and they are defined as key factors; fiscal self-sufficiency rate and average temperature have much lower importance than other factors, and they are defined as auxiliary factors with direct influences that can be ignored; and ventilation coefficient, proportion of population aged 60 and above, GDP, and per-capita GDP are not more or less important and are defined as important factors. For per-capita area of UPGAs, per-capita GDP is a key factor; fiscal self-sufficiency rate, GDP, and average temperature are auxiliary factors; while topography, ventilation coefficient, population density, outflow population, and proportion of population aged 60 and above are important factors (Figure 7).

Table 4. Machine learning regression results based on different algorithm analysis of urban park green areas on the Grand Canal of China. The asterisk represents the result after rounding.

Factors	Supply Scale of UPGAs				Per-Capita Area of UPGAs			
	Decision Tree	Random Forest	Adaboost	Extra Trees	Decision Tree	Random Forest	Adaboost	Extra Trees
X_1	13.00%	5.90%	6.70%	7.60%	24.70%	13.50%	12.00%	12.80%
X_2	4.80%	7.30%	8.80%	5.80%	7.10%	6.70%	7.90%	10.10%
X_3	3.30%	7.40%	11.40%	8.70%	19.50%	18.00%	16.90%	13.50%
X_4	3.10%	5.50%	6.70%	6.00%	3.00%	7.70%	10.20%	8.40%
X_5	57.40%	47.50%	29.60%	28.10%	4.60%	4.90%	8.20%	10.10%
X_6	0.00%	5.00%	6.80%	10.50%	0.90%	6.30%	7.70%	10.80%
X_7	7.40%	10.50%	13.70%	15.00%	33.00%	22.00%	18.60%	13.10%
X_8	0.00%	3.60%	6.80%	7.60%	4.20%	6.00%	5.50%	6.70%
X_9	10.80%	7.20%	9.50%	10.70%	3.00%	14.80%	13.00%	14.60%
R^2	1 *	0.89	1 *	0.90	1 *	0.87	0.99	0.86

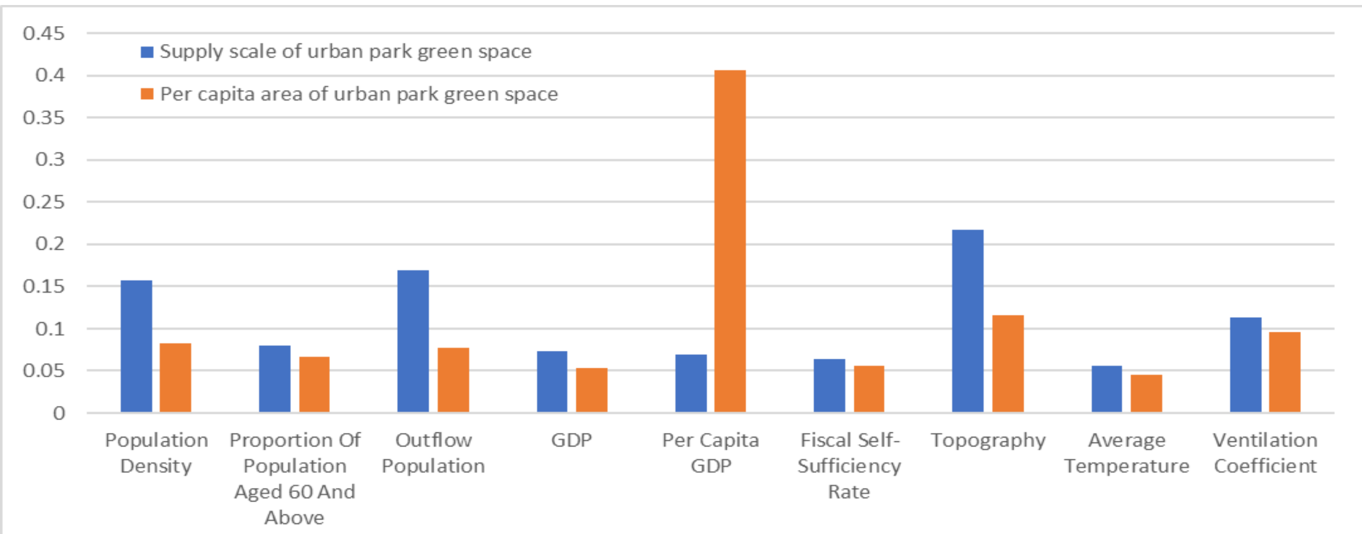

Figure 7. Factor importance analysis of UPGAs in the Grand Canal of China.

3.2.2. Spatial Effect of Factors

From the supply scale of UPGAs, the minimum values of proportion of population aged 60 and above (X_2), GDP (X_4), and fiscal self-sufficiency rate (X_6) are all greater than zero, suggesting that they all play a positive role as a whole. The maximum values of topography (X_7), average temperature (X_8), and ventilation coefficient (X_9) are all less than zero, suggesting that they all act as negative obstacles overall. The maximum values of population density (X_1), output population (X_3), and per-capita GDP (X_5) are greater than zero, while the minimum values are less than zero, indicating that they both have positive driving and negative blocking effects with a complex impact mechanism (Table 5). The influence of population density shows a "dumbbell" pattern geographically, decreasing from the north and south to the middle. Beijing, Tianjin, and Hebei in the north are highlands of positive effects, while Henan is a depression of negative effects and Zhejiang is a new highland of positive effects. The proportion of population aged 60 and above is characterized by coastal highs and inland lows, with Bohai Bay (Beijing, Tianjin, Hebei, Shandong) as the high ground, the Yangtze River Delta as the second high ground, and Henan and Anhui as the depressions, with the weakest in Henan. The influence of the outflow population also presents a "dumbbell" pattern geographically, with the Yangtze River Delta, especially Zhejiang and southern Anhui Provinces, being the highlands of positive effects and Beijing–Tianjin–Hebei being the highlands of negative effects. The depressions are distributed in the border areas of Henan, Shandong, Anhui, and Jiangsu Provinces. The highland of GDP influence is in the west of Anhui and the south of Henan, and it is the origin of the gradient to the north and the coast, reaching the lowest in the Beijing–Tianjin–Hebei region. Per-capita GDP is characterized by a decreasing gradient from south to north, with highlands in Zhejiang and southern Anhui and depressions in Bohai Bay and the Shandong Peninsula. The fiscal self-sufficiency rate has a high impact on the northern region, with Beijing and Hebei as the highlands, and low for the center, with Anhui and the northern border region of Jiangsu as the depressions. The influence increases in a gradient from the depression to the south and reaches the highest in Zhejiang. The influence of topography, average temperature, and ventilation coefficient is characterized by clustering, and the depressions are all located in the Yangtze River Delta, especially in the southern part of Zhejiang and Anhui Provinces. Their highlands are all clustered in bands, but with differences in geographic location, where topography is located in the Shandong Peninsula, the average temperature is located in the junction area of Shandong, Henan, Anhui, and Jiangsu Provinces, and the ventilation coefficient is in the north of Henan and the west of Hebei (Figure 8).

From the per-capita area of UPGAs, only the minimum value of per-capita GDP (X_5) is greater than zero, indicating that it plays a positive driving role. The maximum values of outflow population (X_3), GDP (X_4), topography (X_7), average temperature (X_8), and ventilation coefficient (X_9) are all less than zero, suggesting that they all act as negative obstacles overall. The maximum values of population density (X_1), proportion of population aged 60 and above (X_2), and fiscal self-sufficiency rate (X_6) are greater than zero, while the minimum values are less than zero, indicating that they both have positive driving and negative blocking effects with a complex impact mechanism (Table 6). The influence of population density is characterized by a geographic gradient of "high in the coastal area and low in the inland area", with the two clusters in the Shandong Peninsula and the northern end of Hebei being the highlands, and the contiguous band-like areas in Henan, Anhui, and western Zhejiang being the depressions. The influence of the proportion of population aged 60 and above presents a "dumbbell" pattern geographically, with the Yangtze River Delta as the highland of positive influence and Beijing–Tianjin–Hebei as the highland of negative influence, divided by the border area of Henan, Shandong, and Hebei. The influence of the outflow population is geographically characterized by "high in the north and low in the south", with Beijing–Tianjin–Hebei being the highland and the Yangtze River Delta being the depression. The influence of GDP is characterized by a geographic gradient of "high in the inland area and low in the coastal area", with the highlands located in the border area between Anhui and Henan and the depressions in the Shandong Peninsula and the east coast of Zhejiang. Per-capita GDP and outflow population are highly similar in their geographic patterns of influence, except that the nature of the influence shifts from negative to positive. The influence of the fiscal self-sufficiency rate, the proportion of population aged 60 and above, and topography is geographically characterized by a "low in the center and high at the edge", with depressions located in the border areas of Anhui, Henan, Shandong, and Jiangsu and highlands in the Shandong Peninsula, both with a small spatial scale. The average temperature influence highland is located in the border areas of Zhejiang, Anhui, and Jiangsu Provinces, and the depression is in Henan. The geographic pattern of influence of ventilation coefficient and outflow population is similar; however, the coverage of the latter uplands and depressions is larger than that of the latter, with highlands extending to the north and west of Henan and depressions expanding to the south of Jiangsu and the south of Anhui (Figure 9).

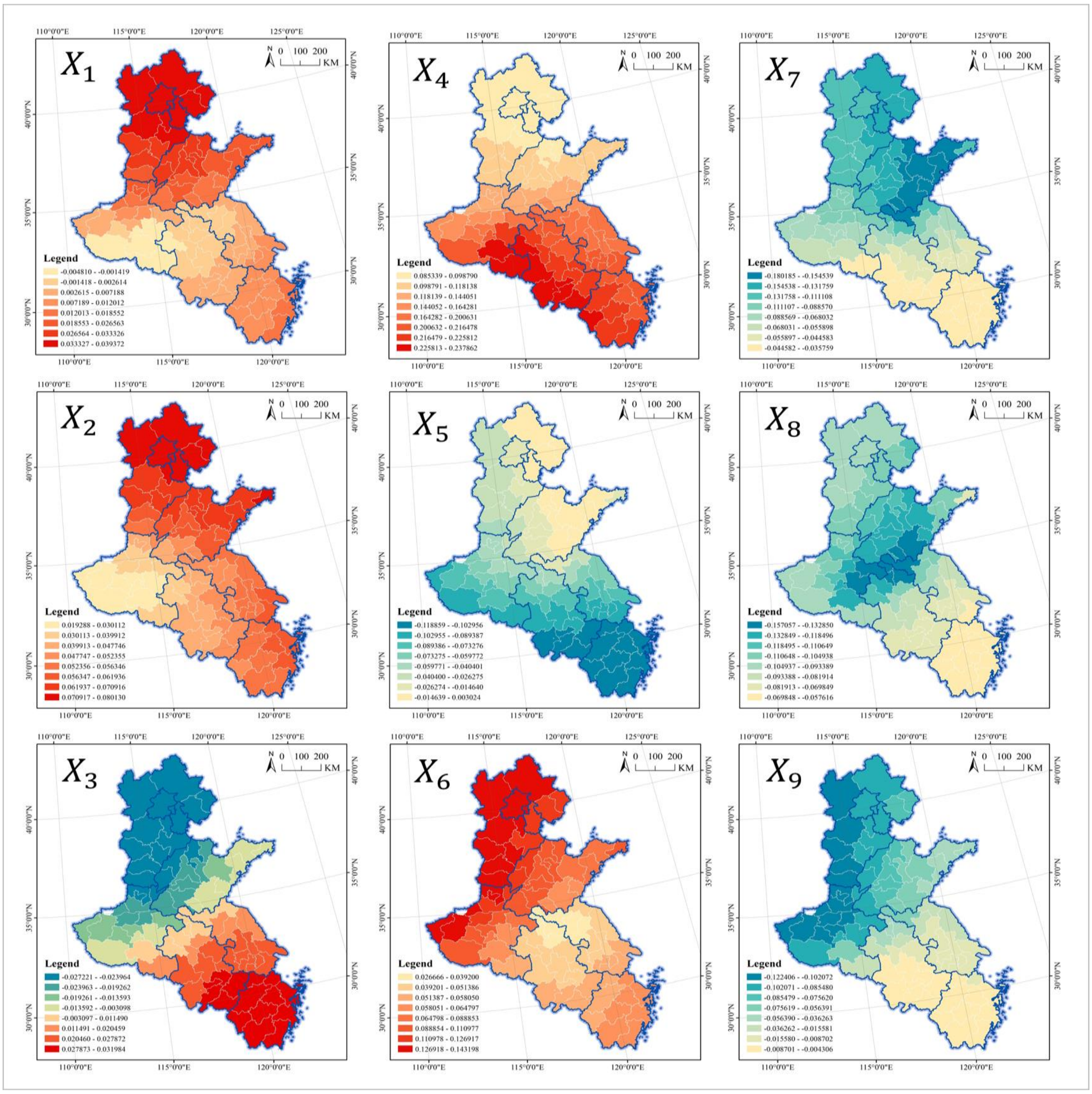

Figure 8. Factor spatial effect analysis of the supply scale of urban park green areas on the Grand Canal of China.

Table 5. Descriptive statistical analysis of GWR parameters for the supply scale of urban park green areas on the Grand Canal of China.

Factors		Min	25% Quantile	Median	75% Quantile	Max
Population density	X_1	−0.0048	0.0043	0.0105	0.0241	0.0394
Proportion of population aged 60 and above	X_2	0.0193	0.0453	0.0541	0.0599	0.0801
Outflow population	X_3	−0.0272	−0.0220	−0.0049	0.0265	0.0320
GDP	X_4	0.0853	0.1141	0.1914	0.2162	0.2379
Per-capita GDP	X_5	−0.1189	−0.0948	−0.0622	−0.0253	0.0030
Fiscal self-sufficiency rate	X_6	0.0267	0.0534	0.0642	0.1181	0.1432
Topography	X_7	−0.1802	−0.1270	−0.0838	−0.0478	−0.0358
Average temperature	X_8	−0.1571	−0.1136	−0.1051	−0.0777	−0.0576
Ventilation coefficient	X_9	−0.1224	−0.0918	−0.0458	−0.0093	−0.0043

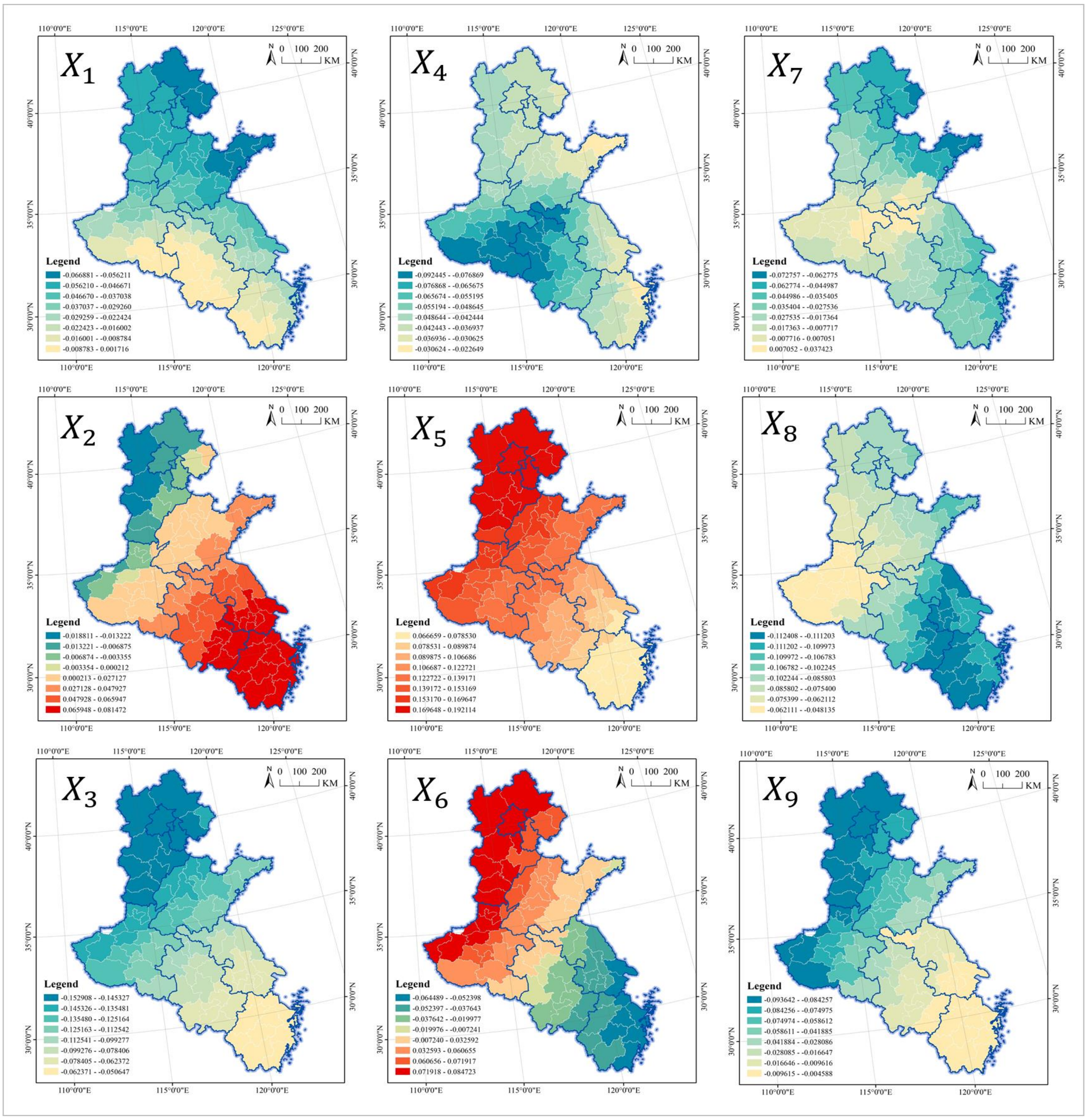

Figure 9. Factor spatial effect analysis of the per-capita area of urban park green areas on the Grand Canal of China.

Table 6. Descriptive statistical analysis of GWR parameters for the per-capita area of urban park green areas on the Grand Canal of China.

Factors		Min	25% Quantile	Median	75% Quantile	Max
Population density	X_1	0.4871	0.5163	0.5195	0.5213	0.5392
Proportion of population aged 60 and above	X_2	−0.0669	−0.0463	−0.0303	−0.0164	0.0017
Outflow population	X_3	−0.0188	0.0008	0.0335	0.0671	0.0815
GDP	X_4	−0.1529	−0.1385	−0.1140	−0.0711	−0.0506
Per-capita GDP	X_5	−0.0924	−0.0607	−0.0462	−0.0397	−0.0226
Fiscal self-sufficiency rate	X_6	0.0667	0.0951	0.1320	0.1579	0.1921
Topography	X_7	−0.0645	−0.0369	0.0147	0.0683	0.0847
Average temperature	X_8	−0.0728	−0.0352	−0.0251	−0.0099	0.0374
Ventilation coefficient	X_9	−0.1124	−0.1106	−0.0939	−0.0724	−0.0481

3.2.3. Interactive Effect of Factors

Different factors show a significant synergistic enhancement effect, mainly in the form of nonlinear enhancement, with only a few factor pairs in double enhancement. For the supply scale of UPGAs, the factor pair of topography ∩ average temperature ($X_7 \cap X_8$) is in double enhancement. For the per-capita area of UPGAs, population density ∩ proportion of population aged 60 and above ∩ proportion of population aged 60 and above ($X_1 \cap X_2$), population density ∩ GDP ($X_1 \cap X_4$), proportion of population aged 60 and above ∩ GDP ($X_2 \cap X_4$), and proportion of population aged 60 and above ∩ average temperature ($X_2 \cap X_8$) are in double enhancement. It is worth noting that a large number of super-factor pairs arise from factor interaction, and their interaction forces are much higher than those of other factor pairs and single factors. Population density ∩ GDP ($X_1 \cap X_4$), proportion of population aged 60 and above ∩ GDP ($X_2 \cap X_4$), outflow population ∩ GDP ($X_3 \cap X_4$), per-capita GDP ∩ GDP ($X_5 \cap X_4$), and ventilation coefficient ∩ GDP ($X_9 \cap X_4$) are super factor pairs of the supply scale of UPGAs, with an interaction force of more than 0.80. Population density ∩ per-capita GDP ($X_1 \cap X_5$), outflow population ∩ Per-capita GDP ($X_3 \cap X_5$), outflow population ∩ average temperature ($X_3 \cap X_8$), outflow population ∩ ventilation coefficient ($X_3 \cap X_9$), per-capita GDP ∩ average temperature ($X_5 \cap X_8$), and per-capita GDP ∩ ventilation coefficient ($X_5 \cap X_9$) are super factor pairs of the per-capita area of UPGAs, with an interaction force of more than 0.5 (Table 7).

Table 7. Factor interactive effect analysis of urban park green areas on the Grand Canal of China.

	Code	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
Supply scale of UPGAs	X_1	0.08								
	X_2	0.54	0.12							
	X_3	0.63	0.63	0.28						
	X_4	**0.84**	**0.80**	**0.84**	0.45					
	X_5	0.61	0.67	0.56	**0.87**	0.26				
	X_6	0.62	0.63	0.65	0.78	0.57	0.25			
	X_7	0.15	0.19	0.43	0.52	0.34	0.33	0.00		
	X_8	0.27	0.35	0.42	0.69	0.38	0.41	0.08	0.05	
	X_9	0.53	0.56	0.69	**0.82**	0.64	0.76	0.16	0.31	0.12
Per-capita area of UPGAs	X_1	0.03								
	X_2	0.09	0.05							
	X_3	0.49	0.36	0.19						
	X_4	0.06	0.07	0.25	0.01					
	X_5	**0.52**	0.34	**0.69**	0.33	0.20				
	X_6	0.28	0.14	0.38	0.12	0.33	0.06			
	X_7	0.11	0.11	0.47	0.07	0.38	0.14	0.02		
	X_8	0.30	0.24	**0.56**	0.25	**0.62**	0.38	0.30	0.18	
	X_9	0.21	0.21	**0.55**	0.11	**0.52**	0.17	0.08	0.35	0.03

3.3. Performance Evaluation

No cities in the Grand Canal region fall into the categories of negative oversupply, negative undersupply, or negative equilibrium. Positive oversupply has the highest proportion, more than 50%, followed by positive equilibrium at approximately 30%. Ma'anshan, Huaibei, Binzhou, Luoyang, Pingdingshan, and Shangqiu are super oversupply members. The only member of the super undersupply group is Chengde, while the only member of the positive undersupply group is Handan. The positive oversupply members include Beijing, Tangshan, Xingtai, Cangzhou, Langfang, Hengshui, Nanjing, Nantong, Lianyungang, Huai'an, and others. Most of these are clustered in Henan and Anhui and extend in a band towards Jiangsu, Zhejiang, and Hebei. The positive equilibrium members include Tianjin, Shijiazhuang, Qinhuangdao, Baoding, Zhangjiakou, Wuxi, Xuzhou, and others. These are distributed in bands in Shandong and Hebei and in clusters in Jiangsu and Zhejiang. Overall, there are three clusters of hotspot cities in Shandong, Jiangsu, and Zhejiang and three clusters of coldspot cities in Henan, the northern end of Hebei, and the border area between Henan and Anhui, with sub-hotspots and sub-coldspots distributed on their periphery, forming a "center-edge" spatial structure (Figure 10).

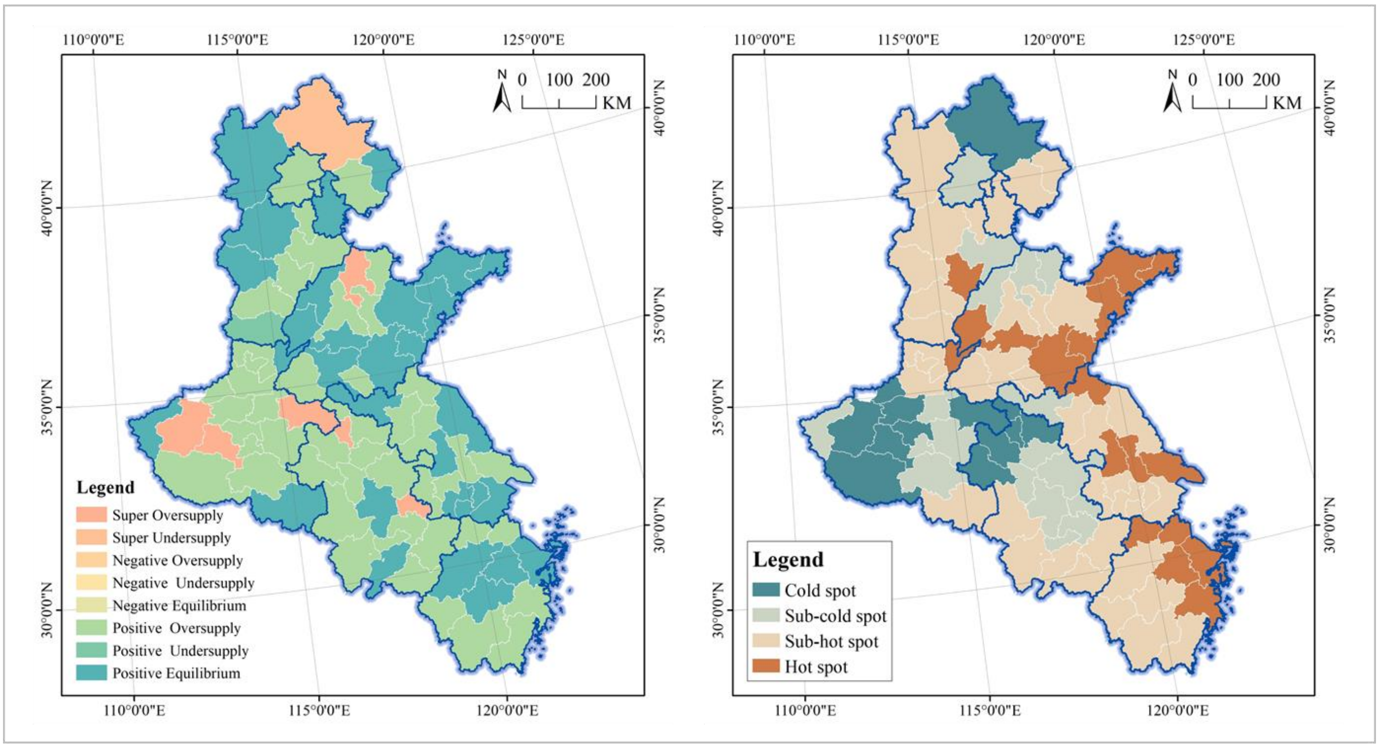

Figure 10. Performance analysis of urban park green areas on the Grand Canal of China.

4. Discussion

4.1. Differentiated Zoning Planning

The study shows significant spatial inequalities and differences in the geographic distribution of UPGAs in the Grand Canal, with huge disparities in the supply scale and per-capita area across cities, including relative shares, growth rates, and spatial and temporal evolution patterns. In addition, most of the UPGA supply is in a mismatch with the population demand, with co-existence of both oversupply and undersupply. The high similarity of these analytical results to the findings of other scholars suggests that spatial imbalances and inequalities, supply–demand imbalances, and mismatches are regular features. For the former, Rigolon [99] concluded that there are significant spatial inequalities in urban parkland and quality and Ren [100] found geographic and social inequalities in the distribution of urban parks in Shanghai based on Gini coefficient analysis.

For the latter, Tan [101], Gao [102], and Zhu [103] in their case studies of Wuhan, Shenzhen, and Beijing found that there is a serious mismatch between UPGA supply and resident demand, which is a great challenge for future planning and management. Unfortunately, current green areas planning, park planning, and green infrastructure planning focuses more on the design of spatial layout schemes for intra-city parks and green area systems, with less attention and planning response to inter-city imbalances and inequalities in general [104].

In summary, we recommend the adoption of differentiated zoning planning strategies in green areas and park planning for the Grand Canal. This takes the evaluation of the performance of matching supply and demand as the core basis to adjust the direction of the control of the supply scale and per-capita area in cities according to the classification results of the spatio–temporal evolution mode of urban parkland. For cities such as Tianjin, Shijiazhuang, Qinhuangdao, Baoding, Zhangjiakou, and Wuxi, as their supply and demand are in positive balance, the focus of their future planning will be to keep their management policies stable and to maintain and contribute to the city's long-term balance of supply and demand. Handan and Chengde face a serious supply shortage, with UPGA supply size and per-capita area in HL and LL states, resulting in weak growth. Therefore, in the future, provincial governments should increase the quota of their UPGAs, and city governments should adopt speed control-oriented planning and policies to accelerate incremental supply and promote a balance between supply and demand. For Tangshan, Xingtai, Cangzhou, Langfang, Hengshui, Nanjing, Nantong, Lianyungang, and other positive oversupply cities, subdivision planning based on spatio–temporal evolution patterns is required. Cities with spatio–temporal evolution patterns in the HH and LH categories, such as Xingtai, Nantong, Dongying, Fuyang, and Anqing, should strictly limit the growth of quotas in the future and promote a balance between supply and demand by reducing land supply. They should focus UPGA planning and management on quality improvement rather than quantity growth in the future, and they could sell their surplus land index to undersupply cities via the regional inter-city trading platform. Cities with spatio–temporal evolution in LL and HL patterns, such as Cangzhou, Tangshan, Jiaxing, Huzhou, Lishui, and Xuancheng, should increase or purchase land quotas and strengthen the planning, design, and management of urban green areas to promote a balance between supply and demand through the growth of land supply and the strict protection of the stock.

4.2. Integrated Symbiotic Planning

We found significant spatial correlations of UPGAs in the Grand Canal in this study, with hotspot and coldspot cities clustering together. It should be noted that Choumert [105] and Kim [106] also noted such correlations, and in common with this paper they both found significant positive spatial autocorrelations in UPGAs between cities in France and South Korea, with local spatial clustering features prominent, although the global correlation is weak or insignificant. However, unfortunately, they did not propose a response strategy for spatial planning and green area management policies based on spatial correlation characteristics. We believe that clustered hotspot and coldspot cities face similar development challenges, and they can maximize their performance with minimum cost through inter-city collaboration in UPGA planning and management. Highly interconnected cities may seek to rapidly increase the quantity and quality of their own and regional green infrastructure through the construction of point-like regional parks and linear inter-city greenways.

For the construction of regional parks, cities can learn from the European experience of building large-scale green parks across administrative districts based on the characteristics of natural resources such as the Grand Canal's green areas and water system, as well as planning and constructing open spaces, high-quality landscapes, and recreational and activity facilities to promote the symbiosis of spatial functions and social needs [107,108]. In urban green area system planning, park system planning, and green infrastructure planning in China, it is common to keep the planning scope in line with the scope of the city's overall planning, i.e., the planning is more confined to the central urban area, which has seriously weakened the overall allocation of green resources in counties and towns within the municipal area and has led to no overall planning for the regional green area system. The construction of regional parks that are not confined to the central city and encouraged coordination between neighboring cities will contribute to the integration of regional ecological, spatial, tourism, and social resources to enhance regional sustainability and competitiveness. The regional greenway is a linear green open space. Natural and artificial landscapes such as mountains, lakes, fields, scenic spots, ancient cities, cultural heritages, traditional villages, and tree-lined roads along the main stream and tributaries of the Grand Canal should be connected together, and landscape recreation routes and service facilities serving pedestrians and cyclists should be built within them [109]. Hotspot cities can link and showcase quality parks and green areas in the united cities through regional greenways to enhance the overall image of the regional habitat. For coldspot cities, they can promote the sharing of parks and green area resources among different cities through regional greenways to enhance utilization efficiency and alleviate, to a certain extent, the imbalance between supply and demand.

4.3. Multi-Policies Mix Management

Both the supply scale and per-capita areas of UPGAs have very complex driving mechanisms. In terms of nature, the ventilation coefficient always plays a negative blocking role, while population density always has both positive driving and negative blocking effects. The roles of other factors are always in a complex state of change and may shift from positive to negative (e.g., GDP), mixed (e.g., proportion of population aged 60 and above), or from negative to mixed (e.g., average temperature and topography) or from mixed to positive (e.g., per-capita GDP) and negative (e.g., outflow population). In terms of intensity, the key factors of supply scales of UPGAs are completely different from those of their per-capita area. Proportion of population aged 60 and above and ventilation coefficient are always important factors for both, while average temperature and fiscal self-sufficiency rate are always common auxiliary factors. The intensity ratings of the other factors differ widely. For example, GDP has been reduced from an important factor of the supply scale of UPGAs to an auxiliary factor of their per-capita area. Per-capita GDP, by contrast, has been upgraded from an important factor to a key factor. In terms of interaction, the super factor pairs of the supply scale of UPGAs are completely different from those of their per-capita area. In terms of spatial effects, all factors show a significant spatial clustering of influence on geographic patterns, but the geographic distribution and spatial extent of highlands and depressions vary widely, with a variety of change patterns such as gradient rise and fall, high in the center and low at the edge, low in the center and high at the edge, dumbbell (high at the ends and low in the middle), contiguous belt, and clustering emerging (Figure 11).

A growing body of research reveals that the planning and management of UPGAs are complex systematic projects subject to the influence of many factors. Many scholars have discussed the factors influencing changes in urban parks. For example, Cheng [110], Nam [111], and Smith [112] argued that government funding plays a key role in the management of urban parks in China and the United Kingdom. Luo [113], Feng [114], and Kim [115] argued that both population density and size had significant spatial correlations with the level of service of urban parks. Guo [116,117] found that house prices, transportation accessibility, and the status of the surrounding commercial facility package are important factors influencing the accessibility of urban parks. Their findings are corroborated with the conclusions of this paper. Different from them, this paper fully explores the spatial effects and interaction effects of different factors, which has a great inspirational value for the design of policy combination. In view of the intensity, nature, and spatial and interaction effects of different factors, future planners and the government should better interconnect the policies for UPGAs. Since a single policy is limited and difficult to operationalize in practice, multiple policies should be designed and implemented in the management. In addition, attention should be paid to the mode of combining policies in policy design and implementation, integrating policies on population, ageing, social mobility, economic and industrial development, financial investment, and the building of an ecological civilization. While ensuring the precision of each policy, it is important to maximize the synergy of different policies and to maximize policy performance by means of the interaction effect of factor pairs.

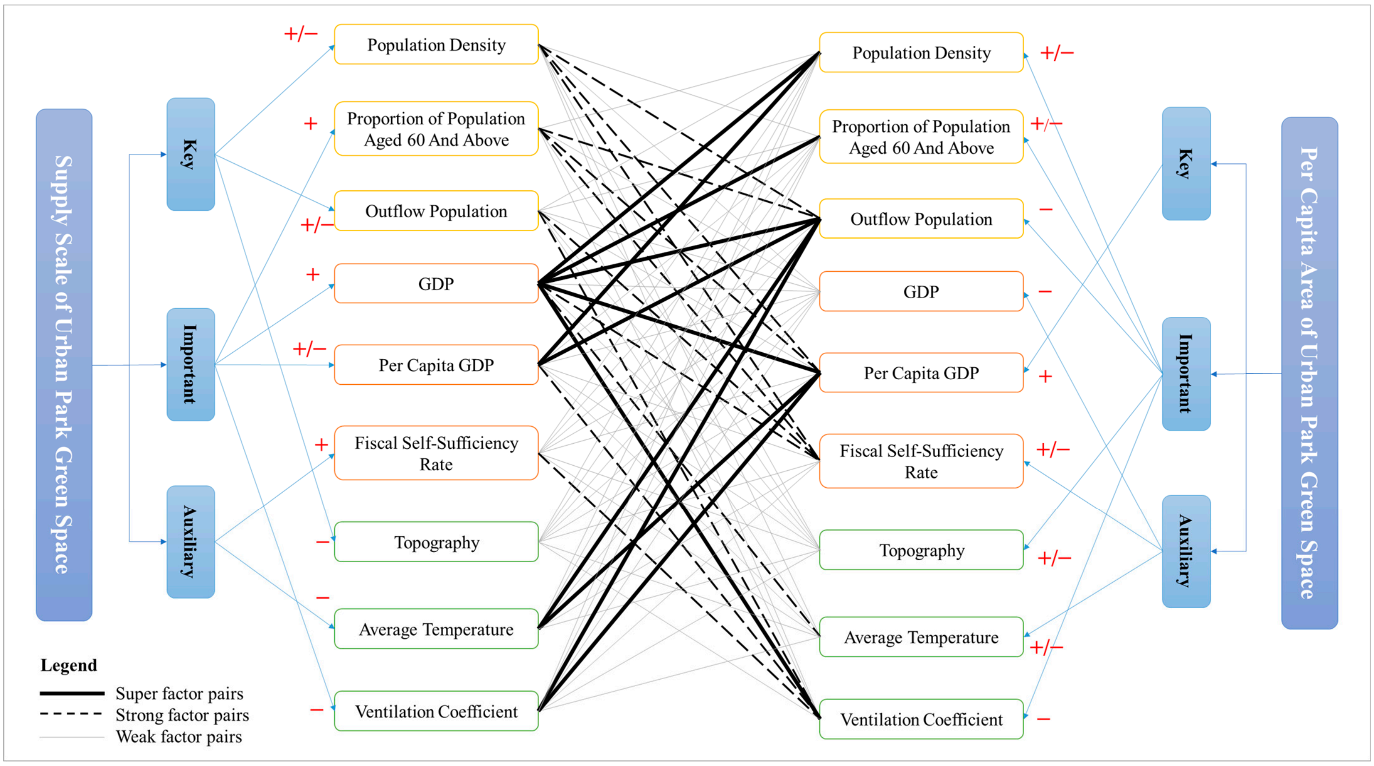

Figure 11. Factor spatial effect analysis of the urban park green areas on the Grand Canal of China.

5. Conclusions

This paper arrives at the following findings: (1) The spatio–temporal evolution patterns of the UPGAs in the Grand Canal of China are diversified, with many types emerging, such as HH (High-scale–High-growth), HL (High-scale–Low-growth), LH (Low-scale–High-growth), and LL (Low-scale–Low-growth). (2) The evolutionary performance of UPGAs in the Grand Canal is mainly characterized by positive oversupply and positive equilibrium, with super oversupply, super undersupply, and positive undersupply found in a small number of cities. (3) The spatio–temporal evolution patterns and performance of UPGAs are characterized by significant spatial heterogeneity and positive spatial autocorrelation, with huge inter-city differences, and both hotspot and coldspot cities are clustered geographically. (4) The spatio–temporal evolution of UPGAs is driven by a complex mechanism, and different factors vary greatly in nature, intensity, spatial effect, and interaction effect. (5) The planning and management of UPGAs in the Grand Canal should be implemented by classifying and zoning, and zoning planning and symbiosis planning should be prepared and implemented based on the results of the analysis. In addition, it is necessary to design differentiated and diversified policies for each planning zone in the future, and to focus on enhancing the synergy of multiple policies in the management, so as to maximize the benefits based on the “combination of policies”.

This paper presents innovations in the following areas: (1) It pushes UPGA research to shift from case studies of a single city to systematic studies of regional urban agglomerations. It is a big step forward as a single system is more than the sum of its parts. Against the backdrop of China’s urban development entering a new era of regional integration dominated by urban agglomerations, urban belts, urban contiguous areas, and metropolitan areas, the research conclusions of individual cities reached in the past are not entirely applicable to current regional green infrastructure planning, although they have provided good guidance for urban scale green space system planning. (2) By integrating the BCG (Boston Consulting Group) matrix, ESDA (Exploratory Spatial Data Analysis), MLR (Machine Learning Regression), GWR (Geographically Weighted Regression), GeoDetector, and LCRPGR (Ratio of Land Consumption Rate to Population Growth Rate), it comprehensively and systematically reveals the driving mechanisms behind UPGAs while quantitatively evaluating their spatio–temporal evolution patterns and performance, especially analyzing in detail the spatial and interactive effects of different factors. It is a brand-new exploration and discovery. (3) Instead of being limited to or stagnated in the analysis of the change characteristics of UPGAs, this study proposes differentiated zoning planning, integrated symbiotic planning, and multi-policies mix management based on the design of spatial planning and management policies for green areas, parks, and green infrastructure in the Grand Canal of China. It is a remarkable fact that canals are common in all countries of the world, and the technical approach, analytical methods, and results of this paper are not only applicable to China, but can also be used as the basis and reference for canal planning and management in Egypt, India, Indonesia, America, and other countries.

There are still some shortcomings in this study: (1) Due to data and information limitations, this study only took into account the effect of population size in the performance evaluation, while it did not include the heterogeneity of the needs of different populations in the analytical model, which may affect the accuracy of the analysis results. (2) This paper is based on a regional inter-city comparative study with no in-depth analysis of parkland in a single city within the Grand Canal, especially within the key cities, which somewhat constrains the breadth of application of the results. The canal is not only a navigation channel and cultural heritage zone for human beings, but also a natural ecological zone and a source of green well-being for the people living along the route. Beginning with the construction of ecological civilization and ending with the sustainable development of the Grand Canal of China, this study focuses on the regional analysis and planning of UPGAs, expanding the field of canal research from the traditional dimensions of shipping and transportation, water resources, and history and culture to the dimension of green areas. It demonstrates certain theoretical innovations while responding to the practical needs of ecological protection and high-quality development of the Grand Canal.

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