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Evolution Pattern and Spatial Mismatch of Urban Greenspace and Its Impact Mechanism: Evidence from Parkland of Hunan Province

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Abstract: Planners need to fully understand the quantity of land supply and its matching relationship with population demand, as these are prerequisites for urban greenspace planning. Most papers have focused on single cities and parks, with little attention paid to comparative analysis between multiple cities on a macro scale, ignoring the influence of spatial effects and leading to a lack of basis for regional green infrastructure planning. This paper selected 102 cities in Hunan province as case studies to comprehensively conduct empirical research using the spatial mismatch model and the geographically weighted regression method. The urban parkland in Hunan province are characterized by significant spatial heterogeneity and correlation, and the mismatch between land supply and population demand should not be ignored, with oversupply and undersupply co-existing. The urban parkland and its mismatch with population are influenced by a number of factors, and each factor has a stronger influence on the latter than the former. Different factors vary widely in the nature and intensity of their effects, and the dynamics are more complex. Economic development, financial capacity, and air quality are key factors, with the former having a negative impact and the latter having opposite (positive) effects. We suggest that when the government allocates land resources and targets for urban parks, it should formulate a differentiated allocation plan based on the supply and demand conditions of each city; besides, it should also place emphasis on regional integration and coordination and support mutual cooperation.

Keywords: land supply; population demand; spatial mismatch; urban park; China

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1. Introduction

Urban parks are a part of greenspace and green infrastructure, and they play a positive role in improving the urban ecological environment and enhancing the well-being of residents. They are an important supply side to meet the needs of urban residents for a better and livable life [1]. The population is the main body of urban life and comprises the demand side of urban parks, which influences and feeds back into urban parks in many ways. The matching between land supply and population demand for urban parks directly determines the quality of the human habitat; furthermore, it is part of the urban planning and public health system, which has become one of the key indicators influencing the design of government policies and project decisions [2]. Therefore, analyzing the dynamic characteristics of land supply and population demand for urban parks, quantitatively measuring the matching relationship between supply and demand, and revealing their driving mechanisms are of great value in promoting sustainable urban development and improving citizens' well-being.

In China's ecological civilization construction, urban parks are regarded as the key hand of livable city and eco-city construction, and the government is calling for a shift from the construction of "urban parks" to the creation of "park cities" [3]. China has seen a spike in the number of urban parks and a rapid expansion of land area in recent years. According to data released by China's Ministry of Housing and Urban-Rural Development, the number of urban parks in China grew from 9955 to 19,823 from 2010 to 2020, with an average annual growth up to 99.13%; during the same period, the amount of land used for urban parks increased from 258,177 hectares to 538,477 hectares, with an average annual growth of 108.57%. It should be noted that because China is still in the rapid development stage of urbanization and industrialization, the expansion of urban industrial, residential, and infrastructure land is in strong demand; however, along with the increasingly stringent protection of arable land, the sprawling expansion of cities to the suburbs is facing more resistance and difficulties, which has led to the transformation of parkland located in urban areas, especially in the city center, into industrial and commercial land from time to time [4]. Therefore, with the increasingly serious contradiction between urban population and land, the expansion of urban parkland is under increasing pressure, and its matching with the demand of the population has received increasing attention. In summary, analyzing the matching between urban-parkland supply and population demand in the context of ecological civilization, as well as revealing their driving mechanisms will provide a basis for green space planning and park city construction.

Urban greenspace planning is an activity that is based on the unified planning and systematic consideration of urban greenspace types to make reasonable arrangements and form a certain layout form, so that the greenspace is capable of ecological protection and satisfies living and production needs [5]. It provides leisure and sociocultural functions. Urban greenspace consists of natural elements/natural remnants and man-shaped green areas, including parks, lawns, flower beds, and other vegetation-covered areas. The research scope of this paper is limited to urban parks. Urban greenspace is characterized by hierarchy, systematicity, and continuity, and in general the green infrastructure inside and outside the city is interconnected [6]. The construction of urban parks in the context of park city and livable city construction, an important guarantee of a good and livable life for urban population, has attracted much attention from the government and scholars, and analyzing the matching relationship between its land supply and population demand holds important value for enhancing the sustainability of urban development and the happiness of residents.

This paper analyzed the evolution pattern of urban parkland in 102 cities in Hunan province using the Boston Consulting Group matrix, the spatial mismatch model, and the geographically weighted regression method; measured the matching relationship between land supply and population demand; and revealed the mechanism of different factors affecting them in an attempt to provide a basis for the higher government's land resource allocation and the local government's green space planning. This paper is committed to the following questions: What is the spatiotemporal evolution pattern of urban parkland in Hunan province? How can we quantitatively measure the matching relationship between land supply and population demand for urban parks in Hunan, especially identifying which cities face spatial mismatch problems? What are the factors influencing the supply of urban parkland and its matching with population demand?

The innovative contributions of this paper are the comparative analysis of multiple cities on a regional scale and the analysis of the mismatch power mechanism of supply and demand. The former is more valuable for the planning, construction, and management of urban parks, while the latter further enriches the theoretical system of supply and demand of urban parks. This paper expanded the study of the relationship between land supply and demand in urban parks from a single-city case study to a multi-city analysis at the regional scale. It also introduced a model that can quantitatively measure the direction and degree of spatial mismatch to identify cities with imbalances in supply and demand, thus providing a basis for land resource-allocation decisions and green space planning by provincial and city governments. In addition, this paper analyzed the nature and direction of the role of multidimensional influencing factors such as demographic and social; economic and financial; and natural and environmental factors on the relationship between supply and demand by means of a geographically weighted regression model. It further revealed the spatial effects of their influencing mechanisms and deepened scholars' understanding of the dynamics of the imbalance between supply and demand and spatial mismatch in urban parks.

2. Literature Review

2.1. Supply and Demand of Urban Parkland

Urban-parkland supply and demand involves the number of parks, land area, spatial distribution, and environmental quality, and relevant studies cover areas such as analysis of urban park site selection and allocation; spatial distribution and planning studies; and needs assessment.

For urban-park siting and land allocation, Li [7] integrated F-AHP (fuzzy hierarchical analysis) and GIS (geographic information systems) to propose a methodology for urban-park siting and made a map of urban-park siting potential in Nanjing, China. Using GIS buffer technology and urban equity theory, Fasihi [8] analyzed and found that urban parks in Ilam, Iran, are disproportionately clustered in the northern part of the city, and that the city center and the southern part of the city need to be allocated more land resources by the government to build urban parks.

For urban park planning and spatial distribution, Li [9] argued that most cities face the challenges of park shortage and uneven distribution and proposed a spatial planning approach for urban parks and green spaces based on equity of opportunity through a case study of Taiyuan. Yilmaz [10] believed that vegetation is the core element of urban parks, and by applying visual analysis and aesthetic theory, he proposed an alternative planting-design method and landscape silhouette-analysis model for urban parks. Li [11] and Liang [12] analyzed the impact of spatial distribution of urban parks on residents' satisfaction in Shanghai using social media data sets.

For the assessment of urban-parkland demand, Zhang [13] identified the space of insufficient urban park supply in the suburbs of Nanjing, China, based on the two-step floating catchment area model, and suggested that the government increase the supply of urban parkland in the identified area. Gelo [14] assessed the demand and willingness to pay for urban parks by Kampala residents based on Bayesian and contingent valuation methods (CVM) and clarified the conditions for the construction of new urban parks.

2.2. Benefits and Value Analysis of Urban-Parkland Use

Post-use evaluation of urban parkland includes economic, social, cultural, and ecological benefits, with most studies focusing on the areas of cooling effect and air quality improvement [15].

Economic effect research focuses on the economic externalities of land use in urban parks, estimation of economic value, and analysis of the impact of industrial and business development [16]. For example, Kim [17] and Long [18] argued that urbanization has exacerbated the scarcity of land for urban parks, arguing that urban parks have positive economic externalities on the value of land use in Korea and China. Neckel [19] and Silva [20] quantitatively assessed the economic value of urban parks in Brazil and Portugal using CVM, WTD (willingness to donate), and questionnaire methods. Kim [21] and Chen [22] assessed the value of parks through changes in residential prices and concluded that urban parks, especially green spaces, have a positive impact on residential prices.

Social benefit research focuses on the social value of land use in urban parks and the analysis of social interactions, which has proposed the concept of green gentrification and evaluated the impact of urban parks in the sense of security (crime) and well-being in human settlements. For example, Baltazar [23] analyzed the social value of urban parks in the Philippines through fsQCA (fuzzy-set qualitative comparative analysis). Mullenbach [24], Triguero-Mas [25], and Zhang [26] argued that urban parks have a positive value in land development (green) gentrification (gentrification) and have become social healers of social space. Nazmfar [27], Sezavar [28], and Taylor [29] tested the spatial association between urban park characteristics and crime based on GIS and generalized structural equation modeling, revealing the impact of environmental variables such as park size, class, features, guardrails, vegetation distribution, and density on crime. Schwartz [30] and Scopelliti [31] measured the well-being benefits of urban parks in the United States and Colombia using Twitter and questionnaire data.

Ecological benefit research focuses on the performance evaluation of urban parks in terms of air quality and heat island effect improvement [32] and has gradually developed an approach to urban planning and park design that is oriented towards carbon reduction and cooling. For example, Yin [33], Ji [34], and Gratani [35] analyzed their impacts on air pollution (PM2.5 and CO_2) and their influencing factors through empirical studies of green spaces in urban parks in Beijing and Rome, providing a basis for improving air quality-oriented green space design and construction. Simsek [36] measured the cooling capacity of an urban park in Istanbul and further analyzed its interaction with the surrounding architectural pattern and morphology. Yao [37], Du [38], Park [39], and Jo [40] proposed a strategy for designing and constructing urban parks based on the life cycle assessment of heat island effect and carbon budget. They analyzed how to plan urban parks in order to obtain better cooling and carbon reduction. Sikorski [41] and Villasenor [42] conducted a comparative analysis of Informal Green Spaces (IGS) and Urban Parks and Green Spaces, revealing that the former has an important value in the conservation of biodiversity (e.g., bird conservation) and that the latter dominates in the area of cultural services.

Historical and cultural benefit studies have shown the mutually reinforcing effects of urban parks and historical and cultural preservation. For one thing, the planning and construction of urban parks is commonly viewed as a spatial tool for the preservation of a city's historical and territorial cultural heritage [43]. For example, Loughran [44] argued that the transformation of historical and cultural heritage in post-industrial cities into urban parks (e.g., High Line Park in New York) through architectural interventions, landscaping, urban horticulture, the curation of cultural activities and events, and the experiencing of creative projects is reshaping the social space of the contemporary city. For another, the presence of cultural heritage has also become an important factor in determining the location and layout of urban parks. For example, Uggla [45] found through a case study of Stockholm's National City Park that historical and cultural heritage and its coherence are key factors in protecting urban parkland from encroachment and the impacts of urban construction. Ozguner [46] found that cultural and ethnic differences lead to significant differences in the attitudes of urban residents towards urban parks and green spaces. For example, Turkish and Western perceptions of the safety of urban parks are opposite, with the former perceiving the parks as safe and positive, while the latter holding that they are negative and generally concerned about the safety of the parks.

2.3. Relationship between Urban Park and Population

The analysis of the relationship between urban parks and population has long been of interest to scholars, with most efforts focused on accessibility and satisfaction evaluations, visitor composition and preference analyses, and their impact on urban park design.

Accessibility and satisfaction evaluation is the most mature field, giving rise to successive analytical models based on spatial distance, time consumption, and spatio-temporal integration. For example, Khahro [47] and Semenzato [48] conducted case studies on spatial accessibility of urban parks in Pakistan and Italy using GIS tools and spatial distance modeling. Li [49] introduced the concept of time sensitivity on the basis of distance accessibility and analyzed the characteristics of the service radius and area of urban parks in Shanghai based on actual time consumption. Shi [50] established an n-minute service circle system for the Hangzhou urban park system based on integrated temporal and spatial parameters. Long [51] further empirically analyzed the comprehensive accessibility of urban parks in Changsha, China. by integrating global accessibility, perceived accessibility, local accessibility, and psychological accessibility through spatial syntax. Maniruzzaman [52] conducted an analysis of satisfaction with urban parks in Saudi Arabia and concluded that developing new parks and upgrading old parks is a priority for the authorities of the city of Dammam.

Most of the analysis of the composition and preferences of visitors (Visitors) focuses on the analysis of a single city park sample, using questionnaires and online big data to analyze the structure and characteristics of the populations entering the park, with an attempt to establish user profiles. For example, Yilmaz [53] studied the user profile of urban parks in Turkey through questionnaire methodology, including parameters such as gender, age, marriage, education, and income. Mantymaa [54] studied urban parks in Finland through a latent class model and found that urban parks were more valued by low-income groups than high-income groups. Van [55] and Song [56] analyzed what attributes of urban parks would affect user preferences, based on online stated-choice experiment and smartphone user mobility big data, in an attempt to provide reference information for urban park planners, landscape architects, administrators, and investors.

2.4. Research Gap and Objectives

Urban parkland and its relationship with population have long been the focus of scholars, and this has led to the production of a large number of high-quality papers that have provided important inspiration and assistance in the design and implementation of this study. However, there are shortcomings in the current research.

Research on land supply and population demand in urban parks is limited to the micro-scale, with less attention to macro-scale analyses, resulting in an insufficient basis for regional land resource allocation in urban parks. Most of the papers study a certain city or park and analyze the match between population distribution and park distribution through questionnaires or spatial econometric models, so as to identify the imbalance points of park distribution, land mismatch, or mismatched space, thus providing a solid basis for decision making by the city government and park managers. For example, Wang [57] argued that the distribution of urban park green space supply in central Beijing, China, is inequitable, and that the supply of land resources is in mismatch with the demand of residents, offering a guide to ecosystem planning in Beijing. Notably, with the construction of ecological civilization and park cities, the demand for park construction in every city is increasing. However, as affected by the cultivated land protection system, the higher government has increasingly less urban-parkland resources. Therefore, how to rationally allocate limited urban-parkland resources to lower-level governments for maximized overall regional efficiency and benefits is becoming a major challenge for higher-level governments. In short, analysis at the micro-scale can serve decision making in the lower levels of government, but it cannot provide decision-making information for higher-level governments in the allocation of urban-parkland resources.

In addition, conducting a multi-city analysis of parkland allocation between cities at the regional scale will provide an important basis for green infrastructure planning at the provincial or central government level. Different cities are significantly different from each other in natural and ecological conditions, resource endowment, stage of development, and population needs, leading to possible spatial heterogeneity in the geographical distribution of their urban parklands. And the greenspace and park planning constitute a complex adaptive system, where the greenspace inside the city extends to the outside and establishes an interrelation with the neighboring city, thus contributing to a regional green infrastructure system. In addition, the quota for urban parkland and the progress of park construction, affected by the development environment and trends, vary across cities, resulting in spatial mismatches within a region and leading to parkland oversupply or undersupply in some cities. In sum, this paper expects to conduct a comparative analysis of greenspace between multiple cities at the regional scale based on different spatial measurement models, so as to identify their evolution patterns and spatial mismatches, and to reveal the driving mechanisms and hidden orders behind them, which will provide a basis for governmental decision making and spatial planning.

3. Materials and Methods

3.1. Study Area

Hunan is located in south-central China, neighboring Guangdong, Jiangxi, Hubei, Chongqing Municipality, Guizhou, and Guangxi. The study area covers all of Hunan, including 102 cities. The study area encompasses 13 prefecture-level cities, with all the rest being county-level cities (Figure 1). The land area of urban parks in Hunan expanded from 6763 hectares to 14,243.57 hectares from 2010 to 2020, with an average annual growth of more than 110%; furthermore, the number of urban parks increased from 175 to 456, with an average annual growth of more than 160%, indicating a rapid growth in the supply of urban parks and land resources in the province. Over the same period, the average urban park area went from 38.65 hectares to 31.24 hectares, indicating that urban parks are becoming smaller. Per capita urban park green space increased from 8.89 m^2 to 12.16 m^2, with an average annual growth of 36.78%, indicating a steady growth in the green space per capita.

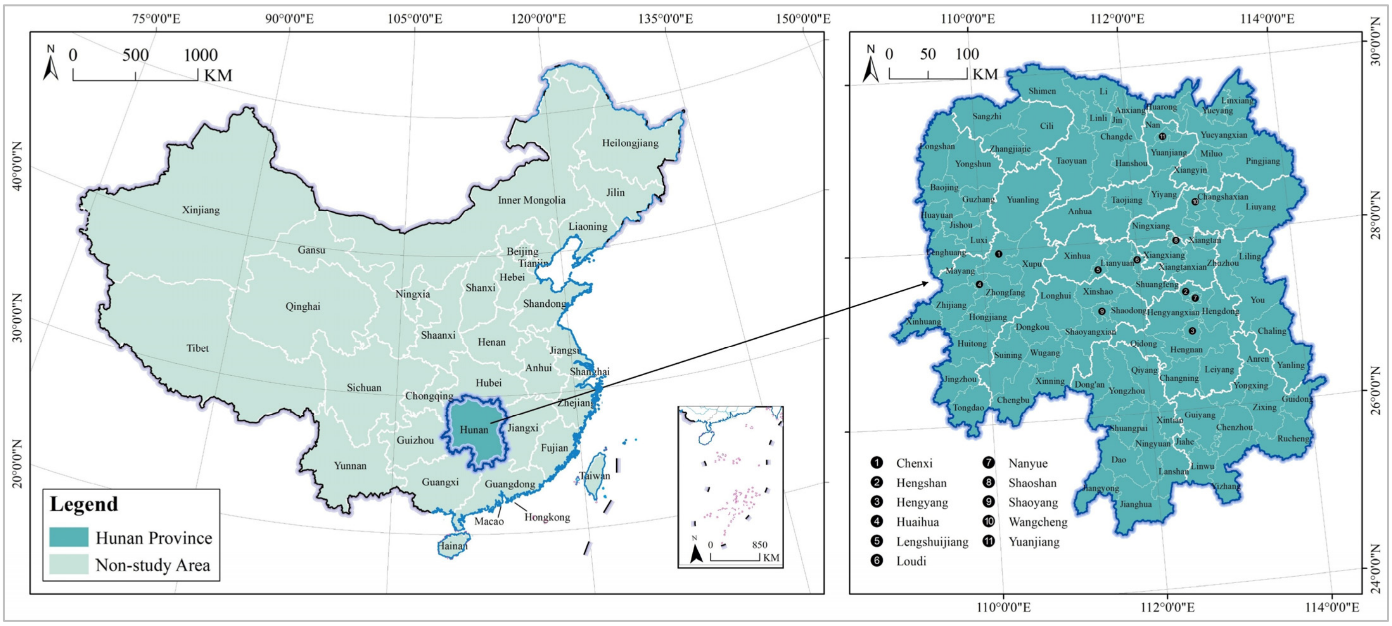

Figure 1. Study area and its location in China.

3.2. Research Steps

The purpose of this research is to comprehensively use multiple methods to analyze the distribution pattern, change trends, and supply and demand relationship, as well as their influencing factors, of urban parkland in order to provide a basis for green space planning and green infrastructure planning. The first step was to collect statistical data on urban parkland, population, economic, and social development for each city in Hunan province, and use the maximum–minimum method to standardize the data for preprocessing. Due to the influence of natural and human factors, urban parks undergo constant changes in time and space. So, the second step was to use the Boston Consulting Group matrix to analyze the spatiotemporal dynamics of urban parkland in each city and reveal the evolution pattern of urban parkland in Hunan province. Due to the multi-dimensional nature of the land change process and its ecological, social, and economic outcomes in urban parks, the third step was to use the spatial mismatch model to identify the relationship between land supply and population demand as well as determine the rationality of land change in urban parks. Natural and human factors may lead to the expansion or contraction of land supply in urban parks, resulting in oversupply or undersupply. Therefore, scientists need to use scientific methods to analyze the impact intensity, nature, and spatial effects of each factor. The fourth step was to use the geographically weighted regression method to analyze the impact of each factor on the land supply of urban parks and its relationship with population demand in Hunan province. Finally, we promote the application of the aforementioned analysis results to provide a basis for green space planning and green infrastructure planning (Figure 2).

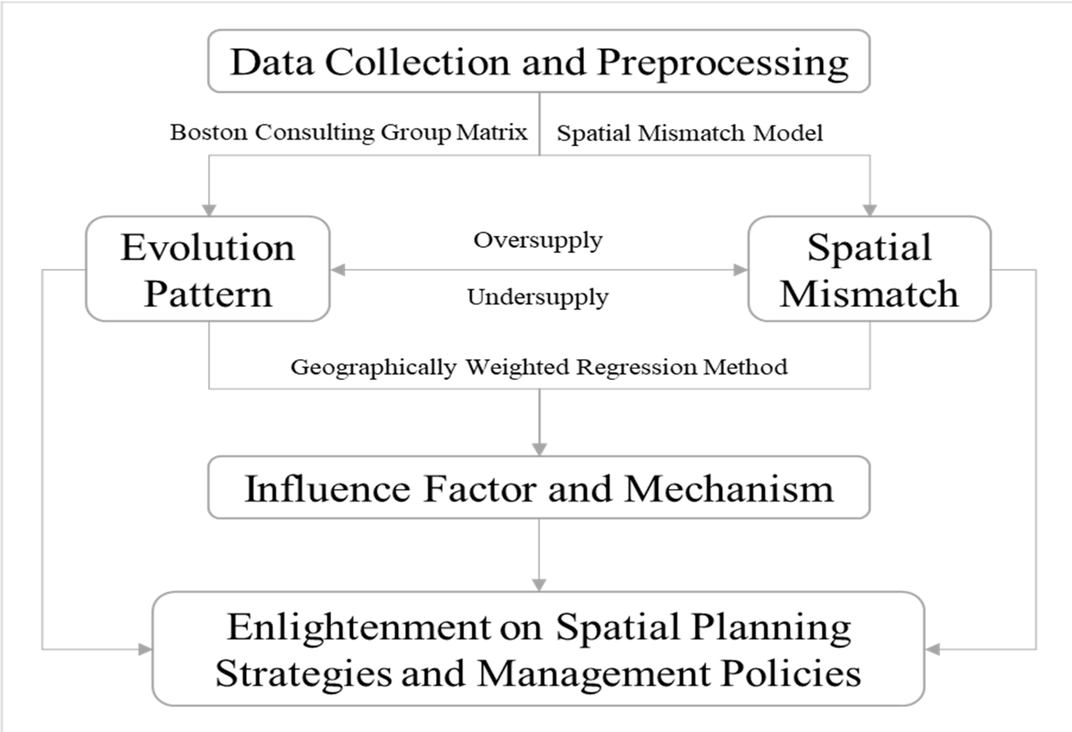

Figure 2. Technical route of research.

3.3. Research Methods

3.3.1. Boston Consulting Group Matrix

For a conglomerate with multiple business departments, selecting the appropriate development strategy for each department is a key task in enterprise strategic planning. The Boston Consulting Group matrix is a commonly used method for enterprise strategic planning, established by the Boston Company in the United States. In the process of enterprise development strategy planning and analysis, the sales growth rate and market share of products are selected, and their high and low (above and below threshold) combinations are divided into four types of business development strategies: star, question, cow, and dog. At present, urban development generally adopts an entrepreneurial model, and for Hunan province, its subordinate cities have similarities in the development of business departments under the group company. This article introduces the Boston Consulting Group matrix to analyze the spatiotemporal evolution dynamics of urban parkland in Hunan province. During the analysis process, relative share (*RS*) and growth rate (*GR*) were used, with their median values as thresholds. Through the Cartesian coordinate system, the spatiotemporal evolution patterns of urban parkland in 102 cities in Hunan were divided into four types (four quadrants)—high-scale–high-growth, high-scale–low-growth, low-scale–high-growth, and low-scale–low-growth. Among them, *RS* represents the competitiveness of urban parkland in Hunan province from the spatial dimension, while *GR* represents the growth power of urban parkland in each city from the temporal dimension. Their calculation formula is [58]:

$$RS = \frac{UPL_i}{UPL_{max}} \times 100\% \tag{1}$$

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

In the formula, UPL_i is the current (2020) statistical value of urban parkland in county or city i, UPL_i' is the statistical value of urban parkland in i county or city base period (2015), UPL_{max} is the maximum value of urban parkland in 102 counties of Hunan province. High-scale–high-growth represents the optimal trend of land change in urban parks, high-scale–low-growth represents a large-scale land supply for urban parks, low-scale–high-growth represents the rapid growth rate of urban parkland, low-scale–low-growth represents the worst trend of land change in urban parks.

3.3.2. Spatial Mismatch Model

With the development of suburbanization and reverse urbanization, a large population work in urban centers while shifting their residence from the center to the suburbs, thus leading to a spatial mismatch between employment and residence. To analyze the degree of occupational and residential spatial mismatch and its influencing factors, Kain created the spatial mismatch index in the 1960s to measure the degree of mismatch between the spatial distribution of urban employment opportunities and places of residence [52]. The spatial mismatch model has a wide application value. On the basis of the research on the spatial separation of urban-population occupation and residence, it has been subsequently introduced into the research fields of urban land spatial allocation [59], spatial allocation of food resources and financial capital [60,61], development of tourism resources and scenic spots [62], and spatial distribution of education and health facilities [63,64] to provide a basis for land-use planning and spatial planning of health facilities. This paper analyzes the relationship between land supply and population demand in urban parks through spatial mismatch modeling to determine whether there is a negative phenomenon of oversupply (waste and inefficiency of land resources) or undersupply (unsatisfactory population demand, reduced green perception and experience). The spatial mismatch and contribution indices were calculated as follows [65]:

$$SMI_i = \frac{\left(\frac{PD_i}{PD} \times UPL - UPL_i \right)}{UPL} \times 100\% \quad (3)$$

$$SMI = \frac{\sum_{i=1}^{n} \left| \frac{PD_i}{PD} \times UPL - UPL_i \right|}{UPL} \quad (4)$$

$$CRI_i = \frac{|SMI_i|}{SMI} \times 100\% \quad (5)$$

where SMI_i is the spatial mismatch index between urban-parkland supply and population demand in the i-th city, UPL_i and UPL represent the number of resident population in the i-th city and Hunan, PD_i and PD represent the area of urban-parkland resource supply in the i-th city and Hunan, respectively, SMI is the sum of the absolute values of the spatial mismatch indexes of all the cities in Hunan, and CRI_i is the contribution of spatial mismatch indexes of the i-th city to the spatial mismatch between urban-parkland supply and population demand in Hunan. Therefore, based on the related research and the characteristics of the distribution of the value of SMI_i in this study, we classified the spatial mismatch into high negative-spatial mismatch, low negative-spatial mismatch, low positive-spatial mismatch, and high positive-spatial mismatch by thresholds of 0.5 and −0.5 (Table 1) [66].

Table 1. Types and meanings of spatial mismatch between urban-parkland supply and population demand.

Type	Index	Meaning
High Positive-Spatial Mismatch	$SMI_i \geq 0.5$	A serious shortage of land supply for urban parks, reducing the quality of urban habitat; a serious imbalance between supply and demand, requiring the government to increase land supply.
Low Positive-Spatial Mismatch	$0.5 > SMI_i > 0$	Slightly insufficient land supply for urban parks, with highly intensive utilization of land resources and self-regulation by the city, requiring no government intervention but to keep the current land supply pattern unchanged.
Spatial Matching	$SMI_i = 0$	Land supply and population demand for urban parks in a mutual match, with supply and demand in balance in an ideal state; rare in reality, requiring the current land supply pattern to remain unchanged.
Low Negative-Spatial Mismatch	$0 > SMI_i > -0.5$	Slight oversupply of land for urban parks, with sloppy utilization of land resources and self-regulation by the city, requiring no government intervention but to keep the current land supply pattern unchanged.
High Negative-Spatial Mismatch	$SMI_i \leq -0.5$	Serious oversupply of land for urban parks, a prominent waste of land resources; serious imbalance between supply and demand, requiring the government to control or reduce land supply.

3.3.3. Geographically Weighted Regression Method

The analysis of influencing factors was based on the regression model. The first step was to test the spatial effects of urban-parkland supply and its mismatch relationship with population demand. If there is spatial heterogeneity and autocorrelation, the analysis requires a spatial regression model [67]. The coefficient of variation was adopted to test spatial heterogeneity during the study and a value greater than 0.36 indicates greater spatial variation in the dependent variable [68,69]. Moran's I index was adopted to test spatial autocorrelation, and a value that is not zero indicates a positive or negative spatial autocorrelation of the dependent variable [70,71]. Larger absolute values of the coefficient of variation and Moran's I represent greater spatial heterogeneity and autocorrelation. The second step was to analyze the covariance of the influencing factors by least squares linear regression model (OLS). VIF (variance inflation factor) is a key indicator for determining the covariance, and a larger value indicates a stronger covariance between the factors. When VIF is less than 10, it indicates that the covariance between the different factors is weak and largely negligible [72]. The third step is to calculate the geographical weighted regression (GWR) analysis results to reveal the local spatial variation in each influencing-factor force. The final step was to determine the influence of each factor on the supply of land in urban parks and its mismatch relationship with population demand through a comparative analysis of GWR and OLS calculations. In the comparative analysis between GWR and OLS, if the R2 of the former is greater than that of the latter, especially if the difference between the AICc (Akaike Information Criterion, corrected) of the former and the latter is more than 3, it indicates that the fitting effect of GWR is better than that of OLS, and that the inclusion of spatial effects in the regression model significantly improves the precision of the results of the analysis [73]. The equations are as follows [74,75]:

$$CV = S/\overline{Y}, = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i - \frac{\sum_{i=1}^{n} Y_i}{n}\right)^2}{n}}, \overline{Y}\frac{\sum_{i=1}^{n} Y_i}{n} \tag{6}$$

$$\text{Moran's } I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right)}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\right)\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2} \tag{7}$$

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

where, CV represents the coefficient of variation of the dependent variable, Y_i represents the dependent variable, $\overline{Y}$ and S represent its mean and standard deviation, respectively, and the dependent variable includes the amount of land supply in urban parks (PD_i), the contribution of spatial mismatch between land supply in urban parks, and the population demand (CRI_i). n represents the number of cities in the study area (i.e., 102). i and j represent the ordinal numbers of the dependent variable and the city, respectively. W_{ij} represents the spatial weights, and the spatial adjacency matrix was used in this paper (i.e., the weight is 1 when the two are adjacent, or zero when not adjacent). β_0 is a constant term, $(\mu_i,\ v_i)$ is the spatial coordinates of the i-th city (the coordinates of the center of gravity point of the city polygon), $\beta_{k_{(\mu_i,\ v_i)}}$ is the regression coefficient of the independent variable of the i-th city, and ϵ_i is the error in the regression equation.

3.4. Variable Selection and Data Source

The dependent variables included urban-parkland supply and the spatial mismatch-contribution rate index, labeled with Y_1 and Y_2, respectively. The former was used to analyze the current urban-parkland supply characteristics of each city in Hunan, and the latter was used to analyze the role each city plays in the spatial mismatch between urban-parkland supply and population demand in the province. The dependent variables were obtained from the statistical yearbooks of the construction of cities and counties in China. Urban-parkland supply and its changes are affected by many factors, so the selection of independent variables should take into account the influence of social, economic, and natural conditions. In this paper, we chose to use 6 factors, labeled with X_1 to X_6 (Tables 2 and A1). The population-related data of the independent variables came from the seventh population census, with the economic obtained data from the Hunan Provincial Statistical Yearbook, the natural environment data obtained from the Global Change Research Data Publishing and Repository [76], and the air quality data obtained from the Atmospheric Composition Analysis Group of Dalhousie University in Canada. The data were standardized by the maximum–minimum method, with 0.001 added to each value to avoid the influence of zero values on the data. Equation (9) was used for positive indicators and Equation (10) for negative indicators in the data normalization. With V_i' as the standardized data of the variable, V_i as the original data of the variable, and V_{Max} and V_{Min} as the maximum and minimum values of the original data of the variable, the calculation is as follows:

$$V_i' = \frac{V_i - V_{Min}}{V_{Max} - V_{Min}} + 0.001 \tag{9}$$

$$V_i' = \frac{V_{Max} - V_i}{V_{Max} - V_{Min}} + 0.001 \tag{10}$$

The F values of the least squares linear regression analysis of urban-parkland supply and spatial mismatch-contribution rate index were 7.51 ($p < 0.001$) and 3.24 ($p < 0.001$), respectively, and the maximum value of VIF for the six independent variables was only 4.72, much smaller than 10, indicating no covariance between the influencing factors (Table 3). In addition, the R2 of GWR was slightly higher than that of OLS, and the difference in AICc between the two was much larger than 3, suggesting that the fit of GWR is superior to that of OLS.

Table 2. Indicator selection of independent variables.

Indicator	Code	Nature	Meaning	VIF
Urban-parkland supply	Y_1	+	The total amount of land allocated by the superior government to each city for the urban park construction.	--
Spatial Mismatch-Contribution Rate Index	Y_2	-	The contribution of each city to the spatial mismatch between urban-parkland supply and population demand in Hunan province.	--
Population Aging	X_1	-	The proportion of population aged 60 and above in the total permanent population [77].	1.69
Population Outflow	X_2	-	The Proportion of population with different registered residence and permanent residence in the total population [78].	1.59
Economic Development	X_3	+	Per capita GDP—the GDP of each city divided by its resident population [79,80].	4.72
Financial Capacity	X_4	+	Fiscal self-sufficiency rate—the fiscal revenue of each city divided by fiscal expenditure [81,82].	4.91
Natural Environment	X_5	+	The undulation of the topography in each city [83].	2.57
Air Quality	X_6	-	The average concentration of PM2.5 in each city [84].	2.84

Table 3. Comparative analysis of GWR and OLS model analysis results.

	Urban-Parkland Supply		Spatial Mismatch-Contribution Rate Index	
	OLS	GWR	OLS	GWR
AICc	−162.42	−156.06	320.10	325.94
R^2	0.32	0.36	0.17	0.22

4. Results

4.1. Evolution Pattern and Spatial Effects Analysis

4.1.1. Urban-parkland supply Scale

By relative share of urban-parkland supply, Changsha city in Hunan had the largest urban parkland, reaching 1809 hectares; Luxi had the smallest area of only 12 hectares, with an average of 166 hectares. We classified urban-parkland supply in Hunan into high, medium, and low levels using the quartile spatial clustering analysis tool of GIS. Yueyang, Chenzhou, Hengyang, Changde, Shaoyang, Yiyang, Xiangtan, Ningxiang, Zhuzhou, Yongzhou, Huaihua, Shimen, Changshaxian, Loudi, Ningyuan, Chaling, Pingjiang, Leiyang, Wugang, Qidong, Xinhua, and others were assigned to the high level with a high supply of land for urban parks. Yanling, Shuangfeng, Shaoshan, Longhui, You, Linli, Sangzhi, Xinhuang, Hengnan, Anhua, Zixing, Li, Shuangpai, Zhijiang, Guidong, Nanyue, Xinshao, Huayuan, Chengbu, Hanshou, Luxi, Datonghu, Huitong, Taojiang, and others were assigned to the low level with a low supply of land. Yizhang, Linwu, Dong'an, Dongkou, Huarong, Guiyang, Cili, Hengshan, Jiangyong, Lanshan, Hongjiang, Shaoyangxian, Tongdao, Nan, Yuanling, Chenxi, Jin, Lianyuan, Jiahe, and others were assigned to the medium level with land supply between high and low levels. From the spatial effects, the coefficients of variation in urban-parkland relative share in 2020 was 1.21, much larger than 0.36, indicating a higher level of spatial heterogeneity; during the same period, the Moran's I value was 0.06 (Z = 2.02, p = 0.04), indicating positive spatial autocorrelation of urban-parkland supply, with statistical significance. Among them, hot cities were mainly distributed in the western part of Changsha, while cold cities were concentrated in the Xiangxi–Huaihua region (Figure 3).

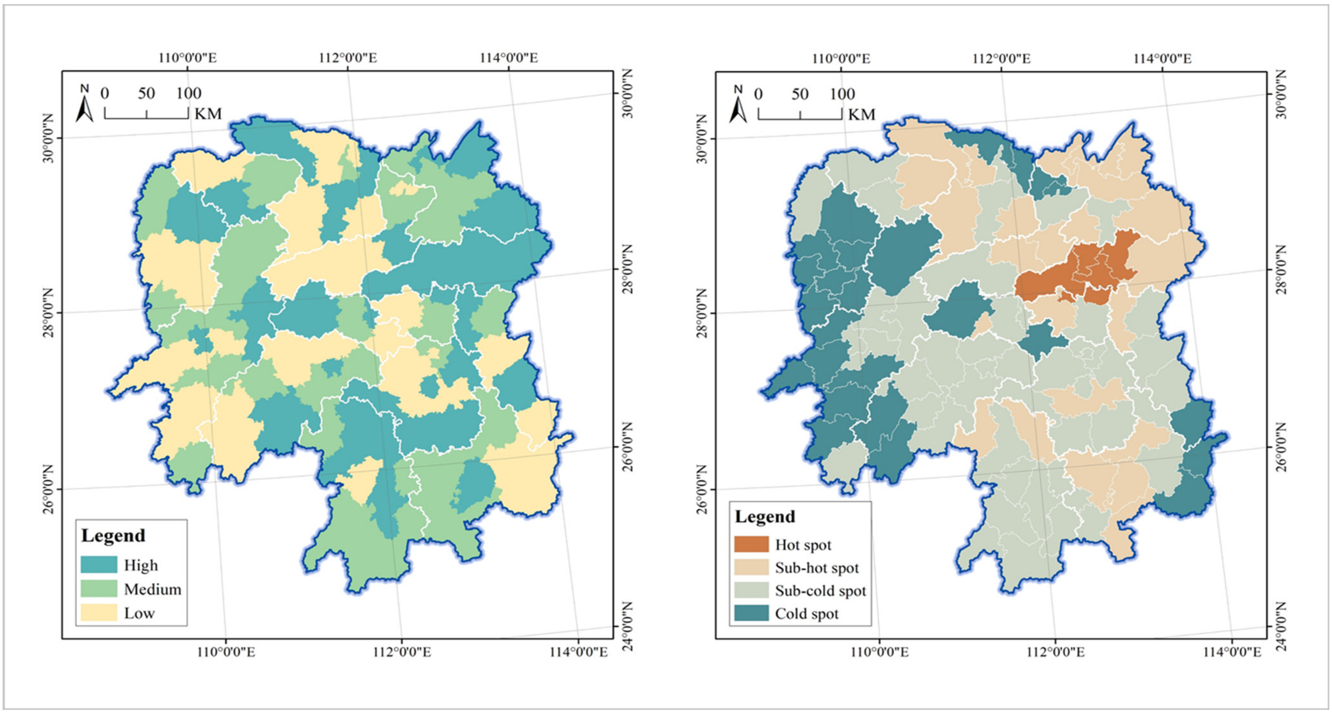

Figure 3. Urban parkland and population geographical distribution pattern in Hunan province.

4.1.2. Urban-parkland supply Speed

By growth rate of urban-parkland supply, the largest was seen in Dong'an, reaching 988.89%; You showed the smallest, at only −84.26%, with an average value of 121.91%. Zhongfang, Guzhang, Huarong, Leiyang, Suining, Jiangyong, Yueyangxian, Dao, Xintian, Ningxiang, Xiangtan, Yongshun, Shimen, Shuangpai, Pingjiang, Ningyuan, Hengshan, Mayang, Liuyang, Xupu, Luxi, Shuangfeng, Linxiang, Zhangjiajie, Nan, Tongdao, Anxiang, Xiangtanxian, Dongkou, Hengdong, Fenghuang, Xinhua, Yueyang, and others have the fastest growth rates, belonging to the high level. Hengnan, Chengbu, Huitong, Miluo, Zhijiang, Changde, Liangshuijiang, Qiyang, Longhui, Shaoshan, Hengyang, Yanling, Li, Sangzhi, Taojiang, Anhui, Datonghu, Guiyang, Jishou, Huayuan, Jiahe, Zixing, Anren, Xinhuang, Xiangxiang, Hanshou, Guidong, Zhuzhou, Baojing, and others' urban-parkland-supply growth rate was the slowest, belonging to low level. Longshan, Qidong, Xiangyin, Xinning, Wugang, Linwu, Changning, Huaihua, Taoyuan, Yuanjiang, Wangcheng, Loudi, Yongxing, Jin, Yiyang, Changshaxian, Jianghua, Rucheng, Changsha, Shaoyangxian, Chenxi, Lanshan, Linli, Yongzhou, Shaodong, Liling, Chaling, Chenzhou, Jingzhou, Cili, Xinshao, and others were assigned to the medium level with a land-supply growth rate between the high and low levels. From spatial effects, the coefficient of variation in urban-parkland growth rate in 2015–2020 was 1.50, much larger than 0.36, indicating a higher level of spatial heterogeneity. During the same period, Moran's I value was 0.01 (Z = 0.45, p = 0.29), indicating a positive spatial autocorrelation in urban-parkland supply-growth rate, which was not statistically significant. Among them, hot spots were mainly distributed in Yongzhou, while the cold spots formed three clusters, including Zhuzhou–Chenzhou, Shaoyang–Loudi–Hengyang, and Changde–Yiyang (Figure 4).

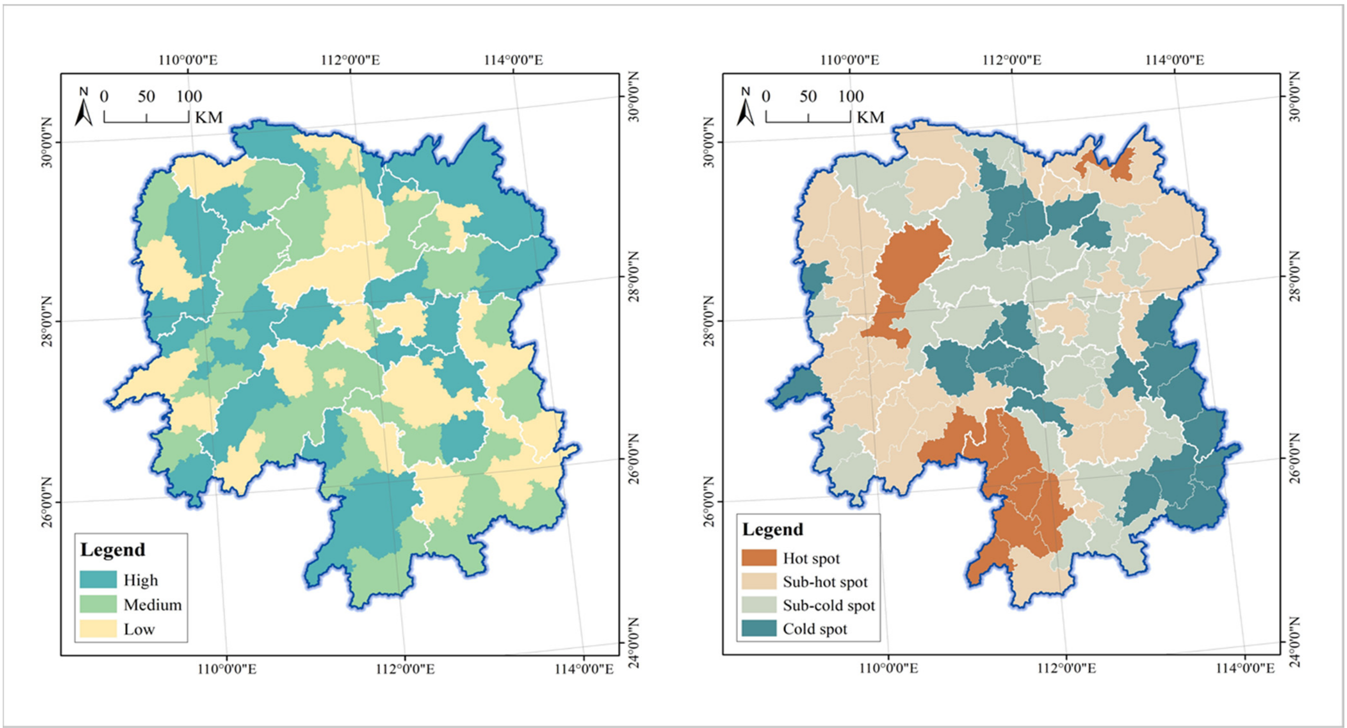

Figure 4. Geographical distribution pattern and spatial effect of urban-parkland growth rate in Hunan province.

4.1.3. Urban-Parkland Supply Trends

The median values of relative share and growth rate were 6.42% and 41.14%, respectively. Using these values as thresholds, 102 cities in Hunan province were classified into four categories (Table 4). The members of high-scale–high-growth were randomly distributed, including Ningxiang, Liuyang, Wangcheng, and others. The members of high-scale–low-growth were relatively concentrated in the Changsha–Xiangtan and Hengyang–Yongzhou regions, including Changsha, Changshaxian, Zhuzhou, Liling, and others. The members of low-scale–high-growth are randomly distributed, including Suining, Yueyangxian, Xiangyin and others. The members of low-scale–low-growth are distributed in a concentrated and continuous belt pattern, including You, Yanling, Xiangxiang, Shaoshan and others. In 2015, Moran's I index was 0.03 (Z = 0.99, p = 0.16), indicating an insignificant positive spatial autocorrelation. In 2020, Moran's I index was −0.06 (Z = −1.37, p = 0.06), indicating a significant negative spatial autocorrelation. Both hot and cold spots formed three small clusters, the former being located in the provincial capital metropolitan area, Yongzhou–Hengyang, and Zhangjiajie–Xiangxi and the latter being located in Xiangxi–Shaoyang, Loudi–Huaihua, and Chenzhou (Figure 5).

Table 4. Evolution pattern of urban parklands in Hunan province.

Type	Cities
High-Scale–High-Growth	Ningxiang, Liuyang, Wangcheng, Xiangtan, Xiangtanxian, Leiyang, Changning, Hengshan, Hengdong, Qidong, Wugang, Dongkou, Xinning, Yueyang, Linxiang, Huarong, Pingjiang, Anxiang, Shimen, Zhangjiajie, Yiyang, Yuanjiang, Yizhang, Linwu, Dong'an, Dao, Jiangyong, Ningyuan, Huaihua, Hongjiang, Xupu, Mayang, Tongdao, Loudi, Xinhua, Yongshun.
High-Scale–Low-Growth	Changsha, Changshaxian, Zhuzhou, Liling, Chaling, Hengyang, Shaoyang, Shaoyangxian, Changde, Cili, Chenzhou, Guiyang, Yongzhou, Qiyang, Lanshan, Lengshuijiang.

Table 4. *Cont.*

Type	Cities
Low-Scale–High-Growth	Suining, Yueyangxian, Xiangyin, Jin, Taoyuan, Nan, Yongxing, Shuangpai, Xintian, Zhongfang, Shuangfeng, Luxi, Fenghuang, Guzhang, Longshan.
Low-Scale–Low-Growth	You, Yanling, Xiangxiang, Shaoshan, Hengyangxian, Hengnan, Nanyue, Shaodong, Xinshao, Longhui, Chengbu, Miluo, Hanshou, Li, Linli, Sangzhi, Taojiang, Anhua, Zixing, Datonghu, Jiahe, Rucheng, Guidong, Anren, Jianghua, Yuanling, Chenxi, Huitong, Xinhuang, Zhijiang, Jingzhou, Lianyuan, Jishou, Huayuan, Baojing.

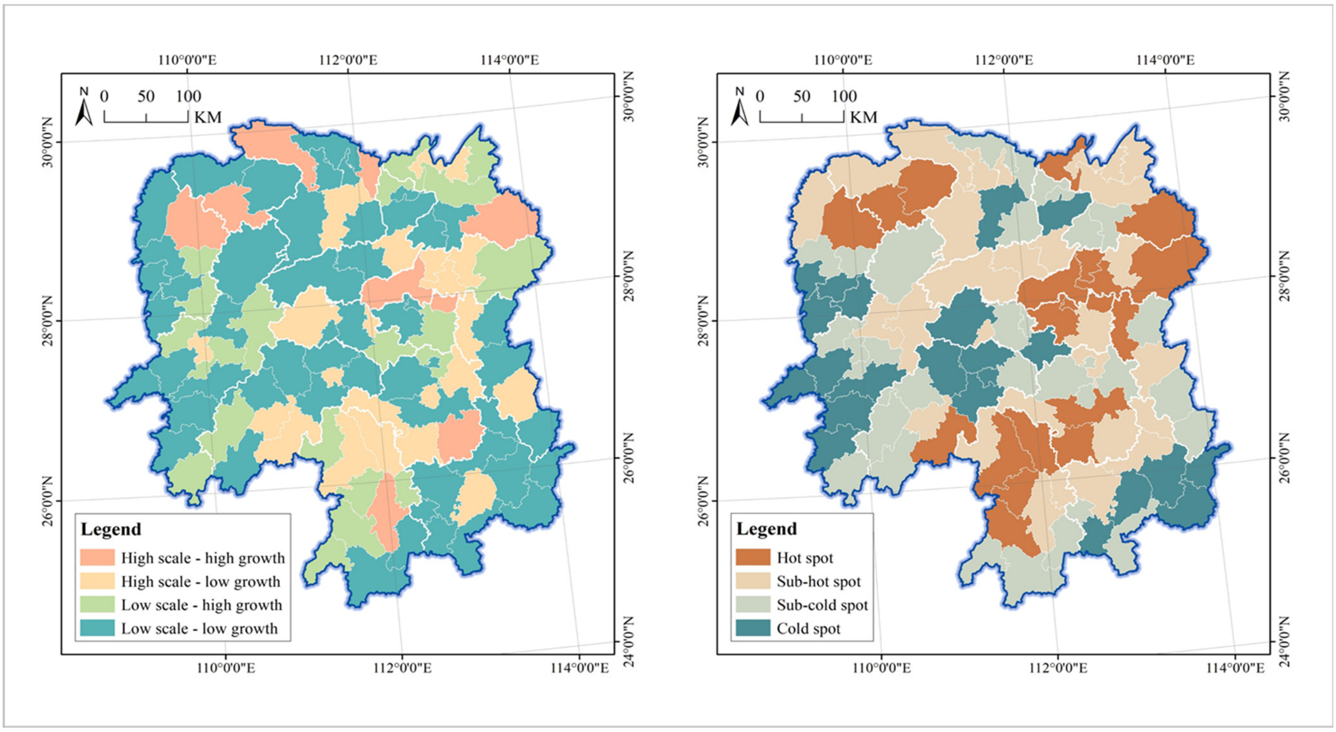

Figure 5. Spatiotemporal evolution pattern and spatial effect of urban parkland in Hunan province.

4.2. Spatial Mismatch and Spatial Effects Analysis

4.2.1. Spatial Mismatch Analysis

The spatial mismatch analysis results between urban-parkland supply and population demand in 2015 and 2020 are shown in Table 5. In terms of the spatial mismatch index, the geographical distribution of cities in low negative-spatial mismatch and low positive-spatial mismatch states in 2015 and 2020 showed agglomeration, while the cities in high positive-spatial mismatch states showed randomness. It is worth noting that the distribution of cities in the high negative-spatial mismatch state has shifted from agglomeration to randomness. In terms of the contribution of spatial mismatch index, most of the high-contributing cities in 2015 were clustered in Changsha–Zhuzhou and its neighboring regions in the east. The year 2020 saw an increase in the number, but they were spatially decentralized and dominated by prefectural-level cities or their peripheral cities. In 2015, low-contribution cities were clustered in Shaoyang and Huaihua in eastern Hunan, and in 2020, only Changde, Yiyang, and Xiangtan regions saw the formation of large, banded clusters. In 2015, the cities with medium contribution were concentrated in Zhangjiajie–Changde in northern Hunan and Loudi–Hengyang in the central part, and in 2020, only Zhangjiajie–Huaihua–Loudi showed the formation of a large agglomeration belt (Figure 6).

Table 5. Spatial mismatch of urban parkland in Hunan province.

Type	2015	2020
High Negative-Spatial Mismatch	Xinning, Wugang, Wangcheng, Jiahe, Qiyang, Lengshuijiang, Changsha, Changshaxian, Chaling, You, Zhuzhou.	Linwu, Qiyang, Lengshuijiang, Jiangyong, Linxiang, Xupu, Mayang, Leiyang, Xinhua, Pingjiang, Xinning, Qidong, Anxiang, Wugang, Hengdong, Yongshun, Ningxiang, Chaling, Ningyuan, Shimen.
Low Negative-Spatial Mismatch	Linli, Jiangyong, Hengshan, Liling, Yongxing, Miluo, Longshan, Lianyuan, Shaoyangxian, Chengbu, Zixing, Huayuan, Datonghu, Linxiang, Zhijiang, Yizhang, Changning, Fenghuang, Ningyuan, Yongshun, Yuanjiang, Mayang, Nanyue, Hongjiang, Tongdao, Sangzhi, Xinhua, Jianghua, Rucheng, Shimen, Xiangxiang, Anxiang, Jin, Qidong, Linwu, Yuanling, Xinhuang, Cili, Chenxi, Yanling, Hengdong, Guidong, Jingzhou, Shaoshan, Anren, Lanshan, Guiyang.	Yongxing, Huayuan, Chengbu, Linli, Datonghu, Yueyangxian, Sangzhi, Lianyuan, Xiangyin, Wangcheng, Shaoyangxian, Miluo, Guiyang, Guidong, Longshan, Shuangpai, Nanyue, Xinhuang, Nan, Suining, Rucheng, Anren, Xintian, Changshaxian, Yanling, Fenghuang, Dongkou, Shaoshan, Jianghua, Yuanling, Huarong, Cili, Zhongfang, Yizhang, Jiahe, Xiangtanxian, Guzhang, Jingzhou, Yuanjiang, Chenxi, Dao, Changning, Jin, Lanshan, Hongjiang, Hengshan, Tongdao, Dong'an.
Low Positive-Spatial Mismatch	Ningxiang, Yueyangxian, Huarong, Changde, Shuangfeng, Dong'an, Shaodong, Hengnan, Hengyangxian, Dao, Xinshao, Li, Nan, Hanshou, Taoyuan, Luxi, Xiangyin, Pingjiang, Suining, Longhui, Xintian, Xupu, Shuangpai, Baojing, Zhongfang, Huitong, Anhua, Dongkou, Chenzhou, Xiangtanxian, Guzhang.	Liuyang, Shaodong, Li, Hanshou, Longhui, Yiyang, Hengnan, Zhangjiajie, You, Xinshao, Hengyangxian, Baojing, Taoyuan, Xiangxiang, Anhua, Shuangfeng, Liling, Xiangtan, Huitong, Zixing, Zhijiang, Luxi.
High Positive-Spatial Mismatch	Yueyang, Yongzhou, Huaihua, Xiangtan, Shaoyang, Jishou, Hengyang, Loudi, Liuyang, Leiyang, Yiyang, Zhangjiajie, Taojiang.	Changsha, Zhuzhou, Shaoyang, Hengyang, Yongzhou, Jishou, Huaihua, Changde, Yueyang, Loudi, Chenzhou, Taojiang.

By high positive-spatial mismatch, about 10% of the cities in Hunan had long-term parkland supply that seriously failed to meet the population demand, while there was the smallest number of cities with serious oversupply. Liuyang, Xiangtan, Hengyang, Leiyang, Shaoyang, Yueyang, Zhangjiajie, Yiyang, Taojiang, Yongzhou, Huaihua, Loudi, and Jishou were clustered in bands in eastern Hunan in 2015. While Changsha, Zhuzhou, Hengyang, Shaoyang, Yueyang, Changde, Taojiang, Chenzhou, Yongzhou, Huaihua, Loudi, and Jishou were spatially dispersed in 2020, and most of them were prefectural-level cities.

By low positive-spatial mismatch, the proportion of cities in Hunan where the land supply of urban parks barely met the population demand decreased from 30.39% in 2015 to 21.57% in 2020, and they formed a number of clusters. Ningxiang, Xiangtanxian, Hengyangxian, Hengnan, and others were concentrated in the junction areas of Huaihua, Shaoyang, Yiyang, and Loudi in 2015. Liuyang, Liling, You, Xiangtan, and others formed cluster-like agglomerations in Changde–Yiyang, Loudi–Xiangtan, and Zhuzhou–Changsha regions in 2020.

By low negative-spatial mismatch, Hunan had the largest number of cities with a slight oversupply of land for urban parks, with more than 45% in the long term, and most of them were in the fringe areas of the province. Liling, Yanling, Xiangxiang, and others had greater concentration densities in the northwest and southeast of the province in 2015. Changshaxian, Wangcheng, Yanling, Shaoshan, and others covered a geographical area that gradually expanded from the fringe to the center, with a high degree of agglomeration in Yongzhou, Shaoyang, and Yueyang in 2020.

By high negative-spatial mismatch, Hunan had an increasing number of cities with land supply seriously exceeding the population demand for urban parks, expanding from 10.78% in 2015 to 19.61% in 2020. This change shows that in the context of ecological civilization and park city construction, more cities have seen the supply of land allocated for urban parks exceeding the demand, and the serious oversupply of land has resulted in wasteful use of land resources. Changsha, Changshaxian, Wangcheng, and others in 2020 were relatively decentralized in space in 2015.

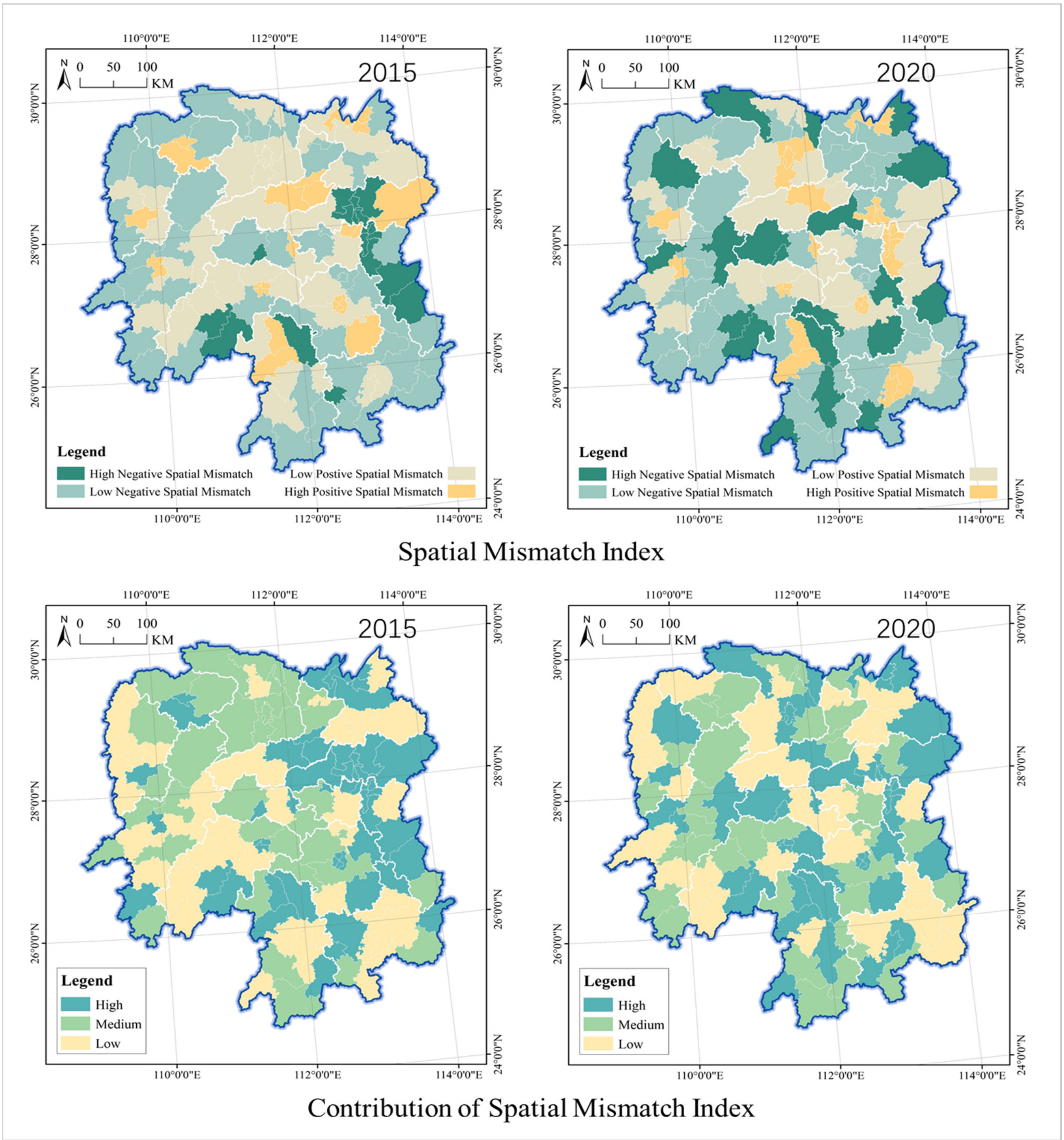

Figure 6. Geographical pattern of mismatch between urban-parkland supply and population demand in Hunan province.

4.2.2. Spatial Effects Analysis

From the spatial effects, the Moran's I values of spatial mismatch index in 2015 and 2020 were 0.03 (Z = 0.99, p = 0.16) and −0.06 (Z = −1.37, p = 0.06), respectively, indicating that the spatial autocorrelation shifted from an insignificant positive to a significant negative. In 2015, most of the hot cities were concentrated on the northeast southwest axis, including

Yueyang, the junction of Changsha–Yiyang–Xiangtan, and Shaoyang–Yongzhou–Hengyang. There were fewer cold spot cities, all located in Zhuzhou City. In 2020, most of the hot cities were concentrated in three clusters in central Hunan province, including the western part of Changsha to the northern part of Zhuzhou, the northern part of Shaoyang to the northern part of Hengyang, and the southern part of Changde. Cold spot cities formed four clusters, including the southern part of Yongzhou, the southern part of Zhuzhou, the junction of Shaoyang–Loudi, and Zhangjiajie–Changde. The Moran's I values for the contribution of spatial misalignment in 2015 and 2020 were 0.02 (Z = 0.78, p = 0.21) and −0.03 (Z = −0.57, p = 0.32), respectively, indicating a shift from positive to negative spatial autocorrelation, but this was not statistically significant. In 2015, most of the hot cities were concentrated in Changsha, Xiangtan, and Zhuzhou. The cold spots formed three clusters, including the junction of Changde–Huaihua–Xiangxi–Yiyang-Loudi, Shaoyang–Huaihua, and Chenzhou–Yongzhou. In 2020, four small clusters of hot cities were formed, including the western part of Changsha, the southern part of Hengyang, the northern part of Yongzhou, and the western part of Changde. During the same period, cold spot cities formed three small clusters, located in the eastern part of Chenzhou, the southern part of Shaoyang, and the junction of Yueyang–Yiyang–Changsha (Figure 7).

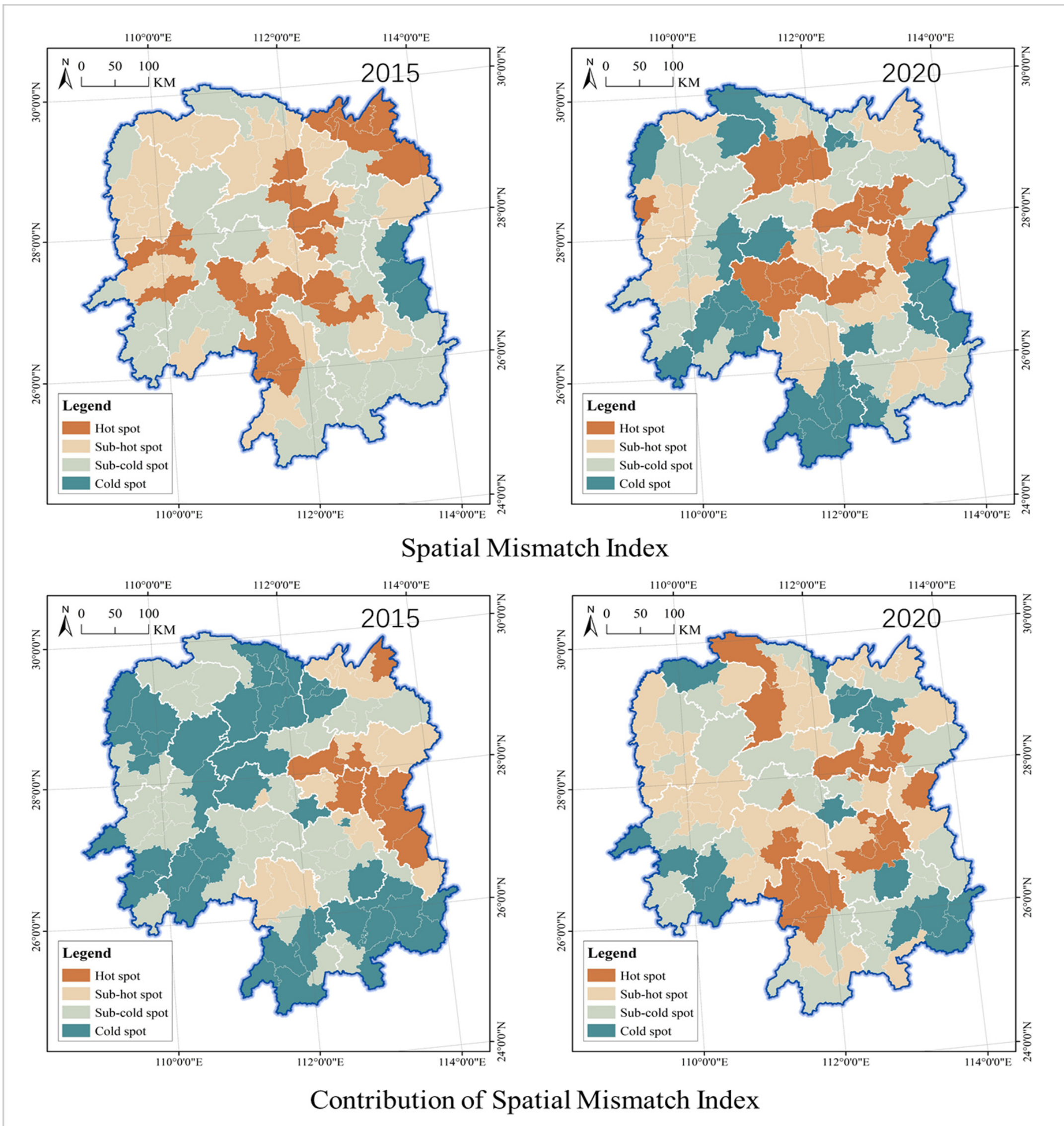

Figure 7. Spatial effect of mismatch between urban-parkland supply and population demand in Hunan province.

4.3. Influencing Factors and Impact Mechanism Analysis

4.3.1. The Impact of Factors on Urban-Parkland Supply

Population aging showed a negative force, with a minimum value of −0.0269 and a maximum value of −0.0050. The population aging factor showed a gradient influence in the spatial pattern, gradually increasing from southwest to northwest with Huaihua as the depression and Changsha and Yueyang as highlands. Population outflow showed a positive force, with a minimum value of 0.0033 and a maximum value of 0.0183. The influence of the population outflow factor was also a gradient in the spatial pattern, with Western Hunan and Zhangjiajie as depressions and Yongzhou as the highland, and gradually increasing from north to south as a whole. Economic development showed a negative force, with a minimum value of −0.0481 and a maximum value of −0.0104. The spatial pattern of its influence was opposite to that of population aging. Financial capacity showed a positive force, with a minimum value of 0.0451 and a maximum value of 0.0703. The force of the factor in the spatial pattern formed a monocentric circle structure, centered on Loudi, with the intensity of influence gradually decreasing in all directions. Of note, the decay was significantly faster to the east than to the east and was essentially similar in both north and south directions. The force of natural environment had two sides, and the influence of the factor formed a double-center circle structure in the spatial pattern. The factor had a minimum value of −0.0131 and, centered on Loudi, formed a depression-collapse structure in southwestern Hunan. The factor had a maximum value of 0.0138 and formed a highland-radiation structure in the northern part of Hunan, centered on Zhangjiajie and Changde. Air quality showed a positive force, with a minimum value of 0.0301 and a maximum value of 0.0480. The air quality factor showed a gradient influence in the spatial pattern, gradually increasing from west to east with Western Hunan as the depression and Changsha as the highland. The mean and median of the different factor forces roughly determined the order of factor influence as financial capacity > air quality > economic development > population aging > population outflow > natural environment (Table 6 and Figure 8).

Table 6. Forces impact statistics on urban-parkland supply based on GWR in Hunan province.

Code	Variable	Min	Max	Mean	Median
X_1	Population Aging	−0.0269	−0.0050	−0.0165	−0.0168
X_2	Population Outflow	0.0033	0.0183	0.0107	0.0099
X_3	Economic Development	−0.0481	−0.0104	−0.0266	−0.0260
X_4	Financial Capacity	0.0451	0.0703	0.0565	0.0566
X_5	Natural Environment	−0.0131	0.0138	0.0005	−0.0006
X_6	Air Quality	0.0301	0.0480	0.0378	0.0366

In summary, different factors had relatively weak but very complex effects on urban-parkland supply in Hunan. From the nature of factor effects, population aging and economic development acted negatively; population outflow, financial capacity, and air quality acted positively; while natural environment acted both positively and negatively. From the intensity of the factors, financial capacity, air quality, and economic development were more influential as key factors, while population aging, population outflow, and natural environment were less influential as auxiliary factors. From the spatial pattern, population aging, population outflow, economic development, and air quality showed a gradient influence, with different axes of the spatial decay direction. The financial capacity and natural environment showed a circular influence. The former displayed a monocentric structure, while the latter showed a bi-center structure.

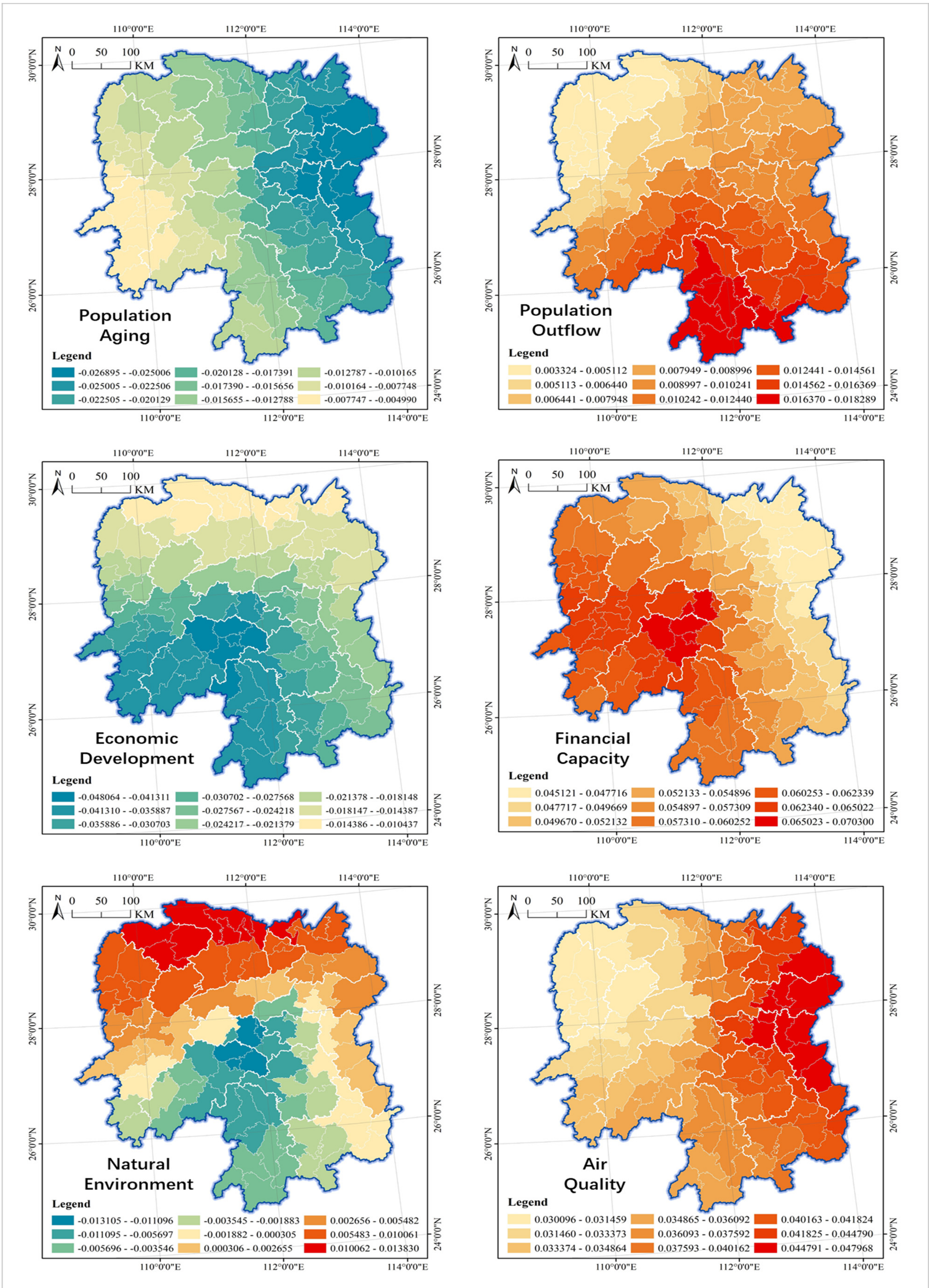

Figure 8. The impact of factors on urban-parkland supply based on GWR in Hunan province.

4.3.2. The Impact of Factors on Spatial Mismatch Contribution Rate Index

Population aging showed a negative force, with a minimum value of −0.1420 and a maximum value of −0.0115. The influence of this factor showed a center-periphery circle in the spatial pattern, centered on Loudi and gradually decreasing to the surrounding areas. It should be noted that the spatial decay of factor influence was symmetrical in the east–west and north–south directions, but the former decayed slower than the latter. Population outflow showed a positive force, with a minimum value of 0.0863 and a maximum value of 0.2711. The influence of the population outflow factor was a gradient in the north–south direction in the spatial pattern, with Zhangjiajie as the depression, and Yongzhou as the highland, gradually increasing from north to south as a whole. Economic development showed a negative force, with a minimum value of −0.8930 and a maximum value of −0.3557. The influence of this factor showed a monocentric circle in the spatial pattern, with Shaoyang as the highland. Notably, this factor's influence decayed fastest spatially in the northeast direction, with Changde and Yueyang being obvious depressions. Financial capacity showed a positive force, with a minimum value of 0.4589 and a maximum value of 0.7209. It was similar to economic development in the spatial pattern of forces, except that the depression expanded in extent and the center of gravity moved further towards Yueyang. Natural environment showed a negative force, with a minimum value of −0.2900 and a maximum value of −0.0290. Its spatial pattern of influence was largely the same as that of economic development. Air quality showed a positive force, with a minimum value of 0.1300 and a maximum value of 0.3797. The spatial pattern of its influence was similar to that of population aging, except that the center of gravity of the depression moved further towards Changde. The mean and median of the different factor forces roughly determined the order of factor influence as economic development > financial capacity > air quality > population outflow > natural environment > population aging (Table 7 and Figure 9).

Table 7. Forces impact statistics on spatial mismatch based on GWR in Hunan province.

Code	Variable	Min	Max	Mean	Median
X_1	Population Aging	−0.1420	−0.0115	−0.0693	−0.0706
X_2	Population Outflow	0.0863	0.2711	0.1788	0.1754
X_3	Economic Development	−0.8930	−0.3557	−0.6040	−0.6138
X_4	Financial Capacity	0.4589	0.7209	0.5867	0.5926
X_5	Natural Environment	−0.2900	−0.0290	−0.1343	−0.1253
X_6	Air Quality	0.1300	0.3797	0.2464	0.2477

In summary, different factors had a strong influence on the spatial mismatch-contribution rate index of Hunan, and the influence of each factor was substantially higher compared to urban-parkland supply, except for a slightly reduced complexity. From the nature of factor effects, population aging, economic development, and natural environment acted negatively, while population outflow, financial capacity, and air quality acted positively. From the intensity of the factors, economic development, financial capacity, and air quality were more influential as key factors, while population outflow, natural environment, and population aging were less influential as auxiliary factors. From the spatial pattern, the population outflow and air quality showed a gradient influence, with axes of the spatial decay in the north–south direction; the population aging, economic development, financial capacity, and natural environment showed a circular influence. All the factors were monocentric.

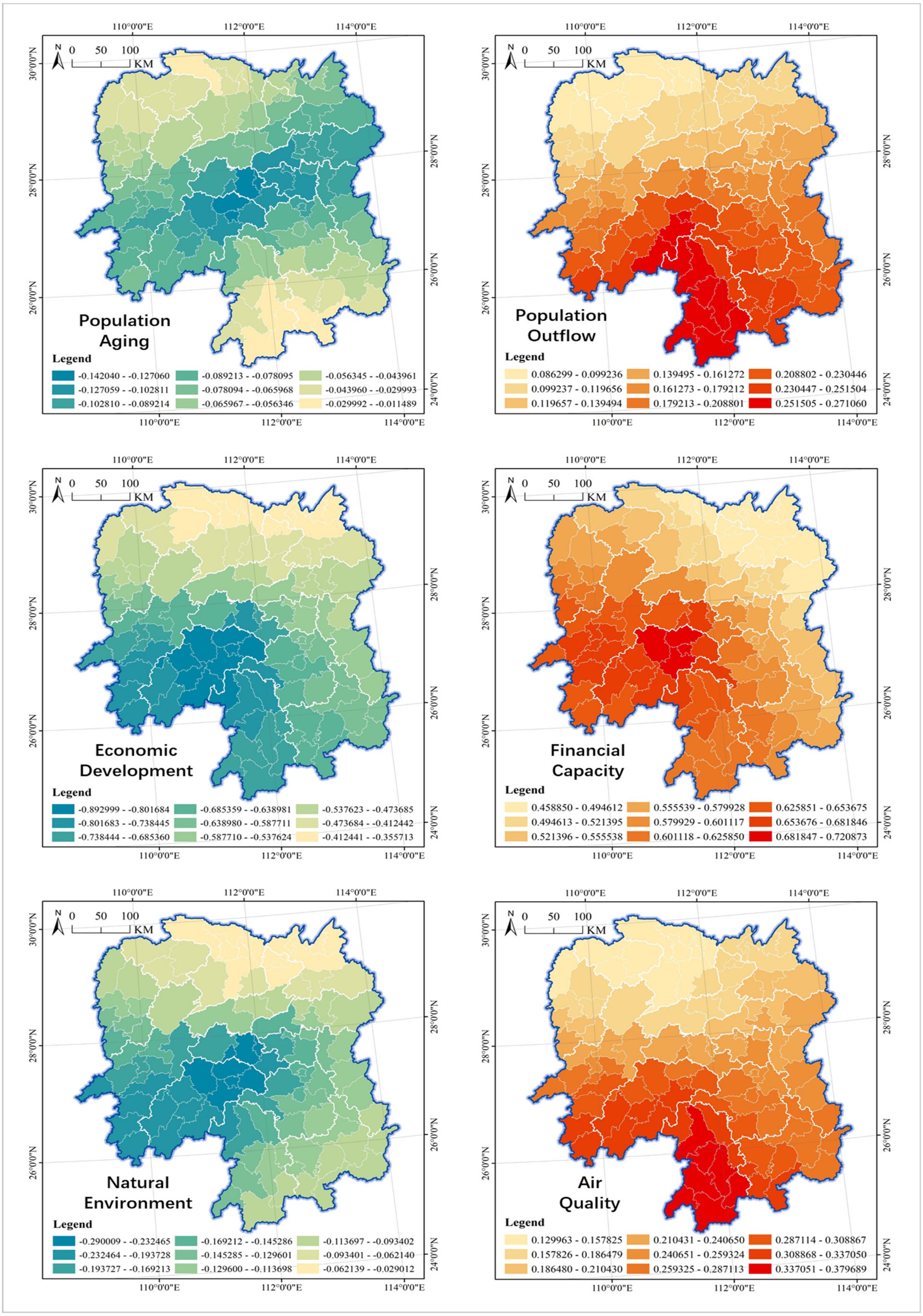

Figure 9. The impact of factors on spatial mismatch-contribution rate index based on geographically weighted regression model in Hunan province.

5. Discussion

In this study, we found that urban-parkland supply and population demand in Hunan are characterized by significant spatial heterogeneity and correlation, and are influenced by many factors. Furthermore, the contradiction between parkland supply and population demand is becoming more acute, and there are more cities with mismatch between supply and demand. These findings are similar to the conclusions of relevant research, including that the distribution of urban parkland is spatially unbalanced and faces the challenge of imbalance between supply and demand [85]. For example, Rigolon [86] concluded that there are significant spatial inequalities in urban parkland and quality, and Tan [87], Gao [88], Zhu [89], and Wang [57] found spatial mismatches between the supply of park services and the demand of user groups in Wuhan, Shenzhen, and Beijing. Lee [90] and Yang [91] further integrated the analysis of supply–demand relationship and accessibility of urban parks, and categorized community spaces into high-supply–medium-demand–medium-accessibility, low-supply–medium-demand–low-accessibility, high-supply–low-demand–high-accessibility, and medium-supply–high-demand–low-accessibility in an attempt to provide a basis for urban planning in Zhengzhou. Notably, all of these studies focus on analyzing park dynamics, spatial patterns, and supply and demand in a single city, and can only help a single city government [92,93]. However, this paper focuses on the analysis of the match between land supply and population demand in regional urban parks, helping to identify cities with imbalance in supply and demand, and to quantitatively measure the direction and degree of spatial mismatch. As a result, it can serve as a basis for the provincial government's allocation of land resources and as a reference for all city governments in the study area.

An urban park is a complex project involving many elements such as nature and ecology, society and system, and history and culture. The balance between supply and demand also requires the collaboration of departments and stakeholders, such as the Urban Landscape Bureau, the Housing and Urban Renewal Bureau, the Land Bureau, and the Cultural Affairs Bureau, making it vulnerable to external factors. This paper found that the urban-parkland supply and spatial mismatch-contribution rate index in Hunan is affected by multiple factors, and that the power mechanism is very complex, with different factors varying greatly in intensity, nature, and spatial effect. Scholars have discussed the factors influencing changes in urban parks. For example, Cheng [94], Nam [95], and Smith [96] argued that government funding plays a key role in the management of urban parks in China and the United Kingdom. Luo [97], Feng [98], and Kim [99] argued that both population density and size have significant spatial correlations with the level of service of urban parks. Guo [100,101] 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 corroborate with those of this paper, but comparative analyses show that scholars mainly used multiple linear regression equations, structural equations, questionnaires, and interview analyses, with ignorance of the spatial effects of factors. The important contribution of this paper is in revealing the spatial effects of factor influences, such as the spatial gradient or circular variability of factor influences, and the opposite role of natural environment on the land supply of urban parks in southwestern and northeastern Hunan (negative for the former and positive for the latter). More importantly, this paper expands the analysis of the driving mechanism from the field of land supply in urban parks to the supply and demand relationship, and it explains the impact of different factors on the spatial mismatch (oversupply or undersupply) of land in urban parks, providing a more precise basis for the government's efforts to promote the balance between supply and demand in urban parks.

Improvement of living standards drives residents' increasing demand for urban parks; however, the mismatch between park supply and demand is becoming more prominent due to a number of factors, thus prompting the research focus to gradually shift from accessibility, satisfaction, and benefit spillover to supply and demand [102]. An urban park is an ecological and cultural service system for the public, and it is impossible to balance supply and demand directly through the market, which requires the government, especially the higher-level government, to further optimize the allocation plan of land resources for urban parks. With the development of urban economy and the gathering of urban population, land has become a scarce resource in cities. Urban land use in the new period should meet the needs of urban industrial and economic development, and it should also constantly meet the needs of urban residents for a better life and the needs of ecological civilization construction, with focus on the harmonious unity of economic, social, and environmental benefits. Urban parkland is an indispensable green, recreational, social, and cultural space for cities and is an important direction for urban land-use transformation. According to this empirical study of Hunan, we suggest to implementing zoning management strategies for 102 cities.

Cities in high positive-spatial mismatch should implement the quantity-priority supply strategy, and provincial governments should give special conditions to cities in this sub-district when allocating land resources for urban parks, provide them with more land resources, and put forward more detailed construction indicators and assessment requirements. Local governments should also actively promote land exchange and build more parks by means of "plugging in greenery wherever possible" during the transformation of old cities, historical buildings, abandoned factories, and old industrial areas [103]. The government should also step up its survey of unused land resources and lost spaces in urban areas, make good use of vacant land such as viaducts and street corners, drive the transformation of lost spaces, and create more pocket parks. In addition, local governments should focus on the implementation of the "neighborhood system" to boost the opening up of more parks and green spaces in private communities, so as to satisfy, to a certain extent, the needs of non-community residents for access to nature and recreation in the vicinity.

Cities in high negative-spatial mismatch should implement the quality-priority supply strategy, and local governments should try to improve the service quality and characteristics of urban parks. For example, as China steps into an aging society, the need for parks for the elderly attracts more attention. The analysis of the driving mechanism showed that population aging has a non-negligible impact on both the land supply and spatial mismatch of parks in Hunan, and the land supply for urban parks in this subregion exceeds the demand. The local government should build age-friendly parks or implement age-adapted renovation in existing parks [104,105], so as to enhance the characteristics and quality of park services. Cities in this policy area should also take advantage of the rich land area of urban parks; seize the opportunity of the provincial government and the central government to support the construction of park cities; accelerate the promotion of the organic integration of park forms and urban space; speed up the construction of parks around the city, community parks, street gardens and pocket parks; enlarge the coverage of parks; and improve the quality of parks to build themselves into demonstration sites of park cities. In addition, cities in the subregion should strengthen intercity cooperation and may jointly establish a trading platform for parkland indicators, so that surplus indicators can be replaced with other resources and elements needed for high-quality urban development.

Cities in the low positive-spatial mismatch and low negative-spatial mismatch should implement a free market debugging strategy. Green infrastructure is regional and systematic, and greenspace planning should meet the needs of population, social, and economic development. According to the natural conditions of plant resources, soil, topography, and climate, as well as the relationship with neighboring land use, this paper proposes the type, area, and distribution structure of parks in the region to shape a complete green network system. Regional cooperation should be strengthened not only among governments, residents, and businesses in the same city, but also among different cities, thus further improving satisfaction and accessibility for residents. For example, the government should take the Changsha–Zhuzhou–Xiangtan Ecological Green Zone as the core to link up with surrounding areas such as Dato, Muyun, Tiaoma, Yunlong, and Shaoshan to create an urban central park in the Changsha–Zhuzhou–Xiangtan metropolitan area. The governments involved in the construction of the Central Park should strengthen regional cooperation;

jointly formulate its spatial planning, protection, and utilization regulations as soon as possible; jointly create a national horticultural (garden) expo and a flower expo; and commit themselves to making it a regional green heart of world-class quality.

A limitation of this paper is the ignorance of the "quality" of the supply of urban parks and the demand of the population, as well as of the influence of the "soft settings" such as planning, policies, and institutions in the analysis of the influencing factors. Due to the limited availability of data, the analysis of parkland supply and population demand in the empirical study only considered quantitative indicators and failed to include "qualitative" indicators—such as park service quality; vegetation condition; brand image; and demographic, education, and income levels—thus falling short of the context of high-quality development [106]. In addition, the "soft settings" such as urban planning, local policies, and park management systems have an impact on changes over the whole life cycles of land supply, planning, development, construction, management, use, renovation, and renewal of urban parks. However, due to the lack of reasonable representing variables, they were not included in the analytical model [107,108].

6. Conclusions

With the advent of the era of ecological civilization, the construction of eco-cities, livable cities, and park cities has called on governments and scholars around the world to further increase their attention on urban parks. The matching of land supply and population demand for urban parks is related to residents' proximity to nature and access to leisure and recreation, and also determines the efficiency and fairness of the government's allocation of land resources. This paper is an analysis of the characteristics of urban-parkland supply and population demand in 102 cities in Hunan using the spatial mismatch model and the geographically weighted regression method. It measures the supply–demand matching between the two and reveals the dynamic mechanism that affects the matching between supply and demand. The main conclusions of this study are as follows.

Land supply and population demand for urban parks in Hunan are characterized by significant spatial heterogeneity and correlation, and the mismatch between supply and demand should not be ignored, with oversupply and undersupply co-existing. It should be noted that, with the rise in the construction of park cities, the increasingly serious oversupply results in sloppy and wasteful use of land resources. Therefore, when allocating future land resources and targets for urban parks, higher-level governments should develop differentiated allocation plans according to local conditions. They should also attach importance to regional integration and coordination, and support cooperation between lower-level governments.

The influence of each factor on the spatial mismatch-contribution rate index is much larger than that of the urban-parkland supply, and different factors vary considerably in their nature and intensity, with a complex dynamical mechanism. From the nature of factor effects, population aging and economic development played a negative role; population outflow, financial capacity, and air quality played a positive role; while natural environment played both positive and negative roles. From the intensity of the factors, financial capacity, air quality, and economic development acted as key factors, while population aging, population outflow, and natural environment acted as auxiliary factors. As for the spatial pattern of influence, population outflow and air quality were gradient, while financial capacity and natural environment were circular. Population aging and economic development showed a gradient influence on urban-parkland supply, and a circular influence on the spatial mismatch-contribution rate index.

In general, it is becoming a new trend in the green and high-quality development of cities around the world to face up to the human–land conflict in urban parks, drive the construction of urban parks in an orderly manner in accordance with the idea of "people-centered and land-based", and build up park cities to enhance the livability and sustainability of cities. On the basis of this research on the "quantitative" supply–demand relationship between land supply and population demand in urban parks, we call for more efforts from scholars and to work together on the "qualitative" supply–demand contradiction and its solution.

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Appendix A

Table A1. (Standardized) Data on the spatial mismatch analysis of urban-parkland supply and population demand in Hunan province.

NO.	Cities	UPL_i	PD_i	CRI_i	X_1	X_2	X_3	X_4	X_5	X_6
1	Changsha	1.00	1.00	6.97	0.14	0.96	0.90	1.00	0.02	0.91
2	Ningxiang	0.22	0.09	1.74	0.55	0.31	0.59	0.73	0.10	0.60
3	Liuyang	0.10	0.10	0.94	0.40	0.39	0.75	0.83	0.23	0.40
4	Changshaxian	0.19	0.12	0.42	0.00	1.00	1.00	0.87	0.04	0.70
5	Wangcheng	0.12	0.08	0.15	0.10	0.96	0.70	0.90	0.02	0.89
6	Zhuzhou	0.20	0.33	4.83	0.47	0.73	0.52	0.56	0.03	0.72
7	Liling	0.09	0.06	0.13	0.59	0.14	0.55	0.49	0.09	0.57
8	You	0.03	0.04	0.50	0.76	0.12	0.40	0.34	0.21	0.45
9	Chaling	0.15	0.03	2.13	0.46	0.05	0.22	0.18	0.29	0.38
10	Yanling	0.04	0.01	0.45	0.62	0.24	0.30	0.19	0.83	0.08
11	Xiangtan	0.28	0.21	0.12	0.61	0.59	0.58	0.50	0.02	0.89
12	Xiangxiang	0.04	0.04	0.27	0.76	0.12	0.42	0.30	0.08	0.62
13	Shaoshan	0.03	0.00	0.50	0.68	0.65	0.64	0.45	0.06	0.70
14	Xiangtanxian	0.09	0.04	0.60	0.78	0.22	0.38	0.34	0.04	0.78
15	Hengyang	0.35	0.43	4.70	0.48	0.45	0.28	0.36	0.03	0.82
16	Leiyang	0.15	0.06	1.15	0.37	0.03	0.13	0.27	0.08	0.53
17	Changning	0.10	0.04	0.70	0.37	0.01	0.21	0.20	0.17	0.62
18	Hengyangxian	0.04	0.04	0.38	0.60	0.19	0.17	0.16	0.11	0.61
19	Hengnan	0.03	0.04	0.56	0.58	0.21	0.21	0.19	0.05	0.66
20	Hengshan	0.07	0.01	0.82	0.67	0.29	0.27	0.32	0.11	0.63
21	Hengdong	0.12	0.02	1.68	0.62	0.10	0.27	0.19	0.07	0.63
22	Qidong	0.13	0.03	1.55	0.65	0.11	0.17	0.16	0.12	0.60
23	Nanyue	0.02	0.00	0.22	0.24	0.90	0.45	0.52	0.68	0.57
24	Shaoyang	0.31	0.41	4.81	0.52	0.29	0.12	0.18	0.13	0.75
25	Wugang	0.14	0.03	1.67	0.56	0.10	0.05	0.12	0.29	0.59
26	Shaodong	0.05	0.07	0.92	0.54	0.18	0.34	0.29	0.15	0.56
27	Xinshao	0.02	0.03	0.47	0.56	0.22	0.05	0.14	0.43	0.55
28	Shaoyangxian	0.06	0.04	0.16	0.61	0.28	0.03	0.05	0.21	0.61
29	Longhui	0.03	0.05	0.66	0.46	0.10	0.02	0.12	0.47	0.46

Table A1. *Cont.*

NO.	Cities	UPL_i	PD_i	CRI_i	X_1	X_2	X_3	X_4	X_5	X_6
30	Dongkou	0.08	0.04	0.47	0.70	0.23	0.07	0.10	0.51	0.44
31	Suining	0.04	0.01	0.38	0.55	0.10	0.12	0.00	0.60	0.27
32	Xinning	0.11	0.02	1.47	0.55	0.11	0.02	0.09	0.59	0.49
33	Chengbu	0.02	0.01	0.06	0.39	0.15	0.04	0.05	0.94	0.23
34	Yueyang	0.39	0.37	2.18	0.49	0.53	0.51	0.33	0.01	0.83
35	Miluo	0.05	0.03	0.17	0.64	0.36	0.54	0.24	0.06	0.75
36	Linxiang	0.10	0.03	1.07	0.49	0.17	0.44	0.18	0.10	0.57
37	Yueyangxian	0.05	0.03	0.11	0.59	0.49	0.39	0.15	0.05	0.68
38	Huarong	0.08	0.03	0.54	0.72	0.16	0.38	0.10	0.01	0.93
39	Xiangyin	0.06	0.03	0.14	0.64	0.32	0.33	0.54	0.01	0.90
40	Pingjiang	0.15	0.06	1.34	0.47	0.17	0.13	0.15	0.23	0.41
41	Changde	0.33	0.35	2.91	0.83	0.47	0.44	0.37	0.02	0.83
42	Jin	0.06	0.01	0.75	0.99	0.33	0.57	0.21	0.01	0.87
43	Anxiang	0.11	0.02	1.61	1.00	0.38	0.28	0.07	0.00	1.00
44	Hanshou	0.02	0.04	0.74	0.66	0.23	0.22	0.16	0.01	0.80
45	Li	0.03	0.05	0.84	1.00	0.18	0.29	0.22	0.04	0.83
46	Linli	0.03	0.02	0.07	0.94	0.32	0.30	0.15	0.03	0.82
47	Taoyuan	0.04	0.04	0.28	0.96	0.20	0.29	0.21	0.14	0.47
48	Shimen	0.19	0.03	2.86	0.94	0.24	0.31	0.19	0.55	0.36
49	Zhangjiajie	0.10	0.09	0.54	0.60	0.30	0.14	0.16	0.65	0.19
50	Cili	0.07	0.03	0.58	0.90	0.15	0.11	0.13	0.44	0.38
51	Sangzhi	0.03	0.01	0.12	0.63	0.06	0.06	0.04	0.78	0.17
52	Yiyang	0.29	0.23	0.57	0.66	0.36	0.24	0.22	0.02	0.77
53	Yuanjiang	0.08	0.03	0.66	0.69	0.19	0.23	0.11	0.00	0.90
54	Nan	0.06	0.03	0.36	0.79	0.19	0.24	0.11	0.00	1.00
55	Taojiang	0.00	0.04	1.02	0.72	0.24	0.18	0.16	0.11	0.45
56	Anhua	0.03	0.03	0.27	0.65	0.26	0.09	0.11	0.37	0.27
57	Chenzhou	0.37	0.33	1.48	0.31	0.34	0.29	0.38	0.49	0.35
58	Zixing	0.03	0.02	0.11	0.63	0.14	0.71	0.48	0.62	0.19
59	Datonghu	0.01	0.00	0.10	0.80	0.95	0.23	0.11	0.01	0.77
60	Guiyang	0.07	0.04	0.21	0.31	0.00	0.29	0.34	0.28	0.44
61	Yizhang	0.08	0.03	0.59	0.21	0.13	0.16	0.25	0.46	0.32
62	Yongxing	0.05	0.03	0.05	0.39	0.02	0.34	0.45	0.18	0.37
63	Jiahe	0.06	0.02	0.60	0.28	0.34	0.19	0.34	0.16	0.55
64	Linwu	0.08	0.02	0.99	0.25	0.02	0.21	0.33	0.48	0.40
65	Rucheng	0.05	0.02	0.39	0.37	0.07	0.06	0.12	0.66	0.07
66	Guidong	0.02	0.00	0.21	0.45	0.14	0.07	0.11	1.00	0.00
67	Anren	0.05	0.02	0.40	0.45	0.05	0.11	0.12	0.18	0.43
68	Yongzhou	0.20	0.30	3.92	0.45	0.21	0.17	0.30	0.18	0.67
69	Qiyang	0.10	0.03	1.02	0.65	0.18	0.19	0.32	0.23	0.60
70	Dong'an	0.08	0.02	0.88	0.64	0.14	0.16	0.29	0.32	0.59
71	Shuangpai	0.02	0.00	0.22	0.41	0.27	0.26	0.27	0.52	0.43
72	Dao	0.08	0.03	0.67	0.35	0.02	0.14	0.27	0.42	0.52
73	Jiangyong	0.07	0.01	1.06	0.40	0.32	0.13	0.19	0.49	0.41
74	Ningyuan	0.17	0.04	2.14	0.44	0.08	0.12	0.31	0.40	0.44
75	Lanshan	0.07	0.02	0.76	0.38	0.12	0.16	0.23	0.54	0.37
76	Xintian	0.05	0.02	0.41	0.38	0.06	0.07	0.17	0.20	0.47
77	Jianghua	0.05	0.02	0.52	0.32	0.22	0.09	0.20	0.63	0.34
78	Huaihua	0.20	0.26	2.97	0.55	0.49	0.14	0.23	0.20	0.33
79	Hongjiang	0.06	0.01	0.80	0.89	0.25	0.14	0.20	0.43	0.29
80	Zhongfang	0.05	0.01	0.59	0.58	0.69	0.29	0.22	0.36	0.31
81	Yuanling	0.06	0.02	0.53	0.72	0.16	0.13	0.20	0.30	0.20
82	Chenxi	0.06	0.02	0.67	0.67	0.06	0.08	0.13	0.27	0.30
83	Xupu	0.09	0.02	1.11	0.63	0.16	0.04	0.08	0.53	0.24
84	Huitong	0.01	0.01	0.12	0.60	0.14	0.09	0.12	0.26	0.30
85	Mayang	0.08	0.01	1.14	0.61	0.12	0.08	0.09	0.21	0.25
86	Xinhuang	0.03	0.01	0.30	0.63	0.39	0.11	0.16	0.36	0.18
87	Zhijiang	0.02	0.01	0.04	0.69	0.16	0.12	0.19	0.25	0.24

Table A1. *Cont.*

NO.	Cities	UPL_i	PD_i	CRI_i	X_1	X_2	X_3	X_4	X_5	X_6
88	Tongdao	0.06	0.01	0.85	0.40	0.21	0.15	0.11	0.40	0.26
89	Jingzhou	0.05	0.01	0.64	0.46	0.10	0.07	0.09	0.34	0.28
90	Loudi	0.19	0.21	2.06	0.42	0.40	0.21	0.28	0.11	0.52
91	Lengshuijiang	0.09	0.03	1.04	0.36	0.44	0.46	0.35	0.26	0.57
92	Lianyuan	0.06	0.04	0.13	0.57	0.18	0.13	0.10	0.22	0.46
93	Shuangfeng	0.03	0.03	0.18	0.63	0.06	0.16	0.12	0.10	0.59
94	Xinhua	0.12	0.04	1.18	0.38	0.12	0.03	0.13	0.43	0.40
95	Jishou	0.04	0.15	3.20	0.40	0.42	0.08	0.19	0.25	0.15
96	Luxi	0.01	0.01	0.04	0.54	0.13	0.09	0.08	0.18	0.20
97	Fenghuang	0.05	0.01	0.46	0.39	0.27	0.04	0.18	0.31	0.15
98	Huayuan	0.02	0.01	0.05	0.36	0.76	0.09	0.13	0.44	0.17
99	Baojing	0.00	0.01	0.28	0.57	0.17	0.10	0.03	0.48	0.15
100	Guzhang	0.04	0.00	0.61	0.57	0.28	0.07	0.09	0.43	0.08
101	Yongshun	0.12	0.02	1.74	0.45	0.05	0.01	0.06	0.47	0.11
102	Longshan	0.05	0.02	0.22	0.41	0.10	0.00	0.09	0.65	0.17

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