

Research on the Spatial-Temporal Evolution of Urban Green Spaces in Jiangxi Province and Its Influencing Factors from the Perspective of Artificial Intelligence

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Abstract. The total area of urban garden green spaces and the per capita area of park green spaces in Jiangxi Province have maintained a steady growth. Based on the data from 2020 to 2025, this paper adopts artificial intelligence tools to analyze the evolution characteristics of garden green space area in Jiangxi Province. It uses the Pearson correlation coefficient to explore the key factors affecting the spatial distribution of garden green spaces in the province, with the aim of optimizing urban planning and improving urban livability. Both Pearson correlation analysis and the CatBoost model demonstrate that ecological factors have an extremely significant positive correlation with green space area and carry the highest importance weight, followed by cultural factors with a significant positive correlation. Economic factors related to forestry show a moderate positive correlation, while population factors have the weakest correlation. The research results indicate that ecological protection and greening construction act as the core driving forces. Cultural factors and forestry economy provide important support, and population factors make limited contributions.

Keywords: garden green space, artificial intelligence, influencing factor, Pearson correlation coefficient

1. Introduction

As an essential part of urban ecosystems, urban green spaces perform multiple ecological functions including climate regulation [1], air purification [2] and provision of biological habitats [3]. They serve as a core indicator for evaluating the quality of residents' living environments. The 13th Five-Year Plan for the Planning and Construction of National Urban Municipal Infrastructure clearly sets forth tasks such as expanding the scale and improving the quality of garden green spaces, and building green and livable spaces in urban and rural areas. Subsequently, the 13th Five-Year Plan for Addressing Climate Change of Jiangxi Province put forward local approaches to optimize the urban green space system and improve the balanced distribution of public green spaces. All of these reflect the strategic importance of green spaces in the construction of a beautiful China. Scientific and accurate analysis on the evolution characteristics of urban green space areas is of great significance for optimizing the spatial layout of green spaces [4] and improving the efficiency of urban

ecological environment governance [5]. The location planning of Jiangxi Province is shown in Figure 1.

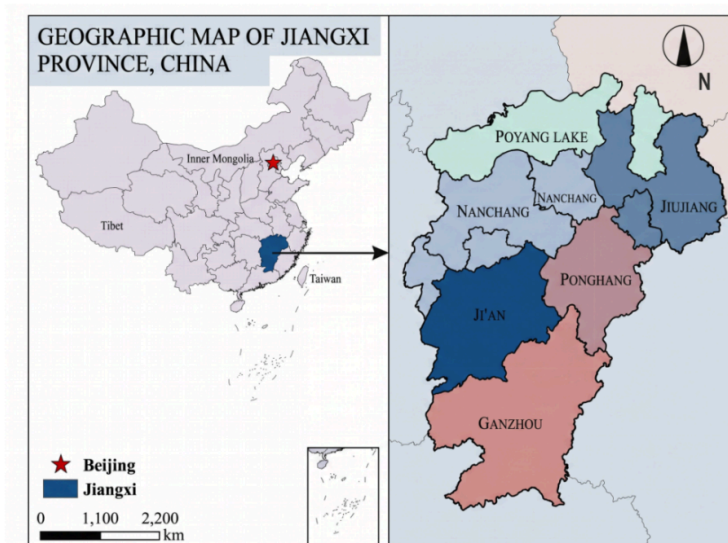


Figure 1. Location planning map of Jiangxi Province

In previous studies on garden green spaces, scholars mainly classified influencing factors into three categories. The first is physical and geographical factors [6], such as elevation, slope and distance to water systems. The second refers to socio-economic factors, including population density, GDP density, road network density and distance to urban centers. The third is policy and planning factors, covering land use types, delineation of ecological red lines and urban development plans. These factors explain the driving mechanisms behind the spatial distribution and area changes of garden green spaces from various perspectives. Meanwhile, machine learning, a core technology in the field of artificial intelligence, boasts powerful capabilities in data processing and pattern recognition. It can deeply explore potential rules hidden in data and provide more accurate and comprehensive support for the processing of multi-source urban data [6].

Numerous studies have been conducted on the changes of green spaces. For instance, Zhao Haixia and other researchers adopted spatial analysis methods to reveal the changing characteristics and evolution mechanisms of green space landscape patterns in Nanjing from 2000 to 2015 [7]. When analyzing the factors influencing the evolution of regional green space patterns, Liu Wei and his colleagues applied the geographically weighted regression model to discuss the impacts of various factors on regional green space patterns.

Nevertheless, green space data in practical research often suffers from missing or incomplete records, which undermines the accuracy of analytical results [8]. In addition, existing methods have certain limitations in reflecting the complexity of land demand and ecological protection under multiple scenarios, as well as capturing subtle ecological changes.

Against this background, this paper proposes an analytical method for the evolution characteristics of urban green space areas based on the Pearson correlation coefficient and the CatBoost model, so as to give full play to the combined advantages of statistical analysis and machine learning [9]. Statistical data of urban garden green spaces and relevant indicators of influencing factors are collected to build an analytical database. The framework for selecting indicators of factors affecting garden green spaces in Jiangxi Province is presented in Figure 2. On

this basis, the Pearson correlation coefficient is used to screen key influencing factors. The CatBoost model is adopted to conduct modeling and analysis on historical data, so as to identify the variation rules of green space areas and the weight of driving factors. This study aims to provide scientific basis and decision-making support for the planning and management of urban green spaces. Taking Jiangxi Province as the research area, this paper explores the spatial-temporal evolution characteristics and influencing factors of its garden green spaces, and offers references for the optimization of regional ecological spaces and sustainable development. The indicator selection system for factors affecting garden green spaces in Jiangxi Province from the perspective of artificial intelligence is shown in Table 1 [10].

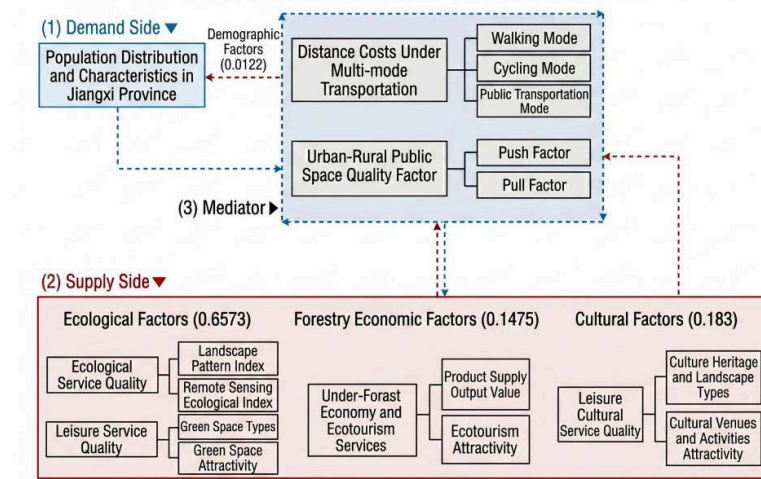


Figure 2. Framework for selecting indicators of factors affecting garden green spaces in Jiangxi Province

Table 1. Indicator selection system for factors affecting garden green spaces in Jiangxi Province from the perspective of artificial intelligence

Primary Indicator	Secondary Indicator	Data Availability Score (ej)	Degree of Feature Variability (Dj)	Preliminary Weight Calculated by AI (Wj)
Population factor (0.0122)	Number of natural villages (villager groups)	0.993	0.006	0.0122
Population factor (0.0122)	Population size	0.999	0.000	0.0122
Population factor (0.0122)	Total number of rural households	0.992	0.007	0.0122
Ecological factor (0.6573)	Number of ancient and famous trees	0.628	0.371	0.6573
Ecological factor (0.6573)	Forest coverage rate of the village	0.993	0.006	0.6573
Ecological factor (0.6573)	Number of village landscape green belts or landmark green spaces	0.911	0.088	0.6573
Ecological factor (0.6573)	Proportion of households with courtyard greening	0.988	0.011	0.6573

Table 1. (continued)

Ecological factor (0.6573)	Number of rural park green spaces	0.877	0.122	0.105 5
Ecological factor (0.6573)	Proportion of mixed forests in the village	0.985	0.014	0.012 5
Ecological factor (0.6573)	Number of main afforestation and greening tree species	0.859	0.140	0.121 3
Ecological factor (0.6573)	Proportion of native tree species	0.992	0.007	0.006 3
Forestry-related economic factors (0.1475)	Proportion of farmers' average annual income from forest-related industries	0.977	0.023	0.1475
Forestry-related economic factors (0.1475)	Number of employed people engaged in forest-related industries in the village	0.851	0.148	0.1475
Cultural factor (0.1830)	Number of deeds of rural celebrities and famous hometowns	0.787	0.212	0.1830

2. Spatio-temporal evolution analysis of urban green spaces in Jiangxi Province

2.1. Data collection

The data adopted in this study are mainly derived from three sources. First, general surveys and statistical documents on urban green spaces in Jiangxi Province, including indicators such as green space area, green coverage rate and per capita green space area recorded in Urban Construction Statistical Yearbook and Landscaping Annual Report of Jiangxi Province and its cities and counties from 2020 to 2025. Second, basic geographic information data, including the 1:100,000 topographic map, administrative division map, water system distribution map, road network map, and green space classification map extracted from the overall urban planning map of Jiangxi Province. Third, socio-economic data including population density and GDP density, which are collected from Jiangxi Statistical Yearbook and statistical communiqués of all districts and counties. Data preprocessing is completed on the ArcGIS 10.8 platform, and a spatial database for urban green spaces in Jiangxi Province is established. Information including the area, type, affiliated administrative region and construction year of each green space is entered into the attribute table, realizing the spatialization and integrated management of green space data [11].

2.2. Time series analysis method for urban green spaces

Based on the statistical data of urban green spaces in Jiangxi Province from 2020 to 2025 and the GIS database, the land use dynamic degree model is applied to quantitatively describe the changing rate of green space area. The calculation formula for the dynamic degree of a single land use type (ξ) is as follows:

$$\xi = \frac{S_b - S_a}{S_a} \times \frac{1}{T} \times 100\% \quad (1)$$

In the formula, S_a and S_b represent the total area of a certain type of green space at the start and end of the research period respectively, and T refers to the length of the research period in years. A

positive value indicates an increase in area, while a negative value indicates a decrease.

Excel 2021 is used for data sorting, and Origin 2021 is adopted to draw the line chart of area changes (Figure 3), bar chart of dynamic degree comparison, as well as trend charts of information entropy and equilibrium degree, so as to analyze the rules of time series evolution.

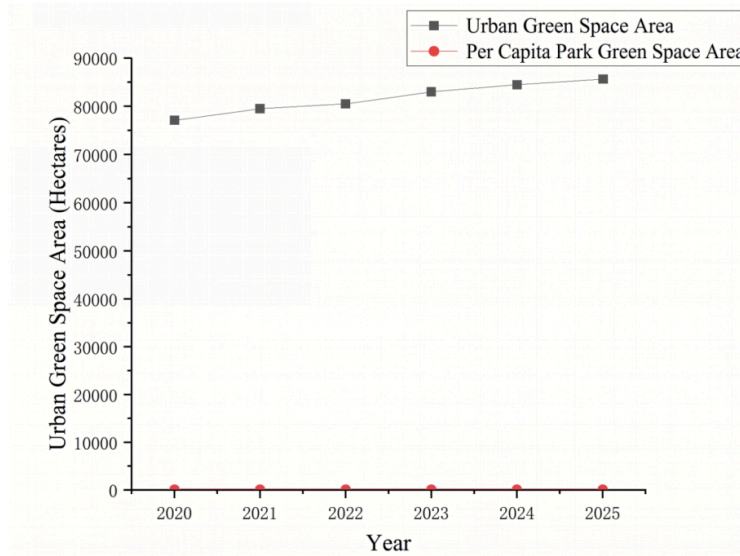


Figure 3. Framework for selecting indicators of factors affecting garden green spaces in Jiangxi Province

2.3. Correlation analysis of influencing factors — Pearson correlation coefficient

Eight factors are selected for analysis, namely elevation, slope, distance to water systems, distance to urban centers, population density, GDP density, road network density and green space type. A total of 1500 sample points are randomly generated in ArcGIS, and the factor values of each point as well as the green space rate of the corresponding grid are extracted [12]. The formula of Pearson correlation coefficient is shown below:

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (2)$$

SPSS 26.0 is used to calculate the correlation coefficient and conduct two-tailed significance test, where $p < 0.05$ is defined as statistically significant. The multicollinearity among factors is also analyzed. Origin 2021 is used to plot the correlation heat map.

2.4. Weight analysis of influencing factors based on CatBoost

(1) Construction of CatBoost model. With Python 3.9 and the CatBoost library, 1500 sample points are taken as research objects. The green space rate is set as the target variable, and the eight selected factors are taken as input features, among which green space type is categorized as a categorical feature.

(2) Calculation of feature importance. The PredictionValuesChange index is adopted to measure the increment of model prediction error when features are shuffled randomly. The formula is as

follows:

$$\text{Importance}_j = \frac{1}{N} \sum_{t=1}^N \Delta \text{Loss}_t^{(j)} \quad (3)$$

In the formula, N stands for the number of decision trees, and $\{\text{Loss}\}_t^{\{(j)\}}$ represents the variation of the loss function after feature j is disturbed in the t-th tree.

(3) Analysis of weight changes in different periods. CatBoost models are trained respectively with 1500 sample points of the year 2013 and 2023, and the corresponding PredictionValuesChange values of the two periods are calculated. In the early stage, elevation and distance to urban centers act as the leading factors. In the later stage, the weights of population density, road network density and green space type rise remarkably, which reflects the driving effect of urbanization.

2.5. Spatio-temporal analysis of urban green spaces in Jiangxi Province

(1) Time Series Change Analysis

Based on the urban topographic maps, green space planning data and Urban Construction Statistical Yearbook of Jiangxi Province from 2020 to 2025, GIS technology is applied to build the green space database of the province. By extracting the green space area of each period and the total volume data from statistical documents, the land use dynamic degree, annual change rate and cumulative change volume are calculated to quantitatively describe the growth and decline trend, changing speed and range of different types of green spaces.

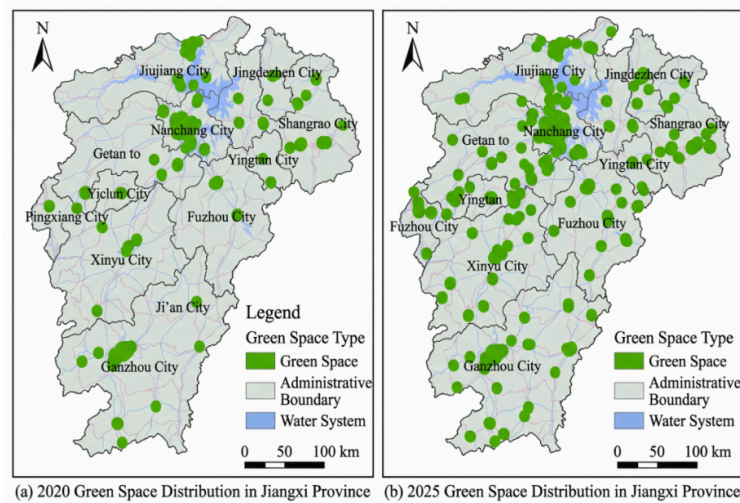


Figure 4. Spatial distribution map of urban green spaces in Jiangxi Province from 2020 to 2025

The analysis results show that the total area of urban green spaces in Jiangxi Province increased continuously from 77149 hectares to 85651 hectares between 2020 and 2025, with a net increase of 8502 hectares and an average annual growth rate of approximately 2.11%. The per capita area of park green spaces rose from 14.53 square meters to 18.59 square meters, with an average annual growth rate of 5.06%. Both indicators maintained a steady growth trend, as shown in Figure 4. The calculation of structural information entropy and equilibrium degree reveals that the structural information entropy of urban green spaces in Jiangxi Province decreased from 1.85 to 1.54, while the equilibrium degree remained above 0.80 all the time. It indicates that the proportion of various green space types has become more coordinated, and the overall development is in a sound state.

Nevertheless, several problems still exist. The connection between newly built green spaces and existing road networks is insufficient, and green spaces in some new urban areas are distributed in isolated patches with poor connectivity. Restricted by land use quotas, the construction of miniature gardens covering an area below 0.5 hectares lags behind, and the progress of creating green spaces by demolishing illegal buildings in old urban areas is hindered. There are obvious regional disparities in funds for green space maintenance, and the compliance rate of green space maintenance in a few counties is less than 60%.

Combined with GIS spatial overlay analysis and kernel density estimation, the green space rates are calculated through grid sampling by comparing the green space distribution maps of 2020 and 2025, and local spatial autocorrelation is used to identify cold spots and hot spots. The results present that the urban green spaces in Jiangxi Province follow a pattern of central agglomeration and marginal dispersion. Hot spots are mainly distributed in Nanchang, Jiujiang and areas along the Ganjiang River, while cold spots are mostly located in remote counties. Over the years, high-value areas of green spaces have evolved from a single center to multiple centers, and the expansion of new urban areas is prominent. However, the growth of green spaces in some old urban areas is slow, forming internal low-value zones [13].

3. Analysis on influencing factors of spatial distribution of urban green spaces in Jiangxi Province from the perspective of artificial intelligence

3.1. Collinearity analysis of influencing factors

Selection of influencing factors: Taking physical geography, socio-economic conditions and policy planning into comprehensive consideration, four potential influencing factors are initially selected, namely ecological factors, cultural factors, forestry-related economic factors and population factors. The correlation analysis results are shown in Figure 5 [14-17].

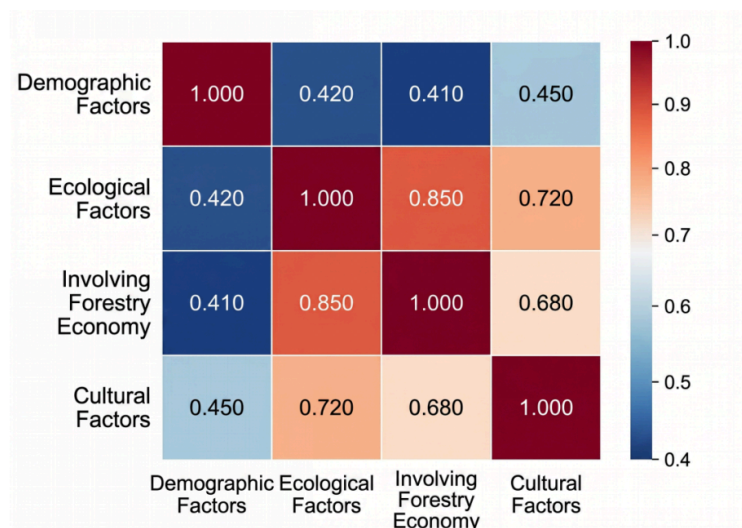


Figure 5. Correlation analysis diagram of influencing factors of urban green spaces in Jiangxi Province from 2020 to 2025

After collinearity processing, the CatBoost artificial intelligence algorithm is adopted. The urban green space rate is set as the target variable, and the screened influencing factors are taken as input

features to train the regression prediction model. Five-fold cross validation is applied to evaluate model accuracy, with the coefficient of determination R^2 reaching 0.94.

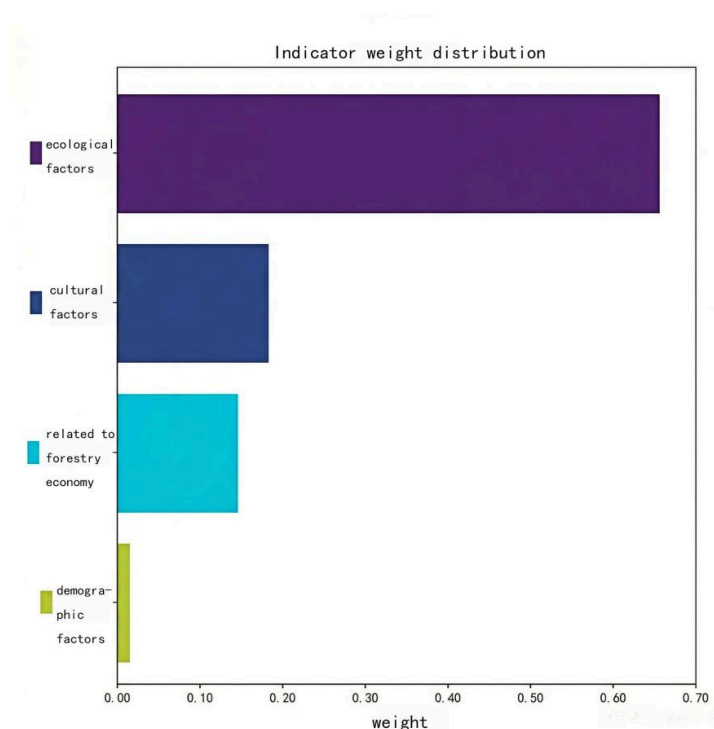


Figure 6. Weight diagram of influencing factors of urban green spaces in Jiangxi Province from the perspective of artificial intelligence

By comparing the weight changes between 2020 and 2025, the temporal and spatial shift of major influencing factors can be identified. In the early stage, elevation and distance to urban centers played leading roles. In the later stage, the weights of population density, road network density and ecological red line policies increased significantly, indicating that urbanization and policy orientation drive the spatial distribution of urban green spaces. The weights of relevant influencing factors are presented in Figure 6. According to the current weight values (ecology 0.657 > culture 0.183 > economy 0.148 > population 0.012), the dominant factors of urban green spaces in Jiangxi Province have shifted from elevation and distance to urban centers in the early stage to the dual driving force of ecology and culture. Ecological red line policies and rural revitalization policies have produced remarkable effects [18]. In the future, efforts should be focused on refined improvement of ecological quality and digital development of cultural heritage. Attention shall be paid to carbon sequestration capacity, green space connectivity and climate-adaptive tree species, so as to realize the transformation from quantity expansion to high-quality maintenance integrating ecology and culture.

3.2. Result analysis

From 2020 to 2025, the total area of urban green spaces in Jiangxi Province achieved an average annual growth rate of 2.11%, and the per capita park green space area grew at an average annual rate of 5.06%. The growth rate of per capita indicators was obviously higher than that of the total volume, showing a sound development trend. The spatial pattern maintained a structure of circular

layers and corridors, and continuous ecological corridors have taken shape around Poyang Lake [19]. Among all driving factors, ecological factors have an extremely significant correlation with green space area with a weight of 0.657, followed by cultural factors with a significant correlation and a weight of 0.183. Forestry-related economic factors show a moderate correlation with a weight of 0.148, while population factors exert only a slight influence. The results prove that ecological protection acts as the core driving force, and culture as well as forestry economy provide important support. It is expected that subsequent studies will conduct spatial heterogeneity analysis across more provinces and cities, adopt longer time spans, incorporate dynamic socio-economic variables and diverse elements, carry out multi-scenario simulation and prediction, focus on service efficiency evaluation, and improve the operational procedures of green space occupation and compensation balance [20].

4. Conclusions

The urban green spaces in Jiangxi Province are characterized by continuous quantity growth, improved per capita indicators and stable spatial pattern. Ecological factors play a leading role, while cultural factors and forestry-related economic factors provide supporting and auxiliary effects in sequence. These three types of factors interact and couple with each other, and population factors have limited impacts. In follow-up work, protection of various types of green spaces shall be strengthened to prevent arbitrary occupation. Since the per capita park green space area still has room for improvement with the target set at no less than 20 square meters, priority should be given to building community parks and pocket parks in underdeveloped counties and districts to promote the dual optimization of total volume and internal structure.

This study provides quantitative reference for the urban green space planning of Jiangxi Province during the 15th Five-Year Plan period. It is suggested that the local government continue to adhere to the ecology-first strategy, tap the potential of regional culture and forestry economy, strive to lift the per capita park green space area above 20 square meters, and build a better living environment for residents.

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