

# Space Accessibility and Equity of Urban Green Space

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**Abstract:** Urban green space is an essential form of infrastructure for cities, providing a significant spatial guarantee for sustainable urban development, an essential ecological, social, and cultural function, and an important symbol of urban modernisation and civilisation. However, with the development of cities, urban problems are becoming more serious, such as the increase in impervious surfaces and urban heat islands and the decrease in urban green space and liveability. Therefore, this study integrates the theories and methods of landscape ecology and spatial syntax with GIS technology to construct a comprehensive model for examining the spatial accessibility of green spaces based on remote images and landscape pattern indices, using Fuzhou City as the study area. The study then incorporates demographic variables to explore the characteristics of an equitable distribution of urban green space at the street scale. The results show that the accessibility of green space in the urban areas of Fuzhou decreases from the centre to the periphery. From north to south, there is a trend of ‘low-high-low’, with the northern region exhibiting the lowest accessibility, followed by the southeastern region, and then the western region. In terms of spatial equity in green space, Fuzhou has a more significant share of surplus green space provision, both in terms of the number of streets and area. This shows that the surplus of green space in Fuzhou is greater than the deficit and that the distribution of space is fair. We hope this study will not only help people gain a deeper understanding of green space but also provide a reference for their rational planning and management, thereby improving the accessibility and equity of urban green space as well as their quality and configuration. We also expect it to provide valuable theoretical and technical support for the planning of ecological functions and sustainable development.

**Keywords:** green space; accessibility; equity; landscape pattern; remote sensing



**Citation:** Huang, B.-X.; Li, W.-Y.; Ma, W.-J.; Xiao, H. Space Accessibility and Equity of Urban Green Space. *Land* **2023**, *12*, 766. <https://doi.org/10.3390/land12040766>

Academic Editor: Michelangelo Savino

Received: 23 February 2023

Revised: 25 March 2023

Accepted: 27 March 2023

Published: 28 March 2023



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## 1. Introduction

Urban green space is open space in cities used as parks or other green spaces [1] and defined by the World Health Organization as ‘urban land with any vegetation cover’ [2], which may be accompanied by artificial features such as playgrounds, blue spaces (water), or natural landscapes [3]. Urban green spaces are sometimes used as private or institutional land for university campuses, community gardens, etc., but are generally open to the public. State parks and national parks located outside urban areas do not belong to urban green spaces. The concept of “rus in urbe” (country in the city), which refers to the integration of green spaces into urban planning, dates back to ancient Rome in the first century [4,5]. Modern urban green spaces can be traced back to the urban squares of London in the 17th and 18th centuries [6]. Urban green spaces can reduce surface runoff and the heat island effect [7], reduce air pollution, and positively impact the physiological and psychological well-being of residents in surrounding communities [8,9]. Urban green space guarantees human survival and ecological balance and allows urban residents to enjoy the services of

their natural ecosystems. Historically, neighborhoods dominated by disadvantaged groups have tended to lack green spaces, due to policies (such as the redlining policy in past US housing policies) and economic inequalities [10]. In recent years, green space planning has begun to emphasize environmental justice and community participation [11]. Clearing pollution and adding green spaces can increase the value of surrounding homes, known as environmental gentrification [12], but this process may also have negative impacts by forcing disadvantaged groups to relocate due to being unable to afford the rising housing prices [13,14]. Among the seventeen Sustainable Development Goals designated by the United Nations [15], goals eight, nine, and eleven refer to “promoting inclusive and sustainable economic growth, a good job for everyone, resilient infrastructure, and inclusive and sustainable cities and human settlements”. Sustainable development, however, can only be achieved if cities provide ecosystem services through ‘green public space’ and coexist in ecological harmony. Furthermore, Section 11.7 states that “by 2030, the provision of safe, inclusive, and accessible green and public space should be universal, especially for women, children, the elderly and people with disabilities”. The World Health Organization’s Healthy Cities Programme, launched in 1986, includes green coverage and green space accessibility among the 32 quantifiable indicators developed in collaboration with European metropolises to assess the effectiveness of promoting healthy cities [2,16]. With the intensification of urban environmental problems, improving the urban environment by introducing green space has become an effective and standard measure [17,18]. However, the distribution of urban green space is often uneven because of design concepts, historical reasons, and other factors [19,20]. Numerous studies have confirmed the importance of urban green space for the health of residents. Chen (2017) analysed 42 urban green space studies, and they concluded that urban green space affects the health of urban residents by improving environmental conditions (air quality, noise, and visual aesthetics), promoting outdoor activities (fitness and social activities), and enhancing social cohesion (neighbourhood satisfaction, sense of security, and sense of belonging or psychological well-being). Studies have also shown that the more parks and green spaces near homes and the more frequently people use them, the better their self-rated health status [21].

The concept of accessibility first emerged in the transportation field. Hansen [22] proposed that accessibility refers to the ease of travel from an origin to a destination using a specific mode of transportation. Accessibility has been studied and applied in various fields, such as behavioral research, resource allocation, and economics. It has also been introduced to urban planning, geographic information systems, and public administration disciplines. There is no accepted definition of accessibility, as scholars have defined the concept using various research fields and perspectives. Some scholars believe that accessibility is the cost individuals incur when participating in social activities, such as traffic congestion and environmental pollution. Others perceive accessibility as the expected quantity of arriving at a destination for activities such as leisure, consumption, and exercise, explaining the relationship between land use and the ease or difficulty of reaching a destination. Other scholars define accessibility as the degree of difficulty in reaching a particular land use in a city. Kongjian Yu [23] believes that accessibility is the relative ease of reaching a landscape destination from a spatial point and uses indicators such as time, distance, and cost to calculate this. Accessibility of green space refers to the ease of reaching a park or green space from a residential area by overcoming spatial barriers while considering the cost, time, and distance of transportation. Mullick argues that the progressively increasing numbers of elderly and disabled people place an increased demand on the accessibility of green space in the U.S. The article argues for several important aspects related to equitable access and the impact of human interference on wilderness, highlighting the need for more effective government policies to maintain the integrity of the natural environment [24]. Oh and Jeong conducted a study on the walkability of streets to urban parks and the suitability of parks with the help of GIS technology, using Seoul as an example [25]. Alexis Comber et al. used the network analysis function of GIS to study green space in the British city of Leicester and concluded that the accessibility of different religious and ethnic groups can

be used as part of the criteria and reference for the provision of green space services by the British government in the future [26].

The concept of equity originated in the western social sciences. It was later applied in urban planning to consider the optimal state of public social services and resource allocation, and this concept has been developed and revised. For example, Kabisch used the Lorenz curve and Gini coefficient to compare the equity of public green space for all residents, immigrants, and adults over 65 years old in Berlin, Germany, and found that the equity of green space for immigrants was the lowest [27]. Jin Y. applied the Lorenz curve to study the equity of green space in terms of quantity but not the equity of green space per capita [28]. The Lorenz curve and Gini coefficient were eventually established as the UN standard to quantify the equity of green space per capita and to judge the equity of green space distribution by the UN standard based on the Gini coefficient of per capita income. Currently, the distinction between the concepts of accessibility and equity is not clear, and evaluations of urban parks and green spaces often focus on accessibility, with less research on equity. Equity in park and green space distribution is a concept derived from accessibility, incorporating the needs of green space users to determine whether the distribution of green space satisfies the needs of residents in a fair manner. It has strong socioeconomic characteristics and is closely related to the spatial distribution and demographic structure of the population. Research on park and green space equity in foreign countries has focused on exploring fairness and justice among different social groups. This study aims to address the limitations of research on green space equity that only considers single social factors, as well as the limited research on green space equity. We develop a supply-demand model of green space accessibility relative to population composition, gender, age, and ethnicity to explore the equity of urban green space distribution.

In recent years, China has experienced rapid socioeconomic development. However, urban problems have also become increasingly severe, with an increase in impervious areas and urban heat islands and a decrease in urban green space and liveability. Urban green space positively impacts the urban environment, can alleviate ecological and environmental problems brought on by urban development, and is a public urban space that cannot be ignored in urban construction. Considering the historical pattern of urban development, high population diversity, and explosive urbanisation rate, the accessibility of green space has also become a vital issue for environmental equity in Chinese cities [29,30]. Especially in recent years, China has proposed the construction of “Beautiful Mainland China, Ecological Cities”, and the liveability of the urban environment has gradually become a topic of concern for government departments, scholars, and the general public.

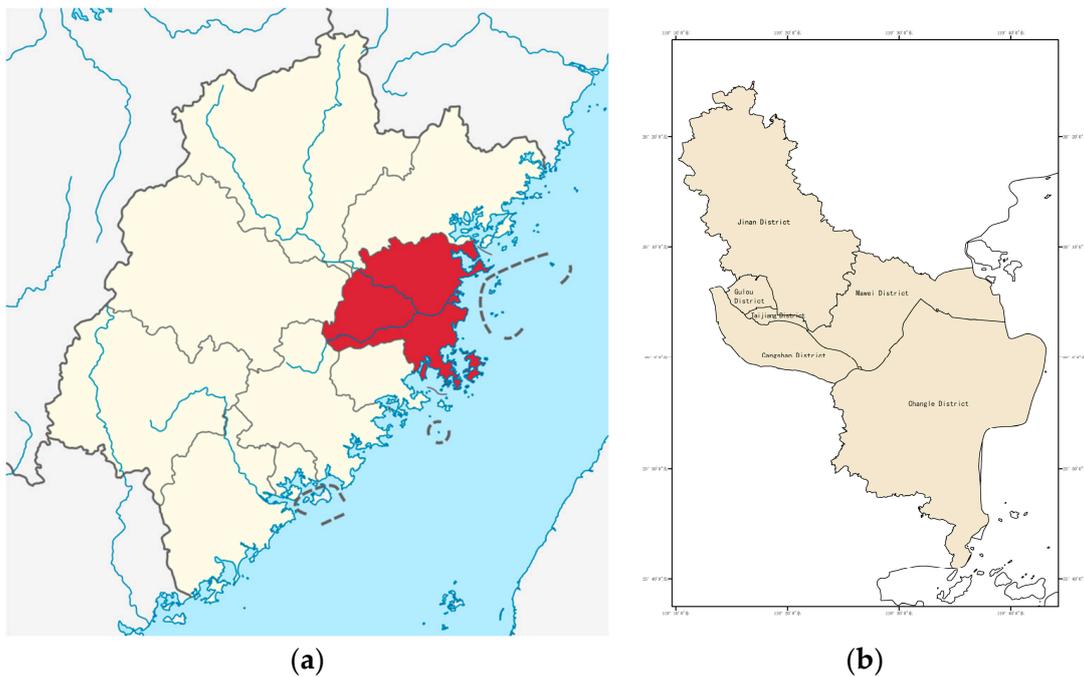
In summary, this study examines the problems of urban green space and people’s demand for green space. By using spatial and statistical analysis, we establish a framework for assessing the equity and accessibility of green space in urban areas and analyse the distribution of accessibility and equity in Fuzhou City, which can be applied to future spatial planning and design.

## 2. Materials and Methods

### 2.1. Study Area

#### 2.1.1. Geographical Location

Fuzhou City is located on the southeast edge of the Eurasian continent, on the south-east coast of China and at the mouth of the Min River in the east-central part of Fujian Province. It is located between latitudes 25°15′ and 26°29′ north and longitudes 118°08′ and 120°31′ east, bordered by Nanping and Sanming to the west, Ningde to the north, Putian to the south, and the East China Sea to the east. In this study, Fuzhou City was chosen as the target, including six districts: Gulou, Taijiang, Cangshan, Jinan, Mawei, and Changle, with 65 streets. The area is 1754.62 km<sup>2</sup>, and the household population is 3,095,000 (Figure 1).



**Figure 1.** Geographic location of Fuzhou City and study area: (a) Fuzhou City location map; (b) Fuzhou City study area.

### 2.1.2. Natural Environment

Fuzhou City is on the southeast edge of the Eurasian continent and faces the Pacific Ocean to the east. It has a typical subtropical monsoon climate. In this city, there have been many meteorological disasters closely related to the construction of green space systems in Fuzhou's urban climate, including typhoons, heavy rain and floods, cold waves, late frosts, and strong convective weather. Fuzhou City is susceptible to typhoons between May and November each year; heavy winds and rain often cause garden trees to fall or break, causing significant damage to the urban green spaces. Fuzhou City has established several protective forest belts in coastal areas; however, effective protective forest belts have not yet been built around the central city. Heavy rain and flooding have greatly damaged the riverside green space on both banks of the Minjiang and Wulong rivers. In addition, landslides associated with typhoons damage suburban forests, and long-term waterlogging can lead to the suffocation and death of some garden trees. Cold waves also threaten tropical and subtropical ornamental trees in Fuzhou's urban green space. Late frosts and strong convective weather can also significantly impact garden plants.

### 2.1.3. Vegetation Status

Fuzhou belongs to two vegetation zones: the South Asian tropical rainforest and the Central Asian subtropical evergreen broad-leaved forest. Influenced by various natural conditions, the vegetation types are complex, and there are many plant species. According to the plan, by 2020, the main indicators for urban landscaping in Fuzhou will be a green coverage rate of 42.25%, a greening coverage rate of 45.41%, a per capita park green space of 15.4 square meters, and a significant improvement in the ranking of per capita park green space. All construction indicators will meet the requirements for the creation of a "National Ecological Garden City".

## 2.2. Research Framework

This study focuses on Fuzhou City as the research subject, using data from remote sensing images, OpenStreetMap (OSM), and demographic variables. GIS and space syntax

methods were used to investigate the distribution of green space accessibility and equity in Fuzhou City. The study has roughly four parts (Figure 2).

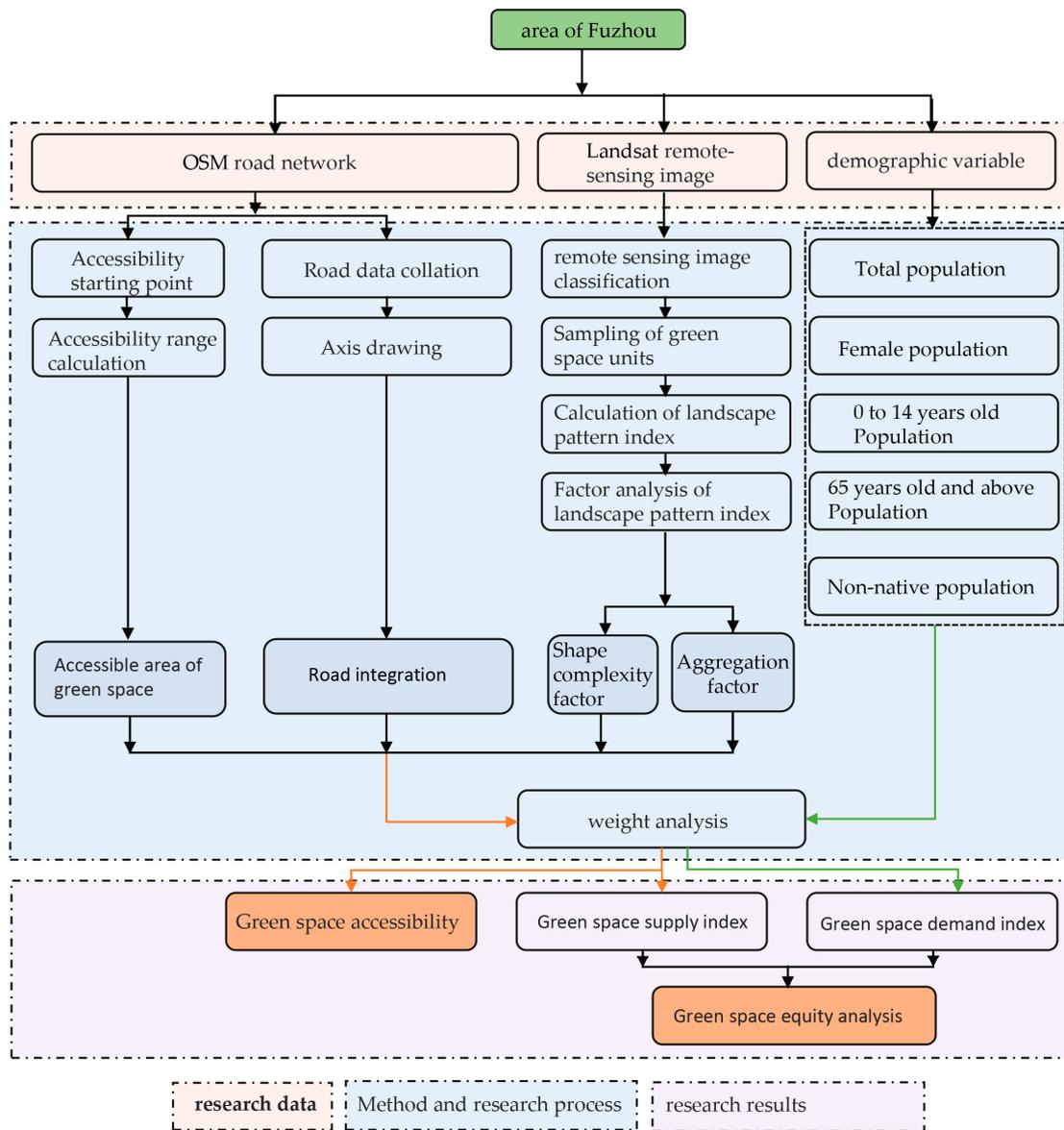


Figure 2. Research Framework.

The first part is based on road data, which is the starting point for analysing the integration and accessibility of urban areas in Fuzhou City and their range of accessibility.

The second part is based on remote sensing images, calculating the green space landscape pattern index, and extracting the landscape pattern index factors through factor analysis.

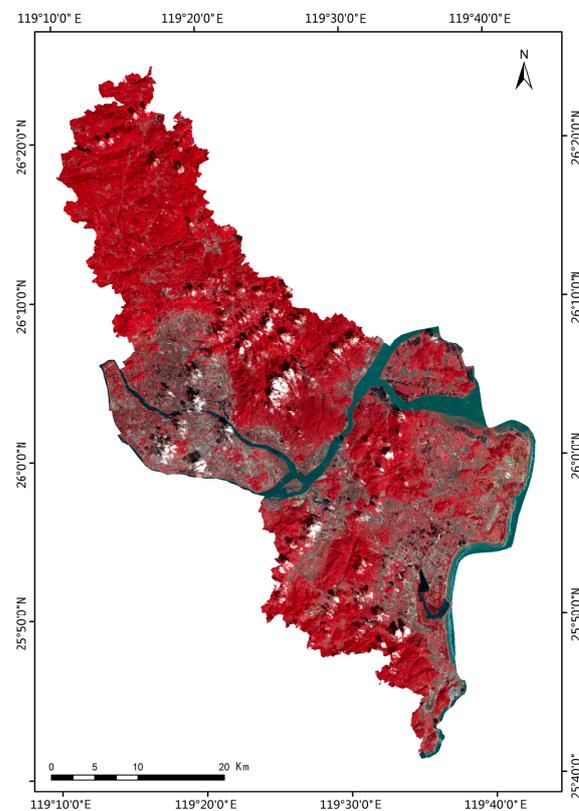
The third part examines the spatial accessibility of green space in urban areas of Fuzhou City based on integration, the landscape pattern index, and the green space accessibility area.

The fourth part examines the spatial equity of green space in the urban areas of Fuzhou City based on demographic variables.

### 2.3. Data Sources

#### 2.3.1. Remote Sensing Images

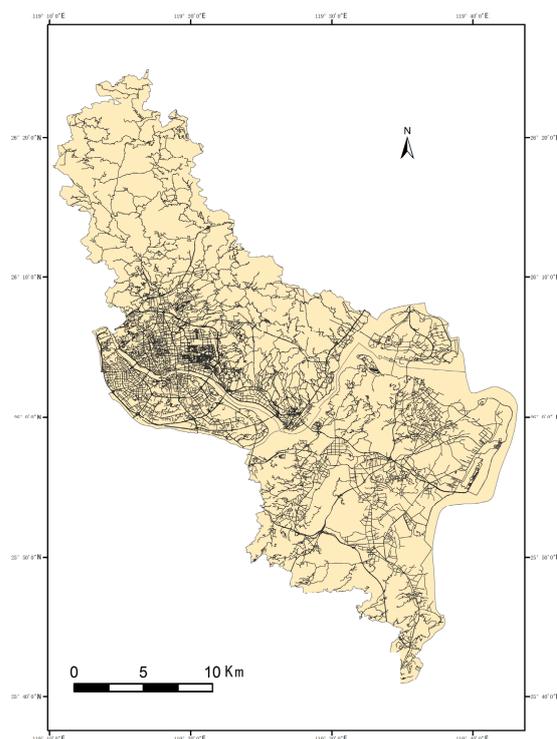
The remote sensing image data for this study were mainly obtained from the Landsat series of telemetry satellites, which provide a large amount of image data that can be used in various fields, such as natural resource exploitation, natural disaster prevention, environmental pollution monitoring, and natural plant growth observation. In addition to the spatial resolution band of 30 m, the panchromatic band with a spatial resolution of 15 m is added to the Operational Lan Imager (OLI) images. The Hue, Saturation, Value (HSV) transform fusion method in the transform domain substitution method is adopted to select the band combinations of the near-infrared, red, and blue bands that are convenient for highlighting vegetation information and fusing with the panchromatic band. After completing the image fusion, a mask is created to crop out the extent of the study area based on the administrative division vector information of the study area. Then, the pre-processing results of the study area images are obtained, as shown in Figure 3.



**Figure 3.** Remote sensing images of Fuzhou city in 2022.

#### 2.3.2. Road Network Data

The road network data used for spatial equity modelling of green spaces were obtained through the official OSM website in November 2022. The downloaded data were cropped and reprojected to obtain the road network corresponding to the study area. In addition, isolated roads and cut-off roads that have an impact on the accessibility analysis are manually identified, and vector modifications are performed (Figure 4).



**Figure 4.** Road network data of Fuzhou City in 2022.

### 2.3.3. Demographic Variables

The socio-demographic data used to study the spatial equity of green spaces were obtained from the sixth census of China in 2010 (the seventh census in 2020 still needs to be completed, so only the sixth census data were used). The “Fuzhou 2010 Census Data—Township and Street Volume” census data mainly reflect the basic situation of the population, covering the total resident population, female population, population aged 0–14, population aged 65 and above, and foreign population (Appendix A, Table A1).

## 2.4. Methodology and Research Process

### 2.4.1. Space Syntax Integration

Space syntax is a mathematical method proposed by British scholar Bill Hillier in the 1970s for describing and analysing spatial relationships. The basic principle involves dividing the space into scales and spatial partitions to describe the quantitative topological relationships between spaces and determine the connection between human behaviour and spatial morphology [31,32]. Integration in space syntax refers to the agglomeration or dispersion between an element of a spatial system and other elements. It measures the ability of a space to attract arrival traffic as a destination, reflecting the centrality of the space in the whole system. The higher the integration, the higher the accessibility, the stronger the centrality, and the easier it is to gather people. Previous studies have utilized spatial syntax theory to study urban green space, such as the use of depth map software to establish a regional spatial model of the urban road network and the analysis of the carrying capacity, penetration, and connectivity of the urban road network. These studies accurately reflect the coupling relationship between urban structure, transportation networks, and human activities [33]. In addition, by analyzing the integration degree of urban roads and park green spaces, researchers can determine the variability of costs, such as time and distance, consumed by citizens to reach the park green space, the permeability of the park green space, and the connectivity of the surrounding environment. This can further determine the ease of use of the park green space within a certain range and judge the accessibility level of this park green space [34,35]. The spatial syntax method studies and analyzes the relationship between urban spatial structure and urban park green space

layout from the perspective of the interactive relationship between people and space. Its advantage is that it not only considers the influence and connection of park green space to the surrounding elements, but also incorporates people's subjective perception of space in the analysis of permeability and accessibility [36]. Therefore, the spatial syntax method enables researchers to make reasonable and effective adjustments to their planning after learning about the current state of the urban structure and issues related to human social activities [37].

To quickly and efficiently facilitate the analysis of samples, this study uses depth map software, which was developed based on the theory of spatial syntax, to analyse the urban street network by axis analysis and line segment analysis. This study mainly adopts line segment analysis. The core work of line segment analysis is the acquisition of the axis map, which can be drawn in two ways, automatically generated by the Axial Map command in the software, or drawn by hand. This study adopts the manual drawing method to obtain the axis map. The basic principle of drawing an axis map is "longest and least" [38]. When expressing a curved street, the axis should be tangent to the boundary as much as possible to ensure the longest and the least number of axes (Figure 5).



**Figure 5.** Basic principles of axis drawing.

Using the space syntax method, the OSM data was employed as the base and combined with the actual urban image map to draw the axis model of the study area in Auto-CAD. The completed spatial syntax model was imported into Depthmap10 in DXF format and then checked for model calibration. The Map-Convert Drawing Map function was applied to convert it into the axial map required for this study. Finally, the spatial syntax-related variables were calculated using Depthmap10, SDNA, and other related software. Thus, Fuzhou City's final road integration was mapped (Figure 6).

The average length of the study (Table 1) is 265.10 m, for a total of 10,409 lane segments in the urban area of Fuzhou, and the integration ranges from 79.36 to 709.54, with an average value of 514.28. The road integration in the urban area of Fuzhou is higher in Taijiang and Gulou districts, at 641.48 and 620.04, respectively, which shows that these two districts have the lowest number of roads but the highest integration. In contrast, Jinan and Changle districts have the highest number of roads and the lowest road integration, with 415.51 and 482.83, respectively. These two districts are relatively large, so the road construction is relatively complex.

#### 2.4.2. Remote Sensing Image Classification

Remote sensing images reveal the differences between features using the difference between high and low brightness values or image element values (representing the spectral information of features) and spatial variations (representing the spatial information of features), which is the physical basis used to distinguish different image features. Remote sensing image classification is achieved using the computer to analyse the spectral and spatial information of various features in remote sensing images, select features, classify each image element into different categories according to some rules or algorithms, and then obtain the corresponding information between images and basic features. The classifier used in this study is the maximum likelihood supervised classifier [39,40]. The maximum likelihood classification is a method of image classification in which a nonlinear set of discriminative functions is statistically established based on the maximum likelihood method (Bayesian judgement criterion method) in two or more classes of judgements, assuming that the distribution functions of each class are normally distributed. The training area is selected to calculate the attribution probability of each sample area for classification [41].

According to the research requirements and the spectral resolution capability of Landsat images, four categories of target features were identified in this study (Table 2): cultivated land, vegetation, construction land, and water (Figure 7).

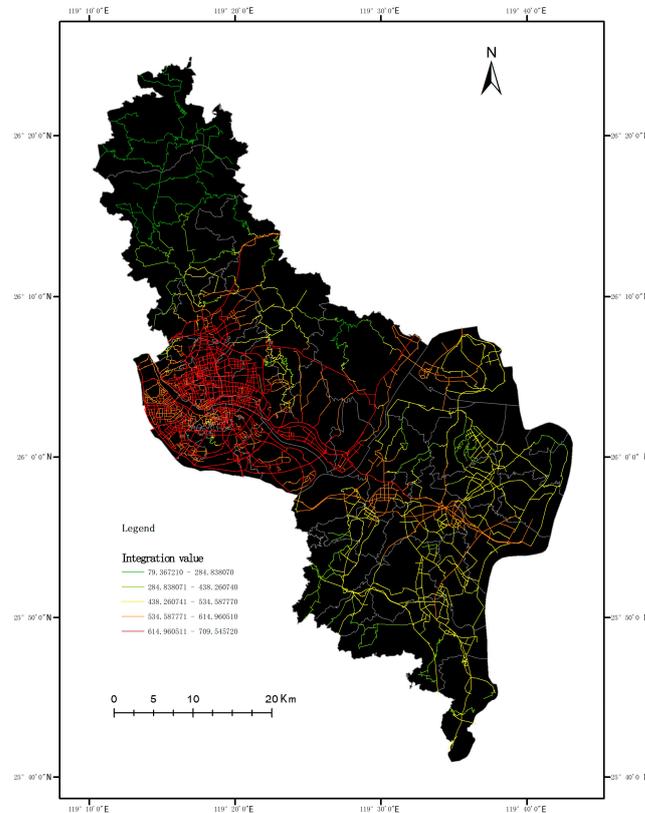


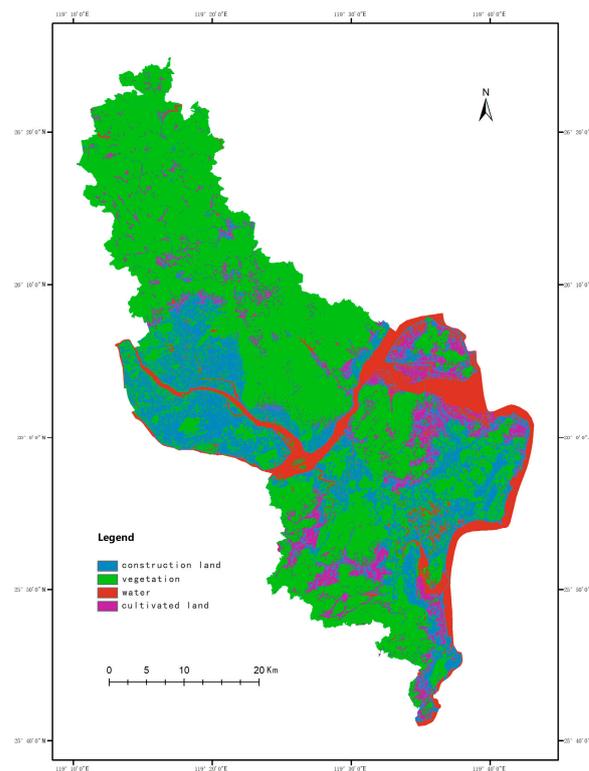
Figure 6. Road integration in Fuzhou city.

Table 1. Fuzhou city road integration statistics table.

	Gulou District	Taijiang District	Cang Shan District	Jinan District	Mawei District	Changle District	Total
Average value	620.04	641.48	619.93	415.51	531.69	482.83	514.28
Standard deviation	58.71	30.15	41.01	203.79	138.83	64.75	150.87
Number of segments	944	541	2017	2983	977	2947	10,409

Table 2. Land classification systems in the study area.

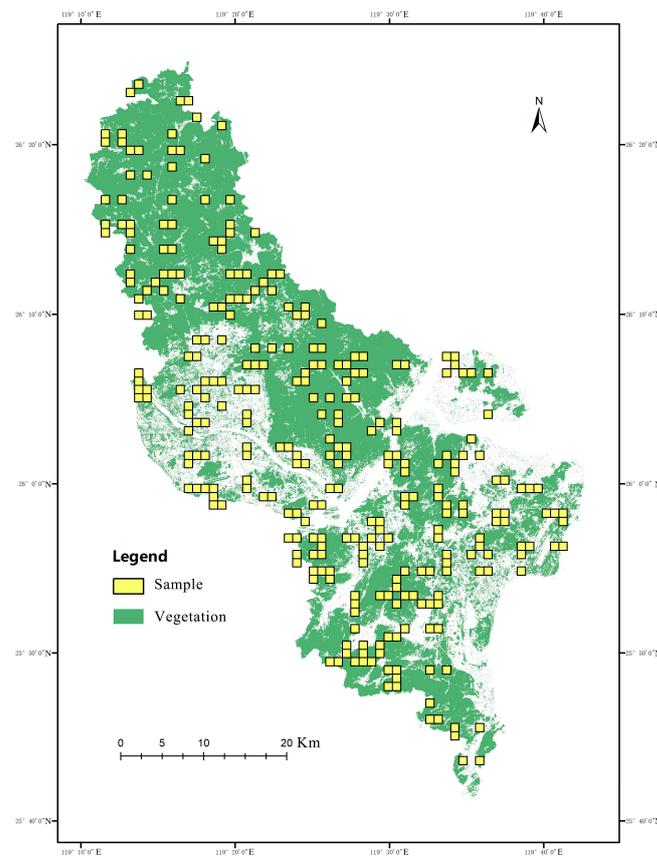
Type Code	Type Name	Description of Land Type
1	vegetation	Urban woodland, park green space, protective green space, subsidiary green space, road green belts, residential area greenery, and green belts around the city.
2	construction land	Includes commercial building land, transportation land, residential land, industrial land, unvegetated bare land, industrial and mining land, special land, etc.
3	cultivated land	Includes land occupied by crop cultivation, including paddy fields, dry land, etc.
4	water	Including rivers, lakes, reservoirs, coastal waters, etc. (excluding paddy fields and mudflats).



**Figure 7.** Land type of Fuzhou City.

### 2.4.3. Green Space Landscape Unit

From the remote sensing images, the green space (vegetation category) in the urban areas of Fuzhou is unevenly distributed, the number of green spaces within the urban area is minimal, and the area of green spaces in the northern and northwestern parts of Fuzhou is large and widely distributed. If the landscape units are randomly selected, the pattern of green space within each is likely similar. Moreover, the proportion of green space area is similar, resulting in insufficient independent variables for landscape analysis. Specifically, we divided the study area into a  $1 \text{ km} \times 1 \text{ km}$  grid and used a stratified sampling method to extract green space landscape units. The stratification was based on the percentage of green space area within the grid [42,43]. According to the previous research results, the number of stratification layers was determined to be six [44]. The stratum boundary was determined by the square root method of cumulative equivalent frequency proposed by Dalenius and Hodges [42]. The sampling rate was determined using the stratified fixed ratio method, i.e., the sampling rate of each stratum was determined to be a fixed value of 20%, whereby the overall number of samples was determined to be 485 and the overall sampling rate was determined to be 20.6%. Figure 8 shows the final extracted green space landscape unit of the study area, and the vector unit was used to crop the classification data of the study area. Thus, the classification data within the landscape unit was obtained (Figure 8).



**Figure 8.** Green space landscape unit sample of Fuzhou City.

#### 2.4.4. Landscape Pattern Analysis

Modern landscape ecology includes various methods for landscape pattern analysis [45], such as textual, graphical [46,47], and landscape pattern indices [48]. According to Turner [49], studying the causes of landscape spatial heterogeneity and its ecological implications requires quantification of landscape patterns [50]. The landscape pattern index is a simple quantitative index that represents the landscape's structural composition and spatial configuration characteristics, which can meet this need. In addition, the landscape pattern index can be used to conduct comparative studies of landscape spatial patterns in different places, simultaneously or over time. A significant number of scholars have conducted applied research on urban green areas in landscape ecology, using various quantitative indicators to analyze the spatial distribution patterns of urban green areas. They emphasize the importance of maintaining and restoring the continuity and integrity of landscape ecological processes and patterns [51,52]. Zhang Liquan et al. applied GIS-based landscape pattern analysis combined with an artificial neural network (ANN) to quantitatively analyze the urban landscape pattern and its change in Shanghai. They established an artificial neural network that better simulates the response of Shanghai's landscape pattern to natural, social, and economic factors, such as residential land use, road diversity, population diversity, urban development history, and the Huangpu River [53]. Based on previous studies, we selected 16 landscape pattern indices: Percent of Landscape (PLAND), Largest Patch Index (LPI), Edge Density (ED), Average Patch Area (AREA\_MN), Area-Weighted Mean Patch Area (AREA\_AM), Standard Deviation of Patch Area (AREA\_SD), Density of Patches (PD), Landscape Shape Index (LSI), Average Shape Index (SHAPE\_MN), Area-Weighted Mean Shape Index (SHAPE\_AM), Standard Deviation of Patch Shape Index (SHAPE\_SD), Area-Weighted Patch Fractal Dimension (FRAC\_AM), Mean Euclidean Nearest Neighbor Index (ENN\_MN), Isolation Index (SPLIT), Aggregation

Index (AI), and COHESION Index (COHESION). The formula and ecological significance of the indices are shown in Appendix A, Table A2.

Each index's basic descriptive statistics (maximum value, minimum value, mean value, and standard deviation) were evaluated to determine whether the landscape index exhibited any abnormal behaviour. If the standard deviation was too large, the index was excluded. Spearman's correlation coefficient was introduced to analyse the correlation among landscape indices. A two-tailed test was used to verify the significance of the correlation between landscape indices [54]. The formula is as follows:

$$r_i = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)},$$

where  $n$  is the number of rank pairs for the two variables in the correlation analysis, i.e., the sample content, and  $d_i$  is the difference between the ranks of the same pair ( $i = 1, 2, 3 \dots, n$ ). If the absolute value of the correlation coefficient is greater than 0.90 and significant for  $p \leq 0.01$ , there is a significant correlation between the indices. If the absolute value of the correlation coefficient is less than 0.90 but significant for  $p \leq 0.01$ , this correlation coefficient can only indicate the trend of the change in the indices, i.e., the change in one index predicts the trend in the other index. If the absolute value of the correlation coefficient is less than 0.90 and  $p \leq 0.01$ , then there is no meaningful correlation between the indices.

After statistical analysis, the average nearest distance index (ENN\_MN) had invalid values in several landscape calculation units (Appendix A, Table A2), which were not representative and were excluded. Table 3 shows the descriptive statistics of each of the remaining landscape indices. The statistics of each index are within a reasonable range, do not appear to be significantly too large or too small, and do not need to be rejected.

**Table 3.** Statistical analysis results of the Landscape Pattern Index.

Landscape Pattern Index	N	Min Value	Max Value	Mean Value	Standard Deviation
PLAND	485	1.2920	99.9322	54.159960	30.7942202
PD	485	0.2475	36.4759	6.299242	7.2109512
LPI	485	0.4233	99.9322	48.134889	34.9398279
ED	485	0.8292	170.0588	61.415113	38.1500532
LSI	485	1.0376	16.1528	5.739334	3.6041949
AREA_MN	485	0.3033	401.4000	72.245199	112.2738604
AREA_AM	485	0.8055	401.4000	182.873622	144.6140559
AREA_SD	485	0.0000	196.1550	50.391546	60.5577562
SHAPE_MN	485	1.0376	3.5625	1.533616	0.3809547
SHAPE_AM	485	1.0376	9.4691	3.128739	1.2533318
SHAPE_SD	485	0.0000	2.2131	0.629029	0.4028415
FRAC_AM	485	1.0049	1.3056	1.152776	0.0531038
COHESION	485	59.6835	99.9995	95.890443	5.9247636
SPLIT	485	1.0014	14,072.0119	190.473403	1012.3020546
AI	485	45.9649	99.9426	86.301793	13.0960904

According to the results of Spearman's correlation analysis for each index (Appendix A, Table A3), within the area-boundary-diversity class indices, the correlation coefficients of indices ED, Area\_SD, and other values were less than 0.90 and significant at  $p \leq 0.01$ , so these two indices were retained, and the rest were excluded. Similarly, within the shape class index and spread index, the indices that did not match were excluded, and SHAPE\_MN, SHAPE\_SD, FRAC\_AM, and COHESION are retained.

In summary, the final indices selected to describe the spatial landscape pattern of the green space were ED, AREA\_SD, SHAPE\_MN, SHAPE\_SD, FRAC\_AM, and COHESION.

#### 2.4.5. Factor Analysis

Factor analysis, an extension of principal component analysis, condenses numerous original variables into a few factor variables with minimal information loss and makes factor variables highly interpretable as a multivariate statistical method [55]. Factor analysis groups variables according to the magnitude of the correlation, revealing the level of correlation between variables within the same group and variables in different groups, with each group representing a basic structure, which is called the common factor. For the problem under study, the original variables can be described as the sum of a linear function of the fewest common and unique factors. The factor analysis modelling process can rotate and transform the loading matrix to help interpret the meaning of each factor [56,57]. Factor analysis can both reduce the dimensionality and achieve the purpose of classification. Factor analysis of the six screened landscape pattern indices resulted in the following factor loading matrix (Table 4).

**Table 4.** Results of the Landscape Pattern Index Factor Analysis.

Landscape Pattern Index	Main Components	
	1	2
Eigenvalue	2.435	1.856
Variance contribution ratio (%)	40.576	30.932
Cumulative variance contribution ratio (%)	40.576	71.508
ED	0.866	−0.322
AREA_SD	0.072	0.811
SHAPE_MN	−0.213	0.526
SHAPE_SD	0.870	0.359
FRAC_AM	0.934	0.089
COHESION	−0.076	0.825

As shown in Table 4, the two extracted principal components explain 71.508% of the total variance of the original variables, with individual contribution rates of 40.576% and 30.932%. SHAPE\_SD, ED, and FRAC\_AM have the highest correlation with the first principal component, and COHESION and AREA\_SD have a higher correlation with the second principal component. Furthermore, SHAPE\_MN has a weak correlation with both principal components; thus, this index was excluded. The remaining five indices were re-run for factor analysis, and the analysis results are shown in Table 5.

**Table 5.** Results of the Landscape Pattern Index Factor Analysis.

Landscape Pattern Index	Main Components	
	1	2
Eigenvalue	2.411	1.699
Variance contribution ratio (%)	48.223	33.978
Cumulative variance contribution ratio (%)	48.223	82.201
ED	0.834	−0.417
AREA_SD	0.134	0.878
SHAPE_SD	0.894	0.304
FRAC_AM	0.948	−0.048
COHESION	0.004	0.812

From Table 5, the first principal component has a strong positive correlation with FRAC\_AM (the higher the number of sub-dimensions, the more complex the landscape geometry); ED (the more significant the edge diversity, the greater the fragmentation); and SHAPE\_SD (the more significant, the greater the landscape patch diversity), indicating that this principal component is mainly related to the diversity of the green space, and the more complex the shape of the green space patch and the greater the boundary length, the greater the value of the first principal component.

The second principal component has high loadings on COHESION (the higher the degree of patch fragmentation, the lower the degree of fragmentation) and AREA\_SD (the more significant the standard deviation of the patch area, the greater the diversity of landscape patch sizes), indicating that this principal component is related to the degree and connectivity of green space patches, and the more aggregated the patch areas, the higher the value of the second principal component. Therefore, the first principal component can be defined as the green space shape complexity factor, and the second principal component is the green space aggregation factor.

The coefficients corresponding to each index in the two principal components were calculated using the main component loading matrix, and the coefficient matrix of the index was obtained as follows (Table 6).

**Table 6.** Score matrix for each Landscape Pattern Index Factor.

Landscape Pattern Index	Main Components	
	1	2
ED	0.362	−0.221
AREA_SD	0.019	0.519
SHAPE_SD	0.357	0.205
FRAC_AM	0.394	−0.001
COHESION	−0.032	0.477

The equations of the two principal component factors and the selected landscape pattern index are expressed as follows:

$$F1 = 0.362 \times ED + 0.019 \times AREA\_SD + 0.357 \times SHAPE\_SD + 0.394 \times FRAC\_AM - 0.032 \times COHESION,$$

$$F2 = -0.221 \times ED + 0.519 \times AREA\_SD + 0.205 \times SHAPE\_SD - 0.001 \times FRAC\_AM - 0.477 \times COHESION.$$

F1 and F2 are the shape complexity and aggregation factor of landscape unit  $i$ , respectively, ED, AREA\_SD, SHAPE\_SD, FRAC\_AM, and COHESION are the edge diversity index, patch area standard deviation, patch shape standard deviation, area-weighted average patch sub-dimension, and patch cohesion index of landscape unit  $i$ , respectively.

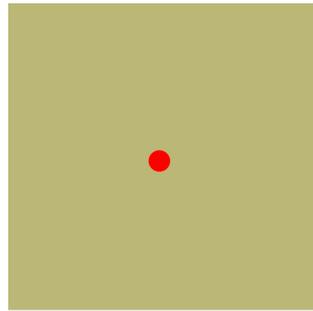
#### 2.4.6. Green Space Accessibility Model Construction

##### 1. Green space accessibility calculation points

Since it is challenging to obtain high-precision building distribution images and to extract buildings from remote sensing images with 30 m resolution, using buildings as target units to calculate their accessibility is not feasible. If the accessibility is calculated using impervious surface image elements as the target unit, the calculation volume is too large, and multiple impervious surface images belong to the same feature. In this study, the accessibility was calculated using a regular grid as the target unit, which is a simple and standard calculation method used in the literature that is feasible and efficient. First, the impervious surface in the study area was divided into 1 km × 1 km grid cells. When applying the grid method, the geometric centre of the grid cells is used as the starting point for calculating the accessibility. Thus, the number of green areas within a specific range was retrieved (Figure 9).

##### 2. Green space accessibility calculation range

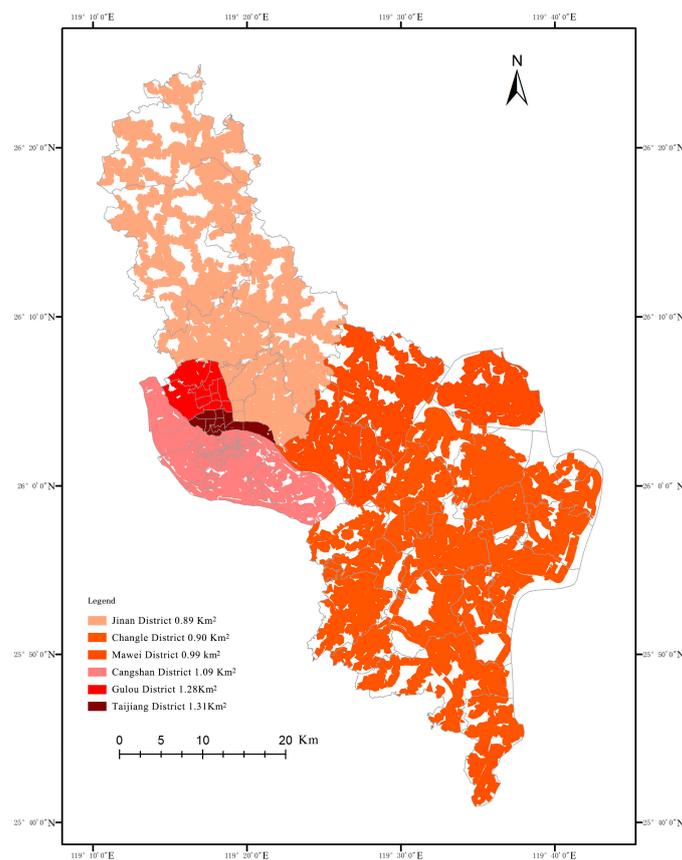
Next, we defined the accessible area and accessible green space in the study area. The “accessible area” is the area enclosed by the target points that can be reached within 2 km of the road network from the centre of the grid. The “accessible green space” is the green space within the reachable area. In this way, each closed area constitutes a spatial unit [58]. The accessibility area, green space shape complexity factor, green space aggregation factor, and road integration of green space within this spatial unit can be calculated.



**Figure 9.** Schematic diagram of accessibility calculation points.

The results are shown in Figure 10. The average accessible area of Fuzhou City is 1.07 km<sup>2</sup>. The accessible area of Fuzhou City is 1.31 km<sup>2</sup> in Taijiang District, 1.28 km<sup>2</sup> in Gulou District, 1.09 km<sup>2</sup> in Cangshan District, 0.99 km<sup>2</sup> in Mawei District, and 0.89 km<sup>2</sup> in Jinan District. The size of the accessible area depends on the development of the transportation network, which can be used as an indicator of the accessibility of the regional transportation network.

### 3. Choice of accessibility factors



**Figure 10.** Accessible area in Fuzhou city.

#### Green space area:

Green space area is the most widely used representative attribute in green space accessibility and equity studies [59,60]. The green space area is associated with the probability that residents can access urban green space in the study area. Urban residents have a higher probability of being exposed to urban green space when the area of green space around the city is significant. In this study, the green space area was the most fundamental indicator of green space accessibility, which was calculated based on the ranges of the available area.

Road integration:

Within the urban space, the higher the integration index value, the higher the road carrying capacity, and the higher the traffic flow. The core expression is the urban spatial structure, which is built along several axes with high integration. Many reports have used the spatial syntax theory to show that the high integration area has high population diversity and high traffic flow. This also indicates that, in this spatial system, the core area of integration with relatively dense axes is usually the area with high activity in the city, where prosperous commercial trade and large populations are gathered. Hence, it is also a central node of a city, and the accessibility is relatively high.

Green space shape complexity factors and aggregation factors:

The landscape pattern index can help concentrate landscape pattern information and represent the structural composition and spatial configuration characteristics of quantitative indicators. It is an essential technical means for assessing landscape patterns, and helps describe the structural characteristics and spatial distribution of urban green space and ecological networks. However, in recent years, different landscape pattern indices have reflected different aspects of the pattern. A single landscape index often requires more work to fully and accurately explain the ecological process. The joint application of the landscape index is an effective way to analyse landscape spatial patterns and examine the explanatory ability of the landscape index when set for the ecological process. Therefore, we selected two representative factors to measure green space landscape structure from complex and redundant landscape indices.

4. Weight analysis

The analytic hierarchy process is used in a multi-objective, comprehensive evaluation. The analytic hierarchy process is used to simulate the human decision-making process. It decomposes and classifies complex target systems and quantifies non-quantitative events with the help of mathematical analysis to provide a reliable quantitative basis for analysing and predicting the development of a system [61].

First, it is necessary to clarify the hierarchy of green space accessibility measurements. According to the purpose of the study, the spatial accessibility of green space was taken as the target layer. The three factors, namely quantity, landscape structure, and road accessibility, were taken as the criteria layer. Then, two indicators of shape complexity and aggregation were included under the criteria layer of landscape structure. Based on these indicators, the Green space accessibility model hierarchy is established in Figure 11. After calculation, the final weight distribution of each indicator was determined, as shown in Table 7.

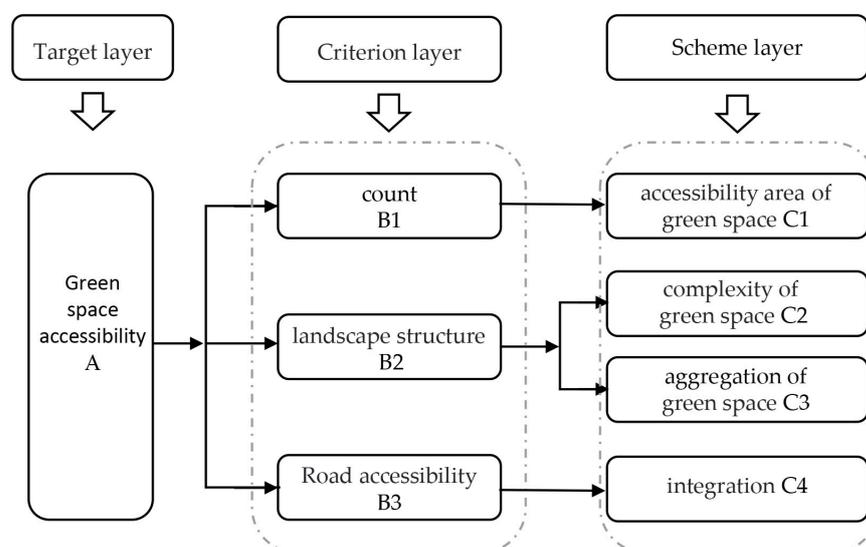


Figure 11. Green space accessibility model hierarchy.

**Table 7.** Weight value of factors.

Accessibility Area of Green Space Factor	Complexity of Green Space Factor	Aggregation of Green Space Factor	Integration
0.38	0.18	0.18	0.26

### 3. Results

#### 3.1. Green Space Accessibility Metric Results

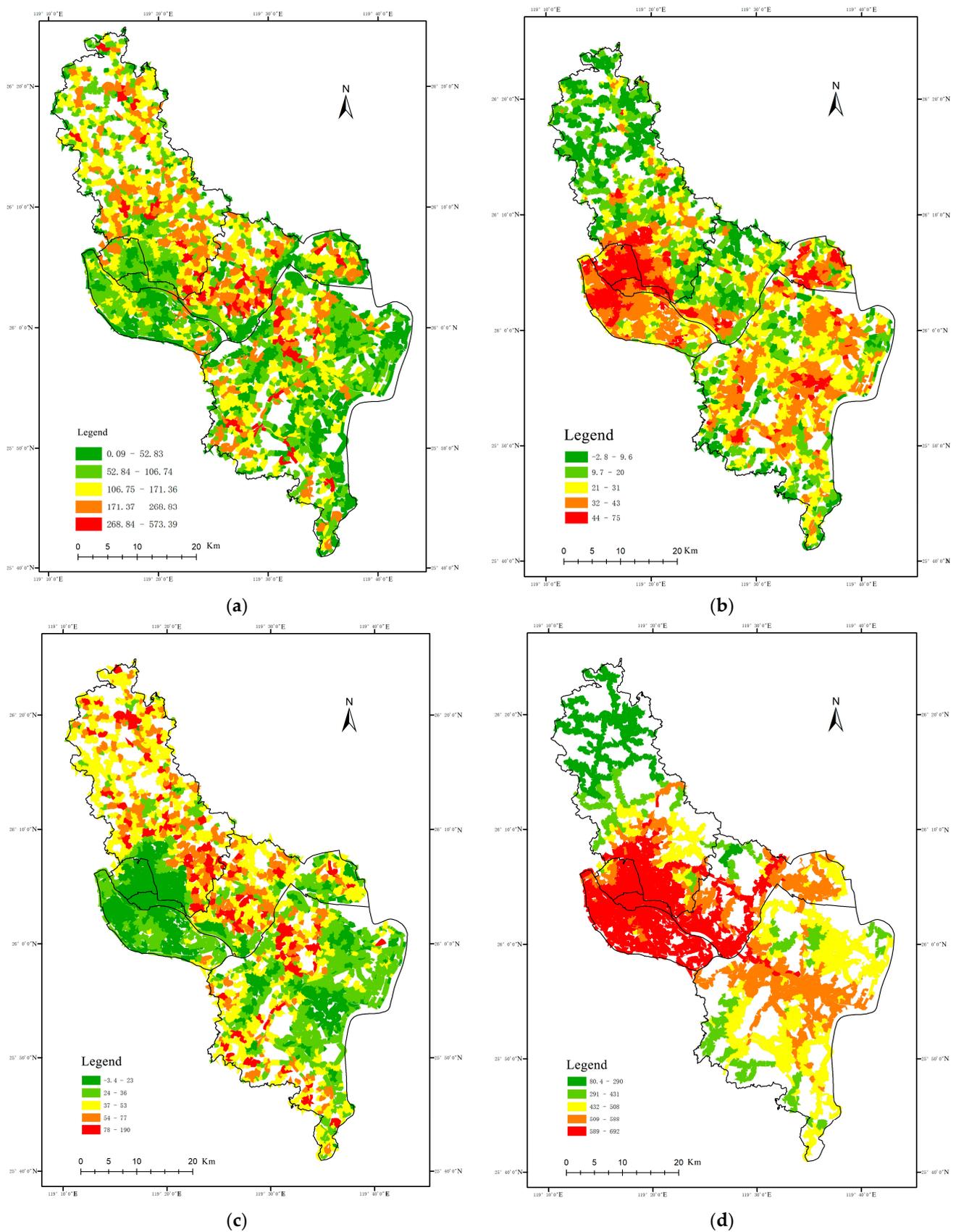
We calculated the area of accessible green space, shape complexity, aggregation factor, and integration value for each grid cell separately (Figure 12). Moreover, the factors were weighted according to the weights determined in Table 7 to obtain the final green space accessibility metric results (Figure 13). The accessibility of green space in urban areas of Fuzhou decreases from the centre of the city to the edge. From north to south, the urban area of Fuzhou shows a trend of “low-high-low”; the northern part of the urban area of Fuzhou is the lowest, followed by the southeastern part, and then the western part. Administrative districts refined the accessibility of Fuzhou’s urban areas, and Fuzhou’s districts were divided into three classes according to their mean values of green space accessibility.

The statistics are shown in Table 8. Gulou District and Taijiang District, classified as the first class, have the highest mean values of 189.49 and 194.95 for green space accessibility in Fuzhou City, respectively. As older urban areas, Gulou District and Taijiang District have the lowest mean areas of accessible green space. The clustering of green areas is also low. However, the complexity of their green area shapes and road integration is relatively high, so their green area accessibility averages are also the highest.

The average values of green space accessibility are also higher in Cangshan District and Mawei District, at 170.06 and 139.94, respectively, classified as the second class. The complexity of the green space shape is relatively high in Cangshan District. Road integration is also high, so the accessibility of green space is relatively high in the whole district. In contrast, the average value of green space accessibility is higher in the part of Mawei District near the city centre and lower in the part far from the city centre, especially in the part adjacent to Jinan District.

Jinan District and Changle District are classified as the third class, with mean green space accessibility values of 112.53 and 120.47, respectively. These values are relatively higher at the border between Jinan District and Gulou District and then decrease as they move away from the city centre. The mean green space accessibility values are higher in the central part of the Mawei District because of its green space area, green space shape complexity, and road integration. However, the values outside the Mawei District are relatively low.

The frequency histogram of green space accessibility in each administrative district of Fuzhou City was drawn based on the statistical data (Figure 14). The maximum frequencies occurred at relatively similar intervals in the six administrative districts. The maximum frequencies of 3.7%, 2.3%, and 1.6% occurred in Taijiang, Gulou, and Cangshan, respectively (180,210). The maximum frequencies of the Mawei and Jinan districts were close to each other, 0.6% and 0.5%, respectively (180,190). The maximum frequency of the Changle District is 1.5%, appearing in the interval (140,160).



**Figure 12.** Distribution of green space accessibility factors in urban areas of Fuzhou: (a) green space accessibility area; (b) green space shape complexity factor; (c) green space aggregation factor; and (d) road integration.

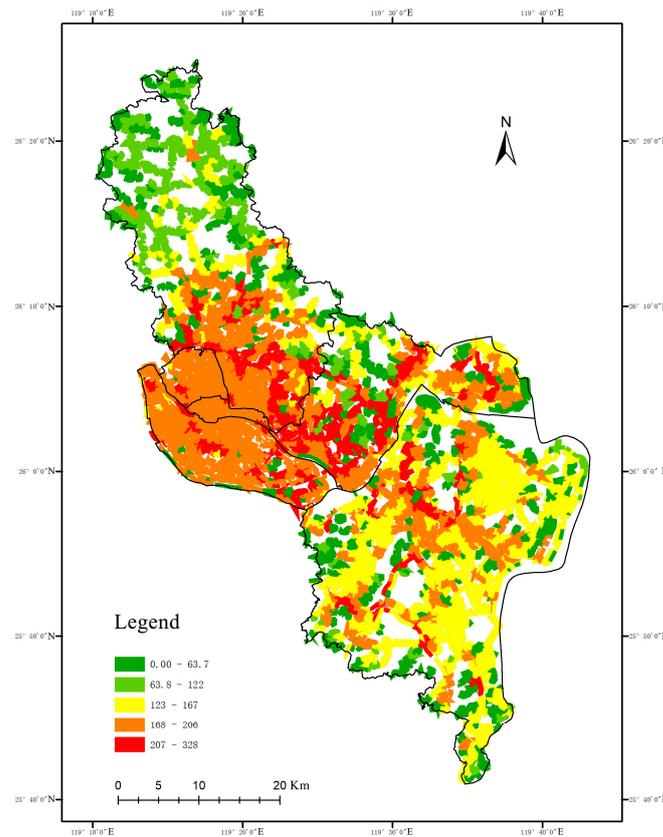


Figure 13. Distribution of accessible green spaces in Fuzhou City.

Table 8. Statistical descriptions of green space accessibility in urban areas of Fuzhou.

Administrative District	Gulou District	Taijiang District	Cangshan District	Jinan District	Mawei District	Changle District
Average value	189.49	194.95	170.06	112.53	140.38	120.47
Standard deviation	29.25	11.34	54.45	66.55	75.81	61.66
Grid number	48	32	171	617	319	806

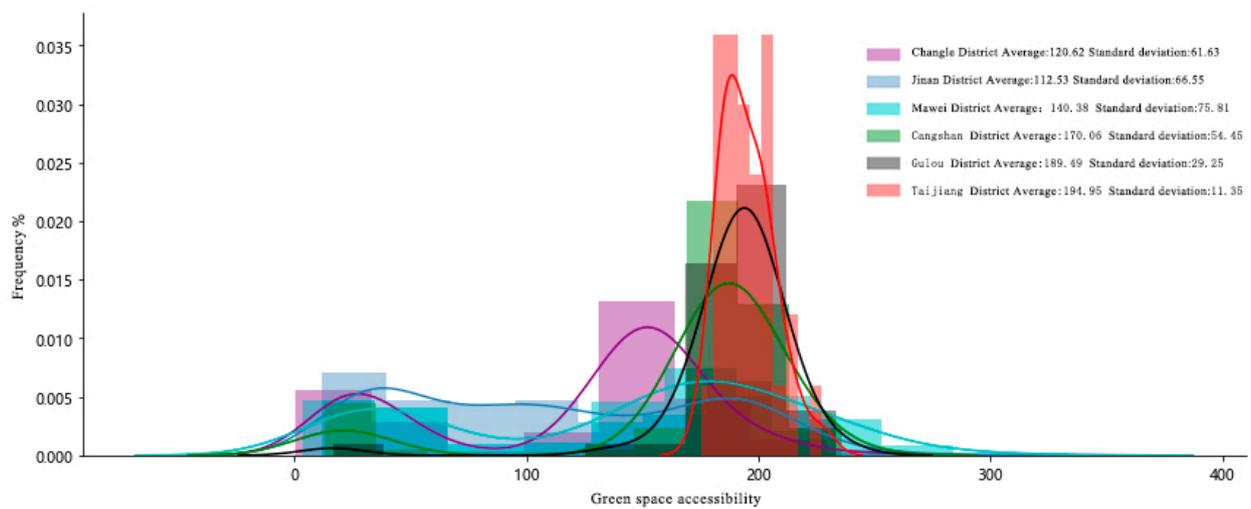


Figure 14. Frequency distribution of green space accessibility in urban areas of Fuzhou.

### 3.2. Fairness of Green Space Based on Supply and Demand Index

#### 3.2.1. Green Space Supply Index in Fuzhou City

Based on the research results on green space accessibility, we selected four indicators for the supply index of green space, namely the green space accessibility area index CA, the green space shape complexity index (F1), the green space aggregation index (F2), and the road integration index (IN). Taking streets as the calculation unit, each index was normalised using the extreme difference standardization method, and then each street's corresponding value was analysed using ArcGIS. Moreover, the ArcGIS natural breakpoint classification method was used to classify the values into five levels: higher, high, moderate, low, and lower (Figure 15).

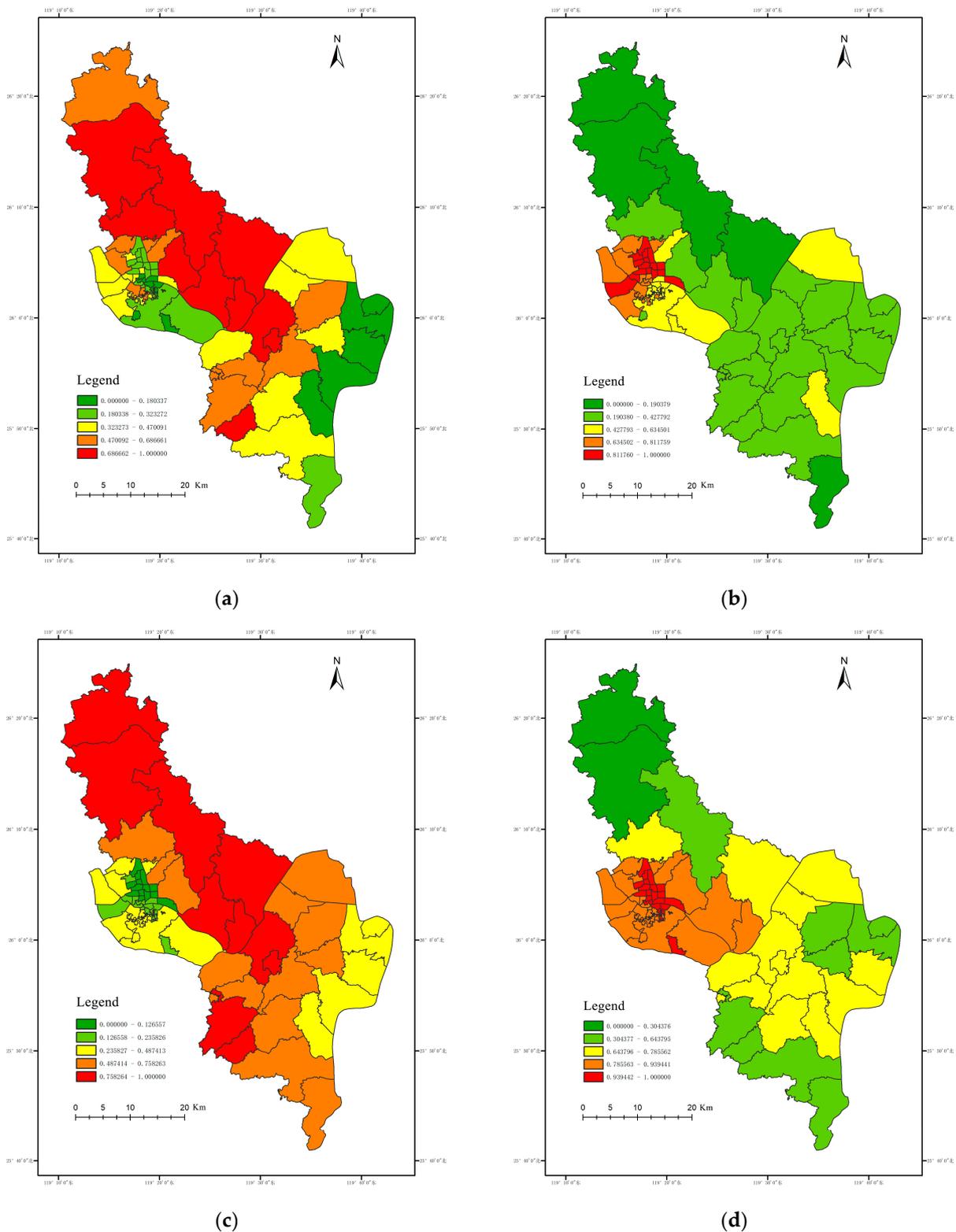
The statistics are shown in Table 9. The majority of streets have low or lower values of the green space accessibility area index, as observed for 30 streets, accounting for 46.15% of the total number. Among them, 17 are classified as low and 13 are classified as lower, which have mean values of 0.274 and 0.098, respectively. There are 10 streets with higher values, 11 streets with high values, and 14 streets with moderate values, which are 0.843, 0.598, and 0.398, respectively.

The statistics of the green space shape complexity index show that 26 streets have low or lower values, accounting for 40% of the total number of streets. The number of streets with low values is 21, with a mean value of 0.332, and the number of streets with lower values is 5, with a mean value of 0.109. Then there are 16 streets with higher values, 10 streets with high values, and 13 streets with moderate values, which are 0.912, 0.754, and 0.543, respectively.

Fuzhou City's low green space aggregation index accounts for 43.08% of the total streets, with 28 streets. The number of streets with low and lower values is 14 and 13, with mean values of 0.083 and 0.193, respectively. There are 10 streets with high mean values, 13 streets with high values, and 15 streets with moderate values, which are 0.899, 0.598, and 0.398, respectively.

In the distribution of green space, the green space accessibility area index, green space shape complexity index, and green space aggregation index are dominated by low values, accounting for 46.15%, 40%, and 43.08% of the total streets, respectively. The performance of the integration index is the opposite. The number of streets with low or lower values is 11, accounting for 16.92% of the total streets, with mean values of 0.152 and 0.587, respectively. At the same time, 63.08% of the total streets exhibit high (20 streets) or higher values (21 streets), which have mean values of 0.973 and 0.908, respectively. There are 13 streets with moderate values, with a mean value of 0.717.

In summary, the four indices of green space supply in urban areas of Fuzhou City have an overall low percentage at the street level. The number of streets with higher values accounted for 15.38% (the green space accessibility area indicator), 24.62% (the green space spatial complexity indicator), 15.38% (the green space aggregation indicator), and 30.77% (the road integration indicator) of the total number of streets, respectively. From Figure 16, the high green space accessibility indicators are concentrated in the newer areas near the city centre, and there is less low street area accessibility in the city centre. The same situation is observed for the green space aggregation indicator, but the opposite situation is observed for the green space shape complexity indicator and the road integration indicator, where the high values of both are concentrated in the city centre area. This shows that the distribution of green space supply indicators at the street level in the urban area of Fuzhou needs to be more equitable.



**Figure 15.** Spatial distribution of the single supply index of green space in urban areas of Fuzhou: (a) green space accessibility area index; (b) green space shape complexity index; (c) green space aggregation index; and (d) road integration index.

**Table 9.** Statistics of green space supply in urban areas of Fuzhou.

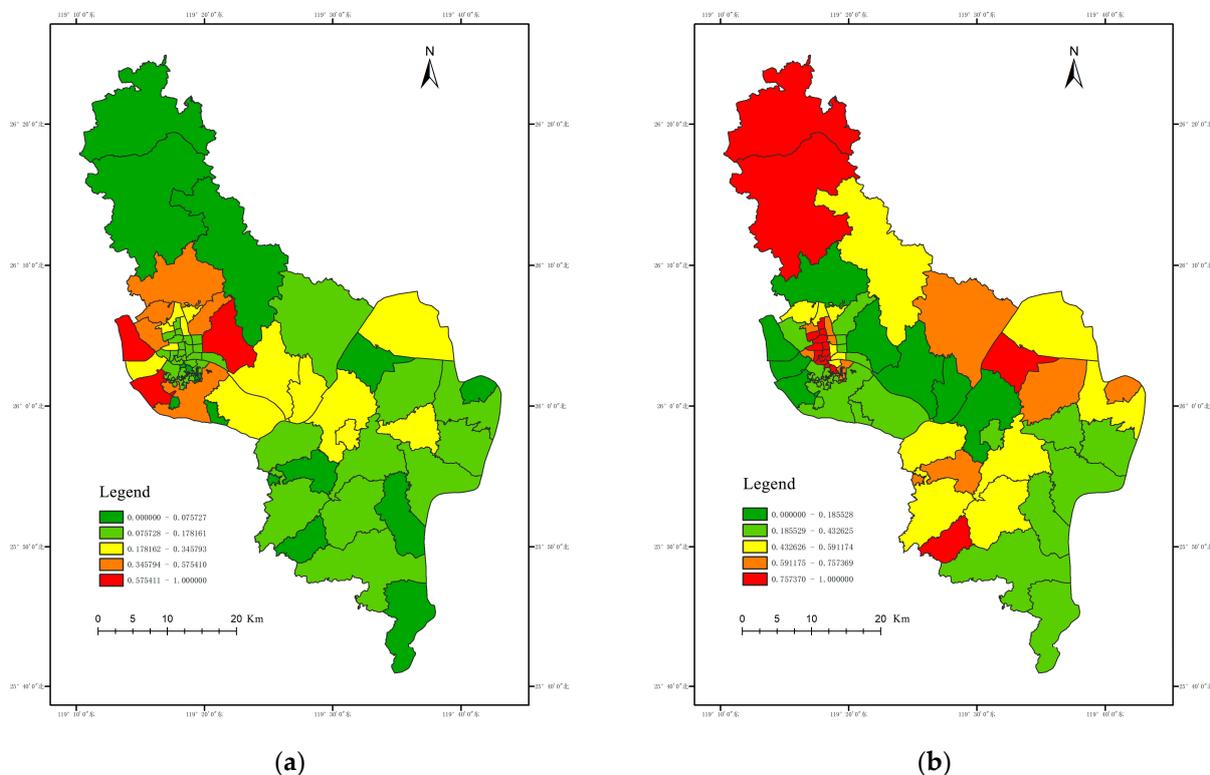
Level	Number of Streets (Blocks)				Average Value				Standard Deviation			
	CA	F1	F2	In	CA	F1	F2	In	CA	F1	F2	In
lower	13	5	14	2	0.098	0.109	0.083	0.152	0.058	0.075	0.039	0.152
low	17	21	13	9	0.274	0.332	0.193	0.587	0.038	0.591	0.026	0.034
moderate	14	13	15	13	0.398	0.543	0.372	0.717	0.041	0.056	0.052	0.042
high	11	10	13	21	0.598	0.745	0.668	0.908	0.058	0.046	0.069	0.026
higher	10	16	10	20	0.843	0.912	0.899	0.973	0.083	0.049	0.056	0.018

### 3.2.2. Green Space Demand Index in Fuzhou City

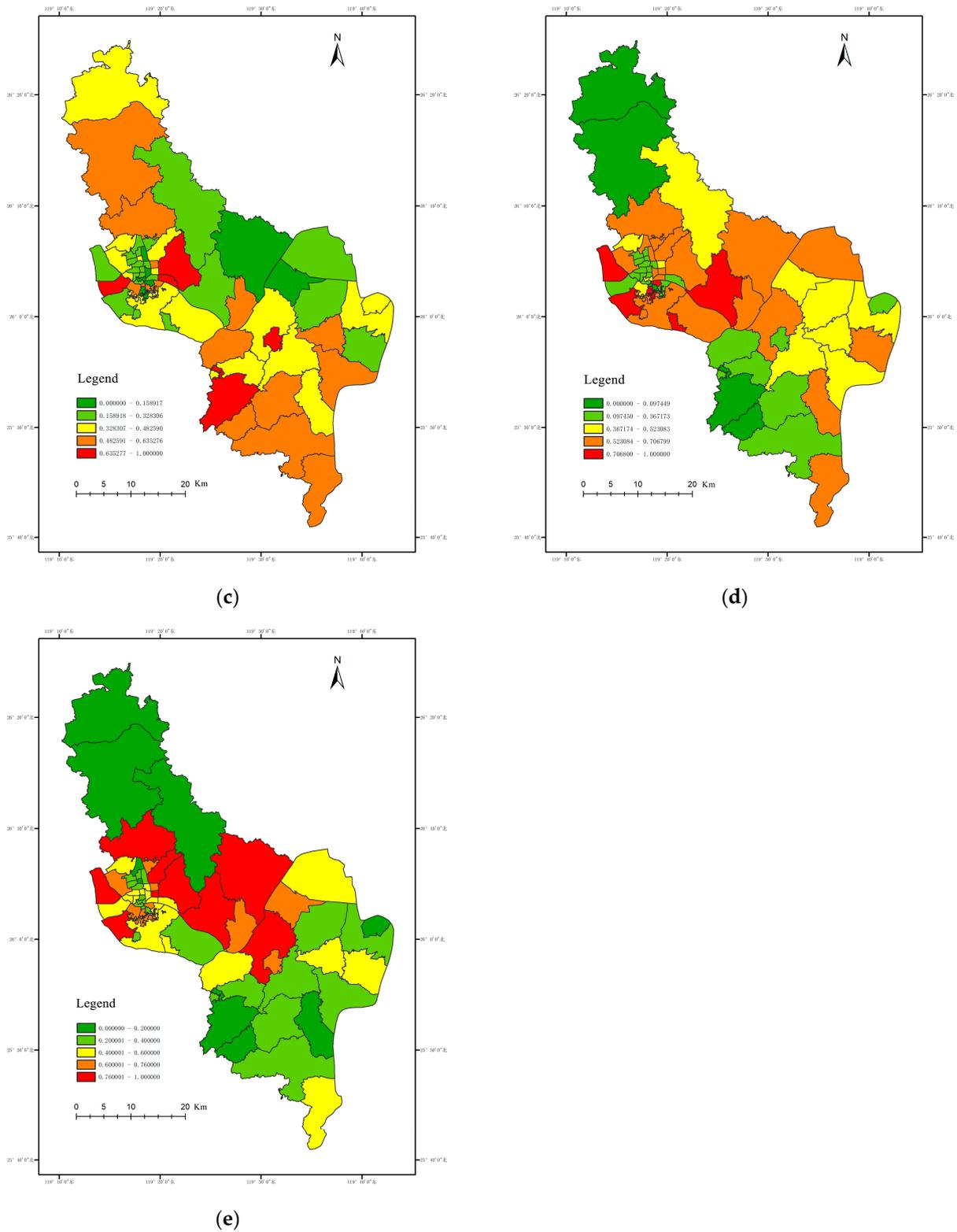
In previous studies on the layout of public resources such as urban green spaces, parks, and schools in foreign countries, the needs index has been widely used to evaluate the fairness of resource allocation [62,63]. According to the sixth census data of Fuzhou City, five indicators were considered as follows:

- total population
- the proportion of the population over 65 years old.
- the proportion of the population aged 0~14 years old.
- the proportion of the foreign population.
- the proportion of females.

The values of the green space demand indicators were calculated in terms of streets, and each indicator was normalized using the extreme difference standardisation method. Moreover, the ArcGIS natural breakpoint classification method was used to organise the values into five classes. (Figure 16, Table 10).



**Figure 16.** Cont.



**Figure 16.** Index of green space demand in urban areas of Fuzhou: (a) total population; (b) female population; (c) population aged 0 to 14; (d) aged 65 and above; and (e) foreign population.

**Table 10.** Green space demand index in Fuzhou city (blocks).

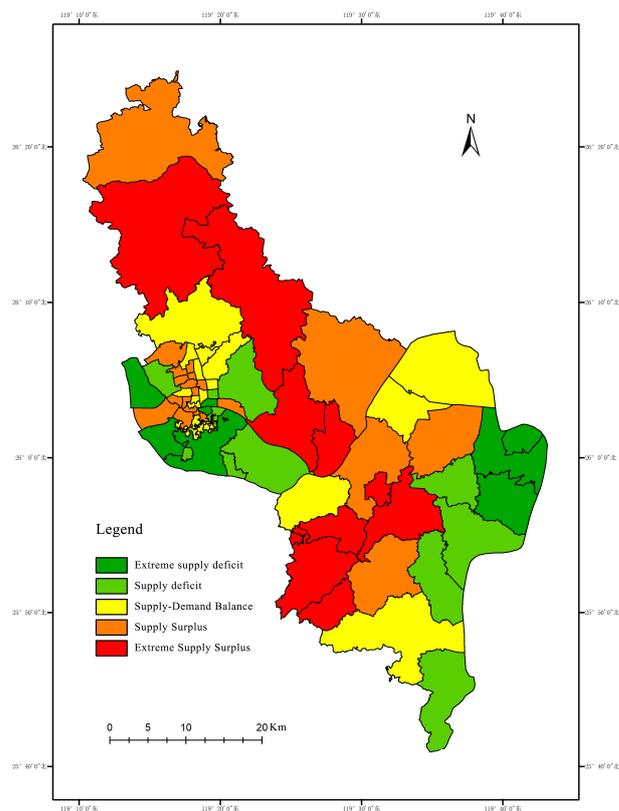
Level	Total Population	Female Population	Population Aged 0 to 14	Population Aged 65 and Above	Foreign Population
Lower	14	7	7	5	9
Low	31	19	21	23	17
Moderate	14	13	18	11	20
High	4	11	14	21	11
Higher	2	15	5	5	8

Table 10 shows that the number of streets in the low area is 31, accounting for 47.69% of the total number of streets. The lower and moderate areas both have the same number of streets, 14, whereas the high and higher areas only have 6 streets, accounting for only 9.23%. For the female population, although the most significant number of streets is 19 in the lower area, the high and higher areas reach 26 streets, accounting for 40% of the total number of streets. In contrast, the lowest percentage of the female population is found in only 7 streets. This shows that Fuzhou has more street pairs with a high percentage of the female population; however, the proportion of the population aged 0 to 14 years old has the opposite trend compared with the female population, with the highest number of streets with a high percentage being 21 blocks of low, which, together with the 7 blocks of low, account for 43.07% of the total number of streets. Furthermore, 14 and 5 blocks of high and higher streets are occupied by people aged 0 to 14 years—old. For people that are 65 years old and older, the lower and higher areas are similar in terms of the population percentage. There are 28 blocks of low streets and 26 blocks of high streets, accounting for 43.07% and 40% of the total number of streets, respectively. There are 5 blocks of lower and higher streets. The statistics of the foreign population show that lower areas have more streets than higher areas, with 26 blocks, which account for 40% of the total number of streets.

In summary, the distribution of population demand indicators in urban areas of Fuzhou is relatively even. The number of streets in higher-value areas is small, and the number in lower-value areas is also small. The number of streets with high numbers is concentrated between low and high values. The distribution map shows that the higher values of total population data are concentrated in the downtown area, whereas most streets with lower ratios are located far from the downtown area, with a few streets in the downtown area. The higher value of the female population is concentrated in the central part of the city, but a few streets are located far from the city centre. The low values for the population aged 0 to 14 years old are found in the majority of streets, and the distribution of higher-value areas is relatively scattered, with only a few higher-value streets in the city centre. The higher values for the population over 65 years old are relatively concentrated in the streets near the city centre. The higher-value distribution of the foreign population is more pronounced, mainly around the streets in the city centre.

### 3.2.3. Fairness Analysis of Green Space

The green space supply indicators and green space demand indicators were also overlaid and analysed using ArcGIS. Then, the combined spatial distribution of green space supply and demand was calculated. Moreover, the ArcGIS natural breakpoint classification method was used to categorise the values into five classes (Figure 17).



**Figure 17.** Fuzhou city’s green space supply and demand balance results.

The statistics are shown in Table 11. The majority of streets (20 blocks) exhibited a surplus supply, accounting for 30.73% of the total number of streets and 30.76% of the total area. The most significant area belongs to the streets with extreme surplus supply; although their number is only nine, they contain 31.37% of the area. The next largest area is the balanced supply and demand area, with 17 streets, accounting for 26.15% of the number of streets and 18.66% of the total area. The total number of streets in these three sections is 46, containing 70.77% of the streets and 74.78% of the area. The total number of streets in the deficit part is 19, accounting for only 29.23% of the number of streets and 25.22% of the area. Thus, the urban areas of Fuzhou City occupy the majority of both the number of streets and the area of streets. This shows that the distribution of green space in the urban area of Fuzhou is relatively fair.

**Table 11.** Fuzhou city supply and demand balance statistics.

Supply and Demand Level	Number of Streets (Blocks)	Number of Streets (%)	Street Area (%)
Extreme supply deficit	7	10.77	9.57
Supply deficit	12	18.46	15.65
Supply-Demand Balance	17	26.15	18.66
Supply Surplus	20	30.76	24.75
Extreme Supply Surplus	9	13.85	31.37

#### 4. Discussion

A large body of research has demonstrated that urban green space can affect people’s health in various ways. For instance, via the physical environment, social interaction, and physical activity. Research has also presented evidence for uneven distributions of green space. An integrated description of the spatial distribution of urban green spaces and the services they provide has been widely discussed. Therefore, this paper investigates the spatial accessibility and equity of green space in urban areas of Fuzhou City based on

telemetry image data, landscape patterns, road data, and spatial syntax. This not only helps to reveal the in-depth influences of green space but also provides a reference for rational planning and management of green space, which can be used to improve the quality and configuration of green spaces.

#### *4.1. Street Network Topology Pattern*

This paper uses space syntax theory to calculate and analyse the accessibility of urban roads. It obtains the street network of Fuzhou City, namely the road integration. It provides factors for the green space accessibility model. As a result, the distribution of road accessibility in Fuzhou City can be observed from the topological form, which is concerned with the distance people have to travel and the convenience of the destination. The accessibility of the urban centre of Fuzhou is higher than that of the peripheral areas. The integration of roads is one of the essential factors affecting the accessibility of green space.

#### *4.2. Remote Sensing Images and Landscape Pattern Analysis*

The development of landscape patterns in urbanisation has increased the alteration and disturbance of the landscape by human activities. The changes in landscape patterns can show the impact of humans on the urban environment under different natural environments and socioeconomic and socio-political conditions, which are caused by the inadequacy of numerous landscape pattern indices in indicating ecological processes. Therefore, in this study, the numerous and ecologically unclear landscape indices were screened and optimised through factor analysis to select representative factors of landscape patterns for a more accurate quantitative analysis of the spatial accessibility of green spaces. We first extracted the green space data of the Fuzhou urban area by analysing Landsat image data. We then used Fragstats software to calculate the relevant landscape pattern indices and then extracted the final landscape pattern index factors by factor analysis. Five landscape indices and two principal component factors were selected by factor analysis: ED, AREA\_SD, SHAPE\_SD, FRAC\_AM, and COHESION. They were then renamed to derive the green space shape complexity factor and green space aggregation factor that can be quantitatively analysed. From these two factors, a calculation for the green space accessibility model can be provided.

#### *4.3. Model of Green Space Accessibility*

Based on the analysis of street network topology and landscape patterns, a model for measuring the spatial accessibility of urban green spaces was constructed using GIS spatial analysis tools. The model yielded valid results in the urban areas of Fuzhou. The results show that the accessibility of green space is decreasing from the centre to the edge of the city. From north to south, Fuzhou City shows a trend of “low-high-low”; the northern part of Fuzhou City is the lowest, followed by the southeastern and western parts.

#### *4.4. Study on the Equity of Green Space*

The spatial equity of green space was mainly calculated according to the accessibility index. Considering the indicators of green space accessibility supply and socio-demographic demand, variable correlation analysis and the spatial superposition of factors were used to quantitatively express the spatial equity of urban green space layout at the street scale. The spatial distributions of supply and demand for green space, based on roads, were derived using the supply and demand overlay model, which expressed the equity of urban green space. In terms of green space equity, Fuzhou City has a majority share in both the number of streets and the amount of area. This indicates that the distribution of green space in the urban area of Fuzhou is relatively fair.

## 5. Conclusions

### 5.1. To Improve the Fairness and Accessibility of Green Spaces in Line with Urban Planning

Urban green spaces are essential to green infrastructure in cities and play a crucial role in sustainable development because they provide vital ecological, social, and cultural functions. The spatial fairness of the layout of public service facilities, such as urban green spaces, directly affects residents' quality of life, especially low-income groups, the elderly, children, and people with disabilities who depend on public service facilities such as green spaces. Therefore, policymakers should focus more on urban green space planning in their spatial policies and pay more attention to the importance of natural environments such as green spaces. Furthermore, to make greenspace central to a city's infrastructure, there should be a review based on the fairness research evaluation model; green space planning should be improved, and relevant regulations should be modified.

### 5.2. Updating and Improving Research Methods and Tools

This study mainly uses GIS spatial analysis, spatial syntax theory, and landscape pattern analysis, which involve some data deficiencies and technical difficulties. For example, spatial syntax cannot handle slope problems, and the road data is analyzed at the same height by default. In subsequent research, high terrain should be removed or height differences should be analyzed. The analysis of landscape indices is based on the processing results of remote sensing images. Therefore, the clarity and classification of remote sensing results are essential, and subsequent improvements should be made to the accuracy of remote sensing images.

### 5.3. Adding Research Data from Different Time Periods

This study is based on a single time point as the time range. It is recommended that future discussions be cut from a longitudinal perspective, exploring the process of changes in the fairness pattern as the characteristics of green spaces, social demographics, landscape indices, and road data change over time.

### 5.4. Failure to Truly Understand the Public's Preferences for Green Space Characteristics and Usage Habits

This study mainly uses a quantitative approach for research and investigation. As for the actual opinions and willingness to use green spaces by the public, which involve more subjective feelings of the users, they have not been reflected. For example, the comfort, safety, and facility conditions of green spaces have not been evaluated.

**Author Contributions:** B.-X.H. contributed to the conceptual design of the study, data collection, drafting of the article, and final approval. W.-Y.L. and W.-J.M. contributed to the conceptual design of the study and data collection. H.X. contributed to the conceptual design of the study. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research is funded by the Social Science Foundation of Fujian Province [Grant No. FJ2021C097]; the 2022 Open Subjects of Rural Revitalization Institute of Fujian Agriculture and Forestry University [Grant No. XCZX2022A13]; and the 2020 Fuzhou Philosophy and Social Science Planning Project [Grant No. 2020FZB21].

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The data presented in this study are available on request from the corresponding author.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Appendix A

Table A1. Demographic variables in urban areas of Fuzhou.

Administrative District	Street	Total Population	Female Population	Population Aged 0 to 14	Population Aged 65 and Over	Foreign Populations
Gulou	Gudong Street	40,769	21,064	4577	5208	13,148
Gulou	Guxi Street	67,420	34,483	7462	7568	25,096
Gulou	Wenquan Street	67,911	33,959	6461	6544	24,603
Gulou	Dongjie Street	32,438	17,033	4013	3891	8410
Gulou	Nanjie Street	45,663	23,480	5102	5537	17,157
Gulou	Antai Street	33,305	17,135	3812	4079	12,046
Gulou	Huada Street	101,489	51,259	10,718	8834	24,416
Gulou	Shuibu Street	45,746	23,463	5200	4930	20,402
Gulou	Wufeng Street	109,429	55,378	13,571	8760	54,162
Gulou	Hongshan Town	143,535	71,430	17,259	10,692	80,796
Taijiang	Yingzhou Street	54,186	26,768	6115	4581	26,184
Taijiang	Houzhou Street	44,047	21,443	3820	5654	13,232
Taijiang	yizhou Street	40,407	20,728	4363	5223	16,839
Taijiang	Xingang Street	49,609	23,930	4625	4298	19,177
Taijiang	Shanghai Street	73,010	37,027	7285	8872	30,579
Taijiang	Cangxia Street	43,654	22,250	4628	5817	15,720
Taijiang	Chating Street	34,441	17,293	3527	4193	13,899
Taijiang	Yangzhong Street	29,195	14,638	3031	3678	10,266
Taijiang	Aofeng Street	43,802	21,258	6981	2754	20,100
Taijiang	Ninghua Street	34,540	17,275	4144	3842	14,278
Cangshan	Cangqian Street	23,663	12,179	3235	2935	6957
Cangshan	Dongshen Street	13,195	6536	1636	1301	7230
Cangshan	Duihu Street	35,785	18,934	2756	2476	20,647
Cangshan	Linjiang Street	29,598	10,751	2457	2413	15,578
Cangshan	Sanchajie Street	23,993	12,170	2850	2696	11,147
Cangshan	Shangdu Street	43,622	22,292	5985	3284	23,736
Cangshan	Xiadu Street	36,275	18,388	5085	3677	15,177
Cangshan	Jinshan Street	80,791	39,762	15,436	3705	37,606
Cangshan	Cangshan Town	30,247	14,496	3663	2007	17,017
Cangshan	Chengmen Town	96,539	47,222	12,245	5893	31,972
Cangshan	Gaishan Town	122,018	58,475	15,630	7042	57,989
Cangshan	Jianxin Town	201,925	93,362	21,498	6348	147,161
Cangshan	Luozhou Town	18,462	8186	1948	1162	8780
Cangshan	Hongxing Street	6633	3217	663	508	1859
Mawei	Luoxing Street	60,117	28,972	8442	2849	34,630
Mawei	Mawei Town	63,299	29,695	6960	3000	41,325
Mawei	Tingjiang Town	39,624	20,896	3560	3857	24,885
Mawei	Langqi Town	68,889	34,770	7059	6025	28,592
Jinan	Chayuan Street	90,045	45,011	9022	7947	52,350
Jinan	Wangzhuang Street	46,980	24,122	6377	3479	26,241
Jinan	Xiangyuan Street	48,717	23,909	6182	3277	30,622
Jinan	Gushan Town	286,095	135,555	43,946	10,220	204,101
Jinan	Xindian Town	166,283	79,337	23,682	8524	116,719
Jinan	Yuefeng Town	130,403	64,362	16,943	8893	84,000
Jinan	Huanxi Town	11,965	5949	1297	1105	2716
Jinan	Shoushan hometown	8091	3900	1080	1076	1122
Jinan	Rixi hometown	3912	1797	498	541	580
Changle	Wuhang Street	76,306	39,429	11,701	5556	38,392
Changle	Hangcheng Street	71,320	34,714	9418	3385	47,713
Changle	Yingqian Street	35,408	17,089	4829	3073	13,863
Changle	Zhanggang Street	46,520	22,610	6446	3613	17,271
Changle	Shouzhuan Town	21,559	10,681	2805	2136	6883
Changle	Yutian Town	32,841	15,927	5328	3107	5601

Table A1. Cont.

Administrative District	Street	Total Population	Female Population	Population Aged 0 to 14	Population Aged 65 and Over	Foreign Populations
Changle	Songxia Town	25,281	11,865	3439	1587	10,512
Changle	Jiangtian Town	44,552	21,213	6659	3352	14,809
Changle	Gukui Town	43,882	21,244	6347	3926	13,407
Changle	Wenwusha Town	19,985	9314	2593	1334	4631
Changle	Heshang Town	51,323	24,482	6285	4485	14,435
Changle	Hunan Town	27,375	13,014	3125	1981	11,307
Changle	Jinfeng Town	84,899	41,596	11,842	5713	39,156
Changle	Wenling Town	27,680	13,655	3414	2617	9226
Changle	Meihua Town	14,216	7214	1710	1502	3504
Changle	Tantou Town	48,026	23,713	5153	4887	17,371
Changle	Luolian hometown	6426	3152	953	780	1222
Changle	Houyu hometown	5027	2677	435	631	2944

(Statistics to: 2010 Sixth Census Population Data).

Table A2. Landscape pattern index analysis table.

Landscape Pattern Index	Expression Formula	Ecological Significance
Landscape (PLAND)	$PLAND = \frac{\sum_{j=1}^n a_{ij}}{A} (100)$	Knowing what proportion of the landscape is covered by patches gives an idea of the abundance of a certain landscape type.
Largest Patch Index (LPI)	$LPI = \frac{\max_{j=1}^n a_{ij}}{A} (100)$	The maximum patch index at the type level describes the percentage of the largest patches in the landscape and is a simple measure of type dominance.
Edge Density (ED)	$ED = \frac{\sum_{k=1}^m l_{ik}}{A} (10,000)$	Edge diversity reveals the extent to which a landscape or type is divided by a boundary and is a direct reflection of the degree of landscape aggregation factors.
Average Patch Area (AREA_MN)	$AREA\_MN = \frac{\sum_{i=1}^n a_{ij}}{n_i} (10,000)$	AREA_MN represents an average condition that characterizes the fragmentation of the landscape type.
Area-Weighted Mean Patch Area (AREA_AM)	$AREA\_AM = \sum_{j=1}^n [a_{ij} (\frac{a_{ij}}{\sum_{j=1}^n a_{ij}})]$	AREA_AM is a statistical form of patch area, which to some extent reflects the diversity of patch areas and the complexity of landscape patterns of landscape types.
Standard Deviation of Patch Area (AREA_SD)	$AREA\_SD = \sqrt{\frac{\sum_{j=1}^n [a_{ij} - (\frac{\sum_{j=1}^n a_{ij}}{n_i})]^2}{n_i}}$	AREA_SD is a statistic of the area complexity of landscape type patches, reflecting the diversity and complexity of their landscape patches.
Density of Patches(PD)	$PD = \frac{N_i}{A_i}$	Landscape patches can reflect the degree of fragmentation of the landscape.
Landscape Shape Index (LSI)	$LSI = \frac{0.25E}{\sqrt{A}}$	When there is only one square patch in the landscape, LSI = 1; when the patch shape in the landscape is irregular or deviates from the square, the LSI value increases.
Average Shape Index (SHAPE_MN)	$SHAPE\_MN = \frac{\sum_{i=1}^m \sum_{j=1}^n (\frac{0.25p_{ij}}{\sqrt{a_{ij}}})}{n_i}$	Reflecting the overall shape characteristics of the landscape pattern, SHAPE_MN = 1 when all patches in the landscape are square, and the value of SHAPE_MN increases when the shape of the patches deviates from square.

Table A2. Cont.

Landscape Pattern Index	Expression Formula	Ecological Significance
Area-Weighted Mean Shape Index (SHAPE_AM)	$SHAPE\_AM = \sum_{i=1}^n \left[ \left( \frac{0.25 p_{ij}}{\sqrt{a_{ij}}} \right) \left( \frac{a_{ij}}{\sum_{i=1}^n a_{ij}} \right) \right]$	SHAPE_AM is one of the most important metrics for measuring the complexity of landscape spatial patterns and has implications for many ecological processes.
Standard Deviation of Patch Shape Index (SHAPE_SD)	$SHAPE\_SD = \sqrt{\frac{\sum_{j=1}^n \left[ \left( \frac{0.25 p_{ij}}{\sqrt{a_{ij}}} \right) - \left( \frac{\sum_{j=1}^n \left( \frac{0.25 p_{ij}}{\sqrt{a_{ij}}} \right)}{n_i} \right) \right]^2}{n_i}}$	SHAPE_SD is a statistic of landscape type patch shape complexity, reflecting the diversity and complexity of its landscape patches.
Fractal Dimension (FRAC_AM)	$D = 2 \log\left(\frac{p}{4}\right) / \log(A)$	The number of sub-dimensions is an important pointer to reflect the overall characteristics of the landscape pattern; the higher the number of sub-dimensions, the more complex the geometry of the landscape.
Mean Euclidean Nearest Neighbor Index (ENN_MN)	$ENN\_MN_i = \frac{\sum_{j=1}^n h_{ij}}{n_i}$	ENN_MN measures the spatial pattern of the landscape. Generally speaking, a large ENN_MN value reflects that the patches of the same type are far apart and have a discrete distribution; on the contrary, it indicates that the patches of the same type are close to each other and have a clustered distribution.
Isolation Index (SPLIT),	$I_i = \frac{\sqrt{n_i A}}{2A_i}$	The separation index shows the relationship between separation and the number of patches, and the effect of the area of patches in the landscape. The greater the separation, the more dispersed the distribution of patches in the landscape.
Aggregation Index(AI)	$AI = \left[ \sum_{i=1}^m \left( \frac{g_{ii}}{\max g_{ij}} \right) p_i \right] (100)$	At the patch type level, the agglomeration index is obtained from the connectivity matrix calculation and is used to measure the maximum number of possible connections for a given patch type.
COHESION Index (COHESION)	$COHESION = \left[ 1 - \frac{\sum_{j=1}^n p_{ij}}{\sum_{j=1}^n p_{ij} \sqrt{a_{ij}}} \right] \left[ 1 - \frac{1}{\sqrt{A}} \right]^{-1} ()$	The cohesiveness of the landscape is related to the distance between similar patches, the presence or absence of corridors, the frequency of intersection of different types of corridors, and the size of the network formed.

**Table A3.** The Spearman analysis results of landscape metrics.

	PLAND	PD	LPI	ED	LSI	AREA_ MN	AREA_ AM	AREA_ SD	SHAPE_ MN	SHAPE_ AM	SHAPE_ SD	FRAC_ AM	COHE- SION	SPLIT	AI
PLAND	1.000														
PD	−0.569 **	1.000													
LPI	0.980 **	−0.664 **	1.000												
ED	−0.263 **	0.832 **	−0.370 **	1.000											
LSI	−0.541 **	0.933 **	−0.636 **	0.920 **	1.000										
AREA_MN	0.820 **	−0.917 **	0.878 **	−0.637 **	−0.854 **	1.000									
AREA_AM	0.967 **	−0.708 **	0.996 **	−0.418 **	−0.677 **	0.901 **	1.000								
AREA_SD	0.493 **	−0.107 *	0.491 **	0.053	−0.133 **	0.276 **	0.484 **	1.000							
SHAPE_MN	0.401 **	−0.588 **	0.429 **	−0.200 **	−0.333 **	0.605 **	0.443 **	0.114 *	1.000						
SHAPE_AM	0.051	0.364 **	0.035	0.701 **	0.542 **	−0.196 **	0.019	0.379 **	0.134 **	1.000					
SHAPE_SD	0.075	0.311 **	0.044	0.599 **	0.473 **	−0.173 **	0.027	0.592 **	0.182 **	0.847 **	1.000				
FRAC_AM	−0.144 **	0.518 **	−0.172 **	0.786 **	0.691 **	−0.390 **	−0.190 **	0.247 **	0.037	0.970 **	0.824 **	1.000			
COHESION	0.942 **	−0.771 **	0.980 **	−0.460 **	−0.713 **	0.937 **	0.989 **	0.443 **	0.506 **	0.011	0.024	−0.196 **	1.000		
SPLIT	−0.986 **	0.651 **	−0.999 **	0.352 **	0.622 **	−0.874 **	−0.994 **	−0.492 **	−0.428 **	−0.039	−0.051	0.166 **	−0.978 **	1.000	
AI	0.756 **	−0.896 **	0.0823 **	−0.745 **	−0.937 **	0.949 **	0.848 **	0.266 **	0.397 **	−0.371 **	−0.331 **	−0.558 **	0.869 **	−0.815 **	1.000

\* Significant at the 0.05 level. \*\* Significant at the 0.01 level.

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