

Article

Spatial–Temporal Evolution and Driving Force Analysis of Blue–Green Space in the Chengdu–Chongqing Economic Circle, China

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Abstract: In the rapid process of urbanization, revealing the patterns and driving forces behind the evolution of blue–green spaces holds significant value for optimizing urban blue–green environments. This study systematically investigates the spatial–temporal evolution characteristics and driving forces of blue–green space in the Chengdu–Chongqing Economic Circle from 1990 to 2020, utilizing GIS technology, landscape pattern analysis, and geographic detectors. The research findings indicate the following: (1) The area of blue–green space in the study area exhibits a general trend of initial growth followed by decline, with significant changes occurring between 2010 and 2020. (2) The fragmentation degree of blue–green space is gradually increasing, while connectivity among landscapes is decreasing; however, there has been an increase in landscape distribution uniformity. More than 90% of blue–green spaces expanded mainly through adjacency patterns. (3) In examining driving forces, it was found that temperature, topographic relief, elevation, population density, and construction intensity are the primary driving factors. Notably, the influence of natural factors has diminished over time while human social factors have significantly intensified. This study offers solutions for optimizing the configuration of blue–green spaces within the Chengdu–Chongqing Economic Circle. It also serves as a reference case for promoting high-quality urbanization in developing countries undergoing rapid urbanization.

Keywords: blue–green space; landscape pattern; spatial–temporal evolution; driving force; Chengdu–Chongqing Economic Circle



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1. Introduction

The “blue–green space” encompasses two types of landscape spaces: blue space and green space. “Blue space” refers to various forms of water bodies such as rivers, lakes, reservoirs, ponds, beaches, and wetlands, while “green space” includes forests, grasslands, parks, and municipal protective green belts [1]. These areas play multiple roles, including climate regulation [2–4], biodiversity protection [5], promoting human physical and mental health [6], and enhancing of quality of life [7,8]. They are essential for maintaining urban ecosystem services and vitality [9,10] and for constructing sustainable, resilient, and adaptive urban ecosystems [11,12]. However, the rapid pace of urbanization has led to changes in land cover types within cities, resulting in significant alterations to urban landscape patterns [13]. The expansion of urban areas has resulted in substantial encroachment on blue–green space by urban development [14], leading to increasing

fragmentation of these landscapes [15] and a gradual loss of their systemic connectivity and diversity which are crucial for regional ecological regulation [10,16]. Both scholars and various levels of government have increasingly recognized the importance of optimizing the layout of blue–green space for high-quality urban development [13]. Currently, research on the spatial–temporal evolution, processes and driving mechanisms associated with blue–green space has become a focal point across multiple disciplines [17,18]. Furthermore, the integration of blue–green space has emerged as a crucial topic in regional ecological governance, urban environmental research, and land spatial planning. It plays a significant role in shaping the development and protection framework of urban ecological space [8,12]. This concept of integrating blue–green space has been incorporated into national strategies and urban development plans across multiple countries and regions worldwide [6,11,19]. These planning strategies aim to construct ecological structures and patterns in a rational manner [3,5].

This study focuses on the Chengdu–Chongqing Economic Circle—the fourth pole of economic growth in China—to analyze the spatial–temporal evolution characteristics driven by rapid urbanization regarding its blue–green space along with their underlying mechanisms. This research aims to reveal evolutionary patterns of blue–green space in high-density urban areas to provide guidance for formulating land spatial planning policies that protect metropolitan ecological environments.

1.1. Existing Knowledge on Blue–Green Space

1.1.1. Research on the Blue–Green Spatial Pattern

In the research on the evolution of blue–green space patterns, scholars predominantly rely on remote sensing data and landscape pattern indices to quantitatively analyze issues such as the scale, quantity, shape, distribution patterns, and intensity of landscape changes in blue–green space [12,15,18]. Commonly employed indices include Patch Density (PD), Shape Index, Connectivity Index (CONNECT), Aggregation Index (AI), and Contagion Index (CONT) [16,17,20–22]. For example, the correlation between the distribution characteristics of the urban blue–green space area ratio index and the distribution of urban economic and social factors is analyzed by quantitative interpretation of remote sensing images within a specific year [21]. The landscape pattern index can also be calculated by Fragstats4.1 [22], and the grey correlation degree between wetland landscape patterns and social, economic, and natural environments is systematically analyzed by using the grey correlation method [17]. Most studies indicate that rapid expansion of built-up areas has densely encroached upon blue–green space, leading to increased landscape fragmentation and reduced heterogeneity [14,15,20]. Some research confirms that the evolutionary characteristics of blue–green space landscapes differ at various stages of urbanization; these characteristics primarily manifest through varying degrees of landscape fragmentation and patch diversity [20–22]. Additionally, there is an emphasis on promoting connectivity within blue–green space due to its significance for urban ecological environments [4,5,9].

1.1.2. Research on the Driving Forces of Blue–Green Space

The exploration of the driving forces behind the evolution of blue–green space is one of the significant aspects in the study of blue–green space research. Scholars have explored the driving factors behind the changes in landscape patterns of blue–green space at different scales through a combination of qualitative and quantitative analyses [21–23]. It is widely acknowledged that the variations in blue–green space landscape patterns are primarily the result of interactions among multiple factors, including socio-economic conditions and natural geography [24–26]. The following specific studies are typical of this view: based on the analysis of urban land use in 13 cities of Jiangsu Province from 2010 to 2016 using the Tobit model, it is concluded that industrial structure, real estate marketization, natural population growth, and urbanization degree jointly drive the evolution of the spatial–temporal pattern in this region [27]. Research on the driving factors of land use change in Tibet from 2015 to 2020 shows that natural factors play a decisive role,

while socio-economic and policy factors play a greater role [28]. The study of land use in Hangzhou using geographic detectors shows that elevation, GDP, night light intensity, and construction intensity are the main driving factors for regional blue–green space evolution; the overall explanatory power of the driving factors has the characteristics of a gradual decline and then increases; and the homogenization of various driving forces gradually increases [20]. The overall explanatory power of these driving factors exhibits characteristics of both phase-specific decline and subsequent increases; moreover, there is a gradual homogenization among various driving forces. Related studies indicate that while natural factors do contribute to the evolution of blue–green space, human activities can directly alter local landscape patterns within short timeframes—an influence that has become increasingly pronounced [20–26]. At different stages of development, both the magnitude and directionality of these influencing factors vary significantly; consequently, blue–green space evolution manifests distinct change patterns. However, it appears evident that regions with higher intensities of human activity experience more pronounced disturbances to their blue–green space [29,30].

1.2. Challenges and Gaps in Existing Research

The existing research on blue–green space is relatively abundant, providing a significant foundation for further discussions regarding the characteristics and driving forces of landscape pattern changes in the study area. However, studies focusing specifically on blue–green space as an integrated unit are scarce. Most current research tends to concentrate on the evolution of overall land use patterns or specific types of blue or green space, such as green lands and wetlands. There is a notable lack of systematic descriptions that address the structure, function, and driving forces of blue–green space as an integrated landscape unit; thus, it fails to adequately reflect its functional value and impact on high-quality human development. Moreover, existing studies predominantly focus on specific years or short-term timeframes [31,32]. However, changes in blue–green space occur over long-term and gradual processes that cannot be fully captured within merely three to five years of short-term research [33]. Therefore, conducting long-time series evolutionary studies on blue–green space is crucial. In examining the driving forces behind landscape pattern changes in blue–green space, previous findings have encountered issues related to limited factors selected for analysis—small quantity, single type, and other problems—and often rely heavily on regression models [21,28,34]. Because the commonly used multiple regression analysis method cannot verify nonlinear relations, outliers, multicollinearity, and other major problems, this study adopts the optimal parameter-based Geographic Detector model, which can effectively use a variety of statistical methods to achieve the discretization of continuous variables to calculate the best results [35]. In this context, this study systematically conducted empirical measurements on the development trend and evolution characteristics of the blue–green space landscape pattern of large-scale urban agglomerations in a long time series; elucidated the dynamic evolution law of blue–green space in terms of area size and spatial distribution; and selected indicators from multiple perspectives such as nature, economy, and society to measure the driving forces of blue–green space by using the Geographic Detector model in order to reveal the evolution law of blue–green space in high-density urban agglomerations and put forward suggestions for promoting the optimization of economic blue–green space landscape patterns and ecological development in Chengdu–Chongqing Economic Circle.

1.3. Hypotheses

This study, grounded in the evolutionary patterns of blue–green space within the Chengdu–Chongqing Economic Circle, focuses on the changes in blue–green space patterns during rapid urbanization and reflections on urban development models. The research perspective adopted focuses on the interconnections among elements, structures, and functions. Based on the research framework of “pattern evolution—model recognition—behavior mechanism—dynamic mechanism—optimization path”, this study

explores the development of blue–green space in the Chengdu–Chongqing Economic Circle in the last 30 years. Based on this framework, the following hypotheses are formulated:

(1) It is hypothesized that the transformation of blue–green space elements in the Chengdu–Chongqing Economic Circle exhibits phased characteristics. Based on the above considerations, it can be posited that during the urbanization process, the transformation of blue–green space elements shows a significant positive correlation with the expansion rate of urban construction during the urbanization process, manifesting as a trend of first rapidly declining and then gradually rising to a stable state.

(2) It is assumed that the patterns of changes in blue–green space in the Chengdu–Chongqing Economic Circle exhibit notable spatial–temporal differences. With reasoning, further assumptions can be made that the pattern of change in blue–green space is primarily characterized by adjacency expansion, with variations in the speed and manner of expansion across different periods.

(3) It is hypothesized that the factors influencing changes in blue–green space patterns within the Chengdu–Chongqing Economic Circle exhibit varying strengths at different developmental stages. To be specific, throughout this development process, the intensity of human disturbance as a driving force will progressively increase, while the influence of natural geographical conditions will gradually diminish.

1.4. Aims and Contributions of the Present Study

The Chengdu–Chongqing Economic Circle boasts the largest population in southwestern China and is also the region with the highest level of urbanization in the southwest. By analyzing the spatial–temporal pattern evolution and driving mechanisms of blue–green space in the Chengdu–Chongqing Economic Circle from 1990 to 2020, a period of rapid urbanization in China spanning 30 years, this study, through a long-term series of research, can delve deeper into the mechanisms of different factors influencing blue–green space evolution. This study aims to provide a reference for the optimization and management of blue–green space in the Chengdu–Chongqing Economic Circle, as well as for regional sustainable development, thereby contributing to the high-quality development of this economic zone.

This study seeks to establish a comprehensive and systematic framework for the assessment and management of blue–green space. This framework aims not only to facilitate high-quality development in the Chengdu–Chongqing region but also to serve as a reference for other regions worldwide that are facing similar challenges. To more clearly portray the dynamic evolution of blue–green space in the Chengdu–Chongqing Economic Circle, this study first conducted a static analysis of the distribution of blue–green space in the study area by establishing landscape pattern indices. Considering that landscape pattern indices alone are difficult to effectively express the dynamic information of changes in blue–green space landscape patterns, the study introduced the Landscape Expansion Index (LEI) to describe the dynamic landscape pattern evolution in terms of the expansion patterns and scales of blue–green space over a long time series in the Chengdu–Chongqing Economic Circle [36]. The Geographic Detector was used as a tool to analyze the driving forces of blue–green space. This approach addresses the limitations of traditional statistical methods and further enables the detection of the interaction effects between two factors on the dependent variable. This represents an innovative methodological advancement in the study of driving forces behind blue–green space [37].

2. Research Design and Methods

2.1. Overview of the Study Area

The Chengdu–Chongqing Economic Circle (Figure 1) is located in the Sichuan Basin, characterized by diverse topographical features. The central region consists of a flat basin, while the periphery is predominantly composed of low mountains and hilly terrain. The region boasts excellent ecological endowments, characterized by a high forest coverage rate and a well-developed water system, which includes the three major river systems

(the Min River, Tuo River, and Fu River) and abundant resources including energy and minerals. This region represents western China's most robust industrial base with the highest innovation capacity, greatest population density, broadest market potential, and highest degree of openness. It occupies a unique and strategically significant position within the broader context of national development. According to the "Outline of the Development Plan for Chengdu-Chongqing Economic Circle", the total area of this study region encompasses 239,500 square kilometers. It has a permanent resident population of approximately 100 million and encompasses 15 cities in Sichuan Province, namely Chengdu, Zigong, Luzhou, Deyang, Mianyang, Suining, Neijiang, Leshan, Nanchong, Meishan, Yibin, Guang'an, Dazhou, Ya'an, and Ziyang, as well as Chongqing Municipality (which is at the same administrative level as Sichuan Province). Considering the landscape connectivity of the study area, certain counties and districts beyond the initial plan have been incorporated into the study's scope to guarantee the completeness of the region being examined. Within the scope of this study area, there are a total of 156 counties, including 118 counties in Sichuan Province and 38 counties in Chongqing Municipality. In 2023, the Chengdu–Chongqing Economic Circle achieved a gross domestic product (GDP) of CNY 8.1987 trillion, accounting for 6.5% and 30.4% of China's and Western China's economies, respectively. Its regional potential energy level has steadily improved, leading to an ever-increasing demonstration and driving effect. In terms of economic development, the economic aggregate of the Chengdu–Chongqing Economic Circle accounted for 78.5% of the Beijing–Tianjin–Hebei region and 26.9% of the Yangtze River Delta Economic Zone, continuously narrowing the development gap with other economic zones.

2.2. Research Methodology

2.2.1. Analysis of Dynamic Changes in Land Use Structure

(1) Dynamic Degree Analysis Method

The dynamic degree of land use measures the speed of land use changes within a specific time frame in the study area, serving as an indicator to reflect the intensity of changes in land use structure [38,39]. Among these, the single land use dynamic degree (K) is used to calculate the change rate of a particular land type, with the formula being

$$K = \frac{U_a - U_b}{U_a} \times \frac{1}{t} \times 100\% \quad (1)$$

where U_a , U_b are the area of a certain land use type at the beginning of the study and at the end of the study period, respectively, and t is the number of years between the study periods, generally measured in years.

(2) Land use transfer matrix method

The land use transfer matrix is derived from the quantitative description of system states and state transitions in system analysis [40,41]. It is based on the Markov model to quantify the dynamic transfers between different land use types. The formula is as follows:

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1N} \\ P_{21} & P_{22} & \cdots & P_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ P_{N1} & P_{N2} & \cdots & P_{NN} \end{bmatrix} \quad (i, j = 1, 2, 3 \dots N) \quad (2)$$

where P_{ij} is the land area where land type i is to be transferred to land type j ; i and j are two types before and after the transfer; N is the number of land use types; $i = j$ indicates the land area with an unchanged land use type.

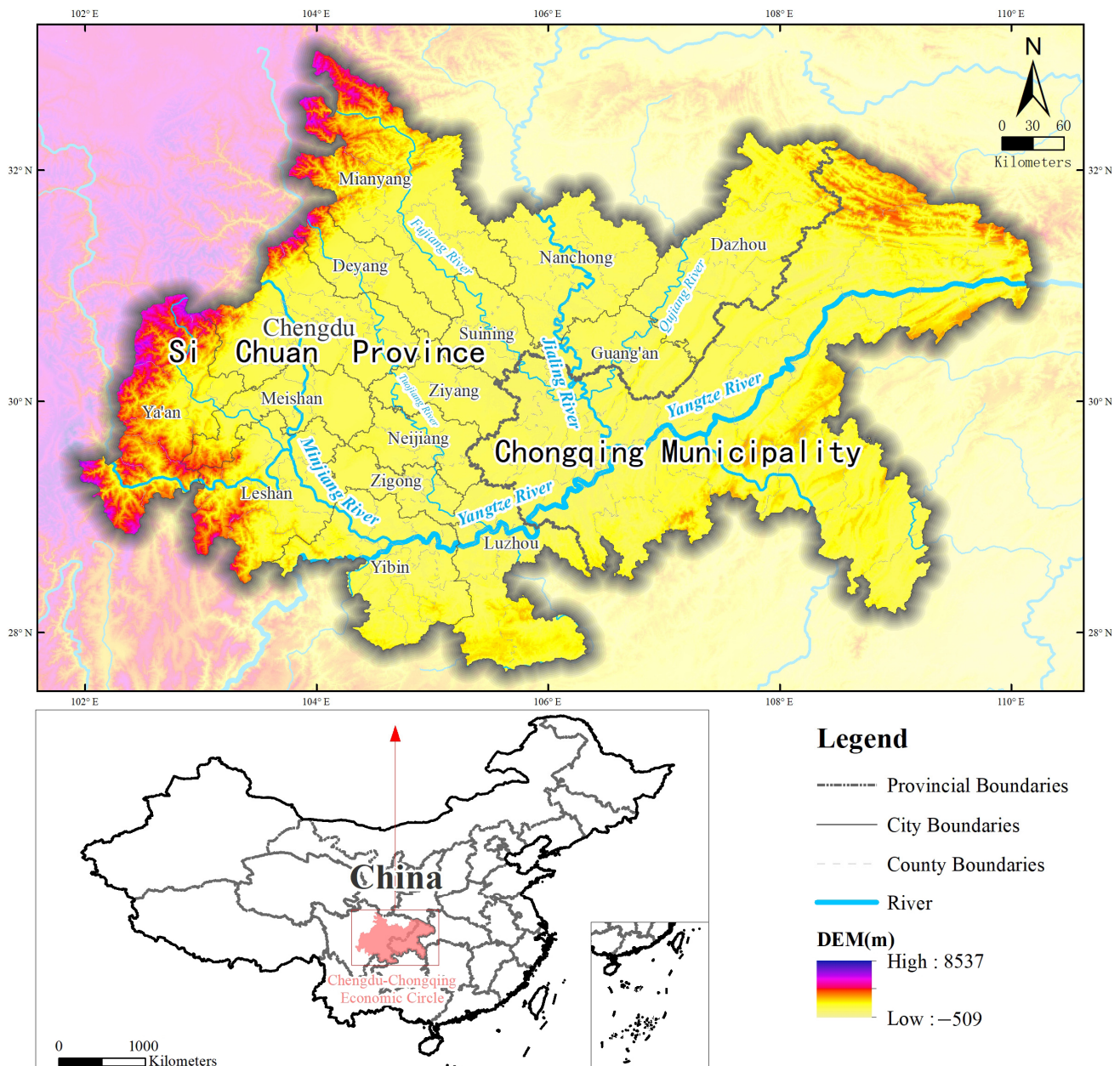


Figure 1. Chengdu–Chongqing Economic Circle geographical location.

2.2.2. Landscape Pattern Index

The Landscape Pattern Index refers to an index that can quantitatively describe the landscape pattern structure and spatial configuration [20,32]. The patch type level can reflect the structural characteristics of different patch types in the landscape, and the landscape level can reflect the overall structural characteristics of the landscape. Therefore, this study selected representative indicators from the patch type level and the landscape level to analyze the landscape pattern. Using Fragstats4.2 software, at the patch type level, the Patch Density (PD) is selected to reflect the degree of consistency in the landscape space [16,17]. The Largest Patch Index (LPI) reflects the dominance of the patch type [17,20]. The Aggregation Index (AI) reflects the degree of aggregation at the landscape level [12,20]. The Landscape Division Index (DIVISION) is selected to reflect the connectivity between landscapes at the landscape level [20,21]. Finally, the Shannon's Evenness Index (SHEI) reflects the degree of heterogeneity in the landscape [20].

2.2.3. Landscape Expansion Index

Compared with the traditional landscape index, the Landscape Expansion Index (LEI) can reflect the spatial–temporal dynamic change information of the landscape pattern [36]. The formula is as follows:

$$LEI = \frac{A_P - A_0}{A_P + A_0} \quad (3)$$

where LEI is the landscape expansion index at the patch level, A_P is the expanded patch area, and A_0 is the patch area adjacent to the expanded patch, which is the original patch. When there is an area where A_P and A_0 are in contact with each other, LEI falls within the range of $(-1, 1)$. A higher LEI value indicates a larger scale of landscape expansion, and the spatial expansion mode of the landscape at this time is contiguous expansion. When $LEI < 0$, it indicates that the expansion area of the expanding patch is smaller than the area of the original patch; when $LEI = 0$, it means that the expansion area of the expanding patch is equal to the area of the original patch; and when $LEI > 0$, it signifies that the expansion area of the expanding patch is larger than the area of the original patch. LEI equals 1 only when $A_0 = 0$, i.e., when the original patch adjacent to the expanding patch does not exist. In this case, the spatial expansion mode of the landscape is external expansion.

2.2.4. Geographic Detector Model and Driving Factors

The basic principle of the Geographic Detector, as a tool for exploring driving forces, is that if a certain independent variable has a significant impact on the dependent variable, then they should exhibit similarity in spatial distribution [37,42]. The Factor Detector within the Geographic Detector can be utilized to calculate the explanatory power of each driving factor on the changes in the characteristics of the blue–green space landscape pattern. The formula of the model is as follows:

$$q = 1 - \frac{1}{N\sigma^2} \sum_{i=1}^L N_i \sigma_i^2 \quad (4)$$

where q is the explanatory power of a certain driving factor, and when $q \in [0, 1]$, a larger value indicates a stronger driving force; N is the number of all samples in the study area; and σ^2 and σ_i^2 represent the total variance of the region and the variable variance of the secondary regions, respectively. Here, $i = 1, 2, \dots, L$, where i denotes the partition and L represents the number of partitions. When $q = 0$, it indicates that there is no spatial heterogeneity in the research object; when $q = 1$, it indicates perfect spatial heterogeneity.

Through the study of relevant literature and considering the representativeness and scientific validity of selected factors, the researchers chose elevation, undulation, soil erodibility factor, temperature (regional average annual temperature), and precipitation (annual total precipitation) as factors representing natural geographical conditions. For human disturbance intensity, GDP, population density, nighttime light intensity, construction intensity, and fertilizer application intensity were selected, totaling 10 factors (except where data for fertilizer application intensity in 1990 were missing, resulting in 9 factors) [20,25,28,39,40]. Referencing relevant studies [33,34] which found a certain correlation between fertilizer use and green–blue space, fertilizer application intensity (i.e., the amount of fertilizer applied per hectare of land in the region) was introduced as an important driving factor [43,44]. These factors were used to analyze the driving forces behind the evolution of the green–blue spatial landscape pattern in the Chengdu–Chongqing Economic Circle. Employing classification methods for discretizing driving factors in related research, and utilizing the latest R language package “GD” for 2020, various discretization methods were applied to different continuous variables [20,45]. The optimal spatial discretization method for each variable was then selected to ensure more objective and reasonable results.

2.3. Data Sources

The following data sources were primarily utilized: ① Land use data for the Chengdu–Chongqing Economic Circle were sourced from the Resource and Environmental Sciences

and Data Center of the Chinese Academy of Sciences (<http://www.resdc.cn>, accessed on 25 May 2023), with a resolution of $30\text{ m} \times 30\text{ m}$. These data have a comprehensive evaluation accuracy of over 90%, and the land use types are mainly classified into six categories: cultivated land, forest land, grassland, construction land, inland waters, and other land. Additionally, the construction intensity data are calculated based on the aforementioned land use data. ② Digital Elevation Model (DEM) data were obtained from ASTER GDEM, jointly measured by NASA and NIMA, with a spatial resolution of 30 m. Furthermore, relief degree was calculated using these DEM data. ③ Temperature and precipitation data were sourced from the National Earth System Science Data Center (<http://www.geodata.cn>, accessed on 25 June 2023), with a spatial resolution of 1 km. ④ Soil erodibility factor data were retrieved from the Earth Resources Data Cloud Platform (<http://www.gis5g.com>, accessed on 25 May 2023), with a spatial resolution of 300 m. ⑤ Nighttime light intensity data were primarily derived from the DMSP-OLS dataset (<https://dataverse.harvard.edu>, accessed on 25 May 2023), with a data resolution of 1 km. ⑥ GDP, population density, and fertilizer application intensity data were compiled and extracted from government statistical yearbooks of Sichuan Province and Chongqing Municipality.

3. Results

3.1. Characteristics of Land Use Change in the Chengdu–Chongqing Economic Circle

Over the 30-year period from 1990 to 2020 (Tables 1–3), the most significant changes in land use types within the Chengdu–Chongqing Economic Circle were observed in grasslands and cultivated land, both of which showed a primary trend of decreasing. The main transformations were towards forestland and construction land, as well as mutual conversions between grasslands and cultivated land. A comprehensive comparison of the changes in land use types over the past 30 years in the study area revealed that the largest 10-year decremental phase for grasslands was 18.09%, while the largest 10-year incremental phase for construction land was 85.13%. Further dividing the land use transitions in the study area into three phases, 1990–2000 (Phase I), 2000–2010 (Phase II), and 2010–2020 (Phase III), it was found that Phase II saw the most intense land use transformations. In Phase I (Figure 2a), cultivated land experienced the greatest reduction, decreasing by 660.51 km^2 (5%), primarily converted to construction land and forestland. Meanwhile, construction land expanded the most, gaining 712.22 km^2 , primarily converted from cultivated land amounting to 689.34 km^2 . In Phase II (Figure 2b), the pattern of land use type shifts remained similar to Phase I, with cultivated land continuing to be the land type with the largest reduction, totaling 1631 km^2 . Grassland also decreased by 297.3 km^2 , while forestland and inland waters increased by 729.04 km^2 and 145.57 km^2 , respectively. In the third stage (Figure 2c), grassland became the main transferred-out type of land use in the study area and was mainly converted into cultivated land and forestland, with a transferred-out area of 2255 km^2 and 4438 km^2 , respectively. The area of land for construction increased significantly to 3554 km^2 , and the main source was still cultivated land, accounting for 49.27% of the total area of land for construction in 2020. Compared to the previous two phases, forestland's growth was notable in Phase III, expanding by 2509 km^2 . Based on the analysis of the characteristics of land use changes and trends in basic land types over the 30-year period in the Chengdu–Chongqing Economic Circle, it is found that the dynamic changes in land use types such as grasslands, forestland, and inland waters serve as prerequisites for accelerating the dynamic evolution of blue–green space in the study area. Additionally, by analyzing the pattern changes in land use types like inland waters and grasslands, one can make basic inferences about the dynamic patterns of blue–green space changes.

Table 1. Land use change (in km²) for the Chengdu–Chongqing Economic Circle from 1990 to 2020.

Land Use Type	Transfer Areas (km ²) from 1990 to Various Land Types						Total for 2000
	Grassland	Cultivated Land	Construction Land	Forestland	Inland Waters	Other Land	
Grassland	24,498.37	30.73	0.55	348.86	0.12	1.65	24,880.28
Cultivated Land	31.21	130,981.78	8.15	204.78	12.73	0.01	131,238.66
Construction Land	6.09	689.34	2416.90	24.06	1.71	0.01	3138.11
Forestland	249.95	176.81	0.18	76,632.22	1.67	1.71	77,062.52
Inland Waters	2.46	20.48	0.12	2.13	2935.09	0.01	2960.29
Other Land	0.01	0.03	0.00	0.56	0.02	213.27	213.89
Total	24,788.09	131,899.16	2425.89	77,212.59	2951.33	216.66	239,493.75

Table 2. Land use change (in km²) for the Chengdu–Chongqing Economic Circle from 2000 to 2010.

Land Use Type	Transfer Areas (km ²) from 2000 to Various Land Types						Total for 2010
	Grassland	Cultivated Land	Construction Land	Forestland	Inland Waters	Other Land	
Grassland	24,045.23	426.58	1.24	128.92	1.46	0.54	24,603.98
Cultivated Land	346.13	128,581.51	28.92	629.38	20.21	1.16	129,607.33
Construction Land	20.33	1005.25	3096.38	48.43	3.91	0.03	4174.33
Forestland	436.20	1129.84	2.84	76,216.79	5.35	0.54	77,791.56
Inland Waters	31.91	94.89	8.72	38.65	2929.04	2.64	3105.86
Other Land	0.47	0.58	0.02	0.34	0.31	208.97	210.69
Total	24,880.28	131,238.66	3138.11	77,062.52	2960.29	213.89	239,493.75

Table 3. Land use change (in km²) for the Chengdu–Chongqing Economic Circle from 2010 to 2020.

Land Use Type	Transfer Areas (km ²) from 2010 to Various Land Types						Total for 2020
	Grassland	Cultivated Land	Construction Land	Forestland	Inland Waters	Other Land	
Grassland	17,886.41	1132.49	24.37	1087.48	12.60	8.95	20,152.30
Cultivated Land	2055.30	118,526.19	635.75	5869.87	288.83	6.88	127,382.83
Construction Land	121.74	3807.70	3393.42	338.83	64.53	1.91	7728.14
Forestland	4438.42	5512.50	67.96	70,231.20	41.11	9.69	80,300.88
Inland Waters	82.99	611.78	52.42	164.36	2693.63	17.14	3622.33
Other Land	19.11	16.68	0.40	99.81	5.16	166.12	307.28
Total	24,603.98	129,607.33	4174.33	77,791.56	3105.86	210.69	239,493.75

3.2. Structural Evolution Characteristics of Blue–Green Space in the Chengdu–Chongqing Economic Circle

The green space in the Chengdu–Chongqing Economic Circle is mainly concentrated in the east and west of the study area and close to the boundaries, while the coverage of green space along the southern boundary is relatively low, which is related to the prevalence of mountainous and hilly terrain and high forest coverage in these areas (Figure 3). The blue–green space in the central region of the study area accounts for a relatively small proportion, which is closely related to the relatively flat terrain and concentrated urban agglomeration construction in these areas. The blue space is mainly dominated by the Yangtze River and its tributaries running through the Chengdu–Chongqing Economic Circle, accompanied by waters such as lakes concentrated around some cities. Between 1990 and 2020 (Figure 4), the most dramatic phase of dynamic changes in blue–green space in the study area was Phase III. The basic trend of the total area of blue–green space in the region was first to increase and then to decrease, from 104,517 km² in 1990 to 105,146 km² in 2010, and then decreased to 104,124 km² in 2020; the total area decreased by 393.53 km², with a periodic dynamic degree of −0.38% and an annual dynamic degree of −0.01% over the past 30 years.

The changing trend of green space in the study area is consistent with the overall trend of blue–green space. The total area of green space decreased by 898.61 km² from 1990 to 2020, and the proportion of blue–green space in the total area of the study area decreased by 0.38%. The main component of blue–green space in the region is green space, accounting for about 97% of the total area of blue–green space between 1990 and 2020. Among the development phases, the largest decrease in green space occurred in Phase III, with a decrease of 1294 km². The dynamic trend of blue space increased year by year, with a total increase of 505.07 km² from 1990 to 2020, a periodic dynamic degree of 16.72% over 30 years, and an average dynamic degree of 5.85% over 10 years. The largest increase occurred in Phase III, reaching 270.75 km², with an increase rate of 9.84%. This trend reveals that from 1990 to 2020, the Chengdu–Chongqing Economic Circle experienced rapid economic development, with significant improvements in urbanization and industrialization levels, leading to a notable decrease in green space. At the same time, the regional government attached great importance to watershed management and ecological protection [46], gradually recognizing the need for further protection and construction of terrestrial waters during urban construction [47], resulting in an increase in the area of blue space. However, since the increase in blue space was far lower than the decrease in green space, the overall blue–green space in the region decreased significantly.

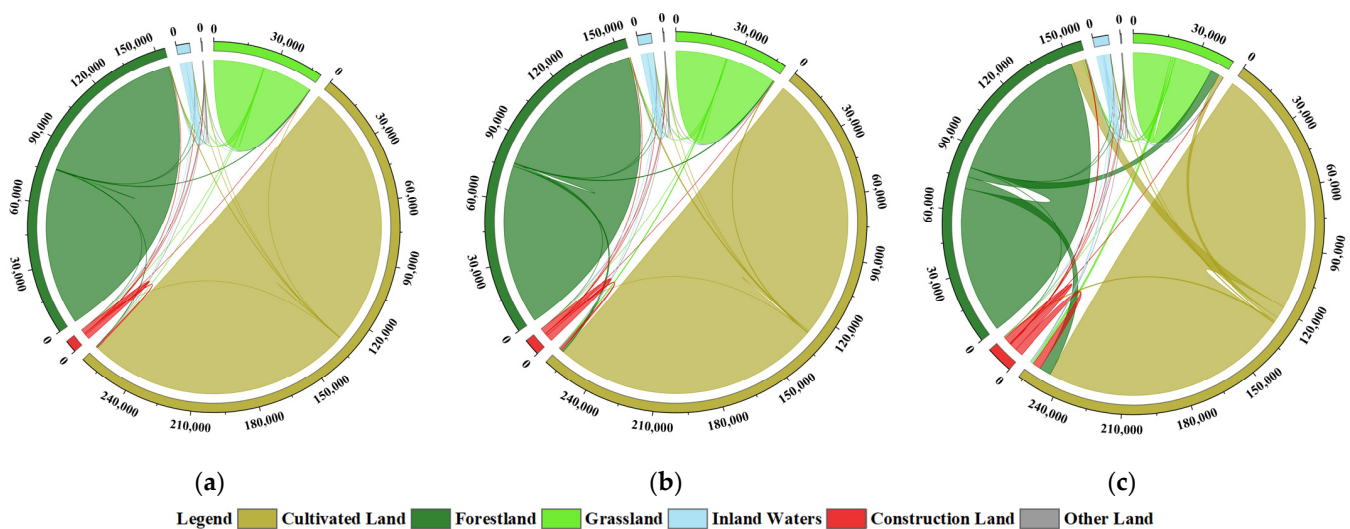


Figure 2. Land use change map (in km²) for the Chengdu–Chongqing Economic Circle from 1990 to 2020: (a) 1990–2000; (b) 2000–2010; (c) 2010–2020.

3.3. Landscape Pattern Evolution Characteristics of Blue–Green Space in the Chengdu–Chongqing Economic Circle

By comparatively analyzing the numerical changes in the landscape pattern indices of the Chengdu–Chongqing Economic Circle from 1990 to 2020, various characteristics of the changes in blue–green space during the urbanization process in this region can be discerned. On the whole, the significance of changes in Phase III is more pronounced than that in Phase I and Phase II (Table 4). Overall, the significance of changes in the Phase III is stronger than those in the first and second phases. The Patch Density (PD) Index describes the evolution characteristics of patches in terms of type and aggregation [17]. From 1990 to 2020, the PD Index exhibited an inverted U-shaped pattern, with the declining trend notably weaker than the growth trend. An increase of 3% in the PD Index over 30 years indicates that the overall blue–green space tended towards fragmentation. Specifically, when comparing blue–green space, the PD's regional changes were unstable, tending towards completeness in the first 10 years and then becoming more structurally complex in the subsequent 20 years, contributing to the fragmentation of blue–green space. The Largest Patch Index (LPI) and Division Index (DIVISION) can characterize landscape

fragmentation [20,21]. Between 1990 and 2020, the highest LPI value occurred in 2000, with an overall increase followed by a decrease, suggesting strong human activity interference and a decrease in blue–green space’s dominance. DIVISION peaked in 2020, showing an initial decrease followed by an increase. The decrease in the LPI was significantly more pronounced than the increase in DIVISION, indicating that as urban construction accelerates, the degree of blue–green space fragmentation is also gradually increasing. The Shannon’s Evenness Index (SHEI) reflects the degree of landscape diversity [20]. From 1990 to 2020, the evenness of regional landscapes gradually increased, with the fastest growth occurring in Phase III, suggesting an increase in the evenness of blue–green space distribution within the Chengdu–Chongqing Economic Circle. A higher Aggregation Index (AI) indicates the presence of dominant patches with high connectivity and good connectivity, whereas a lower AI indicates the existence of numerous small patches and a higher degree of fragmentation [17,20]. Over the 30-year period, the AI showed an overall downward trend, indicating that the connectivity of blue–green space within the study area is gradually deteriorating, with the rate of decrease accelerating significantly in Phase III.

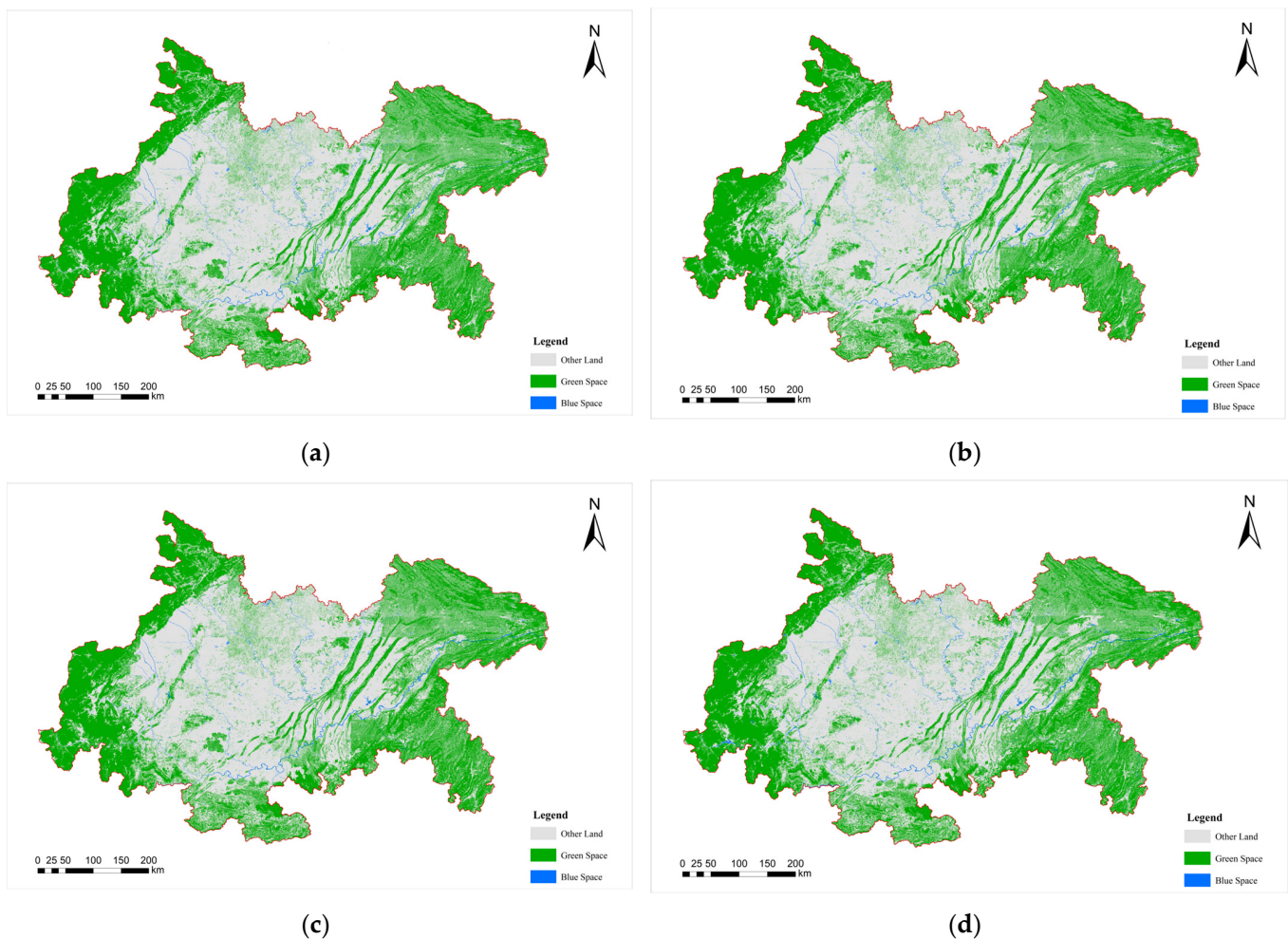


Figure 3. Distribution map of blue–green space in the Chengdu–Chongqing Economic Circle from 1990 to 2020: (a) 1990; (b) 2000; (c) 2010; (d) 2020.

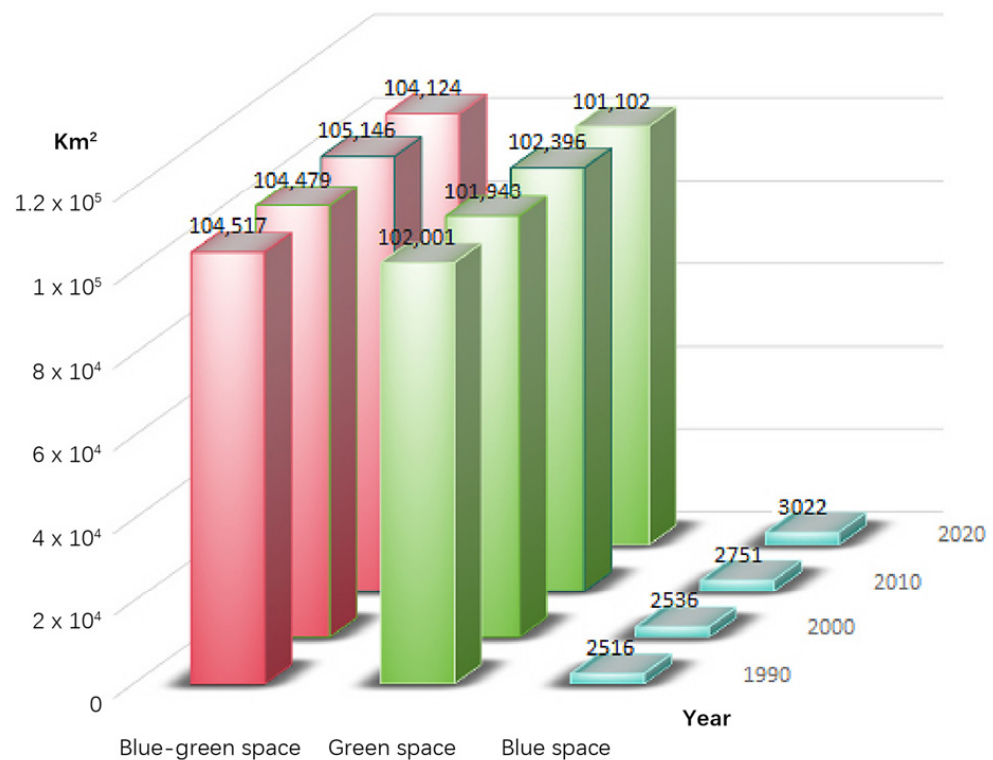


Figure 4. Overall structure analysis of land use for blue–green space in the Chengdu–Chongqing Economic Circle.

Table 4. Landscape pattern indices in the Chengdu–Chongqing Economic Circle from 1990 to 2020.

Landscape Pattern Index	1990	2000	2010	2020
Patch Density (PD)	0.5211	0.5177	0.5213	0.5523
Largest Patch Index (LPI)	21.6126	21.6153	21.5455	21.0833
Aggregation Index (AI)	87.8087	87.8170	87.7230	87.6549
Landscape Division Index (DIVISION)	0.8565	0.8563	0.8569	0.8667
Landscape Evenness Index (SHEI)	0.1634	0.1645	0.1744	0.2062

3.4. Landscape Evolution Modes of Blue–Green Space in the Chengdu–Chongqing Economic Circle

By comparing the evolution and expansion patterns of blue–green patches in the Chengdu–Chongqing Economic Circle from 1990 to 2020 (Table 5), it is found that the overall intensity of blue–green area expansion follows the order of Phase I (1990–2000) < Phase II (2000–2010) < Phase III (2010–2020). However, the basic rule of its expansion is consistent, with both the gradual expansion of phased areas and the increasing weight of the number and area of blue space patches in the overall expansion of blue–green patches. Comparing the periods from 1990 to 2020, each spanning ten years, it is found that the expansion of blue–green patches is mainly contiguous. The contiguous expansion patches of green space account for 98.65%, 97.76%, and 96.05% of the overall green space expansion, with their proportions gradually decreasing. The contiguous expansion patches of blue space account for 93.82%, 97.88%, and 90.62% of the overall blue space expansion. In the expansion range of $(-1, 1)$, the number of expansion patches of green space in the ranges of $(-1, -0.8)$, $(-0.2, 0)$, and $(0, 0.2)$ experienced significant fluctuations. Specifically, the weight of the number of patches in the range of $(-1, -0.8)$ decreased by 85.61% from the previous period in Phase III, while the weights of the number of patches in the ranges of $(-0.2, 0)$ and $(0, 0.2)$ increased by about 44% during the same period. The main fluctuation range of blue space expansion patches is close to that of green space, and significant fluctuations also occurred in the ranges of $(-0.8, -0.6)$ and 1. Between 2010 and 2020, the proportion of patches in the range of $(-1, -0.8)$ decreased significantly by 81.46% compared to the previous period,

while the number of patches in the ranges of $(-0.2, 0)$ and $(0, 0.2)$ increased by about 40% during the same period. In summary, the expansion of blue–green patches, characterized by a large number of small-scale trends, has gradually changed the pattern of the blue–green area of the Chengdu–Chongqing Economic Circle over the past 30 years.

Table 5. Statistical results of LEI interval distribution in the Chengdu–Chongqing Economic Circle from 1990 to 2020.

Landscape Expansion Pattern	LEI Range	1990–2000				2000–2010				2010–2020			
		Green Space		Blue Space		Green Space		Blue Space		Green Space		Blue Space	
		No.	Per.	No.	Per.	No.	Per.	No.	Per.	No.	Per.	No.	Per.
Adjacent Expansion Pattern	−1~−0.8	3915	94.25	330	78.38	40,068	90.65	3099	83.35	2748	5.04	96	1.89
	−0.8~−0.6	52	1.25	13	3.09	1814	4.10	322	8.66	264	0.48	10	0.20
	−0.6~−0.4	20	0.48	6	1.43	305	0.69	70	1.88	229	0.42	15	0.29
	−0.4~−0.2	7	0.17	4	0.95	146	0.33	22	0.59	388	0.71	15	0.29
	−0.2~0	10	0.24	4	0.95	126	0.29	19	0.51	24,026	44.04	2080	40.89
	0~0.2	24	0.58	8	1.90	126	0.29	20	0.54	24,008	44.01	2055	40.40
	0.2~0.4	9	0.22	7	1.66	110	0.25	14	0.38	188	0.34	25	0.49
	0.4~0.6	8	0.19	4	0.95	126	0.29	19	0.51	163	0.30	20	0.39
	0.6~0.8	11	0.26	4	0.95	186	0.42	22	0.59	165	0.30	16	0.31
	0.8~1	42	1.01	15	3.56	202	0.46	32	0.86	541	0.99	60	1.18
External Expansion Pattern	1	56	1.35	26	6.18	991	2.24	79	2.12	1833	3.36	695	13.66

Note: “No.” is short for number. “Per.” is short for percentage.

A detailed analysis of the evolution characteristics of blue–green space patches in the three stages from 1990 to 2020 reveals the following: In Phase I (Figure 5a), among the patches with LEI values indicating contiguous expansion, there were 395 blue space patches, accounting for only 9.39% of the total number of green space patches. In contrast, blue space patches accounted for 46.43% of the total number of green space patches when LEI was equal to 1. The expansion of blue–green space areas was concentrated in the range of $(-1, -0.8)$, with a total of 4245 patches, representing 92.79% of all areas. From a regional perspective, during this period, there were very few externally expanding patches. The contiguous expansion areas dominated by green space were concentrated in Mianyang, Nanchong, and Yibin in Sichuan Province, as well as near the main urban patches of Chongqing. Blue space areas were primarily located near the major river channels in Mianyang and Chengdu in Sichuan Province, as well as in the main river systems of Chongqing, particularly in proximity to the Yangtze River and its tributaries. In Phase II (Figure 5b), the number of blue space patches with a negative LEI was 3532, accounting for 95% of all blue space patches, while the number of green space patches with a negative LEI was 42,459, representing 96% of all green space patches. In terms of externally expanding patches with LEI values equal to 1, the number of blue space patches only accounted for 7.97% of the total number of green space areas. During this period, there was a significant increase in the number of both contiguous and externally expanding blue–green space patches in terms of regional distribution. The characteristics of the urban distribution of blue–green space patches dominated by contiguous expansion were consistent with those in Phase I, but the number of patches also increased significantly in the other 12 cities in Sichuan and the surrounding urban areas of Chongqing. The number of expanding blue space patches also increased markedly near water bodies in various regions. The notable increase in the number of expanding blue–green space patches during this period was primarily attributed to the significant expansion of blue space areas near rivers, while the expansion of green space, such as forests and grasslands, near mountains and urban peripheries also contributed significantly to the overall increase in green space expansion patches. Compared with the previous two periods, the number of blue–green space patches

in Phase III has increased more significantly, and the number of patches with positive LEI values has increased notably (Figure 5c). Among green spaces, patches with negative LEI values account for 50.69%, those with positive LEI values account for 49.31%, and patches with LEI values equal to 1 account for 3.36%. In blue spaces, patches with negative LEI values account for 43.56%, those with positive LEI values account for 56.44%, and patches with LEI values equal to 1 account for 13.66%. Among the blue–green space expansion areas within the range of (−0.2 to 0.2), the largest number of areas, totaling 52,169, accounts for 87.47% of all blue–green space patches. Compared to the previous two decades (1990–2010), the number of adjacent expansion patches in both green and blue space has increased significantly, and the growth trend of externally expanding areas is generally consistent with that of adjacent expansion areas. Blue space expansion not only occurs around the original major river areas but also shows significant expansion trends in some urban parks, artificial lakes, and other areas. Due to the significant increase in the scale of adjacent expansion areas in the blue–green space of the Chengdu–Chongqing Economic Circle, the expansion trends of various cities are basically similar, and the number and area of externally expanding patches in blue–green space have also increased significantly, resulting in an increasingly widespread distribution of green space in the entire study area and a more pronounced expansion trend than the previous 20 years (1990–2010). Additionally, the number of blue–green space patches in externally expanding patches during the three periods from 1990 to 2020 were 82, 1070, and 2528, respectively. The externally expanding patches in green space have consistently been the primary type. Over the 30-year period of external expansion of blue–green space patches, the number of blue spaces increased by 25.73 times, while the corresponding increase in green space patches was 31.73 times.

3.5. Driving Force Results of Blue–Green Space Evolution in the Chengdu–Chongqing Economic Circle

In studies that use the results of Geographic Detectors to analyze driving forces, the number of factors and the q -values vary significantly depending on the study area and landscape characteristics. A larger q -value indicates a more significant spatial differentiation effect of the factor on the variable [37,45]. In this study, the q -values generally ranged from 0.1 to 0.6, indicating a polarization in the influence of the selected driving factors on the spatial differentiation of variables. Meanwhile, in the studies on the driving factors of cultivated land spatial evolution in Henan Province and the evolution and driving forces of landscape patterns in the Guangdong–Hong Kong–Macao Greater Bay Area [48,49], the q -value ranges of these studies are 0.3–0.5 and 0.2–0.6, respectively. The results are relatively close to those of this study, indicating that the q -values obtained in this study are reasonable. Using $p < 0.05$ as an important indicator to determine whether a factor has a significant driving effect [42], the passing rates of significance tests for driving factors on landscape pattern indices (PD, LPI, DIVISION, SHEI) in this study all reached 90%, and the overall passing rate for all landscape pattern indices exceeded 80%. Under the condition of passing the significance test, the q -value effectively reflects the intensity of the impact of driving factors on landscape pattern indices [37].

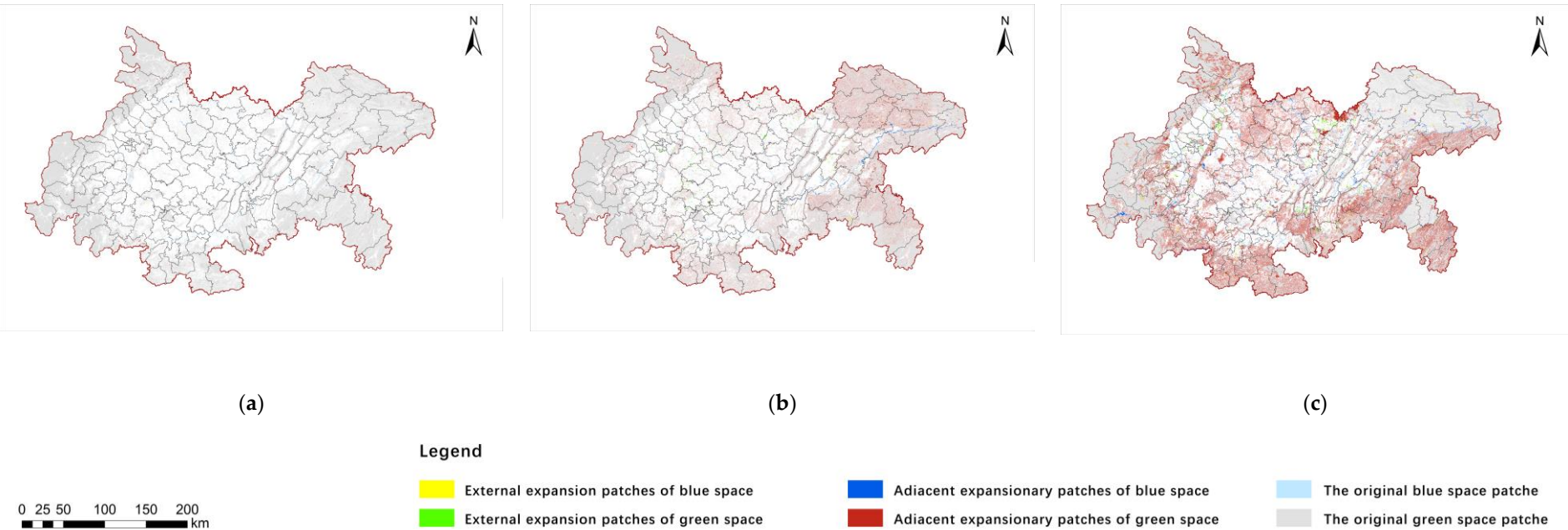


Figure 5. Expansion results of blue–green space in the Chengdu–Chongqing Economic Circle from 1990 to 2020: (a) 1990–2000; (b) 2000–2010; (c) 2010–2020.

According to the specific driving force analysis of each landscape pattern index based on different driving factors (Figure 6), the order of driving influences on PD is as follows: relief > population density > construction intensity > temperature > elevation > precipitation > GDP > fertilizer application intensity > night light intensity > soil erodibility factor. This result indicates that relief, population density, and construction intensity have the most significant impact on landscape consistency. The driving force of relief on PD gradually decreases, while the driving force of human disturbance intensity factors such as population density and construction intensity gradually increase. The analysis of the driving factor influence on LPI shows that temperature and elevation have the most obvious driving force on LPI, while the soil erodibility factor has the smallest influence on both LPI and PD among all driving factors. The analysis of DIVISION reveals that temperature has the greatest impact on regional landscape fragmentation, but its driving force decreases year by year. Population density and soil erodibility have relatively stable driving forces on regional landscape fragmentation from 1990 to 2020, with population density ranking second among all driving factors. Among the driving forces of various factors on SHEI, although the driving forces of GDP, night light intensity, construction intensity, and soil erodibility are relatively small, their driving effects on SHEI are increasing year by year, which also indicates that related human disturbance intensity factors are gradually increasing the heterogeneity of regional landscape distribution. As an important indicator reflecting the degree of horizontal aggregation of blue–green space landscapes in a region, AI shows that the driving forces of precipitation, GDP, night light, and fertilizer application intensity on AI have increased year by year, while the driving forces of other natural geographical conditions on AI have decreased year by year. Therefore, it is observed the same set of driving factors has different impacts and driving forces on different landscape pattern indices, but there are certain correlations and patterns in the overall trend.

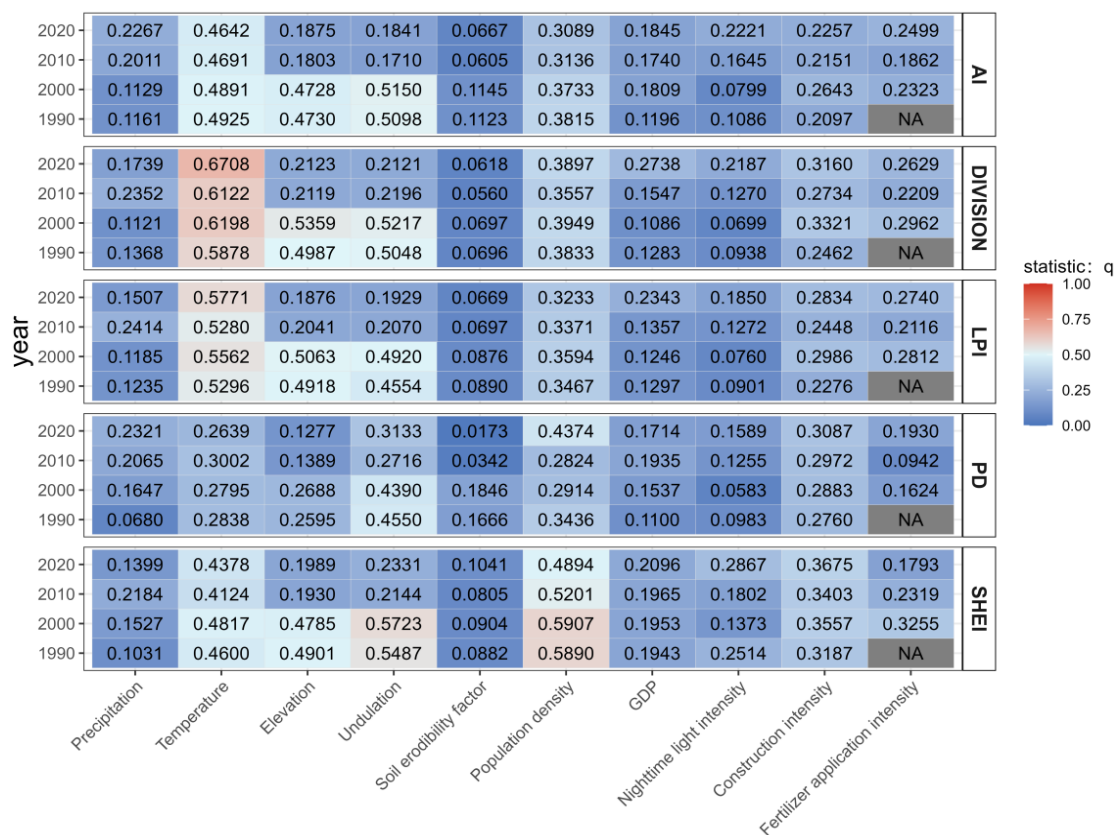


Figure 6. Variation chart of contribution rates of different driving factors to each landscape pattern Index.

Overall, from 1990 to 2020, the primary driving forces influencing the fragmentation and diversity of blue–green space in the Chengdu–Chongqing Economic Circle were temperature, relief degree, elevation, population density, and construction intensity. From the perspective of driving factor changes, precipitation and temperature in natural geographical conditions showed similar trends in driving various landscape indices, and their influence measured by the average value of driving factors remained relatively stable. The driving effects of elevation and relief degree on various landscape indices gradually decreased, with a more pronounced decline in Phase II. The driving force of soil erodibility remained at the lowest level among the same group of driving factors and was the least significant driving factor for landscape pattern indices. Among human disturbance intensity factors, population density was a prominent driver of landscape pattern indices, with a relatively stable driving force that played a crucial role in the evolution of various landscape pattern indices. GDP, nighttime light intensity, and construction intensity gradually increased their driving forces on landscape pattern indices over the years. Furthermore, this study is the first attempt to use fertilizer application intensity as a driving factor to verify its impact on the landscape pattern of blue–green space. Its driving force, which is concentrated in the range of 0.15 to 0.35, exerts a relatively significant influence on various landscape pattern indices. This fully validates the practical value and rationality of incorporating fertilizer application intensity in the analysis of driving factors for blue–green space.

4. Discussion

4.1. Dynamic Evolution of Blue–Green Space in the Chengdu–Chongqing Economic Circle

From 1990 to 2020, the landscape pattern changes in blue–green space in the Chengdu–Chongqing Economic Circle exhibited a characteristic of initially increasing and subsequently decreasing. Specifically, the overall trend indicates an expansion in the area and distribution of blue space, while green space exhibits a trend of reduction. Notably, the most pronounced phase of change occurred between 2000 and 2010, which aligns with Hypothesis (1). Furthermore, the predominant change pattern for blue–green space landscapes is characterized by an adjacent expansion model, corroborating Hypothesis (2). The reasons for the above changes are as follows: At the end of the 20th century, China began to prioritize the implementation of policies such as the Grain for Green Program, the Natural Forest Protection Program, the construction of non-commercial forests, and the establishment of nature reserves [50,51], which played a crucial role in protecting the region's green spaces. With the acceleration of urbanization in the Chengdu–Chongqing Economic Circle, the scale of construction land has continued to expand, gradually encroaching on more cultivated land, forestland, and grassland on the outskirts of cities, leading to a continuous decline in green space [51]. Since the 21st century, some regions have begun to implement policies such as “Park City” (e.g., Chengdu) [6,19,52], which have increased the demand and emphasis on urban green space and artificial water bodies during their development, thereby promoting an increase in blue–green spaces within cities [19]. Changes in blue spaces are primarily due to the diversification of functions assumed by inland waters with urban expansion, as some riverfront areas, lakes, and rivers within cities have been encroached upon and developed, participating in ecological restoration projects such as waterway convergence management [53]. Based on the above analysis, the evolution of blue–green space in the Chengdu–Chongqing Economic Circle is primarily related to human activities. During the period of rapid economic development in the Chengdu–Chongqing Economic Circle, urbanization has accelerated, and the demand for land for industrial development has surged rapidly [51]. The types of land use in the region have gradually become more complex and diverse, resulting in a faster decline in the connectivity of blue–green space, an increase in landscape fragmentation, a compression of the landscape space of blue–green space, and an overall downward trend in landscape dominance.

4.2. Driving Mechanisms Behind the Evolution of Blue–Green Space in the Chengdu–Chongqing Economic Circle

Taking each county as a measurement unit, the driving factors and landscape pattern index affecting the blue–green space landscape expansion index of these counties were analyzed. Based on the analysis of the data results, it can be found that all the driving factors have an obvious weakening trend in general. Specifically, the driving trends and forces of similar factors within natural geographical conditions and human disturbance intensities from 1990 to 2020 exhibit similar patterns of change. Both natural geographical conditions and human disturbance intensities play a jointly dominant role in the evolution of blue–green space in the Chengdu–Chongqing Economic Circle. Regarding the impact trends on landscape pattern indices, the driving force of natural geographical conditions decreased annually from 1990 to 2020, while the intensity of human disturbance increased annually, which aligns well with the increased human disturbances such as regional planning in the evolution of blue–green space.

A detailed analysis of the driving factors reveals that precipitation and temperature, as strongly correlated drivers, play significant roles in the development of blue–green space, further affecting the water area extent and green vegetation growth regions in the Chengdu–Chongqing Economic Circle. Elevation and relief degree influence the natural evolution and human planning of regional blue–green space. The Chengdu–Chongqing Economic Circle is a typical basin and hilly settlement area, with blue space concentrated in lower elevation areas, while the relief degree affects the growth of regional green vegetation. Soil erodibility factors can impact soil erosion in the region, and severe soil erosion is detrimental to green space development. However, the decreasing driving force of soil erodibility factors in this study is closely related to the central government's policy requirements and the increasing emphasis on soil erosion control during the development of the Chengdu–Chongqing Economic Circle [50,54]. Population density, GDP, nighttime light intensity, construction intensity, and fertilizer application intensity exhibit strong interrelationships. Changes in population density and construction intensity reflect the basic development trends and the evolution of the urban–rural dual structure, subsequently leading to a notable increase in nighttime light intensity in cities and affecting fertilizer application intensity in rural areas, which ultimately reflects in regional GDP changes [55–57]. These are important driving factors characterizing human socio-economic activities. Compared to the slowly changing natural geographical conditions, the impact of human disturbance intensity is more evident and dynamic, as consistently evidenced in other related studies [17,20].

4.3. Policy Recommendations for Optimizing Blue–Green Spaces

Based on the above findings, the following strategies are proposed to optimize the blue–green space pattern in the Chengdu–Chongqing Economic Circle:

(1) Protect the land area of blue–green spaces in the region. The decline in blue–green space in the Chengdu–Chongqing Economic Circle has hindered the further improvement in the quality of the regional ecological environment to a certain extent and has also intensified the urban heat island effect. It is essential to strengthen land use planning for blue–green space in the region; protect the land area allocated for blue–green space construction; enhance protection measures for vital urban ecological parks, wetlands, and forests; and implement strict protection of both natural and artificial water bodies.

(2) Improve the dynamic monitoring and protection mechanism for blue–green space. Neglecting the protection monitoring of regional ecosystems and failing to intervene and manage them promptly during the initial stages of urban development are significant reasons for the decline in regional ecological quality. Employing modern monitoring technologies and establishing necessary management and monitoring systems to continuously improve the monitoring frameworks for different land use types and scales, blue–green space distribution and scales, and land carrying capacity are crucial means to prevent and control regional ecological security threats and ensure high-quality urban ecological development.

(3) Optimize the blue–green space landscape pattern and enhance spatial connectivity. The high fragmentation and poor spatial connectivity of blue–green space in the Chengdu–Chongqing Economic Circle have severely impacted the further enhancement of regional ecological environment quality. Based on the current blue–green space distribution pattern, referring to regional construction planning requirements and human settlement considerations, efforts should be made to connect scattered and fragmented blue–green space. Simultaneously, attention should be paid to the coordination of blue–green space, improving the ecological layout of regional mountains, rivers, forests, fields, lakes, and grasslands, and enhancing the ecological functions of blue–green space.

(4) Implement categorized planning and management for blue–green space. Considering the human influence factors and geographical environment conditions that affect the distribution of blue–green space in the region, as well as the imbalance in the distribution of blue–green space within cities in the Chengdu–Chongqing Economic Circle, it is necessary to implement necessary urban blue–green space renovation and suburban blue–green space beautification for different terrain areas and city clusters, taking into account regional planning requirements for urban economic development and the planning directions and functional positioning of blue–green space. Based on the structural characteristics and landscape requirements of blue–green space in different areas, categorized and scientific management and protection measures should be implemented to expand the ecological regulation capabilities of blue–green space.

5. Conclusions and Future Prospects

5.1. Conclusions

Using remote sensing image data from 1990, 2000, 2010, and 2020 as data sources, this study analyzed the evolution characteristics of blue–green space in the Chengdu–Chongqing Economic Circle and its constituent cities from 1990 to 2020, from both the perspectives of scale and landscape pattern, through calculating dynamic changes in land use structure and landscape patterns employing the Geographic Detector model with counties as measurement units. In the context of natural geographical conditions, elevation, undulation, soil erodibility, temperature, and precipitation were selected as driving factors. In terms of human disturbance intensity, GDP, population density, nighttime light intensity, construction intensity, and fertilizer application intensity were chosen as influencing variables. The following conclusions were drawn regarding the driving mechanisms of blue–green space landscape pattern evolution in the Chengdu–Chongqing Economic Circle.

(1) In terms of blue–green space change types, the changes in blue–green space within the Chengdu–Chongqing Economic Circle exhibit distinct phase characteristics, indicating an initial increase in area followed by a subsequent decrease. This finding is consistent with Hypothesis (1). The main land use changes in the Chengdu–Chongqing Economic Circle involve conversions between cultivated land and construction land, as well as transitions from grassland and cultivated land to construction land and forest land. Among these, the most prominent trend is the increase in construction land, while cultivated land experiences the largest reduction. The overall trend of blue–green space in the study area is one of decrease, characterized primarily by a reduction in green space and an increase in blue space. Additionally, the dynamic changes in green space are more pronounced than those in blue space across all cities in the study area, closely linked to the significant conversion of forest land and grassland over the past 30 years.

(2) In terms of landscape patterns, based on the maximum, average, and changing trends of PD, LPI, and DIVISION, it was found that the fragmentation of blue–green space in the Chengdu–Chongqing Economic Circle gradually increased from 1990 to 2020. The changing trends of the SHEI and AI indicated that the landscape distribution evenness of blue–green space in the region increased, while the connectivity between landscapes gradually deteriorated. Regarding the expansion and evolution of the predominant expansion mode was adjacency expansion, with a gradually strengthening trend from 1990 to 2020. The expansion of green space was concentrated in urban development zones,

such as residential areas and suburban regions, while the expansion of blue space relied mainly on major river tributaries or artificial water bodies in cities. The findings of the aforementioned study are consistent with Hypothesis (2).

(3) In terms of driving forces, the driving force from natural geographical conditions gradually weakened, while the driving force from human disturbance intensity gradually strengthened. The research results on the driving forces influencing the landscape pattern of blue–green space are close to Hypothesis (3). The main driving factors shifted from temperature, relief degree, and elevation to population density and construction intensity, with a notable trend of decreasing disparities in driving forces among factors.

5.2. Limitations and Future Prospects

The current study still has some limitations. Firstly, the selected research years are spaced 10 years apart, which may be too long, and there is a potential issue of insufficient comprehensiveness in terms of representative years. Secondly, due to limitations in data precision and difficulties in data collection, this study primarily focused on analyzing the driving mechanisms at the county-level scale within the study area, without further exploring the micro-level analysis of driving factors at the grid granularity. Thirdly, there are certain limitations in the selection of driving factors. For example, factors such as regional elevation, relief degree, and soil erodibility related to water and soil loss exhibit interrelationships, which may reduce the accuracy of the data.

After completing this study, it is realized that analyzing the driving mechanisms of blue–green space solely at the county scale is insufficient. For more microscopic and detailed analysis, it will be possible to further identify the various drivers at the grid scale. In terms of research methods, subsequent studies will also consider the use of multiple regression methods combined with Geographic Detector to jointly analyze the evolution and driving force of the blue–green space in the Chengdu–Chongqing Economic Circle. For counties with significant changes in the landscape patterns of blue–green space, conducting more in-depth field investigations with a long-term research cycle but shortened phased analysis periods, such as every five or two years, may yield more precise results. This approach would facilitate the further discovery of other driving factors influencing the changes in the landscape patterns of blue–green space.

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