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Integration of In-VEST Habitat Quality Model with Landscape Pattern Indices to Assess Habitat Fragmentation Under the Dynamic Development of Park City: Southwest China Case

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Abstract: With rapid urbanization, the types of land in China's cities are continuously evolving, irreversibly impacting the habitat patches within urban areas. However, the development of park cities has reversed this trend to some extent, particularly in Chengdu, China. To investigate the influence of land use type changes on habitat quality in Chengdu Tianfu New District, the research team selected remote sensing imagery data from the Landsat satellite for three distinct periods: 2014, 2019, and 2024. By employing a comprehensive approach that includes land cover trajectory analysis, land transfer matrices, FRAG-STATS landscape pattern indices, and the habitat quality module within the In-VEST model, this study analyzes the spatial and temporal evolution of land use patterns and the dynamics of habitat quality categories. The findings reveal: (1) the coverage of trees and shrubs in the study area initially declined but later increased, primarily driven by anthropogenic construction activities. Specifically, the land use types in the built-up areas on the northern side of Tianfu New District underwent notable fluctuations, whereas those on the southern side, adjacent to the Longquan Mountain Range, remained relatively stable. (2) From 2014 to 2019, high-quality habitats were predominantly distributed in the southeast of Tianfu New District, characterized by a robust ecological foundation, high landscape integrity, and strong connectivity of ecological land. In contrast, the areas with the poorest habitat quality were situated in the northern built-up areas of Tianfu New District, exhibiting highly fragmented habitat patches, simple edge shapes, and low connectivity. However, between 2019 and 2024, the overall habitat quality within the study area improved, characterized by an increase in the number of high-quality habitats and continuous expansion of habitat areas. The research findings offer valuable insights into future urban planning, ecological restoration, and conservation efforts in Chengdu Tianfu New District, providing critical guidance for the implementation and strategic development of the park city policy.

Keywords: land use; habitat quality; spatio-temporal characteristics; landscape pattern; spatial pattern; landscape pattern indices

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1. Introduction

The *Global Biodiversity Outlook* reveals that global biodiversity targets have not been fully achieved, with biological habitats facing severe threats [1]. Amid global population shifts, an increasing number of people are migrating to urban areas. Currently, approximately 55% of the global population resides in cities, and an estimated 2.5 billion more urban dwellers are projected to be added over the next 30 years, with future populations expected to become increasingly concentrated in urban centers [2]. Urbanization stands as one of the primary culprits affecting species diversity and habitats [3–5]. As urbanization accelerates, the conflict between urban development and habitat conservation has intensified. This rapid urbanization transforms the spatial patterns, structures, and compositions of habitat patches, inevitably resulting in significant negative impacts on local habitats [3,4,6]. It induces changes in urban land cover types, with high-rise buildings and densely developed areas encroaching on biological habitats and leading to a decline in biodiversity [7]. Furthermore, it heightens the risk of homogenizing ecosystems and fragmenting habitat patterns, altering interspecific relationships, species richness, and structural hierarchies within habitats, ultimately undermining ecosystem functionality [8].

On the other hand, urbanization also creates new habitat patches and forms novel habitats [9,10]. From an ecological and technical perspective, the research methods for urban ecological spaces mainly include ecological space identification, network construction, and characteristic evolution, among others. Under the concept of park cities, the ecological elements need to be enriched and expanded based on the specific built environment in response to the complexity of urban construction. Various concepts have emerged to address these changes [11]. The concept of a park city represents a new phase in urban development, drawing inspiration from notions such as garden cities [12,13], shan-shui cities [14], and national park cities [15]. The park city concept is not merely a straightforward combination of "park" and "city" [16]; rather, it strives to harmonize human–nature interactions by integrating diverse ecological elements within urban areas, including mountains, waterways, forests, and farmland. Grounded in the principles of ecological priority and green development, the concept aims to protect urban ecological foundations, promote sustainable urban growth, and achieve harmony among people, cities, environments, and industries [17]. The park types in the park city concept are categorized into regional park systems, urban park systems, park complex systems, ecological corridor systems, etc. Among these, the regional park system is the supporting framework for the ecological security pattern of park cities. The Longquan Mountain Forest Park area plays an important role in the planning and research of the regional park system in Chengdu [18]. Although there have been many studies on the concepts of ecological cities and "park cities", there is still a lack of in-depth analysis of the specific implementation effects of these concepts in the context of rapid urbanization. This is particularly true in countries like China, where rapid urbanization and high population density intensify the conflict between ecological conservation and urban development. Taking Tianfu New District as an example, its long-term ecological effects and sustainability have not been fully studied. Exploring the dynamic impacts of the policy on landscape patterns and habitat quality over different time periods is an important direction for future research.

To study habitats at the urban regional scale, it is essential to consider spatial precision [19,20]. Land cover data serve as a vital foundation for investigating urban changes, providing insights into the spatial patterns of vegetation and acting as an indicator of habitat transformations [21]. Over the past three decades, remote sensing techniques have facilitated accurate land cover mapping, with Landsat imagery archives forming an indispensable baseline dataset [22,23]. Researchers often utilize imagery data from different years to conduct dynamic inter-annual analyses of land use changes [24,25]. Nevertheless, in urban studies, most land use classification methods identify vegetation, bare land, water bodies, etc. [26], which often fail to adequately reflect biodiversity and habitat conditions due to their limited correlation with vegetation cover. Guilherme et al. (2022) employed the UrHBA method, leveraging aerial photography and satellite imagery, to classify urban land cover. With sufficient data, this approach can capture urban habitats at a fine scale and infer habitat continuity efficiently [27].

The fragmentation of habitats and the quality of habitat environments have been discussed in previous studies. Landscape pattern indices, as ecological indicators reflecting the composition and spatial configuration of landscapes, are crucial for monitoring land cover patterns. Researchers often employ FRAG-STATS software (The University of Vermont, Burlington, USA) for conducting detailed landscape pattern analyses [28,29]. Gong et al. selected 28 indices from three categories to analyze the correlation between landscape pattern indices and vegetation coverage in the central urban area of Guangzhou [30]; Li et al. studied the selection of landscape pattern indices from the perspectives of landscape configuration and components and explored the relationships between landscape patterns and ecosystem carbon storage, habitat quality, as well as the supply and demand of air purification [31]; Qin et al. analyzed the relationship between the value of multiple ecosystem services and the urban–rural changes in landscape patterns in Xi'an based on the equivalent factor method [32]. Researchers typically choose "area indices", "shape indices", "diversity indices", "spatial configuration indices", and "landscape fragmentation" for analysis [33]. With over 100 available indices, selection should be tailored to specific regional conditions.

Habitat quality, an integral part of ecosystem service functions, refers to the ability of ecosystems to sustain viable species populations, reflecting biodiversity levels [34,35]. In recent years, scholars at home and abroad have conducted extensive research on habitat quality and proposed various models, such as In-VEST [36,37], GAPP [38], and pressure–state–response (PSR) [39]. Among them, the In-VEST model is widely used for its reliability, simplicity, and strong analytical capabilities [40]. Zhou et al. used the HQ model to assess the habitat quality in the Dianshan Lake area and proposed optimization suggestions [41]; Zhang et al. reconstructed the habitat quality pattern of a region using the HQ model, revealing its ecological evolution [42]; He et al. combined cellular automata and the HQ model to simulate habitat quality assessments [43]. The HQ model can provide scientific habitat quality assessments, but few studies have integrated it with landscape pattern indices to evaluate the impacts of urban land cover changes on landscape ecological patterns.

China, one of the world's most biodiverse countries, faces significant challenges due to habitat fragmentation and quality degradation caused by urbanization. Many Chinese cities are actively promoting the park city policy. Since the concept of a park city was first introduced in 2019, Chengdu Tianfu New District, the origin and pilot area of this policy, has undertaken extensive theoretical research and practical explorations, achieving remarkable outcomes. This paper focuses on Tianfu New District, utilizing Landsat imagery from 2014, 2019, and 2024. By employing methodologies such as land classification, land transfer matrices, FRAG-STATS analysis, and the In-VEST model, we investigate habitat evolution patterns in the region. The research objectives are to: (1) analyze land cover and its changes over a five-year period, both before and after the implementation of the park city concept, using three representative time points. (2) Quantify changes in habitat fragmentation using spatial indicators, including landscape pattern indices and habitat quality models. (3) Identify major trends and provide a scientific basis for future studies on habitat conservation, restoration, and urban land use planning within park cities.

2. Materials and Methods

2.1. Case Study: Tianfu New District—A Typical Park City in Southwest China

The study focuses on Tianfu New District, Chengdu City, Sichuan Province, which has a planned total area of 1578 km^2 [44]. It is located between 103°47′59″ to 104°15′34″ E and 30°13′38″ to 30°40′23″ N in southwest China (Figure 1a–c). With a planned population of 5 million, the district currently hosts a permanent population of approximately 2.8 million. Tianfu New District is situated on the southeastern edge of the Chengdu Plain, bordered by the Longquan Mountains to the east and the Pengzu Mountains to the southwest. The area's main topographical features include plains and hills, offering extensive land suitable for construction [45]. The region primarily comprises two major habitat systems: aquatic systems and woodland systems [46]. Aquatic and green ecosystems account for more than 70% of the district's area, with rivers and waterways running north to south, creating a dense network of waterways and a robust ecological foundation (Figure 1d). The region belongs to the subtropical humid monsoon climate zone, featuring mild temperatures with an annual average temperature of 16.4 °C, relatively high humidity, and abundant rainfall in summer and autumn, with annual precipitation reaching up to 1300 mm [47].

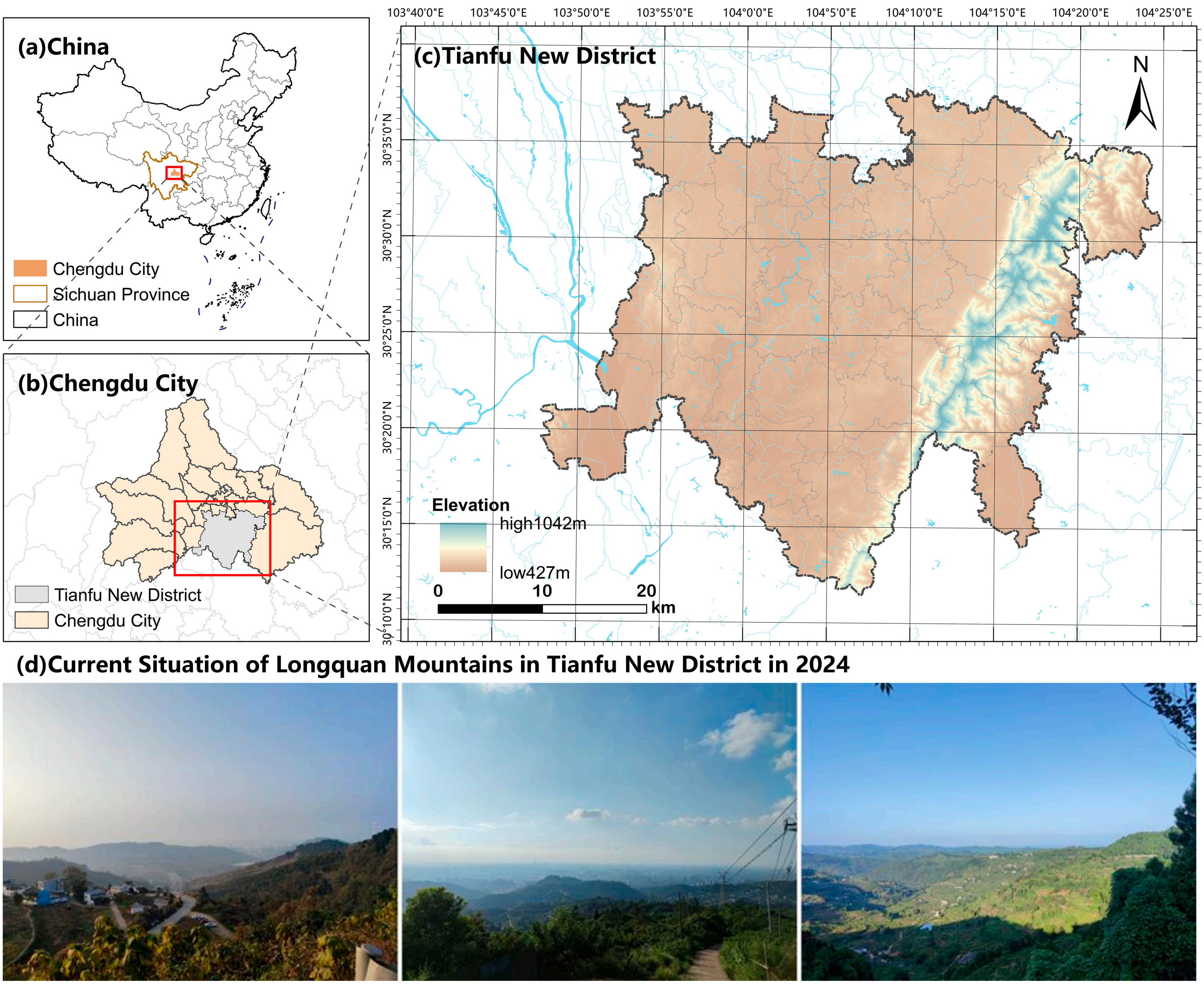

Figure 1. Location of the Study Area. (**a**) China; (**b**) Chengdu District; (**c**) Tianfu New District; (**d**) Current Situation of Longquan Mountains in Tianfu New District in 2024.

In terms of development milestones, Tianfu New District became the 11th national-level new area in China in 2014, marking the beginning of large-scale urbanization and construction efforts. In 2019, it became the first pilot area for the "park city" policy, initiating the creation of a sustainable urban development model. Looking ahead, the government aims to establish a five-level ecological and cultural landscape structure, comprising "one mountain, two wedges, three corridors, five rivers, and six lakes". Additionally, a spatial layout network for the Tianfu Center will feature "one axis, one corridor, one core, and three districts". This design intends to integrate natural environmental elements, including mountains, rivers, farmland, forests, and lakes, to build a world-renowned park city by 2035.

2.2. Data and Methods

2.2.1. A General Overview of the Study

Our research framework (Figure 2) is structured into several critical steps to assess the spatio-temporal evolution of habitat fragmentation in Tianfu New District. First, remote sensing data from the Landsat satellite for 2014, 2019, and 2024 were collected and preprocessed. These data were then classified using the UrHBA land classification method to generate land use maps for each period. Subsequently, a land transfer matrix analysis was performed to quantify changes in land use types over time. FRAG-STATS software (v.4.2.1; The University of Vermont, Burlington, VT, USA) was then applied to calculate landscape pattern indices, enabling the assessment of changes in the spatial configuration of habitat patches. Finally, the In-VEST Habitat Quality module was utilized to analyze habitat quality, offering insights into how land use changes affect both habitat fragmentation and quality.

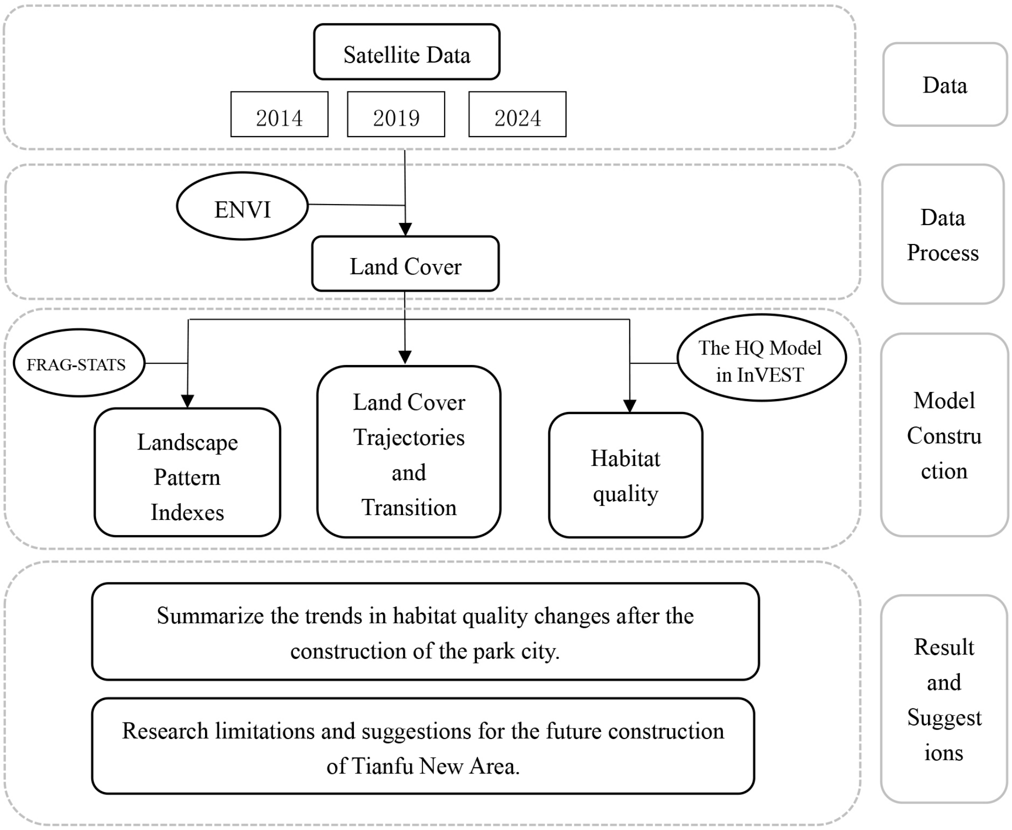

Figure 2. Framework of the research.

The combination of these methods provides a comprehensive evaluation of landscape changes and their ecological implications within the context of the evolving park city development.

2.2.2. Land Cover Mapping and Classification

This study focuses on three distinct time periods: before the proposal of the park city, at the time of the proposal, and after the proposal, with a five-year interval between each period. Satellite remote sensing images for 2014, 2019, and 2024 were obtained from the USGS (https://earthexplorer.usgs.gov/ accessed on 11 September 2024) using the Landsat 8 satellite. The imaging time for the satellite images was selected between April and August, with cloud cover less than 10% (Table 1). After undergoing radiation calibration and atmospheric correction in ENVI (v.5.3; Harris Geospatial Solutions, Boulder, CO, USA), the preprocessed remote sensing data were classified using a supervised classification approach with a support vector machine classifier.

Table 1. Statistical Information of Remote Sensing Image Data from the USGS Landsat 8 Satellite in the United States.

Year	Satellite	Resolution	Band	Image Name
2014	Landsat 8	30 m × 30 m	Band1-11	LC08_L2SP_129039_20140813_20200911_02_T1
2019	Landsat 8	30 m × 30 m	Band1-11	LC08_L2SP_129039_20190811_20200827_02_T1
2024	Landsat 8	30 m × 30 m	Band1-11	LC08_L2SP_129039_20240418_20240424_02_T2

The land cover classification method utilized in this study is a simplified version of UrHBA, specifically designed for remote sensing data [48]. The reason for adopting the UrHBA classification is that it categorizes land units based on the life characteristics of vegetation (rather than species or plant communities), which provides greater habitat continuity. As a result, classification based on vegetation life features more effectively reflects biodiversity continuity. Additionally, UrHBA is a spatially explicit method of landscape visual interpretation grounded entirely in land cover data, enabling fine scale descriptions of urban environments. This approach is also versatile and can be applied across a wide range of geographical contexts. The data were classified into five categories: artificial built elements (ABE), sparsely vegetated-terrestrial (SPV), trees and shrubs (TRS), sparsely vegetated-aquatic (AQU), and herbaceous (HER). Using the spatial analysis functionality of ArcGIS, techniques such as overlay analysis, extraction analysis, and distance analysis in ArcMap were employed to extract, transform, and map the relevant data. By comparing the land type transition matrices, trends in land cover types over time were observed, and patterns of regularity were identified (Table 2).

Table 2. Land cover categories.

Land Cover Categories	Abbreviation	Description
Artificial Built Elements	ABE	Impervious surfaces, buildings, and other constructed elements.
Trees and Shrubs	TRS	Woody vegetation, including all phanerophytes and shrubby chamaephytes.
Herbaceous	HER	Herbaceous vegetation, including hemi-cryptophytes, therophytes, and geophytes.
Sparsely Vegetated—Terrestrial	SPV	Every type of non-vegetated soil, such as bare soil, sand, and rock.
Sparsely Vegetated—Aquatic	AQU	Every type of water surface, such as the sea, rivers, lakes, and ponds (including artificial elements).

2.2.3. Analysis of Land Cover Trajectories and Transition Matrices

Land cover trajectories are commonly employed to evaluate the continuous temporal changes in landscapes, typically derived from satellite imagery captured at multiple time points. By overlaying and merging the three land use maps of 2014, 2019, and 2024, and utilizing the Dissolve and Intersect tools in ArcMap Desktop, a new layer containing information about the regional land cover trajectories was created. In the resulting new layer, each polygon is described by a sequence of three land cover categories, including artificial built elements (ABE), sparsely vegetated-terrestrial (SPV), trees and shrubs (TRS), sparsely vegetated-aquatic (AQU), and herbaceous (HER). These land cover trajectories depict the evolution of land cover types in the region from 2014 to 2019 to 2024. For example, the ABE → TRS → ABE trajectory represents a transition from artificial built elements (2014) to trees and shrubs (2019) and back to artificial built elements (2024). Due to the large number of land cover trajectory types, which complicates subsequent graphical analysis, the 16 trajectories with the largest areas were extracted, while the remaining types were grouped into an “other” category.

A land use transfer matrix provides a quantitative representation of trends in land use structure changes, land function characteristics, and the amount of area converted between land use types over a specified period. This study utilizes the analysis tools in ArcGIS software (v.10.8; Esri, Redlands, USA) to calculate and analyze the land use data from the three periods pairwise, resulting in land use transfer matrices for 2014→2019 and 2019→2024. The formula for the transfer matrix is as follows:

$$S_{ij} = \begin{vmatrix} S_{11} & S_{12} & \dots & S_{1n} \\ S_{21} & S_{22} & \dots & S_{2n} \\ \dots & \dots & \dots & \dots \\ S_{n1} & S_{n2} & \dots & S_{nn} \end{vmatrix} \tag{1}$$

In Equation (1), S represents the area; n denotes the number of land use types; and i, j are the land use types at the beginning and end of the study period.

2.2.4. Spatial Metrics

Landscape pattern refers to the spatial metrics that describe relationships between different ecosystems and landscape units, highlighting the heterogeneity of different patches, classes, and landscapes. By evaluating and analyzing the current status and ecological conditions of the study area, landscape pattern analysis provides an optimal solution and serves as a crucial indicator for assessing spatial metrics.

Specifically, landscape patterns can be analyzed at three hierarchical levels. In this study, the landscape index software FRAG-STATS 4.2.1 was employed to conduct the analysis. Indicators are selected from three levels: "landscape", "class", and "patch". The indicators are divided into four categories (Table 3): (1) area and edge metrics—used to analyze the area, perimeter, and number of patches; (2) shape metrics—used to analyze geometric diversity; (3) aggregation metrics—used to analyze the trend of landscape fragmentation and reduction of separation; (4) diversity metrics—used to understand the composition of the landscape and are only calculated at the landscape analysis level [28].

Table 3. Landscape metrics selected for this study.

Level	Type	Metric
Landscape	Area and edge metrics	TA: Total area (ha) LPI: Largest patch index (%) MPS: Mean patch size (ha) MPE: Mean patch edge (m) ED: Edge density (m/ha)
	Shape metrics	MPAR: Mean perimeter–area ratio MSI: Mean shape index MFD: Mean fractal dimension
	Diversity metrics	NP: Number of patches MENND: Mean Euclidean nearest neighbor distance (m) MPROX: Mean proximity index

Table 3. *Cont.*

Level	Type	Metric
Class	Area and edge metrics	CA: Total class area (ha) CP: Class proportion (%) LPI: Largest patch index (%) MPS: Mean patch size (ha) MPE: Mean patch edge (m) ED: Edge density (m/ha)
	Shape metrics	MPAR: Mean perimeter–area ratio MSI: Mean shape index MFD: Mean fractal dimension
	Aggregation metrics	NP: Number of patches MENND: Mean Euclidean nearest neighbor distance (m) MPROX: Mean proximity index DIV: Division index
Patch	Area and edge metrics	Area (ha) Edge (m)
	Shape metrics	Perimeter–area ratio Shape index Fractal dimension
	Aggregation metrics	Euclidean nearest neighbor distance (m) Proximity index

2.2.5. Habitat Quality Spatial Model

In-VEST is an assessment model that comprises multiple modules, including water conservation, ecological value evaluation, and carbon storage calculation and plays a significant role in estimating the value of ecosystem services. This study employs the Habitat Quality module in In-VEST (v.3.13.0; Stanford University, Standford, CA, USA) to evaluate the habitat quality in the Tianfu New District from 2014 to 2024. Since our research focuses on an urban context, the habitat quality model was adapted from the original In-VEST framework. The habitat quality index is calculated by establishing the weights of threat sources, their distances, and their relationships with different land covers (Table 4). Threat factors considered in this study include artificial land, railways, and unknown land (Table 5). We posit that a higher regional habitat quality index indicates higher biodiversity and a more stable ecosystem. The calculation formula for the Habitat Quality module is as follows:

Table 4. Sensitivity of Land Use Types to Various Threat Factors.

Land Cover	Habitat Suitability	Weight	Decay Type	Unknown Land
ABE	0	0	0	0
AQU	0.6	0.6	0.6	1
HER	0.6	0.65	0.15	1
SPV	0.3	0.6	0.5	1
TRS	1	0.7	0.6	1

Table 5. Parameters of Threat Factors.

Threat	Maximum Impact Distance/km	Weight	Decay Type
Artificial land	0.8	0.6	Exponential
Railway	1	0.4	Linear
Unknown land	0.5	0.11	Exponential

Habitat quality index:

$$Q_{xj} = H_j\left[1 - \left(\frac{D_{xj}^z}{D_{xj}^z + k^z}\right)\right], \tag{2}$$

In Equation (2), Q_{xj} is ecological habitat quality value of grid x in land use type j; D_{xj} represents the degradation degree of grid x in land use type j; H_j represents the ecological suitability of land use type j; k represents half of the half-saturation constant taken as D_{xjmax}; z represents the model parameter.

Habitat degradation degree:

$$D_{xj} = \sum\nolimits_{r=1}^{R}\sum\nolimits_{y=1}^{Y_r}\left(\frac{w_r}{\sum_{r=1}^{R} w_r}\right) r_y i_{rxy} \beta_x S_{jr}, \tag{3}$$

In Equation (3), r represents the threat source; y represents the grid in threat factor r; R represents the set of all degradation sources; Y_r represents a set of grids in r; w_r represents a set of grids in r; r_y represents the r value of grid y; i_{rxy} represents the proximity level of x; β_x represents the proximity level of x; S_{jr} represents the sensitivity of j to r.

Linear decay function:

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{rmax}}\right), \tag{4}$$

Exponential decay function:

$$i_{rxy} = exp\left[-\left(\frac{2.99}{d_{rmax}}\right)d_{xy}\right], \tag{5}$$

In Equations (4) and (5), d_{xy} represents the distance between r and the habitat; d_{rmax} represents the maximum radiation range of r.

3. Results

3.1. Land Cover Trajectories and Transition Matrices

Based on the data of land use type changes in Tianfu New District in 2014, 2019, and 2024, the following trends can be observed (Figure 3). From the overall urbanization perspective, the artificial built elements (ABE) in Tianfu New District have always remained below 35%, indicating a relatively low degree of artificialization. The urban areas are mainly located in the northwest of the study area. Over 60% of the land is covered by trees and shrubs (TRS), which are situated in the east and south of the study area, showing good habitat conditions. However, the sparsely vegetated—aquatic (AQU), sparsely vegetated—terrestrial (SPV), and herbaceous (HER) patches in the study area are relatively scarce, accounting for less than 5% each.

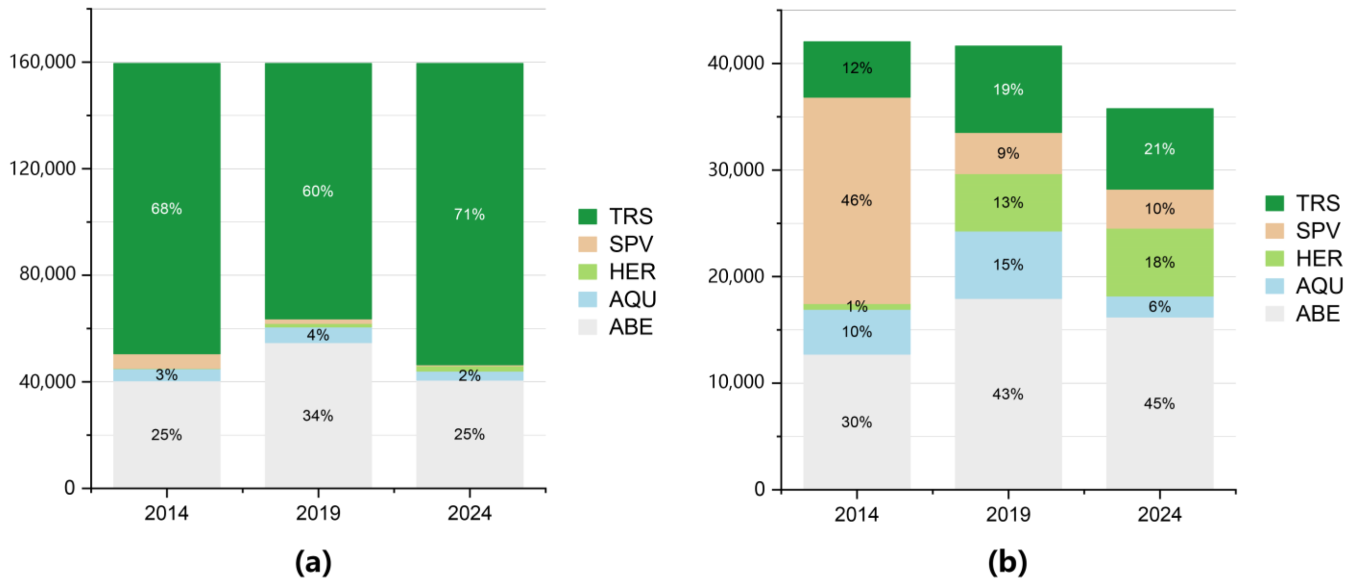

Figure 3. (**a**) The proportion of land cover categories in 2014, 2019, and 2024. (**b**) The number of patches for each class in 2014, 2019, and 2024.

Between 2014 and 2024, the most significant changes in land area occurred in artificial built elements (ABE) and trees and shrubs (TRS). The area of artificial built elements (ABE) and sparsely vegetated—aquatic (AQU) initially increased but subsequently decreased, while the area of trees and shrubs (TRS) exhibited the opposite trend, decreasing first and then increasing.

During the same period, the number of patches of different land types in Tianfu New District also underwent significant changes. The total number of patches gradually decreased, but the number of patches of artificial built elements (ABE), trees and shrubs (TRS), and terrestrial herbaceous (HER) patches gradually increased. Among them, the number of patches of sparsely vegetated—terrestrial (SPV) decreased the most significantly, from 46% in 2014 to 10% in 2024, accompanied by the most significant change in area. The number of patches of sparsely vegetated—aquatic (AQU) first increased and then decreased. Overall, sparsely vegetated—terrestrial (SPV) patches gradually become continuous, while artificial built elements (ABE), trees and shrubs (TRS), and terrestrial herbaceous (HER) patches become increasingly fragmented. The continuity of sparsely vegetated—aquatic (AQU), on the other hand, followed a trend of initial improvement followed by a decline.

From 2014 to 2019 (Table 6), the area of trees and shrubs (TRS) and sparsely vegetated—terrestrial (SPV) decreased by 130.86 km^2 and 37.37 km^2, respectively, while the area of artificial built elements (ABE), sparsely vegetated—aquatic (AQU), and herbaceous (HER) patches increased by 143.08 km^2, 13.49 km^2, and 11.67 km^2, respectively. Specifically, the main transformation of trees and shrubs (TRS) was towards artificial built elements (ABE); approximately two-thirds of the sparsely vegetated—terrestrial (SPV) transformed into trees and shrubs (TRS), while one-third transformed into artificial built elements (ABE). The reasons for these changes may be related to the rapid urbanization and expansion of Tianfu New District before 2019. Additionally, about 18.52% of the artificial built elements (ABE) transformed into trees and shrubs, which were mainly distributed evenly in the construction areas in a dotted pattern, related to the construction of various types of green spaces within the city. During this period, the changes in other land use types were relatively minor.

Table 6. Land cover conversion matrix from 2014 to 2019 (km^2).

Land Cover		2019						
		ABE	**AQU**	**HER**	**SPV**	**TRS**	**Total**	**Change**
2014	ABE	314.03	9.11	2.90	3.59	74.93	404.55	35.37%
	AQU	2.52	39.86	0.35	0.20	2.72	45.66	29.56%
	HER	0.33	0.13	0.18	0.01	0.38	1.03	1127.51%
	SPV	17.01	1.00	0.92	0.93	34.78	54.64	−68.40%
	TRS	213.74	9.05	8.35	12.53	845.33	1089.00	−12.02%
	Total	547.63	59.15	12.70	17.27	958.14	1594.88	

From 2019 to 2024 (Table 7), the areas of artificial built elements (ABE), sparsely vegetated—aquatic (AQU), and sparsely vegetated—terrestrial (SPV) decreased by 141.23 km^2, 24.87 km^2, and 13.16 km^2, respectively, while the areas of trees and shrubs (TRS) and herbaceous (HER) patches increased by 172.36 km^2 and 6.9 km^2, respectively. This conversion trend is almost the reverse of the pattern observed between 2014 and 2019. A significant amount of artificial built elements (ABE) transformed into trees and shrubs (TRS), almost equivalent to the amount of trees and shrubs (TRS) that transformed into artificial built elements (ABE) between 2014 and 2019. This shift reflects the implementation of the park city concept, with extensive construction of park green spaces resulting in marked improvements in the ecological environment of Tianfu New District. The continuous decline in sparsely vegetated—terrestrial (SPV) may be attributed to the natural succession of original vegetation on the site or changes in land use types due to artificial planting.

Table 7. Land cover conversion matrix from 2019 to 2024 (km^2).

Land Cover		2024						
		ABE	**AQU**	**HER**	**SPV**	**TRS**	**Total**	**Change**
2019	ABE	300.43	0.75	6.00	2.21	238.24	547.63	−25.79%
	AQU	4.87	32.32	2.43	0.19	19.35	59.15	−42.05%
	HER	3.33	0.15	0.57	0.02	8.64	12.70	54.35%
	SPV	11.23	0.13	0.12	0.02	5.77	17.27	−76.21%
	TRS	86.55	0.92	10.49	1.67	858.51	958.14	17.99%
	Total	406.40	34.28	19.60	4.11	1130.50	1594.88	

From 2014 to 2024, the transition matrix of the five land cover categories revealed a total of 125 transition trajectories, of which 16 were more prominent, accounting for over 95% of the total area (Figure 4). According to the land cover trajectory results (Table 8), the area where the land use type remained as trees and shrubs (TRS TRS TRS) throughout all three time periods was approximately 796.20 km^2, representing around 48.23% of the study area. These patches have persisted throughout the construction process, exhibiting higher species richness, greater stability, and better ecological benefits. In some regions, the land type changed from artificial built elements (ABE) to trees and shrubs (TRS), with the TRS ABE TRS area accounting for 127.40 km^2; the ABE ABE TRS area accounting for 101.11 km^2; and the ABE TRS TRS area accounting for 61.15 km^2. The combined area of these three trajectories represents approximately 18.16% of the study area. These patches, which did not exist initially but gradually formed later, exhibit relatively low species richness, fragile ecosystems, and limited habitat functionality. Therefore, it is necessary to enhance protection measures in these areas.

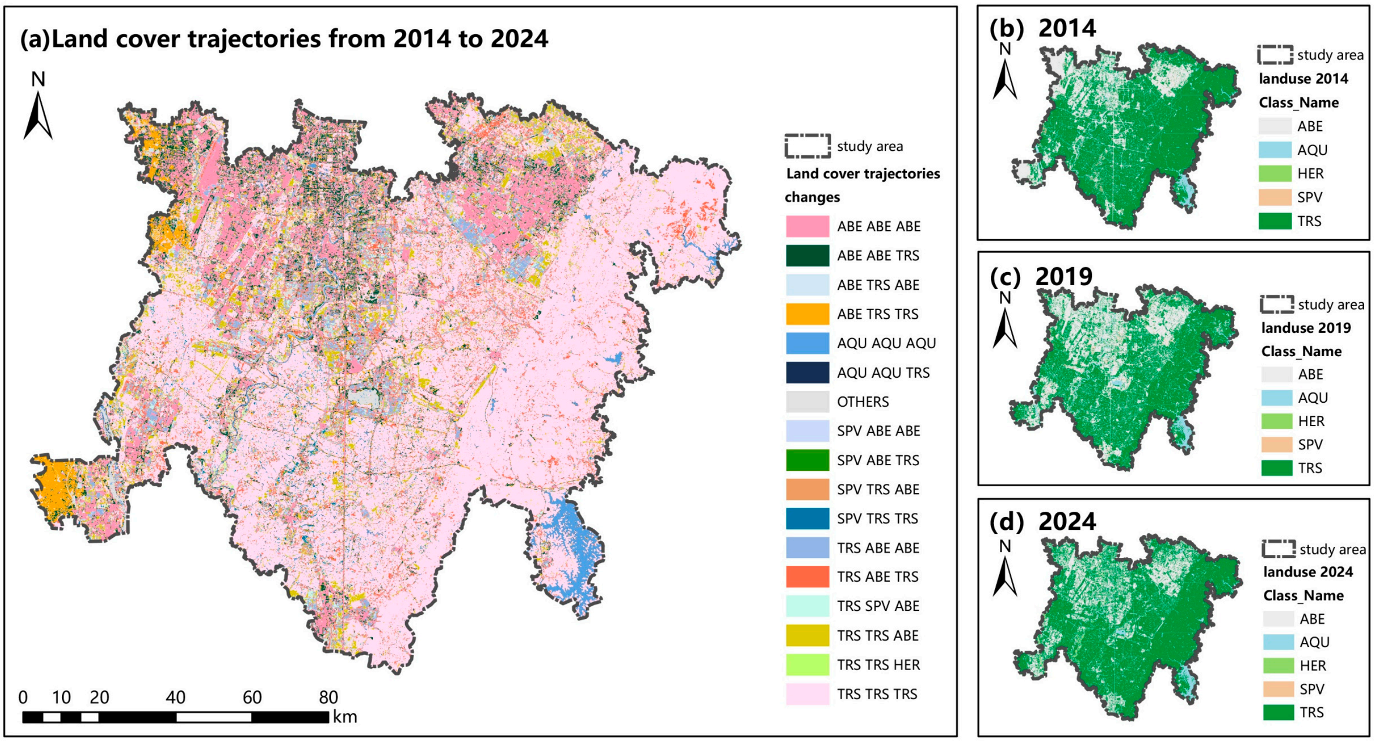

Figure 4. Land Cover Trajectories in Tianfu New District from 2014 to 2024.

Table 8. The statistics of land cover trajectories from 2014 to 2024.

Type	Land Cover Trajectories	Area/km^2	Rate/%
Stable Land Cover Type	ABE ABE ABE	209.22	13.12
	AQU AQU AQU	27.21	1.71
	TRS TRS TRS	769.20	48.23
Fluctuating Land Cover Type	ABE ABE TRS	101.11	6.34
	ABE TRS ABE	12.09	0.76
	ABE TRS TRS	61.15	3.83
	AQU AQU TRS	9.15	0.57
	SPV ABE ABE	7.89	0.49
	SPV ABE TRS	8.54	0.54
	SPV TRS ABE	6.53	0.41
	SPV TRS TRS	25.83	1.62
	TRS ABE ABE	81.78	5.13
	TRS ABE TRS	127.40	7.99
	TRS SPV ABE	8.09	0.51
	TRS TRS ABE	67.34	4.22
	TRS TRS HER	6.91	0.43
	other	65.45	4.10

From the Sankey diagram of land transitions (Figure 5), the most significant transitions are observed between artificial built elements (ABE) and trees and shrubs (TRS). Specifically, the area of ABE first increased and then decreased, while the area of TRS followed an opposite trend, decreasing first and then increasing. These changes are closely related to the construction of the park city. For example, the proportion of ABE initially increased and later decreased. Following the implementation of the Tianfu New District construction policy in 2014, urban land gradually expanded southward from the northernmost end. By 2019, the proportion of built-up areas increased from 25% to 34%. After the introduction of the park city concept in Chengdu in 2019, green spaces were enhanced within existing built-up areas, and the integration of green spaces was prioritized in new urban developments. This resulted in the proportion of built-up areas decreasing from 34% in 2019 to 25% in 2024.

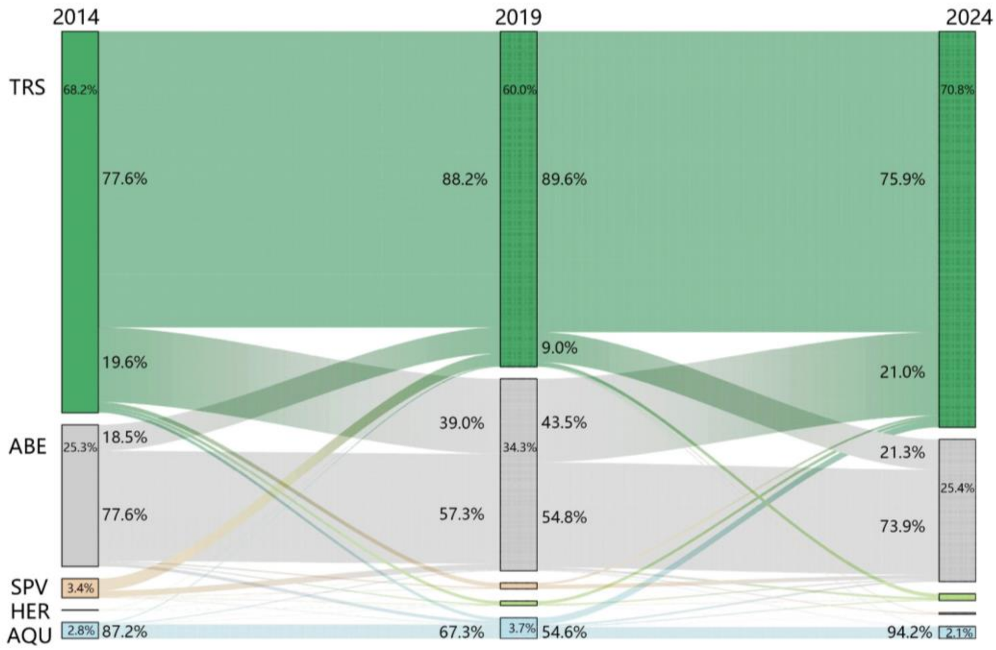

Figure 5. Sankey Diagram of Land Use Type Transition Data in Tianfu New District from 2014 to 2024.

Additionally, a pattern of continuous mutual transformations between trees and shrubs (TRS) and artificial built elements (ABE) is evident during the periods of 2014–2019 and 2019–2024. From 2014 to 2019, 19.6% of TRS transformed into ABE, while 18.5% of ABE transformed into TRS. From 2019 to 2024, 9.0% of TRS transitioned into ABE, while 43.5% of ABE transitioned into TRS. The continuous mutual transformations between ABE and TRS reflect the instability of the habitat conditions in the study area during the construction process, characterized by significant dynamic changes in patches and sensitive habitats.

The coverage of trees and shrubs (TRS) highlights the dynamic changes associated with the development of the park city. Comparing data from 2014 to 2024 (Figure 6), although the proportional area of TRS remained relatively consistent over these two years, a substantial portion of TRS was lost (177.07 km^2, accounting for 11.1% of the study area). The two largest contributors to this loss were the TRS $\rightarrow$ ABE $\rightarrow$ ABE patch (81.78 km^2, 5.1% of the study area) and the TRS $\rightarrow$ TRS $\rightarrow$ ABE patch (67.34 km^2, 4.2% of the study area). Large areas of forestry and tree crops were gradually replaced by urbanization, particularly in the northern regions.

At the same time, new TRS patches were formed (218.56 km^2, 13.7% of the study area), primarily concentrated in the northwest and southwest regions, with some distribution in the northern central urban area. Notably, after significant portions of TRS were replaced by urbanization, they were subsequently recovered and re-covered by TRS in 2024 (142.73 km^2, 8.9% of the study area). The largest proportion of this reformation occurred in the TRS $\rightarrow$ ABE $\rightarrow$ TRS patch (127.40 km^2, 8.0% of the study area). These recovered patches are mainly distributed in two distinct patterns: firstly, sporadic distribution within the built-up areas of the north. Secondly, linear distribution along the Longquan Mountains on the eastern side of the study area.

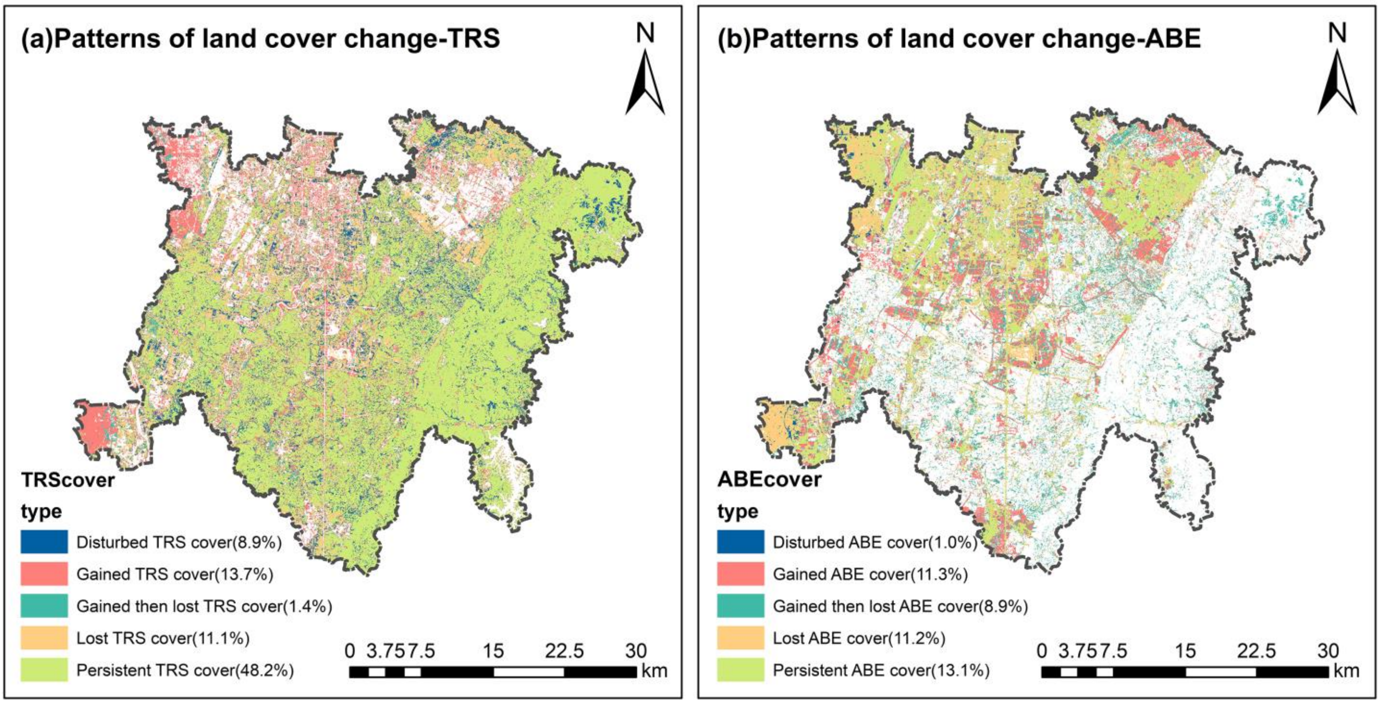

Figure 6. Patterns of land cover change: (**a**) TRS, Trees and Shrubs, (**b**) ABE, Artificial Built Elements.

A more detailed analysis on a finer scale can provide insights into specific parts of the city. Eastern part of the city (Figure 7a): in the Longquan Mountains area, the originally continuous trees and shrubs (TRS) patches were eroded by newly built buildings, roads, and other infrastructure (artificial built elements, ABE) due to accelerated urbanization after 2014. However, after 2019, most ABE patches were restored to TRS patches. Southern part of the city: Xinglong Lake area (Figure 7b): before 2014, this area remained undeveloped marshland (ABE). After the establishment of Tianfu New District in 2014, Xinglong Lake was formed by utilizing the Luxi River channel and the area's original topographical features. At that time, Xinglong Lake was relatively isolated within the ecosystem and surrounded by extensive construction land (ABE). After 2019, with the implementation of the park city concept, the lake island area expanded, and the surrounding parks and greenways were gradually improved. By 2024, ABE patches around the lake became more continuous. Northern part of the city: central urban area (Figure 7c): this region illustrates a clear scenario of remediation following rapid urban expansion. Farmland dominated by TRS coverage was replaced by urban development in 2019, leading to significant fragmentation and loss of plant areas. Some TRS-covered areas degraded into sparsely vegetated—terrestrial (SPV) patches.

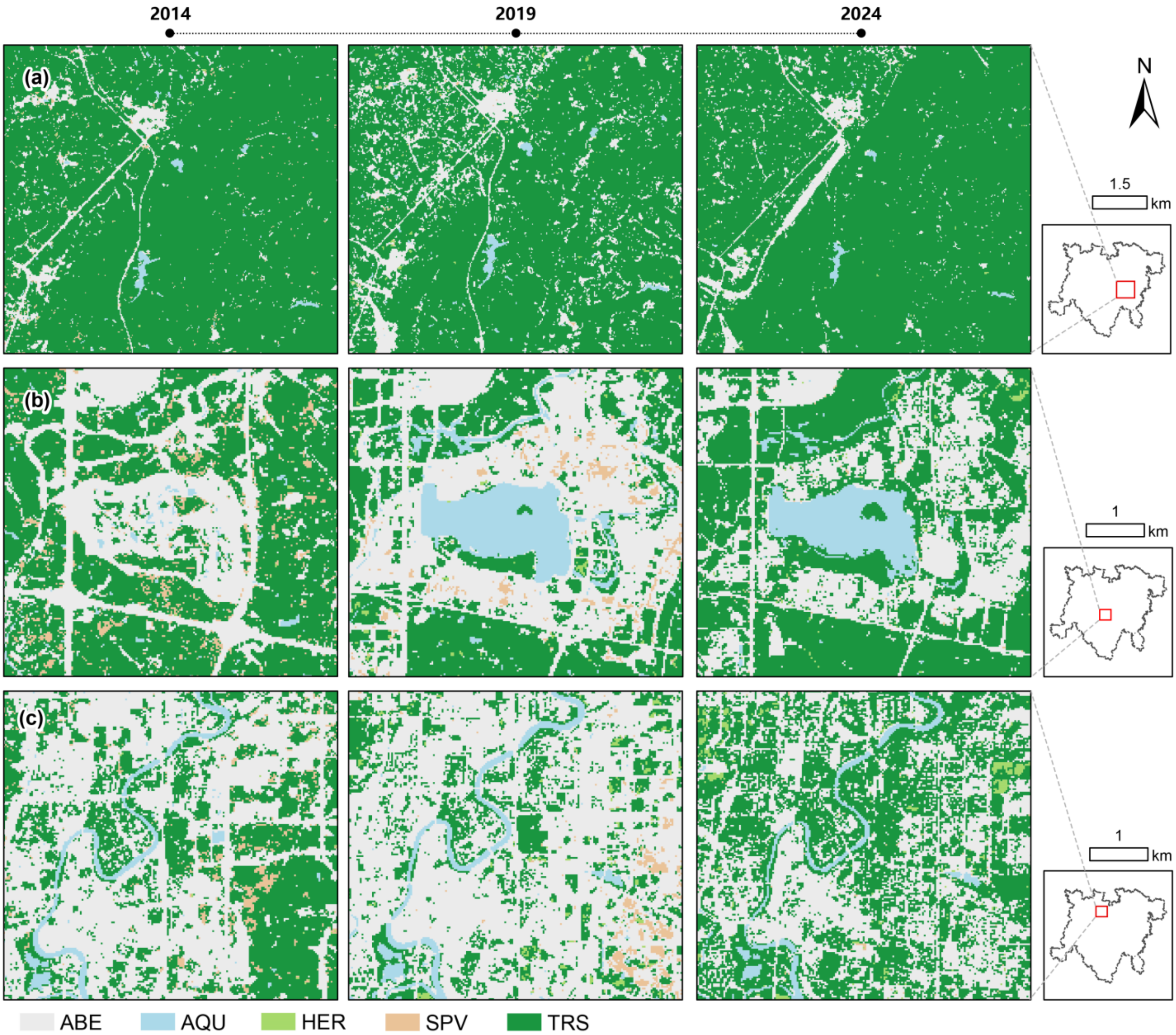

Figure 7. The main trends in land cover evolution observed in different areas of the city: (**a**) regions adjacent to mountain ranges; (**b**) key expansion areas in the southern part of the city; (**c**) sections of the city's northern part near the central urban district.

3.2. Spatial Metric

3.2.1. Landscape-Level Analysis

At the landscape level, spatial indicators generally exhibit increasing complexity and fragmentation (Figure 8). The number of patches (NP) decreases over time, with the total number of patches gradually declining and showing a more pronounced drop between 2019 and 2024. This reduction in patch number leads to an increase in the mean patch size (MPS), with a more significant upward trend observed during the 2019–2024 period. Simultaneously, the mean patch edge (MPE) gradually increases, reflecting ongoing patch integration and a gradual improvement in habitat connectivity. Edge density (ED) and the mean shape index (MSI), indicators of patch shape complexity, initially increase and then decrease, but their overall trend remains upward, peaking in 2019. Combining the analysis of these indicators, from 2014–2019, their overall trend remains upward, peaking in 2019. Combining the analysis of these indicators, the 2014 to 2019 period shows a decline in patch number, but patch shapes become increasingly complex and irregular, indicating greater landscape fragmentation and the development of more intricate patch structures.

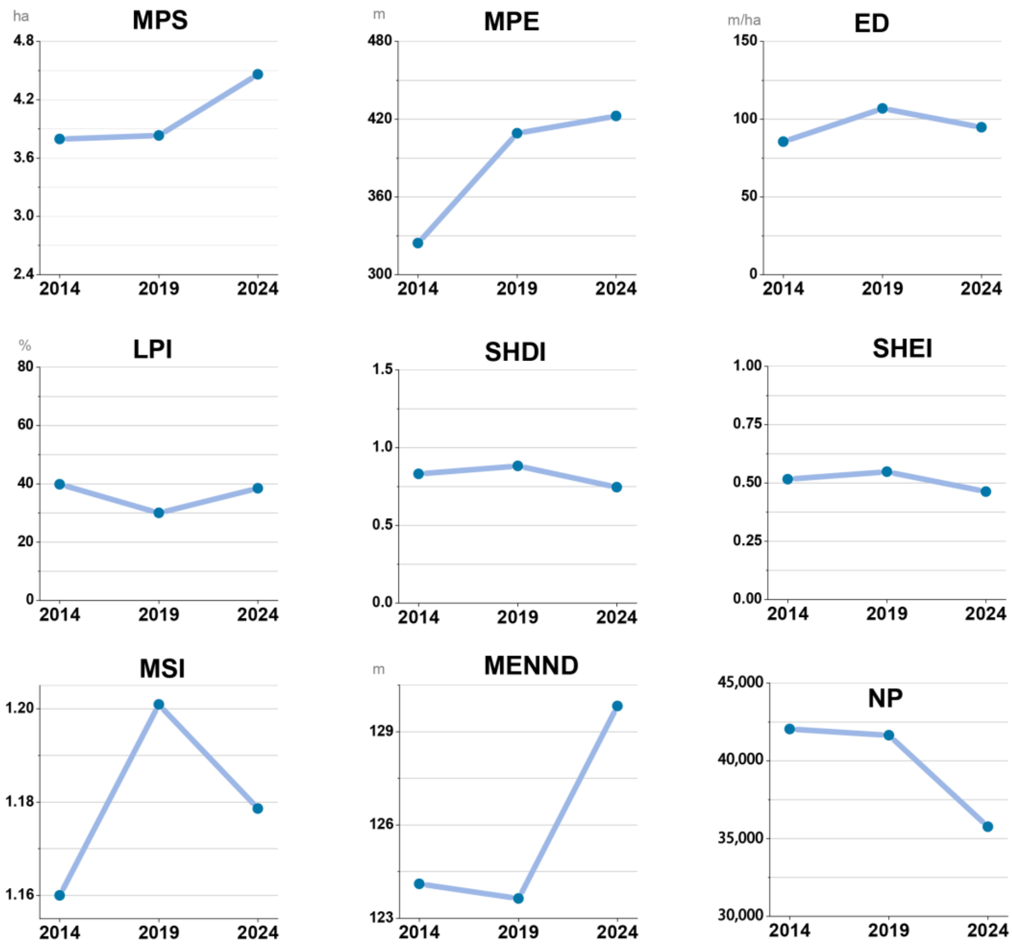

Figure 8. The evolution of spatial indicators at the landscape level from 2014 to 2019 to 2024. MPS: Mean patch size (ha); MPE: Mean patch edge (m); ED: Edge density (m/ha); LPI: Largest patch index (%); SHDI: Shannon's diversity index; SHEI: Shannon's evenness index; MSI: Mean shape index; MENND: Mean Euclidean nearest neighbor distance (m); NP: Number of patches.

From 2014 to 2024, the mean Euclidean nearest neighbor distance (MENND) of patches first decreases and then increases, suggesting that the spatial correlation between patches first weakens and then strengthens. This implies the possibility that ecological connections or corridors between patches are first established and then disrupted. Both the Shannon's diversity index (SHDI) and the Shannon's evenness index (SHEI) display a trend of first increasing and then decreasing. This indicates that species diversity within the community and the uniformity of species distribution initially rise but subsequently decline. These changes also suggest that the dominance of one or more land cover categories relative to others first diminishes but later increases.

3.2.2. Class-Level Analysis

Despite being important components of ecologically significant habitats, the sparsely vegetated—terrestrial (SPV), sparsely vegetated—aquatic (AQU), and herbaceous (HER) categories remained relatively consistent from 2014 to 2024 and consistently accounted for less than 5% of the study area. Therefore, terrestrial (SPV), aquatic (AQU), and herbaceous (HER) categories will not be analyzed in detail as they play a minor role in explaining the evolution of land cover in Tianfu New District. In the class-level analysis, we select the dominant artificial built elements (ABE) and trees and shrubs (TRS) for detailed analysis (Figure 9).

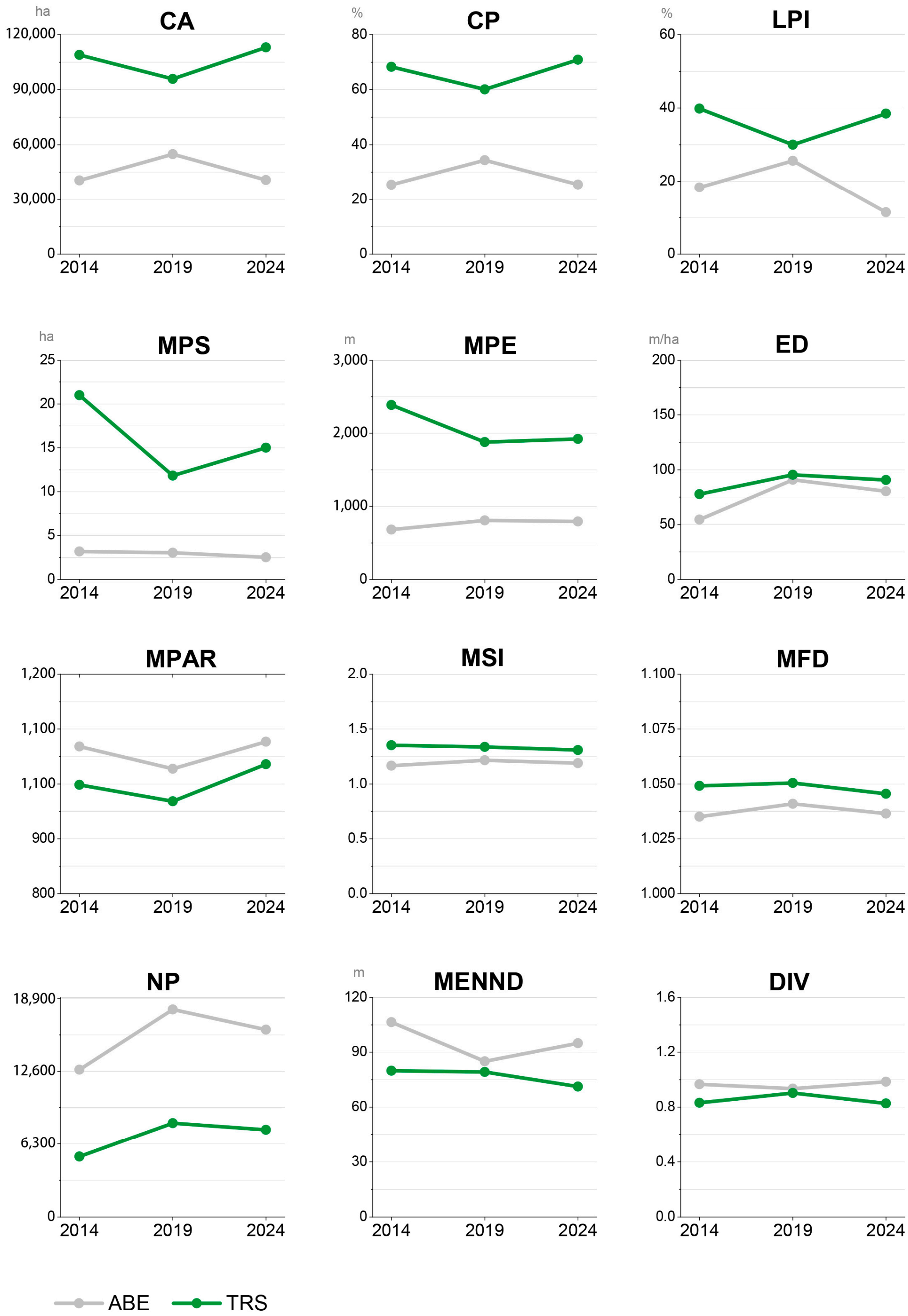

Figure 9. The evolution of spatial indicators at the class level from 2014 to 2019 to 2024. CA: Total class area (ha); CP: Class proportion (%); LPI: Largest patch index (%); MPS: Mean patch size (ha); MPE: Mean patch edge (m); ED: Edge density (m/ha); MPAR: Mean perimeter–area ratio; MSI: Mean shape index; MFD: Mean fractal dimension; NP: Number of patches; MENND: Mean Euclidean nearest neighbor distance (m); MPROX: Mean proximity index; DIV: Division index.

From 2014 to 2024, the artificial built elements (ABE) exhibited a trend where their total class area (CA), number of patches (NP), and class proportion (CP) first increased and then decreased. Along with the development and construction of Tianfu New District from 2014 to 2019, patch area and number gradually grew, and their proportion in the landscape also increased. However, between 2019 to 2024, as the park city was established and promoted, the number and proportion of patches decreased. The largest patch index (LPI), mean patch size (MPS), mean patch edge (MPE), and edge density (ED) all followed a similar trend of first increasing and then decreasing. This reflects an initial rise and subsequent fall in the fragmentation and centralization of ABE patches, transitioning towards dispersion over time.

The aggregation indices of artificial built elements (ABE) from 2014 to 2024 indicate a general decreasing trend in both mean Euclidean nearest neighbor distance (MENND) and division index (DIV). This suggests that, over time, the connectivity between ABE patches has decreased. The shape index results show a trend of decreasing mean perimeter–area ratio (MPAR) and increasing mean fractal dimension (MFD), indicating that while overall shape complexity changed relatively little, it tended to stabilize.

From 2014 to 2024, trees and shrubs (TRS) exhibited a trend of first decreasing and then increasing over time in terms of class area (CA), number of patches (NP), and class proportion (CP). Similarly, the largest patch index (LPI), mean patch size (MPS), mean patch edge (MPE), and edge density (ED) followed a similar pattern of an initial decline followed by an increase. This indicates that the quantity area and proportion of TRS in the ecosystem initially decreased but later rebounded. Concurrently, the importance of TRS within the ecosystem followed a similar trend, while the degree of landscape fragmentation first increased and then decreased. This pattern suggests that the activity level of ecological processes within patches and opportunities for species interactions initially declined but later recovered.

The aggregation indices for trees and shrubs (TRS) from 2014 to 2024 indicate that the mean perimeter–area ratio (MPAR) values first decreased and then increased. During the 2014–2019 period, TRS patches became more regular in shape due to factors such as urbanization or land use planning, leading to trends of environmental degradation and reduced biodiversity. After 2019, patches gradually became elongated and irregular in shape, suggesting a gradual recovery in biodiversity within TRS patches. The division index (DIV) values also exhibited a trend of first increasing and then decreasing, indicating that the connectivity between patches initially improved but later declined. During the urban expansion period from 2014 to 2019, discrete TRS patches within ABE patches were encroached upon, with higher patch continuity in the southeastern region dominating the numerical results, leading to a relatively concentrated overall patch distribution. After 2019, land use changes resulted in the re-embedding of TRS patches within ABE patches, increasing the spatial separation and distance between TRS patches and making their distribution more fragmented and discrete. Since landscape pattern indices primarily provide a numerical reference for global changes, while habitat quality analysis offers insights into the spatio-temporal evolution of habitat fragmentation, it is essential to conduct a habitat quality analysis to explore the specific spatial distribution of these changes.

3.3. Habitat Quality

The habitat quality is calculated using the habitat quality index within the Habitat Quality assessment module of the In-VEST model. The closer the index value is to 1, the higher the habitat quality. According to Table 9, the average habitat quality in Tianfu New District in 2014, 2019, and 2024 was 0.563, 0.483, and 0.580, respectively. Overall, the habitat quality is moderate and exhibits a macro trend of first declining and then rising. The average habitat degradation values were 0.022, 0.018, and 0.017, showing a gradual decrease at the macro level. The highest average habitat degradation degree was 0.225, indicating a relatively low overall degree of degradation. The habitat quality degradation was more significant between 2014 and 2019.

Table 9. Average Statistics of Habitat Quality and Degradation Degree in Tianfu New District from 2014 to 2024.

Year	Maximum Habitat Quality	Average Habitat Quality	Maximum Habitat Degradation	Average Habitat Degradation
2014	1	0.563	0.225104	0.022
2019	1	0.483	0.225104	0.018
2024	1	0.580	0.225104	0.017

To further explore the spatial distribution of habitat quality in Tianfu New District, this study used ArcGIS to reclassify the habitat quality assessment results for the three periods in 2014, 2019, and 2024. The habitat quality results were equally divided into five intervals: extremely poor (0–0.2), poor (0.2–0.4), moderate (0.4–0.6), good (0.6–0.8), and excellent (0.8–1). Statistical analysis was conducted on the proportion of each habitat quality area for the three years. The results (Table 10) indicate that the habitat quality proportions in the three years are relatively consistent, showing significant habitat polarization, primarily characterized by excellent and extremely poor habitats. Extremely poor and excellent habitats each account for approximately 40% of the total, and the overall habitat quality is mainly influenced by these two types of habitat areas. Between 2014 and 2024, the area of excellent habitat quality showed a trend of first declining and then rising, from 767.16 km^2 to 596.26 km^2 and then back up to 761.31 km^2. In contrast, the area of extremely poor habitat quality showed a trend of first rising and then falling, from 550 km^2 to 628 km^2 and then down to 485 km^2. This trend in data indicates that urban construction under the concept of a park city focuses on and implements the restoration of originally fragmented and ecologically fragile habitat areas.

Table 10. Habitat Quality Index Statistics of Tianfu New District from 2014 to 2024.

Year		Extremely Poor (0–0.2)	Poor (0.2–0.4)	Moderate (0.4–0.6)	Good (0.6–0.8)	Excellent (0.8–1)
2014	Area (km^2)	550.18	145.59	28.01	103.88	767.16
	Rate (%)	34.50	9.13	1.76	6.51	48.10
2019	Area (km^2)	628.28	249.45	15.47	105.34	596.26
	Rate (%)	39.40	15.64	0.97	6.60	37.39
2024	Area (km^2)	485.71	227.59	20.95	99.25	761.31
	Rate (%)	30.46	14.27	1.31	6.22	47.74

From the perspective of overall spatial layout (Figure 10), the spatial variation in habitat quality within Tianfu New District is significant, with higher quality in the southwest and lower quality in the north and central regions. Combining land use and terrain analysis, it was found that habitats of superior quality are mainly distributed along the Longquan Mountains on the southeast side of Tianfu New District. These areas feature extensive forest resources, have experienced minimal development and utilization, and are located at a relatively high average altitudes, making development challenging and leaving the habitats virtually untouched by human interference. In contrast, habitats of extremely poor quality are predominantly located in the northern part of Tianfu New District, adjacent to the central urban area, where rapid urbanization, high road density, and well-developed infrastructure have significantly degraded habitat quality. Additionally, smaller areas of extremely poor-quality habitats are scattered across unused lands within the study area. These areas characterized by weak ecological backgrounds, significant human disturbance, and low habitat quality. Overall, the construction of road infrastructure has played a crucial role in fragmenting habitats, creating a northern core spatial pattern that expands outward.

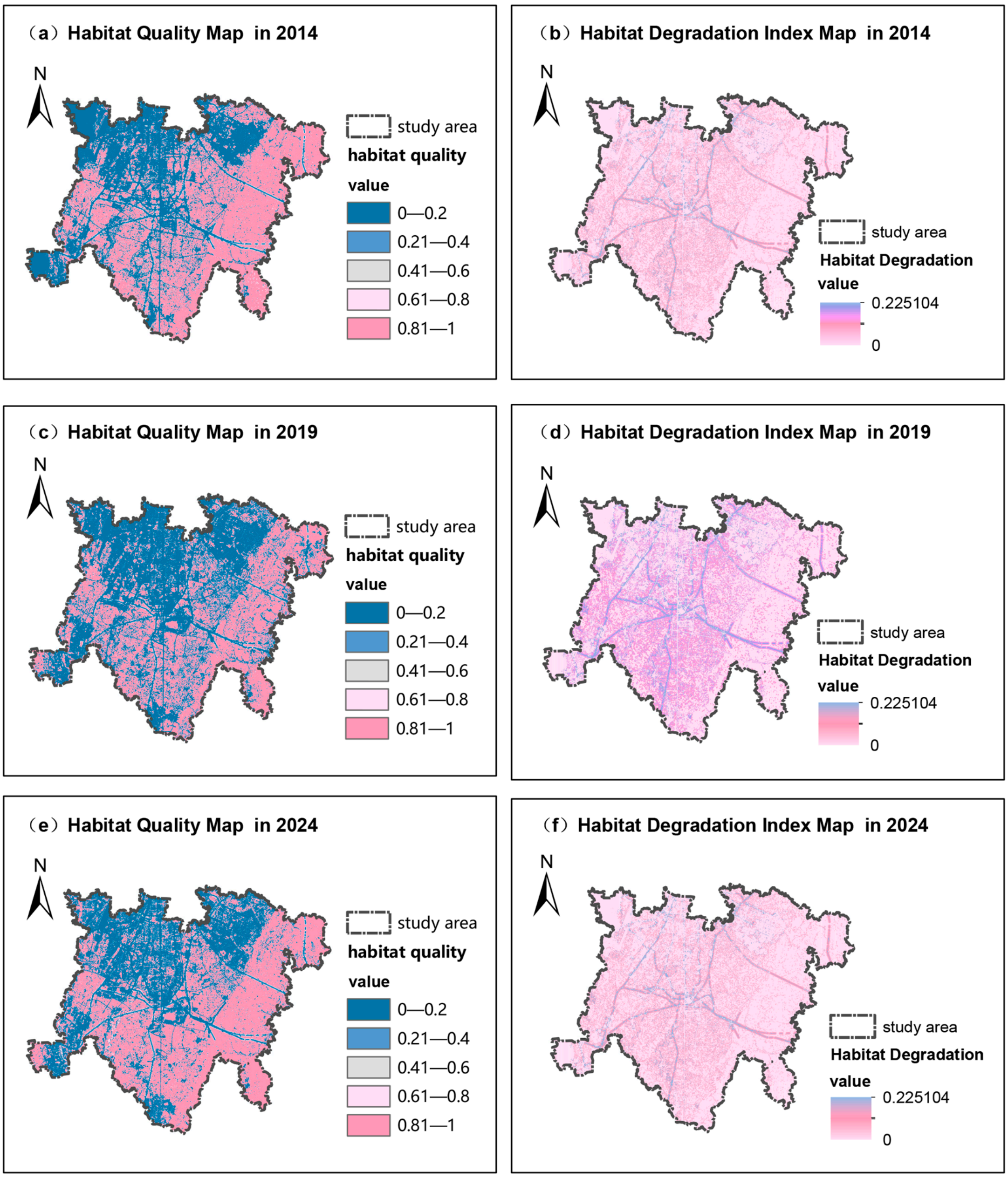

Figure 10. Habitat Quality Map of Tianfu New District from 2014 to 2024.

Assessing habitat degradation over three periods in 2014, 2019, and 2024, it is evident that the degree of habitat degradation has gradually increased since 2014. In 2019, the overall degree of habitat degradation was high, covering a large area. However, after 2019, the pace of degradation slowed as urban ecological construction improved extremely poor-quality habitat patches within the original urban development zones and expanded higher-quality habitat patches.

4. Discussion

4.1. Impacts of Park City Policy on Habitat Quality and Landscape Patterns

This study establishes the land use patterns of Tianfu New District for three different years using the ENVI model based on the UrHBA land classification method. Further, it assesses the overall trend of landscape pattern changes through FRAG-STATS. On this basis, In-VEST is utilized to analyze and discuss the spatial changes in habitat quality.

The analysis of land cover in Tianfu New District reveals the impact of the park city policy on the dynamic changes of habitats [49]. During the study period, approximately 60% of the land cover remained dynamically stable, mainly involving the forested areas in the east and south, as well as the land already urbanized in the north by the end of the 20th century. The process of urbanization has led to the reduction and fragmentation of plant patches, which is similar to urban changes in other regions [50,51]. Unlike plant patches, the changes in sparsely vegetated—aquatic (AQU) patches within the city are relatively stable. Herbaceous (HER) and sparsely vegetated—terrestrial (SPV) patches account for a relatively small proportion, possibly because the city experienced significant loss of herbaceous habitats as early as before 2014.

Based on the analysis of landscape composition, shape description, and diversity indices, the overall patches in the study area have become more fragmented and complex. Biodiversity in 2024 has declined compared to 2019. The trend of trees and shrubs (TRS) patches aligns with the overall landscape pattern. Despite ecological restoration efforts after 2019 leading to a gradual recovery in TRS biodiversity, it has not yet returned to its 2014 levels. Additionally, the integration of fragmented green spaces into the central urban area has resulted in more dispersed distributions and further habitat fragmentation.

In terms of habitat quality, the average habitat quality in 2024 is higher than in 2014, while average habitat degradation has gradually decreased since 2014. However, significant polarization in habitat quality persists. Combining these analyses, it is evident that relatively continuous ecological spaces in the eastern part of Tianfu New District, which experienced less damage, have recovered from habitat fragmentation and improved in quality, surpassing their 2014 levels [52]. In contrast, the northern central urban area and southern expansion zone, which experienced greater damage and human interference, continue to exhibit high landscape heterogeneity. The fragmented spatial pattern in these areas requires further adjustment [53]. Urban expansion triggers turbulent land changes, increasing landscape heterogeneity [54], making it difficult for urban organisms to adapt to rapidly changing environments, thereby reducing species diversity and pushing some species towards extinction [55].

These findings align with previous studies conducted on Tianfu New District. Like most cities, Tianfu New District has also experienced trends of intensified urbanization and reduced vegetation cover [56]. Before 2019, construction land continued to increase, while farmland and grassland areas continued to decrease, and the landscape became increasingly fragmented. The "Overall Upgrading Plan for the Park City in Tianfu New District" proposes that the park city form of Tianfu New District should have been initially formed by 2022 [57]. From the land changes and landscape patterns between 2019 and 2024, it can be seen that in the current northern built-up area, the park form is organically integrated with urban space, with suitable production, living, and ecological spaces, initially forming a nested pattern of urban–park integration and consolidating a harmonious and unified state of "people, city, environment, and industry" [58]. After a certain degree of destruction, the eastern mountainous area has gradually established an ecological barrier after five years of restoration.

The trends observed in Tianfu New District are consistent with findings from similar urban initiatives elsewhere. For example, Vitoria-Gasteiz in the Basque Country and Singapore's Garden City initiative both demonstrated that well-managed green spaces could effectively improve habitat quality and support urban biodiversity [59,60]. Similarly, ecological restoration efforts in other Chinese cities like Guangzhou and Beijing have shown that the expansion of urban green spaces is associated with increased biodiversity and improved habitat conditions [61,62]. However, in Tianfu New District, the implementation of park city policies post-2019 has led to a more rapid recovery in habitat quality compared to other cities, where urban pressures have slowed the pace of recovery.

4.2. Broader Implications and Policy Recommendations

The success of the park city concept in Chengdu demonstrates a positive correlation between well-managed urban green spaces and biodiversity conservation. With the implementation of park city policies, habitat quality has shown signs of recovery, although polarization in habitat quality persists in certain areas. From the perspective of landscape pattern indices, newly created green spaces exhibit increasing complexity and fragmentation.

Future development should prioritize ecological restoration projects within urban areas while adopting refined landscape management strategies. This approach should focus not only on increasing the quantity and area of green spaces but also on optimizing their spatial layout to enhance connectivity and overall ecological functionality. Creating ecological corridors to connect fragmented habitat patches will support the formation of a more continuous and interconnected green network. The study reveals that the impacts of urbanization and policy implementation on habitats are complex and dynamic. Therefore, long-term ecological monitoring and adaptive management plans are essential to assess the ongoing impacts of urban development on habitat quality. City planning and ecological protection strategies must be adjusted accordingly to ensure sustainable urban ecosystems.

High urbanization is a defining feature of many cities today, and other cities in China are also adopting park city policies. Urban planners in these cities can draw inspiration from Chengdu's park city development model to combat habitat fragmentation and enhance ecological connectivity. The successful increase in high-quality habitats in Tianfu New District suggests that strategic expansion of green and blue spaces, combined with policies prioritizing ecological corridors, can serve as a blueprint for sustainable urban development.

Policymakers should focus on maintaining and expanding ecological buffers and improving habitat continuity to ensure the long-term sustainability of biodiversity. Future research should explore the applicability of the park city concept across diverse urban settings, particularly in cities facing varying levels of urban pressure. Comparative studies assessing habitat quality and urban fragmentation across multiple park cities could provide deeper insights into the effectiveness of different ecological interventions.

4.3. Advantages of the Methodology

Urban habitats are typically classified based on primary land use, which often overlooks critical information about vegetation and species, thereby failing to incorporate urban biodiversity as a criterion for land classification. Vegetation provides essential resources for fauna, such as habitat and food. In this study, the UrHBA classification method was employed with the primary objective of assessing urban habitats. This method classifies land based on vegetation cover, using metrics such as vegetation coverage and vertical structure, making it more consistent with habitat classification principles. The UrHBA approach offers a standardized methodology for mapping and classifying urban habitats, applicable to diverse urban contexts. It provides a robust framework for landscape ecology research and serves as a reliable spatial analysis unit for understanding habitat distribution patterns in urban areas, contributing significantly to the conservation and management of urban ecosystems.

In this study, we integrated landscape pattern indices with habitat quality assessments to evaluate habitat fragmentation. Landscape pattern indices quantify the spatial characteristics of landscapes, revealing the spatial configuration of different land use types and the structure of patches. This analysis provides insights into fragmentation at both large and local scales. Habitat quality assessments further refine the understanding of ecological functions by considering habitat sensitivity to threats and their impacts, based on landscape pattern indices [63]. Through this approach, we examined how structural changes influence habitat suitability and the functional capacity of ecosystems, including habitat carrying capacity and overall ecosystem health.

The combined application of these two approaches offers a more systematic, comprehensive, and in-depth evaluation of habitat fragmentation. This integration facilitates the development of more reliable recommendations for ecological conservation and restoration.

The multi-scale integration ensures that the spatial impacts and ecological consequences of habitat fragmentation are understood with greater precision. By combining landscape pattern indices with habitat quality assessments, this study establishes a connection between landscape structure and ecological function, moving beyond merely describing spatial changes to providing a deeper understanding of how these changes affect ecosystem services and biodiversity.

4.4. Limitations of the Study

Despite the positive findings, this study has several limitations related to data quality and model accuracy. The analysis relied on landscape pattern indices and habitat quality models (e.g., the In-VEST model) to assess ecological changes. These methods may introduce subjectivity in defining land use types and setting ecological sensitivity parameters. Given that the resolution of the remote sensing images used was 30 m $\times$ 30 m, some errors in the classification of urban land use types are inevitable. Additionally, the use of habitat quality indices derived from remote sensing and GIS may introduce uncertainties, particularly in assessing habitat quality for smaller patches, which could affect the overall accuracy of the results.

To address these limitations, future research should narrow the scope and collect more detailed data. For instance, incorporating more specific vegetation classifications and adopting a finer spatial resolution could improve accuracy [64]. Subsequent studies should also aim to enhance the precision of remote sensing images to obtain more useful ecological information, enabling a deeper analysis and more accurate predictions of actual habitat conditions.

Furthermore, the study period from 2014 to 2024, while providing insights into trends, is relatively short for fully assessing the long-term ecological benefits and sustainability of the park city policy. The study assumes that ecological policies have positively impacted landscape patterns and habitat quality; however, in a highly complex urban environment, ecological changes are also influenced by numerous other factors. These factors are often intertwined and may not be fully captured or distinguished by existing models. As a result, the findings may underestimate or overestimate the actual impact of specific policies.

5. Conclusions

Based on the satellite remote sensing data from 2014, 2019, and 2024, this paper analyzes the characteristics of land use and transfer changes as well as habitat quality evaluation in Tianfu New District, Chengdu. The conclusions are as follows:

(1) From 2014 to 2024, the area of trees and shrubs in Tianfu New District experienced a decrease from 1089.00 km^2 to 958.14 km^2 and then an increase to 1130.50 km^2. Among them, 796.20 km^2 represents habitat patches that have always existed, while 289.66 km^2 represents habitat patches that have been transformed later. This phenomenon indicates that after the introduction of the concept of a park city, Chengdu has increasingly prioritized the protection of ecological resources, achieving significant progress. However, the rapid urban expansion of previous years caused irreversible damage to certain habitats, underscoring the need for greater efforts to strengthen ecological restoration and sustainable development.

(2) From 2014 to 2024, the area of excellent habitat quality in Tianfu New District decreased from 767.16 km^2 to 596.26 km^2 before rebounding to 761.31 km^2. The overall habitat quality in the south of Tianfu New District is significantly higher than that in the north. Therefore, it is important to intensify efforts to protect the habitats in the southern Longquan Mountain range, ensure consistent monitoring of their status, and utilize these high-quality habitats to compensate for fragmented patches nearby. This approach can help expand the range of excellent habitats and maximize ecological benefits.

The research findings provide valuable insights for future urban planning, ecological restoration, and conservation efforts in Tianfu New District, Chengdu. They also support the advancement of Tianfu New District's development under the innovative framework of the park city concept. This concept, originally proposed by the Chinese academic community, builds upon the principles of eco-city development and has been steadily promoted across Chinese cities. The implementation of the park city model in Tianfu New District stands as a pioneering and exemplary effort, charting a course for ecological civilization in urban development. Analyzing the spatio-temporal changes in land cover types, the distribution of landscape patterns, and the evolution of habitat quality in Tianfu New District provides crucial guidance for the implementation and development direction of park city policies.

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Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy and anonymity.

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Conflicts of Interest: The authors declare no conflicts of interest.

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