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Assessment of the Impact of Land Use on Biodiversity Based on Multiple Scenarios—A Case Study of Southwest China

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Abstract: The main causes of habitat conversion, degradation, and fragmentation—all of which add to the loss in biodiversity—are human activities, such as urbanization and farmland reclamation. In order to inform scientific land management and biodiversity conservation strategies and, therefore, advance sustainable development, it is imperative to evaluate the effects of land-use changes on biodiversity, especially in areas with high biodiversity. Using data from five future land-use scenarios under various Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs), this study systematically assesses the characteristics of land-use and landscape pattern changes in southwest China by 2050. This study builds a comprehensive biodiversity index and forecasts trends in species richness and habitat quality using models like Fragstats and InVEST to evaluate the overall effects of future land-use changes on biodiversity. The research yielded the subsequent conclusions: (1) Grasslands and woods will continue to be the primary land uses in southwest China in the future. But the amount of grassland is expected to decrease by 11,521 to 102,832 km^2, and the amounts of wasteland and urban area are expected to increase by 8130 to 16,293 km^2 and 4028 to 19,677 km^2, respectively. Furthermore, it is anticipated that metropolitan areas will see an increase in landscape fragmentation and shape complexity, whereas forests and wastelands will see a decrease in these aspects. (2) In southwest China, there is a synergistic relationship between species richness and habitat quality, and both are still at relatively high levels. In terms of species richness and habitat quality, the percentage of regions categorized as outstanding and good range from 71.63% to 74.33% and 70.13% to 75.83%, respectively. The environmental circumstances for species survival and habitat quality are expected to worsen in comparison to 2020, notwithstanding these high levels. Western Sichuan, southern Guizhou, and western Yunnan are home to most of the high-habitat-quality and species-richness areas, while the western plateau is home to the majority of the lower scoring areas. (3) The majority of areas (89.84% to 94.29%) are forecast to undergo little change in the spatial distribution of biodiversity in southwest China, and the general quality of the ecological environment is predicted to stay favorable. Except in the SSP1-RCP2.6 scenario, however, it is expected that the region with declining biodiversity will exceed those with increasing biodiversity. In comparison to 2020, there is a projected decline of 1.0562% to 5.2491% in the comprehensive biodiversity index. These results underscore the major obstacles to the conservation of biodiversity in the area, highlighting the need to fortify macro-level land-use management, put into practice efficient regional conservation plans, and incorporate traditional knowledge in order to save biodiversity.

Keywords: southwest China; land-use change; biodiversity; landscape pattern; InVEST model

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1. Introduction

Land-use change reflects the complex interactions between climate change and human activities and is closely associated with biodiversity [1]. It serves as the most direct manifestation of human's impact on the Earth's surface system. In the 21st century, China's urban agglomerations have experienced rapid development, driven by a growing population. According to the National Bureau of Statistics of China, the national population reached 1409.67 million in 2023, with an urbanization rate of the permanent population at 66.16%. The rapid expansion of urban areas has significantly altered land-use patterns and land-cover types [2]. These changes affect the spatial structure and ecological balance of ecosystems, increasing the risk of biodiversity loss and leading to a series of negative environmental impacts.

Biodiversity encompasses the full range of ecological complexes formed by organisms and their environments, along with the various ecological processes they entail, including genetic, species, and ecosystem diversity [3]. It provides stability to ecosystems and sustains the ecological balance [4]. As a fundamental resource for human survival, biodiversity also serves as a critical foundation for the formation and evolution of human culture [5]. Land-use change is the biggest direct driver of global biodiversity loss [6]. Irrational land use has ca sed severe ecosystem degradation and disruption of the balance within wildlife communities, contributing to global biodiversity loss and posing significant threats to achieving the Sustainable Development Goals [7,8]. Consequently, research on the relationship between land-use change and biodiversity in biodiversity hotspots is essential, as it provides valuable insights and guidance for global biodiversity conservation efforts.

In recent years, scholars globally have extensively investigated the impact of future land-use changes on biodiversity, with particular emphasis on the effects of agricultural and urban expansion on species habitats, habitat quality, and species richness [9–11]. Rapid urbanization and agricultural expansion are recognized as the most significant threats to terrestrial organisms, primarily due to habitat loss [12,13].

It is predicted that by 2050 the world will require an additional 500 million hectares of cropland to meet the demands of a growing population [14], resulting in the anticipated loss of millions of square kilometers of natural ecosystems. Agricultural expansion is projected to impact approximately 17,409 species of terrestrial birds, amphibians, and mammals globally, with around 1200 species expected to lose more than 25% of their habitats [15]. Similarly, rapid urban expansion significantly threatens global biodiversity through habitat conversion, degradation, fragmentation, and species extinction [16]. By 2050, an estimated 280,000 to 490,000 square kilometers of urban land will be developed, directly resulting in the loss of 110,000 to 190,000 square kilometers of natural habitat [17]. The rapid cultivation of land and expansion of construction areas have led to the degradation, fragmentation, and disappearance of habitats, disrupting the balance and stability of the original ecosystems. This degradation poses serious threats to regional ecological security and may compel some species to migrate to new areas, thereby increasing the risk of biodiversity loss.

However, land-use change extends beyond agricultural expansion and urban sprawl, encompassing ecological land uses such as forests, grasslands, and watersheds. Changes in these land types can also significantly impact biodiversity [18–20].

Over the past 30 years, with the rapid development of geographic information technology, such as geographic information systems (GIS), remote sensing (RS), and global positioning systems (GPS), remote sensing satellite data have been widely used in the field of land use and biodiversity research. Land-use spatial distribution data are generated through human–computer interactions and interpretations based on Quickbird, IKONOS, GeoEye, WorldView, and Landsat land satellite image data, providing information on the status of and pressures on biodiversity at the landscape, regional, ecosystem, continental, and global spatial scales [21]. However, the combined effects of future land-use changes and the intensity of human activities on biodiversity remain uncertain [22].

Scenario- and model-based approaches for simulating the impacts of future land-use changes on biodiversity are increasingly becoming key tools for guiding future land-use planning [23,24]. In terms of scenario design, most contemporary studies establish future land-use targets based on historical land-use change patterns or regional land-use planning documents. These studies then simulate land-use changes under various scenarios, including natural development, ecological protection, farmland preservation, and urban expansion [25,26]. However, these scenarios often overlook the combined effects of climate policy implementation and socioeconomic development on land-use change, introducing a degree of uncertainty into the simulation results [27].

Several models are widely used to assess biodiversity responses to land-use change, including the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model, Global Biodiversity Modeling Framework (GLOBIO3), Fragstats 4.2 software, and Maximum Entropy (MaxEnt) model [28,29]. The InVEST model, in particular, is frequently employed to simulate the effects of land-use change on ecosystem services. It is known for its accuracy and suitability in regional-scale studies [30], allowing for the exploration of the relationships between threat sources and land-use types, as well as the impacts of different ecosystem types on habitat quality [31], but cannot thoroughly analyze the causes of land change. WU [32] et al. used the PLUS-InVEST model to simulate dynamic adjustment of land-use types and the spatio-temporal evolution of carbon storage in Dalian city under multiple scenarios in 2030 based on land-use type data from 2000 to 2020.

Fragstats 4.2 is software designed to reveal species distribution patterns and calculate various landscape indices [33]. Landscape pattern indices offer condensed information on landscape patterns, providing quantitative indicators of their structural composition and certain aspects of the spatial configuration. Zakariya [34] et al. used Fragstats and ArcGIS to analyze the influence of landscape patterns and land use on the spatial variation in water quality in the urbanized watershed of Bentong, Malaysia. However, the Fragstats model only provides a small number of vector-based indicators, which cannot meet the growing needs of GIS and landscape design research [35].

Southwest China is recognized as a biodiversity hotspot, harboring approximately 50% of the country's birds and mammals, as well as over 30% of its higher plant species, thereby rich in biological resources [36]. In terms of plant species, this region ranks among the richest in the world for temperate flora. However, recent population growth and accelerated urbanization have induced significant alterations in land-use patterns. According to statistics from the Institute of Geographic Sciences and Natural Resources Research of the Chinese Academy of Sciences, the grassland area in southwest China decreased from 49.29% in 2000 to 36.48% in 2020, while the proportion of construction land increased from 0.27% to 0.70%, representing an increase of approximately 1,006,845 square kilometers. These changes pose varying degrees of threat to biodiversity conservation [37]. As a critical ecological security barrier in China, investigating the relationship between biodiversity and land-use changes in southwest China provides valuable theoretical support for optimizing the region's ecological environment.

This study systematically analyzed the characteristics of land-use and landscape pattern changes under the SSP–RCP scenarios, utilizing high-resolution future land-use data. It elucidates the impact of various land-use changes and land-use intensities on species richness and habitat quality, while also assessing the overall implications of these land-use changes on biodiversity.

2. Materials and Methods

2.1. Research Area

The southwest region of China (97°21′ E–110°11′ E, 21°08′ N–33°41′ N) encompasses Sichuan, Guizhou, Yunnan, Tibet Autonomous Region (TAR), and Chongqing Municipality, covering an area of approximately 2,341,500 km^2 (Figure 1). Situated in the southeastern part of the Tibetan Plateau, this region constitutes the southwestern border of China and is classified as one of the country's seven natural geographic subregions. It exhibits diverse topographic conditions, including plateaus, hills, mountains, and karst landforms. The area encompasses the Sichuan Basin, the Yunnan–Guizhou Plateau, and the southern Qinghai–

Tibet Plateau, resulting in a wide variety of climatic types and a rich array of biological resources [38].

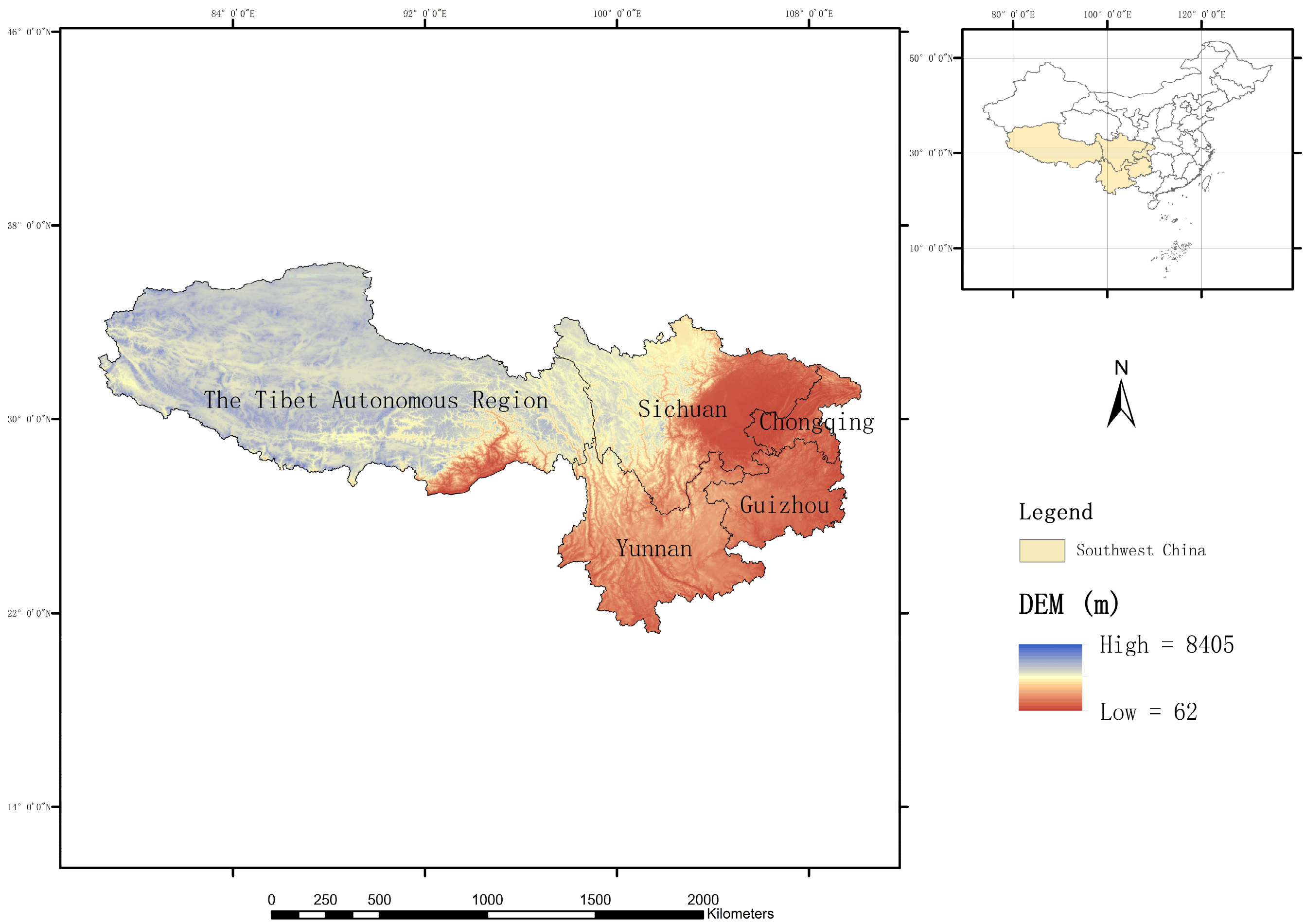

Figure 1. Research area.

Due to the uplift of the Qinghai–Tibet Plateau, there are significant differences in temperature and precipitation from northwest to southeast in the southwestern region. The annual maximum precipitation can exceed 1600 mm [39], while the annual average temperature ranges from 3 °C to 23 °C. In the context of global warming, the southwestern region exhibits a trend of increasing high temperatures and more frequent drought events, with numerous instances of extreme heat and drought recorded [40]. In the summer of 2022, the southwestern region, along with the entire Yangtze River basin, experienced a rare and significant compound event characterized by extreme high temperatures and drought, setting historical temperature records. Simultaneously, Southwestern China is recognized as one of the 36 global biodiversity hotspots, housing at least 20,000 species of higher plants and approximately 2000 species of vertebrates [41]. This region is also home to several endemic animals, as well as rare and endangered species, including the golden monkey, snow leopard, white-lipped deer, green-tailed pheasant, and white horse chicken. The region's biodiversity plays a crucial role in supplying ecosystem services and supporting local socioeconomic development while also influencing broader ecological and socioeconomic dynamics across China and Asia.

Furthermore, the spatial heterogeneity of natural geographic conditions in southwest China affects the distribution of populations and economic activities within the region [42]. For instance, Sichuan and Chongqing serve as major centers for population, agriculture, and economic activity, whereas the Tibetan Plateau and its surrounding areas are characterized by sparse populations and lower levels of economic development.

2.2. Data Sources

The land-use type data used in this study were obtained from Tianyuan Zhang [43] et al. "https://doi.org/10.6084/m9.figshare.23542860 (accessed on 7 October 2024)", with a spatial resolution of 1 km. This gridded dataset is superior to other future land-use/land-cover (LULC) products, as it fully integrates the impacts of temporally adjacent simulations and enhances accuracy by employing future suitability probabilities for land-use projections.

In this study, the Tier-1 base scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) from the CMIP6 Scenario Model Intercomparison Programme (ScenarioMIP) were selected for analysis. Details of these SSP–RCP scenarios are provided in Table 1. Additionally, to account for potential future land-use changes under varying socioeconomic pathways and data availability, SSP4-3.4 was included as a supplementary scenario [44].

Table 1. Descriptions of the scenarios in the LUH2 dataset [a].

Scenario		Description
Tier-1	SSP1-RCP2.6	Combination of low societal vulnerability and a low forcing level, with substantial land-use change (in particular, increased global forest cover)
	SSP2-RCP4.5	Combination of intermediate societal vulnerability and an intermediate forcing level
	SSP3-RCP7.0	Combination of relatively high societal vulnerability and a relatively high forcing level, with substantial land-use change (in particular, decreased global forest cover)
	SSP5-RCP8.5	Combination of high societal vulnerability and a high forcing level
Tier-2	SSP4-RCP3.4	Combination of lower-mitigation-challenge scenarios and lower-radiative-forcing scenarios

[a] SSPx-y denotes a scenario designed with a combination of an SSP level (x) and an RCP level (y).

2.3. Research Methods

2.3.1. Landscape Index

For the analysis, we selected the following three key landscape indices: number of patches (NP), patch density (PD), and landscape shape index (LSI). These indices are indicative of landscape fragmentation and the complexity of landscape types. Higher values of NP, PD, and LSI suggest greater fragmentation, increased irregularity of patches, and more complex landscape shapes. Definitions of these landscape indices are provided in Table 2.

Table 2. Selected landscape index and significance.

Landscape Index	Significance	Formula	Unit
Number of Patches (NP)	Landscape fragmentation, NP value is proportional to landscape fragmentation, reflecting the spatial heterogeneity of landscape elements	NP = n	patch
Patch Density (PD)	Landscape fragmentation, the larger the PD value, the more fragmented the landscape	PD = NP/A	patch·hm^2
Landscape Shape Index (LSI)	Landscape fragmentation, the larger the LSI value, the higher the degree of patch irregularity, the more complex the landscape shape	LSI = $\frac{25\sum_{k=1}^{m} e_{ik}}{\sqrt{A}}$	

2.3.2. Habitat Quality Index

1. Habitat quality index formula

The parameter settings for stressors and weights within the InVEST model, as well as habitat suitability across different land-use types and their sensitivity to stressors, were adapted from the research conducted by Xie Yanglin et al. [44]. The calculation formula is as follows:

$$Q_{xj} = H_j(1 - (\frac{D_{xj}^z}{D_{xj}^z + k^z}))$$

where Q_{xj} denotes the quality of the habitat in grid x, H_j denotes the habitat suitability for land-use category j, D_{xj} denotes the level of stress to which grid x is subjected, k is the half-saturation coefficient, which is usually taken as half of the maximum value for D_{xj}, and z is the normalization constant, which is usually taken as 2.5.

2. Habitat quality index parameters

This paper reviewed the relevant research and analyzed the results. It is found that the attribute table compiled by Zhou Liang [45] and Xie Yanglin [46] is more in line with this paper. The specific threat factor parameters are shown in Table 3.

Table 3. Table of threat factor attributes.

Threat Factor	Maximum Distance (km)	Weight	Degeneration Type
Cropland	2	0.6	linear
Urban	5	1	exponential
Barren	4	0.5	linear

The suitability of habitats for different land-uses/coverages is not the same, and the sensitivity of each threat factor is also different. Data on cultivated land and urban land use are used as threat factors to derive the sensitivity of land-use types. The parameters in this paper are obtained by collating the previous literature. The specific parameters are as shown in Table 4.

Table 4. Sensitivity to suitability of different habitats and different threat factors.

LULC	NAME	HABITAT	Cropland	Urban	Barren
1	Cropland	0.3	0	0.7	0.4
2	Forest	1	0.5	0.8	0.2
3	Grassland	0.8	0.4	0.7	0.6
4	Urban	0	0	0	0.1
5	Barren	0	0	0	0
6	Water	0.7	0.6	0.8	0.2

2.3.3. Biological Richness Index

Using the biological richness index calculation model, we first computed the index for the two time periods before normalization, utilizing the Raster Calculator tool in ArcGIS based on land-cover data. The normalized biological richness index was subsequently obtained through additional raster calculations by the normalization coefficient formula [46]. This study adheres to the standards outlined in the Technical Specification for Evaluation of Ecological Environmental Conditions (HJ 192-2015) [47], issued by the former State Environmental Protection Administration.

$$\text{Biological richness index} = A_{\text{bio}} \times (0.35 \times \text{Forest} + 0.21 \times \text{Grassland} + 0.28 \times \text{Water} + 0.11 \times \text{Cropland} + 0.04 \times \text{Urban} + 0.01 \times \text{Barren})/\text{Area size}$$

where A_{bio} denotes the normalization factor of the habitat quality index with a reference value of 511.2642131067.

2.3.4. Composite Biodiversity Index

To quantify the overall impact of land-use change on biodiversity, this study employs the calculation method for the biodiversity index (BI), as outlined in the Biodiversity Evaluation Criteria, issued by the Ministry of Environmental Protection. We construct the composite biodiversity index (CBI) by integrating the species richness and habitat quality [12].

$$\text{CBI} = \text{S} \times \omega_1 + \text{Q} \times \omega_2$$

where CBI denotes the composite biodiversity index; S and Q denote the normalized species richness and habitat quality, respectively; ω_1 and ω_2 denote the weights of the species richness and habitat quality indicators, respectively, and both of them were taken as 0.5 in this study.

3. Results

3.1. Characterization of Changes in Land-Use and Landscape Patterns

3.1.1. Land-Use Transfer Matrix

The land-use transfer matrix quantifies the relationships among different land-cover types over multiple time periods, illustrating how land types transition from one category to another. This matrix provides a detailed quantification of changes in the areas of various land-cover types, specifically outlining the inflows and outflows of each land-use category within the region. Consequently, it reliably assesses land-cover changes, habitat diversity, richness, and heterogeneity [48].

In 2020, land-use types in the southwest region were predominantly grasslands and forests, covering 44.49% and 29.97% of the total area, respectively. Urban and cropland areas accounted for 14.51% and 9.13%, respectively. By 2050, under the five SSP–RCP scenarios, the areas designated for forest, urban, barren, and water are projected to increase by 1441–29,486 km^2, 4028–19,677 km^2, 8130–16,293 km^2, and 1085–1146 km^2, respectively (Figure 2). In contrast, grassland is projected to decrease by 11,521–102,832 km^2 across the future scenarios. The area of cultivated land is expected to decline by 1382–18,616 km^2 in all scenarios, except for the SSP2-RCP4.5 scenario, where it is anticipated to increase by 82,237 km^2.

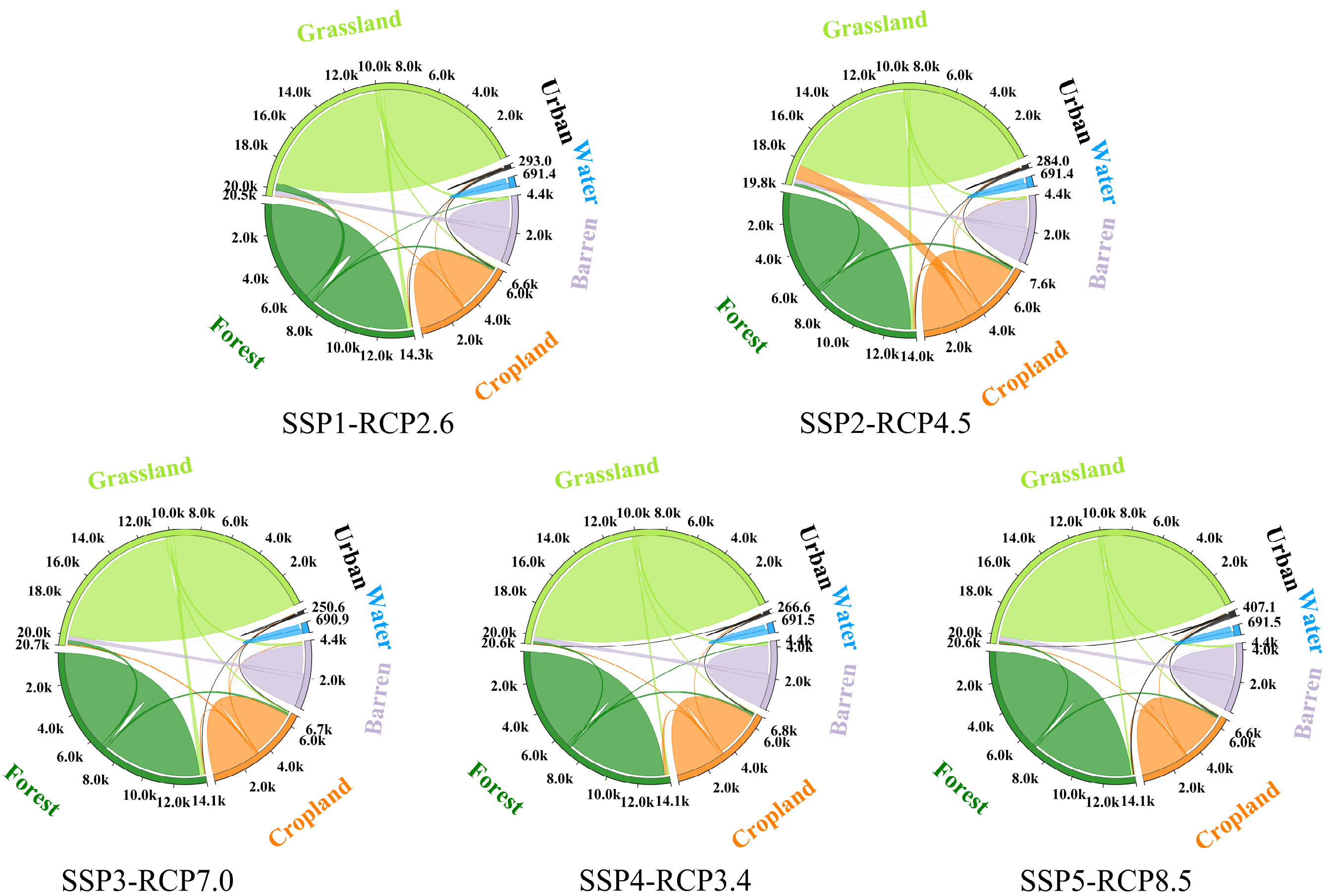

Figure 2. Chord diagram of land-use transitions in southwest China in 2050 under different Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs).

The spatial distribution of land-use changes (Figure 3) reveals notable similarities across the five SSP–RCP scenarios. Barren and grassland areas are predominantly located in Tibet, with 93,824 km^2 of grassland projected to convert to cropland under the SSP2-RCP4.5 scenario. Forest cover is most extensive in Yunnan, where forests constitute the dominant land type. Cropland is primarily concentrated in the eastern regions, such as Guizhou and Chongqing, and under the SSP2-RCP4.5 scenario, a significant portion of other land types is expected to convert to cropland.

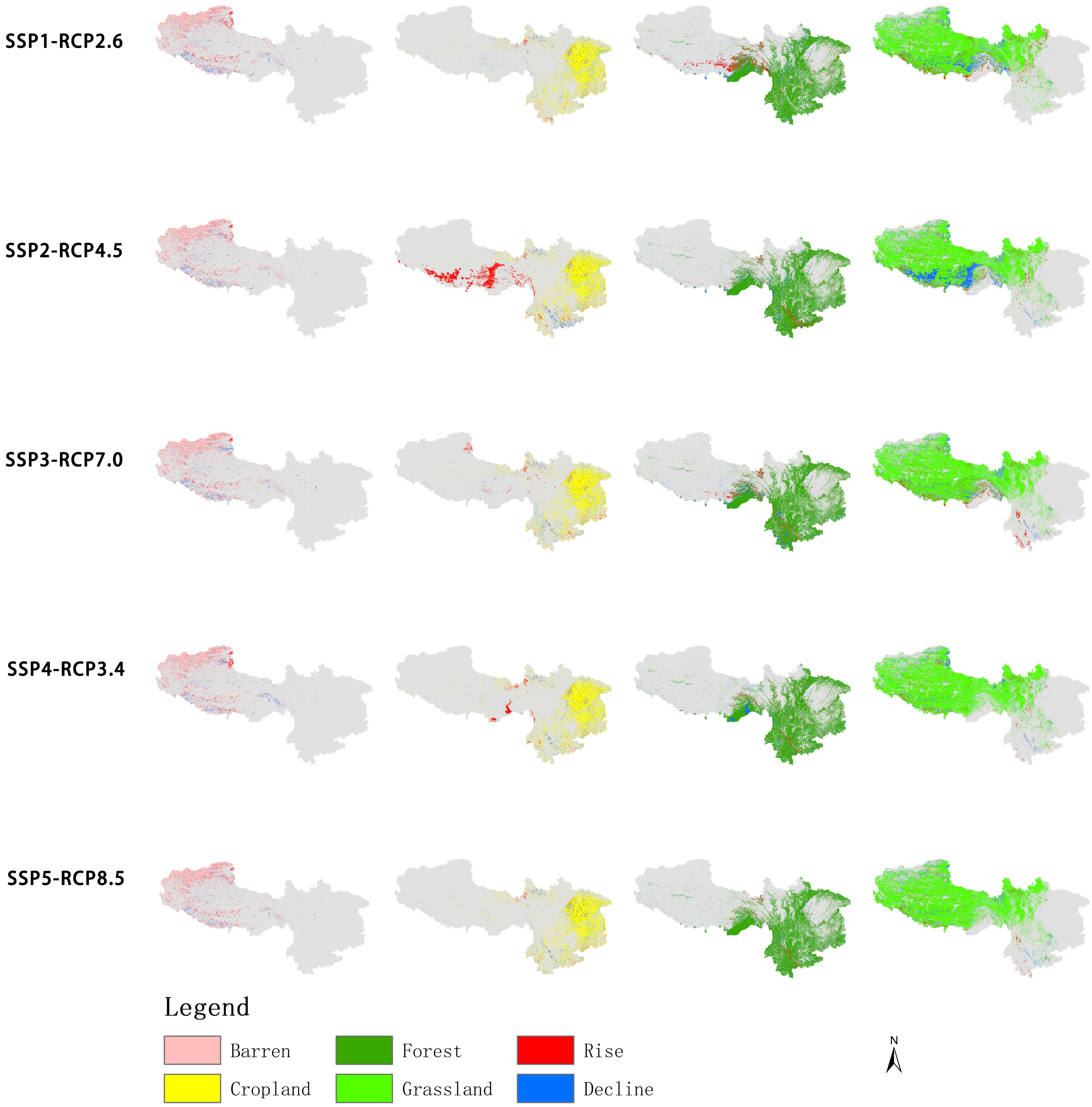

Figure 3. Spatial distribution and change in major land-use types in southwest China in 2050 under different Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs).

3.1.2. Landscape Pattern

Landscape pattern refers to the spatial arrangement resulting from both natural factors and human activities [35]. The analysis of landscape patterns was conducted at both the landscape and type levels, leveraging previous research and correlations among landscape indices [49].

As illustrated in Figure 4a,b, cropland exhibited the highest values for number of patches (NP), patch density (PD), and landscape shape index (LSI) in 2020, followed by forests. This indicates that these land-use types experience relatively high levels of fragmentation and spatial pattern complexity. In contrast, water and urban areas display lower NP and PD values, suggesting simpler patch shapes and reduced fragmentation.

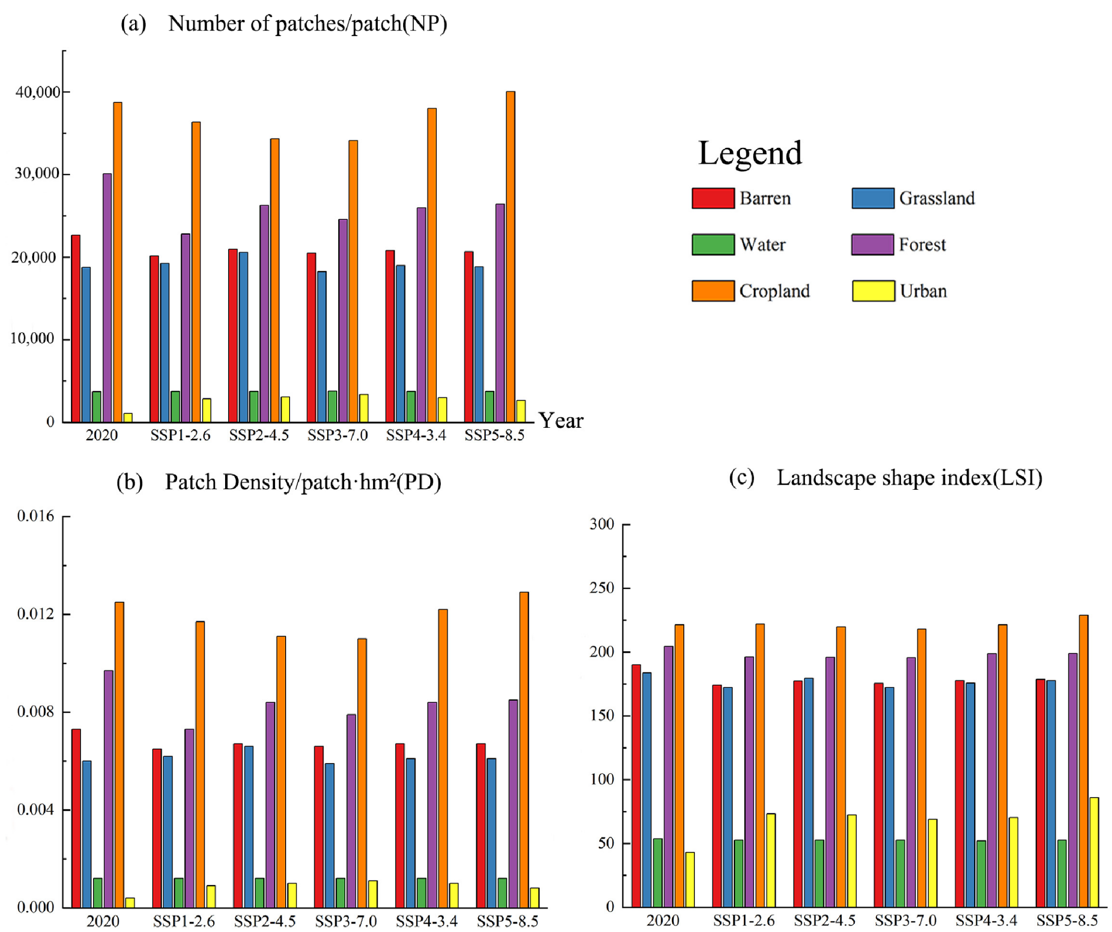

Figure 4. Variations in landscape indices for land use in the southwest region by 2050, under different SSP–RCP scenarios: (**a**) variation in the number of patches; (**b**) variation in patch density; (**c**) variation in landscape shape indices.

Compared to 2020, the number of patches (NP), patch density (PD), and landscape shape index (LSI) for forests decreased under all five scenarios, indicating reduced fragmentation and simpler landscape shapes for forests in southwest China. Similarly, the trends in the barren landscape pattern indices (LSIs) mirrored those of forests. Specifically, the NP of barren areas decreased by 1713 to 2536, while the PD decreased by 0.0006 to 0.0008 per hectare. This suggests that barren areas are expected to become more concentrated and less fragmented as a result of human activities and climate change in the future.

Under the SSP5-8.5 scenario (Table 5), the number of patches (NP) and patch density (PD) of cropland increased from 38,744 and 0.0125 in 2020 to 40,064 and 0.0129, respectively. This increase can be attributed to rapid urban expansion under the SSP5 scenario, which has led to the conversion of cropland and grassland into urban areas. Consequently, this conversion has resulted in a higher number of landscape patches in cropland, increased land-use fragmentation, and greater spatial heterogeneity. In the multiscenario simulations, the LSI of grassland decreased, indicating a trend toward simpler landscape structures and more homogeneous vegetation types. Additionally, the NP, PD, and LSI of urban areas increased, reflecting the ongoing trend of urban expansion in China.

Table 5. Landscape configuration indexes in southwest China under different Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs), and their changes compared to the year 2020.

Scenario	NP	Change (%)	PD	Change (%)	LSI	Change (%)
2020	115,085		0.037		194.4393	
SSP1-RCP2.6	105,118	−8.66	0.0338	−8.65	187.6363	−3.50
SSP2-RCP4.5	108,973	−5.31	0.0351	3.85	192.5969	2.64
SSP3-RCP7.0	104,505	−9.19	0.0336	−4.27	186.5817	−3.12
SSP4-RCP3.4	110,489	−3.99	0.0356	5.95	190.0201	1.84
SSP5-RCP8.5	112,366	−2.36	0.0362	1.69	193.4749	1.82

3.2. Impacts of Land-Use Change on Biodiversity in Southwest China

3.2.1. Habitat Quality

Habitat quality refers to the environmental conditions that support the survival of species within a specific spatial and temporal context, serving as an indicator of biodiversity status in a given region [50]. In the model, the habitat quality index ranges continuously from 0 to 1 on the raster layer, with values closer to 1 indicating higher habitat quality. This suggests that the habitat is relatively intact and supports the necessary structures and functions required for maintaining biodiversity [51]. Generally, increased land-use intensity correlates with a rise in the number and intensity of threat sources, which in turn degrades the quality of nearby habitats.

To compare and illustrate the effects of land-use changes on habitat quality within the study area, the habitat quality index results for the five periods were categorized into the following four intervals: 0–0.3, 0.3–0.7, 0.7–0.8, and 0.8–1. This classification utilized the natural breakpoints method. Consequently, habitat quality was classified into the following four grades: low, medium, good, and excellent. The percentage of habitats within each grade was subsequently calculated.

Under the multiscenario simulations (Figure 5), the habitat quality index in southwest China is projected to be generally high in 2050, with areas classified as having excellent and good habitat quality indexes comprising approximately 30.03–31.23% and 40.1–44%, respectively. However, compared to 2020, there will be a decrease in the proportion of areas classified as good, alongside an increase in the proportions of areas with poor and excellent habitat quality indexes. This indicates that ecological and environmental protection in southwest China will face significant challenges related to polarization.

In terms of spatial patterns (Figure 5), Sichuan, Yunnan, and Guizhou exhibited a higher concentration of habitats with scores above 0.7, indicating relatively good habitat quality. In contrast, Tibet and Chongqing show poorer habitat quality overall. Notably, the border region between Sichuan and Chongqing experiences significantly low habitat quality, with many areas scoring below 0.3. This region, primarily located within the economically developed Sichuan Basin, faces high levels of human activity. The intensive land use and development in this area have resulted in substantial ecological degradation, contributing to the observed decline in habitat quality.

In terms of temporal patterns (Figure 6), the scenarios SSP1-RCP2.6, SSP3-RCP7.0, and SSP5-RCP8.5 exhibited more stable changes in habitat quality, with the spatial distribution of changes being more dispersed. Conversely, under the SSP2-RCP4.5 scenario, the Tibet region experienced the most significant alterations in habitat quality, with a substantial area undergoing a decline.

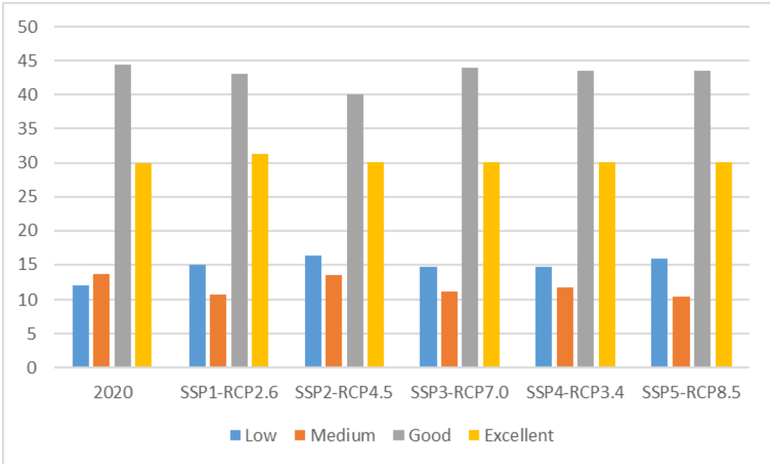

Figure 5. Proportional chart of the habitat quality classification under different SSP–RCP scenarios in southwest China.

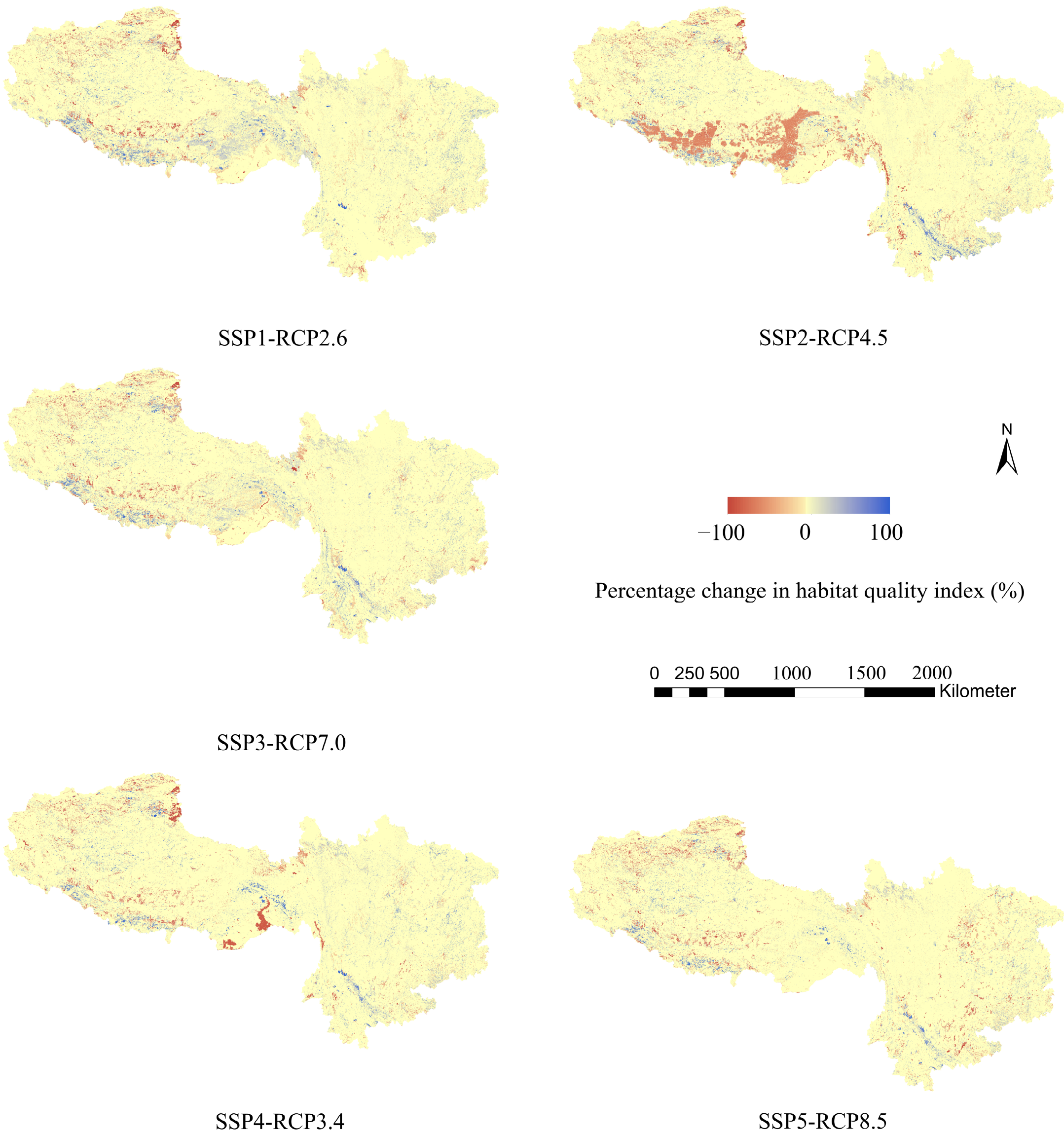

Figure 6. The percentage changes in the habitat quality indexes for southwest China by 2050 under various Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs).

The mean value of the habitat quality index in southwest China decreased under all five scenarios (Figure 7). Compared to the habitat quality index in 2020, the most significant decline occurred under the SSP2-RCP4.5 scenario, with the Tibet Autonomous Region experiencing the largest reduction of 0.04664 in its habitat quality index. Notably, Yunnan Province recorded the highest mean habitat quality index, while Chongqing exhibited the lowest average habitat quality index at 0.55972 under the SSP5-RCP8.5 scenario. In the future land-use multiscenario simulation, both Yunnan and Sichuan maintained average habitat quality indices higher than the regional average, indicating that these provinces exhibited the best habitat integrity in southwest China.

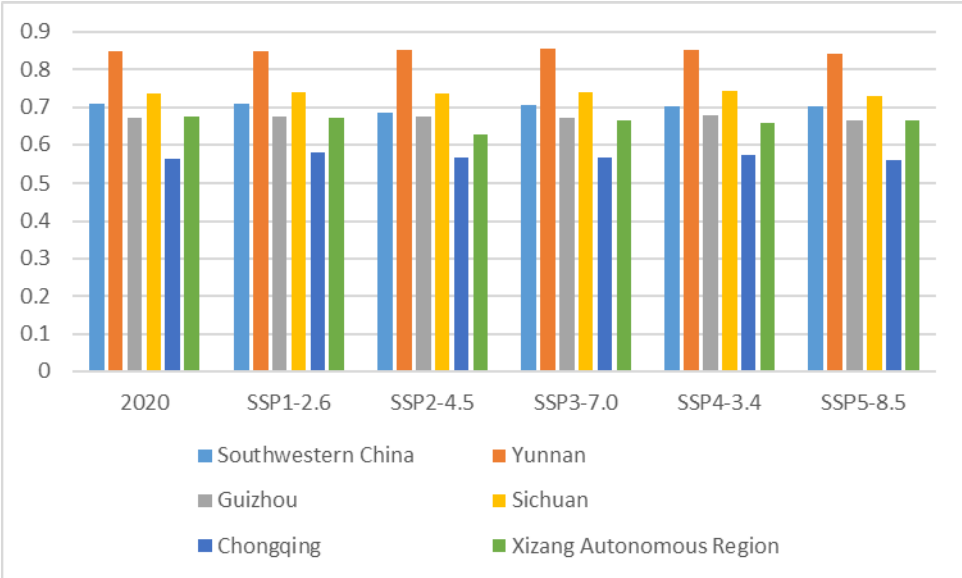

Figure 7. Mean habitat quality index for southwest China and its provinces in 2050 under various Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs).

3.2.2. Biological Richness

The biological richness index quantifies the variation in species richness across different ecosystem types per unit area, thereby indirectly reflecting the abundance of organisms within the assessed region [52]. To compare and illustrate the effects of land-use changes on habitat quality in the protected area, the biological richness index results from the five periods were categorized into the following four intervals: 0–0.09, 0.09–0.29, 0.29–0.59, and 0.59–1. Consequently, the habitat quality index was segmented into the following four categories: low, medium, good, and excellent, with the proportion of each habitat type subsequently calculated.

Under the multiscenario simulations (Figure 8), the biological abundance in southwest China was relatively high, with the areas rated as good or excellent accounting for 40.1% to 44.49% and 31.42% to 32.73%, respectively. Overall, the proportion of the areas with good biological abundance is expected to decrease, while the proportions of low and excellent categories are projected to increase. The trend of polarization in the biological abundance is anticipated to intensify by the year 2050.

In terms of temporal patterns (Figure 9), the three scenarios SSP1-RCP2.6, SSP3-RCP7.0, and SSP5-RCP8.5 showed more stable changes in biological richness, and the spatial distribution of the areas of change was more dispersed. Under these five scenarios, biological richness change in Sichuan was the most stable, while biological richness change in the Tibet region was the most drastic. Under the SSP2-RCP4.5 scenario, changes in the western part of the southwest region of China are very drastic, with a significant decline.

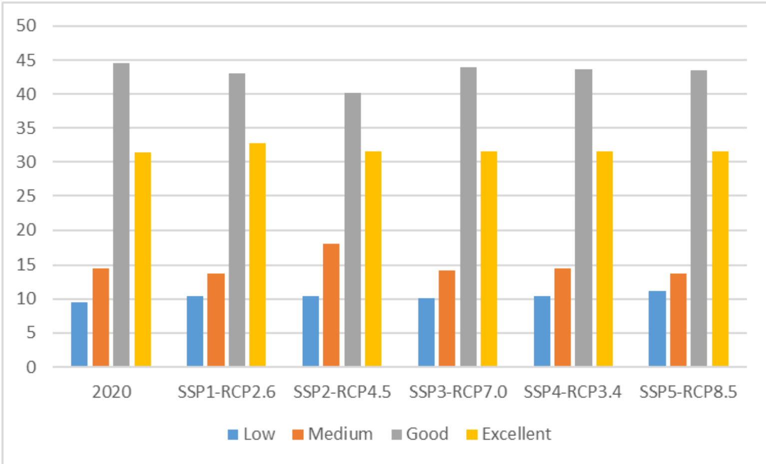

Figure 8. Proportional chart of the biological richness classification under the different SSP–RCP scenarios in southwest China.

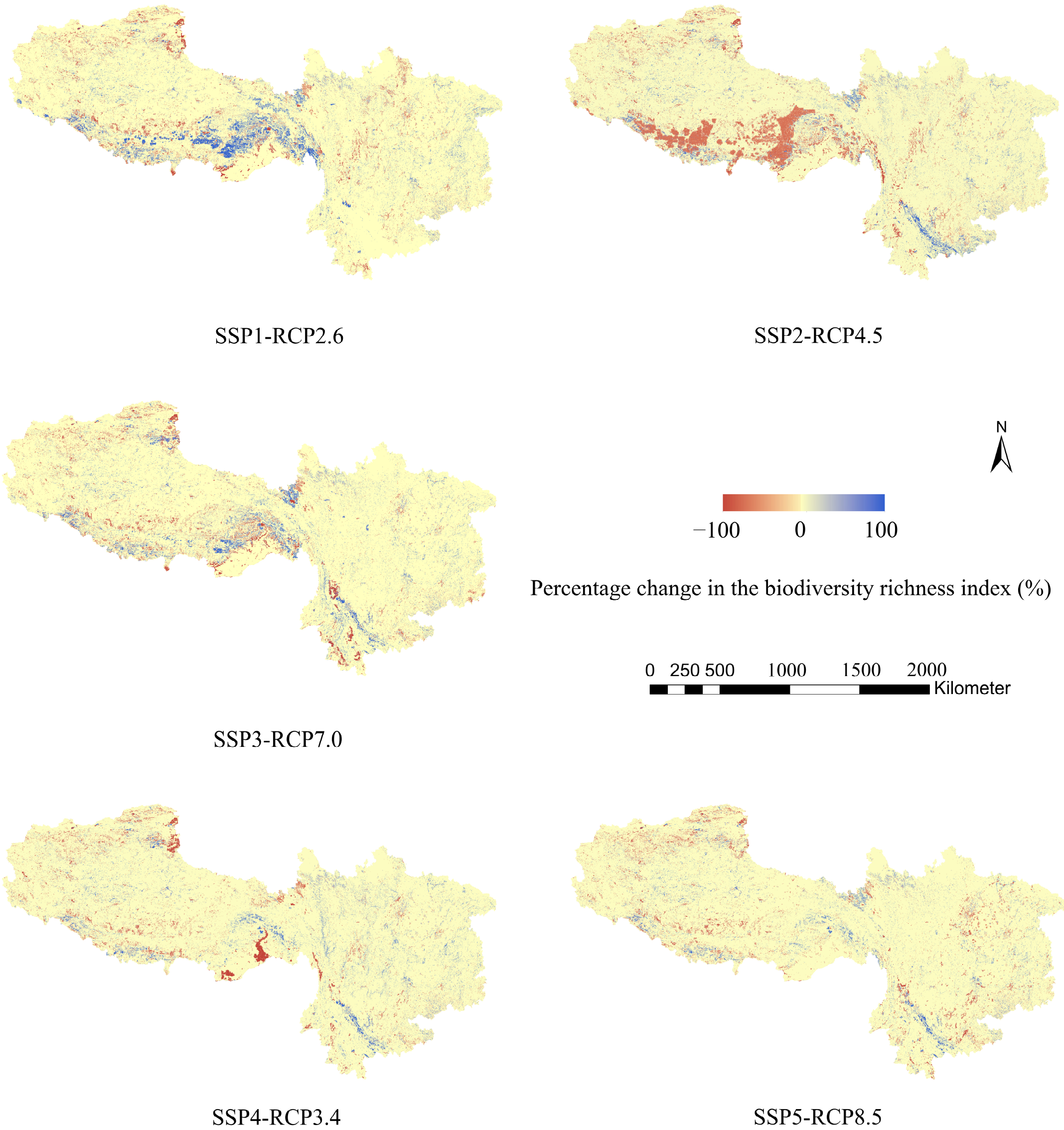

Figure 9. The percentage change in the biodiversity richness index in southwestern China by 2050 under different Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs).

3.2.3. Integrated Biodiversity

The composite biodiversity index (CBI) serves as an indicator of the overall status of biodiversity. As illustrated in Figure 10, the average CBI values for Yunnan and Sichuan were relatively high, exceeding the average value for the southwest region. This trend is attributable to the predominant distribution of forest land and grassland in these two provinces. Conversely, the average CBI values in areas with lower forest and grassland coverages, such as Guizhou and Tibet, are comparatively low. Under the SSP5-RCP8.5 scenario, the CBI values across the five provinces exhibited a decline. Except for the SSP1-RCP2.6 scenario, the CBI in the Tibet Autonomous Region (TAR) experienced varying degrees of decrease, with the most significant reduction of 6.3105% occurring under the SSP2-RCP4.5 scenario. In contrast, the CBI in Yunnan predominantly increased in the multiscenario simulations of future land use, with the largest rise of 0.6841% noted under the SSP3-RCP7.0 scenario.

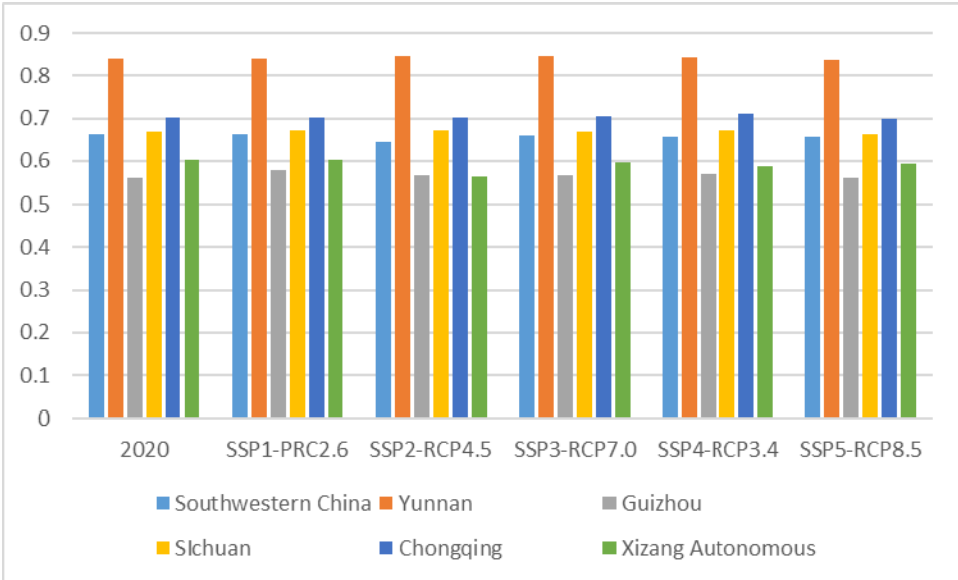

Figure 10. Integrated biodiversity index for Southwestern China and its provinces in 2050 under various Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs).

To more clearly illustrate the spatial changes in biodiversity across southwest China, this study calculated the variations in CBI under different SSP–RCP scenarios relative to the baseline period and represented them in a hierarchical manner (Figure 10). Areas with changes of ±0.1 were defined as essentially unchanged. Other classifications included severe decline (<−0.5), moderate decline (−0.5 to −0.3), mild decline (−0.3 to −0.1), mild increase (0.1 to 0.3), moderate increase (0.3 to 0.5), and large increase (>0.5).

The results (Figure 11) indicate that the majority of areas (89.84–94.29%) remained essentially unchanged across all scenarios. Among the regions exhibiting change, severe decreases in the composite biodiversity index (CBI) are predominant, ranging from 1.88% to 2.43%, with the total area of declining regions constituting 3.44–7.29%. In contrast, the area of regions showing an increase in CBI accounted for 2.27–4.24%. With the exception of the SSP1-RCP2.6 scenario, the area of decline exceeded the area of increase across all scenarios.

The change of vast grassland and woodland areas into cultivated land and urban areas was a major factor in the declines in CBI in the Southwest. In the SSP2-RCP4.5 scenario, 93,824 km^2 of grassland were converted to cultivated land, demonstrating this tendency in especially. The conversion of cropland and grassland into woodland is the main cause of the observed increase in CBI in the northeastern portion of the region, with grassland conversion accounting for a considerable portion of this increase. The conversion of grassland to woodland is another factor contributing to the minor increase in CBI in the northwest. However, the primary cause of the CBI reduction in the middle southwest is the severe urbanization of grassland encroachment.

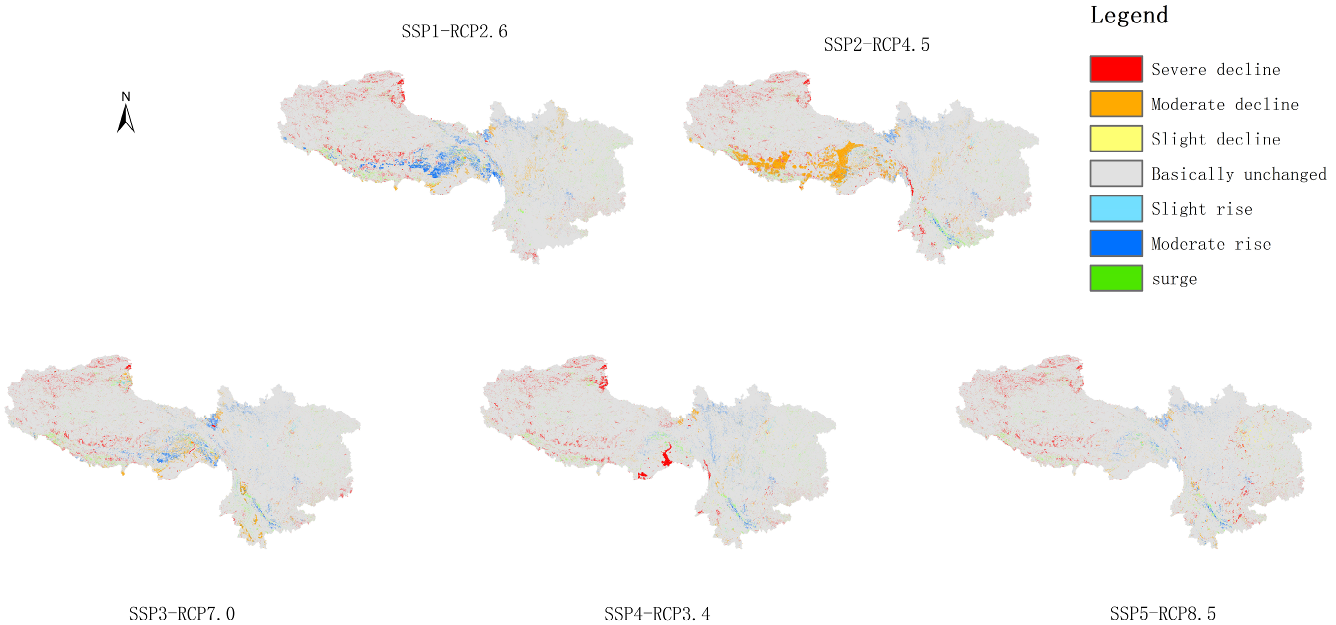

Figure 11. Spatial variation in the comprehensive biodiversity index in southwest China in 2050 under different SSP–RCP scenarios.

4. Discussion

4.1. Future Land Use Change under Different SSP–RCP Scenarios

The major cause of the worldwide decline in biodiversity is the widespread loss and fragmentation of natural ecosystems [53]. Using datasets for Chinese land-use types under different SSP–RCP scenarios, we investigated the future features of land-use pattern changes in southwest China. According to the findings, through 2050, urban areas (+38.3% to +187.08%) and forested regions (+0.21% to +4.2%) will show increasing trends across all scenarios, whereas grassland areas (−1.1% to −9.87%) will show falling trends. These tendencies are mostly associated with the various SSP–RCP scenarios' parameters and presumptions.

Among the several SSP–RCP scenarios, SSP1 represents a sustainable development model that emphasizes environmentally beneficial behaviors. Under this scenario, global forest cover expands dramatically, improving ecological quality. Furthermore, middle- and high-income countries are shifting to plant-based or vegetarian diets for health reasons, resulting in lower meat consumption and a consequent reduction in grassland area. The SSP1-RCP2.6 scenario, in example, shows the greatest increase in forest area in southwest China, owing largely to the adoption of reforestation initiatives, whereas farmland expansion is very limited.

In the SSP2 scenario, natural land-use changes result in a moderate expansion of both cropland and urban areas, both of which exhibit increasing trends. The SSP2-RCP4.5 scenario amplifies this effect, driven by escalating demands for food and subsistence. This scenario leads to significant increases in cropland (+24.2%) and urban areas (+70.02%), culminating in the substantial erosion of grassland, which aligns with the development objectives of the scenario.

The SSP3-RCP7.0 scenario embodies a regional competition model characterized by intensified inter-country rivalry that prioritizes food and energy security. This shift results in the expansion of agricultural land, leading to increases in both cropland and grassland, a reduction in barren land, and a significant decline in forest cover due to heightened deforestation rates. However, in China, forest area is projected to increase by 0.57%, likely reflecting the impact of policies such as afforestation, with forest cover demonstrating a notable growth trend.

In the SSP4 scenario, despite a significant development gap among areas, there is a worldwide consensus on climate policy at the same time that low-carbon energy technologies are advancing quickly. Less developed regions still use conventional fuels like wood and animal manure. Policy interventions, such as the strategic placement of the national ecological security barrier, limit the rate of ecosystem extension and urbanization in southwest China (+53.45%) under the SSP4-RCP4.5 scenario. This region deviates from the overall trend of land-use change by experiencing an increase in forest area (+0.35%) and a smaller decline in grassland conversion (−2.06%).

Under the SSP5 scenario, the global economy experiences rapid growth, accompanied by a faster rate of urban expansion compared to other scenarios, with the highest rate of urban expansion observed in southwest China (+187.08%). By 2050, the global population is projected to reach 10 billion, driving a substantial increase in human demand for food and living materials which, in turn, results in significant growth in cropland area [53]. However, in southwest China, cropland (−4.94%) and grassland (−2.21%) areas decline, while forest and barren land expand by 0.39% and 7.62%, respectively—indicating a divergence from global land-use change patterns under this scenario.

Additionally, under various SSP–RCP scenarios, the landscape pattern indices in southwest China declined to varying degrees, indicating a reduction in landscape fragmentation. This suggests that patch irregularity would decrease and landscape shapes would become simpler. Under the SSP3 scenario, intensified regional competition diminishes global attention toward environmental concerns, leading to severe ecological degradation in certain areas and further simplification of landscape patterns. Consequently, the number of patches (NP), patch density (PD), and landscape shape index (LSI) reached their lowest values under the relatively high social vulnerability (SSP3) and high radiative forcing (RCP7.0) simulations.

4.2. Biodiversity Response to Land-Use Change

Land-use types and changes are inextricably linked to biodiversity [54]. In Yunnan, where forest and grassland predominantly characterize land use within the southwest region, there exists a high level of species richness and habitat quality. In contrast, areas exhibiting significantly low biodiversity are primarily found in barren regions, such as western Tibet, which demonstrate low species richness and poor habitat quality. Similar patterns are observed in the primary cropland areas along the perimeter, where biodiversity and habitat quality are notably diminished.

This study reveals that land-use changes across all scenarios, with the exception of SSP1-RCP2.6, contributed to varying degrees of biodiversity loss in southwest China (Figure 12).

The SSP1-RCP2.6 scenario, characterized by sustainable development, exerts a positive influence on biodiversity conservation due to policies that promote the return of farmland to forests and an enhanced focus on environmental protection. These measures resulted in an increase in ecological land use (+4.43%) and a reduction in agricultural land use (−5.48%). Consequently, the comprehensive biodiversity index in southwest China increased by 0.1708%.

A continuation of past development trends, the SSP2-RCP4.5 scenario is defined by moderate rates of urbanization and population increase. In comparison to the SSP1-RCP2.6 scenario, agricultural development (+24.2%) is noticeably higher, while ecologically sustainable land usage (−6.31%) is noticeably lower. As a result, southwest China's biodiversity is on the decline (−2.86%). In this scenario, the amount of land experiencing a moderate reduction was the largest, mostly concentrated in the Tibet region, with the exception of areas where biodiversity remained reasonably steady (Figure 9).

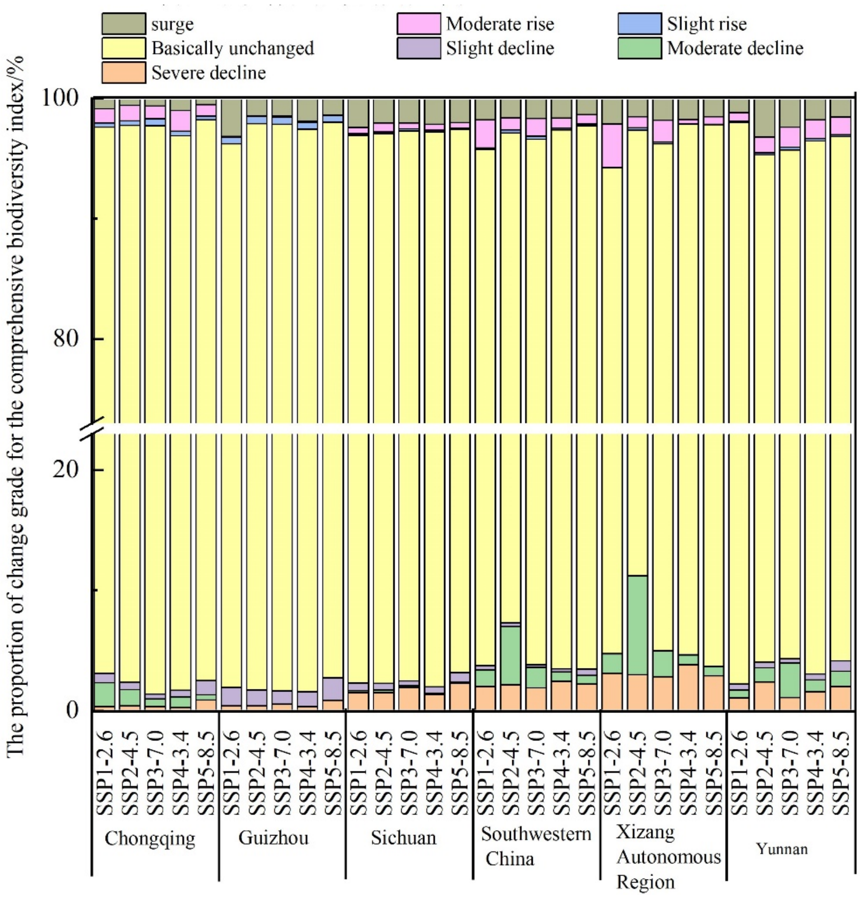

Figure 12. Percentage of areas with different levels of changes in the comprehensive biodiversity index in southwest China and each province in 2050 under different SSP–RCP scenarios.

Under the SSP3-RCP7.0 scenario, increased international rivalry causes global CO_2 emissions to nearly double from their current levels. The greenhouse effect causes a 0.3071% drop in biodiversity, a 0.57% decrease in grassland area, and an expansion of 38.3% and 3.8%, respectively, in urban and barren regions in southwest China. Ecosystem health is significantly impacted by these changes in land use.

Large tracts of forest (18,294 km^2) and grassland (4975 km^2) are turned into agriculture in the SSP4-RCP3.4 scenario in order to meet the biomass needed for China's climate mitigation efforts. The change in land use causes the composite biodiversity index to decrease by 2.3305%.

Similar to the SSP5-RCP8.5 scenario, increased urbanization and fast economic growth lead to a major loss of grassland (23,063 km^2) and a disregard for ecological sustainability, which significantly degrades biodiversity (−1.0675%).

Furthermore, Tibet is expected to see the largest rise in desert area in the future in terms of spatial patterns. The primary targets of this expansion are grasslands with high species richness and excellent habitat quality, which lowers the composite biodiversity index. The primary causes of this transformation are the unjustified uses of grasslands, such as overgrazing and unauthorized encroachment. The number and variety of animals and plants will decline as grasslands deteriorate, and rodent infestations will rise along with the likelihood of sandstorms and other natural disasters. These effects will have a significant negative impact on local production activities and biodiversity security. In contrast, Guizhou shows the most favorable trend among southwest regions, with species richness and habitat quality improving, and the composite biodiversity index increasing by 0.9416% to 3.002%.

Furthermore, the landscape pattern index shows that the southwest region is being impacted by both high-intensity human activities and considerable land-use changes. These variables contribute to the increasingly complicated processes of ecosystem degradation, such as changes in habitat quality and spatial patterns. These findings highlight the crucial importance of comprehensive land-use planning in southwest China, notably in balancing economic development and environmental conservation. Effective land management and conservation strategies will not only assist in maintaining the region's biodiversity but will also create the groundwork for future sustainable development.

4.3. Countermeasures and Recommendations

The study's findings demonstrate that species richness, habitat quality, and total biodiversity in southwest China are diminishing under most development scenarios, notably in the Tibet region. In contrast, western Sichuan and south-central Yunnan see either a smaller reduction or a tiny increase in biodiversity. As a result, it is critical for southwest China to take effective steps to maintain and increase biodiversity in the future.

Firstly, macro-level land-use management in southwest China must be improved in order to eliminate landscape fragmentation and diversify landscape structures via optimum land-use planning [55]. In Tibet, where the biodiversity index is extremely low, efforts should be directed at reducing ecological land fragmentation. This can be accomplished by taking steps such as converting cropland back to grassland to counteract the negative effects of land-use changes on biodiversity. These initiatives will help in maintaining the local biodiversity and promote the long-term growth of both ecology and the economy [56].

Secondly, other effective conservation measures (OECMs) should be undertaken in areas with good natural ecological conditions and existing conservation frameworks, such as western Sichuan and south-central Yunnan [57]. OECMs have the potential to significantly enhance protected land and sea areas, hence complementing the objectives of the post-2020 global biodiversity framework [58]. Expanding effective conservation areas within well-defined geographic regions, outside current nature reserves, aids in bridging conservation gaps and improving long-term biodiversity results [59].

Furthermore, local traditional biodiversity knowledge should be actively researched and implemented at the community level to counteract the effects of climate change and human activities on biodiversity [60]. Southwest China, which has the biggest population of ethnic minorities in China, is also a biodiversity hotspot and cultural hub [61]. Local communities have gained considerable traditional knowledge via their interactions with nature over time, which has greatly aided in the conservation of the local ecology and biodiversity [62].

5. Conclusions

The land-use pattern changes predicted for 2050 under the SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-3.4, and SSP5-8.5 scenarios were examined in this study, which was centered on the southwest. By creating a composite biodiversity index, it assessed the effects of these land-use changes on habitat quality and species richness and examined their combined effects on biodiversity.

This research, in contrast to other studies, offers a thorough evaluation of the effects of land-use changes on biodiversity that go beyond simple urbanization or agricultural development. Furthermore, rather than using a conventional land-use planning model, this study is based on land-use simulations under SSP–RCP scenarios. Because it completely takes into account how different socioeconomic hypotheses and policies aimed at mitigating climate change would affect future changes in land use, the research findings have more immediate applications.

To summarize, the application of Fragstats and InVEST models in combination with high-resolution future land-use data under different SSP–RCP scenarios allows for the precise and thorough assessment of biodiversity indicators, including species richness, habitat quality, and landscape patterns. This method can support the peaceful coexistence of humans and nature in southwest China, thoroughly investigate the combined effects of land-use change on biodiversity, aid in the development of scientific land management policies and conservation measures, and offer insightful information for the creation of successful biodiversity conservation policies and strategies. The following are the primary conclusions:

(1) Land-use change types and patterns of landscape change in the southwest region by 2050 will exhibit some similarities among the various SSP–RCP scenarios. It is anticipated that the region's primary land-use types will continue to be forests and grasslands. Multiscenario simulations show that while urban and desolate areas will mostly rise, the acreage of grassland will decline to variable degrees. In contrast to urban areas, forests and arid regions will see a decline in the degrees of landscape fragmentation and shape complexity. Multiscenario modeling shows that grassland area will decrease to varying degrees, while urban and wasteland areas will mainly increase, which will lead to an increase in the number of sandstorms, an enhancement of the heat island effect, and an impact on the development of animal husbandry.

Afforestation and the construction of a robust ecological security barrier in southwest China are two initiatives that have influenced the region's land-use types and changes in landscape patterns, which deviate from global trends and more closely follow domestic ones. SSP1 and SSP2 scenarios are examples of worldwide trends. In order to guarantee sustainable land use and conservation, it is essential to take a number of elements into account while creating land-use planning and management strategies in southwest China, including legislation, population increase, and economic development.

(2) In southwest China, there is a comparable regional pattern change and a synergistic relationship between species richness and habitat quality. The total quality of the environment that is favorable for species habitat and survival is predicted to decline in comparison to current conditions in 2050, even if species richness and habitat quality are predicted to stay high across all SSP–RCP scenarios.

The regions with the highest concentrations of forests include Yunnan, eastern Guizhou, and western Sichuan. These areas are also home to high-value and enhancement zones. In contrast, because of the ongoing encroachment on grasslands, low-value and decline zones are more common in the western plateau region. As a result, it is critical to improve monitoring in regions like the Tibet Autonomous Region that are seeing a decline in species richness and habitat quality. Creating protected areas, regulating livestock husbandry on a reasonable scale, and reverting farmland to grassland are some ways to preserve the biodiversity of the area.

(3) Under different SSP–RCP scenarios, integrated biodiversity in the southwest is predicted to stay mostly constant by 2050, with overall environmental quality doing well. On the other hand, the area with folding is smaller than the area experiencing a reduction in integrated biodiversity under scenarios other than SSP1-RCP2.6, with the top portion of the regions seeing a reduction in the integrated biodiversity.

There will be several obstacles along the way for the southwest region's integrated biodiversity conservation in the future. To effectively protect biodiversity in the region, it is imperative to employ other effective conservation measures (OECMs), improve macro-level land-use management, and incorporate traditional knowledge.

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