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Landscape Dynamics in a Poverty-Stricken Mountainous City: Land-Use Change, Urban Growth Patterns, and Forest Fragmentation

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Abstract: For poverty-stricken mountainous cities in China, both poverty alleviation and ecological restoration projects are sources of land-use change in urban development. However, the patterns in changes are understudied in light of sustainable forest management. The study aims to explore the characteristics of land-use change in a poverty-stricken mountainous city with a focus on forests. This research proposed a three-step approach to explore the multi-aspect dynamics of land change, including the differences among land-use categories, spatial characteristics of urban expansion, and forest fragmentation. This study investigated Enshi City, China, based on land-use data from 2000, 2010, and 2020. Throughout the two intervals, the gain of water bodies and the loss of grassland were active. Artificial surfaces increased most intensively from 2010 to 2020, with transitions from grassland and cultivated land. Edge-expansion was the dominant type of artificial surface growth. Furthermore, forests had the largest size of gain across the two intervals, and there was a substantial reduction in forest fragmentation in the western part of the city. The findings confirm that recent planning measures are effective in restoring the natural environment. The identified key areas can support sustainable forest management in urban growth.

Keywords: forest fragmentation; land-use change; landscape pattern; mountainous city; urban growth

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1. Introduction

With a unique topography and climate, mountains provide a number of crucial benefits and services, such as fresh water supply and biodiversity maintenance [1–6]. However, mountain ecosystems are fragile. For example, a mountain's steep slope might facilitate erosion, thus leading to poor soil quality [7]. They are sensitive to anthropogenetic impacts, natural disasters, and climate change [2,3,7]. In recent decades, many mountainous regions have undergone changes in their socioecological systems as a result of human activities [6,8].

Mountains are home to 12% of the world's population, and this proportion is even higher in developing countries [4,9]. In China, many inhabitants of mountainous areas live in poverty, partly because of transportation difficulties and limited cultivated land [10]. Subsequently, poverty alleviation through urban development is an important task for local authorities [11]. While human settlement expansion and infrastructure construction can make people's lives more convenient, some activities might lead to the deterioration of the local environment [12]. For instance, some of the forest and grassland in sloping areas has been converted to farmland, leading to soil erosion, sandstorms, and other disasters [13,14].

In order to alleviate the anthropogenetic damages to natural environments, ecological restoration has been playing a more significant role in mountainous areas in recent decades. Typical ecological restoration projects include forestation, water source protection, restoration of rocky desertification, and treatment of mine areas [15]. Since 1999, China has widely implemented a "Grain for Green" policy, which aims to convert farmland back to forest and grassland [13]. At the same time, built-up areas are being expanded in mountainous regions because of urban and rural development. Both urban growth and ecological restoration projects would lead to land-use changes.

In such contexts, a better understanding of land-use dynamics would contribute to sustainable regional development and harmonized human–nature relationships [16]. It would benefit both current land-use management and future planning in mountainous areas. To understand the detailed land-use and land cover changes for decision making, many researchers have monitored and investigated the changes spatiotemporally [1–3,9,17–19]. For instance, one study in Peruvian Jalca has identified threatened areas based on monitoring landscape change [1]. Researchers also explored land-use transitions in peri-urban areas and discussed the associations with human activities [17]. Spatiotemporal analysis can help investigate where and when land-use transitions occur, providing additional information about how much has changed and how fast [20]. Since land-use change is a continuous process, spatiotemporal analysis at several time points can help build a conceptual model to quantify landscape patterns and understand trends. These insights provide a detailed perspective to investigate human–nature relationships and the interactions between biophysical structures and socioeconomic changes [21]. When focusing on a single land-use category—for example, artificial surfaces—the analysis is able to identify the trends and direction of urban expansion [22]. When focusing on the differences between rates of change in various land-use categories, it helps researchers to understand how overall landscape pattern change and which ecosystem might be the leading source of change [20]. In mountainous areas, a growing number of studies have explored urban development spatiotemporally, and the increase in built-up areas has been confirmed globally [3,6,8,9,17,23]. Because of topographical restrictions, the urban growth and land-use change of cities in mountainous areas might show different characteristics compared to cities in plain areas [3]. A recent study modeling and predicting land-use change in a mountainous region of Oman found that, in spite of the complex terrain, the built-up area will continue to grow and occupy more local arable land in the future [9]. A study in the mountainous area of Brazil found significant transitions between natural vegetation and agriculture. Several studies have focused on the impact of land-use change on ecosystems in mountainous regions [2,18,19], and one study in Zhangjiakou City found that the changes in forestland, arable land, and grassland greatly impacted the local ecosystem [18].

Despite the increasing number of studies that have explored land-use change spatiotemporally, studies in mountainous cities remain insufficient [3], particularly in poverty-stricken mountainous areas [11]. For poverty-stricken mountainous cities in China, both poverty alleviation and ecological restoration projects are key tasks. Many cities are experiencing rapid urban growth in recent years. Different land-use changes can be associated with landscape patterns and ecological processes [24]. Monitoring land-use and landscape pattern change helps design efficient forest management and nature conservation strategies [1,8,25], which are critical for poverty-stricken mountainous areas [11,18]. In China, many mountainous cities are in the western or central regions, which are economically disadvantaged. The reasons include not only location, transport, and regional economic geography, but also the mountainous environment that may hinder industrial development [26,27]. Therefore, practices related to poverty alleviation in the city often focus on agriculture, urban development, and harvesting value from the forests. These practices can impact the sustainable management of forests [28]. However, an insufficient number of studies have spatial-explicitly evaluated the change of ecological conditions from the perspective of landscape pattern. Existing studies of monitoring land-use change in mountainous areas often neglected the socio-historical background and therefore did not integrate the related key points into the analysis. Studies on land-use change should investigate the change intensity of different land cover categories for exploring potential sources and driving forces for forest change in poverty alleviation. Moreover, close attention should be paid to areas that are undergoing the rapid process of urban expansion, which is often considered a challenge to sustainable forest management.

For supporting sustainable forest management, this study aims to explore the land use and landscape dynamics in Enshi City, applying a framework that considers different aspects of dynamics in the poverty-stricken mountainous area. Enshi City is located in one such area in China. Based on the land-use data from Enshi City in 2000, 2010, and 2020, this study integrates the methods of intensity analysis, landscape metrics, and mapping. The overarching objective of this study is to explore the characteristics of land-use change in a poverty-stricken mountainous city. The specific research questions are: (1) To what extent have different types of land use changed in Enshi city from 2000 to 2020? (2) What are the characteristics of the expansion of urban areas in the study area? (3) What are the spatiotemporal changes in the fragmentation of forests in the study area from 2000 to 2020?

2. Methodology

2.1. Study Area

Enshi City is the seat of Enshi Tujia and Miao Autonomous Prefecture, located in the southwest mountainous region of Hubei Province, spanning latitudes 29°50′33″–30°39′30″ N and longitudes 109°4′48″–109°58′42″ E. The total area is 3972 km^2. Enshi City has a subtropical climate. The mean annual temperature is 16 °C and the mean annual precipitation is between 1400 and 1600 mm [29]. As part of the Wuling Mountain area, Enshi City has a varying elevation (Figure 1). The city center is in the middle of the region, where the terrain is relatively flat. The elevation is much higher in the northwestern and southeastern parts of the city. The Wuling Mountain area is one of the key regions in China for implementing the “Grain for Green” policy [30]. With a large area covered by forest, Enshi City is rich in natural resources and biodiversity. Since many areas are ecologically fragile zones, the conservation of the natural environment is one of the city’s most important tasks. The northeastern part of the city belongs to a national nature reserve. Enshi City is also considered a suitable place for recreation and tourism because of its diverse landscape, fresh air, and cultural heritage.

The Wuling Mountain area is a typical poverty-stricken area in China. This is also the case for Enshi City [31]. It was not until April 2020 that Enshi City was excluded from the National Poverty-Stricken County list [32]. As a transport hub, Enshi City is the political, economic, and cultural center of the prefecture, so its development is crucial to the region’s economic growth and for alleviating poverty. The population of Enshi City has risen over the last two decades, increasing from 0.764 million in 2000 to 0.795 in 2010, and to 0.813 million in 2019 [33]. Ethnic minorities consist of 41.12% of the total population [29]. A recent study analyzing the urban expansion of 275 Chinese cities found that Enshi Prefecture is among the top ten cities with regard to the development level of outlying expansion patches [34]. Therefore, a specific investigation of Enshi City can improve our understanding of land use and landscape change in mountainous regions, where rapid urban growth is taking place against the background of nature conservation and poverty alleviation.

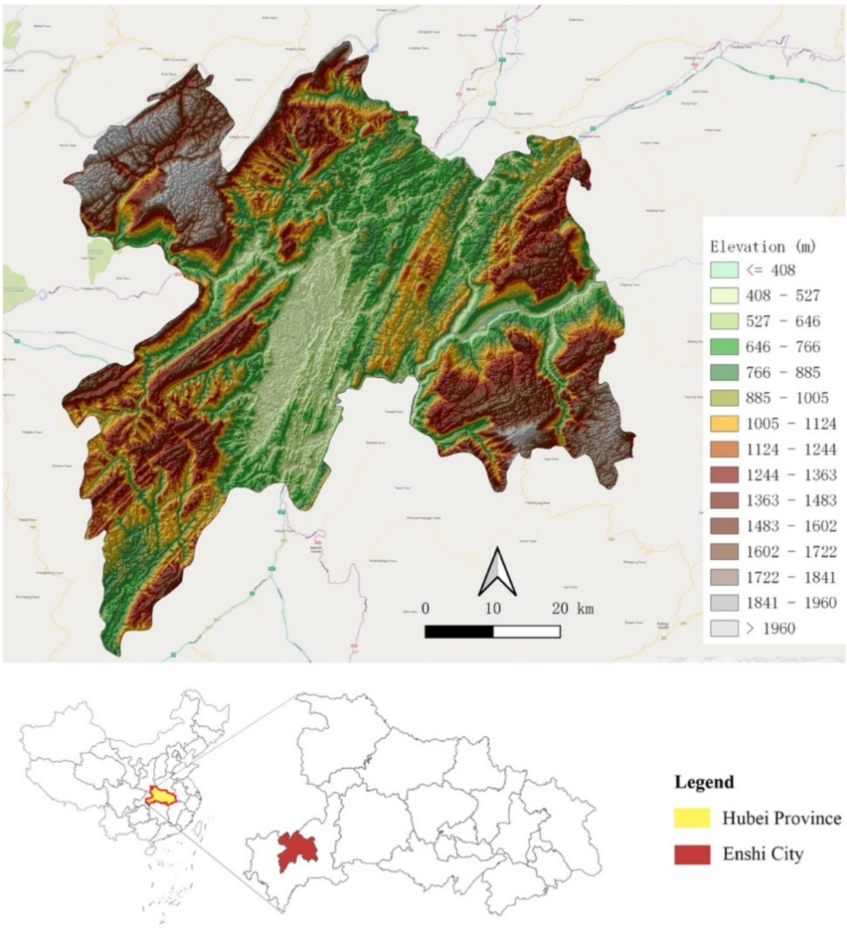

Figure 1. Location and elevation of Enshi City. Elevation data was obtained from the ASTER global digital elevation model [35].

2.2. Data Sources and Analysis

2.2.1. Data Sources and Analytical Framework

In order to explore the land-use and landscape changes in Enshi City in recent decades, this study used the GlobeLand30 dataset [36]. The dataset includes land use data from 2000, 2010, and 2020, with a resolution of 30 m. Ten types of land use are classified: cultivated land, forest, grassland, shrubland, wetland, water bodies, tundra, artificial surfaces, bare land, and permanent snow and ice [37]. This dataset has been proven by previous studies to have sufficient accuracy in analyzing land-use change [38,39].

In the early stage of the study, different dataset options are considered and tested based on a review of the data. For the research objectives, the choice of input data should meet the following requirements simultaneously: (1) The time span of the spatial data must be over 20 years, during which Enshi City has undergone rapid urbanization and development. (2) The spatial data must be fine-scaled so that the land-use change can be investigated at the city scale. (3) The dataset is validated and standardized in the study region. This is for the purpose of generalizing the proposed methods in the future to a larger scale or other mountainous study sites with similar situations. Therefore, we did not consider classifying our own land-use data based on historical satellite images. For these criteria, we tested but decided not to use some other commonly used land cover datasets. For example, the datasets FROM-GLC10 and WorldCover-10 m may have a finer resolution, but they do not offer historical data over twenty years [40–43]. The LC-CCI data have long time spans, but their spatial resolution is relatively scarce. After comparison, GlobeLand30 is by far the most suitable dataset for our study purpose, and it meets all three above criteria and has relatively high accuracy.

For exploring the complex nature of mountainous urban areas, this research proposed a three-step approach to explore the dynamics of land-use and landscape change (Figure 2). Each step addressed one research question, linking different facets of the changes. The first was to investigate the differences in changes among land-use categories by using the method of intensity analysis. The second was to explore the types and locations of urban expansion with the Landscape Expansion Index (LEI). The third was to explore forest fragmentation by calculating the spatiotemporal change of effective mesh size with cross-boundary connections (CBC) methods. All of the analyses were conducted using software (ArcGIS 10.5, QGIS 3.16, and R 4.0) through packages [44–48].

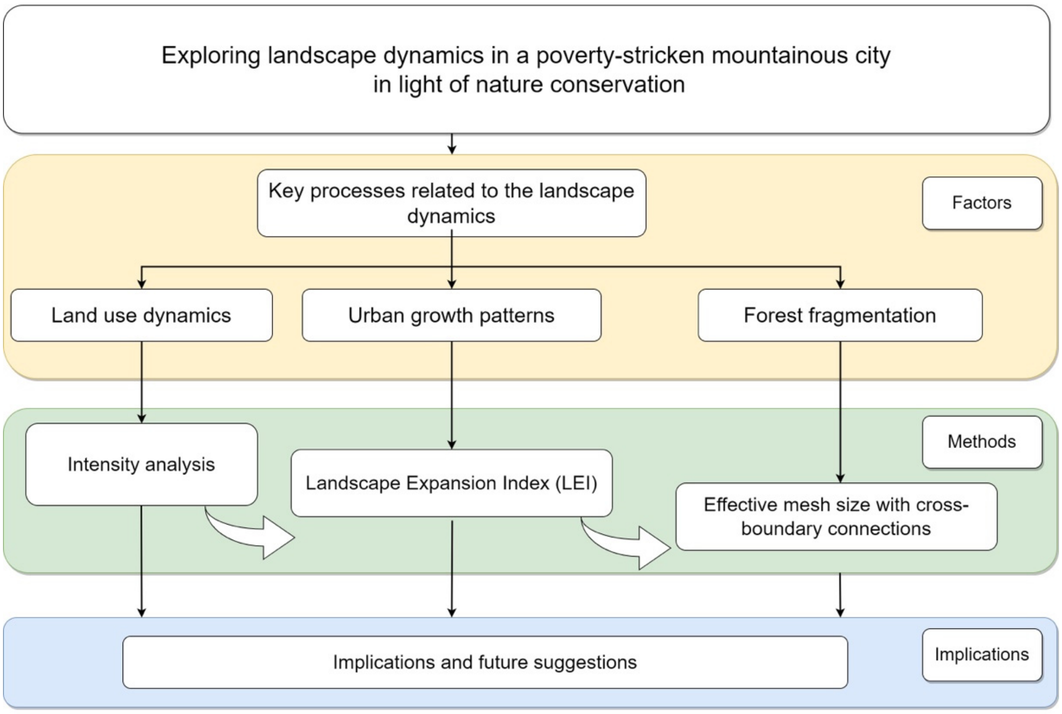

Figure 2. Analytic framework of this study.

2.2.2. Intensity Analysis

Intensity analysis provides a mathematic framework to examine land-use change for three or more time points (i.e., two time intervals or more). It is a unified approach to draw insights into different aspects of land-use change, and it has been widely used by scholars around the world (for example: [24,39,49–51]).

Intensity analysis concerns three levels: interval, category, and transition [16,52]. The interval level focuses on the speed of change across intervals. It compares the speed of change of each time interval with the speed of change of the overall interval. If any interval's speed of change is larger than the overall interval's, the change of this interval would be considered fast, and vice versa [16,52]. At the categorical level, this method compares the annual intensity of loss and gain of each category with the uniform intensity of annual change. The uniform intensity supposes that each category was to gain or lose with the same intensity. If one category's intensity of change (gain or loss) is larger than the uniform intensity, then the change is active. If one category's intensity of change is smaller than the uniform intensity, then the change of this category is dormant [16,52]. The transition level helps identify whether a specific category's loss or gain is targeting or avoiding other categories. It assumes that the selected category gains or loses uniformly across the spatial extent. If the intensity of transition (gain or loss) of the selected category to another category is larger than the uniform intensity, then the transition is targeted. If the transition is smaller than the uniform intensity, then the gain or loss of the selected category avoids the another category [16,52]. Furthermore, at the categorical and transition level, if a given category's change is always on one side of the uniform intensity (either larger or smaller than the uniform intensity) for all time intervals, the change or transition of this category would be considered stationary [16]. One previous study has successfully applied intensity analysis to compare the land-use transformation of two mountainous areas in Athens, and a variety of systematic stationary transitions were detected [17].

2.2.3. Urban Growth Pattern Analysis

The second step was to investigate the characteristics of urban growth patterns in Enshi City. We adopted a widely used index called the Landscape Expansion Index (LEI) invented by Liu et al. [53]. This index is calculated based on buffer analysis of the geographic information system (GIS) using the following formula:

$$\mathrm{LEI} = 100 \times \frac{A_o}{A_o + A_v} \tag{1}$$

where A_o refers to the intersection area between the buffer zone of the newly grown patch and the old urban patch, and A_v is the intersection between the buffer zone of the newly grown patch and the vacant land (non-urban patch). It differentiates urban growth patterns according to the results of the LEI, which ranges from 0 to 100. Three urban growth types are defined, namely edge-expansion ($0 < \mathrm{LEI} \leq 50$), infilling ($50 < \mathrm{LEI} \leq 100$), and outlying ($\mathrm{LEI} = 0$). Infilling is when the buffer zone of a newly grown patch primarily belongs to an old patch. Edge-expansion is when a newly grown patch's buffer zone is a combination of vacant land and an old patch. Outlying is when the buffer zone of a newly grown patch belongs only to vacant land [53]. The LEI is confirmed by studies in different contexts to characterize urban growth patterns [3,34,54–56]. For example, a study in the large mountainous city, Chongqing, found that the city showed different dominant modes of urban growth during different periods of development [3].

2.2.4. Fragmentation Analysis

The third step was to explore the fragmentation of the forest landscape by applying landscape metrics. Landscape metrics are widely used in quantifying and assessing landscape patterns [1,57–62]. While intensity analysis provides details of the interval, size, and intensity of the land-use change in the study area, calculating the landscape metrics for different time points helps provide further information about the changes in landscape patterns. Regarding fragmentation, several metrics are frequently used, such as patch density, number of patches, landscape division index, and effective mesh size [63–67]. This study chose an effective mesh size for its high reliability in measuring fragmentation [67,68]. Effective mesh size measures the landscape fragmentation based on the probability that two randomly chosen animals in different areas of the same region can find each other. Mathematically, it calculates the size of patches when the investigated region is divided into S areas (each of the same size) with the same degree of landscape division as obtained for the observed cumulative area distribution [67,69]. It can be calculated using the following formula:

$$\mathrm{m} = A_t \sum_{i=1}^{n} \left(\frac{A_i}{A_t}\right)^2 = \frac{1}{A_t} \sum_{i=1}^{n} A_i^2 \tag{2}$$

where A_t is the total area, n is the number of patches in the study area, and A_i is the size of each patch ($i = 1, \ldots, n$). While effective mesh size is widely used in quantifying landscape fragmentation, it suffers from "boundary problems" [70]. Because boundaries are also considered to be fragmenting the landscape, the results can be biased. To address this problem, the study proposed a new method called cross-boundary connections (CBC) [70].

This method improves the accuracy of comparing the fragmentation of different areas within a region. Mathematically, it is calculated using the following formula:

$$m_{eff}^{CBC} = \frac{1}{A_t} \sum_{i=1}^{n} A_i \times A_i^{cmpl} \quad (3)$$

where A_t is the total area, n is the number of patches in the study area, A_i is the size of the n patches (i = 1, . . . , n), and A_i^{cmpl} is the size of the complete patch (including the area outside the boundaries) [70]. Previous studies have used the CBC method to calculate effective mesh size in different contexts for a more accurate measurement of fragmentation [64,71]. In order to help visualize the spatiotemporal dynamics of landscape fragmentation, we used an R package called *zonebuilder* [48]. This package can uniformly break the analytical unit (e.g., the city) into zones of different rings and segments so that we can better investigate the direction of change and compare the differences across time periods [48].

3. Results

3.1. Land-Use Change

3.1.1. Land Use of Enshi City in 2000, 2010, and 2020

Figure 3 presents the land use of Enshi City in 2000, 2010, and 2020. The land use consists of forest, grassland, cultivated land, water bodies, and artificial surfaces. The primary land-use categories are forest and cultivated land. From 2000 to 2010, grassland decreased noticeably, and water bodies became more visible. From 2010 to 2020, artificial surfaces increased notably. Figure 3d exhibits the detailed locations where land-use changes occurred. While 72.26% of the area did not experience any changes in land use across the two time intervals, 22.52% of the area changed once (either from 2000 to 2010 or from 2010 to 2020), and 5.23% of the area changed twice.

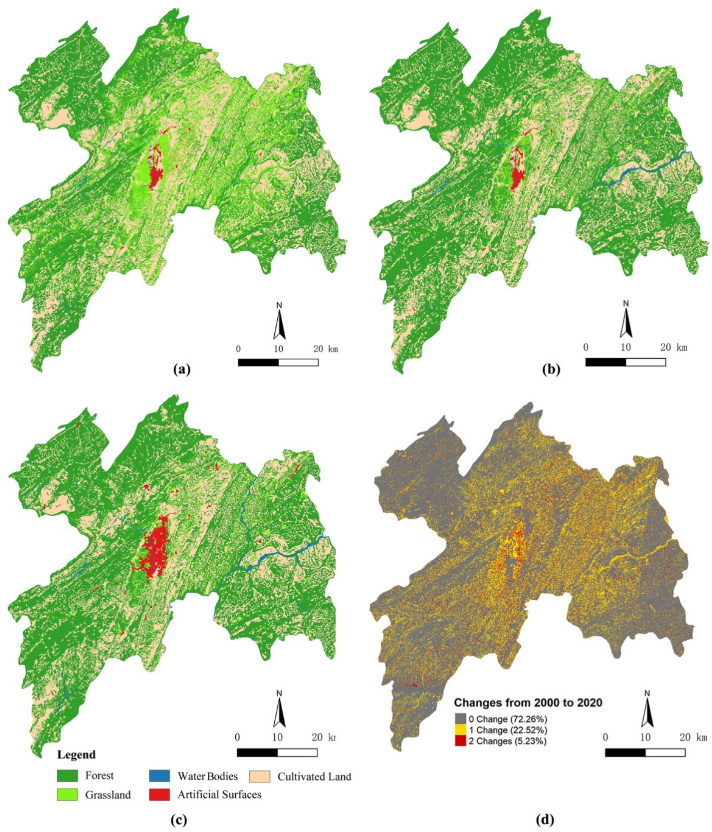

Figure 3. Land use in Enshi City. (**a**) Land use in Enshi City in 2000; (**b**) Land use in Enshi City in 2010; (**c**) Land use in Enshi City in 2020; (**d**) Accumulated changes from 2000 to 2020.

An overview of the changes in the five categories is presented in Figure 4. From 2000 to 2020, while artificial surfaces, forest, and water bodies experienced a net gain in land-use area, cultivated land and grassland experienced a net loss. Forest and grassland had relatively larger changes in size. Cultivated land experienced the smallest net change size; however, its gross change area is much larger than those of artificial surfaces and water bodies. This suggests that, despite the small change in the total area of cultivated land from 2000 to 2020, there has been intensive land-use exchange between cultivated land and other land categories. Tables 1–3 demonstrate the transition matrix of land-use types in Enshi City from 2000 to 2020.

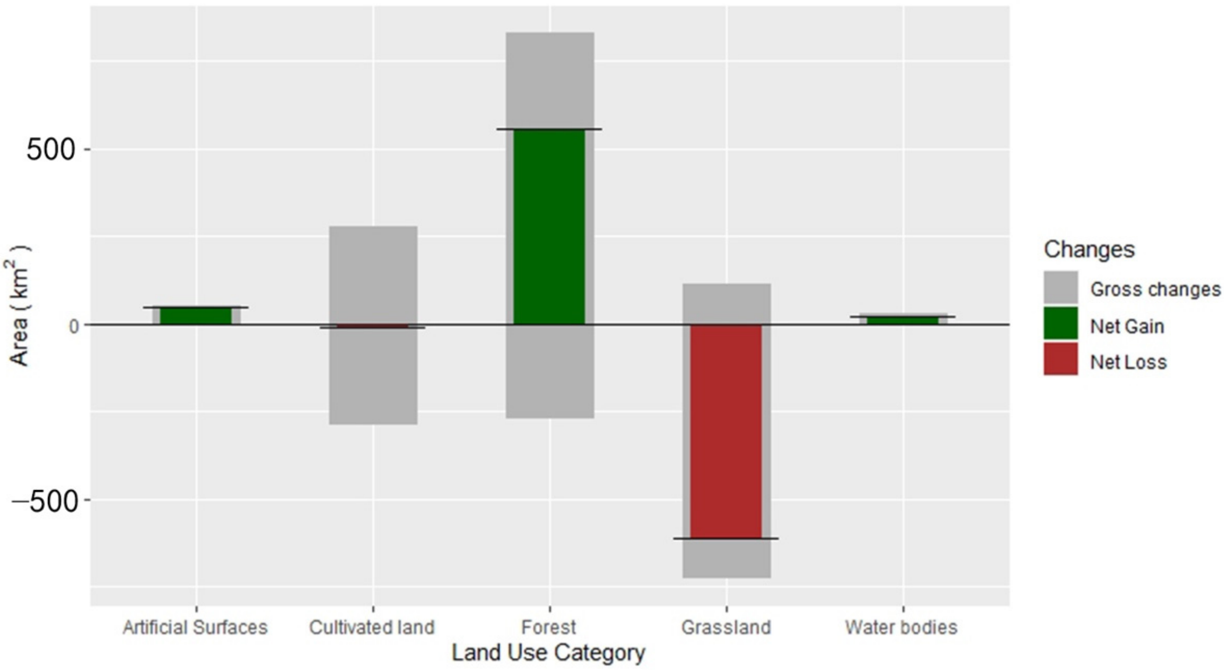

Figure 4. The area of land-use change in Enshi City from 2000 to 2020. The bar plot combines both gross changes and net changes. Bars extending to the upper side of zero refer to gross gain (shown in grey) and net gain (shown in green). Bars extending below zero refer to gross loss (grey) and net loss (red).

Table 1. Transition matrix of land-use types in Enshi City from 2000 to 2010 (km^2).

			2000–2010		
	Cultivated Land	**Forest**	**Grassland**	**Water Bodies**	**Artificial Surfaces**
Cultivated land	1167.0030	90.9099	24.1812	5.4252	0.5931
Forest	59.787	1756.0611	3.0996	2.6145	0.0216
Grassland	70.2594	549.6012	184.7556	8.4069	0.2412
Water bodies	3.0717	1.7901	0.4329	7.3557	0.0225
Artificial surfaces	0.7551	0.0891	0.2196	0.2061	18.9495

Table 2. Transition matrix of land-use types in Enshi City from 2010 to 2020 (km^2).

			2010–2020		
	Cultivated Land	**Forest**	**Grassland**	**Water Bodies**	**Artificial Surfaces**
Cultivated land	1132.5762	129.1041	12.3498	2.4021	24.444
Forest	111.1356	2191.0716	75.2436	9.0846	11.916
Grassland	31.1373	56.313	109.0953	1.5453	14.598
Water bodies	0.8046	1.0908	0.0162	21.8385	0.2583
Artificial surfaces	0.6093	0.1341	0.0738	0.1476	18.8631

Table 3. Transition matrix of land-use types in Enshi City from 2000 to 2020 (km^2).

	2000–2020				
	Cultivated Land	**Forest**	**Grassland**	**Water Bodies**	**Artificial Surfaces**
Cultivated land	1136.4705	107.6472	14.8239	6.4845	22.7358
Forest	74.0268	1691.9811	45.8109	7.8462	2.0853
Grassland	63.1512	577.2888	135.8649	11.3265	25.659
Water bodies	2.1555	0.8217	0.225	9.1089	0.369
Artificial surfaces	0.5112	0.1467	0.0639	0.2673	19.2303

3.1.2. Results of Intensity Analysis

This section presents the results of the intensity analysis, which includes three levels: interval, categorical, and transition. The interval level helps identify which time interval changes fast or slow compared with the overall annual rate of change. As shown in Figure 5, compared with the uniform rate (1.65%), the first time interval changed fast (2.08%), and the second interval changed slowly (1.22%). It also shows that a greater area underwent change in the first interval.

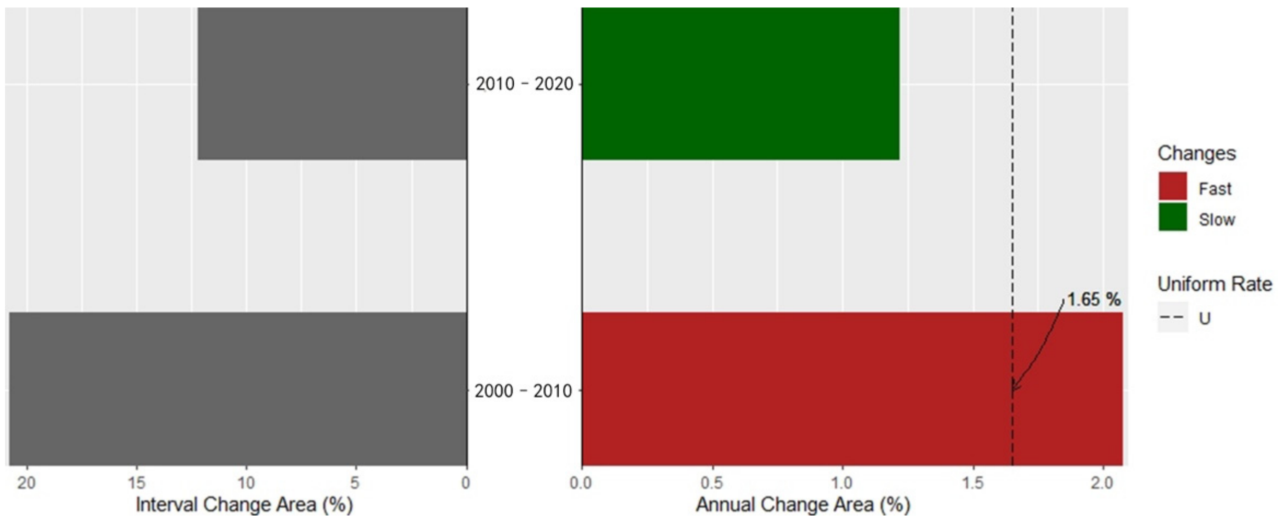

Figure 5. Time intensity analysis for two time intervals: 2000 to 2010 and 2010 to 2020. The left side represents gross area of overall change in each interval, and the right side represents the intensity of annual area of change within each interval. The dash line represents the uniform annual intensity of change from 2000 to 2020. If a category's bar extends beyond the uniform line, then the change of intensity is fast. If a category's bar ends before the uniform line, then the change of intensity is slow.

The category level further explores the detailed change of each land-use category and helps detect which categories are dormant or active during different time intervals. Figure 6a shows the detailed situation of area gain and intensity of each category over the last two decades. The dash lines represent the uniform annual intensity of change in the respective time interval. The interval from 2000 to 2010 (2.08%) had a larger annual rate of intensity gain than the interval from 2010 to 2020 (1.22%). From 2000 to 2010, the gain of artificial surfaces, cultivated land, and grassland was dormant, and the gain of forest and water bodies was active. Although forest had the largest size of gain, the gain of water bodies was more intensive. From 2010 to 2020, artificial surfaces experienced the largest gain intensity, followed by grassland and water bodies. The gain of cultivated land and forest was dormant.

Figure 6. Intensity of change at the categorical level. Each bar plot combines the area of change (bars that extend to the left of zero) and intensity of change (bars that extend to the right of zero). (**a**) Gain intensity analysis for two time intervals: 2000–2010 and 2010–2020. (**b**) Loss intensity analysis for two time intervals: 2000–2010 and 2010–2020. If a category's bar extends beyond the uniform line (the dash line), then the gain or loss of intensity is active. If a category's bar ends before the uniform line, then the gain or loss of intensity is dormant.

As regards the loss intensity and size (Figure 6b), grassland lost most intensively across the two time intervals. Water bodies lost actively in the first interval and became dormant in the second interval. Artificial surfaces and forest show stationarity across the two intervals as they stayed on the left side of the uniform rate line. The loss of cultivated land was dormant in the first interval and active in the second interval.

The transition level analyzes the gain of artificial surfaces and loss of grassland. According to the research objectives and site background, the study pays close attention to the risks and challenges to forests and the ecological environment under the pressure of urban expansion. As known from the category level, artificial surfaces gained intensively from 2010 to 2020. Figure 7a indicates that the gain of artificial surfaces from 2010 to 2020 mostly targeted grassland and cultivated land. Although cultivated land contributed the largest area, the gain from grassland was the most intensive, meaning that the gain from grassland had the largest rate of transition. The gain of artificial surfaces avoided forest and water bodies, because the transition rate is lower than the annual transition rate (0.13%).

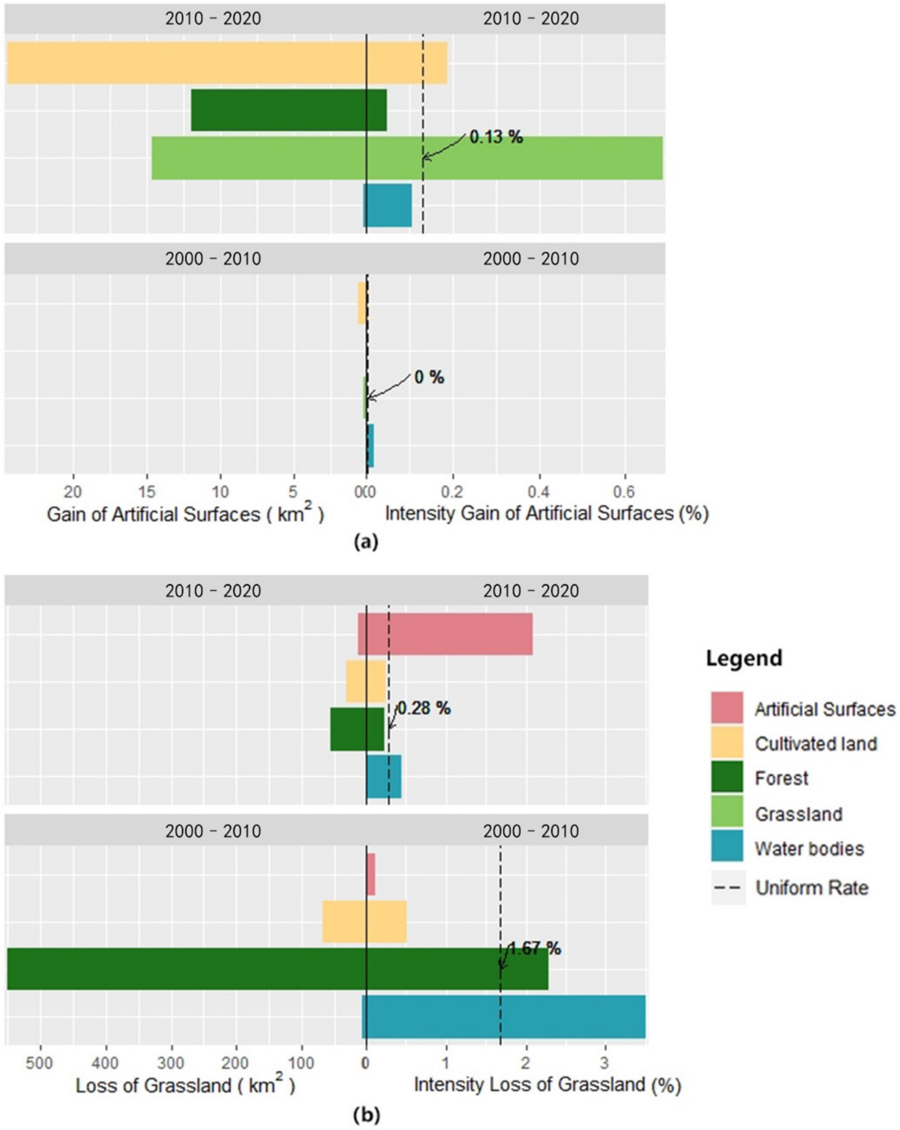

Figure 7. Intensity of change at the transition level. Each bar plot combines the area of change (bars that extend to the left of zero) and intensity of change (bars that extend to the right of zero). (**a**) Transition intensity analysis to artificial surfaces for two time intervals: 2000–2010 and 2010–2020. (**b**) Transition intensity analysis from grassland for two time intervals: 2000–2010 and 2010–2020. If a category's bar extends beyond the uniform line (the dash line), then the gain or loss of the selected category targets this category. If a category's bar ends before the uniform line, then the gain or loss of the selected category avoids this category.

The loss of grassland was analyzed because grassland is the only category that is active in loss in both time intervals. From 2000 to 2010, water bodies and forest targeted the loss of grassland, and artificial surfaces and cultivated land avoided it (Figure 7b). Although the size of the loss to forest is the largest, the loss to water bodies is most intensive because water bodies have the largest rate of transition. From 2010 to 2020, artificial surfaces and water bodies targeted the loss of grassland. The loss of grassland to forest remains the largest in terms of size, but it avoided forest as the transition intensity is less than the uniform intensity. The loss to artificial surfaces is the most intensive.

3.2. Urban Growth Pattern

The urban growth pattern of Enshi City from 2000 to 2020 is presented in Figure 8. The main location of growth is in the central part of the city, with a large newly developed area being detected as the edge-expansion type. As shown in Table 4, edge-expansion is the dominant mode of urban growth in Enshi City, and this type accounted for 83.05% of the new artificial area. Most edge-expansion areas are found in the north of the old urban center, and they are now shaping the urban forms of the Enshi City center into a north–south strip of land. Infilling and outlying accounted for 4.09% and12.86%, respectively. Overall, the artificial land use of Enshi City increased from 20.22 km^2 in 2000 to 70.08 km^2 in 2020.

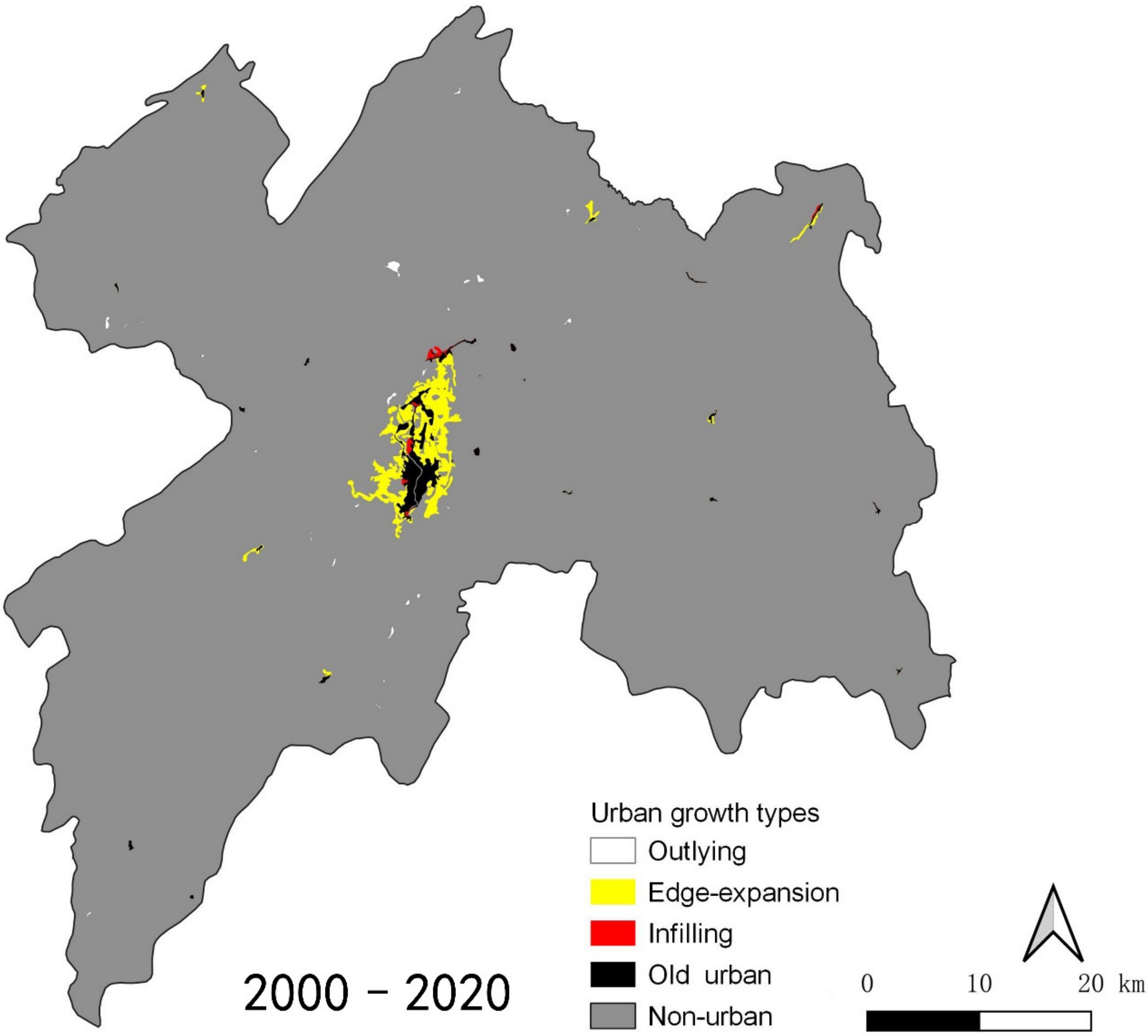

Figure 8. Urban growth pattern of Enshi City.

Table 4. Results of urban growth types of Enshi City from 2000 to 2020.

	Urban Growth Type (2000–2020)		
	Outlying	**Edge-Expansion**	**Infilling**
LEI interval	0	$0 < \text{LEI} \leq 50$	$50 < \text{LEI} \leq 100$
Area (km^2)	6.54	42.23	2.08
Area (%)	12.86	83.05	4.09

3.3. Forest Fragmentation

We used effective mesh size with cross-boundary connections to quantify the fragmentation of forests. Figure 9 indicates that the central part of the city was the most fragmented from 2000 to 2020, as the value of effective mesh size was relatively smaller. The degree of fragmentation reduced substantially in the western part of the area from 2000 to 2010, particularly in the northwestern part. From 2010 to 2020, although there was a significant increase in the artificial area of the city, the fragmentation of the forest only increased slightly. The southwestern part became a little bit more fragmented. However, the eastern part of the city did not show noticeable improvement regarding forest fragmentation. This region is fragmented and densely covered by small agricultural land slots.

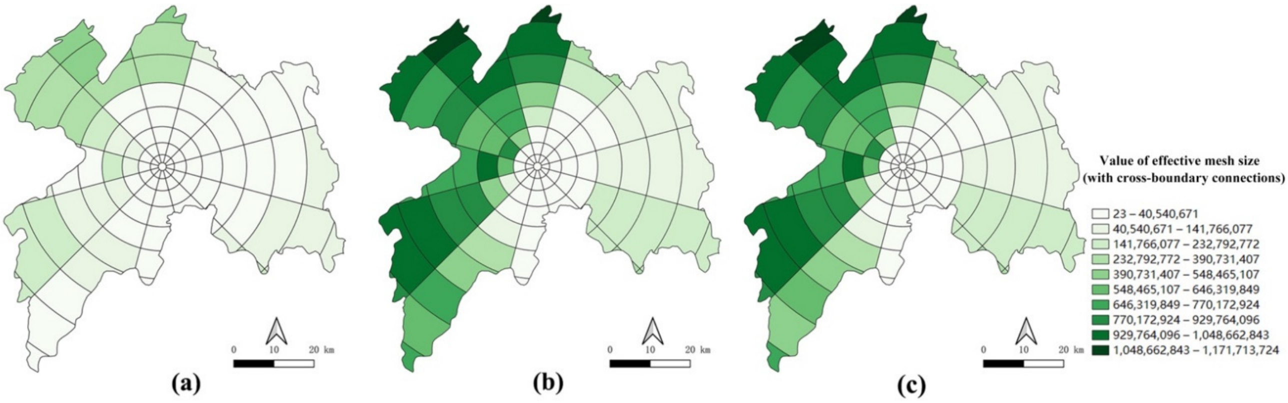

Figure 9. Results of the value of effective mesh size of forest land use in Enshi City. (**a**) Results from 2000; (**b**) Results from 2010; (**c**) Results from 2020.

4. Discussion

4.1. Insights from Analysis of Land-Use Change

In summary, this study explored the dynamics of land use and landscape pattern change in Enshi City from 2000 to 2020 by combining different methods. According to the intensity analysis, the speed of land-use change was much faster from 2000 to 2010 than from 2010 and 2020. At the categorical level, throughout the two intervals, water bodies and cultivated land showed stationarity in terms of the intensity of gain. Artificial surfaces, forest, and grassland showed stationarity in terms of the intensity of loss. At the transition level, we focused on two specific types of land: artificial surfaces and grassland. Artificial surfaces gained the most intensively from 2010 to 2020, with transitions from grassland and cultivated land. Grassland showed stationarity across the two intervals, as it continued an active trend of area loss. We confirmed that the losses were mostly transitioned to water bodies and forest from 2000 to 2010 and artificial surfaces and water bodies from 2010 to 2020.

The intensive loss of grassland is in line with several studies [1,11,39,66]. For example, a recent study on land-use transformation in Sangzhi County in the Wuling Mountain area found that the area of grassland decreased significantly from 2010 to 2018 [11]. They also confirmed a significant increase in cultivated land, driven by the implementation of policies relating to the protection of cultivated land [11]. This finding differs from ours because the total area of cultivated land in Enshi City is relatively stable. Our findings also reflect the implementation of policies regarding the remediation of water bodies. The area of water bodies continued an active trend of gain from 2000 to 2020. Local authorities have efficiently protected and remediated the main rivers in Enshi City. It also showed an active trend of loss from 2000 to 2010. It is possible that some scattered distributed water patches have vanished. Attention should be paid to small and scattered water bodies to maintain biodiversity and landscape connectivity.

Since the artificial area of Enshi City has increased rapidly, we further explored the urban growth pattern from 2000 to 2020 by calculating the LEI. The results showed that the expansion of artificial surfaces in Enshi City is primarily occurring in flat areas close to the urban center. This echoes previous findings that, in mountainous regions, flat areas are more inclined to be transitioned to built-up areas [9]. While previous studies in larger mountainous cities (e.g., Chongqing) found that the dominant urban growth mode is outlying in recent years [3], we found that the dominant mode in Enshi City is edge-expansion, which is similarly occurring in other cities in plain areas. This is partly because Enshi City is underdeveloped, with plain (vacant) space surrounding old urban areas. For Enshi City, the intensive gain of artificial surfaces began after 2010, which is relatively late compared to many other cities and counties in China. Since the terrain is relatively flat in the middle of the city, it is possible that the built-up area of Enshi City will continue to grow in this locale in the future. Local decision-makers should carefully control the boundaries of artificial surfaces and consider the possible negative impacts of land transitions, for instance, the loss of biodiversity, the creation of urban heat islands, poor air quality, and the decrease in landscape connectivity [3,9].

4.2. Impacts of Land-Use Change on Landscape Fragmentation

We confirmed a substantial reduction in the degree of forest fragmentation from 2000 to 2010, which primarily occurred in the western part of the city. For ecologically fragile mountainous areas, our findings clearly reflect the successful implementation of forestation projects aiming to restore the natural environment. The notable increase in forest between 2000 and 2010 echoes many Chinese studies and is a result of the nationwide "Grain for Green" policy [2,18,39]. While urbanization frequently leads to landscape fragmentation [72], the rapid growth of urban areas in Enshi City from 2010 to 2020 did not seem to influence the fragmentation of local forest areas. Nevertheless, it is necessary to identify and fortify urban forests that are located near the boundary of current built-up environments. Some of them are vital for maintaining ecological integrity but are also in potential danger of land-use transition. It is crucial to continuously monitor land-use change and spatially model different scenarios for future development.

For mountainous cities to be lifted out of poverty, it is vital to monitor how poverty alleviation practices can be reflected in the landscape dynamics and how they can impact sustainable forest management. In Enshi City's case, recent urban development has been focused on developing agriculture and expanding urban areas for housing and industry. Therefore, social contexts are meaningful in analyzing decades of change centering around forests via potential driving forces and impacts. This study proposed a framework of three analytical modules. First, it investigates the land-use change intensity of different categories. It explores potential sources and driving forces for forest change in poverty alleviation practices. Second, it investigates areas that are undergoing the process of urban expansion. Third, it evaluates the ecological conditions of forests under those driving forces, using the indicators of landscape fragmentation.

4.3. Limitations

The data have an issue that Qingjiang River was not clearly displayed in 2000. This inconsistency could impact the analysis of land cover in some river segments. This is an issue related to the original data of GlobeLand30. However, the central objective of this study is to serve sustainable forest management by analyzing land-use change, urban development and expansions, and forest fragmentation. The impacted analysis is limited in the transition between water bodies and agriculture, but less in forests. Using our pixel-based evaluation, the influenced area covers less than 0.3% of the study area. The influenced area is relatively small.

5. Conclusions

According to the intensity analysis, the speed of land-use change was much faster between 2000 and 2010 than between 2010 and 2020. The gain of water bodies and loss of grassland were active throughout the two intervals. Artificial surfaces increased most intensively from 2010 to 2020 with transitions from grassland and cultivated land, indicating a rapid urbanization process. Edge-expansion was the dominant type of artificial surface growth. Furthermore, forests had the largest size of gain across the two intervals, and there was a substantial reduction in forest fragmentation in the western part of the city.

Overall, this research contributes to our understanding of land-use change and urbanization in poverty-stricken mountainous cities. The proposed analytical framework helps synthesize and understand various characteristics of land-use dynamics, ranging from the overall trends, differences among land-use categories, types and locations of urban expansion, forest fragmentation, and spatially explicit evaluation. The research findings reflect that some recent planning measures are effectively restoring the natural environment. For sustainable land management in mountainous areas, it is necessary to further refer to comprehensive spatial analysis to identify key areas to protect ecological integrity and harmonize the relationship between nature conservation and urban growth.

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