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SPATIOTEMPORAL CHANGES OF THE HABITAT QUALITY AND THE HUMAN ACTIVITY INTENSITY AND THEIR CORRELATION IN MOUNTAINOUS CITIES

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Highlights

- The overall habitat quality in mountainous cities tended tends to decrease, while an increase was is identified in the human activity intensity.
- A significant negative correlation was is reported between habitat quality and human activity intensity in mountainous cities.
- The significant variations of artificial land and the natural land act as the vital crucial factors leading to the variations of the habitat quality and the human activity intensity, as well as their correlation in mountainous cities.
- The results can be applied to ecological management and land use planning in mountain cities.

Abstract. As the urbanization is being rapidly boosted, the urban habitat quality has been significantly disturbed by human activities through land use, which highly affects the urban ecological environment and sustainable development of social economy. However, the change characteristics of the habitat quality and human activities in different topographic gradients in rapidly urbanized mountainous cities remain unclear. Accordingly, Guiyang in China, is selected as the representative of typical mountain cities. The change characteristics of the habitat quality, the human activity intensity and their correlation in mountainous cities from 2000 to 2020, are analyzed using the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model, as well as the ArcGIS software based on the remote sensing interpretation data in 2000, 2010 and 2020. The results demonstrate that the overall habitat quality in Guiyang decreased by 0.0304, while the human activity intensity increased by 0.0287 from 2000 to 2020. The amount of changes of the habitat quality and the human activity intensity in Guiyang from 2010 to 2020, are higher than those from 2000 to 2010. The amount of changes of the habitat quality and the human activity intensity in Guiyang decreases with the increase of the slope. The central and southern parts of Guiyang are the highlight areas with a significant decline of habitat quality and significant increase of human activity intensity. The areas with an increased habitat quality and decreased human activity intensity are sporadically distributed. A significant negative correlation is reported between the change of the habitat quality and human activity intensity in Guiyang. In addition, a prominent spatial heterogeneity is identified in the local indicators of the spatial association (LISA) map. The significant increase in the artificial land and the decrease in the natural land as affected by the rapid urbanization, act as crucial factors leading to the decline of the habitat quality and the increase in the human activity intensity in mountainous cities. This also facilitates the formation of the negative correlation between the habitat quality and the human activity intensity.

Keywords: habitat quality, human activity intensity, spatial pattern, correlation, mountain city.

Introduction

Habitat quality refers to the ability of the ecological environment to offer suitable conditions for the biological survival. It acts as a vital function of ecosystem services (Buddendorf et al., 2019; Upadhaya & Dwivedi, 2019). Human activities (e.g. land use change) are important factors that threaten the habitat quality (Zhang et al., 2020a). Human activities can cause the fragmentation and loss of natural habitats by regulating the structure and function of the ecosystem, which results in the decline of the habitat quality (Yohannes et al., 2021; Alaniz et al., 2021). As the typical areas with strong disturbance of the human activities, the ecological environment in cities has undergone a

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deep transformation (Li et al., 2018). The studies on the urban habitat quality and the human activity intensity is of great scientific significance for clarifying the change trend and the interaction between urban habitats and human activities. Moreover, these studies lay a scientific basis for improving the urban ecosystem services and regulating human activities (Han et al., 2019; Song et al., 2020).

Existing studies on the habitat quality are primarily performed for the habitat quality assessment, by developing an evaluation index system based on the biological survey data (Diaz et al., 2004; Kantharajan et al., 2022). For instance, Van Dolah et al. (1999) evaluate the estuarine habitat quality in the southeastern United States by setting a benthic index of the biological integrity based on the field sampling data. As the remote sensing (RS) and the geographic information system (GIS) technologies are leaping forward, the geospatial technology has been extensively applied in the assessment of habitat quality and its spatial presentation (Randhir & Ekness, 2013). Nine-surface, ecological, hydrological and anthropogenic parameters are considered to evaluate the habitat quality using the GIS technology in the study conducted by Pal et al. (2020). Over the past few years, researchers tend to quantitatively analyze the habitat quality based on ecological models (Zlinszky et al., 2015). As affected by the advantages of Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model (e.g. a convenient data acquisition, fewer demand parameters, an accurate analysis ability and a simple data processing), their models have been widely applied in the habitat quality assessment. For instance, Sun et al. (2019) monitor the spatio-temporal change characteristics of the habitat quality in the Nansihu Basin of China during 1980–2015, using the InVEST model.

With the increasing impact of human activities on global environmental problems, human activities have become a crucial topic in the study of global environmental change. The natural and social-economic indicators are considered to evaluate the intensity of human activities using the multi-index superposition analysis method. For instance, gross fomestic product, population, distances to town and road, normalized difference vegetation index, grazing intensity and ratio of cultivated land are used to calculate the intensity of human activities in Qinghai-Tibet Plateau (Sun et al., 2020). Simultaneously, under the promotion of "Land Use/Cover Change Scientific Research Program", the evaluation method of human activity intensity based on built-up land equivalent has attracted attention by several researchers. This method has been widely used due to its simplicity in data acquisition and convenience in comparison between different regions (Xu et al., 2016). With the development of the spatial analysis technology, the spatial expression of human activity intensity has been widely studied. For instance, Lan et al. (2021) use points of interest data, openstreet map data, net primary productivity data and nighttime light data to perform spatial evaluation of human activity intensity.

The studies on the relationship between human activities and habitat quality mainly focuse on the impacts of land use change on the habitat quality (Lee & Jeon, 2020; Aneseyee et al., 2020). The significant increase in the industrial land, residential land and cultivated land can lead to a significant decline in the habitat quality, as reported by existing studies (Zhang et al., 2020b). The decline of the industrial and mining lands after the cessation of production increases the richness of the regional habitat, and the habitat turnes out to be more fragmented (Antwi et al., 2008). An increase or decrease of the habitat quality, affected by difference changes of various land use types, will be presented in different urban development scenarios in the future (He et al., 2017). Although some researchers stress the relationship between the urban habitat quality and the human activities (He et al., 2017; Han et al., 2019), the relevant studies in mountainous cities from different terrain gradients are still rare. In other words, the differences in habitat quality and human activities between mountainous and non-mountainous areas were analyzed by only a few scholars (Yang, 2021), but the analysis on the habitat quality and human activities in mountainous areas with different slopes was ignored. Thus, considering the Guiyang city in China as example, this study first explores the overall and topographic gradient characteristics of the changes of the habitat quality and the human activity intensity in mountainous cities, and then explores the correlation between the habitat quality and the human activity intensity. The research content of this paper is as follows: (1) The changes of the habitat quality and the human activity intensity in mountainous cities are different in different terrain gradients. (2) The correlation between habitat quality and human activity intensity varies with terrain gradient. This study is of great significance to the ecological environment planning and human activities regulation in mountain cities.

1. Methods

1.1. Overview of the study area

Guiyang (106°27′–107°03′ E, 26°11′–26°55′ N) is the capital city of Guizhou Province, China. It is located in the central part of Guizhou Province, which pertains to the upper reaches of the Yangtze River and the Pearl River. In general, the landforms are mountainous, hilly and basin, with highest and lowest elevations of 1,762 m and 506 m, respectively. The topographic relief is large, the elevation in the north and south parts is high, and the elevation central part is low (Figure 1). It has a subtropical humid climate, with an average annual temperature of 15.3 °C and an average annual precipitation of 1129 mm. By the end of 2020, the Gross Domestic Product of Guiyang has reached 431.2 billion CNY (Chinese Yuan), with an average annual growth rate of 14.2% for the last ten years. The total population in Guiyang is 4,971,400 at the end of 2020, with an average annual growth rate of 14.83% over the past decade. The conflict between the urban development and the

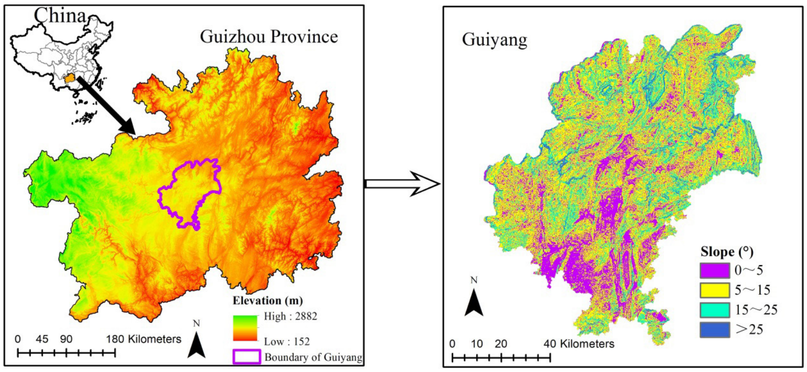

Figure 1. Location of Guiyang city

ecosystem protection in Guiyang has recently become serious due to the rapid expansion of the urban area and the sharp increase of the population (Liu et al., 2014, 2021).

1.2. Data source and processing

The land use data of Guiyang in 2000, 2010 and 2020 originate from Landsat TM/ETM remote sensing image interpretation with a spatial resolution of 30×30 m. The processing steps include the pretreatment, radiation and geometric corrections, and image registration to generate standard images. The human-computer interactive interpretation method is used for image interpretation with the help of the ENVI5.0 software (Rahnama, 2021). More precisely, (1) a visual interpretation of the study area is carried out according to the empirical knowledge. (2) Representative training areas are selected and classification templates are established. (3) The images are interpreted by combining classification templates, Google Earth high-resolution images and topography based on the maximum likelihood method. (4) Subsequently, based on the local ecological environment characteristics (Liu et al., 2014), the land use types in the study area are divided into eleven types: paddy field, dry land, forestland, shrubland, grassland, urban land, rural settlement, industrial and mining land, road land, railway land and water body (Figure 2). The elevation data with a spatial resolution of 30×30 m are downloaded from ASTER GDEM in the geospatial data cloud (www.gscloud.cn), and the slope data are generated with the surface analysis tool of the ArcGIS software. Given the topographic characteristics of the study area, the slopes fall to gradient I (0~5°), gradient II (5~10°), gradient III (10~15°), gradient IV (15~20°) and gradient V (>20°) (Figure 1). The gross domestic product density, population density and night light are downloaded from Resource and Environment Science and Data Center (www.resdc.cn/), and National Earth System Science Data center (www.geodata.cn).

1.3. Methods

1.3.1. Habitat quality assessment method

The habitat quality is assessed by considering the relative impact of the respective ecological threat factor, the sensitivity of each habitat type to each ecological threat factor, the distance between the habitat and the source of ecological threat factors, as well as the degree of land legal protection in habitat quality module of the InVEST model (Sallustio et al., 2017; Tang et al., 2020):

$$D_{xj} = \sum_{r=1}^{R}\sum_{y=1}^{Y}\left(\frac{w_r}{\sum_{r=1}^{R} w_r}\right) r_y i_{rxy} \beta_x S_{jr}; \tag{1}$$

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

where H_j denotes the habitat quality index, D_{xj} represents the habitat degradation index, Z is a normalized constant equal to 2.5, K is the half-saturation coefficient equal to half of the resolution size of the raster cell, R is the number of threat factors, W_r denotes the weight of the threat

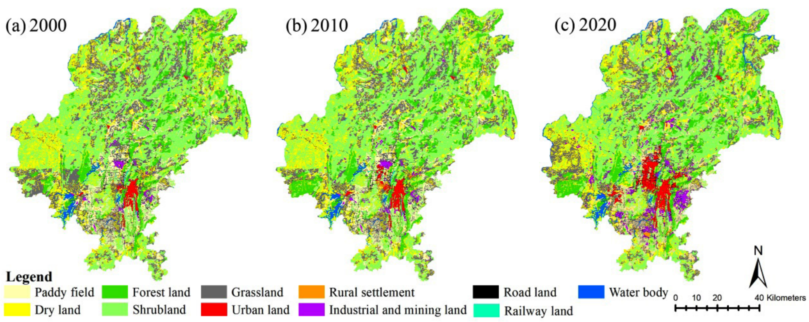

Figure 2. Spatial map of land use types in Guiyang

factor, Y is the total number of grid units of ecological threat factors, r_y is the number of ecological threat factors on the respective grid of the land use layer, i_{rxy} is the influence of the threat factor r in grid y on grid x, β_x is the degree of legal arrival for protection (unconsidered here), and S_{jr} is the sensitivity of the land use type to different ecological threat factors.

The data required for model operation mainly include the land use map, ecological threat factor layer, attribute table of ecological threat factor and sensitivity table of land use types to each ecological threat factor. The land use maps of the study area in 2000, 2010 and 2020 are derived from the remote sensing interpretation. Paddy field, dry land, urban land, rural settlement, industrial and mining land, road land and railway land are considered as the land use types threatening the ecological environment in the ecological threat factor layer. The sensitivity of threat factors to the respective habitat type refers to the instructions of the InVEST user's guide (Sharp et al., 2014), relevant cases (Han & Dong, 2017; Zhu et al., 2020) and expert scores (Tables 1 and 2).

1.3.2. Calculation method of the human activity intensity

In this paper, four indicators (gross domestic product density, population density, built-up land equivalent from different land use types and night light) are considered to calculate the human activity intensity. Thereinto, the built-up land equivalent from different land use types can be calculated by referencing the method proposed by Liang and Liu (2011).

$$HAI = G \cdot P \cdot B \cdot N; \tag{3}$$

$$B = \sum_{i=1}^{n} A_i \cdot S_i / TA, \tag{4}$$

where HAI denotes the human activity intensity index, G is the density of gross domestic product, P is the population density, B is the built-up land equivalent from different land use types, N is the night light index, n is the number of land use types, A_i represents the area of land use type i, S_i denotes the intensity coefficient of the human activity of land use type i (Xu et al., 2016) (Table 3), and TA is the total area. The weight of gross domestic product density, population density, built-up land equivalent and night light are respectively 0.2, 0.25, 0.3 and 0.25, which is obtained from the scores of 15 experts.

Table 3. Human activity intensity coefficient of each land use type

Land use types	Intensity coefficient
Paddy field, Dry land	0.61
Forestland, Shrubland	0.14
Grassland	0.09
Water body	0.32
Urban land, Rural settlement, Industrial and mining land, Road land, Railway land	0.95

1.3.3. Methods for analyzing the correlation between the habitat quality and the human activity intensity

The band collection statistics tool of the ArcGIS software is able to describe the spatial relationship between two raster datasets (Bennett & Smith, 2017). The calculation formula is expressed as:

$$Corr_{ij} = \frac{\sum_{k=1}^{n}(z_{ik} - u_i)(z_{jk} - u_j)}{(n-1)\delta_i\delta_j}, \tag{5}$$

where $Corr_{ij}$ denotes the correlation coefficient, Z_{ik} represents the k^{th} pixel value of layer i, z_{jk} is the k^{th} pixel value of layer j, μ_i and μ_j are respectively the pixels mean values of layer i and layer j, n represents the number of pixels, δ_i and δ_j are the pixels standard deviations of layers i and j, respectively.

Table 1. Maximum influence distance and weight of threat factors

Impacts	Paddy field	Dry land	Urban land	Rural settlement	Industrial and mining land	Road land	Railway land
Maximum influence distance/km	4	5	10	5	6	2	3
Weight	0.7	0.7	1	0.9	0.8	0.7	0.6

Table 2. Sensitivity of the threat factors to the respective habitat type

Habitat types	Paddy field	Dry land	Urban land	Rural settlement	Industrial and mining land	Road land	Railway land
Forestland	0.4	0.6	0.8	0.5	0.7	0.5	0.5
Shrubland	0.6	0.8	0.9	0.7	0.7	0.5	0.5
Grassland	0.2	0.4	0.5	0.4	0.5	0.4	0.3
Water body	0.5	0.6	0.9	0.6	0.8	0.5	0.5

Under the positive correlation coefficient, there will be a positive spatial correlation between the two raster data. A negative value indicates a negative correlation between the two raster data.

The local indicators of the spatial association (LISA) map in the GeoDA software can analyze the spatial pattern of correlation between two spatial data based on the calculation results of Moran's I (Anselin, 1995). The method in this study is introduced to explore the spatial pattern of correlation between the habitat quality and the human activity intensity. The calculation formula is written as:

$$I = Z_i \sum_{j=1}^{n} W_{ij} Z_j, \quad (6)$$

where I denotes the Moran's I index value, Z_i and Z_j are respectively the normalized values of the spatial layers i and j, W_{ij} represents the spatial weight between layers i and j.

According to Moran's I value, the regions in the LISA cluster map fall to the high-high area (high-value area adjacent to the high-value area), low-low area (low-value area adjacent to the low-value area), high-low area (high-value area adjacent to the low-value area), low-high area (low-value area adjacent to the high-value area) and no significant area (no correlation between the two spatial data). The grid (2×2 km) in this study acts as the basic geographic unit. The average habitat quality and human activity intensity of the respective grid on the raster layer are extracted using the zoning statistics tool in ArcGIS. The Moran's I between the habitat quality and human activity intensity is then calculated. Finally, the LISA cluster map is generated using the GeoDA software.

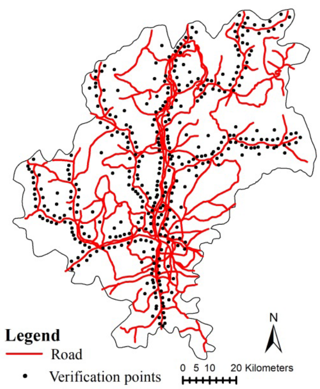

Figure 3. Location of verification points

2. Results

2.1. Remote-sensing imagery interpretation accuracy

400 checking points are selected along ring city road of Guiyang for accuracy verification of remote sensing interpretation (Figure 3). Through field verification, it is deduced that the proportion of correct polygon in the interpretation results is 88.25%, which can meet the requirements of this study.

2.2. Temporal and spatial change of the habitat quality

The habitat quality in Guiyang increases with the slope increase in 2000, 2010 and 2020. The habitat quality in the area with slope gradient V is the highest, while the habitat quality in the area with slope gradient I is the lowest. The habitat quality in the whole region and in each slope gradient decreases during 2000–2010, 2010–2020 and 2000–2020. The decreasing amount of the habitat quality from 2010 to 2020 is higher than that between 2000 and 2010. The decreasing amount of the habitat quality in Guiyang is reduced with the increase of the slope. The habitat quality change in the slope with 0–20° in three periods is significantly higher than other slopes (Table 4 and Figure 4).

Table 4. Whole change of habitat quality in Guiyang

Regions	2000	2010	2020	2000–2010	2010–2020	2000–2020
Gradient I	0.4647	0.4401	0.4196	−0.0246	−0.0205	−0.0451
Gradient II	0.5884	0.5729	0.5551	−0.0155	−0.0178	−0.0333
Gradient III	0.6535	0.6438	0.6303	−0.0097	−0.0135	−0.0232
Gradient IV	0.7011	0.6942	0.6821	−0.0069	−0.0121	−0.0190
Gradient V	0.7536	0.7522	0.7428	−0.0014	−0.0094	−0.0108
Whole study area	0.6050	0.5911	0.5746	−0.0139	−0.0165	−0.0304

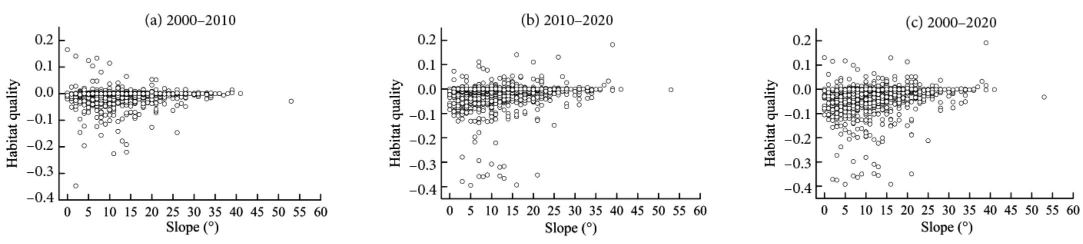

Figure 4. Habitat quality change function of the slope at the pixel scale in Guiyang

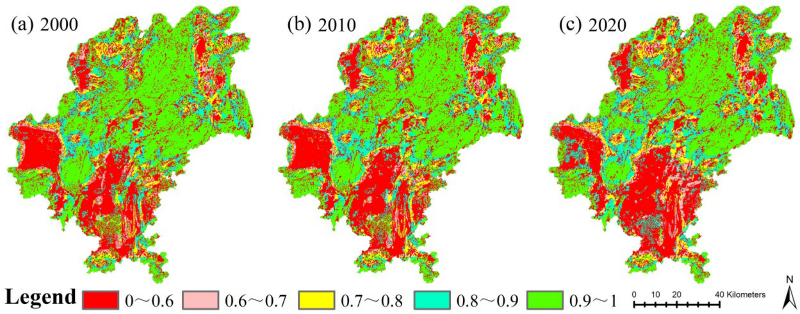

Figure 5. Spatial pattern of the habitat quality in Guiyang

The spatial patterns of the habitat quality in Guiyang are close to each other in 2000, 2010 and 2020. Most parts of the study area in three periods are in the range of 0~0.6 and 0.9~1, while the regional distribution of the habitat quality value in the range of 0.6~0.9 is scattered. The regions with the range of 0~0.6 are mainly located in the central, southern and western parts of Guiyang. The regions in the range of 0.9~1 are mainly in the north part, and the regions in the range of 0.6~0.9 are mainly located in the surrounding of low value area (0~0.6) (Figure 5).

The habitat quality in most areas of Guiyang decreases, and only few areas increase during 2000–2010, 2010–2020 and 2000–2020 (Figures 6a, 6b and 6c). The area achieving high value of the habitat quality decline (<–0.04) is scattered in the central and northern parts. Those with medium value of the habitat quality decline (–0.04~–0.02 and –0.02~0) are mainly located in the northern part. That with increasing habitat quality (>0) is scattered and distributed from 2000 to 2010 (Figure 6a). The spatial pattern of the habitat quality change in Guiyang during 2010–2020 and 2000–2020 is similar. The high value area (<–0.04) of the habitat quality decline is mainly located in the central and southern parts. The medium value area (–0.04~–0.02 and –0.02~0) of the habitat quality decline is mainly located in the central and north parts. The increase area (>0) is mainly in the northeast and west parts. Furthermore, the area with a high value of decline (<–0.04) from 2000 to 2020 is scattered in the northern part, which is inconsistent with that from 2010 to 2020 (Figures 6b and 6c).

2.3. Temporal and spatial change of the human activity intensity

The human activity intensity in Guiyang for the 2020 year is high, while the low value is in 2000. The human activity intensity in 2000, 2010 and 2020 gradually decreases with the increase of the slope. During 2000–2010, 2010–2020 and 2000–2020, the human activity intensity in the whole region and each slope gradient of Guiyang show an increasing trend. In addition, the increase amount of the human activity intensity from 2010 to 2020 is higher than that between 2000 and 2010. The increase amount of the human activity intensity in low slope with 0–20° is higher than that in high slope (Table 5 and Figure 7).

Table 5. Changes of the human activity intensity in Guiyang

Regions	2000	2010	2020	2000–2010	2010–2020	2000–2020
Gradient I	0.1847	0.1949	0.2339	0.0102	0.0390	0.0492
Gradient II	0.1212	0.1339	0.1542	0.0127	0.0203	0.0330
Gradient III	0.1024	0.1087	0.1201	0.0063	0.0114	0.0177
Gradient IV	0.0911	0.0968	0.1049	0.0057	0.0081	0.0138
Gradient V	0.0753	0.0792	0.0851	0.0039	0.0059	0.0098
Whole study area	0.1235	0.1326	0.1522	0.0091	0.0196	0.0287

Most parts of the human activity intensity are between 0 and 0.1, that are mainly distributed in the northern and western parts of Guiyang in three periods. The areas with

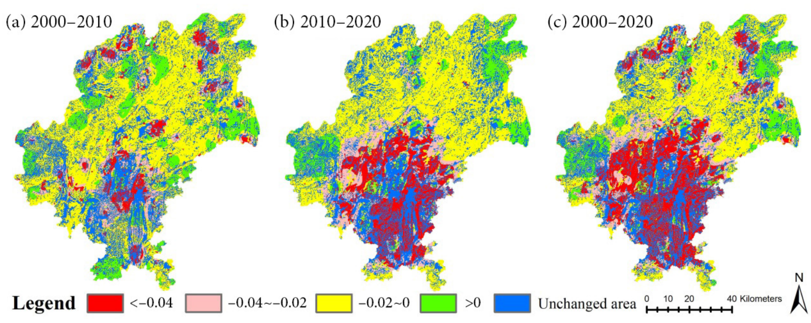

Figure 6. Spatial pattern of the habitat quality change in Guiyang

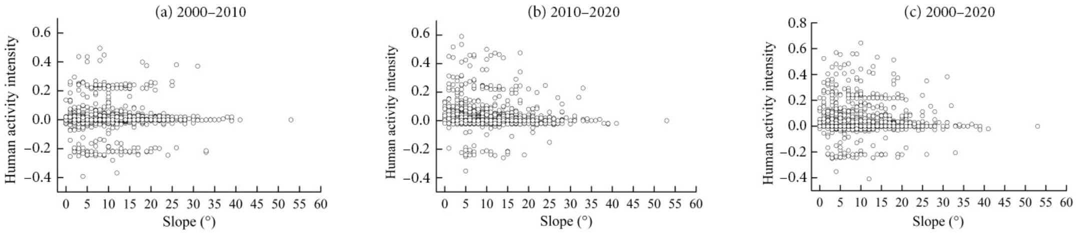

Figure 7. Changes of human activity intensity function of the slope at the pixel scale in Guiyang

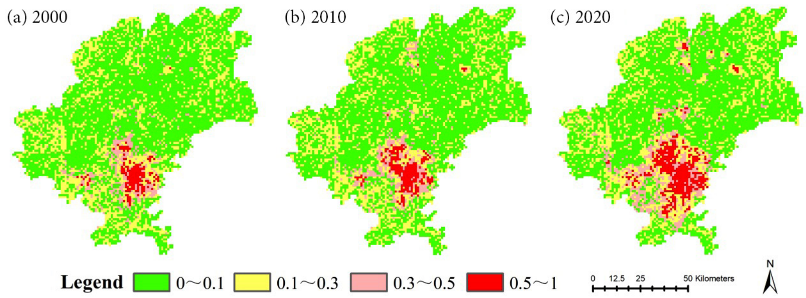

Figure 8. Spatial pattern of the human activity intensity in Guiyang

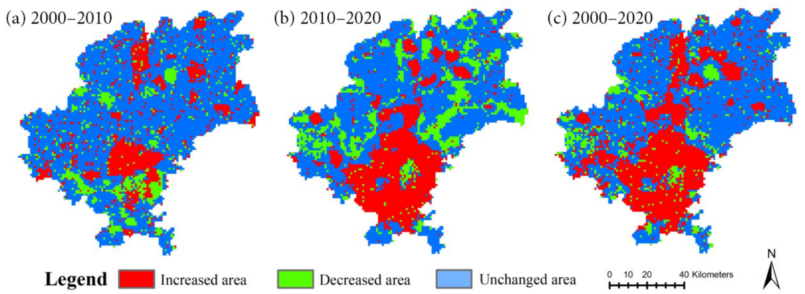

Figure 9. Spatial pattern of the human activity intensity change in Guiyang

moderate and high human activity intensity (0.3~0.5 and 0.5~1) are mainly located in the central and southern parts of Guiyang in 2000, 2010 and 2020, while the areas with low human activity intensity (0.1~0.3) are mainly sporadically distributed (Figure 8).

The areas of the increased human activity intensity in Guiyang are mainly concentrated in the central and northern parts, while the areas of the decreased human activity intensity are located in the southern part from 2000 to 2010 (Figure 9a). The areas with the increased human activity intensity are mainly located in the southern part, and the areas the with decreased human activity intensity are scattered and distributed from 2010 to 2020 and from 2000 to 2020 (Figures 9b and 9c).

2.4. Correlation between habitat quality and human activity intensity

A negative correlation is deduced between the habitat quality and human activity intensity in Guiyang as a whole, and in each slope gradient in 2000, 2010 and 2020. The correlation coefficient increases in 2000, 2010 and 2020 with the slope increase, except for the slope gradient V. The habitat quality change is negatively correlated with the human activity intensity change as a whole, and in each slope gradient in Guiyang during 2000–2010, 2010–2020 and 2000–2020. The correlation degree between them from 2010 to 2020 and from 2000 to 2020, is lower than that in 2000 to 2010. The correlation degree between them increases with the slope increase (Table 6).

The LISA cluster map between the habitat quality and the human activity intensity in Guiyang were primarilyis mainly the low-high area and the high-low area in 2000, 2010 and 2020. The low-high area displayed displays the major distribution in the north part of Guiyang, and while the high-low area was is largely distributed in the western and southern parts of Guiyang (Figures 10a, 10b and 10c). The LISA cluster map between the habitat quality change and the human activity intensity change in Guiyang was is dispersed from 2000 to 2010, whereas while the LISA cluster mapthose from 2010 to 2020 and that from 2000 to 2020 in Guiyang were are similar, which displayed displays a centralized distribution. The high-low area achieved achieves the primary locations in the central and southern parts of Guiyang, while the low-high area was is mainly concentrated in the western and northeastern parts of Guiyang (Figures 10d, 10e and 10f).

Table 6. Correlation coefficient between habitat quality and human activity intensity in Guiyang

Regions	2000	2010	2020	2000–2010	2010–2020	2000–2020
Gradient I	–0.5314*	–0.5545*	–0.5387*	–0.3867*	–0.3641*	–0.2388*
Gradient II	–0.5572*	–0.5670*	–0.5450*	–0.4255*	–0.3783*	–0.2916*
Gradient III	–0.5708*	–0.5781*	–0.5571*	–0.4384*	–0.3895*	–0.2976*
Gradient IV	–0.5911*	–0.5798*	–0.5692*	–0.4459*	–0.3906*	–0.3453*
Gradient V	–0.5239*	–0.5672*	–0.5446*	–0.4780*	–0.4152*	–0.3628*
Whole study area	–0.5560*	–0.5773*	–0.5513*	–0.4463*	–0.3736*	–0.3858*

Note: * indicates significant correlation at the significance level of 0.05.

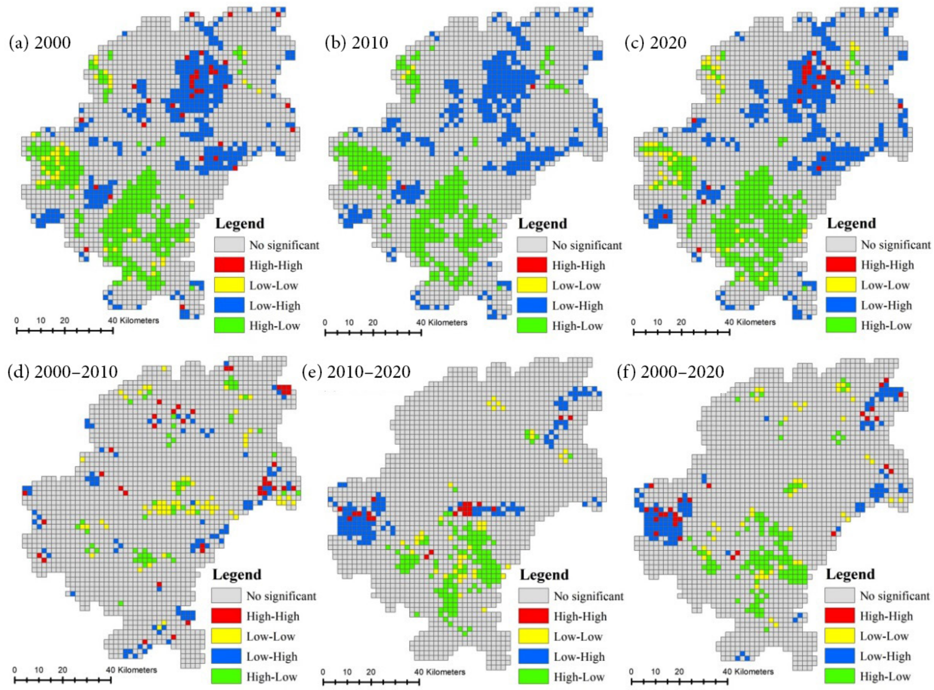

Figure 10. Spatial pattern of the LISA cluster map between the habitat quality and the human activity intensity in Guiyang

2.5. Impacts of land use change on the temporal and spatial change of the habitat quality and human activity intensity

The land use change in the study area highly affects the spatiotemporal change of the habitat quality and the human activity intensity. The main results are as follows: (1) The decrease in the natural land and the increase in the artificial land result in the increase of the human activity intensity. The disturbance to the ecological environment then continuously increase, which leads to the decline of the habitat quality in th ewhole study area. (2) With the slope increase, the difficulty of resource and environment development and utilization increases, and the human activities decrease. Consequently, the decreasing amount of the habitat quality is gradually reduced with the slope increase, under the rapid urbanization. (3) The significantly increased artificial land is affected by the rapid urban expansion. It enhances the human activity intensity in the southern part of Guiyang, and results in the significant decline of the habitat quality. However, the human activity disturbance intensity in the northern part of Guiyang city is weak, due to the fact that it is affected by the complex and fractured terrain. Consequently, the decline of the habitat quality is insignificant in the southern area (Table 7 and Figure 11).

3. Discussion

3.1. Impacts of the land use change on the correlation between the habitat quality and human activity intensity

This study reports a negative correlation between the human activities and habitat quality intensity in Guiyang, since this area is dominated by the natural land, which is more vulnerable to the disturbance and destruction of the human activities. With the rapid social and economic development, the increase in the artificial land greatly enhanced the intensity of the human activities, leading to ecological degradation, and then reduced the overall habitat quality of Guiyang. It is important to mention

Table 7. Land use change of Guiyang (hm^2)

Regions	Land use types	2000	2010	2020	2000–2010	2010–2020	2000–2020
Gradient I	Agricultural land	73 583	74 168	66 034	585	–8134	–7549
	Natural land	103 460	99 359	96 005	–4100	–3354	–7454
	Artificial land	14 561	18 051	29 532	3489	11 481	14 970
Gradient II	Agricultural land	73 189	73 893	70 713	704	–3180	–2476
	Natural land	165 435	163 345	160 450	–2091	–2894	–4985
	Artificial land	6947	8329	14 397	1382	6068	7450
Gradient III	Agricultural land	45 447	45 527	44 339	79	–1188	–1109
	Natural land	136 956	136 506	135 481	–450	–1025	–1475
	Artificial land	2641	3015	5222	373	2207	2581
Gradient IV	Agricultural land	20 600	20 435	20 025	–164	–411	–575
	Natural land	78 287	78 335	78 047	48	–288	–241
	Artificial land	902	1008	1703	106	695	801
Gradient V	Agricultural land	13 140	12 589	12 562	–551	–27	–578
	Natural land	67 919	68 375	68 202	456	–173	283
	Artificial land	535	638	838	104	199	303
Whole study area	Agricultural land	226 054	226 798	213 761	744	–13 037	–12 293
	Natural land	553 026	546 813	539 168	–6213	–7646	–13 858
	Artificial land	25 573	31 042	51 724	5469	20 682	26 151

Note: the agricultural land includes paddy field and dry land. The natural land comprises forestland, shrubland, grassland and water body. The artificial land covers urban land, rural settlement, industrial and mining land, road land and railway land.

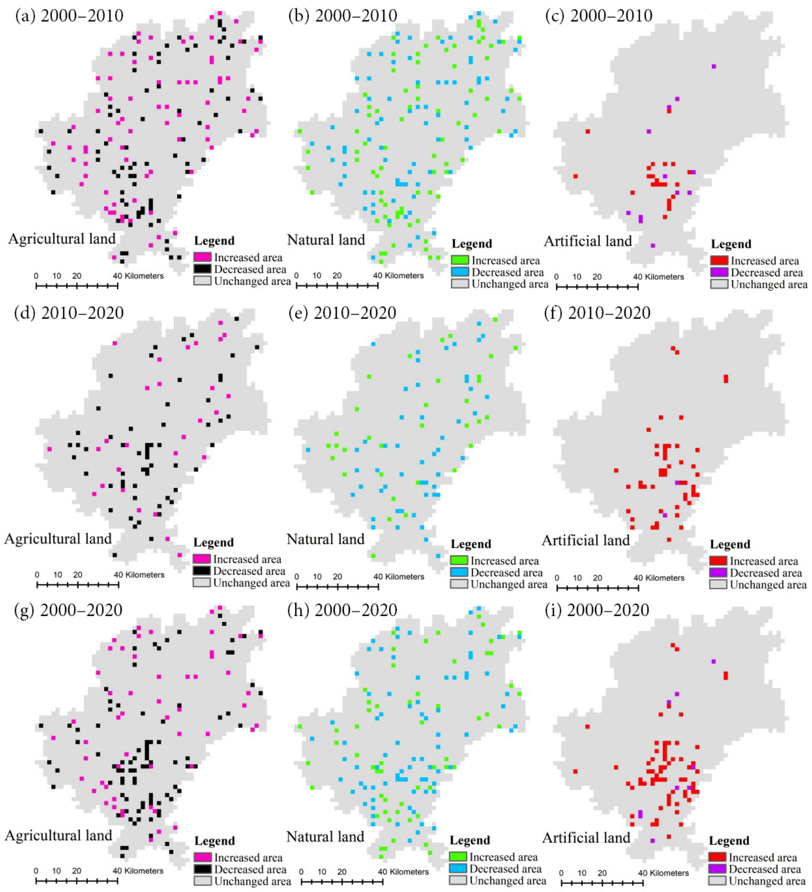

Figure 11. Spatial pattern of land use change in Guiyang city. The agricultural land includes paddy field and dry land. The natural land includes forestland, shrubland, grassland and water body. The artificial land consists of urban land, rural settlement, industrial and mining land, road land and railway land

that although the decrease in the agricultural production land during 2010–2020 and 2000–2020 reduced the intensity of the human activities, which was advantageous to the habitat quality improve, it cannot offset the negative effects of the habitat quality resulting from the decrease in the natural land and the increase in the artificial land. Thus, the negative correlation between the habitat quality and human activity intensity is presented. As the slope increases, the increase amount of the artificial land significantly decreases, which weakens the increase in the human activity intensity and reduces the negative impacts on the habitat quality. Thus, there is still a negative correlation between them in each slope gradient. The area around the main urban area in southern Guiyang is the key area of the human activities expansion from 2010 to 2020, and 2000 to 2020. However, the habitat quality in this area is relatively low, and the change is insignificant (remaining at a low level). Consequently, a high-low concentration area is formed in this area. Similarly, the western part of Guiyang is far away from the city, the intensity of the human activities is weakened, and the decline of the human disturbance results in the habitat quality improvement. Consequently, this area forms a low-high concentration area.

3.2. Land use optimization strategy

The considerable artificial land is transformed from the agricultural land and natural land, due to the fact that it is affected by the rapid urbanization over the past two decades, which is particularly prominent in the areas with slope gradients below 15°. Thus, the natural land (e.g. forestland, shrubland, grassland and water body) in the slope gradient less than 15° should be well protected in the future. Moreover, it is suggested to increase the policy implementation of returning the farmland to the shurbland and the grassland in the slope gradient above 15°, and reduce the disturbance of the human activities. In addition, the artificial land acts as a key factor of the intensity of the human activities. The expansion of the artificial land (e.g. the urban land) should be controlled in the future, and its economical use degree should be elevated in the study area. Affected by the spatial heterogeneity of the human activities and the habitat quality, the development and protection strategies for different regions should also be proposed according to the characteristics of social economy and ecological functions in different regions. The south part of Guiyang is exposed to the serious habitat degradation and the strong human activities. This area should be the critical region of ecological protection and control of the human activity. Finally, the natural vegetation restoration should be facilitated, in order to improve the ecological environment quality in the north part of Guiyang with the steep slope gradient above 20°. It is advantageous to perform the rational utilization of land resources and the protection of ecological environment in Guiyang.

3.3. Limitations

The habitat quality evaluation in the InVEST model mainly depends on the parameter setting of threat factors. Although this paper refers to relevant studies and recommended model values to set the parameters of the impact factors, subjectivity exists in the parameter setting of the influence distance, weight and sensitivity of threat factors, which is a defect of the proposed method (Sharp et al., 2014). In addition, due to the difficulty in obtaining direct observation indicators of habitat quality, this study does not verify the evaluation results of the InVEST model. Although factors such as population density, economy density, land use and night light index, are considered in the spatial evaluation of human activity intensity, other factors such as tourism activity, economic policy and population flow are not considered due to the difficulty in spatial quantification, which affects the assessment accuracy of human activity intensity.

Conclusions

The rapid development of mountainous cities is increasingly disturbed by human activities, which seriously threatens the ecological environment quality of the cities. Based on rapid urbanization, the habitat quality in mountainous cities was observed to decline, while human activity intensity increased. This was closely related to the significant increase of artificial land and the decline of natural land. In addition, the relatively flat terrain area was the dominant expansion area of the artificial land driven by the rapid urbanization of mountainous cities. This area also exhibited a sharp decline in the habitat quality and a significant increase in the human activity intensity, which was particularly prominent in the central and southern parts of Guiyang. The reduced habitat quality and increase in human activity intensity decreased with the increase in slope, resulting from the restriction of human activity by topographic conditions. Moreover, a negative correlation between the habitat quality and human activity intensity was observed, and varied with slope gradient. The steep slope area should promote the conversion of farmland to forest and natural vegetation protection planning. In relatively flat areas, controlling artificial land expansion is the focus of landscape management in the future work. Note that additional factors should be considered in the evaluation of human activity intensity, and the accuracy of the habitat quality evaluation should be further improved.

Conflicts of interest

The authors declare no conflict of interest.

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