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Response of habitat quality to land use change in urban bulilt-up area of karst mountainous city

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Abstract: There are a large number of urban remnant mountains (URMs) in the built-up areas of karst mountainous cities, which are the main components of urban habitats and play a variety of irreplaceable ecosystem services functions such as maintaining local biodiversity. Based on InVEST model and Geographically Weighted Regression (GWR) model, this study quantitatively analyzed the spatial-temporal evolution characteristics of land use/land cover (LULC), landscape pattern and habitat quality (HQ), and explored the relationship between LULC and HQ in a typical karst mountainous city. Results showed: (1) From 2008 to 2018, LULC change in the study area was intense, with cultivated land and URMs being converted into construction land. Moreover, urban landscape fragmentation was serious and landscape patch spatial heterogeneity was high; (2) The overall level of HQ in the study area was low and the spatial aggregation characteristics were obvious. The high value area was mainly distributed in the area of large urban green space (UGS) and URMs, while the low value area was mainly concentrated in the area of construction land and traffic land;(3) GWR analysis showed that LULC was significantly correlated with HQ change, natural environment determined the overall distribution of HQ, human activities played a leading role in HQ change, and urbanization process had spatial heterogeneity on HQ change; (4) URMs iwas the main contributor of high level HQ, but its encroachment by construction land and the increase of surrounding building density make the quality of URMs habitat degraded obviously. It is urgent to strengthen the management of urban ecological environment and properly deal with the relationship between urban expansion and urban natural environment. This study is helpful to further understand the relationship between LULC and HQ evolution in karst mountainous cities, and is of great significance for urban biodiversity conservation, ecological security protection and high-quality urban development.

Keywords: Mountainous city; Land-use and land-cove; Landscape pattern; InVEST model; Habitat quality

1. Introduction:

Habitat quality (HQ) refers to the ability of ecosystem to provide suitable living conditions for maintaining species, which can reflect regional biodiversity and ecological service level to a certain extent (Hall et al., 1997; Zhang et al., 2020). With the rapid growth of global urbanization and urban population, about 70% of the global population will live in cities by 2050 (Muller A et al., 2015). The connection between human and nature is rapidly weakening, and the quality of habitat in urban areas will become an important factor in evaluating high-quality sustainable development of cities and ecological well-being of urban residents (Soga M and Gaston K J, 2016). Many cities are undergoing large-scale LULC conversion (Ramalho C E et al, 2014). Urban areas are constantly expanding to natural areas outside the boundary, and a large number of natural areas are rapidly losing, splitting and degrading (Esbah H et al, 2009). A series of urban environmental problems, such as soil erosion, environmental pollution, habitat degradation, biodiversity reduction, ecosystem imbalance, etc. (Su W et al., 2010; Xu, Y et al., 2018; Huang J et al., 2017; Fan F et al., 2022). Improving the urban ecological environment, enhancing the quality of urban living environment, and realizing the harmonious coexistence of man and nature in sustainable development have become a key goal of urban planning (Lin J et al., 2020; Peng J. Etal., 2020). As an important representation of urban ecological security, HQ assessment can reflect regional biodiversity and ecological service level, and has increasingly become a research hotspot in the field of ecological security (Bai L et al., 2019).

According to current studies, HQ assessment mainly includes two methods: field investigation and model simulation (Yu W et al., 2020). HQ parameters in the study area were obtained and evaluated through field investigation and evaluation index construction (Liu Het al., 2012). However, the field investigation is time-consuming and labor-intensive, and it is only suitable for small area or specific environmental habitat survey, and it is difficult to carry out long-term dynamic monitoring of HQ changes. With the development of remote sensing technology, many scholars have studied HQ changes by using dynamic analysis method based on multi-phase remote sensing image construction model, such as Habitat Suitability Index Model (HSI) (Yu W et al., 2021; Liu W et al., 2021), Maximum Entropy Model (MaxEnt)(Wang Y et al., 2021), Integrated Valuation of Ecosystem Services and Trade-offs Model(InVEST)(Yang Y; 2021), Social Values for Ecosystem Services Model(SolVES) (Zhang H et al., 2018; Huo S et al., 2018) are applied in HQ assessment studies. Among them, InVEST model has the characteristics of accurate calculation, visualization of results and low application cost, which has been widely used in ecosystem service evaluation studies (Dai L et al., 2019). The habitat quality module in InVEST model, as a powerful tool for HQ assessment, can draw HQ maps combining habitat suitability of species habitats and threats to biodiversity caused by human disturbance (Li, M et al., 2021).

In recent years, although domestic and foreign scholars have carried out a large number of studies on urban HQ evaluation and its influencing factors, and achieved fruitful results, the results varied widely due to different regions, targets and objects. Previous studies mainly focused on the impact of human activities on natural habitats at the watershed scale and administrative scale (Bai L et al., 2019; Chen M et al., 2021; Wu L et al., 2021; Fan X, et al., 2021). However, in urban built-up areas, urban HQ evaluation is more significant in guiding the planning, construction, management and upgrading of urban green infrastructure, as well as the optimization of urban green space landscape patterns. As is known to all, the urban built environment is mainly dominated by impervious surfaces, and all kinds of construction land and artificial landscape have a negative impact on the urban habitat (Xu et al., 2019). Although some scholars have assessed the HQ of built-up areas in some cities, the research results are not universal because the green space types in the study area are mainly artificial green space (Gomes E et al., 2021; Li Y et al., 2022), especially in mountainous urban areas. In karst mountainous cities, there are a large number of URMs in the city and a large number of natural habitats with high quality are preserved. It is of great practical significance to evaluate the HQ of the cities embedded with the URMs for protecting the natural habitat of URMs and guiding the planning and construction of UGS ecosystem. However, there are few reports on HQ assessment in karst mountainous cities.

Land use/land cover (LULC) directly represents the utilization and transformation of natural ecosystems by human activities (Chen W et al., 2021), which is regarded as a key factor of HQ deterioration (Otto et al., 2016). LULC includes changes in proportion, structure and intensity that fundamentally alter the composition and configuration of ecosystems, and ultimately affect energy flow and material cycling between species habitat patches (Xu et al., 2019). Domestic and foreign scholars have carried out a large number of studies on the relationship between LULC and HQ evolution, mainly focusing on the current HQ assessment (Cheng P et al; 2021), future HQ simulation (Gao Z et al., 2021; Chu L et al., 2018) and drivers of HQ evolution (Cheng P et al; 2021). Although there are many researches on the correlation between LULC and HQ evolution at present, they mainly focus on non-karst areas, and relatively few scholars have conducted researches on karst mountainous cities (Jing X and Zhao, 2021). In karst mountainous urban built-up areas, a large number of URMs in urban artificial environment. With the acceleration of urbanization, urban land use types are complex, and a large number of urban remnant mountains (URMs) are eroded by excavation (Ren M et al., 2018), the urban natural habitat has been destroyed. This paper evaluated the HQ of karst mountainous urban built-up area and studied the relationship between HQ evolution and LULC. What impacts of urban LULC, urban development intensity and impervious surface on urban habitat can be analyzed? The research results are of great significance for the theoretical exploration of mountainous urban habitat protection.

Therefore, taking Guiyang, a mountainous city in typical karst region in central

Guizhou, southwest China, as an example, this study used land use transfer matrix and landscape pattern index method to reveal the transition relationship between various land uses and landscape patch evolution process during urbanization in the study area. InVEST model was used to evaluate the HQ in the study area, and GWR was used to reveal the correlation between LULC and HQ evolution. The research objectives are as follows: (1) Analysis of LULC changes and the evolution of landscape patches in the study area from 2008 to 2018. (2) Mapping the spatial distribution of HQ at each study node and the spatio-temporal variation of HQ during the study period. (3) Revealing the correlation between LULC change and HQ evolution. The research results can provide reference value for high quality development, urban planning and management of mountainous cities.

2. Study area

Guiyang (26°11 '- 26°55N, 106°07' - 107° 17'E) is located in central Guizhou Province of China, in the middle of the Yunnan-Guizhou Plateau and in the watershed zone between the Yangtze River and the Pearl River. The landform belongs to the hilly basin area and is mainly composed of karst mountains and hills, the whole terrain is high in the southwest and low in the northeast, with an altitude of about 1100 m. Guiyang belongs to subtropical humid mild climate, the annual mean temperature is 15.3 °C, and the annual mean total precipitation is 1129.5 mm. By the end of 2018, it has jurisdiction over 6 districts, 3 counties and 1 county-level city, with a permanent resident population of 4.8819 million and an urban population of 3.6824 million, with an urbanization rate of 75.43%. The built-up area of the central urban area is 368.68 km^2, and there are 527 Karst remnant mountains in the urban area, with a total area of 44.94 km^2, and 416 small and medium-sized URMs smaller than 10 hm^2. This study takes the central urban area of Guiyang as the study area (Fig. 1).

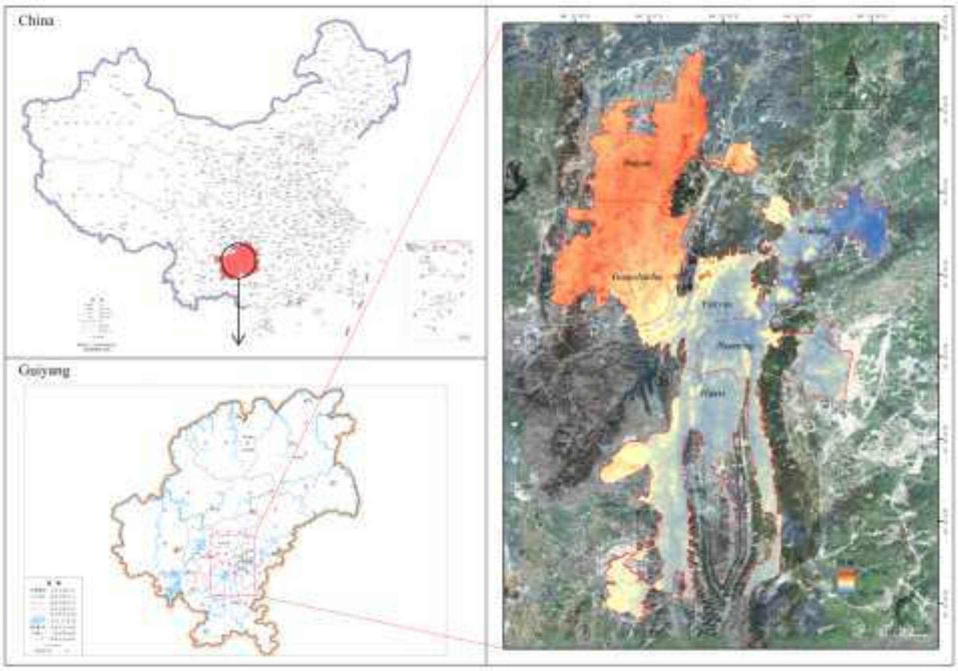

Fig.1. Location and scope of the study area

3. Data sources and research methods

3.1. Data sources and processing

Pleiades satellite high-resolution images of Guiyang built-up area in 2008, 2013 and 2018 (0.5m spatial resolution) were obtained. Taking the boundary of Guiyang city built-up area in 2018 as the research scope, preprocessing such as image enhancement, geometric correction and map projection, According to the *land use classification standard (GB/T 21010-2017)* based on ArcGIS 10.2 software through visual interpretation from one period to the proper land will be divided into land for construction land, traffic land, urban green space (UGS), URMs (natural green space with obvious surface undulation changes), woodland (natural green space with less obvious surface undulation), water, cultivated land, unused land eight types. The spatial attribute database of the study area was established to analyze the LULC change in Guiyang built-up area. The digital elevation model (DEM) were obtained from the official website of Geospatial Data Cloud (http://www.gscloud.cn/). The relevant planning information of the built-up area of Guiyang City, *Guiyang City General Urban Planning (2009-2020)*, *Guiyang City Park City Construction Planning (2015)*, *Guiyang City Mountain Park Planning (2015-2020)*, and *Guiyang City Central District Mountain Protection and Utilization Special Planning (2016-2030)* were obtained from the relevant departments of Guiyang City. Socio-economic statistics were obtained from the Guizhou Provincial Bureau of Statistics, Guiyang City Bureau of Statistics and the official website of the Guiyang Municipal Government.

3.2. Research methods

3.2.1. Landscape Pattern Index Analysis

In this study, the following landscape pattern indexes were selected at the class level and landscape level to test the changes of LULC in the study area. Patch Density (PD), Mean Patch Area (AREA_MN), Largest Patch Index (LPI), Landscape Shape Index (LSI), Area-Weighted Mean Fractal Dimension Index (FRAC_AM), Contagion (CONTAG), Interspersion and Juxtaposition Index (IJI), Aggregation Index (AI) , Shannon's Diversity Index (SHDI), Shannon's Evenness Index (SHEI) at landscape level, and PD, AREA_MN, LPI, LSI, FRAC_AM, IJI and AI at class level. The ecological significance and calculation of the above landscape indicators are shown in Fragstats 4.2 software tutorial.

3.2.2. HQ evaluation of InVEST model

In this study, the habitat quality module of InVEST (V.3.9.0) model was used to evaluate the HQ of the study area in combination with land use suitability and biodiversity information.

Setting of key parameters for HQ evaluation:

(1) Threat source and maximum influence distance. Based on the existing studies and the characteristics of a large number of URMs in the study area, cultivated land, construction land, traffic land and unused land were regarded as threat sources in this paper. Through literature review and expert interviews, the weight of threat factors and their maximum impact distance were determined (Table 1).

(2) The sensitivity of each land use type to each threat source and the habitat suitability provided by each land use type. Sensitivity is mainly set based on the basic theories of ecology and landscape ecology, basic principles of biodiversity conservation, habitat suitability of different land use types and sensitivity to threat factors (Table 2) (Yang Y, 2021; Jing X and Zhao, 2021).

Table 1. Weight assignment and maximum influence distance of threat factors

Threat factor	The maximum influence distance/km	Weight	Decay type
Cultivated land	1	0.7	Linear
Construction land	5	1	Exponential
Traffic land	5	0.5	Linear
Unused land	2	0.4	Linear

Table 2. Sensitivity of different land types to threat factors

Land-use type	Habitat	Threats			
	Suitability	Cultivated land	Construction land	Traffic land	Unused land

Natural rivers	0.8	0.65	0.75	0.7	0.2
Dry land	0.4	0.3	0.5	0.45	0.3
Residential land	0	0	0	0	0
Shrub	0.5	0.5	0.5	0.4	0.5
Reservoir pond	0.4	0.4	0.5	0.5	0.2
Rigid pavement	0	0	0	0	0
Forest	0.9	0.8	0.5	0.5	0.7
Unused land	0	0	0	0	0
Grassland	0.5	0.3	0.7	0.7	0.3

Based on the above parameters and LULC data, the InVEST model finally generates the HQ map. To calculate the HQ, the habitat degradation degree should be calculated first, and the calculation formula is as follows:

$$D_{xj}=\sum_{r=1}^{R}\sum_{y=1}^{Y_r} r_y\left(\frac{\omega}{\sum_{r=1}^{R}\omega_r}\right)\times \mathrm{i}_{rxy}\beta_x S_{jr} \quad (1)$$

$$\mathrm{i}_{\mathrm{rxy}}=1-\left(\frac{d_{xy}}{d_{r\max}}\right)(if\ linear) \quad (2)$$

$$\mathrm{i}_{rxy}=\exp\left(\frac{-2.99d_{xy}}{d_{r\max}}\right)(if\ \exp onential) \quad (3)$$

Where D_{xj} is the habitat degradation degree in the grid x of the habitat type j; R is the number of threat sources; Y_r is the grid number of threat source; ω_r is the weight of threat source r; r_y is the stress value of grid y; i_{rxy} is the stress level of grid y to grid x. β_x is the accessibility of threat source to grid x; S_{jr} is the sensitivity of habitat j to threat source r; d_{xy} is the Euclidean distance between habitat and threat source; $d_{r\,max}$ is the maximum disturbance radius of the threat source r to the habitat

HQ was calculated on the basis of habitat degradation, and the formula was as follows:

$$Q_{xj}=H_j\left[1-\left(\frac{D_{xj}^{z}}{D_{xj}^{z}+k^{z}}\right)\right] \quad (4)$$

Where Q_{xj} is the HQ index in the grid x of the habitat type j; D_{xj} is the habitat degradation degree in the grid x of the habitat type j; H_j is the suitability of different habitat types; k is the semisaturation constant, that is, half of the maximum degree of degradation; z is a normalized constant, generally 2.5.

3.2.3. Spatial auto-correlation analysis

Spatial auto-correlation can analyze the spatial distribution rules of things and study the correlation degree of a certain attribute between the unit in space and surrounding units. It is divided into global spatial auto-correlation and local spatial auto-correlation. In this study, global spatial auto-correlation was used to describe the overall distribution of HQ. The formula is as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{n=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})^2} \quad (5)$$

Where I is the global Moran's index; n is the number of spatial units, x_i and x_j are the observed habitat quality values of region i and j, respectively. w_{ij} is the spatial adjacency relation between regions i and j. The value of I is generally between [-1,1]. Less than 0 means negative correlation in space, greater than 0 means positive correlation in space; 0 means irrelevant random distribution. The closer this value is to 0, the weaker the global correlation between the two variables is. Significance tests are usually performed with Z values, and when $| Zscore | > 1.96$ ($p = 0.05$), it indicates the presence of significant spatial auto-correlation.

3.2.4. Geographically Weighted Regression (GWR) model

This study examined the spatial relationship between LULC and HQ evolution using a GWR model. An adaptive method was used to determine the weights, and the corrected Akaike information criterion (AICC) samples were selected to determine the optimal bandwidth (Wang H et al.; 2019). A 200 m×200 m grid was used to extract HQ and LULC area. With the change of LULC as the explanatory variable and the change of HQ as the dependent variable, the GWR tool of ArcGIS 10.2 platform was used to analyze the correlation. The GWR model is formulated as follows(Cleveland W S，1979)：

$$Y_i = \beta(u_i, v_i)\sum_{k=1}^{p}\beta_k(u_i, v_i)x_{ik} + \varepsilon_i \quad (6)$$

Where (u_i,v_i) is the coordinate of the *ith* sampling point, β_0 is the constant of the model, β_0 is the *k* regression parameter of the *ith* sampling point, ε_i is the residual of the *ith* sampling point, and β is the function of geographical coordinates (u_i,v_i). If independent of geographic coordinates, the above formula is converted into a general linear regression. The parameter estimates for each sampling point are related to the weighted distance matrix constructed from the spatial weight function. The spatial weight is based on the points in a specific region around the fixed point *i*, which reflects the points closely related to the fixed point and represents the degree of correlation. Brunsdon, Fotheringham and Charlton (Brunsdon C et al., 1999) proposed a monotonically decreasing function Gaussian function to represent the relationship between spatial weights and spatial distances, with the following equation:

$$\omega_{ij} = e^{-\left(\frac{d_{ij}}{b}\right)^2} \quad (7)$$

Where ω_{ij} is the spatial weight between sampling point *i* and sampling point *j*, d_{ij} is the distance between the two points, b is the bandwidth, which indicates the non-negative decay parameter between the distance and the weight. The larger the value of b, the slower the weight increases or decreases with distance, and vice versa. When the bandwidth b tends to infinity, the weights of all immobile points are equal to 1. When b is at a certain distance from observation point i, the weights will approach 0.

4. Results

4.1. LULC pattern dynamics

As shown in Fig 2, land use types in built-up areas of Guiyang have changed to varying degrees during 2008-2018, and construction land has always been the main land use type in the study area. From 2008 to 2013, the dominant land use types in the study area were cultivated land, construction land, URMs, and UGS, accounting for 87.99% of the total area in the study area. From 2013 to 2018, traffic land replaced cultivated land as the dominant land use type, indicating the rapid expansion of built-up areas driven by urban road construction in these five years. In addition, cultivated land, URMs and woodland decreased by 94.56 km^2, 8.74 km^2 and 6.8 km^2, respectively. On the contrary, construction land continued to expand (Fig. 3d), with the area proportion increasing from 31.21% in 2008 to 47.89% in 2018 (1.54 times of 2008). The area of UGS increased significantly by 26.26 km^2, while the change of water and woodland area was not obvious.

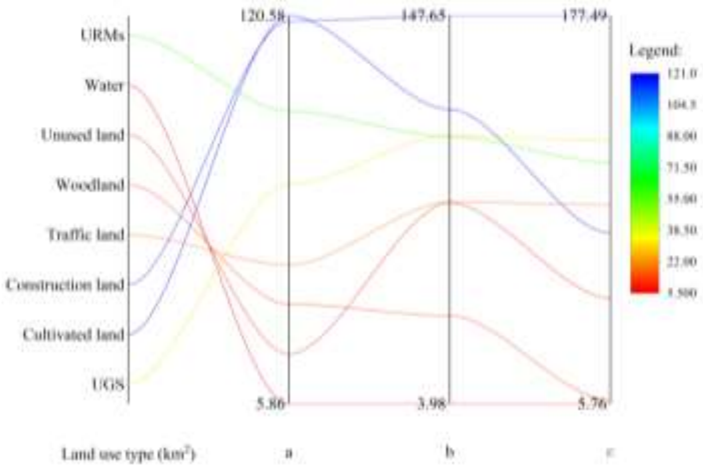

Fig 2. Temporal evolution of land use transfer in the study area (a.2008, b.2013, c.2018)

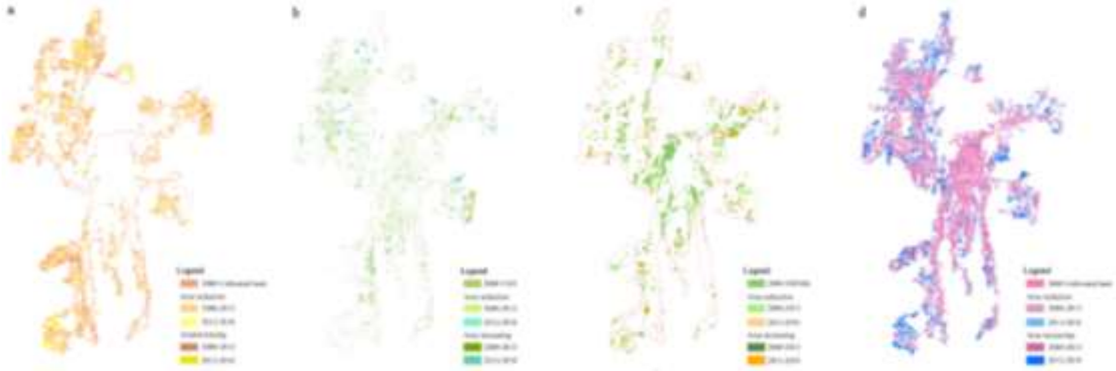

Fig 3. Spatial variation of main land use types from 2008 to 2018 (a. Cultivated land , b. URMs, c. UGS, d. Construction land)

Table 3 exhibited the land use transfer of Guiyang. From 2008 to 2018, cultivated land and URMs conversion to construction land were the main types of land use change. Especially from 2008 to 2013, the changed area accounted for 51.64% of the decreased area of cultivated land. The conversion of cultivated land to construction land is mainly concentrated in Guanshanhu District, Baiyun District, southern Huaxi District and northeastern Wudang District (Fig. 3a). The land converted from URMs to construction land is mainly distributed around the URMs and the rapidly urbanized area of Guanshanhu District and Huaxi District (Fig. 3b). From 2008 to 2018, the URMs was reduced by 8.74 km^2, accounting for 15.24% of the URMs area in 2008. From 2013 to 2018, 3.07 km^2 of cultivated land was converted into woodland, and the area of URMs increased by 0.79 km^2. Through the analysis of relevant policy documents, it was found that the increase of URMs was related to the special *Plan for Mountain Protection and Utilization in Guiyang Central Urban Area (2016-2030)* issued by Guiyang Municipal government. From 2008 to 2018, UGS increased by 26.26 km^2, mainly cultivated land and construction land were transferred, while some UGS was transferred to construction land, with a transfer area of 9.34 km^2 (Fig. 3c). In general, LULC changes rapidly in the study area, urban development is rapid, and there is a great contradiction between human and land in the process of urban expansion. The characteristics of land use change are rapid expansion of construction and traffic land, large area decrease of cultivated land and URMs, and slow increase of UGS.

Table 3. 2008-2018 land use change matrix for built-up areas in Guiyang (km^2)

Time interval	Land use type	UGS	Cultivated land	Construction land	Traffic land	Woodland	Unused land	Water	URMs	Total area
In	UGS	18.18	1.30	9.34	1.48	0.43	0.80	0.15	0.84	32.51
2008-2013	Cultivated land	11.40	51.56	30.40	5.65	3.39	13.47	0.46	4.24	120.58
	Construction land	9.92	2.78	93.69	3.53	0.41	4.16	0.07	1.11	115.67
	Traffic land	1.86	0.32	2.19	12.42	0.05	0.23	0.09	0.13	17.28
	Woodland	1.72	1.62	2.10	0.51	3.11	2.52	0.03	1.13	12.74
	Unused land	1.59	0.34	4.02	1.23	0.02	1.10	0.01	0.32	8.64
	Water	1.38	0.49	0.51	0.15	0.04	0.08	3.13	0.08	5.86
	URMs	2.48	3.30	5.40	1.09	1.58	3.47	0.04	39.99	57.36
	Total area	48.53	61.71	147.65	26.06	9.04	25.84	3.98	47.83	370.64
In	UGS	31.33	1.28	10.59	1.47	0.24	0.98	1.05	1.59	48.53
2013-2018	Cultivated land	8.29	20.50	18.59	3.38	2.00	5.28	0.60	3.07	61.71
	Construction land	8.13	1.96	127.03	4.10	0.43	4.18	0.17	1.66	147.65
	Traffic land	1.77	0.10	2.34	21.54	0.03	0.16	0.01	0.10	26.05
	Woodland	2.32	0.31	1.79	0.33	2.23	0.61	0.01	1.43	9.04
	Unused land	4.93	0.35	14.04	2.10	0.38	2.53	0.37	1.13	25.84

Water	0.17	0.06	0.18	0.06	0.00	0.01	3.49	0.01	3.98
URMs	1.84	1.46	2.93	0.39	0.62	0.91	0.05	39.63	47.83
Total area	58.77	26.02	177.49	33.38	5.94	14.66	5.76	48.62	370.64

4.2. Landscape pattern pattern index change analysis

The changes of landscape indexes at landscape level in the study area from 2008 to 2018 were shown in Fig 4. PD continued to increase, while AREA_MN continued to decrease, indicating that landscape spatial heterogeneity and fragmentation degree increased in the study area. The significant increase of LPI indicates that the influence of maximum patch on landscape pattern was gradually weakened. The rapid increase of LSI after a slow increase indicated that landscape patches gradually became irregular from 2008 to 2018. The FRAC_AM index decreased first and then increased, indicating that the complexity degree of landscape patch shape decreased from 2008 to 2013, but increased from 2013 to 2018, and the intensity of urban construction was great. CONTAG first decreased by 5.42% and then increased by 6.33%, indicating that the landscape patches in the study area experienced spatial segmentation in the initial stage and landscape fragmentation was serious, and the spatial aggregation degree of landscape patches increased in the later stage. The decrease of IJI by 12.56% indicated that the degree of landscape distribution and aggregation gradually weakened. SHDI increased first and then decreased, indicating that LULC type complexity in the study area increased first and then decreased. The change trend of SHEI was similar to that of SHDI. The increase of SHDI from 2008 to 2013 indicated that the diversity, complexity and uniformity of landscape in the study area increased, the difference of landscape type area proportion decreased, and the landscape aggregation increased. The decrease of SHDI from 2013 to 2018 indicated that the diversity, complexity and uniformity of landscape in the study area were weakened, the difference of area proportion of landscape types was increased, and the landscape aggregation was decreased. In general, the diversity, complexity and uniformity of landscape in the study area decreased from 2008 to 2018, while the proportion difference of landscape type area increased, and the spatial heterogeneity of landscape patch increased.

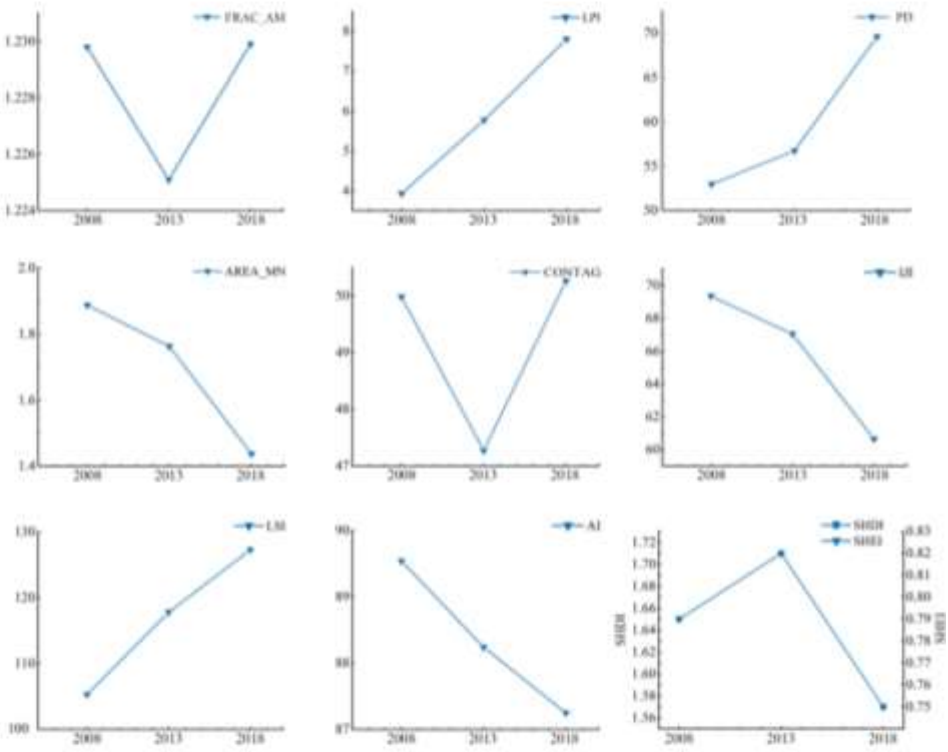

Fig 4. Index change of landscape pattern at landscape level

As for the landscape pattern index at the class level, analyzing a set of indexes can well explain the dynamic change of landscape structure of each urban land use. The change of landscape index at the class level in the study area was shown in Fig 5.

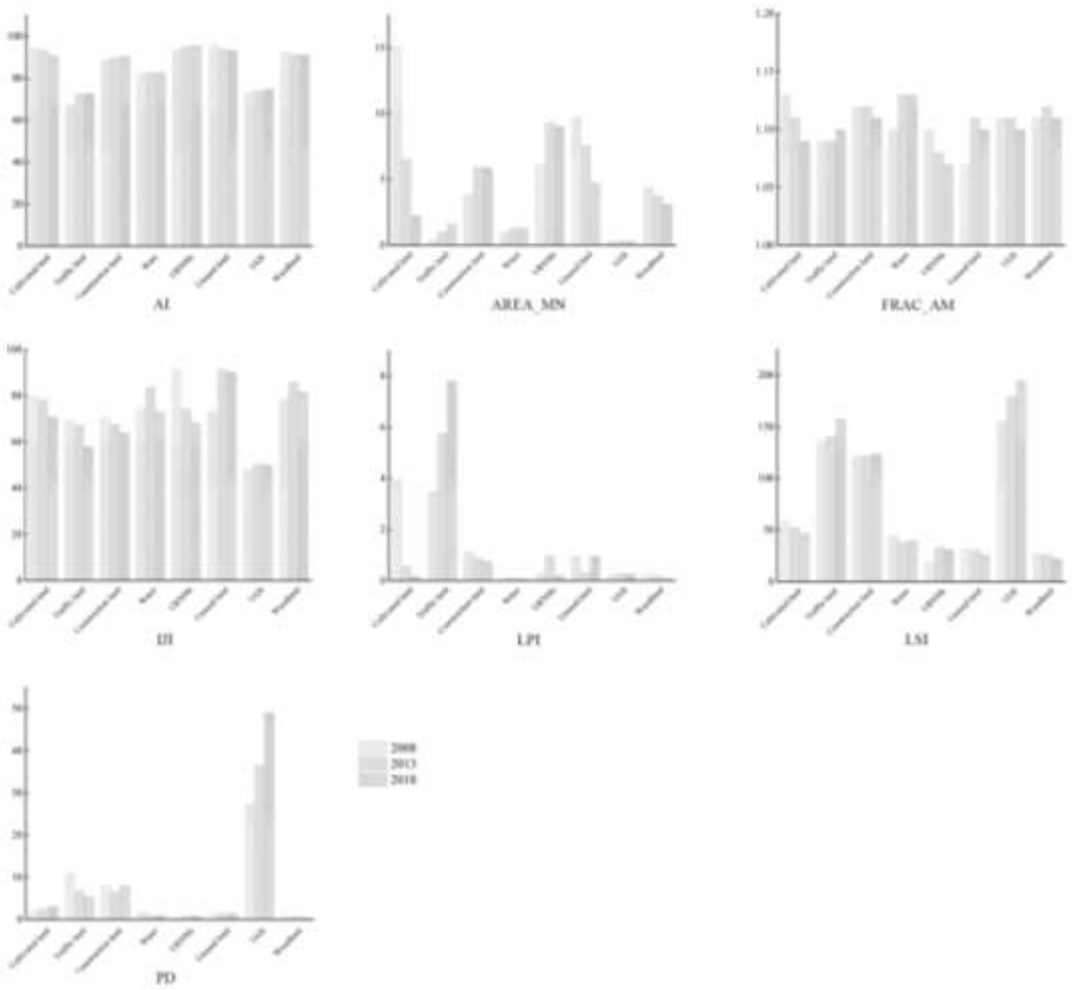

Fig 5. Index change of landscape pattern at class level

(1) The PD of UGS were the largest during the study period, and the PD of unused land and woodland were smaller, indicating a high degree of landscape heterogeneity and fragmentation of UGS patches. Less pronounced changes in the PD of URMs reflecting more stable changes in the landscape patches of URMs during the study period. (2) The decrease in AREA_MN of cultivated land, URMs and woodland indicated that the spatial heterogeneity and fragmentation of these three types of landscape patches decreased. A significant increase in AREA_MN of traffic land, construction land and unused land indicated an increase in spatial heterogeneity and fragmentation of these three types of landscape patches. (3) The decrease of

FRAC_AM in cultivated land, unused land and construction land indicated that the complexity degree of patch boundary shape decreases. (4) According to the change of LPI, cultivated land, traffic land and construction land are the dominant landscapes in the study area. The landscape dominance of traffic land increased, but the landscape dominance of construction land and cultivated land decreased. In addition, the landscape dominance of UGS, woodland and water remained at a relatively stable level. (5) The smallest IJI value of UGS indicated that the adjacency of UGS with other land types was relatively homogeneous and vulnerable to the influence of human activities. The decreasing IJI value of URMs indicated that the adjacency of URMs with other urban land types had increased and the surrounding land types were complex. (6) The AI of traffic land and UGS fluctuated between 67.18% and 74.82%, while the AI of other land types were all at a higher level. This indicated that the connectivity of traffic land and UGS was low compared with other land use types.

4.3. Spacio-temporal evolution patterns of habitat quality from 2008 to 2018

The HQ values calculated by the InVEST model showed a continuous change from 0 to 1. The closer the value was to 1, the better the HQ was and the better it was for maintaining biodiversity. Habitat quality module of InVEST model (V.3.9.0) was used to obtain the spatial distribution of HQ in built-up areas of Guiyang in 2008, 2013 and 2018, as shown in Fig 6. Natural breakpoint method was used to classify the HQ evaluation results of each study node from 2008 to 2018 into five levels: poor (0-0.2), relatively poor (0.3-0.4), moderate (0.5-0.6), relatively good (0.7-0.8) and good (0.9-1.0).

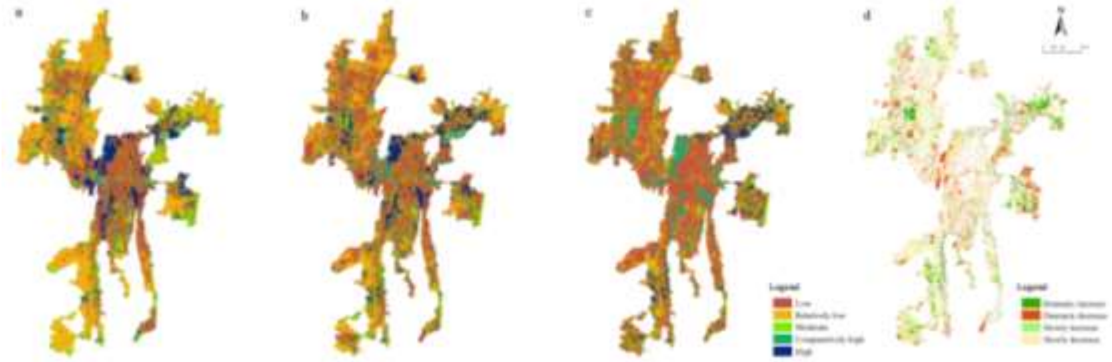

Fig 6. HQ assessment and spatial evolution analysis diagram of InVEST model at different time points in the study area (a. 2008, b. 2013, c. 2018, d. spatial distribution of spatial and temporal changes in HQ from 2008-2018)

4.3.1. Temporal evolution of HQ

As shown in Table 4, the average HQ in the study area from 2008 to 2018 was 0.267, 0.201 and 0.177, showing a gradual decline trend. The HQ of the study area was mainly in the poor and relatively poor classes. The area of moderate horizontal HQ was relatively large. Overall, the quality of habitat in the study area was relatively poor. As can be seen from Fig 6 and Table 4, the HQ in the study area changed dramatically from 2008 to 2018, and the area of poor class HQ increased from 38.29% to 60.32% . In addition, the area proportion of moderate and good classes HQ decreased by 1.95% and 4.15%, respectively. The area proportion of relatively good HQ increased by 3.98%. The areas of poor and relatively good classes HQ increased by 82.72 km^2 and 14.74 km^2, respectively, while the areas of the other three classes continued to decrease. From 2008 to 2013, the areas of poor and relatively poor classes HQ increased significantly, while the areas of other class HQ did not change significantly. The HQ area of all classes changed significantly from 2013 to 2018. Speciallt, the HQ area of poor and relatively poor classes decreased .from 2013 to 2018, while other classes were found to had a inverse trend. The HQ area of relatively good class increased by 4.4%, which was related to the release of URMs protection documents by Guiyang city and the construction of urban parks in 2016.

Table 4. Area and proportion of HQ at different classes in the study area from 2008 to 2018

Habitat quality class	Natural breakpoint method classification interval	2008		2013		2018	
		km^2	%	km^2	%	km^2	%
Poor	0-0.2	141.91	38.29	199.59	53.85	224.69	60.62
Relatively poor	0.2-0.4	124.33	33.54	65.97	17.80	49.46	13.34
Moderate	0.4-0.6	54.38	14.67	58.40	15.76	47.14	12.72
Relatively good	0.6-0.8	17.94	4.84	17.71	4.78	32.68	8.82
Good	0.8-1	32.08	8.65	28.97	7.82	16.67	4.50
Highest habitat quality		0.895		0.878		0.869	
Average habitat quality		0.267		0.201		0.177	

4.3.2. Spatial pattern changes of HQ

Fig 6 described that the spatial aggregation effect of HQ in the study area was significant and the distribution range of HQ had a certain edge effect. High class HQ areas are mainly concentrated at high elevations and in areas with low building density, with the areas where URMs and woodlands are located being the main areas of concentration. High vegetation coverage and relatively high altitude lead to low human disturbance in these areas, resulting in relatively good HQ. The areas of moderate horizontal HQ were mainly concentrated in Huaxi district, Nanming District and Wudang District, and most of the land use types were mainly UGS covered by grassland and isolated mountains surrounded by construction land, with obvious random distribution. The poor class HQ area was dominated by the old city area, which was mainly concentrated in the land use aggregation areas such as construction and traffic land, and showed a strong spatial aggregation effect in the spatial distribution. It could be seen that the urban densification process and urban road construction have greatly exacerbated the degradation and loss of urban HQ.

In this study, Global Moran Index (GMI) and hot spot analysis were used to investigate the horizontal spatial aggregation effect and distribution characteristics of HQ. The GMI of 2008, 2013 and 2018 were 0.476, 0.431 and 0.425, respectively (P = 0 and $Z \geq 2.58$), indicating that the HQ in the study area had a significant spatial agglomeration effect from 2008 to 2018. The GMI decreased to some extent during the study period, indicating that the spatial aggregation effect of HQ in the study area gradually diminished.

Fig 7. Hot spot analysis of HQ (red is hot spot area, blue is cold spot area, yellow is not significant area; a. 2008, b. 2013, c. 2018)

Fig. 7 showed that the spatial aggregation effect of HQ in the study area was obvious, and the spatial distribution and aggregation effect of cold hot spots of HQ in the study area was obvious. The hot spots were mainly concentrated in the areas with high coverage by tree irrigation and relatively high altitude, while the cold spots were mainly distributed in the high-density construction areas with strong human disturbance. The insignificant area is mainly located in the area where the cultivated land around the built-up area is located. In 2008, the insignificant area of Huaxi

District and Baiyun District accounted for a relatively large area, while other areas were relatively small. In 2018, the distribution area of cold and hot spots changed drastically, in which Wudang District and Huaxi District were dominated by an increase in hot spot areas, while Baiyun District was dominated by an increase in cold spot areas. According to the analysis of Guiyang planning documents, the increase of HQ hot spots in Wudang and Huaxi districts was closely related to the return of cultivated land to woodland, the construction of urban parks and the protection of URMs. The increase of cold spots in Baiyun District was due to the fact that this area was an industrial area with a large number of factories. The HQ of Guanshanhu Park, Shilihetan Wetland Park, Qianlingshan Park, Xintian Park, Guiyang Forest Park, Guiyang Medicinal Botanical Garden and other urban park areas was relatively stable, and remained in hot spots during the study period. This is another way of showing that the construction of large urban parks can improve the level of urban habitat quality.

4.4. Relationship between HQ evolution and land use change

Table 5. GWR model parameter estimation and test results

Year	Bandwidth	Residual Squares	Effective Number	Sigma	AICc	R^2	R^2 Adjusted
2008-2018	391.531701	290275156346.7486	2336.430446	5962.635855	213633.960336	0.829036	0.780133

As shown in Table 5, R^2 was 0.829 before adjustment and 0.780 after adjustment, which was at a high level, indicating that GWR model was well fitted. The results showed that the land use change of UGS was positively correlated with the evolution of HQ, and the area with positive regression coefficient accounted for about 70% (Fig 8). Which was right in the regression coefficient of area mainly concentrated in the area of rapid urbanization, land use in urban construction land, cultivated land and URMs land use types into UGS is given priority to, a larger area of regression coefficient is negative, has distribution in the whole study area, mainly for UGS into land for construction and traffic land. The areas with positive regression coefficient were mainly concentrated in Guanshan Lake District, Huaxi District and Wudang District. Combined with LULC changes, it can be found that from 2008 to 2018, a large number of URMs were transformed into urban mountain parks, and some URMs were converted to woodland, indicating that parkerization of URMs had a low impact on HQ. The areas with negative regression coefficient are mainly Yunyan District, Nanming District and Baiyun District. During the study period, yunyan District and Nanming District mainly convert URMs into urban residential land and traffic land, while Baiyun District mainly converts URMs into industrial buildings.

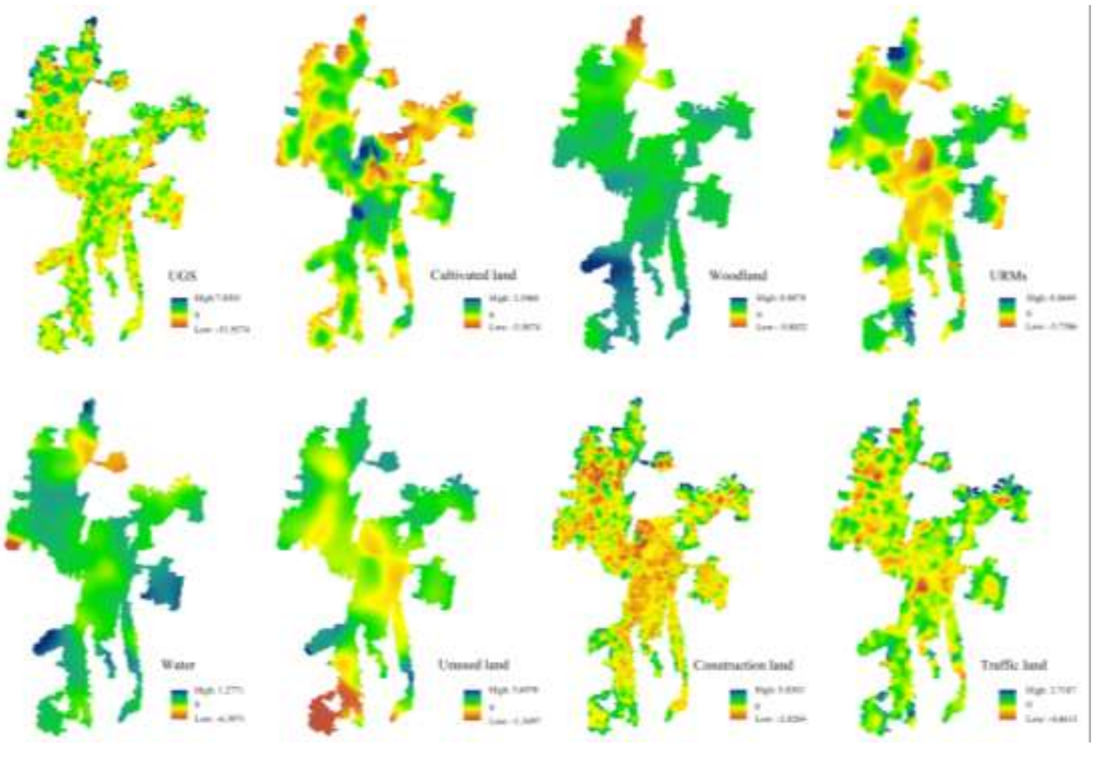

Fig 8. Spatial distribution of GWR regression coefficients of LULC and HQ evolution

Land use changes in woodland and cultivated land were positively correlated with HQ changes from 2008-2018. Guiyang city has a special location, containing a large number of URMs within the city and a relatively small proportion of relatively flat woodland area, so the relationship between woodland land use change and HQ evolution is not as significant as other land use types. The negatively correlated areas are mainly in Guanshan Lake, the southern part of Yunyan District and Wudang District, and the LULC changes show the conversion of woodland to construction land, traffic land and unused land. The positive correlation between the change of cultivated land LULC and the change of HQ is that the cultivated land is converted to woodland or the cultivated land is converted to the URMs. The area with negative correlation coefficient has obvious spatial aggregation effect, which is mainly concentrated in the area where cultivated land is converted into construction and traffic land. The LULC of water and unused land was positively correlated with the change of HQ, and only a few areas were negatively correlated. The conversion of water to UGS is positively correlated with the change of HQ, while the conversion of water to construction land and traffic land is negatively correlated. The positive correlation between land use change of unused land and HQ change is mainly distributed in the periphery of the study area, and the unused land is mainly converted into UGS. The negative correlation is concentrated in the south of Huaxi District and the central old city, and the unused land is mainly converted into construction land. In the southern part of Huaxi district, due to the construction of university town, the unused land is extremely negatively correlated with the change of HQ. The LULC of construction and traffic land was negatively correlated with the change of HQ. The negative correlation coefficient is concentrated in old urban areas and rapidly urbanized areas. Meanwhile, the land type is mainly converted from URMs, UGS and cultivated land to construction and traffic land. The positive correlation was distributed at the urban boundary, and the construction and traffic land were mainly converted into UGS.

5. Discussion

5.1. Urban LULC has spatially heterogeneous characteristics on urban HQ impacts

The spatial pattern distribution of HQ reflects that human activities and natural factors are important factors affecting the spatial distribution of HQ, which is consistent with the research results of Yohannes et al. (Yohannes H et al., 2021).. The increase in the area of land use types with low habitat suitability, such as construction land, traffic land, unused land, and cultivated land, has a negative effect on the evolution of habitat HQ. The increase in the area of URMs and UGS, water, woodlands with high habitat suitability has a positive effect on the evolution of HQ, which is similar to other scholars studies in the Taihang Mountains of Hebei, Changchun, Jilin, and the Pearl River Delta. Guiyang city is located in the central Guizhou karst area, and the URMs resources left in the built-up area are rich. With the urbanization process, a typical unique regional landform of "city in the mountains, mountains in the city" has been formed (Tang N and Wang Z, 2021), compared with other regions, urban LULC is more complex and landscape patch spatial heterogeneity is higher (Ren M et al., 2018). The unique geographical environment makes the construction land scattered in the process of urban development. From 2008 to 2018, construction land area in downtown Guiyang gradually increased, presenting a "spreading" pattern of flooding expansion, and construction land encroached cultivated land and URMs in the way of infiltration. The impact of the continuous expansion of construction land on the changes of HQ is mainly reflected in the substantial reduction of habitat area and spatial fragmentation of species, which leads to serious landscape fragmentation and reduced landscape connectivity (Li W et al., 2021).

There was obvious spatial heterogeneity in the HQ of the study area. The high level HQ area was mainly distributed in the high-density gathering area of trees and shrubs, while the low level HQ area was mainly distributed in the construction and traffic area, which was similar to the research results of Xie, Bai and other scholars in other cities. (Xie Y et al., 2018; Bai L et al., 2019). The natural ecological conditions and HQ are better in the areas with higher vegetation coverage rate of URMs and UGS. With the acceleration of urbanization, economic development and population increase, the contradiction between man and land has become increasingly prominent. Urban expansion has changed the land use types of original species habitats and formed new threat sources. The surrounding habitats of species have been squeezed and divided, leading to a continuous decline in the quality of regional habitats (Ding Q et al., 2021). Therefore, at the same time of rapid economic development, we should strictly control the blind expansion of construction land and improve the distribution of urban landscape pattern (Tang Y et al. 2020).

5.2. URMs has a high contribution to the improvement of urban HQ

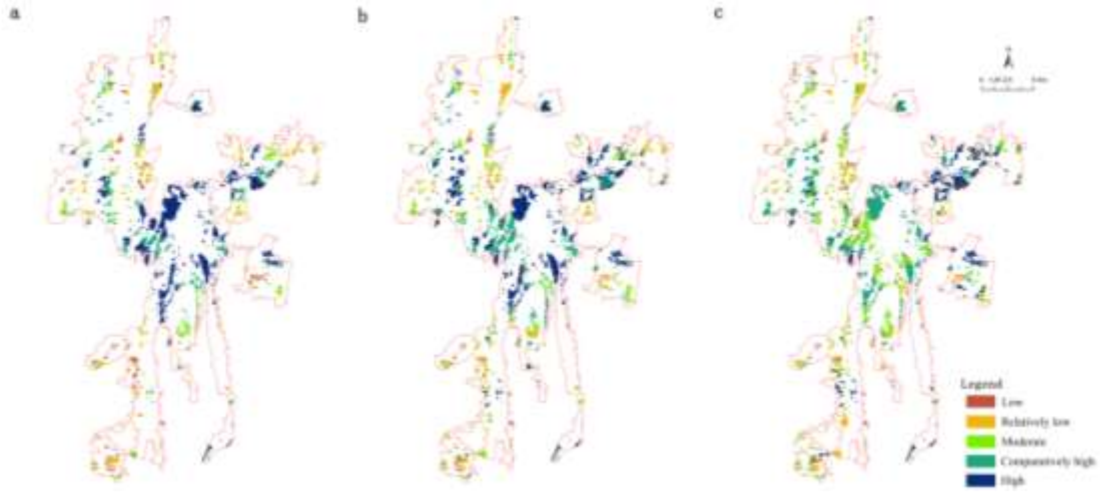

Fig 9. Temporal and spatial evolution of HQ of URMs (a. 2008, b. 2013, c. 2018)

The karst region in south China, centered on Guizhou Plateau, is the most typical, complex and abundant karst landscape type in the world, as well as the largest and most concentrated ecologically fragile region (Wang S et al., 2015). With the expansion of cities, a large number of natural mountains exist in the artificial environment of built-up areas in the form of solitary peaks or clusters of peaks, forming islands or island-like natural and semi-natural remaining habitats (Tang N and Wang Z, 2021). Different from other artificial natural environments in cities, urban natural mountains have rich vegetation resources and unique characteristic forms (Xiang X et al., 2021).Most of the areas with high HQ in the study area are the areas where the URMs are located. With the impact of LULC change in the study area, With the impact of land use change in the study area, URMs HQ is degraded, but it is generally at a good level. Meanwhile, URMs HQ has a certain edge effect (Fig 11). Meanwhile, the URMs HQ of urban remains has a certain medge effect (Fig. 11), which indicates that the change of urban environment around the URMs has a great impact on the quality of URMs.

As an important basic data for HQ assessment, scholars found that the response relationship between plant diversity and urban spatial morphology of URMs mostly started at the 400 m scale, and the significance was mainly at the 600 m scale (Kong N and Wang Z, 2021). Tang Na et al. found that the difference between the plant diversity of URMs in the natural state and the plant diversity of URMs in parkland use was not too great, but the URMs were severely faulted in community structure under the combined effect of internal ecological harshness and external urban substrate disturbance (Tang N and Wang Z, 2021). Other scholars have found that URMs can provide a variety of ecosystem services, especially in alleviating urban heat island effect, purifying urban water environment and maintaining urban biodiversity (Yu D et al., 2013; Brunbjerg A K et al., 2018; Chen X et al., 2021; Zhou H et al., 2021). With the rapid development of urbanization, large areas of URMs are reduced. Although relevant policy makers issued relevant protection policies for URMs in 2016, the protection of URMs is not only a landscape type. It is necessary to improve the anti-interference ability of URMs by arranging artificial green patches reasonably at a reasonable location away from the URMs, so as to improve the HQ of URMs and provide ecological guarantee for the high-quality development of the city.

5.3. Limitations and Prospects

Considering the limitations of the study data and the accuracy of the model measurements, there are some shortcomings in this study that need further improvement: (1) InVEST model evaluation requires many parameters, and the uncertainty of parameter input will affect the model evaluation results. Since InVEST model has no accurate parameter setting and standard calculation method, relevant parameters used in this study are set according to InVEST model operation manual, relevant literature and expert experience. Too subjective parameter setting may lead to deviation of model evaluation results. (2) Spatial heterogeneity is a comprehensive reflection of landscape patch space patchiness and spatial gradient, which is overly dependent on the choice of spatial scale. 200m×200m grid was used for extraction analysis in this study, and the scale size is subject to further discussion. Although the InVEST model has some limitations, it can calculate and map HQ by using LULC change data and setting relevant parameters, which provides a scientific basis to guide the creation of ecological environment. Besides InVEST model integrates a variety of ecosystem service evaluation models, besides HQ module, such as carbon storage and soil and water conservation can be used to analyze the future changes of integrated ecosystem service function in Guiyang city, which provides theoretical support for urban ecological security protection (He F et al., 2021).

6. Conclusion

This study is the first to study the spatial-temporal relationship between LULC and HQ in karst mountainous city Guiyang, Guizhou Province, China. The results of the study showed that: (1) The land use transfer in the study area is complex, which is mainly manifested by the decrease of cultivated land and URMs, and the increase of construction land, traffic land and UGS. The landscape pattern of different land use types shows different trends. (2) The spatial distribution of HQ was similar to that of land use type. The average HQ was 0.267, 0.201 and 0177 in the study area, respectively, and the URMs and large UGS had higher HQ. (3) The change of HQ was significantly correlated with the change of LULC, and the change of land use type such as URMs, UGS and woodland was positively correlated with the change of HQ, while the change of land use type such as construction and traffic land was negatively correlated with the change of HQ. The results will provide scientific basis for the spatial planning and habitat protection of mountainous cities.

Author contribution

Wenfei Wei: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Writing - original draft. Xintong Chen: Investigation, Validation, Visualization, Formal analysis, Writing - review & editing. Yu Bao: Supervision. Yuzhen Sun, Mulin Zeng and Yaguo Mo: Resources. Zhitai Wang: Resources, Funding acquisition, Supervision, Writing - review & editing.

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Data availability

The acquisition, processing and writing of data and materials in this paper were conducted in accordance with the author's guidelines and did not pose any threat to personal or national security.

Declaration of interests

Ethics approval: All authors have read and approve this version of the article, and due care has been taken to ensure the integrity of the work. No part of this paper has published or submitted elsewhere.

Consent for publication: All authors have read and consented to the article being submitted or published in the journal.

Conflicts of interest: The authors have no conficts of interest to declare that are relevant to the content of this article.

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