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Habitat Quality Analysis and Future Simulation Based on Artificial Neural Network-cellular Automata Model

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As the economic center of western China, the Chengdu Chongqing Economic Zone holds a unique and important strategic position for China's overall development. However, rapid economic growth in the region in recent years has led to an increase in the number of urban areas that threaten the preservation of local ecosystems. Therefore, it is crucial that long-term analyses and projections of habitat quality conditions in the region are conducted to ensure sustainable development, and the habitat quality index provides a valuable measure of the ecosystem health of a region. In this study, we utilized land use/land cover data of 2000–2020 to predict land use cover in the study area in 2040. A natural development scenario, a cultivated land security scenario, and an ecological priority development scenario were simulated, and the results were subsequently explored. Future land use projections were based on the artificial neural network-cellular automata model, and habitat quality details were calculated using the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model. These methods allowed for an evaluation of the evolution of the Chengdu Chongqing Economic Zone over the past 20 years as well as predictions about the course of its development and habitat quality over the next 20 years. The results revealed the following: (1) The Chengdu Chongqing Economic Zone is mainly composed of cultivated land and forest land, followed by urban land and grassland. Between 2000 and 2020, there was a significant increase in the number of urban areas and a continuous decrease in cultivated land. On the basis of simulations and analyses of different scenarios, urban land areas are projected to increase between now and 2040. (2) In 2000, 2010, and 2020, the average habitat quality indices of the Chengdu Chongqing Economic Zone were 0.6494, 0.6432, and 0.6336, respectively, indicating good habitat quality, but one that is in decline, particularly in the urban areas of Chengdu and Chongqing. Spatial analysis revealed a pattern in which the habitat quality may be described as "high at the periphery, low in the center." Our findings showed that over the next 20 years, the best potential for a high-quality regional habitat depends on a scenario in which ecological protection is emphasized. In 2000,

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2010, and 2020, the average habitat degradation indices were 0.0935, 0.0938, and 0.0949, respectively, indicating an increasing threat to the region's habitat. This conclusion will be beneficial to the future urban spatial planning of the area: the government should prevent the disorderly expansion of cities and maintain the biodiversity of the Chengdu Chongqing Economic Zone. The analyses and evaluation methods used in this study can also serve as a valuable reference for other regions seeking to improve their habitat quality and land use.

1. Introduction

Land is the foundation and carrier of various ecosystems. The main purpose of land use/land cover (LULC) change research is to investigate the impact of human activities on the natural environment and how this impact can be further fed back into the development of human society and economy. These changes can cause ecological effects, such as changes in biodiversity, ecosystem functions, and ecological environment.(1) Habitat quality indicates the quality of the environmental conditions that determine the survival and reproductive capacity of organisms. The quality of a habitat directly affects the survival and reproduction of organisms and is a vital factor in maintaining ecological balance and biodiversity.(2,3) The degree of habitat quality, therefore, ultimately determines an ecosystem's potential for sustainable development. Currently, accelerating global urbanization poses significant threats to the quality of many habitats. Hence, it is essential to assess changes in how land is used, identify developmental trends, and explore the patterns and drivers that cause changes to habitat quality. These endeavors are critical if sustainable land development is to be achieved in the long term.

Habitat quality not only reflects regional biodiversity and ecological conditions, but also represents the quality of human production and living conditions. In recent years, population growth and rapid socioeconomic development have led to an increasing demand for land and natural resources, resulting in their overexploitation.(4) Changes in land use patterns and intensity have severely damaged ecosystems, which have also led to a decline in the value of these natural resources. Research on the evolution of habitat quality plays an important role in formulating effective land and environmental protection policies.(5)

Theories and analyses of LULC change have continued to advance, and research has been accelerated by the implementation of new technologies, such as geographic information systems.(6,7) These tools have allowed for the evaluation of land use change features at various scales, including analyses of land use based on landscape patterns and comprehensive analyses of land use changes on a national level. Moreover, these resources have elucidated many of the characteristics and driving forces behind land use changes. For example, geographic detectors have been employed to assess the impact of factors such as precipitation, while Normalized Difference Vegetation Index (NDVI) has been used to explore watershed ecology.(8) Additionally, data on historical changes can be used to simulate future LULC scenarios using cellular automata, the Future Land Use Simulation (FLUS) model, and the Cellular Automata (CA) Markov model, which predict future urban morphology.(9) Furthermore, new statistical methods are continuously being integrated into land change analysis.(10) The application of these innovative technologies and methodologies has significantly advanced the field of LULC research.

LULC is the main factor causing changes in habitat quality, leading several scholars to conduct increasingly in-depth research in this area. Methods such as landscape pattern analysis allow researchers to better assess the characteristics of a habitat and focus on how habitat quality affects animals and plants(11) as well as special ecosystems.(12) The impact of human activities on habitat quality must include the consideration of the value of ecosystem functions and ecological security. Mathematical and statistical methods can be combined to analyze changes in biomimetic lens quality,(13) and quantitative research based on ecological indicators can be used to analyze the changes in biomass caused by land use changes.(14,15) One quantitative method, known as the Integrated Valuation of Ecosystem Servicer and Trades (InVEST) model, can more accurately reflect changes in land patch use levels compared with other models. It combines the information and driving factors of LULC change to analyze the quality of ecological mirrors in specific regions.

The Chengdu Chongqing Economic Zone(16) serves as the economic hub of western China. However, in recent years, rapid economic development and substantial urban expansion in the region have highlighted the conflicts that arise when ecological land is confronted with transformation into urban areas. Therefore, conducting long-term analyses and simulating future outcomes are vital for promoting green, sustainable development and ensuring habitat quality. In this study, we investigated LULC changes in the Chengdu Chongqing Economic Zone over the past 20 years and analyzed the features of the region's habitat quality during its evolution from 2000 to 2020. Using analyses from the artificial neural network-cellular automata (ANN-CA) and InVEST models, we then predicted the changes and new trends in LULC and habitat quality, which are expected to occur by 2040 under a natural development scenario (NDS), a cultivated land security scenario (CLSS), and an ecological priority development scenario (EPDS). The purpose of analyzing changes in the ecological environment is to help the government determine the potential and limitations of economic development and formulate appropriate policies and plans to achieve the sustainable development of the economy and ecological environment.

2. Materials and Methods

2.1 Study area

The Chengdu Chongqing Economic Zone (Fig. 1) is situated in the upper reaches of the Yangtze River and the Sichuan Basin and encompasses 15 cities in Sichuan Province, including Chengdu, Meishan, and Suining, as well as 29 districts and counties in Chongqing, including Fuling. The total area of the Chengdu Chongqing Economic Zone is approximately 185000 km^2, and it holds an important position in western China owing to its sizable population, rate of urban development, and industrial activities. Having witnessed rapid economic growth, the cities within the region have expanded significantly, resulting in swift changes in urban LULC, which have led to the need for the in-depth analysis of the evolving trends in habitat quality.(17)

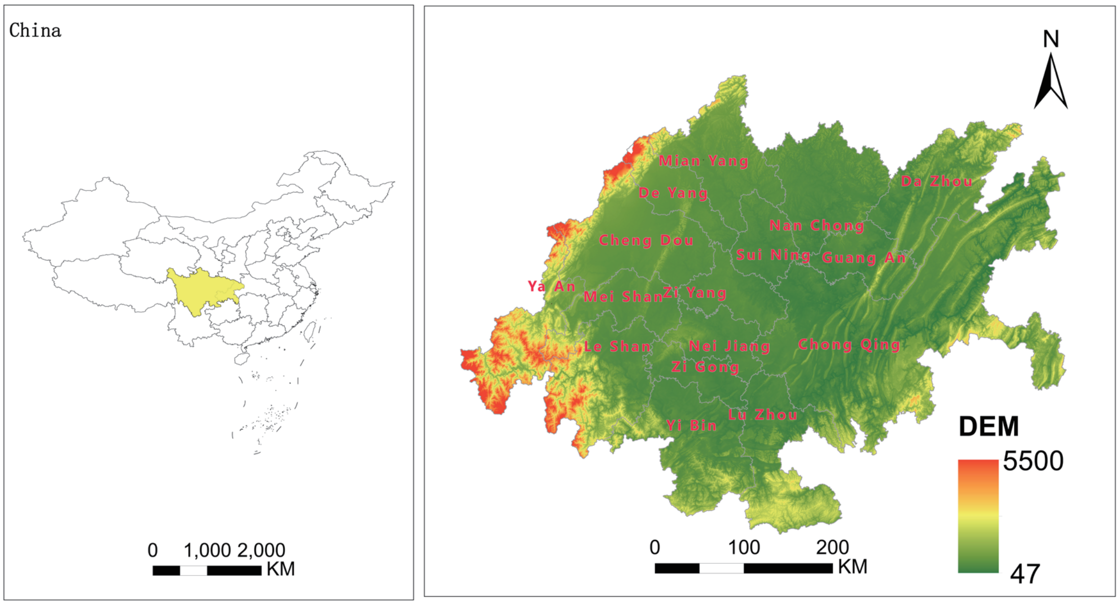

Fig. 1. (Color online) Location and topography of Chengdu Chongqing Economic Zone.

2.2 Data sources

LULC data for the years 2000, 2010, and 2020 were selected for the research. The research data have been reclassified into six categories:[18] forest land, cultivated land, grassland, water area, urban area, and bare area. To analyze the factors driving LULC changes, eight natural, social, and economic aspects were decided upon to represent the variables that primarily affect urban expansion, and these were chosen in accordance with prior research.[19] The natural factors included variables such as digital elevation model (DEM) data and terrain slope, while economic and demographic variables included measures such as population density and GDP. The human impact variable, which represents human proximity to cities, roads, railway networks, and water bodies, was also considered, as this potential interference inevitably affects the development of urban land (Table 1). All data were projected using the Albers Equal Area Conic projection.

2.3. Research framework

The total study area is approximately 184860 km^2, with a spatial resolution of 300 × 300 m^2. In this study, we employed the ANN-CA model and a habitat quality model to analyze and evaluate land change and habitat quality from 2000 to 2020. Three future scenarios of habitat quality, namely, NDS, CLSS, and EPDS, were analyzed and simulated using data from 2000 to 2020.

First, LULC data from the year 2000, namely, road network information, DEM, and other data, were used to generate probability maps of different land use types. These data were then

Table 1
Dataset description and sources.

Data type	Variable	Data interpretation and data unit	Data source
Natural factors	Elevation	Elevation in m	GLSDEM (www.gscloud.cn/)
	Slope	Slope in degrees	GLSDEM
	Distance to river	Euclidean distance to river in m	OSM (https://www.openstreetmap.org.)
Geographical factors	Distance to city center	Euclidean distance to city center in m	OSM
	Distance to road	Euclidean distance to road network in m	OSM
	Distance to railway	Euclidean distance to railway in m	OSM
Human activity factors	Gross domestic product	Spatial distribution of GDP at a resolution of 1 km^2. Unit: 10000 RMB/km^2	RESD (www.resdc.cn)
	LULC	Land cover map with a spatial resolution of 300 m	CRDP (https://cds.climate.copernicus.eu)
	Population	Spatial distribution of population at a resolution of 3 arc	Worldpop (www.worldpop.org)

used to simulate LULC in 2020. The simulation results were compared with actual LULC data to determine the accuracy of the model. When training the model based on the ANN-CA method, it should to repeatedly fit the model parameters to achieve the highest simulation effect. The final scheme is to train the network with a sampling ratio of 5%, 300 iterations, and 5 × 5 neighborhood. Second, the model was again employed to simulate and predict LULC in 2040 according to the three scenarios. Finally, the results of the habitat quality index (HQI) and habitat degradation index (HDI) from 2000 to 2040 were calculated using the InVEST model. The overall process is shown in Fig. 2.

2.4 Methods

2.4.1 ANN-CA model

The ANN-CA model is a grid-driven model with discrete temporal and spatial characteristics that can capture local spatial interactions and temporal–causal relationships. It allows us to achieve detailed simulations of the evolution of complex systems. In addition, it includes a probability calculation module based on neural networks and a cellular automata module based on adaptive inertia models. The probability calculation module was used to perform data sampling and neural network training on the spatial distribution of the driving factors to calculate the grid suitability probabilities of different land types. The cellular automata module then utilized the results of these calculations to determine the total conversion probabilities of each grid within a specified time. At the same time, the model was able to incorporate iterative simulations, including parameter settings for future land prediction, neighborhood factor debugging, and model verification. The iteration process continued until the specified time or future quantity target was reached, at which point the iteration was stopped, and the spatial characteristics of each land category were simulated. The relevant parameters and specific settings were as follows.

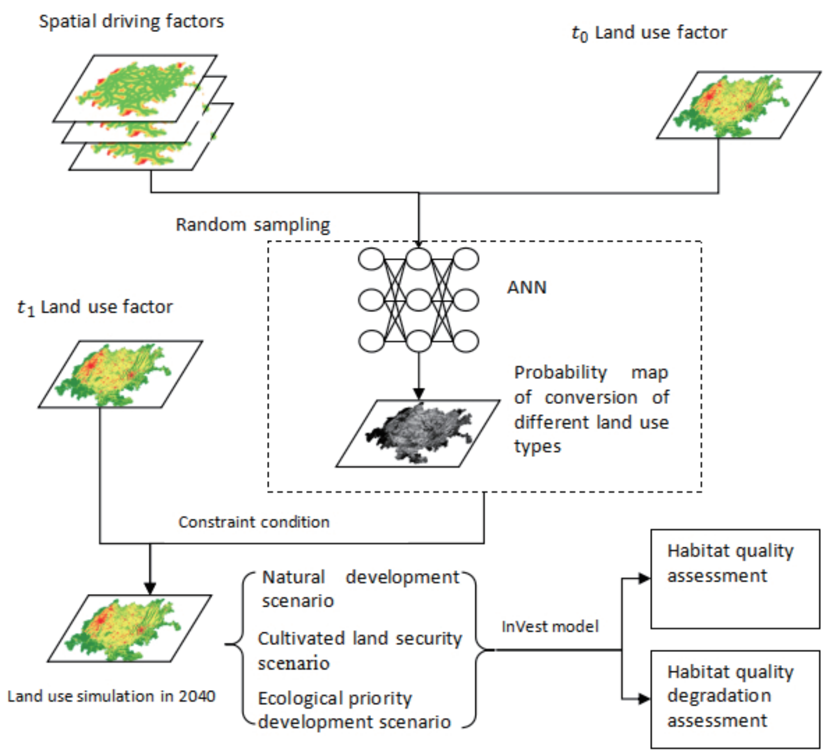

Fig. 2. (Color online) Flow chart for analysis of urban mirror quality and multiscenario simulation based on ANN-CA model.

$$p(k,t,l) = RA \times \sum_j W_{j,l} \frac{1}{1+e^{-net_j(k,t)}} = \left[1+(-\ln\gamma)^a\right] \times \sum_j W_{j,l} \frac{1}{1+e^{-net_j(k,t)}} \tag{1}$$

Here, $p(k, t, l)$ is the conversion probability of grid cell k from the current category to the l category at simulation time t; RA is a random number; γ is a random number greater than 0 and less than 1; a is a parameter that limits random variables; $W_{j,l}$ is the number of weights between two layers; $net_j(k, t)$ is the signal received by the jth neuron in the hidden layer. During each cycle calculation, the conversion probabilities of different types of LULC are calculated using neural networks. Finally, the land use type was determined according to the maximum value among these conversion probabilities.

The simulation accuracy of the ANN-CA coupling model is mainly tested using the Kappa coefficient. The Kappa coefficient is mainly used to verify the consistency between data. This coefficient is usually between 0 and 1. Its value can be divided into five groups to represent different levels of consistency: 0.0–0.20 for slight consistency, 0.20–0.40 for fair consistency, 0.40–0.60 for moderate consistency, 0.60–0.80 for high consistency, and 0.80–1 for almost perfect consistency.

$$\text{Kappa}=\frac{P_0-P_e}{1-P_e} \tag{2}$$

$$P_0=\frac{n_1}{n},\ P_e=\frac{1}{N}. \tag{3}$$

Here, n is the total number of grids; N_1 is the number of grids that simulate consistency; N is the number of land use types. In this study, N = 6. P_0 represents the proportion of simulated consistent grid numbers. P_e is the reciprocal of the number of land types.

2.4.2 Habitat quality model

HQI refers to the level of living environment conditions provided by ecosystems for the survival of individuals and populations. Higher habitat quality is associated with greater stability in the ecological structure and function of the habitat patch.[20] In this model, it was represented as a continuous value ranging from 0 to 1. The closer the HQI is to 1, the higher the habitat quality. It is affected by the manner and intensity of human LULC with increased intensity typically resulting in a decrease in habitat quality. The habitat quality was evaluated using Eqs. 4–6.

$$D_{xj}=\sum_{r=1}^{R}\sum_{y=1}^{Y_r}\left(\frac{W_r}{\sum_{r=1}^{R}W_r}\right)r_y i_{rxy}\beta_x S_{jr} \tag{4}$$

$$i_{rxy}=1-\frac{d_{xy}}{d_{rmax}} \tag{5}$$

Here, D_{xj} is the HDI of grid unit x in type j; R is the number of threat factors; W_r is the weight; Y_r is the number of grids that pose a threat; r_y is the number of threat factors; i_{rxy} is the threat degree of the risk factor to the habitat; β_x is the accessibility of threat factors; S_{jr} is the sensitivity coefficient of j-type habitats to threat factors; d_{xy} is the distance between two grid cells (x, y); d_{rmax} is the maximum effect distance of the factors.

$$Q_{xj}=H_j\left(1-\frac{D_{xj}^z}{D_{xj}^z+K^z}\right) \tag{6}$$

Here, Q_{xj} is the HQI of habitat type j at grid unit x, with a value range of [0, 1] (The higher the index value, the higher the ecological environment quality); H_j is the habitat suitability coefficient[20] for habitat type j; K is a semi-saturated parameter (usually 0.5); D_{xj}^z is the HDI of grid unit x in habitat type j; z is the default parameter of the model.

In this study, cultivated land and urban areas were determined to be habitat threat factors due to their intense human activity. Moreover, the degree of the threat posed by these factors decreases as the distance from the habitat increases. To model the threat from cultivated land, a linear attenuation model was adopted, while for urban areas, an exponential attenuation model was used.

2.4.3 Scenario simulation

For the simulation, three different conversion cost matrices based on three development scenarios were designed (Table 2).[21] In the NDS, the future land change rate was assumed to be consistent with the changes that occurred from 2000 to 2020. A linear model was utilized to simulate future land demand, and all land types were treated as interchangeable under these conditions. In the CLSS, the primary objective was to protect essential farmland. Therefore, the conversion of farmland to other land types was strictly prohibited, particularly in cases where it would otherwise be converted into an urban area. According to the EPDS, the ecological benefits of various types of land were prioritized as follows: forest land > water area > grassland > cultivated land > urban area > bare area. A conversion principle prohibited the transition from high- to low-ranked land types. The conversion rules are shown in Table 2.

Additional information regarding the specific scenarios is as follows:

(1) Under the NDS conditions, the LULC in the Chengdu Chongqing Urban Zone in 2040 was predicted on the basis of LULC trends between 2000 and 2020. In this scenario, it was assumed that each land type was not affected by external factors and continued to follow a linear trajectory consistent with its past development.

(2) Under the CLSS conditions, strict control was exercised over the amount of cultivated land that could be transformed, especially in cases where it was threatened by urbanization. In this model, urban area development mainly involves utilizing other land types, such as forest land. In addition, it is allowed to convert other land types into cultivated land.

(3) Under the EPDS conditions, environmental protection is prioritized. The principle of conversion between different land types under this scenario is that it is not allowed to convert land with high ecological benefits into land with low ecological benefits. The order of ecological benefits of different land types was as follows: forest land > water area > grassland > cultivated land > urban area > bare area. This development model emphasizes the balance

Table 2
Conversion parameters under different scenario conditions.

Land-use type	NDS						CLSS						EPDS					
	I	II	III	IV	V	VI	I	II	III	IV	V	VI	I	II	III	IV	V	VI
I	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	0
II	1	1	1	1	1	1	1	1	1	1	0	0	0	1	0	0	0	0
III	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0
IV	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	1	0	0
V	1	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	1	0
VI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

I: cultivated land, II: forest land, III: grassland, IV: water area, V: urban land, VI: bare land.

and coordination between environmental protection and economic development to achieve sustainable development. At the same time, it is also conducive to maintaining biodiversity and mitigating global issues such as climate change.

3. Results and Discussion

3.1 Accuracy analysis of LULC scenario simulation in Chengdu Chongqing Economic Zone

After completing the construction of the ANN-CA coupling model, the LULC of 2020 in the study area was simulated and predicted to test the accuracy of the model. The accuracy analysis results demonstrated that the Kappa coefficient for the period from 2000 to 2020 was 0.76. This confirmed that the model was capable of accurately simulating the LULC conditions in the study area for the year 2020. Therefore, it is also reasonable for this model to simulate the future LULC in the region.

3.2 Analysis of the evolution of LULC in the Chengdu Chongqing Economic Zone from 2000 to 2040

LULC in the Chengdu Chongqing Economic Zone exhibited the following notable features (Fig. 3): the predominant land use types within the zone are cultivated land, forest land, and urban areas. Cultivated land accounts for 58.08% of the total research area, while forest land accounts for 34.37%. Urban areas account for 4.90% of the total area, while grassland and water areas account for a relatively small proportion. Cultivated land is mainly concentrated in the Chengdu Plain and low-altitude areas of Chongqing, forming continuous patches of flat terrain, rivers, and favorable agricultural conditions. Forest land is mainly distributed in a fragmentary fashion in the hilly areas around the Chengdu Chongqing Economic Zone, including Anxian County, Shimian County, and Qianjiang District, as well as in the surrounding mountainous areas of Chongqing, including Huaying Mountain, Yunwu Mountain, and Jinyun Mountain. The urban areas are primarily located in regions with rapid economic development, such as Chengdu, Chongqing, and Mianyang.

Viewed in terms of changes over time, the following are several characteristics worth noting:

(1) Urban areas within the Chengdu Chongqing Economic Zone exhibited a multipolar explosive growth trend. Between 2000 and 2020 (Fig. 3), the total urban area increased by 5813 km^2. On the basis of the NDS model, an increase of 5820 km^2 between 2020 and 2040 was predicted, but this growth was limited to increases of 4226 and 3593 km^2 in the CLSS and EPDS models, respectively. It was clear that under conditions of strict farmland and ecological protection policies, the urban area growth rate was restricted. The 2040 simulation predicted urban area growth rates that declined by 17.31 and 24.18% in the CLSS and EPDS models, respectively, compared with the NDS.

In terms of space (Fig. 4), the surrounding areas of Chengdu and Chongqing are the main areas of urban land use, while Mianyang, Wanzhou District, Nanchong City, Changshou

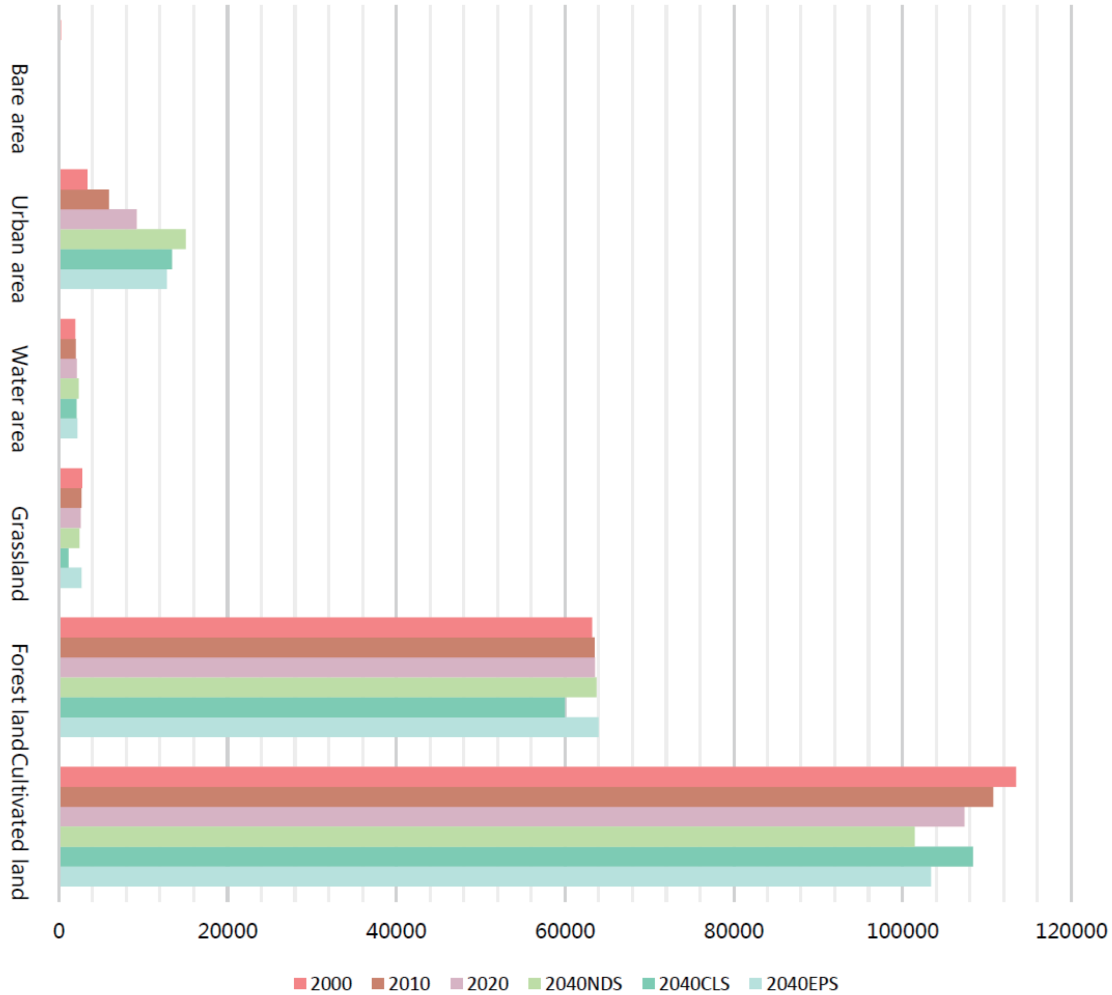

Fig. 3. (Color online) LULC in Chengdu Chongqing Economic Zone from 2000 to 2040.

District, and Fuling District, among others, served as secondary growth areas. These regions feature relatively developed economies, dense populations, and high levels of urbanization, along with concentrations of contiguous cultivated land, leading to a high demand for land resources for construction purposes.

(2) Owing to the predominance of plain areas within the Chengdu Chongqing Economic Zone, there was little change in the amount of forest land between 2000 and 2020. From 2020 to 2040, the NDS model projected a decrease of 1037 km^2 (approximately 2%) in forest land; however, in the CLSS model, forest land decreased by 1309 km^2, mainly due to strict farmland protection policies and urban land expansion, which led to a portion of the forest land being converted into urban areas. Conversely, the EPDS model predicted an increase of 2146 km^2 in forest land, with an average annual increase of 100 km^2. This increase suggests development favorable to the ecological environment.

(3) From 2000 to 2020, the cultivated land area sharply decreased by 6088 km^2. This was mainly driven by the region's rapid development, which led to the occupation and conversion of the

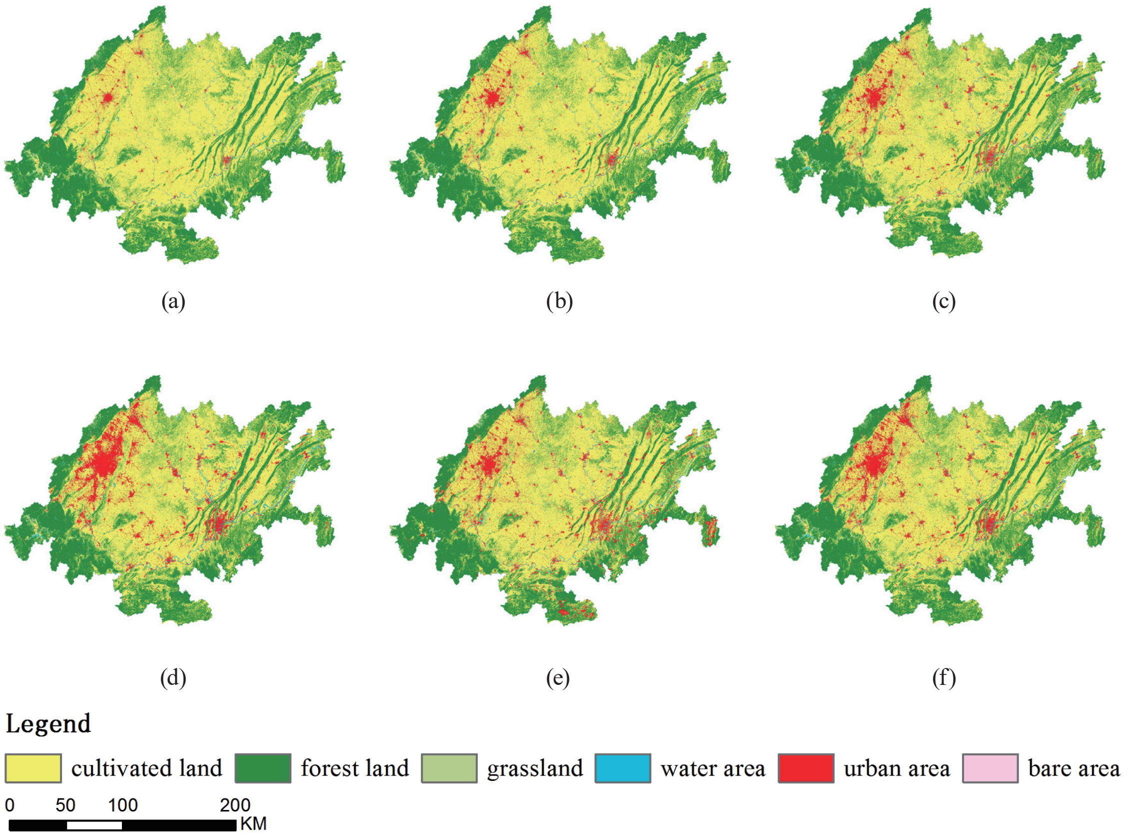

Fig. 4. (Color online) Spatial distribution of land in Chengdu Chongqing Economic Zone from 2000 to 2040. (a) 2000, (b) 2010, (c) 2020, (d) 2040NDS, (e) 2040CLSS, and (f) 2040EPDS.

surrounding farmland. The NDS model predicted a decrease of approximately 2000 km^2 in cultivated land area by 2040, while the CLSS model projected a slight increase. The implementation of strict farmland protection policies in the latter scenario ensured complicity with the minimum area requirements for the remaining cultivated land. In the EPDS model, cultivated land decreased by 4116 km^2, with 39% being converted into urban areas and the remaining portion transitioning to forest land.

(4) A small amount of grassland is distributed in the mountainous areas surrounding the Chengdu Chongqing Economic Zone. Between 2000 and 2020, these grassland areas decreased by 179 km^2. The NDS model predicted that these areas would continue to decrease by about 100 km^2 by 2040. In the CLSS model, grassland area was projected to decrease by 1378 km^2, mainly due to the strict control of cultivated land, leading to its conversion into urban areas. In the EPDS model, the grassland area slightly increased. Protecting grasslands is of great significance as they have important ecological, economic, social, and cultural values.

Regardless of the scenario [Figs. 4(d)–4(f)], cultivated land, especially in the cities' outskirts, is the land type subject to the most changes, making it the primary target of competition among various stakeholders.[22] This is because cultivated land accounts for the largest proportion of land among any of the land types and is widely distributed throughout the Chengdu Chongqing Urban Zone. On the other hand, although cultivated land may not possess the greatest economic or ecological value, it often features natural and geographical attributes such as fertile soil, flat terrain, a suitable climate, and favorable hydrological conditions. These characteristics contribute to the enormous economic and ecological value output potential of cultivated land, thereby positioning it as a "key zone" in mitigating LULC conflicts.

3.3 Analysis of habitat quality in the Chengdu Chongqing Economic Zone

3.3.1 Analysis of the changing characteristics of habitat quality

The HQI and HDI were used to evaluate the overall environmental quality within the study area.(23) The HQI quantifies the environmental conditions and resource capacities that support the sustainable survival and reproduction of species and populations.(24) Data were input into the InVEST model's habitat quality evaluation module to obtain the HQI and degree of habitat degradation for the years 2000, 2020, and 2040. On the basis of the actual habitat quality of the study area, the classification was divided into four levels: low, medium, good, and excellent. The corresponding habitat quality indices ranged from 0 to 0.2, 0.2 to 0.5, 0.5 to 0.8, and 0.8 to 1, respectively.

In 2000–2020 [Figs. 5(a)–5(c)], the average HQI values of the Chengdu Chongqing Economic Zone were 0.6494, 0.6432, and 0.6336, indicating a downward trend in habitat quality. The number of areas with low habitat quality increased by 5743 km^2. However, areas with good and excellent habitat quality levels increased by 219 km^2 over the same timeframe. In the later stage, the region embraced a green development path and vigorously implemented ecological protection projects such as the "Grain for Green Project", as well as various construction projects, which effectively promoted the improvement of environmental quality.

The simulation results predicted significant changes in the overall habitat quality of this area from 2020 to 2040. In the NDS model, areas [Fig. 5(d)] with low habitat quality increased by 5690 km^2, while areas with medium habitat quality decreased by 6040 km^2, mainly transforming into areas with low habitat quality. In this scenario, areas with good habitat quality increased by 194 km^2, and excellent-level areas increased by 155 km^2.

In the CLSS model, areas [Fig. 5(e)] with low habitat quality increased by 4139 km^2, a difference of 1550 km^2 compared with the previous scenario (NDS). The medium-habitat-quality area increased by 864 km^2, while areas with good and excellent levels decreased by a total of 5003 km^2. This decline can be attributed to strict farmland protection policies, where the cultivated land area not only remained stable but actually increased slightly, while the urban land area expanded by 4226 km^2. The increases in cultivated land and urban areas mainly stemmed from the reclamation of grass and forests, which involved the replenishment of reserve resources and the reclamation of shrubbery and other land into cultivated land. These changes led to a decrease in the overall habitat quality of the region.

Finally, in the EPDS model, areas [Fig. 5(f)] with low habitat quality increased by 3559 km^2 between 2020 and 2040 compared with the prior 20 years. However, their growth rate decreased

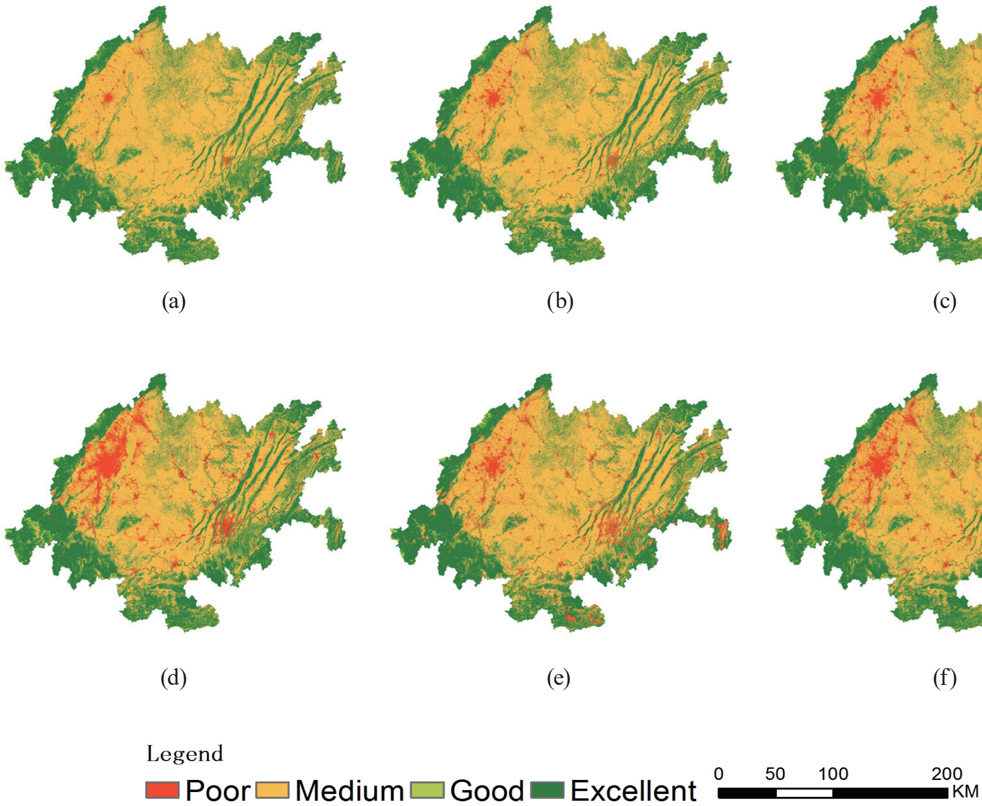

Fig. 5. (Color online) Distribution map of habitat quality in the study area from 2000 to 2040. (a) 2000, (b) 2010, (c) 2020, (d) 2040NDS, (e) 2040CLSS, and (f) 2040EPDS.

from 3.10% during the first 20 years to 1.92% between 2020 and 2040. Medium-habitat-quality areas decreased by 4111 km^2 in this model, while areas classified as good and excellent increased by 327 and 223 km^2, respectively. The increase in good-habitat-quality areas was attributed to strategies prioritizing ecological development. Since economic development in this scenario must be predicated on ecological protection, industrial and mining land was reclaimed and afforested, urban expansion was strictly controlled within the limits of the "ecological red line", and unsuitable farmland was converted into ecological land.

Clearly, the habitat quality patterns of the Chengdu Chongqing urban agglomeration from 2000 to 2040 featured both commonalities as well as significant distinctions in the different scenarios. For example, the spatial distribution characteristics of LULC in these simulation scenarios generally remained consistent with the distribution characteristics of the research area in the previous 20 years, suggesting a certain degree of dependence and lag in the evolutionary process that affects changes in habitat quality. Spatial analysis revealed that the overall habitat quality of the study area gradually decreased from the periphery to the center from 2000 to 2040, demonstrating a distribution pattern that can be described as "low in the two centers and high in the suburbs" (Fig. 5).

The surrounding areas of Chengdu and Chongqing, limited by terrain height, slopes, water content, soil conditions, and other factors, are largely covered by forest land. With limited suitability for residence and farming in these areas, they remain relatively unaffected by human activity, and the HQI was therefore high. Hongya County, Muchuan County, Xingwen County, Nanchuan District, and other regions exhibited comparatively high habitat quality indices, most of which were above 0.8. On the other hand, the Chengdu Plain, a small terrain with a large distribution of plains and river basins, was greatly affected by human interference. The areas with low HQI were distributed in Chengdu and Chongqing. These low-habitat-quality areas displayed a “two-core-centered, multilevel distribution” spatial morphology. The changes in habitat quality were mainly due to changes in LULC patterns caused by human activities, such as agricultural development, mining, and urbanization. Therefore, we must moderately develop the economy while protecting the natural environment.

3.3.2 Changes to habitat degradation levels in the Chengdu Chongqing Economic Zone

The HDI was analyzed by the natural breakpoint classification method in ArcGIS. This approach allows for the qualitative analysis and interpretation of spatial distribution patterns. By this method, the ecological degradation index of the Chengdu Chongqing Economic Zone was divided into four levels: basically unchanged, slightly degraded, moderately degraded, and highly degraded. The corresponding ranges of values for the HDI were 0–0.05, 0.05–0.10, 0.10–0.15, and above 0.15, respectively. The HDI is an indicator used to measure the degree of decline in habitat quality, with a higher HDI indicating a greater impact and more severe degradation.

The significance of HDI is to evaluate the impact of human activities on the natural environment, especially the degree of degradation of habitat quality. The larger the degradation index of habitat quality, the more severe the degradation of habitat quality. The average habitat degradation indices in the study area for the years 2000, 2010, and 2020 were 0.0935, 0.0938, and 0.0949, respectively, indicating an overall intensification of habitat degradation. By 2020, areas with nearly no habitat quality degradation accounted for 23.10% of all areas; 46,738 km^2 (25.26% of the total area) and 73,143 km^2 (39.53% of the total area) were classified as slightly degraded and moderately degraded, respectively. Highly degraded areas comprised 22,409 km^2, accounting for approximately 12% of all areas.

From Fig. 6, changes in habitat degradation levels between 2000 and 2020 were found. The area classified as “basically unchanged” exhibited a growth trend, with an increase of approximately 4682 km^2 over this period. Conversely, “slightly degraded” areas decreased by approximately 8411 km^2. Areas found to be moderately degraded showed an initial decrease before increasing, but the total amount of change was not significant. Highly degraded areas occurred in an increasing trend, with a total increase of 3755 km^2 over the 20-year period, ultimately accounting for 2.03% of the total area. This was because urban expansion requires a significant amount of land resources, and forest land was usually one of the first choices for urban expansion.

The HDI values for the year 2040 were 0.0968, 0.0973, and 0.0953 for NDS, CLSS, and EPDS, respectively, which were simulated using the ANN-CA model. To ensure the minimum

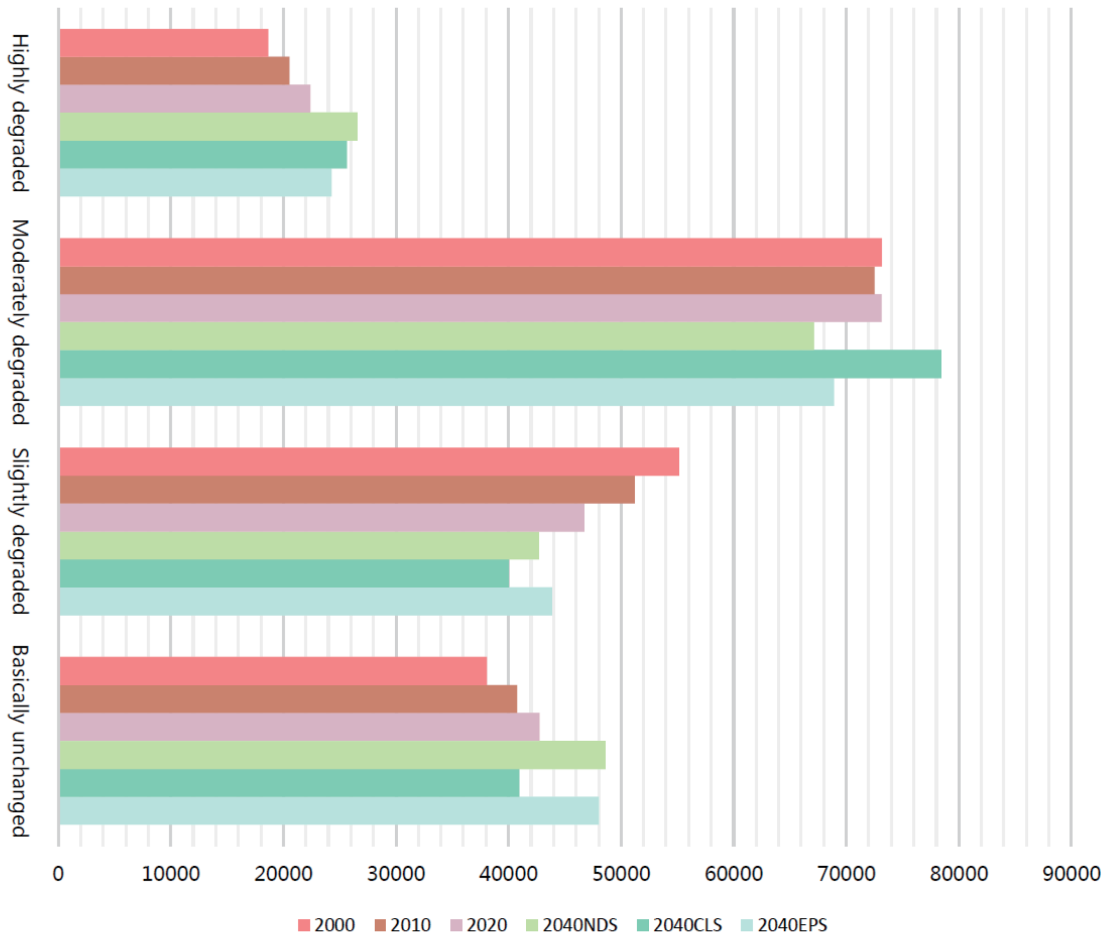

Fig. 6. (Color online) Statistical charts of habitat degradation indices at different stages and levels.

amount of cultivated land and urban development in the CLSS model, some forest lands are reclaimed for cultivation and construction, which disrupt the balance of the ecosystem and lead to higher levels of degradation. In the EPDS model, the HDI was the lowest. In NDS, forest land and grassland remained almost unchanged, with the significant conversion of farmland to urban area exacerbating the deterioration of regional habitat quality.

It can be seen from Figs. 7(a)–7(c) that between 2000 and 2020, areas with high HDI in the Chengdu Chongqing Economic Zone are mainly distributed across Shuangliu District, Xinjin District, Wenjiang District, Xindu District, Meishan's Pengshan District, Chongqing's Beipei District, Yubei District, Jiulongpo District, and other areas where rapid economic development took place. However, Lushan County, Hongya County, Xuanhan County, and other locales within the region have HDI values near 0. These regions feature relatively high altitude, limited human activity, and land use types characterized by forest land and grassland, which contribute to their higher ecosystem conservation capacity.

Areas with moderately degraded habitat quality include Lezhi, Tongnan, Wusheng, and Nanbu counties. These areas primarily consist of cultivated land and water area. The analysis of

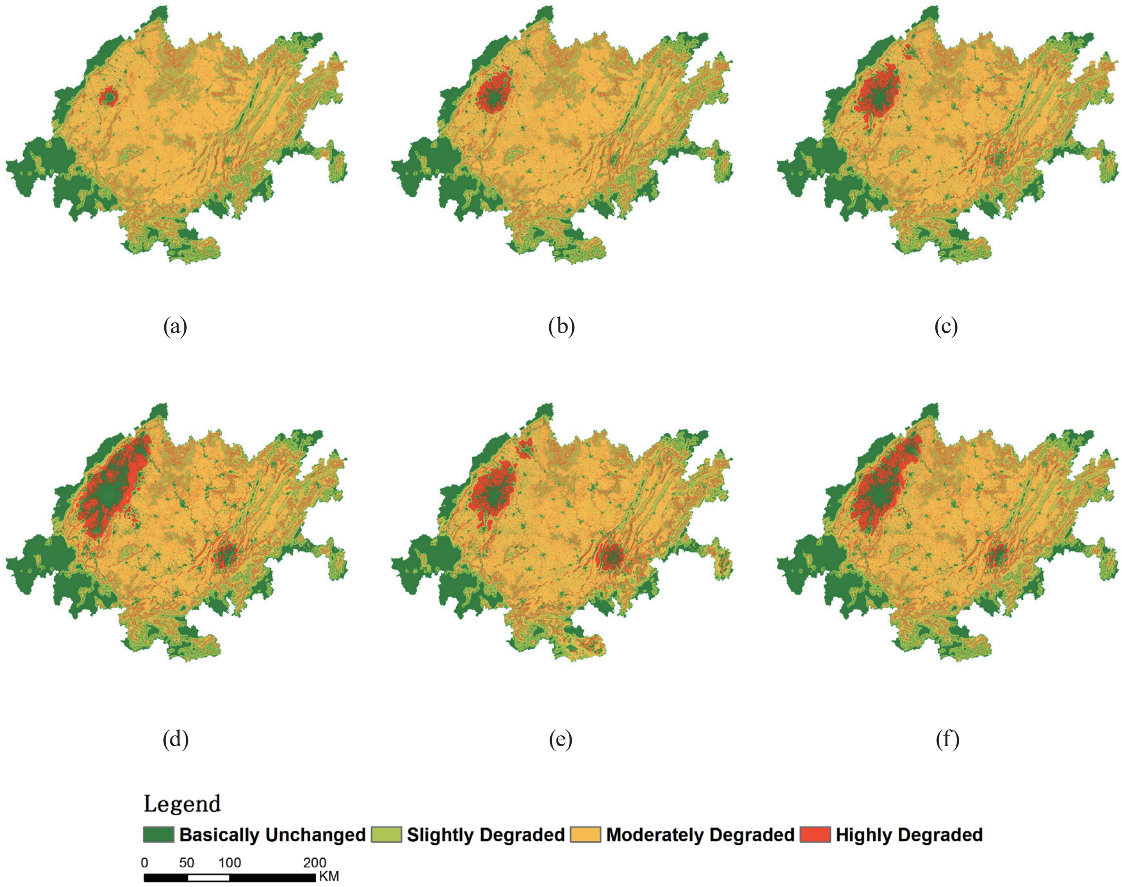

Fig. 7. (Color online) Spatial distribution map of habitat degradation during different periods.

the stochastic matrix of LULC change revealed that the main LULC changes involved transitions from cultivated land to grassland or grassland to water area, which are typically less affected by human activities.

Overall, the areas with highly degraded habitat quality were located in the surrounding areas of Chengdu and Chongqing, with the level of degradation decreasing as one moves away from these two centers. By 2040, the NDS model [Fig. 7(d)] predicted an expansion of the severely degraded areas, with gradual distributions occurring in Chengdu, Meishan, Deyang, and Mianyang. Surrounding areas of degradation in Chongqing were projected to spread to the periphery. The degree of degradation is related to trends in urbanization, industrialization, human activities, and rapid urban expansion, all of which exert pressure on the ecological environment.

In the CLSS model [Fig. 7(e)], areas with high degradation have also expanded, mainly due to frequent human activities such as the cultivation of arable land. Highly degraded areas still surround the urban centers of Chengdu, Chongqing, Mianyang, Meishan, Deyang, and Dazhou, and spread outward. Additionally, large areas of severe degradation appeared in Sichuan, while Chongqing's degradation was mitigated by its terrain.

Following the EPDS model simulation [Fig. 7(f)], this model also exhibited smaller impacts of habitat degradation in Chengdu and its surrounding areas compared with the NDS and CLSS models, owing to ecological measures that to some extent limit urban development.(25) However, the degree of degradation in regions such as Chongqing remained higher than that, which was observed in the NDS and EPDS models. This can be attributed to urban development in Chongqing encroaching upon the forests of the surrounding mountainous and hilly regions, intensifying degradation. Overall, owing to the implementation of active ecological priority development strategies and policies in some regions, such as the "Natural Forest Protection Project", the "Key Protection Forest System Construction Project in the Middle and Lower Yangtze River Region", and the "Wildlife and Plant Protection and Nature Reserve Construction Project", the degree of habitat quality degradation under this model is relatively low. These measures will help alleviate habitat quality degradation.

4. Conclusions

The spatial heterogeneity of LULC and habitat quality in the Chengdu Chongqing Economic Zone from 2000 to 2020 were analyzed and studied using the InVEST habitat quality model. To predict and simulate habitat quality in 2040, three scenario simulations were conducted and the following conclusions were drawn:

(1) From 2000 to 2020, the urban land in the study area exhibited continuous growth, while the areas of forest land, grassland, and arable land continued to decrease. The transformations of LULC, particularly among cultivated land, grassland, forest land, and urban land, were evident, with the transfer of cultivated land to urban area being especially notable. The simulation results indicated varying degrees of increases in urban land use by 2040. The increase is the largest in NDS and the smallest in EPDS. In CLSS, the cultivated land area slightly increased. The EPDS model is characterized by relatively unchanged distributions of forest land, water area, and grassland, with increases in urban land area coming primarily from cultivated land.

(2) The overall habitat quality in the Chengdu Chongqing Economic Zone was rated as "good", but indicated a downward trend. Medium-habitat-quality areas comprised the majority of the region but also displayed a downward trend. Areas with good and excellent habitat quality levels initially increased but were followed by slight decreases. A close relationship between habitat quality and LULC was also identified. This means that the way people use land can directly affect the quality of habitats, thereby affecting the survival status of organisms in the habitats. Forest land, grassland, and water areas maintained high habitat quality levels, while in urban areas, these values were notably lower. The decline in habitat quality was mainly due to reductions in forest and grassland areas. From a spatial perspective, areas with higher elevations around the Chengdu Chongqing Economic Zone generally had a higher habitat quality than plain areas. Areas with frequent human activities were often areas with low habitat quality. The conclusion also indirectly confirms the negative impact of human activities on habitat quality. Therefore, we should not only formulate strict ecological protection policies, but also strengthen the public participation and supervision of

environmental protection activities. At the same time, developing green industries reduces the contradiction between ecological protection and economic development, thus forming a virtuous cycle.

(3) The HDI in the Chengdu Chongqing Economic Zone showed an upward trend from 2000 to 2020. Projecting to 2040, the EPDS model featured the lowest degradation index compared with the NDS and CLSS models. The implementation of ecological priority development strategies ensured the preservation of ecological land such as forests and limited the uncontrolled expansion of urban areas. To maintain the biodiversity of the region, it is crucial that the development and utilization of land be managed scientifically and legally. This involves enhanced planning to strengthen the protection of grasslands and forests and maintain ecological land areas. Additionally, attention should be paid to the composition and spatial allocation of land structures as well as further improvements to the overall quality of existing ecological land, thus enhancing the overall habitat quality within the region. At the stage of urban spatial planning, attention should be paid to the coordination of urban development, ecosystem protection, and cultivated land protection. For example, a compensation mechanism for cultivated land should be established in the surrounding areas of cities to reduce the decline of habitat quality caused by urbanization. In the future urban planning, the government should prevent the disorderly expansion of a city and build green spaces inside the city, so as to slow down the decline of the habitat quality in this area.

There are certain limitations of this study. First, some evaluation factors in the model were difficult to classify, such as the lack of road grading, which limited the scientific evaluation of changes in habitat quality risk factors. Second, all threats to land use types in the model were simply aggregated, neglecting the cumulative impact of multiple threats.(26)

This research provides valuable insights into the LULC dynamics and habitat quality of the Chengdu Chongqing Economic Zone, highlighting the need for sustainable land management practices and ecological protection measures to ensure the long-term well-being of the region's ecosystems.

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