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Research Article

Dynamic change of habitat quality and its key driving factors in Ningxia Hui Autonomous Region, China

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Abstract

Habitat quality reflects the level of biodiversity, and habitat maintenance functions are related to human well-being and ecosystem stability. Ningxia Hui Autonomous Region is a typical ecologically fragile region in Western China with complex human-nature relationships. Maintaining good habitat is not only a fundamental requirement for biodiversity conservation but also a necessary path for sustainable regional development. In this study, we assessed and analysed the spatial and temporal patterns and changes in habitat quality in Ningxia from 2000 to 2020, and explored the driving factors of habitat quality using a geographically weighted regression (GWR) model. The results indicated: (1) The overall habitat quality level in Ningxia was low to intermediate, with an upwards and then downwards trend during the past 20 years, showing a small change in overall magnitude. (2) The high- and higher-level habitat quality patches in Ningxia were mainly distributed in areas with high vegetation cover, such as the Helan Mountain and Liupan Mountain. The patches of moderate-level habitat quality mainly included cultivated land, while the low- and lower-level patches were mainly distributed in areas subjected to more frequent human activities, such as cultivated land and construction land. (3) The spatial and temporal distribution patterns and changes in habitat quality in Ningxia from 2000 to 2020 were mainly influenced by fractional vegetation cover (FVC), soil moisture content (SMC), proportion of construction land area (PCL), and proportion of cultivated land area (CLP). Among them, FVC and SMC were positive driving factors, and PCL and CLP were negative driving factors. The results support that increasing vegetation cover and reducing anthropogenic disturbance to natural habitats are important measures to maintain fragile habitats and that key ecological function areas such as nature reserves are crucial for habitat quality protection in ecologically fragile areas.

Key words: Driving factors, geographically weighted regression (GWR), habitat quality, Ningxia Hui Autonomous Region, spatiotemporal pattern

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Introduction

Habitat quality refers to the ability of an ecological environment to provide suitable conditions for the sustainable survival and development of individuals, populations or communities, reflecting the richness of biodiversity in a region, and it is related to human well-being (Yohannes et al. 2021). The concept of habitat was first introduced by Grinnel in 1917 (Riedler and Lang 2018), and the study of habitat quality can be traced back to the 1960s (Goertz 1964; Rosenzweig and Winakur 1969; Janzen 1970) which fully developed by field surveys (Van Horne 1983; Congdon 1974), habitat indices (Berger and Hodge 1998), model simulations (Dunning et al. 1992; Roth et al. 1996) and other stages. Currently, since the introduction of the United Nations Sustainable Development Goals (SDGs) and the convening of the Conference of the Parties to the United Nations Convention on Biological Diversity (UN CBD-COP), governments and researchers have agreed to stabilize and enhance the global biodiversity level (Hale and Swearer 2016).

A favourable habitat condition means that various ecological factors in the ecosystem meet the needs of population survival and reproduction, and the orderly differentiation of biological ecological niches will achieve a balanced and stable ecosystem function. Additionally, habitat maintenance is an ecosystem service that is of great concern to humans (Celina et al. 2022), and habitat quality is a comprehensive representation of habitat maintenance capacity, which fully connects ecological processes with human needs. Habitat quality is deeply related to regional biodiversity levels, ecosystem service trade-offs and synergies, and ecological security patterns (Wu et al. 2013; Wang et al. 2022); habitat quality determines the balance of ecosystems, laying the foundation for sustainable development prospects of social-economic-natural complex systems (Wu et al. 2017). Managing and maintaining habitat functions and improving habitat quality can effectively maintain biodiversity and provide a good base of ecosystem services that ultimately meet the needs of the human economy and society (Peggy et al. 2021). Ecologically fragile areas are located in the cross-transition zone of different types of ecosystems, with weak system resistance to disturbance, sensitivity to global climate change, and generally low habitat quality as well as biodiversity levels (Prasad and Ramesh 2019). For ecologically fragile areas with poor ecological backgrounds, measures such as curbing urban expansion and maintaining landscape integrity can enhance regional habitat quality, thereby improving and enhancing ecosystem structure and function, which can promote a continuous supply of ecosystem services to human society (Ramachandra et al. 2019).

Habitat quality assessments include both ecological and geographic perspectives. Early studies focused on the substantial impacts of human activities on plant and animal habitats, and the research methods and contents were more biased towards natural and ecological properties (Dallimer et al. 2012). Such studies usually used relevant parameters obtained by field survey methods to construct indicator systems; additionally, hierarchical analysis, grey correlation models, and entropy weighting methods were used to synthesize habitat conditions, and the natural or anthropogenic driving factors of habitats of single or homogeneous species were analysed. These studies were mostly conducted on a small scale, such as small cities, rivers, and nature reserves, and usually used the sample strip method or sample method of investigation to obtain various parameters related to the quality of plant and animal habitats; moreover, these studies commonly used indicators including species richness, vegetation types, topographic indicators, and water quality (Harper and Everard 1998). The advantage of this method is that it can reflect the habits and habitat conditions of the evaluated objects more comprehensively, and the indicators are more sensitive and detailed. However, due to the high time and labour costs and the difficulty of obtaining data over long-time spans for dynamic analysis, such methods cannot be applied to habitat quality studies at larger spatial and temporal scales (Wang et al. 2017).

As land use/land cover (LULC) change has become the focus of global change research (van Vliet et al. 2015), habitat quality assessment models developed by remote sensing and GIS technologies have been widely used in practice, forming a paradigm for habitat quality research based on a geographic perspective (Romero-Calcerrada and Luque 2006). In recent years, many scholars have performed many studies on habitat quality at large-scale scales, such as across regions, from the perspectives of ecological service function, ecological risk and early warning and the relationship between urbanization development and ecosystem conservation (Nagendra et al. 2013; Chen et al. 2016; Gomes et al. 2021; Duan and Yu 2022). Commonly used mature habitat quality assessment models include Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) (Bao et al. 2015), Habitat Suitability Index Model (HSI) (Wang et al. 2009), Maximum Entropy Model (MaxEnt) (Radosavljevic and Anderson 2014), Artificial Intelligence for Ecosystem Services (ARIES) (Villa et al. 2009), and Multiscale Integrated Models of Ecosystem Services (MIMES) (Roelof et al. 2015), among others. Among them, the Habitat Quality module in the InVEST model is widely used (Kareiva et al. 2011) because of its low application cost and high assessment accuracy, and the evaluation results support the spatial visual representation of regional habitat distribution as well as habitat degradation.

Currently, humans are facing a serious biodiversity crisis, and habitat destruction is one of the most serious challenges threatening biodiversity conservation (Crooks et al. 2017). Population growth, economic development, and continuous changes in land use and its structure profoundly affect the material and energy flow circulation processes between habitat patches, which in turn change the distribution patterns and functions of regional habitats (Haddad N et al. 2015). The level of habitat quality is highly dependent on natural conditions and on its proximity to human land uses and the intensity of land use (Sobhani et al. 2022). Therefore, exploring the relationships among ecological factors, ecological processes and habitat quality is important for maintaining regional biodiversity and even ecosystem functions and provides a basis for improving regional ecological security patterns and the sustainable development of land resources (Kalacska et al. 2017; Hao et al. 2019).

The current methods used to investigate the factors affecting habitat quality mainly include spatial exploratory analysis, spatial econometric analysis, multiple regression analysis, grey correlation analysis, and Moran's I spatial autocorrelation index (Zhu and Alimujiang 2020; Moëzzi et al. 2022; Raimundo Lopes et al. 2022); moreover, these methods focus on the spatial and temporal patterns, multiscale change characteristics, and evolutionary mechanisms of habitat quality (Wu et al. 2021; Xiao et al. 2022). However, most of the studies have been conducted at the scale of administrative units, usually using methods such as indicator methods and spatial autocorrelation analysis, and they have failed to fully consider the heterogeneity of different geographic spaces and the spatial scales at which different influencing factors act (Chisholm et al. 2011; Smith et al. 2011). Based on Tobler's (1970) first law of geography, Brunsdon proposed the geographically weighted regression (GWR) model (Brunsdon et al. 1996), which allows for spatial heterogeneity in the coefficients of independent variables and can effectively detect the spatial nonstationarity characteristics of regression variables; this method is widely used in geography, economics, ecology and the environment (Zhu et al. 2020; Hu et al. 2022). The GWR model performs distance-weighted regression with the help of observations from neighbouring sample points, which can reveal the quantitative relationships between factors and impact factors more accurately, thus improving the goodness of fit of the model and solving the deficiency of using exploratory spatial data analysis (ESDA) tools that can solve only time-sectional data (Qin 2007).

In summary, this study selected the Ningxia Hui Autonomous Region (hereinafter referred to as Ningxia), a typical ecologically fragile region in Western China, as the study area, collected raw data on land use, NDVI, and temperature from 2000 to 2020, and analysed the spatial and temporal patterns of habitat quality and their changes in the past 20 years based on remote sensing and GIS analysis. Based on the objective fact that the distribution of habitat quality in Ningxia is spatially heterogeneous, the GWR model with optimal fitting parameters was finally used to investigate the key factors driving the distribution and changes in habitat quality in Ningxia.

Materials and methods

Study area

Ningxia (35°14'–39°23'N, 104°17'–107°39'E) (Fig. 1) is located in Western China in the middle and upper reaches of the Yellow. The climate is temperate continental, with an average annual temperature of 6–10 °C, an average annual precipitation of approximately 220 mm, and more than 3,200 h of sunshine. The topography is high in the south and low in the north, with an altitude of 1,100–1,200 m. The ecological geography is divided into 3 parts. The Yellow River flows through the northern irrigation area, which has a gentle topography and superior soil and water conditions. The central area is the arid wind-sand belt, which is subject to perennial drought and poor soil and water conditions; and the southern mountainous area is full of ravines and gullies, with complex topography and a cold and wet climate. Ningxia has a well-developed agriculture and animal husbandry industry, but water resources are concentrated with a small and uneven spatial distribution. Ningxia is located in the interlocking agricultural and pastoral areas of northern China, with a fragile ecological environment and simple species composition and ecosystem diversity. Due to its location in the transition zone of the arid and semiarid climate zones, Ningxia has become an important ecological security barrier in Western China. There was still 15,534.84 km^2 of soil erosion in the region, accounting for 23.40% of the total area of the region, and the contradiction between ecological and environmental problems and economic and social development was still relatively prominent.

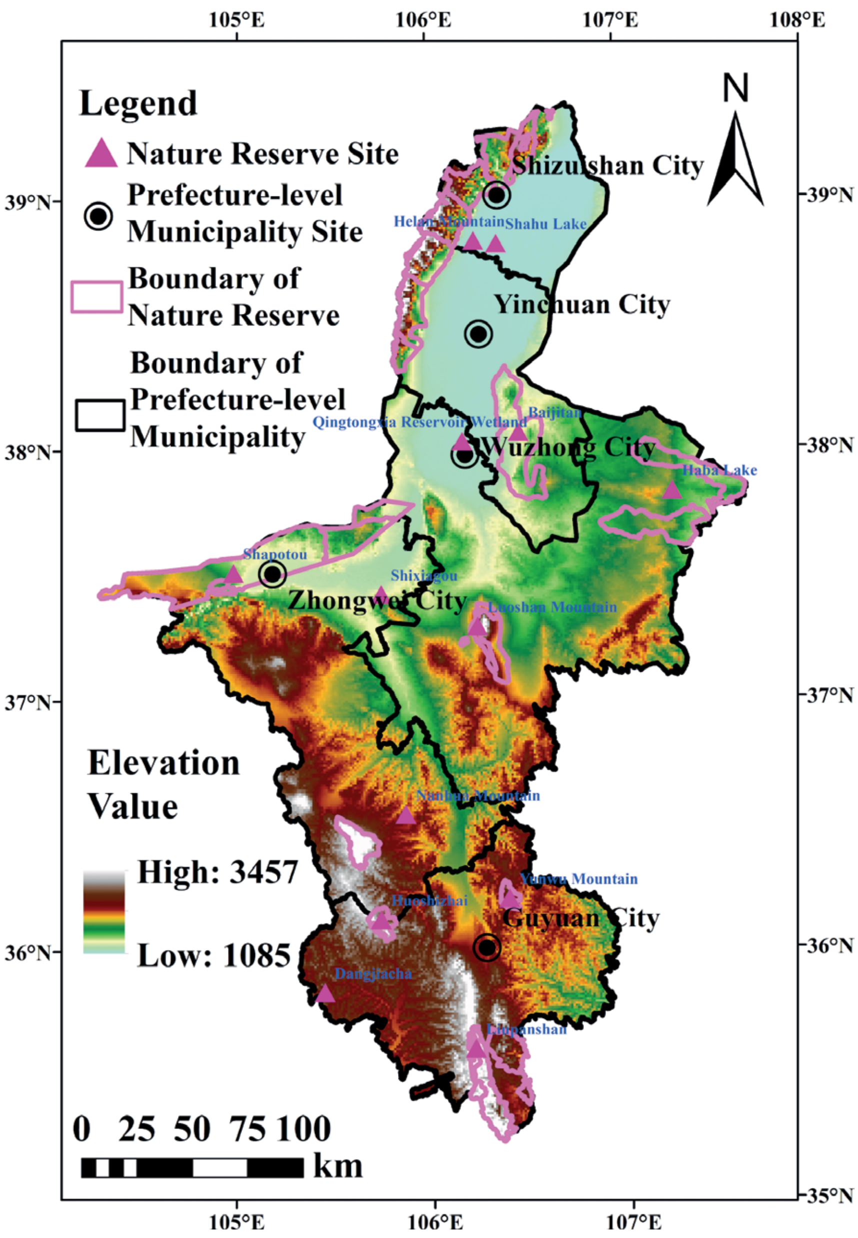


Figure 1. Topography, natural reserves and administrative division of Ningxia.

Research methods

Habitat quality assessment methods

In this study, the habitat quality module of the InVEST model was used to assess habitat quality in Ningxia, and the habitat quality index was calculated as follows:

$$Q_{xj} = H_j[1 - (\frac{D_{xj}^z}{D_{xj}^z + k^z})] \tag{2.1.1}$$

where Q_{xj} is the habitat quality of raster x in land use type j; k is the half-saturation parameter, whose value is half of the resolution of the raster data in the study area and is generally 1/2 of the maximum value of habitat degradation; H_j is the habitat suitability of land use type j, whose value is usually 0~1; z is the normalization constant, which is usually set to 2.5; and D_{xj} is the level of stress to which raster *x* of land use type *j* is subjected, i.e., the degree of habitat degradation. The degree of habitat degradation is the intensity of habitat disturbance by threat sources and is calculated as follows:

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{y_r} \left(\frac{\omega_r}{\sum_{r=1}^{R} \omega_r}\right) r_y i_{rxy} \beta_x s_{jr} \quad (2.1.2)$$

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{rmax}}\right) \text{ (Linear decay)} \quad (2.1.3)$$

$$i_{rxy} = \exp\left(\frac{-2.99 d_{xy}}{d_{rmax}}\right) \text{ (Exponential decay)} \quad (2.1.4)$$

where D_{xj} is the degree of habitat degradation; *R* is the number of stressors; *y* is the number of grids in the raster layer of stressor *r*; y_r is the number of grids occupied by stressors; w_r is the stressor weight; r_y is the stressor value of raster *y*; β_x is the accessibility level of raster *x*, which is not considered in this study; s_{jr} is the sensitivity of habitat type *j* to stressor *r*; i_{rxy} is the stress factor value r_y of raster *y* on the stress level of habitat raster *x*; d_{xy} is the linear distance between raster *x* and raster *y*; and d_{rmax} is the maximum stress distance of threat source *r*. The higher the calculated score is, the greater the threat level caused by the threat factor to the habitat and the higher the degree of habitat degradation.

Based on the InVEST model manual and with reference to previous research results on habitat quality in Ningxia and the arid and semiarid regions of Northwest China (Wu et al. 2020; Bao 2022; Ren et al. 2022), this study used paddy fields, drylands, urban land, rural settlements and other construction land as threat factors and determined the habitat suitability of habitat types and the sensitivity of different habitat types to stress factors (Tables 1, 2).

The rate of change in habitat quality was calculated using the terminal habitat quality minus the initial habitat quality with the following equation:

$$K_T = \frac{HQ_i - HQ_0}{HQ_i} \times 100\% \quad (2.2)$$

where K_T is the rate of change in habitat quality over time *T*. This study had a 5-year cycle; HQ_o is the size of habitat quality at the beginning of the study, HQ_i is the size of habitat quality at the end of the study, and the raster resolution is 30 m.

Spatial autocorrelation analysis

In this study, the global Moran's I index was used to describe whether habitat quality in the study area had a clustering effect on a global scale, and the local Moran's I index was used to reflect the spatial autocorrelation of habitat quality in the subregion. The spatial autocorrelation analysis was performed in ArcGIS 10.7 software.

$$Global\ Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2\left(\sum_i\sum_j\omega_{ij}\right)}(i \neq j) \quad (2.3.1)$$

$$local\ Moran's\ I = \frac{n(x_i-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sum_{j=1}^{n}\omega_{ij}(x_i-\bar{x})(i \neq j) \quad (2.3.2)$$

where x_i and x_j are the values of variable *x* taken on neighbouring cells, *x* is the attribute value of the n location variables, $\bar{x}$ is the mean of the attribute values of the spatial variables, ω_{ij} is the spatial weight matrix of raster *i* and raster *j*, and *n* is the total number of rasters.

Table 1. Ecological threat factors and their maximum impact distances and weights.

Threat Factor	Impact Distance/km	Weight	Spatial Decline Type
Paddy Field	4	0.15	Linear Decline
Dryland	3	0.2	Linear Decline
Urban Land	5	0.3	Exponential Decline
Rural Settlements	4	0.3	Exponential Decline
Other Construction Land	8	0.2	Linear Decline

Table 2. Habitat suitability and relative sensitivity to threat factors.

Type	Habitat suitability	Paddy field	Dryland	Rural settlement	Urban land	Other construction land
Paddy Field	0.6	0.3	0.2	0.35	0.5	0.45
Dryland	0.4	0.3	0.2	0.35	0.5	0.4
Forested Land	1	0.8	0.7	0.85	1	0.6
Shrubland	1	0.4	0.3	0.45	0.6	0.4
Sparse Woodland	1	0.85	0.75	0.9	1	0.65
Other Forest Land	1	0.9	0.8	0.95	1	0.7
High Coverage Grassland	0.85	0.4	0.3	0.45	0.6	0.6
Medium Coverage Grassland	0.8	0.45	0.35	0.5	0.65	0.7
Low Coverage Grassland	0.75	0.5	0.4	0.55	0.7	0.8
Canal	1	0.7	0.6	0.75	0.9	0.5
Lake	1	0.7	0.6	0.75	0.9	0.5
Reservoir Pit	1	0.7	0.6	0.75	0.9	0.5
Beach Land	0.6	0.75	0.65	0.75	0.95	0.55
Urban Land	0	0	0	0.8	0	0
Rural Settlements	0	0	0	0	0	0
Other Construction Land	0	0	0	0	0	0
Unused Land	0	0	0	0	0	0

Geographically weighted regression

Pearson correlation regression, the least squares model (OLS), and geographically weighted regression models were used to explore the characteristics of driving factors acting on habitat quality in Ningxia. The GWR model is a local regression model that embeds the geographic location of the data into the regression parameters, allowing for local parameter estimation. In this study, the geographically weighted regression weight function was chosen as a Gaussian function (Adaptive Gaussian), and its calibration was performed using an adaptive approach (Adaptive).

$$y_i = \beta_0(\mu_i, v_i) + \sum_{i=1}^{k} \beta_k(\mu_i, v_i) x_{ik} + \varepsilon_i \tag{2.4}$$

where y_i is the dependent variable at sample point *i*, x_{ik} is the observed value of the *kth* variable at the *ith* point, $(\mu_i, v_i)$is the location coordinate of the ith point, $\beta_o(\mu_i, v_i)$ is the intercept, $\beta_k(\mu_i, v_i)$ is the regression coefficient of the *ith*, and ε_i is the error term.

Based on the results of previous studies on the driving factors of habitat quality in the Loess Plateau and Western China and the actual characteristics of the ecological environment in Ningxia (Yang et al. 2021; Bai et al. 2020), 16 indicators of physical geographic and socioeconomic factors were selected to analyse the key driving factors and characteristics of their effects on the status and dynamic change of habitat quality in Ningxia, as shown in Table 3.

Data sources and processing

The data in this study included habitat quality assessment data and driving regression data, and the InVEST model habitat quality assessment mainly used five periods of land use dataset from 2000 to 2020. The dataset were obtained from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/) at a resolution of 30 m. NDVI data were obtained from the 30 m annual maximum NDVI dataset of China at the National Ecological Science Data Center of China (http://www.nesdc.org.cn/). Net primary productivity data were obtained from the MOD17A3HGF Version 6.0 product (https://www.earthdata.nasa.gov/). Geospatial information data included the 2021 version of 1:1 million public geographic basic information dataset (https://www.webmap.cn/commres.do?method=result100W) and ALOS 12.5 m DEM data (https://www.gscloud.cn/). GDP and Population data were obtained from the 1 km-grid GDP dataset of China (https://www.resdc.cn/) and the 1 km-grid population dataset of China (https://www.resdc.cn/). Soil water content data were obtained from the Soil Moisture in China dataset (2002–2018) (http://data.tpdc.ac.cn/zh-hans/). A 1-km monthly mean temperature dataset for China (1901–2021), a 1-km monthly precipitation dataset for China (1901–2022), and the Prolonged Artificial Nighttime-light Dataset of China (1984–2020) were obtained from the National Tibetan Plateau Scientific Data Center (http://www.tpdc.ac.cn/).

Table 3. Selection of regressors for habitat quality driving factors in Ningxia.

Indicators	Abbreviation	Unit
Net Primary Productivity	NPP	gC/(m^2*a)
Fractional Vegetation Cover	FVC	%
Mean Annual Precipitation	MAP	mm
Drainage Density	DRA	km/km^2
Elevation	ELE	m
Slope	SLP	°
Degree of Relief	DRF	m
Soil Moisture Content	SMC	m^3/m^3
Average Annual Temperature	AAT	°C
Proportion of Cultivated Land	PCL	%
The Proportion of Construction Land	CLP	%
Population Density	POP	person/km^2
Road Network Density	RND	km/km^2
Nighttime Light Index	NLI	DN
Regional GDP	GDP	10^4 Yuan (¥) /km^2
Closest Distance to Road Network	DRN	m

The original spatial raster data of river network density, road density, distance to the nearest road, elevation, slope, topographic relief, GDP, population density, nighttime lighting index, proportion of construction land area, and proportion of cultivated land area for the whole Ningxia region in 2000, 2005, 2010, 2015 and 2020 were obtained by processing the above datasets. Based on the zoning of Ningxia and the accuracy of the data, a suitable 5 km × 5 km fishing grid was built, excluding the grid with null values, to obtain the final 2290 grids. The raw data were partitioned in tabular form to obtain the final data results for each impact factor as well as the raw data results for habitat quality for the period 2000–2020, with 17 categories and 85 datasets in five periods.

Results and analysis

Spatial and temporal patterns of habitat quality in Ningxia

The habitat quality of Ningxia was classified into five levels: low level (0–0.25), lower level (0.25–0.4), moderate level (0.4–0.6), higher level (0.6–0.75), and high level (0.75–1.0) (Fig. 2). The results showed that the proportion of high-level habitat quality patches in Ningxia in 2020 was the highest (29.27%), followed by lower-level (25.08%) and higher-level (22.62%) patches, while the proportions of low-level and moderate-level habitat quality patches were lower, at 13.41% and 9.61%, respectively. The proportion distribution of habitat quality patches in Ningxia in 2000, 2005, 2010 and 2015 was similar to that in 2020, which showed the distribution of high level > lower level > higher level > low level > moderate. From 2000 to 2020, the average habitat quality of the whole region of Ningxia was approximately 0.58, which was at a moderate-good level. Combined with the proportional distribution of high-level and higher-level habitat quality patches, the habitat maintenance function in Ningxia has been relatively healthy over the past 20 years.

In terms of spatial distribution (Fig. 3a–f), the high-level habitat quality patches in Ningxia from 2000 to 2020 were mainly distributed in nature reserves with high forest cover and excellent ecological conditions, such as in the south, Helan Mountain in the north, Shixia Gorge in the east and Luoshan in the centre. The higher-level habitat quality patches were scattered around the higher-level habitat quality patches. The moderate-level habitat quality patches mainly included most of the cultivated land types. The lower-level habitat quality patches contained some cultivated land and were more randomly distributed. The low-level habitat quality patches mainly included most of the construction land and unused land with harsh natural conditions, such as the central wind-sand region area, the sandpots in the west, and the foothills of the Helan Mountain and the edge of the Ningxia Plain, which are strongly disturbed by humans.

The results of spatial autocorrelation analysis showed (Fig. 4) that the distribution of habitat quality in Ningxia from 2000 to 2020 was significantly autocorrelated geographically and spatially, with Moran indices of 0.619, 0.604, 0.588, 0.581, and 0.144 ($P < 0.01$), all with a 90%+ credibility level. The results of local spatial autocorrelation coefficients showed (Fig. 5a–e) that the habitat quality aggregation in Ningxia mainly included two types of high-high value aggregation and low-low value aggregation, while the high-low value aggregation and low-high value aggregation types had poor significance levels and more random distributions.

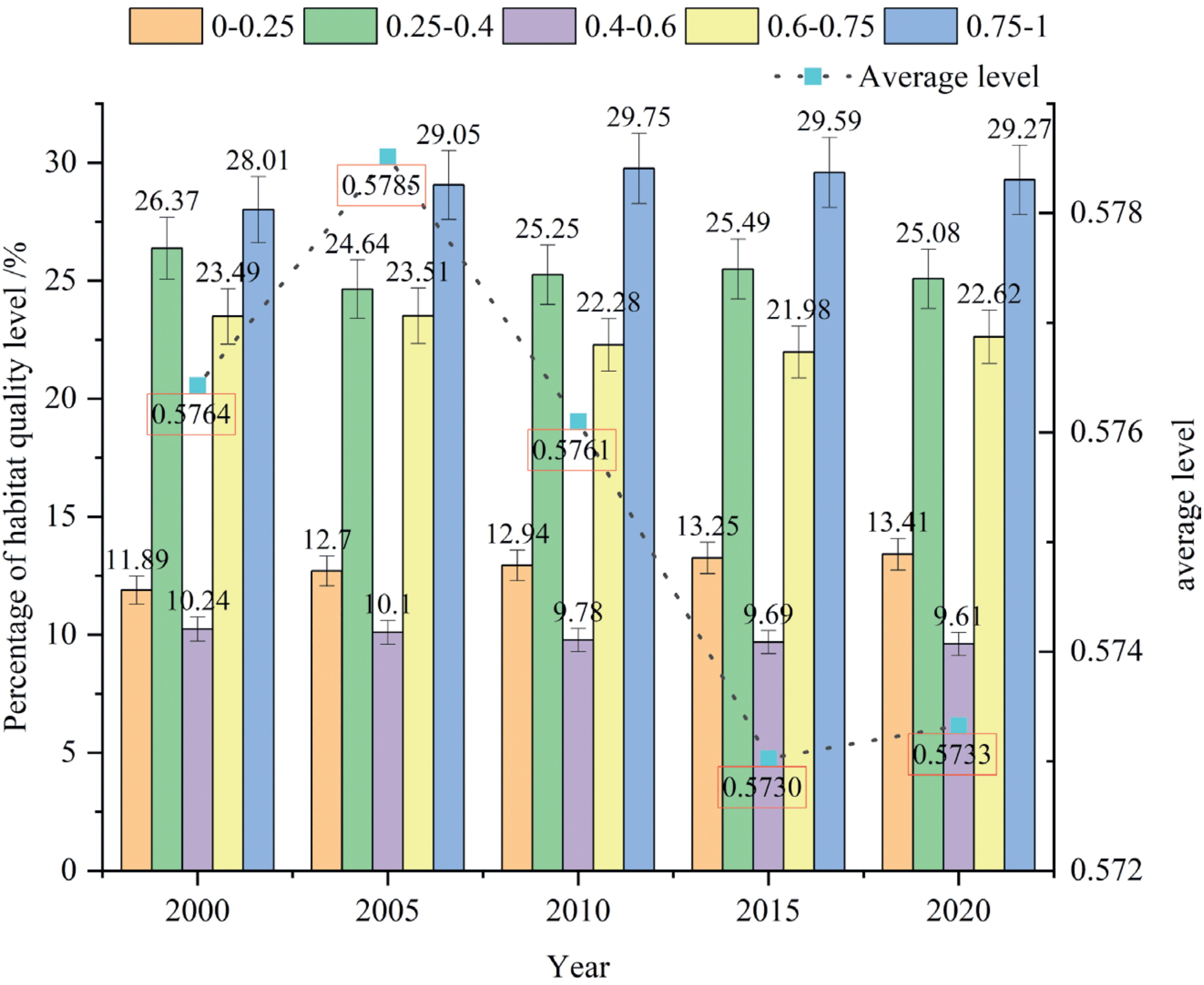


Figure 2. Proportion of habitat quality levels in Ningxia from 2000–2020.

Combining the distribution of patches with the different habitat quality levels in Ningxia, we found that habitat quality in Ningxia was closely related to patch type and was influenced by both natural conditions and human activities. Our study found that habitat quality levels were highest in primary forest reserves that were not disturbed by human activities, where precipitation, temperature, topography and elevation were suitable for the survival and reproduction of organisms. In contrast, habitat quality was significantly lowest in construction sites strongly disturbed by human activities, where the climate is arid, vegetation is sparse, and land use changes are frequent, i.e., they lacked the basic conditions needed to meet biological survival. In addition, although cultivated land is used as an artificial landscape, it possesses a moderate level of habitat maintenance function, and the habitat quality was generally categorised at the moderate level. Nature reserves concentrate the most fully functional ecosystems, which are crucial for protecting habitat quality and improving biodiversity levels. By identifying key areas and delineating priority protection areas, it will further contribute to the stability and improvement of regional biodiversity levels.

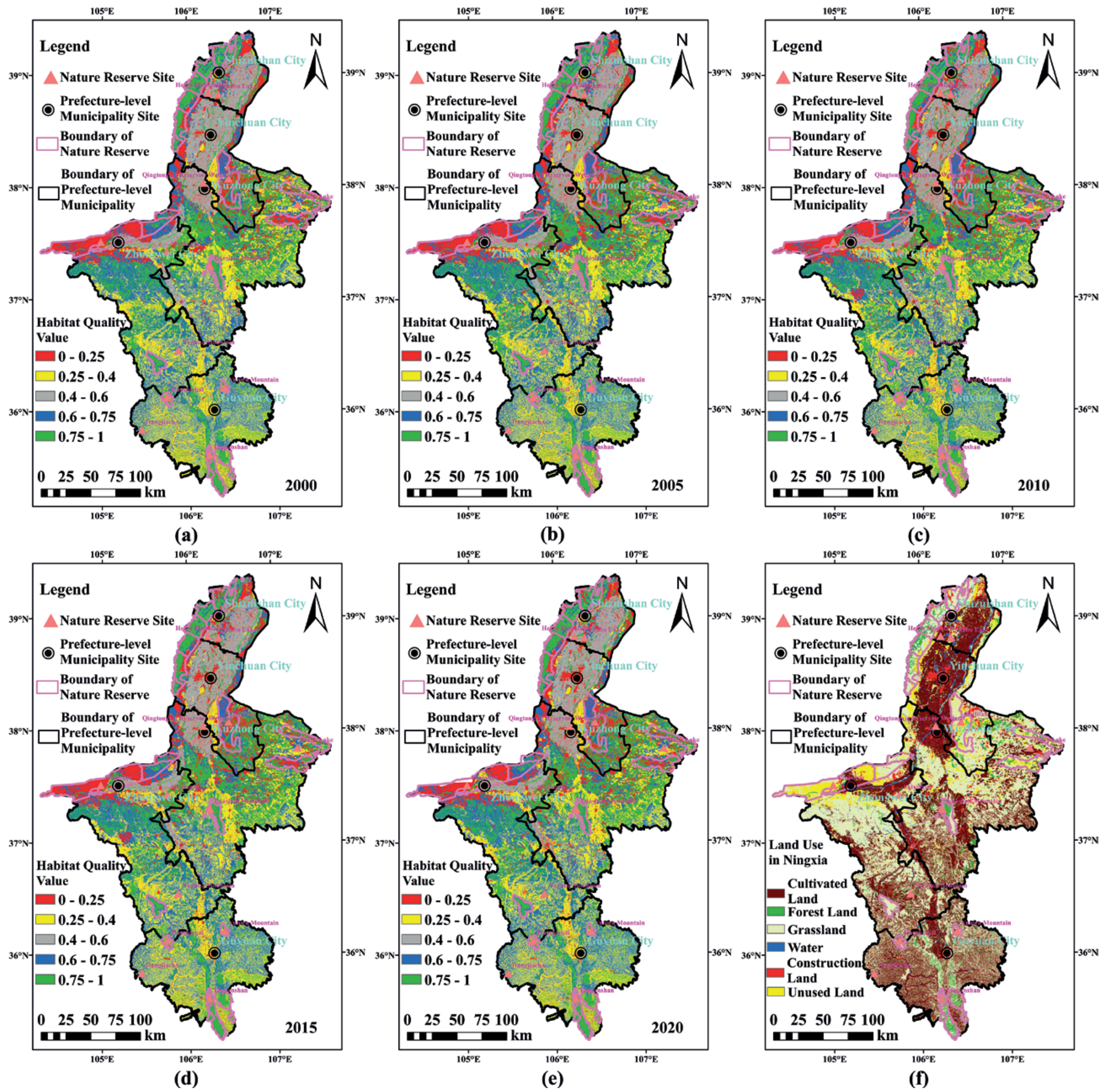


Figure 3. Spatial distribution of habitat quality and nature reserves in Ningxia from 2000 to 2020.

Dynamic changes of habitat quality in Ningxia

In terms of different levels of habitat quality (Fig. 6a), the proportion of high-level habitat quality patches in Ningxia increased by 1.26% from 2000 to 2020, while the low-level habitat quality patches also increased by 1.53%. The proportions of lower-level, moderate-level and higher-level habitat quality patch areas decreased by 1.29%, 0.62% and 0.87%, respectively. From different periods (Fig. 6a, b), the area of low-level habitat quality patches in Ningxia from 2000 to 2020 increased, the area of moderate-level habitat quality patches decreased, and the area of lower-level habitat quality patches was more volatile. While the area of higher-level habitat quality patches decreased and then increased, the high-level patches showed a trend of increasing and then decreasing. From 2000

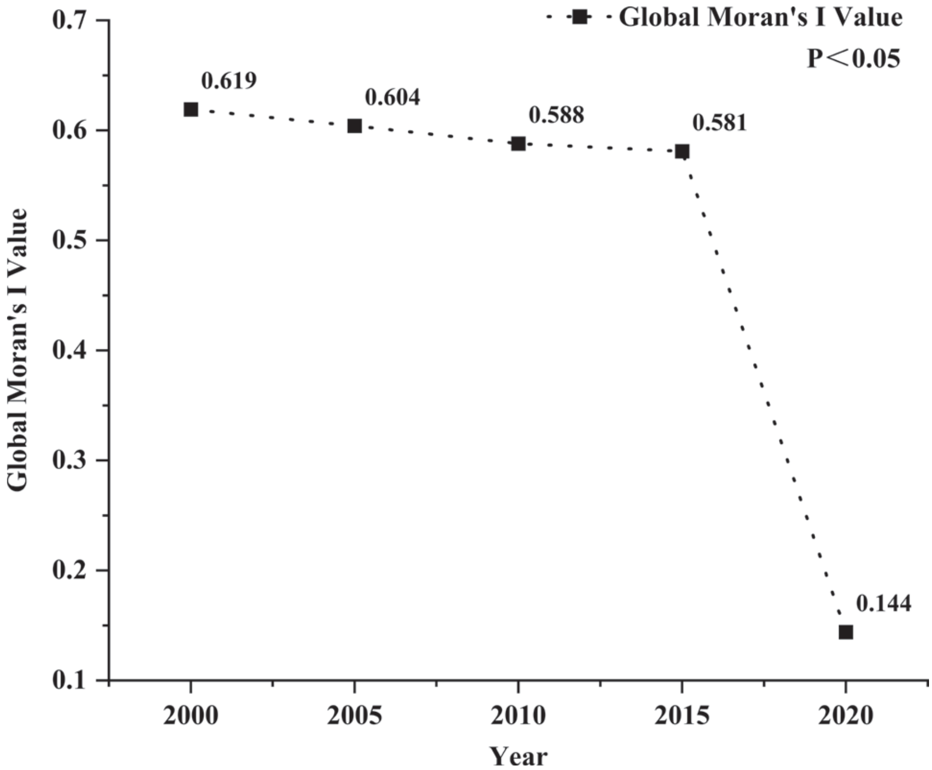


Figure 4. Spatial autocorrelation global Moran's I values of habitat quality in Ningxia from 2000–2020.

to 2020, the average habitat quality in Ningxia was maintained at a moderate level with small changes (<0.005) (Fig. 6b). On the one hand, ecological protection measures such as returning farmland to forests and grasses and ecological restoration have increased the habitat quality of some patches, but factors such as population growth and construction land expansion have caused the habitat quality of some patches to decrease, resulting in the contradiction between human activities and natural habitats remaining very prominent.

The spatial variation in habitat quality in Ningxia was divided into five classes: significantly decreasing (-1– -0.5), slightly decreasing (-0.5–-0.25), remaining stable (-0.25–0.25), slightly increasing (0.25–0.5), and significantly increasing (0.5–1) (Fig. 7a–f). In terms of spatial variation, habitat quality decreased more (-1–0.25) in areas such as Ningxia with a high density of construction land and some scattered cultivated land from 2000 to 2020. In contrast, significant increases in habitat quality were more concentrated in the central area where the cultivated land was returned to forest and grass (0.25–1). Habitat quality was stable in most areas of Ningxia over the 20-year period, with small changes (-0.25–0.25). In different periods (Figs 6a, b, 7a–f), the patches with decreasing habitat quality in Ningxia basically decreased continuously during the 20 years from 2000 to 2020. Most of the patches with habitat quality changes from 2000–2005 showed increases. From 2005 to 2010, habitat quality decreases were dominant. From 2010–2015, the decreasing trend remained severe. The decreasing trend improved only during 2015–2020.

The analysis of habitat quality in Ningxia showed (Fig. 7a–f) that the overall habitat quality of construction land and unused land was decreasing over the past 20 years, and these areas were severely disturbed by humans or had

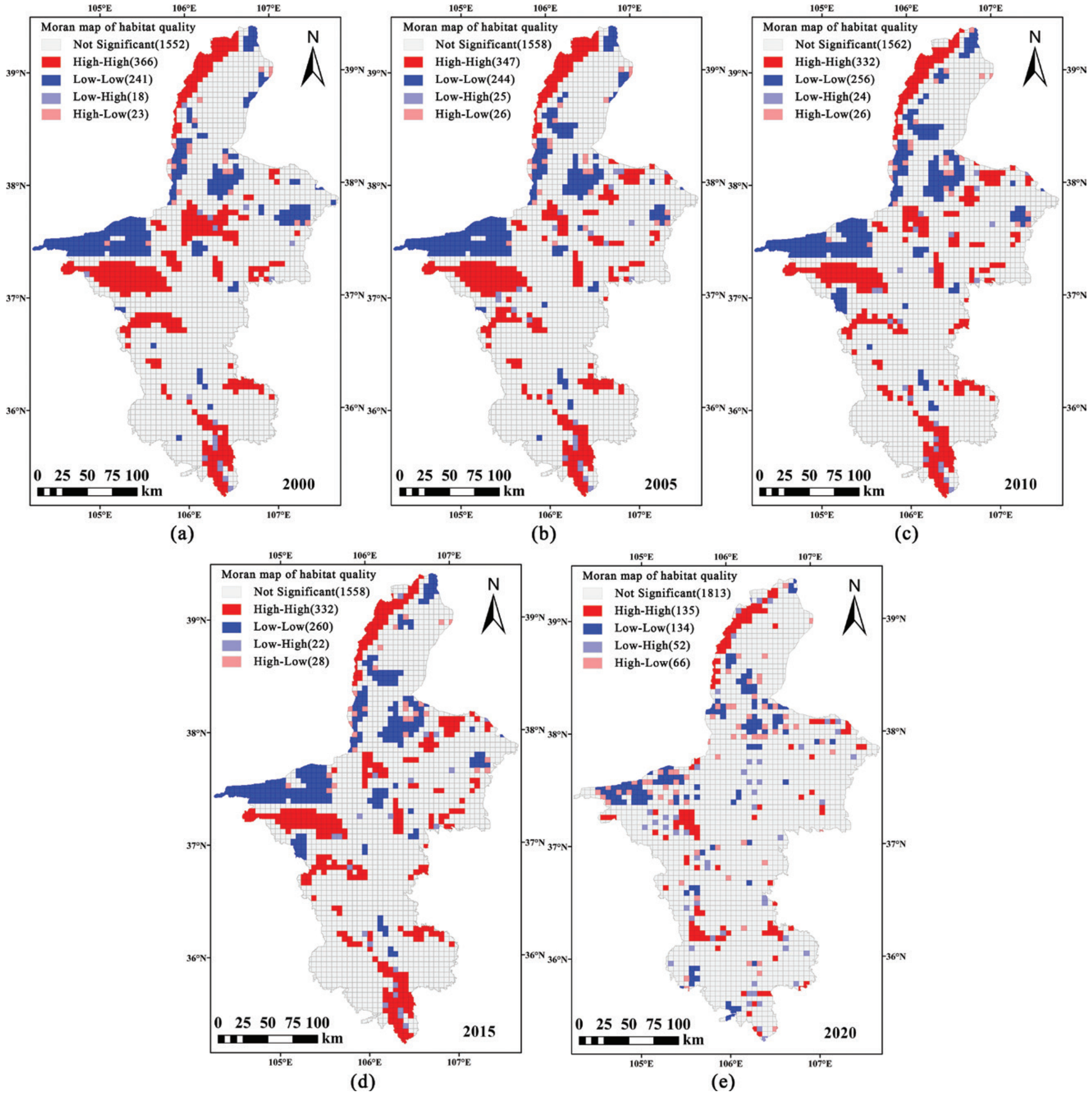
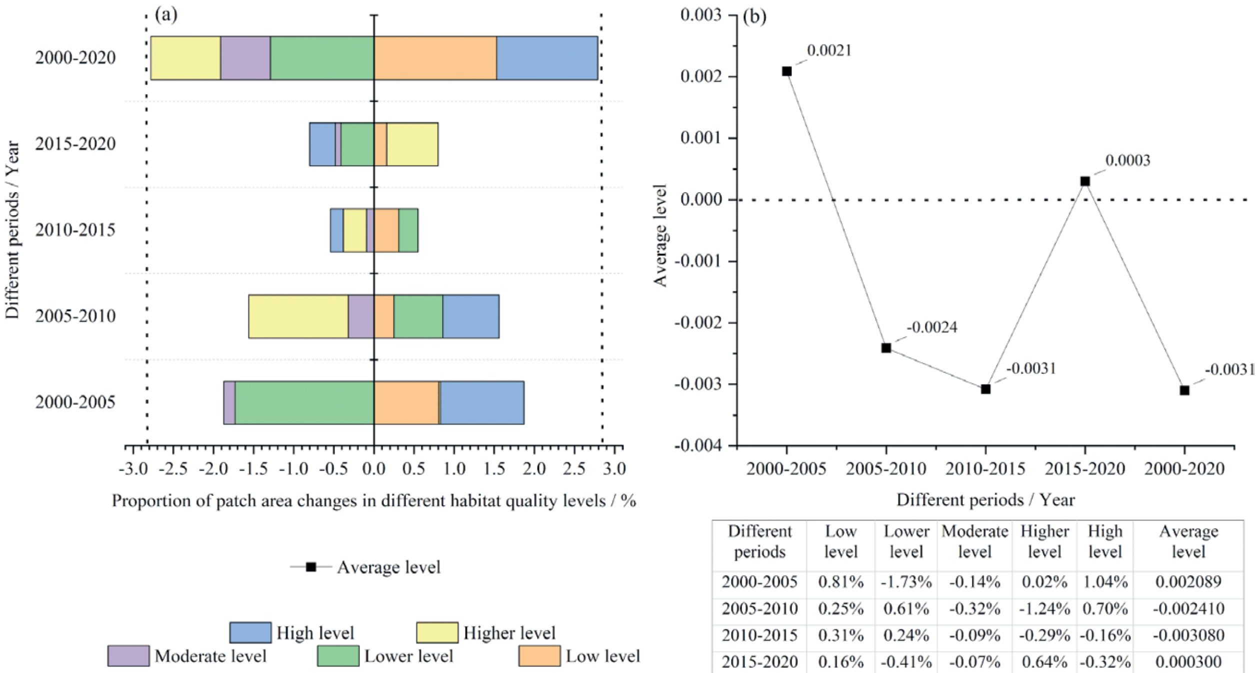


Figure 5. The results of spatial autocorrelation analysis of habitat quality in Ningxia from 2000 to 2020.

poor natural conditions. The patches with improved habitat quality were more randomly distributed, mostly in areas returned to forest and grass. By comparing the results with the land use change, we found that the changes from other types of patches to forest, grassland and water improved habitat quality, while the change from other types of patches to construction land, cultivated land and unused land obviously forced the habitat quality to decrease. When the habitat quality remained stable, the land use type remained the same over 20 years or the habitat quality remained the same after the transformation. Human activities not only cause damage to biological habitats, but also take proactive measures to control urban expansion and arable land development. The application of reasonable ecological restoration technologies and projects can promote habitat improvement. In this process, natural reserves, especially those designated for biodiversity, provide a stable and complete habitable environment, which has received significant attention and protection from humans, Integrating ecosystem functions and human needs.



Different periods	Low level	Lower level	Moderate level	Higher level	High level	Average level
2000-2005	0.81%	-1.73%	-0.14%	0.02%	1.04%	0.002089
2005-2010	0.25%	0.61%	-0.32%	-1.24%	0.70%	-0.002410
2010-2015	0.31%	0.24%	-0.09%	-0.29%	-0.16%	-0.003080
2015-2020	0.16%	-0.41%	-0.07%	0.64%	-0.32%	0.000300
2000-2020	1.53%	-1.29%	-0.62%	-0.87%	1.26%	-0.003100

Figure 6. Dynamic changes in the area proportion of patches with different levels of habitat quality in different periods in Ningxia from 2000 to 2020.

Analysis of the driving factors of habitat quality in Ningxia

Analysis of the applicability of the driving factor regression model

First, the analysis of 16 driving factors using Pearson's method found that the R^2 values for 2000–2020 (Fig. 8) were 0.327, 0.312, 0.325, 0.325, and 0.121, and the adjusted R^2 values were 0.322, 0.307, 0.320, 0.320, and 0.114, respectively (P < 0.05). From the sum of relative coefficients over the 20-year period (Fig. 9), factors such as AAT (-1.562), PCL (-1.302), and CLP (-0.895) had a strong negative effect on habitat quality in Ningxia, and factors such as RFI (2.158), SLP (2.142), ELE (1.604), and NPP (0.915) had a strong positive effect. Since the correlation analysis could not determine the covariance between the factors, OLS linear regression and GWR models were further adopted to explore the role of the 16 factors on habitat quality.

A comparative analysis (Table 4) revealed that the 2000–2020 GWR model AIC and AICc values were -4,365.10, -4,436.45, -4,302.96, -4,425.03, and -2,263.94 and -3,060.87, -2,542.82, -2,402.95, -2,525.42, and -1,769.53, respectively, which were significantly smaller than the OLS model AIC and AICc values. The R^2 and adjusted R^2 of the GWR model for 2000–2020 were 0.735, 0.779, 0.762, 0.777, and 0.202 and 0.692, 0.721, 0.700, 0.719, and 0.158, respectively, with a higher fitting effect and higher accuracy than the OLS model (0.70). In addition, OLS regressions of K(BP)-Prob and JB-Prob were significant (P < 0.01) in terms of regression coefficients and significance levels, indicating that the OLS regressions were robust and redundant in terms of the effect of each factor on habitat quality. The relative sum of OLS regression coefficients over the 20-year period indicated that habitat quality in Ningxia was strongly driven negatively

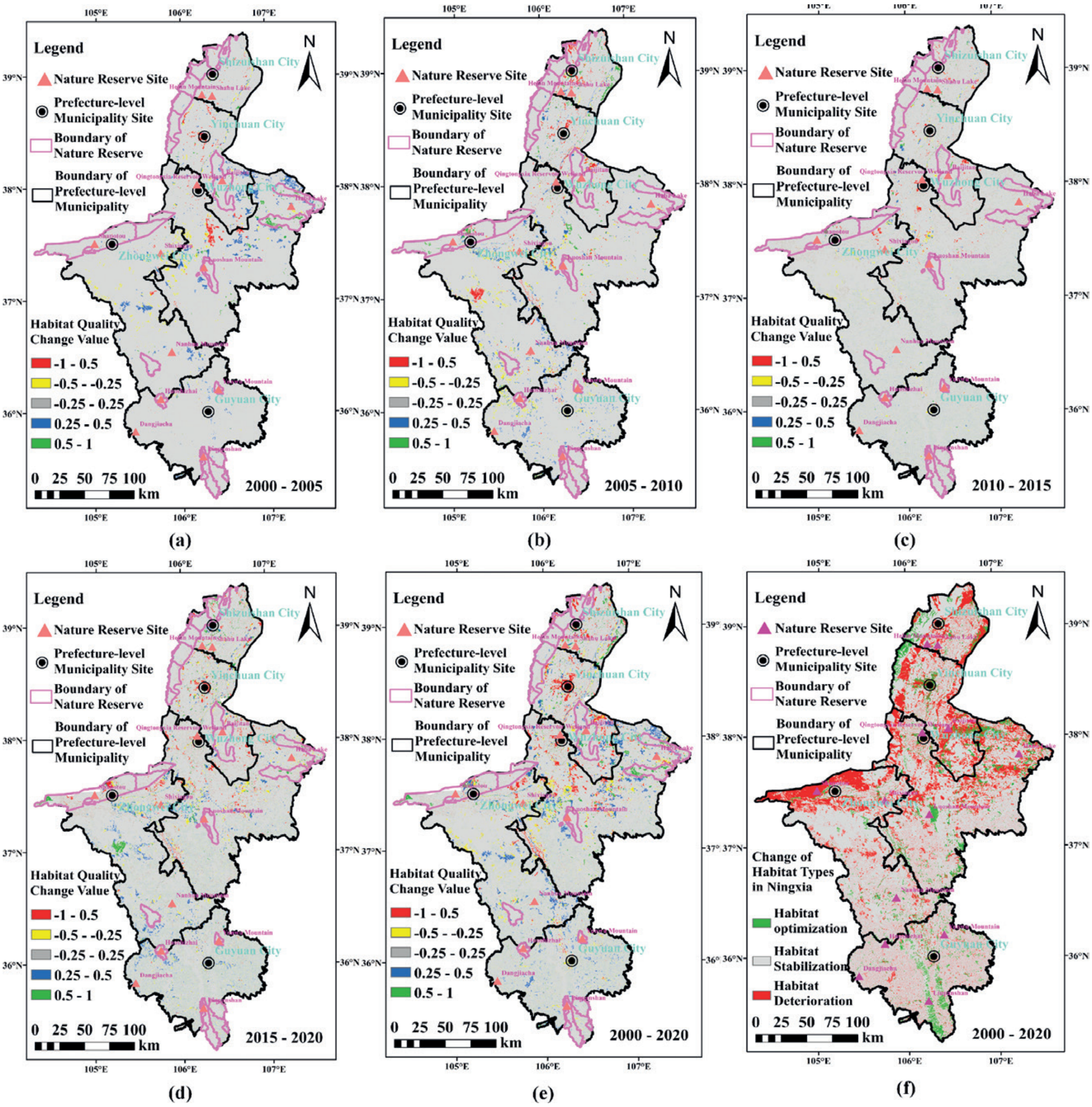


Figure 7. Spatial distribution of habitat quality and land use change in Ningxia in different periods from 2000 to 2020.

by PCL (-2.418), CLP (-0.485), and SLP (-0.083) and positively by SMC (1.215), NPP (1.109), and FVC (1.004). However, OLS regression is not applicable to the analysis of the driving effect of the factor random distribution due to the limitations of the small absolute values of the coefficients, the unmet significance level, and the significant aggregation of the residual results (Fig. 10a–e) (Global Moran's I = 0.618, 0.589, 0.591, 0.589, 0.086). Based on the results of Pearson correlation and OLS regression analysis (Fig. 11), the five driving factors with the strongest effects of multicollinearity (VIF: AAT, ELE, NPP, RFI, SLP > 7.5) were removed, the GWR model considering spatial heterogeneity was used to explore the driving effects of 11 factors including DRA, DRN, FVC, GDP, PCL, MPA, NLI, CLP, POP, RND and SMC on habitat quality in Ningxia.

Table 4. Comparison of regression test indicators between OLS and GWR models.

Year	AIC		AICc		R^2		Adj R^2	
	OLS	GWR	OLS	GWR	OLS	GWR	OLS	GWR
2000	-2,818.34	-4,365.10	-2,818.02	-3,060.87	0.327	0.735	0.322	0.692
2005	-2,754.45	-4,436.45	-2,754.14	-2,542.82	0.312	0.779	0.307	0.721
2010	-2,829.25	-4,302.96	-2,828.93	-2,402.95	0.325	0.762	0.320	0.700
2015	-2,832.13	-4,425.03	-2,831.81	-2,525.42	0.333	0.777	0.328	0.719
2020	-2,198.45	-2,263.94	-2,198.14	-1,769.53	0.121	0.202	0.114	0.158

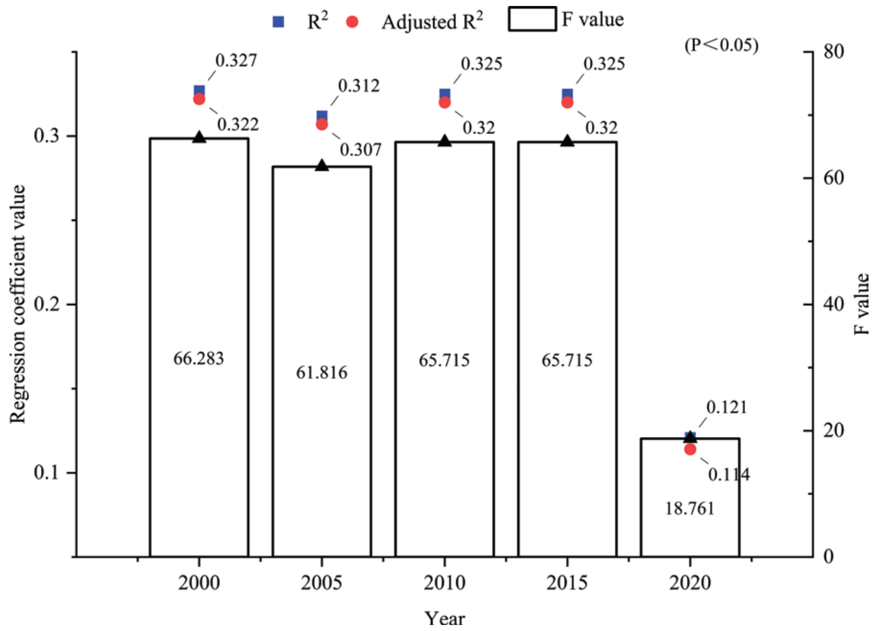


Figure 8. Pearson correlation significance results for each driving factor from 2000–2020.

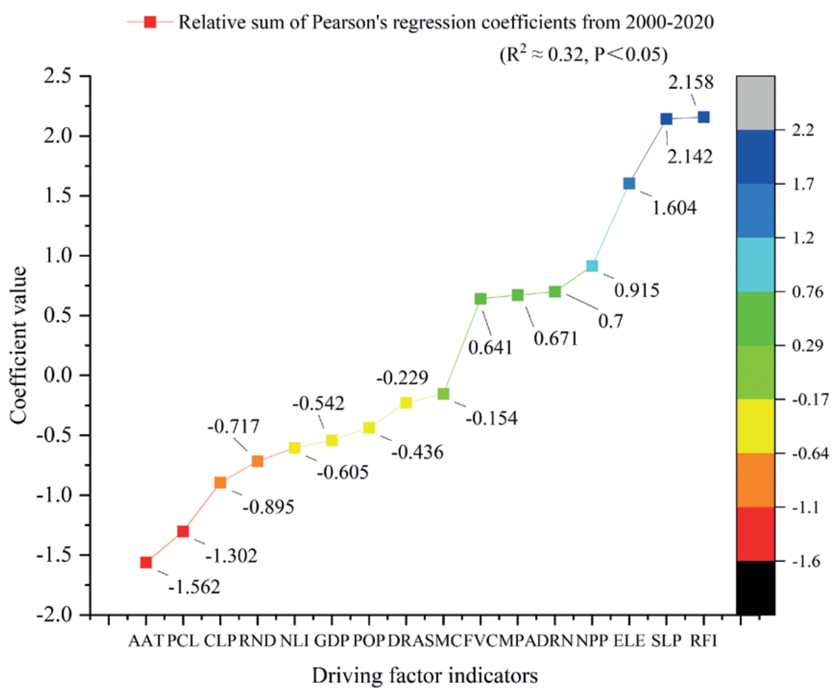


Figure 9. Relative sum of coefficients of Pearson correlation analysis of driving factors from 2000–2020.

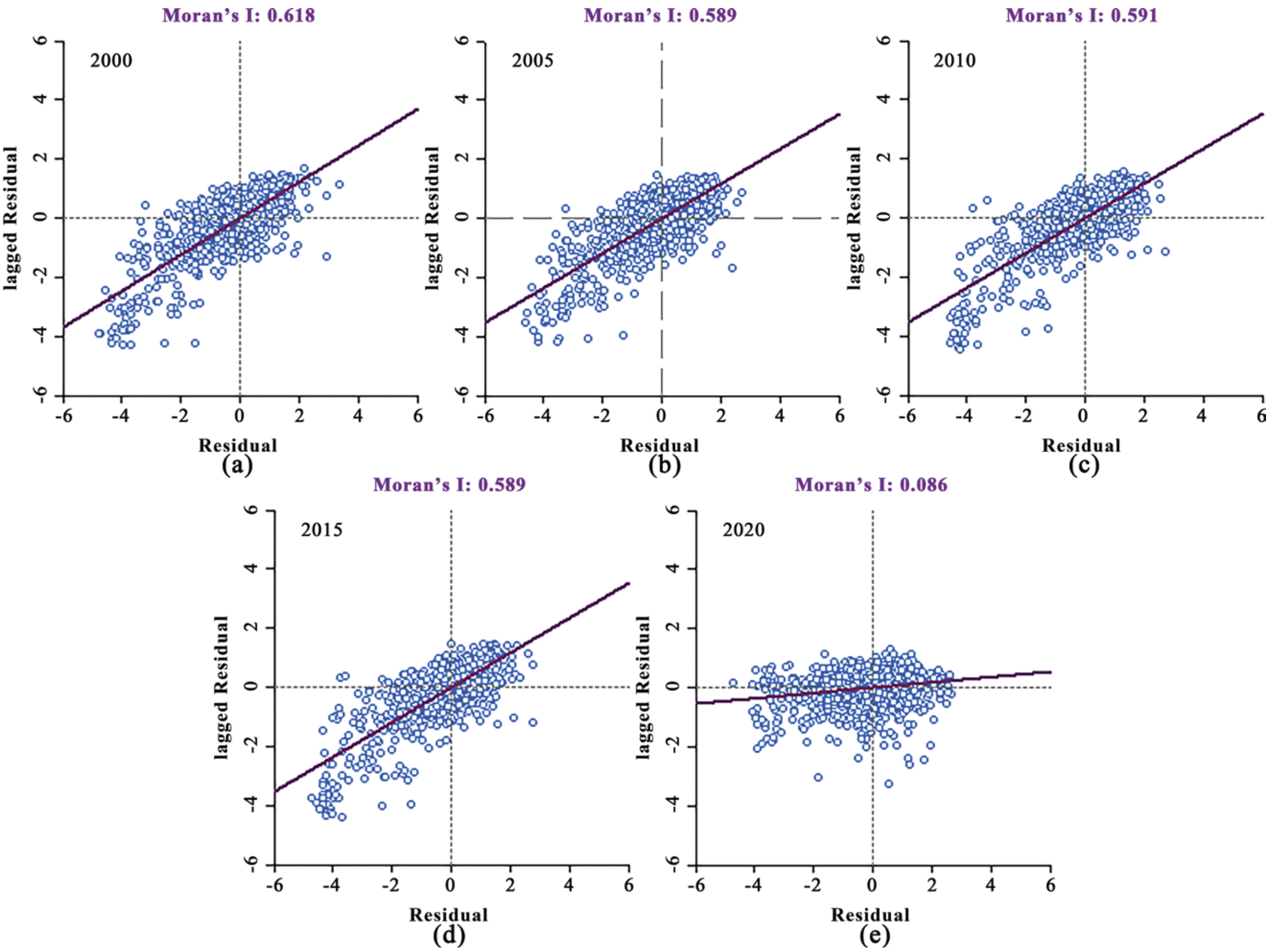


Figure 10. Results of spatial autocorrelation analysis of OLS regression residuals for habitat quality in Ningxia, 2000–2020.

Key driving factors of habitat quality in Ningxia

The results of GWR analysis showed (Table 5) that GDP (-0.001), NLI (-0.184), CLP (-1.413), and PCL (-3.260) negatively affected the habitat quality level in Ningxia, while FVC (1.765), SMC (0.619), DRA (0.023), POP (0.016), DRN (0.014), MPA (0.009), and RND (0.000) were positively correlated with habitat quality in Ningxia. Combining the absolute values of coefficients and driving effects over 20 years, we found that FVC (0.431, 0.392, 0.419, 0.256, 0.267), SMC (0.324, 0.097, 0.116, 0.089, -0.008), PCL (-0.687, -0.733, -0.687, -0.674, – 0.479), and CLP (-0.269, -0.356, -0.322, -0.327, -0.139) (Fig. 12) were the four factors with the strongest combined explanatory power for the spatial and temporal patterns and changes in habitat quality in Ningxia. Among them, FVC and SMC were positively correlated with habitat quality, PCL and CLP were negatively correlated with habitat quality, and the explanatory power of the remaining driving factors was weaker. This result indicates that higher vegetation cover and soil water content can significantly promote ecosystem habitat maintenance function. In contrast, a larger area of cultivated land and construction land within the unit grid will decrease the habitat quality.

From the local R^2 distribution map of Ningxia (Fig. 13a–e), it can be seen that from 2000 to 2005, the R^2 was higher in the Helan Mountain in northern Ningxia and in the Liupan Mountain in the south, while the R^2 was relatively smaller in the central and eastern regions, indicating that nature reserves such as the Helan Mountain and Liupan Mountain strongly affected habitat quality. Combined with the decreasing R^2 explanatory power of the key driving factors of FVC, SMC, PCL, CLP and habitat quality from 2000 to 2020, it was clear that the driving factors affecting habitat quality in Ningxia had complex nonlinear intersection characteristics during the 20 years, while the role of human disturbance became increasingly prominent.

Table 5. GWR regression coefficient values of habitat quality in Ningxia from 2000 to 2020.

Variable	2000	2005	2010	2015	2020	Relative sum of coefficients
Intercept	0.041	0.025	0.121	0.163	0.498	0.849
DRA	0.007	0.002	0.007	0.005	0.002	0.023
DRN	0.003	0.002	0.002	0.002	0.004	0.014
FVC	0.431	0.392	0.419	0.256	0.267	1.765
GDP	0.002	-0.001	0.000	-0.002	0.000	-0.001
PCL	-0.687	-0.733	-0.687	-0.674	-0.479	-3.260
MPA	0.002	0.002	0.001	0.001	0.002	0.009
NLI	-0.061	-0.054	-0.059	-0.010	0.000	-0.184
CLP	-0.269	-0.356	-0.322	-0.327	-0.139	-1.413
POP	0.001	0.004	0.001	0.010	0.000	0.016
RND	-0.002	-0.002	-0.001	0.000	0.004	0.000
SMC	0.324	0.097	0.116	0.089	-0.008	0.619

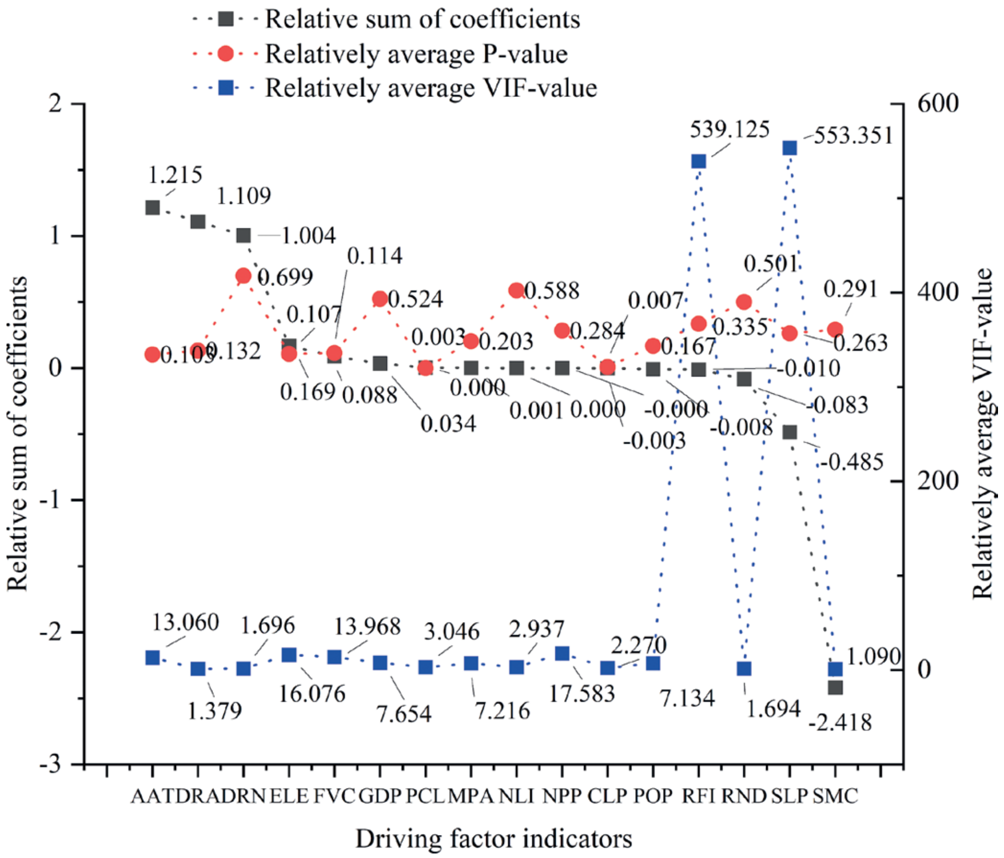


Figure 11. OLS regression coefficients, P values and VIF values of the driving factors from 2000 to 2020.

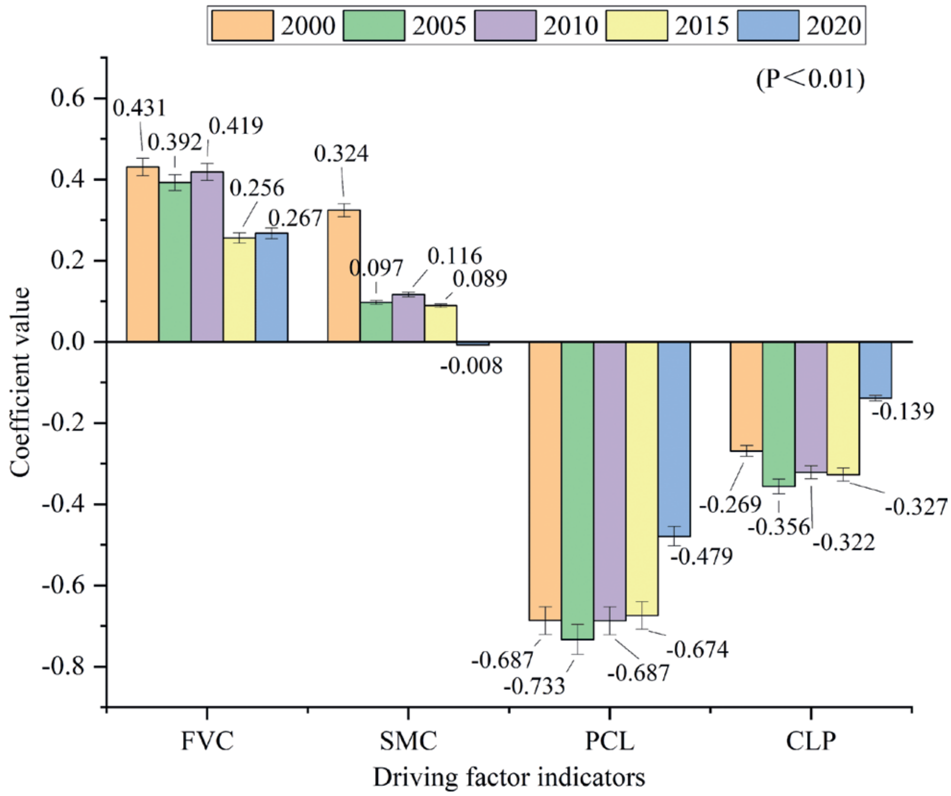


Figure 12. GWR regression coefficients of the main driving factors of habitat quality in Ningxia, 2000–2020.

Selecting the spatial distribution of the GWR regression coefficients of the main driving factors of habitat quality in 2020 as an example, spatially (Fig. 14a–d), the positive regression coefficients of FVC in Ningxia from 2000 to 2020 were concentrated in the central and northern Helan Mountain and the southern Liupan Mountain. These areas had a relatively high level of habitat quality, and the positive impact of FVC on habitat quality was very significant. The areas with positive SMC regression coefficients mainly included the central cultivated areas with good irrigation conditions and sufficient soil moisture, and a higher SMC had a stronger effect on habitat quality in these areas. The areas with negative PCL regression coefficients were mainly concentrated in the northern part of Ningxia with a high density of construction land and high developed urbanization level, and the habitat quality in these areas was generally low. The areas with negative CLP regression coefficients were mainly located in cultivated land in the yellow irrigation area, which retained part of the habitat maintenance function and had a moderate level of habitat quality. The spatial distribution of the regression coefficients of FVC, SMC, PCL, CLP and GWR of habitat quality had a small threshold of change during the 20 years, and the driving effects spread from the most accurate and close areas of their respective regression effects to the surrounding areas and gradually weakened, together with the interactions of other influencing factors, thus driving the distribution and evolution of habitat quality in Ningxia in the past 20 years. The driving effect of these key driving factors is particularly evident in the nature reserves of Ningxia, and the changes in key driving factors of habitat quality in nature reserves will largely drive changes in biodiversity, reflecting the importance of nature reserve delineation for biodiversity conservation under conditions of avoiding more human activities and sufficient ecological factors.

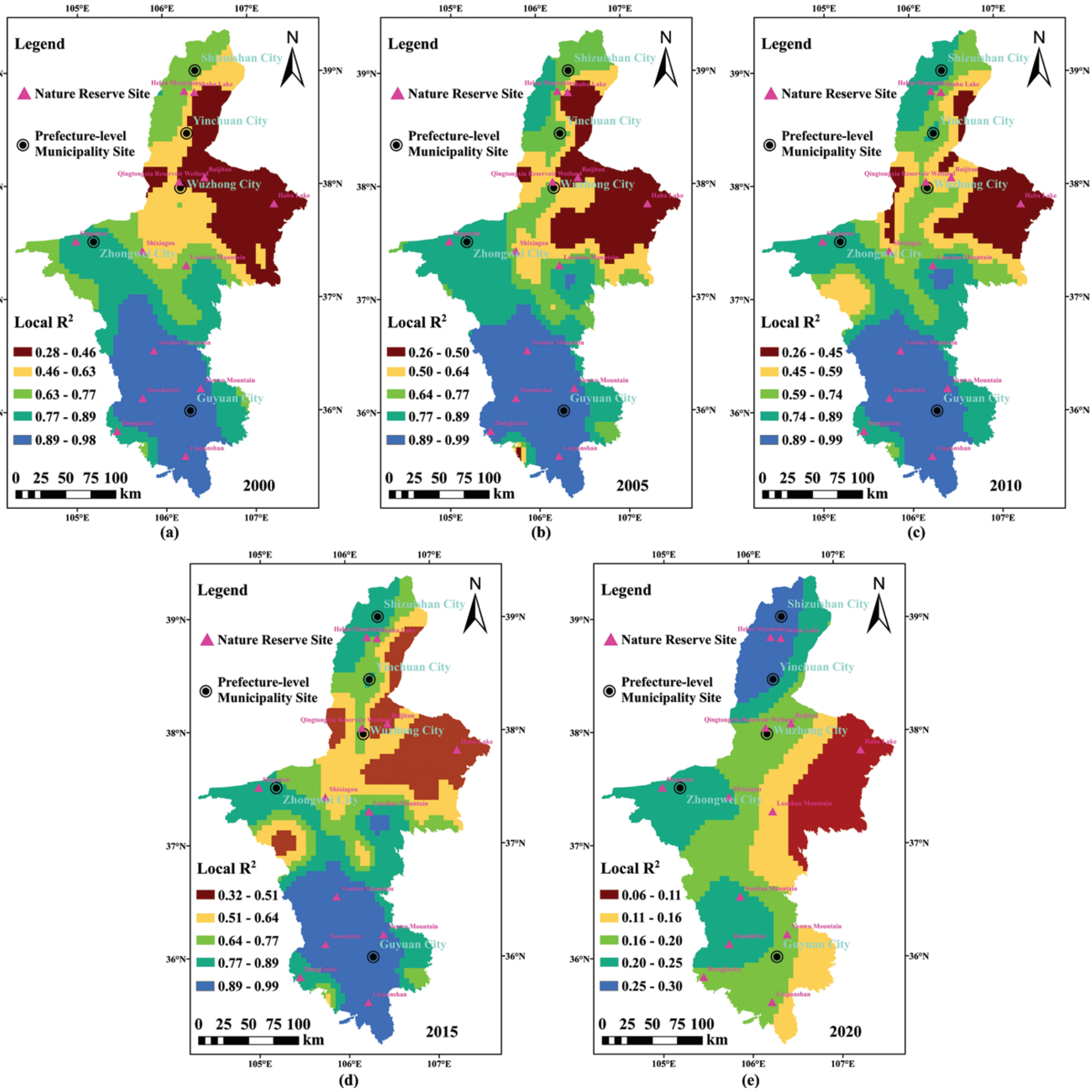


Figure 13. Local R^2 distribution of GWR regressions of the driving factors of habitat quality in Ningxia from 2000 to 2020.

Discussion

Habitat quality and biodiversity distribution in Ningxia

We conclude that the distribution and evolution of habitat quality in Ningxia were mainly driven by fractional vegetation cover, soil moisture content, cultivated land expansion, and construction land expansion, where high vegetation cover and soil moisture content were suitable for biological habitats; in contrast, cultivated land and construction land expansion reduced habitat suitability. The habitat quality of forestland, grassland, water area and some cultivated land in Ningxia was high, and these patches were in good condition as ecological source land and were far from human activity areas, so they were less disturbed by resource development and utilization. The habitat quality of areas such as urban land, which had a high intensity of human activities, was obviously extremely low. The

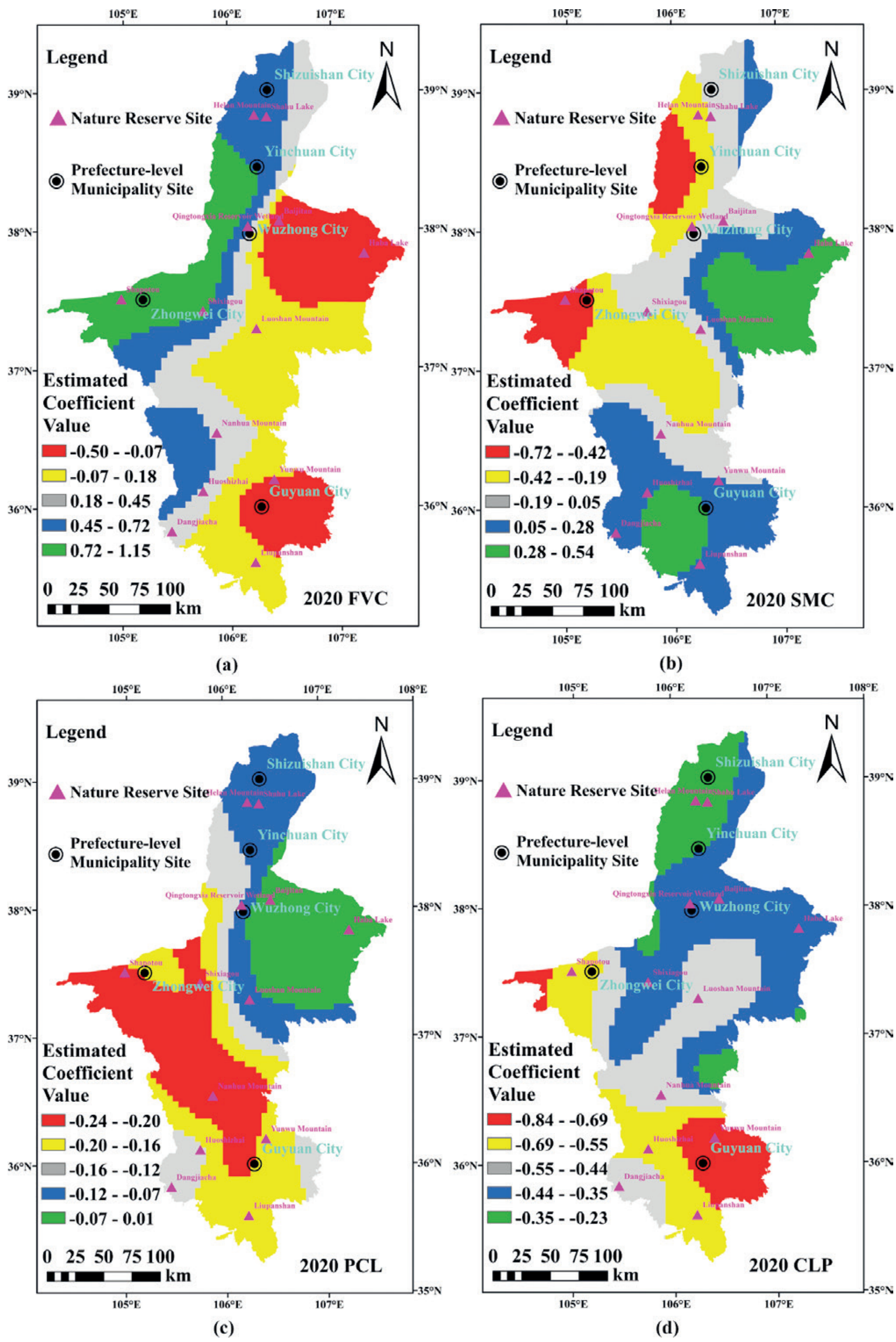


Figure 14. Distribution of GWR regression coefficients for the main driving factors of habitat quality in Ningxia from 2000 to 2020.

relationships between soil moisture content, some cultivated land, pasture land and habitat quality were more specific. On the one hand, higher soil water content in the natural state means lush vegetation, and the expansion of cultivated land is not conducive to habitat maintenance. However, on the other hand, due to the construction of artificial cultivated land and artificial wetland, the investment of human and material resources, green funds and ecological technology can maintain the fragile habitat to a certain extent. Therefore, there is uncertainty regarding the role of factors such as cultivated land and soil water content on habitat quality. In response to the weak natural foundation, from 2000 to 2020, Ningxia continuously improved its vegetation cover through the project of returning farmland to forest and grass, and the level of habitat quality in nature reserves such as Liupanshan and Luoshan increased significantly. Due to frequent industrial and agricultural activities such as food production and mineral extraction, the habitat quality fluctuated in some areas of Ningxia over the course of 20 years, and the results showed a decrease in habitat function. In conclusion, urban and cultivated land expansion are the most critical factors reducing habitat suitability in Ningxia, and protecting and utilizing grassland, vegetation, wetland and other ecosystems can effectively improve habitat suitability in Ningxia.

In addition, although other factors, such as topographic relief, had insufficient explanatory power for habitat quality in Ningxia, related studies have shown that rainfall, slope, elevation, and temperature are important conditions that influence the distribution and ecological niche of organisms within small-scale habitats (Rahbek et al. 2019; Chase et al. 2020). Combining field surveys and indoor ecological experiments to obtain detailed habitat data for all or key species in a region is essential in driving factors studies of habitat quality (Forister et al. 2015). Therefore, in specific habitats and typical ecosystems such as grasslands, deserts, and forests, we need more refined work to obtain the total number of various ecological factors and their thresholds required for birth, death, migration, dispersal, and reproduction during the life cycles of key species in the region to determine the causes of habitat quality heterogeneity within small and medium scales (Fahrig 2017). Additionally, these elements are the focus of ecological niche, biodiversity, and ecosystem conservation studies (Xiao et al. 2004).

GWR modelling can fully reflect the spatial non-smoothness of the region and select the optimal spatial weights in combination with spatial heterogeneity; the results have higher accuracy and credibility than Pearson correlation analysis and OLS regression for exploring the role of driving factors at large spatial and temporal scales. Although, the results are consistent with the trend of habitat quality changes in Ningxia over the past 20 years. However, some studies have shown that GWR is essentially a one-dimensional linear regression with parameters that fail to consider multivariate and correlational settings (Fotheringham and Oshan 2016; Fotheringham et al. 2017), while the occurrence of some human irresistible factors, causing the Moran Index and the R^2 results after regression in 2020 in this study were less satisfactory. To improve the exploration method of driving factors, future research can utilize multivariate nonlinear regression, image-by-image correlation analysis, and artificial neural network models (Fotheringham et al. 2015; Li and Fotheringham 2020). Meanwhile, the sampling accuracy of the unit grid was improved, which eventually made the results match the actual influence of driving factors (McGarigal et al. 2016).

Habitat maintenance and ecosystem protection in ecologically fragile areas

Ningxia is a typical ecologically fragile area with relatively poor natural foundations, and the habitat quality is at an intermediate level with a wide scope for improvement. This study explored the driving effects of habitat quality in Ningxia based on 16 physical geographic, economic and social factors and found that habitat quality tended to be higher in areas with higher vegetation cover and lower in patches with a high proportion of construction land and cultivated land. The results demonstrate that for ecologically fragile areas with similar characteristics to Ningxia's ecological environment, enhancing vegetation cover can effectively improve habitat structure and function. For ecologically fragile areas, poor conditions such as low precipitation, loose soils, and low biodiversity, coupled with the frequent use of natural resources due to economic development, have led to further anthropogenic damage to the already fragile habitats. Ecologically fragile areas often lack biologically beneficial ecological factors, and due to the harsh natural conditions and prominent human-land conflicts, humans must sacrifice habitat quality in exchange for improved well-being, thus leading to a vicious circle of economic and social development and ecosystem decline in ecologically fragile areas (Tong and Long 2003). Therefore, it is of great practical significance and scientific value to find a way to maintain habitat quality, ecological environmental protection and sustainable and healthy economic and social development in both directions in ecologically fragile areas (Len and Liu 1999; Aksoy and Bayram Arli 2020). Of course, achieving a synergistic promotion of natural systems and economic society depends on rich biodiversity and on the frequency and cost of investment of time, money, technology, and methods by government, society, the public, and researchers and conservation agencies.

In this study, we considered 16 factors that are critical for influencing biodiversity levels in ecologically fragile areas, and these factors fully reflected the natural climatic conditions and human activity disturbances in ecologically fragile areas. The results can be used as a reference for the conservation of ecosystems in other ecologically fragile areas internationally. In the future, studies on biodiversity conservation and habitat quality in ecologically fragile areas should combine model simulations and biodiversity field surveys to summarize the distribution and change characteristics of habitat quality over a long time series. It is also important to understand the habitats of specific species from the key areas of habitat quality maintenance, such as nature reserves and ecological functional areas, which will give more full play to the natural stability (resistance and resilience) and human maintenance of the habitat systems in ecologically fragile areas (Geldmann et al. 2013; Gray et al. 2016). For example, Ningxia has designated a priority area for biodiversity conservation (24,409.7 km^2), which accounts for 47.1% of the national territory, effectively covering the typical ecosystems, biodiversity hotspots, and important ecological function areas within the territory and will play a leading role in long-term biodiversity conservation. How to build ecological barriers, ecological corridors and ecological nodes using nature reserves, nature protection areas and other ecosystems with strong habitat suitability to protect the landscape diversity and functional integrity of ecologically fragile areas for biological survival and reproduction will be important for future policy-makers and academic research. Our research supports that focusing on important natural conditions such as vegetation and precipitation in ecologically fragile areas and reducing excessive resource claims will benefit the natural vitality and well-being of human in ecologically sensitive and fragile areas.

Global changes such as climate change and cultivated land expansion have increased the instability of ecosystems in ecologically fragile areas (Garcia et al. 2014; Hautier et al. 2015; Venter et al. 2016; Newbold 2018), leading to a deterioration in biodiversity levels. Studies on global biodiversity suggest (Waldron et al. 2013; Gray et al. 2016; Lepczyk et al. 2017; Wintle et al. 2019; Maxwell et al. 2020; Xu et al. 2021) that the main measures that can be applied to biodiversity conservation in ecologically fragile areas are (1) the use of small patches to protect the minimum suitable habitat for very small populations and in this way consolidate the basis of biodiversity; (2) strengthening the intensification of cultivated land, the construction of nature reserves and the investment of green funds at the regional scale and focusing on the creation of good biodiversity landscapes in urban spaces; and (3) relying on international cooperation such as the Convention on Biological Diversity, in which we will link biodiversity and ecosystem services and improve human well-being to enhance genetic, species, and ecosystem diversity. Under the above opportunities, the identification of habitat suitability and ecological factors that cause habitat changes, the introduction of nature-based solutions to biodiversity dilemmas, and the realization of the systematic assessment, monitoring and management of biodiversity and ecosystems in multiple spatial and temporal sequences will further contribute to the achievement of the UN CBD goals.

Summary

This study evaluated the habitat quality of Ningxia from 2000 to 2020 based on the InVEST model, analysed the spatial and temporal patterns and changes during the 20-year period, and explored the role of driving factors on habitat quality using correlation analysis, the OLS model, and the GWR model in combination with 16 physical-geo-socioeconomic factors. The main results of this study are as follows:

(1) From 2000 to 2020, the average habitat quality in Ningxia was 0.576,428, 0.578,517, 0.576,102, 0.573,025, and 0.573,325, respectively, which increased and then decreased over 20 years, with a small overall decrease. The high-level habitat quality patches in Ningxia were mainly distributed in areas with high vegetation cover, while the low-level habitat quality patches were mainly distributed in areas subject to more frequent human activities, such as construction land and cultivated land. The habitat quality level in Ningxia had significant high-high value aggregation and low-low value aggregation characteristics, which basically overlapped with the distribution of high-level habitat quality and low-level habitat quality, respectively, while the area of patches with low-high value and high-low value aggregation characteristics was small.

(2) From 2000 to 2020, the regression results R^2 of 16 driving factors and the GWR model of habitat quality in Ningxia were 0.691,66, 0.721,169, 0.699,633, 0.718,556, and 0.158,344, respectively. By comparing R^2, AIC, AICc and other test indicators, we found that the GWR regression model in this study was able to fit the driving effects of different factors on habitat quality in Ningxia at different spatial scales. The results showed that FVC, SMC, PCL and CLP were the most important driving factors affecting the spatial distribution and evolutionary characteristics of habitat quality in Ningxia. Among them, high vegetation cover and soil water content positively promoted habitat suitability, and construction land and cultivated land expansion negatively affected habitat suitability.

(3) The integrity of habitats can ensure the ecological factors required for biological survival, while the multifunctionality of landscapes enriches the diversity of biological evolution. In natural ecosystems and socio-economic systems, the positive or negative role played by human activities is increasingly becoming an important driving factor for the quality of habitats. Whether policy formulation and public participation prioritize, coordinate, or lag the development of natural biodiversity, it determines the indispensable harmony between human and nature in the region. By integrating the distribution, evolution and driving factors of habitat quality in Ningxia, we found that for the conservation of biodiversity and habitat quality in ecologically fragile areas, it is first necessary to maintain the integrity of the original natural habitats as much as possible and increase the multifunctionality of the landscape so that organisms can survive, reproduce and spread smoothly. Second, it is necessary to minimize human interference with the natural landscape and to carry out human activities such as urban construction and cultivated land production in an appropriate and reasonable manner to avoid habitat fragmentation and improve the connectivity of habitat patches. Finally, it is necessary to protect already fragile natural habitats by delineating nature reserves and to develop suitable ecological environmental protection policies for targeted protection and restoration of habitat-sensitive and fragile areas.

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Additional information

Conflict of interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Ethical statement

No ethical statement was reported.

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Author contributions

H.H. constructed the concept and overall framework of the research and provided the necessary funding sources and other funding for the research; D.W. collected and sorted out the research data and designed and visualized the charting of the research results; L.S. and H.L. helped D.W., to skillfully use relevant software and charts; D.W., has written and reviewed the first draft, and Y.L. has given great creativity in polishing and improving the article; H.H., L.S., H.L., and Y.L. have all made great contributions to the writing, revision, editing of articles and the management, investigation and implementation of projects. All authors have read and agreed to the published version of the manuscript.

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Data availability

Not applicable.

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