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RESPONSE OF HABITAT QUALITY TO TEMPORAL AND SPATIAL LAND USE CHANGE AND ITS DRIVING FACTORS: A CASE STUDY OF GANJIANG RIVER BASIN

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Abstract

The Ganjiang River Basin, situated within the Yangtze River Basin, holds substantial ecological significance. A comprehensive understanding of the spatial-temporal variations and underlying drivers of habitat quality in this region is imperative for ensuring ecological security and upholding national ecological rights and interests. In this study, we utilized a remote sensing dataset and employed the InVEST model to analyze habitat quality distribution across both watershed and sub-watershed scales. Additionally, we integrated a land use transfer matrix and Moran's I index to examine the spatial and temporal patterns of habitat quality variation. The impact of 12 primary driving factors on habitat quality distribution was assessed using the geo-detector method. Our findings indicate the following: (1) Over the past two decades, the overall habitat quality in the Ganjiang River Basin has remained high, albeit exhibiting a consistent downward trend. (2) Approximately 60% of the basin area experienced degradation in habitat quality, primarily concentrated in the upper reaches characterized by initially favorable ecological conditions. Conversely, approximately 14% of the area demonstrated improvements in habitat quality, suggestive of the efficacy of select environmental protection initiatives. (3) Land use intensity emerged as the predominant factor influencing habitat quality, with inter-factor interactions exhibiting greater explanatory power than individual factors. Notably, the interaction between land use intensity and terrain exerted the strongest influence, underscoring the disproportionate impact of economic activities in rugged terrain on habitat quality decline. Our findings hold significant implications for guiding ecological protection efforts in critical regions and provide a robust scientific foundation for ecosystem management and sustainable development initiatives.

Key words: Ganjiang River Basin, habitat quality, InVEST model, land use change

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1. Introduction

Habitat quality (HQ)refers to the ability of the ecological environment to provide suitable living conditions for the sustainable development of individuals and groups. The change of habitat quality is the common result of regional location, geographical characteristics, climate conditions and human activities (Liu et al., 2019). The quality of an area's habitat reflects the synthesis of many natural and societal elements (Kar and Gupta, 2023; Mortelliti et al., 2010; Wu, 2021). The value of HQ indicates the ecological carrying capacity and potential production, which can be applied to gauge the level of regional biodiversity (Firmansyah et al., 2023). Improving habitat quality is helpful to protect and restore biodiversity and ensure regional ecological security (Terrado et al., 2019). Investigating the spatial distribution and evolutionary mechanism of HQ can provide statistics for regional landscape planning, landscape pattern optimization, and ecological surroundings safety (Li et al., 2021; Zeng et al., 2023).

The Ganjiang River Basin, situated in the hilly and mountainous belt of southern China, is the primary tributary of the Yangtze 6River located in the key ecological function zone of the Yangtze River (Fu

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et al., 2023). Abundant in water, soil, forest, and wildlife resources, it serves as a vital guarantor for China's ecological and economic development (Deng et al., 2019; Yang and Wu, 2023). Simultaneously, the Ganjiang River Basin lies within the economic growth belt of the middle and lower reaches of the Yangtze River, significantly influenced by the human-land relationship. In recent years, rapid socio-economic development (Cao and Xie, 2023; Junwen and Yuxin, 2023),) has intensified in the Ganjiang River Basin, leading to notable land use changes and ecological transformations in this region (Liu et al., 2021; Miserendino et al., 2011). Therefore, the dynamic assessment of HQ and its driving forces assumes paramount importance for rational land surface layout and ecosystem stability and restoration maintenance (Shu et al., 2019).

Land use serves as the cornerstone for biodiversity, and its alteration disrupts the flow of material and energy across habitat patches, leading to habitat quality degradation and posing threats to ecological environments and regional biodiversity conservation (Huang et al., 2019; Liccari et al., 2022; Wang et al., 2017). Therefore, land-use change analysis forms the bedrock of HQ research (Erdogan and Salis, 2023). Local governments can implement policies for local ecological protection and achieve sustainable regional development by analysing the ramifications of HQ and land-use change (An et al., 2021; Betul and Onur, 2023; Gao et al., 2017; Liu et al., 2022).

HQ evaluation techniques encompass two approaches. The first is the index system method based on landscape patterns (Zlinszky et al., 2015), primarily leveraging field research to derive HQ metrics and construct comprehensive assessment indices (Wei et al., 2022; Zlinszky et al., 2015), However, due to constraints in time and manpower, field survey sample methods tend to focus solely on HQ of specific species or narrow regions, rendering long-term research endeavors challenging. The second approach evaluates HQ utilizing ecological models (Xu et al., 2019; Zhang et al., 2020). The Integrated Valuation and Trade-off of Ecosystem Services (InVEST) model, Social Value of Ecosystem Services (SoLVES), and Species Distribution Models (SDMs) are common assessment models. Powerful spatial visualization and accurate calculation results are also used to evaluate HQ (Irman et al., 2023; Tang et al., 2015). The InVEST model, renowned for its robust spatial visualization and accurate calculation results, facilitates HQ evaluation by examining and computing several criteria, such as habitat degradation extent and ecological sensitivity across different habitat types (Fellman et al., 2015; Johnson, 2007; Sallustio et al., 2017; Stanford University, 2023). The InVEST model finds widespread application in assessing HQ in areas of significant ecological value, primarily nature reserves (Terrado et al., 2016; Wang and Cheng, 2022; Wei et al., 2022), river basins (Berta Aneseyee et al., 2020; Bi et al., 2023; Guihua et al., 2016), and urban centers (Chen et al., 2023; Han et al., 2019; Nematollahi et al., 2020; Zhu et al., 2020). For instance, Liu et al. (2019) examined the spatial and temporal changes in HQ in the Yangtze River Economic Belt using the InVEST model, GIS spatial analysis methods, regression analysis, and topographic position index. The authors discovered that the research area's mean value of HQ had a tendency to decline due to the trend of deterioration. Additionally, Berta Aneseyee et al. (2020) conducted a qualitative case study of the Winike watershed using land-use/cover change information and the InVEST model and found that agricultural land encourages the diversity of wildlife and birds in the region, thereby demonstrating the InVEST model's utility in HQ evaluation.

The Ganjiang River Basin belongs to both the Yangtze River economic development belt and the Yangtze River Ecological protection area. Since 2000, advancements in socio-economic development and ecological engineering have intensified land use change, rendering it a focal point for urbanization development and ecological conflicts. Frequent human activities have undermined natural ecosystem functions in certain areas, imperiling the living environment of numerous plant and animal species. However, there remains a dearth of long-term studies on habitat quality in this region. Therefore, this study focuses on the Ganjiang River Basin, utilizing remote sensing data to systematically investigate land use changes from 2000 to 2020. At the same time, statistical tools and geographic information system tools were used to deeply analyze the spatio-temporal change pattern of HQ in the past 20 years. As a driving factor analysis tool, geodetector has been widely used and verified in the field of ecology. Therefore, this study selected 12 environmental factors and human factors, and introduced geodetector to explore the main driving force causing the change of HQ spatial distribution.

This study aims to (1) identify the temporal and geographical changes in land use and HQ in Ganjiang River Basin between 2000 and 2020, (2) determine the spatial heterogeneity of HQ, and (3) analyze the relationship between influencing factors and HQ. Our findings offer deeper insights into how human activity-driven land use changes influence biodiversity, provide recommendations for land management for development and conservation in the Ganjiang River Basin, and furnish theoretical support for ecological sustainability.

2. Materials and methods

2.1. Study area

The Ganjiang River is the primary tributary of the Yangtze River and the largest river in Jiangxi Province. The basin is 766 km long and 83.500 km^2 in size located at 24°30‘–27 °10’ E and 113°55‘-116 °35N. It is demarcated into three sections: the upper segment, which extends from the river's source to Ganzhou, traversing hills and valleys; the middle segment, stretching from Ganzhou to Xingan through hilly terrain; and the downstream segment, which flows from Xingan to Wu-cheng, coursing through hills and connecting to the Yangtze River via Poyang Lake (Bi et al., 2023). Recently, Jiangxi Province is experiencing fast socioeconomic growth, with major increases in urbanization and industrialization. Between 2000 and 2020, the collective population of prefecture-level cities within the Ganjiang River Basin surged from 38.956 to 42.435 million individuals, accompanied by a corresponding rise in GDP from 179.94 to 2.379.52 billion yuan (Lang et al., 2023).

Over the past few decades, the ecosystem of the Ganjiang River Basin has faced mounting pressure stemming from industrial pollution, land development, and excessive logging (Xu et al., 2020). These factors have detrimentally affected the quality of the ecosystem, jeopardizing its sustainable development, and leading to the degradation of natural habitats and loss of biodiversity.

2.2. Data source and processing

Land use data were obtained from the land use data set in 2000, 2010 and 2020 of the Center for Resources and Environmental Science and Data, Chinese Academy of Sciences (https://www.resdc.cn/). These data, featuring a spatial resolution of 30 meters, were generated utilizing a human-computer interaction interpretation method. Additionally, a digital elevation model (DEM) generating slope and aspect information was derived from a geospatial data cloud platform (http://www.gscloud.cn). The Normalized vegetation index (NDVI) data were provided by the National Data Center for Ecological Sciences (http://www.nesdc.org.cn/).

Socio-economic data primarily comprised population density data from RESDC (http://www.resdc.cn) and GDP per capita data sourced from the statistical yearbook. The National Geographic Information Directory Service (https://www.webmap.cn) provides grid data on road and waterway networks. For this study, the fishing net creation tool of ArcGIS10.8 was used to create nets with a size of 2kmx2km, and 113996 grids were generated. The statistical tool for zoning facilitated the acquisition of mean or sum values for land use intensity, slope, population density, precipitation, and temperature within each grid. Finally, geodetector was introduced to analyze the driving force of spatial differentiation.

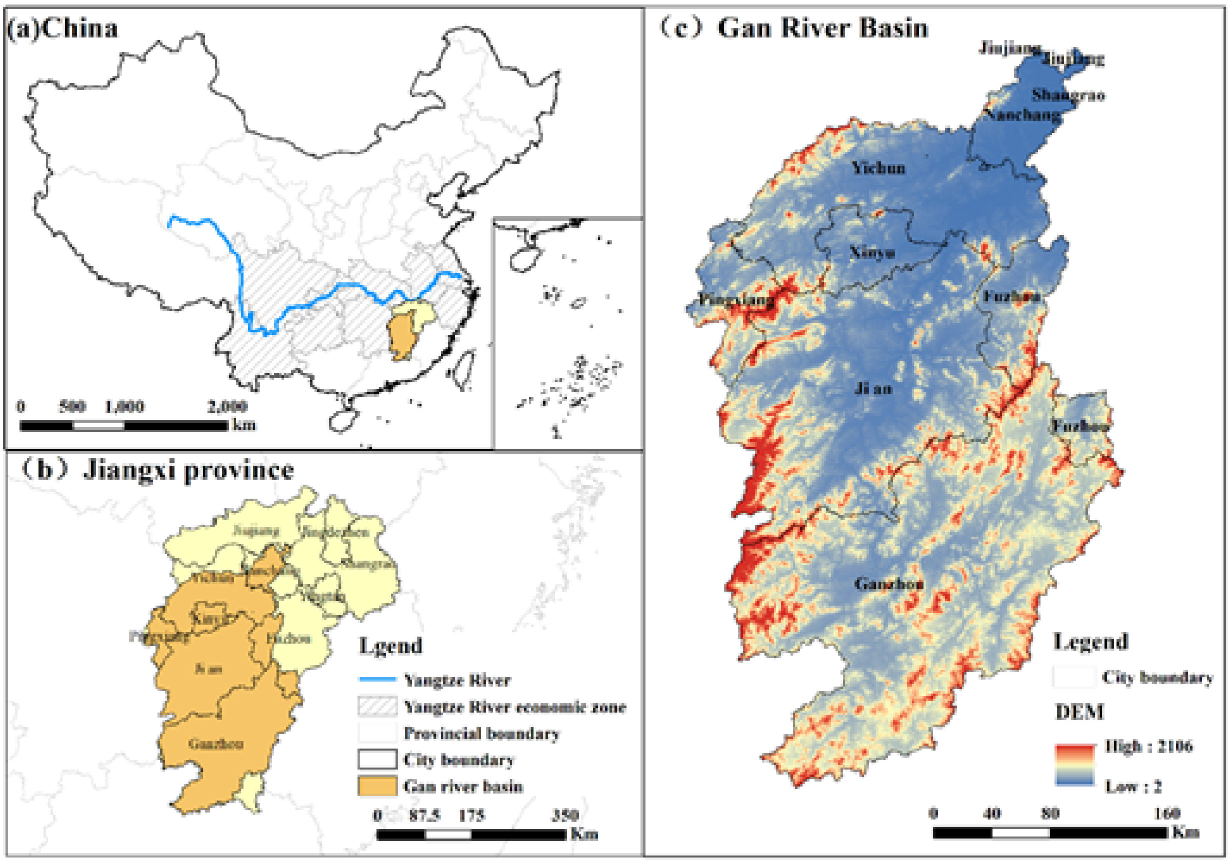

Fig. 1. Study area of the Ganjiang River Basin, (a) Location of the Ganjiang River Basin in China, (b) Location of the Ganjiang River Basin in Jiangxi Province, (c) Digital elevation model of the Ganjiang River Basin

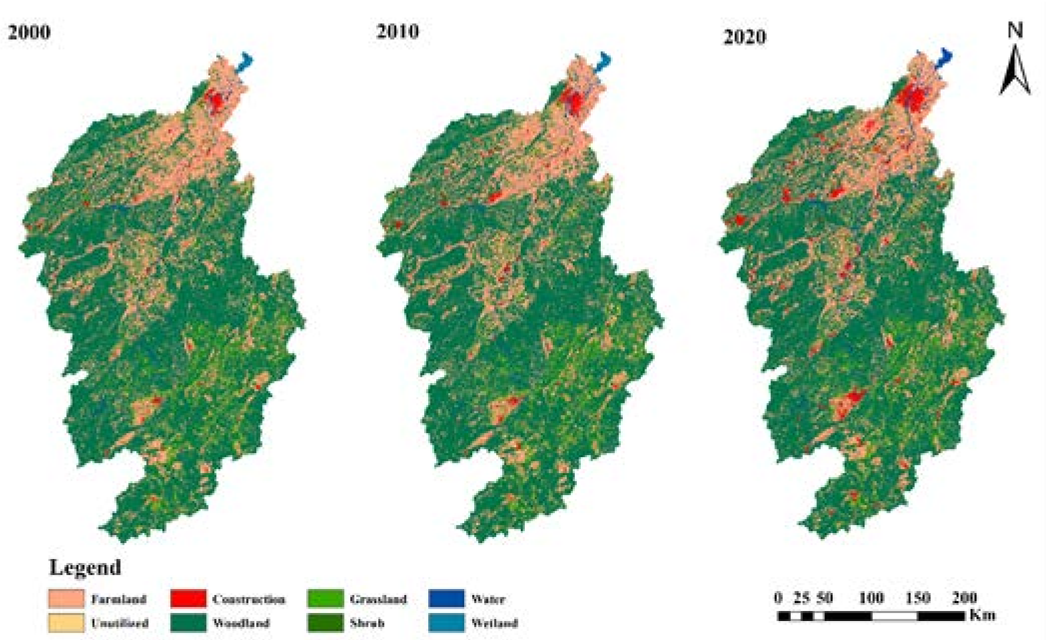

Fig. 2. Land use patterns in the Ganjiang River Basin in 2000, 2010, and 2020

2.3. Methodology

2.3.1. Land use transfer

The Land Use Transfer Matrix model serves to comprehensively elucidate the structural characteristics of land use type changes across various habitats, distinguishing between transfers among different categories and quantifying the transfer area of each land type during both initial and subsequent phases (Dai et al., 2019). This model facilitates insights into the evolutionary patterns of different land use categories. The mathematical formulation of the transfer matrix model is presented as follows (Eq. 1):

$$S_{ij} = \left\{ \begin{matrix} S_{11} & S_{12} & S_{1n} \\ S_{21} & S_{22} & S_{2n} \\ \dots & \dots & \cdots \\ S_{n1} & S_{n2} & S_{nn} \end{matrix} \right\} \tag{1}$$

where: n is a kind of land use, and S_{ij} is the area of type i land that was converted to type j land after the research period. Each cell in the matrix represents the area that altered from the kind of land use corresponding to the row and the land use type over the research period corresponding to the column.

The sum of each row in the transfer matrix displays the land-use/cover type's total area at the start of the study. Each value within a row of the transfer matrix signifies the direction and magnitude of the transfer for the corresponding land-use/cover type. Furthermore, the sum of each column provides an overview of the total area occupied by each land type throughout the duration of the investigation, with individual values within columns indicating the various magnitudes and types of transfers for each land type. To complete the data extraction process for constructing the transfer matrix, we conducted an analysis of land-use status data spanning different time periods within the Ganjiang River Basin, processed spatial data using ArcGIS, and generated an attribute table.

2.3.2. Habitat quality models

The Habitat Quality (HQ) indicator quantifies the extent of fragmentation within habitat patches and assesses an area's resilience against potential habitat degradation resulting from human activities. Using the HQ module of the InVEST model, we derived the HQ index and conducted an evaluation of habitat changes within the study area (Tang et al., 2015). This model primarily accounts for threat sources and ecological sensitivity. The HQ of the research region was statistically analyzed using remote sensing data analysis of land cover types, assess ecological sensitivity, and evaluation the proximity and spatial influence of each threat source.

1)Habitat degradation assessment principles

Habitat degradation refers to the extent to which an ecological environment becomes unsuitable for human activities or other influences. It can be quantified based on the degree of threat and ecological suitability, considering land-use types and the magnitude of threat factors. When the land-use type is j, the habitat degradation degree D_{xj} of grid x can be calculated as follows (Eq. 2):

$$D_{xj} = \sum_{r=1}^{R}\sum_{r=1}^{Vr}(W_r/\sum_{r=1}^{R}W_r)r_y i_{rxy}\beta_x K_{jr} \tag{2}$$

where: r is the threat factor and y denotes the quantities of grids in which r threatens the raster graph, Vr is a collection of threat grids in the threat grid diagram, and W_r is the threat factor's weight, from 0 to 1, r_y indicates whether the grid y is a threat grid, i_{rxy} is the threat degree of threat factor value of threat grid y to x in the region; β_x is the degree of accessibility of grid x, from 0 to 1; and K_{jr} is the sensitivity of land-use type j as a threat factor r, with values between 0 and 1. The following formula was adopted to calculate the i_{rxy} value (Eqs. 3-4):

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{r\max}}\right) \text{iflinear} \tag{3}$$

$$i_{rxy} = \exp\left(-\left(\frac{2.99}{d_{r\max}}\right) d_{xy}\right) \text{ifexponential} \tag{4}$$

Equations (3-4) are the linear and exponential distance decay functions, respectively. Grids x and y are separated by a linear distance denoted by d_{xy}, while $d_{r\max}$ is the threat factor r's maximum action distance.

(2)Principles of HQ evaluation

HQ is a key indicator for measuring ecological health and preserving biodiversity, with a rating between 0 and 1, with 1 being the most stable ecological structure and function(“InVEST | Natural Capital Project” n.d.). The manner and intensity of land use by humans influenced the quality of the habitat, and the more intense the usage, the more visible the degradation of the HQ became. The HQ index was created using the following formula based on the InVEST model's assessment of habitat degradation (Eq. 5):

$$Q_{xj} = H_j\left(1 - \frac{D_{\mathrm{xy}}^{z}}{D_{\mathrm{x}j}^{2} + k^{z}}\right) \tag{5}$$

where: Q_{xj} is is the habitat quality of raster x in land use j, H_j denotes the habitat attribute of land use j, and z denotes the normalization index.

Additionally, the model’s parameter is its default value and the half-saturation constant is k, the value of which is generally half of the maximum value of habitat degradation. For example, when the k value is 1, the software enters 0.5, which is its default value.

In this study, habitat danger variables were classified into three land-use types, namely cultivated, urban building, and barren lands, with the most concentrated human activity and a relatively substantial direct influence on HQ (Bai et al., 2019). Moreover, following the guidelines outlined in the InVEST model usage manual, we applied the maximum affected range of threat variables (MAX-DIST) to the model. We determined the threat element's weight (0–1), decline index, kind of threat factor influence on the habitat, and sensitivity index of the habitat to each threat factor (0–1). The parameters presented in Table 1 represent the suggested reference values provided by the model, while those in Table 2 encompass the model's recommended reference values along with pertinent literature (Bai et al., 2019; Gong et al., 2020; Zhang et al., 202).

2.3.3. Analysis of HQ influencing factors and mechanisms

(1) Selection of factors influencing HQ

Numerous and intricate factors contribute to changes in Habitat Quality (HQ), which can be broadly categorized as natural and anthropogenic, with human disturbances being the primary drivers of alterations in the natural environment. Considering the existing literature and available data, we identified 12 natural influencing factors for analysis, encompassing precipitation, altitude, slope, aspect, Normalized Difference Vegetation Index (NDVI), and proximity to the river system. Altitude plays a crucial role in shaping vegetation composition and structure, thereby indirectly influencing animal habitat preferences (Yu et al., 2020). NDVI serves as a metric for assessing vegetation growth and coverage (Chen et al., 2023). Human influences include population density and land use intensity (Xinge et al., 2016). The rapid pace of urbanization increasingly disrupts environmental processes, with population density serving as an indicator of population distribution (Zhu et al., 2020). Additionally, areas with higher HQ typically experience lower levels of human disturbance, and land use intensity serves as a proxy for human economic activities.

(2) Analysis of habitat quality influencing factors

Geographical phenomena are spatially heterogeneous, and geodetector analysis, as a method of geographical inquiry, serves to identify and elucidate the underlying drivers of these phenomena and their changes (Wang and Xu, 2017). Combining empirical mode decomposition and multi-scale spatial analysis, the geo-detector dissects spatial data into various scale components to discern the principal factors shaping geographical phenomena. The assessment of geodetector results involves quantifying the influence level of driving factors, measuring the contribution of each scale component to the observed geographical phenomena. The results are expressed by the q statistic, ranging from 0 to 1, with a higher q-value indicating a greater explanatory power of the independent variable over the dependent variable.

Table 1. Weights for the research area's threat factors

Threat factor	***Maximum impact distance (kilometers)***	***Weight***	***Decay type***
Farmland	8	0.6	linear
Urban Land	12	1	Exponential
Rural Resident Land	2.5	0.5	Exponential
Bare Land	5	0.4	linear

Table 2. Sensitivity of different landscape types to threat factors

Habitat type	***Habitat suitability***	***Farmland***	***Urban land***	***Rural resident land***	***Bare land***
Farmland	0	0	0	0.35	0
Woodland	1	0.65	0.75	0.85	0.6
Grassland	1	0.50	0.60	0.35	0.40
Shrub	1	0.60	0.65	0.35	0.50
Wetland	1	0.55	0.70	0.70	0.55
Water	1	0.30	0.50	0.70	0.30
Construction	0	0	0	0	0
Bare land	0	0	0	0	0

Table 3. Index system of influencing factors of habitat quality

	First-level indicators	***Secondary indicators***	***Data source/Description***
HQ	Natural factor	Annual precipitation (X1)	China National Meteorological Science Data Center (http://data.cma.cn/)
		DEM (X2)	Geospatial Data Cloud (http://www.gscloud.cn/)
		Slope (X3)	Obtained by DEM calculation
		Aspect (X4)	Obtained by DEM calculation
		The distance to the water (X5)	Water system vector data analysis
		NDVI（X6）	Chinese Academy of Sciences (https://www.resdc.cn)
	Human factor	GDP(X7)	Obtained from the statistics yearbook
		Density of village (X8)	Obtained from the statistics yearbook
		Population density (X9)	Chinese Academy of Sciences (https://www.resdc.cn)
		Road density (X10)	Analysis of road vector data
		Distance from the county（X11）	IDW (InverseDistanceWeighted)
		Land use strength (X12)	Obtained from the statistical yearbook

In this study, the Habitat Quality (HQ) of the Ganjiang River Basin served as the dependent variable, while the ecological and social environments of the study area acted as independent variables. Natural factors encompassed the vegetation index (NDVI), terrain, slope, and slope direction, while social factors included land use/land cover, per capita GDP, number of villages, and night light index. The "factor detector" and "interaction detector" functionalities of the geodetector were employed to scrutinize the impact of individual drivers on the spatial heterogeneity of HQ within the Ganjiang River Basin and to explore potential interactions between these drivers. The calculation formulas utilized are as follows (Xinge et al., 2016) (Eqs. 6-8):

$$q = 1 - \frac{\sum_{i=1}^{L} N_i \sigma_i^2}{N\sigma^2} = 1 - \frac{\text{SSW}}{\text{SST}} \tag{6}$$

$$\text{SSW} = \sum_{i=1}^{L} N_i \sigma_i^2 \tag{7}$$

$$\text{SST} = N\sigma^2 \tag{8}$$

where: i is the stratification of independent or dependent variables, N is the total quantity of units in the domain, and N_i is the number of units in layer i. Additionally, the variance of the factor variable in layer i and the entire domain are also indicated by the symbols σ_i^2 and σ^2, respectively. Finally, SSW is the overall variance of the area, whereas SST is the total of the variances of the individual strata.

Interaction factor detection, in comparison with statistical methods, exhibits superior geographical detection capabilities. Through contrasting the dimensions of a single component q and a binary factor q, and by discerning the direction and nature of the interaction, we can effectively identify interactions between two variables. The foundation of these interactions is summarized in Table 4.

Table 4. Criteria for interaction

Interaction	***Criterion***
Weaken Weaken, nonlinear Bi-enhance Independent Enhance, nonlinear	q(X1∩X2) > Minq(X1), q(X2) Min(q(X1), q(X2)) <q(X1∩X2)<Max(q(X1), q(X2)) q(X1∩X2) > Max(q(X1), q(X2)) q(X1∩X2) = q(X1) + q(X2) q(X1∩X2) b0 q(X1) + q(X2)

3. Results and discussion

3.1. Land use transfer

Between 2000 and 2010, land-use change in Ganjiang River Basin was characterized primarily by the converting of farmland to construction land, alongside increased utilization of grassland, construction land, and water. Construction land saw a notable surge, expanding by 320.29 km^2 (14%), while the area of cultivated land decreased by 256.82 km^2 (1.1%). Subsequently, from 2010 to 2020, land-use changes in the research area were marked by the conversion of farmland, woodland, and grassland into construction land.

The amount of farmland, woodland, and grassland experienced substantial declines of 825.24 km^2 (4%), 952.25 km^2 (1.8%), and 532.27 km^2 (1.2%), respectively (Table 5 and Fig. 3). Furthermore, the dominant land use types in the upper, middle, and lower reaches were primarily farmland and woodland (Fig. 4). The maximum area of construction land relative to woodland was observed in the upper reaches, followed by the middle reaches, whereas the forested area was the smallest.

Conversely, the lower reaches exhibited the greatest extent of construction land and the lowest forested area. Additionally, there was a notable increase in development land in the downstream region, while both forested and farmland regions experienced a declining trend.

Between 2000 and 2020, the Ganjiang River Basin underwent significant land-use transitions. Construction land increased by 18.881.71 km^2, whereas farmland, woodland, and grassland decreased by 991.37 km^2 (4%), 981.45 km^2 (2%), and 608.40 km^2 (1.4%), respectively. Severe deforestation led to inappropriate land use practices, resulting in the conversion of several farmland and grassland areas. Consequently, the ecosystem services provided by the region, such as soil and water conservation and air purification, witnessed a decline.

Table 5. Land use transition matrix in the Ganjiang river basin from 2000 to 2020

Period	***Landscape types***	***Farmland (km^2)***	***Woodland (km^2)***	***Grassland (km^2)***	***Shrub (km^2)***	***Wetland (km^2)***	***Water (km^2)***	***Construction (km^2)***	***Bare land (km^2)***
2000-2010	farmland	23.988.79	22.84	18.03	1.12	4.47	5.21	204.87	0.29
	woodland	33.47	55.214.11	78.46	13.24	0.01	0.87	30.91	0.04
	grassland	17.35	80.99	7.705.02	4.53	0.00	0.37	78.10	0.02
	shrub	1.92	13.22	5.38	45.72	0.00	0.87	0.05	0.00
	wetland	0.54	0.00	0.08	0.00	201.51	0.04	2.68	0.00
	water	8.34	6.41	1.53	1.06	0.00	1.425.24	3.26	0.06
	construction	29.00	3.86	2.12	0.08	0.08	0.89	1.824.38	0.34
	bare land	0.01	0.11	0.02	0.00	0.00	1.71	0.42	149.09
2010-2020	farmland	20.164.77	1.711.49	603.64	1.96	1.22	426.80	1.160.40	8.71
	woodland	1.903.18	50.352.72	2.291.74	18.97	1.69	361.95	362.92	41.74
	grassland	827.03	2.184.05	4.318.20	6.23	1.15	151.41	301.89	18.75
	shrub	3.10	17.14	5.47	37.05	0.00	1.92	1.01	0.00
	wetland	5.97	0.26	0.12	0.00	24.62	169.15	5.51	0.09
	water	97.74	54.17	18.42	0.11	2.94	1.222.57	33.08	6.24
	construction	236.13	34.13	20.75	0.05	0.10	17.56	1.835.00	0.44
	bare land	15.81	28.70	18.10	0.00	0.05	47.13	5.77	34.03

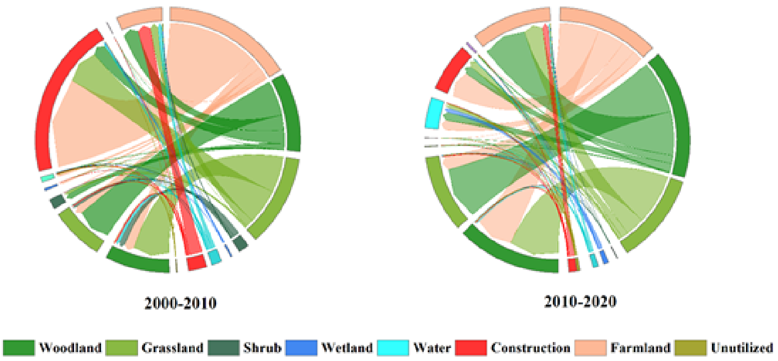

Fig. 3. The Ganjiang River Basin land use circulation diagram

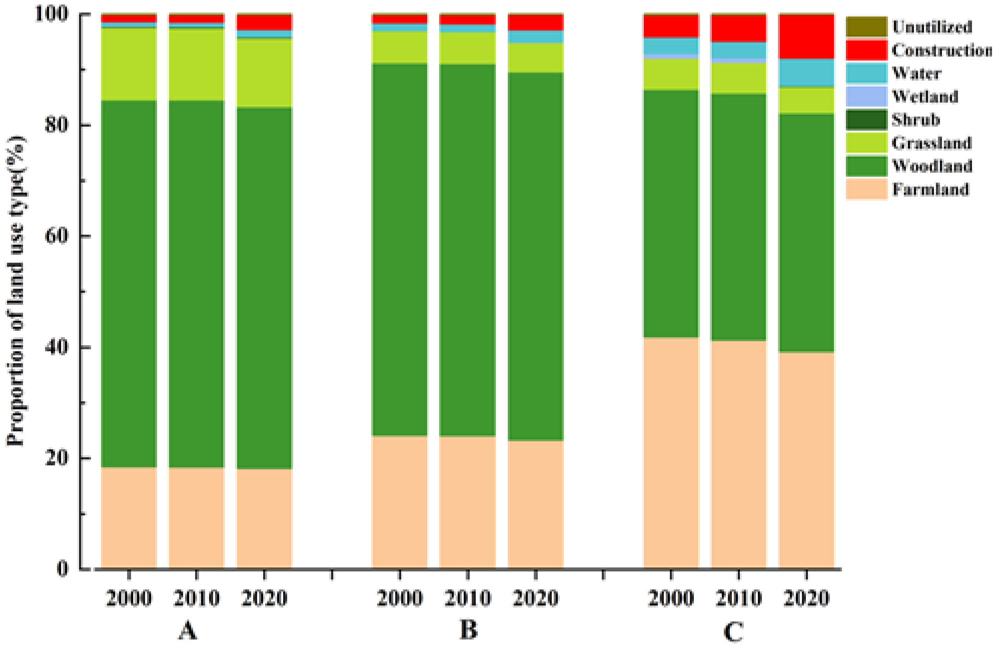

Fig. 4. Proportion of land use types in the subsection of the Ganjiang River Basin in 2000-2020, (a) Upstream, (b) Midstream, (c) Downstream

Table 6. Ganjiang River Basin habitat quality changes from 2000 to 2020

Grade	***Value range***	***2000***		***2010***		***2020***	
		Area (km^2)	***Percentage (%)***	***Area (km^2)***	***Percentage (%)***	***Area (km^2)***	***Percentage (%)***
Low	0–0.2	26,238.11	28.76	26,356.05	28.89	27,042.90	29.64
Relatively low	0.2–0.4	240.15	0.26	294.92	0.32	210.49	0.23
Medium	0.4–0.6	1,354.24	1.48	1,547.38	1.70	1,745.81	1.91
Relatively high	0.6–0.8	3,934.12	4.31	4,043.24	4.43	5,064.23	5.55
High	0.8–1.0	59,466.37	65.18	58,991.41	64.66	57,169.62	62.66

3.2. Temporal and spatial changes in HQ in the Ganjiang River Basin from 2000 to 2020

In the Ganjiang River Basin, the geographic distribution of the changes in HQ was evident (Figs. 5-6). Between 2000 and 2020, there was a significant decline in HQ from the upper to the lower reaches of the river throughout the entire basin.

Furthermore, the high-grade and relatively high-grade habitats were widely dispersed. In the upper reaches of the Ganjiang River Basin, topographical features, elevation, moisture levels, and soil conditions constrained habitat alterations. The predominant land-use types, including woodland and grassland, remained largely unaffected by human activities, resulting in excellent HQ. At the county-level administrative divisions, the HQ indices of Duchang, Yihuang, Yongxiu, Yugan, Jinxian, Tonggu, and Nanfeng Counties were relatively high (> 0.7). Conversely, areas with low and relatively low HQ were predominantly located in the lower reaches of the Ganjiang River Basin and were widespread across the basin, resembling the distribution pattern observed in built-up areas. The rapid expansion of construction land, posing a significant risk to habitat, coupled with the progressive reduction of habitat-friendly land use categories such as farmland and woodland, has led to severe environmental degradation, thereby endangering the HQ of the Ganjiang River Basin. The regional HQ indices of built-up areas, such as Xihu District, Qingshanhu District, Zhangshu City, Xinjian County, and Gao'an City were relatively low (< 0.3).

3.3. Temporal and spatial changes in habitat degradation degree in Ganjiang River Basin

We utilized ArcGIS to examine the temporal and geographical differentiation features of habitat degradation distribution maps and analyze the HQ in the Ganjiang River Basin between 2000 and 2020. Habitat degradation within the Ganjiang River Basin was classified using the natural breakpoint approach, resulting in five levels of degradation: unaltered (0–0.013), mild (0.013-0.038), moderate (0.038-0.067), relatively high (0.067-0.107), and high (> 0.107).

From 2000 to 2020, the proportion of the Ganjiang River Basin exhibiting essentially unchanged HQ increased from 36.85% to 38.84%, while the area of highly degraded habitat rose from 3.09% to 3.58% (refer to Fig. 7). Additionally, areas characterized by mild, moderate, and high levels of degradation witnessed annual reductions. Thus, an unchanged HQ does not necessarily indicate an improved HQ. Fig. 8 illustrates that regions with unaltered habitat degradation in the middle and lower portions of the Ganjiang River Basin predominantly corresponded to low HQ zones. Given that these areas are primarily comprised of construction lands with inherently low HQ, they are incapable of experiencing further degradation, thereby explaining the stable pattern of habitat degradation depicted in Fig. 8.

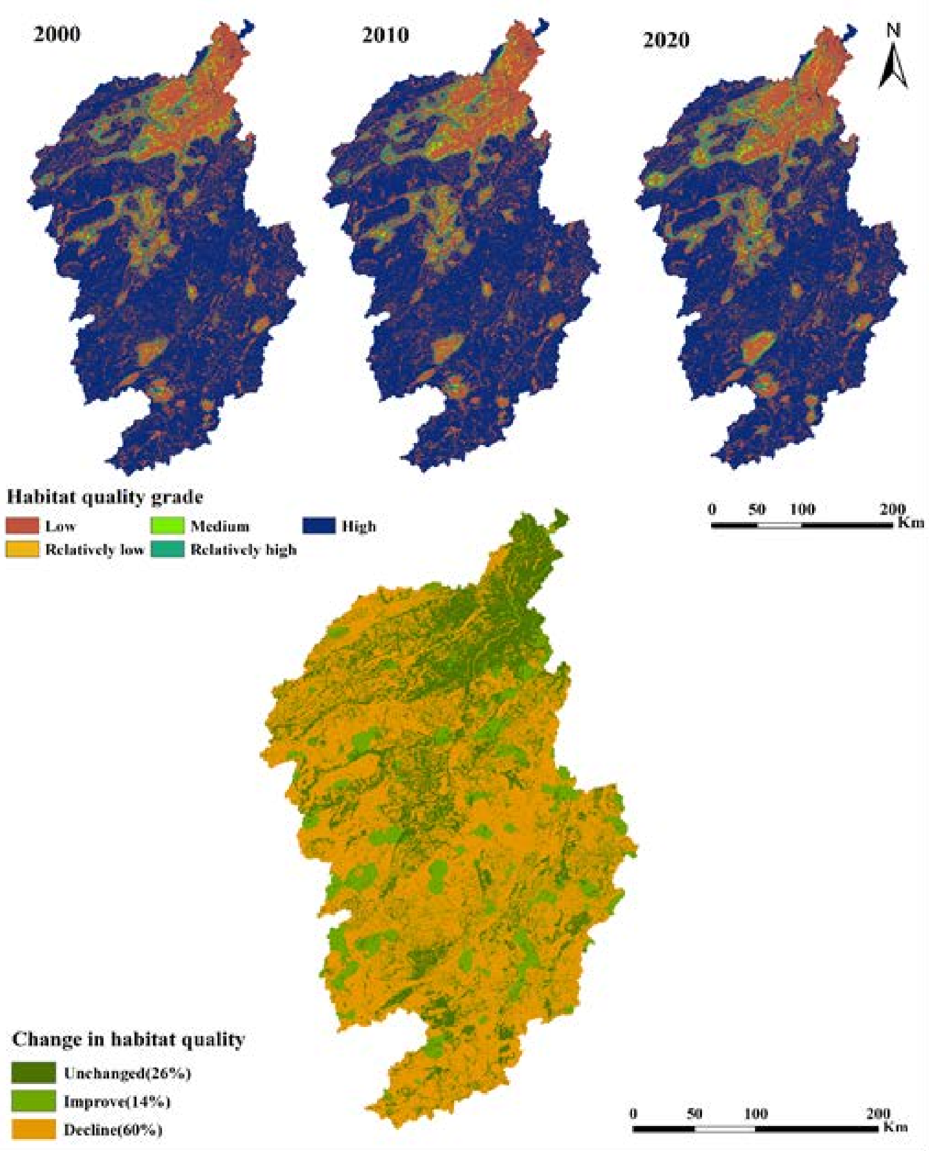

Fig. 5. Spatial pattern and changes of habitat quality in the Ganjiang watershed in 2000-2020

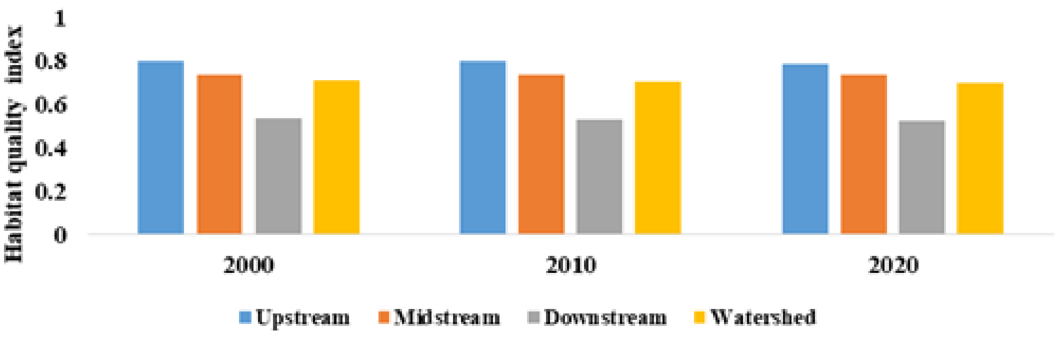

Fig. 6. Average habitat quality of each section of the Ganjiang River Basin in 2000-2020

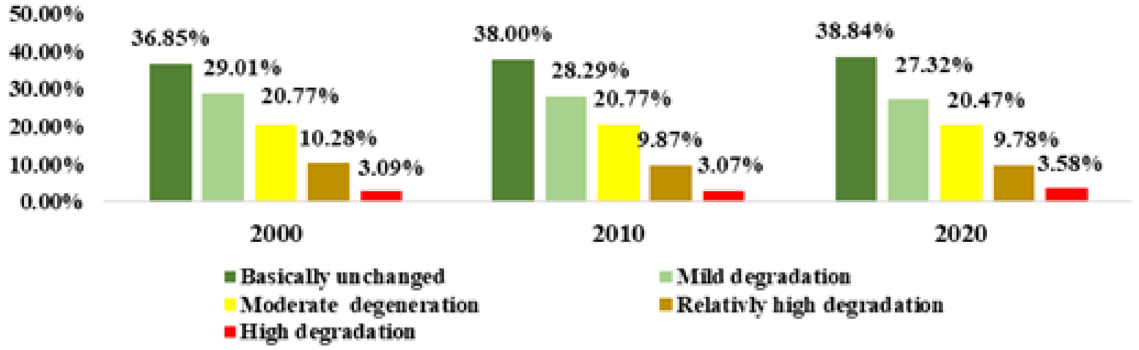

Fig. 7. Habitat quality degradation changes in the Ganjiang River Basin in 2000-2020

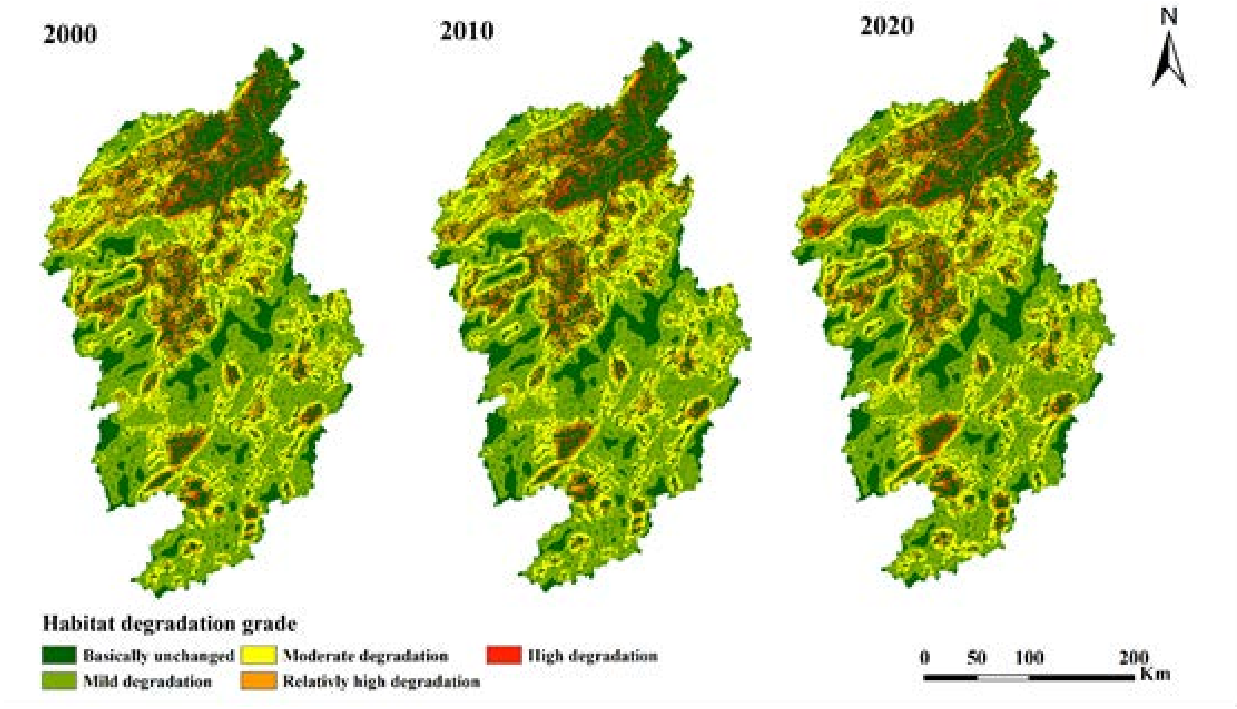

Fig. 8. Spatial pattern of habitat degradation in the Ganjiang River Basin in 2000-2020

3.4. Spatial autocorrelation analysis

We used a LISA cluster map to evaluate the local spatial correlation patterns of eco-environmental quality, aiming to gain a clearer understanding of the geographical and temporal distribution of HQ. Fig. 9 illustrates the HQ Moran's I scatter plot, wherein the first and third quadrants encompass the majority of scatter points, indicating a high positive spatial association of ecological environment quality within the research region. The Moran's I indices for the years 2000, 2010, and 2020 were recorded as 0.719, 0.721, and 0.725, respectively, all of which surpassed the 1% significance threshold. This suggests that the spatial distribution of HQ in the Ganjiang River Basin exhibits clustering rather than randomness.

The GeoDa global spatial autocorrelation research found a spatial autocorrelation of HQ within the Ganjiang River Basin. Regions depicted in red, along with their adjacent areas, exhibit high (high-high) HQ values on the LISA cluster map. Pink-colored areas signify high HQ values, surrounded by regions with low values (high-low). Similarly, dark blue regions and their surrounding areas denote low (low-low) HQ indices, whereas light blue areas indicate low HQ indices, bordered by regions with high (low-high) values.

The spatial pattern of HQ values in the study area reveals clustering of both high and low values across the years 2000, 2010, and 2020 (refer to Figure 10). The upper and middle reaches of the basin predominantly exhibit high-high clustering, with scattered instances in the lower reaches. Conversely, the low-low cluster areas are dispersed throughout the middle and upper reaches but are primarily concentrated downstream. These regions are characterized by dense farmland and high population densities associated with poor HQ. Notably, in 2020, certain portions of the lower region's HQ witnessed a partial transition from poor to high values.

3.5. Identification of driving factors for spatial heterogeneity of HQ in Ganjiang River Basin

(1) Single factor attribution of spatial heterogeneity of HQ

The q-statistics, indicative of each factor's explanatory power, were ranked as follows: land use intensity (X12), DEM (X2), precipitation (X1), village density (X11), road density (X9), NDVI (X6), slope (X3), population density (X8), river distance (X5), distance to county seat (X7), GDP (X10), and slope aspect (X4). With the exception of aspect (X4), which met the 0.05 threshold for significance in the upstream region, the explanatory power of the remaining components passed the 0.01 significance level. Furthermore, factors were prioritized based on their q-statistics as follows: X12 > X2 > X1 > X11 > road X9 > X6 > X 3> X 8> X 5> X 7> X10 > X4.

In the midstream area, each factor's explanatory power also passed the 0.01 significance level test, and their rankings based on q-statistics were as follows: X12 > X2 > X11 > X6 = X3 > X9 > X8 > X5 > X4 > X7 > X10.

In the downstream area, each factor's explanatory power passed the 0.01 significance level test lastly. The criteria were ordered according to their q-statistics as follows: X12> X2 > X3 > X1 > X6 > X11 > X10 > X8 > X5 > X9 > X4 > X7.

(2) Single factor attribution of spatial heterogeneity of HQ

In comparison with single-factor interaction, the interactions between each influencing variable and the other components were strengthened to varying degrees (refer to Fig. 11). From a view of the entire basin (Fig. 11a), the geographical pattern of HQ in the Ganjiang River Basin was best elucidated by the interplay between land use and other variables. Notably, land use intensity ∩ slope (0.884), land use intensity ∩ NDVI (0.883), and land use intensity ∩ DEM (0.884) provided a more comprehensive explanation for spatial heterogeneity in habitat quality. This indicates that, under the same land use type, disparities in slope, NDVI, and elevation exert a more significant impact on the spatial pattern of HQ and yield. Moreover, it was evident that DEM and road density interact with village density, NDVI, and other variables, potentially influencing alterations in land use type and HQ. The interaction of village density with NDVI and slope exhibited notably greater strength in explaining regional heterogeneity in HQ compared to individual effects, underscoring the indispensable contributions of both factors to spatial heterogeneity in HQ.

In the sub-regions of the Ganjiang River Basin, aside from the dominant interaction between land use and DEM, the explanatory power of the other factors exhibited varying degrees of enhancement. The relationship between village density, GDP, and other factors was better explicated in the upstream region (Fig. 11a) than in other regions, signifying the substantial influence of human economic activities on HQ in the up-stream region. Conversely, the interaction between village density, NDVI, and other factors was more pronounced in the mid-stream region (Fig. 11b) than in other regions, suggesting the combined impact of human and natural factors on HQ in this area. Notably, the strength of the interaction between slope, precipitation, and other components increased noticeably compared to other regions, while the interaction between land use, DEM, and various parameters peaked in the downstream zone (Fig. 11c).

These observations align with the regional development status at the time of the study. Village density serves as an indicator of urbanization, and increasing GDP drives new land-use demands. Consequently, greater strain is imposed on adjacent natural environments when development land encroaches on other land use categories. Therefore, optimizing urban spatial patterns is imperative for enhancing local HQ and promoting the implementation of ecological restoration projects.

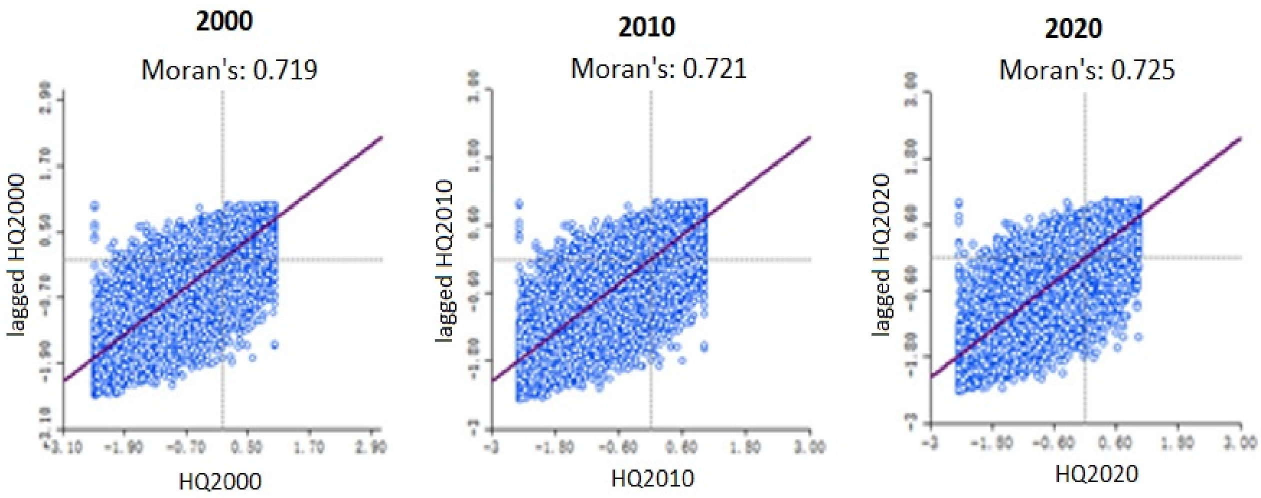

Fig. 9. Moran's I habitat quality scatter plot

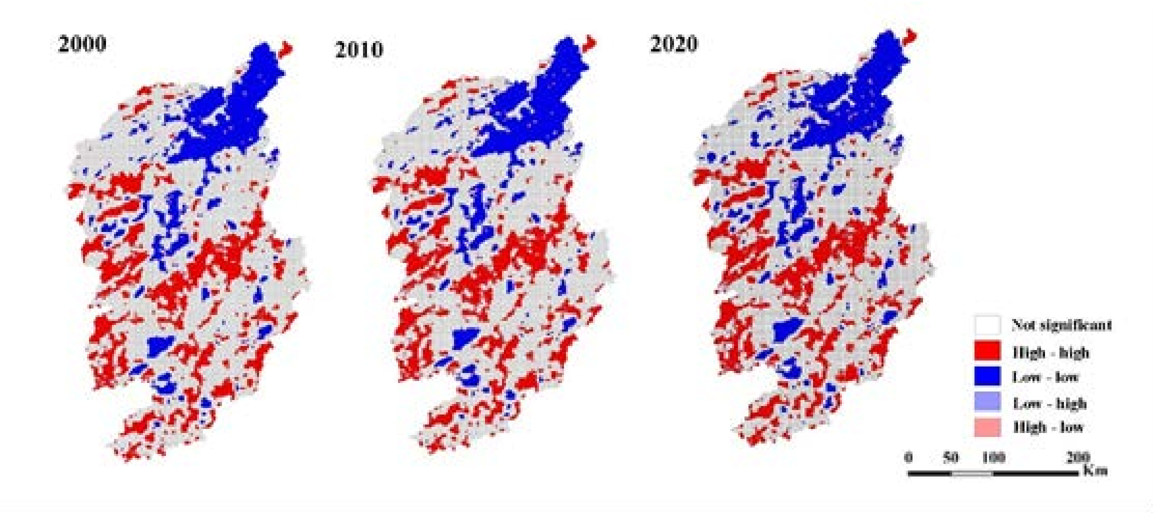

Fig. 10. Habitat quality of the LISA clustering diagram in the Ganjiang River Basin

Table 7. Impact of driving factors on spatial heterogeneity of habitat quality

Factor	*Watershed*		*Upstream*		*Midlestream*		*Downstream*	
	q	*p*	*q*	*p*	*q*	*p*	*q*	*p*
X1	0.066	0.000	0.072	0.000	0.090	0.000	0.182	0.000
X2	0.250	0.000	0.167	0.000	0.227	0.000	0.274	0.000
X3	0.160	0.000	0.051	0.000	0.090	0.000	0.189	0.000
X4	0.020	0.000	0.004	0.011	0.010	0.000	0.049	0.000
X5	0.019	0.000	0.022	0.000	0.018	0.000	0.060	0.000
X6	0.134	0.000	0.054	0.000	0.092	0.000	0.144	0.000
X7	0.034	0.000	0.013	0.000	0.009	0.000	0.031	0.000
X8	0.092	0.000	0.045	0.000	0.061	0.000	0.082	0.000
X9	0.097	0.000	0.065	0.000	0.077	0.000	0.058	0.000
X10	0.080	0.000	0.012	0.000	0.001	0.820	0.113	0.000
X11	0.137	0.000	0.069	0.000	0.098	0.000	0.127	0.000
X12	0.882	0.000	0.839	0.000	0.894	0.000	0.910	0.000

X1, precipitation; X2, DEM; X3, slope; X4, slope aspect; X5, water distance; X6, NDVI; X7, distance to the county seat; X8, population density; X9, road density; X10, GDP; X11, village density; X12, land-use intensity.

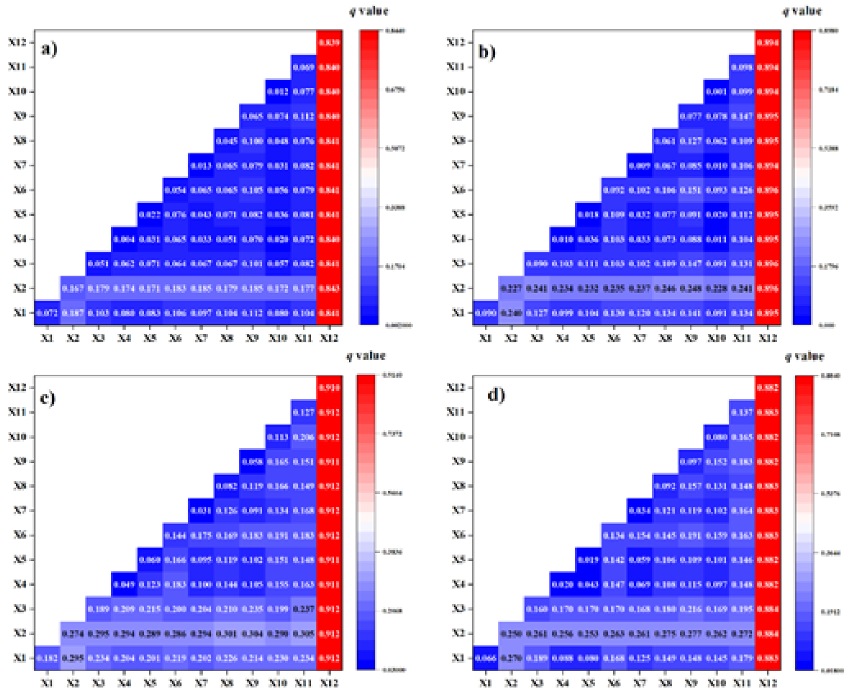

Fig. 11. Habitat quality drive factor interaction detection results, (a) Upstream, (b) midstream, (c) downstream, (d) watershed

3.*5. Discussion*

As a significant component of the Yangtze River's primary ecological functioning region in China, it is imperative for the government to address the key ecological security issues within the Ganjiang River Basin and implement corresponding preventive and policy measures to safeguard and restore ecological functions. Between 2000 and 2020, the Ganjiang River Basin witnessed rapid urbanization, with the overall population increasing from 38.956.000 to 42.435.000, and the GDP of prefecture-level cities rising from 179.94 to 237.952 billion Yuan, indicative of substantial economic growth. However, these economic development and infrastructure construction have led to significant impacts on land use patterns due to various unscientific resource utilization methods and excessive development practices, resulting in soil erosion, drastic declines in biodiversity, and other ecological challenges, ultimately diminishing habitat quality within the Ganjiang River Basin.

Natural forces have contributed significantly to the variation in HQ. The upper portions of the Ganjiang River Basin, situated in hilly errains, experience limited human interference and development impacts on account of topographical constraints. This observation aligns with prior research that has established a correlation between topography, land use, and HQ within the Ganjiang River Basin (Liu et al., 2021; Xu et al., 2020). High-quality habitats are predominantly found in mountainous and hilly regions characterized by dense forest cover and abundant water bodies, whereas low-grade habitats are primarily situated in flat, low-altitude areas with extensive construction land. Over time, the influence of topographic features on HQ remains consistent, emphasizing the importance of reducing land-use intensity to enhance HQ in the Ganjiang River Basin.

However, the medium-and long-term time series study provided robust evidence for the changes in habitat quality. Sixty percent of the areas experiencing habitat quality deterioration were initially situated in mountainous and hilly areas with high-quality habitats. Despite the abundance of forests and shrubs in these areas, factors such as thin soil layers, poor fertility, frequent heavy rainfall, and severe surface water erosion render them highly vulnerable to the impacts of human economic activities. Therefore, this study indicates that the degradation of habitat quality becomes more pronounced in areas initially characterized by better habitat quality.

Based on the findings of this investigation, the following policy recommendations are proposed: Firstly, regions with high-value HQ in the upper reaches of the Ganjiang River Basin should receive enhanced ecological protection, with high-value HQ areas potentially designated as ecological protection red lines to safeguard their ecological security. Conversely, areas downstream with low-value HQ should undergo strict monitoring of urbanization and land use intensity, avoiding disorderly development of built-up land and considering redevelopment of underutilized properties to enhance land-use efficiency. Moreover, efforts should be directed towards optimizing economic layout, promoting green development, and strengthening the linkage between economic construction and ecological protection to enhance HQ. Secondly, given the propensity for urban expansion to disrupt the environment in the Ganjiang River Basin, economic development plans must adopt a dynamic perspective, incorporating a sustainable development model capable of adapting to ecological changes and spatial dynamics within urban and rural areas. Thirdly, to enhance the ecological, habitational, and agricultural conditions of the Ganjiang River Basin, spatial structures should be further refined based on the principle of human-land cooperation. Rational landscape pattern configurations, in accordance with ecological protection schemes, should be implemented to elevate the overall HQ of the watershed.

This study is not without limitations. Certain parameters of the InVEST model, such as the sensitivity of land-use types to stress variables, were adjusted according to the model user handbook, potentially concealing inaccuracies in the analytical outcomes. Future research endeavors should prioritize the acquisition and utilization of measured data to bolster the accuracy of the results.

4. Conclusions

In this study, we used a geodetector to evaluate the influences of natural and socioeconomic variables on the spatial heterogeneity of HQ in the Ganjiang River Basin from 2000 to 2020, utilizing the InVEST model and ArcGIS.

The results of this research are as follows:

(1) Woodland and farmland constituted the primary land-use types in the Ganjiang River Basin. Over the study period (2000-2020), notable land-use changes included an increase in construction land and reductions in farmland, woodland, and grassland. Urbanization drove the conversion of farmland and woodland into construction land, while transitions between grassland and woodland were also observed.

(2) Despite the overall high HQ in the Ganjiang River Basin, there was a discernible downward trend over time, with the average habitat quality decreasing from 0.7104 to 0.7000. However, habitats categorized as low, relatively low, and medium exhibited an upward trajectory.

Geographically, areas with higher HQ indices were predominantly located in the upper reaches of the basin, characterized by woodland, grassland, and farmland as dominant land-use types. These regions typically featured hilly terrain, limited human development, and minimal anthropogenic impact, contributing to their high HQ.

(3) The principal factors influencing the HQ index in the Ganjiang River Basin encompassed land-use intensity, DEM, NDVI, slope, village density, resident density, and per capita GDP. Notably, land use intensity and DEM emerged as pivotal contributors. Each factor exhibited varying effects on HQ gradients.

This study quantitatively illustrates declining trends in habitat quality within a crucial ecological region of China through sophisticated spatiotemporal analysis methods. The findings underscore the environmental challenges posed by economic expansion and urbanization in the Ganjiang River Basin. Addressing these challenges necessitates a balanced approach by policymakers, balancing natural resource conservation with socioeconomic development. The insights provided by this research serve as a valuable analytical foundation for informed decision-making. Future research endeavors should prioritize enhancing model accuracy, mapping ecological networks, and exploring nature-based solutions.

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References

An Y., Liu S., Sun Y., Shi F., Beazley R., (2021), Construction and optimization of an ecological network based on morphological spatial pattern analysis and circuit theory, *Landscape Ecology*, **36**, 2059-2076.

Bai T., Zhang N., Chen Y., Mercatoris B., (2019), Assessing the performance of the WOFOST model in simulating jujube fruit tree growth under different irrigation regimes, *Sustainability*, **11**, 1466, http://doi.org/10.3390/su11051466

Berta Aneseyee A., Noszczyk T., Soromessa T., Elias E., (2020), The InVEST habitat quality model associated with land use/cover changes: a qualitative case study of the winike watershed in the Omo-Gibe Basin, Southwest Ethiopia, *Remote Sensing*, **12**, 1103, https://doi.org/10.3390/rs12071103.

Betul U.E., Onur B.S., (2023), Spatio-temporal analysis of land use and land cover changes in Bogacayi watershed in a tourstic region in Turkey, *Environmental Engineering and Management Journal*, **22**, 183-197.

Bi M., Zhong Y., Xiao Z., Feng X., Ma H., (2023), Spatial and temporal change of habitat quality of poyang lake basin in china at small watershed scale and its multidimensional response to landscape pattern, *Chinese Geographical Science*, **33**, 565-582.

Cao J., Xie Y., (2023), Research on regional ecological compensation in China: a focus on carbon equality, *Environmental Engineering and Management Journal*, **22**, 1283-1292.

Chen X., Yu L., Cao Y., Xu Y., Zhao Z., Zhuang Y., Liu X., Du Z., Liu T., Yang B., He L., Wu H., Yang R., Gong P., (2023), Habitat quality dynamics in China's first group of national parks in recent four decades: Evidence from land use and land cover changes, *Journal of Environmental Management*, **325**, 116505, https://doi.org/10.1016/j.jenvman.2022.116505.

Dai L., Li S., Lewis B.J., Wu J., Yu D., Zhou W., Zhou L., Wu S., (2019), The influence of land use change on the spatial–temporal variability of habitat quality between 1990 and 2010 in Northeast China, *Journal of Forestry Research*, **30**, 2227-2236.

Deng Z. B., Zong S.W., Su C.W., Chen Z., (2019), Research on coupling coordination development between ecological civilization construction and new urbanization and its driving forces in the Yangtze River economic zone, *Economic Geography*, **39**, 78-86.

Erdogan B.U., Salis O.B., (2023), Spatio-temporal analysis of land use and land cover changes in Bogacayi watershed in a touristic region in Turkey, *Environmental Engineering and Management Journal*, **22**, 183-197.

Fellman J.B., Hood E., Dryer W., Pyare S., (2015), 3Stream physical characteristics impact habitat quality for pacific salmon in two temperate coastal watersheds, *PLOS ONE*, **10**, e0132652, https://doi.org/10.1371/journal.pone.0132652.

Firmansyah E.A., Umar U.H., Jibril R.S., (2023), Investigating the effect of ESG disclosure on firm performance: The case of Saudi Arabian listed firms, *Cogent Economics & Finance*, **11**, 2287923, http://doi.org/10.1080/23322039.2023.2287923

Fu B., Liu Y., Meadows M.E., (2023), Ecological Restoration for Sustainable Development in China, *National Science Review*, **10**, nwad033, https://doi.org/10.1093/nsr/nwad033.

Gao Y., Ma L., Liu J., Zhuang Z., Huang Q., Li M., (2017), Constructing ecological networks based on habitat quality assessment: a case study of Changzhou, China, *Scientific Reports*, **7**, 46073, https://doi.org/10.1038/srep46073.

Gong S., Cartlidge J., Bai R., Yue Y., Li Q., Qiu G., (2020), Extracting activity patterns from taxi trajectory data: a two-layer framework using spatio-temporal clustering, Bayesian probability and Monte Carlo simulation, *International Journal of Geographical Information Science*, **34**, 1210-1234.

Guihua L., Shuhua Q., Jingxuan Z., Mengya X., Dian W., (2016), Quantitative estimation of runoff changes in Ganjiang River, Lake Poyang Basin under climate change and anthropogenic impacts, *Journal of Lake Sciences*, **28**, 682-690.

Han Y., Kang W., Thorne J., Song Y., (2019), 4 Modeling the effects of landscape patterns of current forests on the habitat quality of historical remnants in a highly urbanized area, *Urban Forestry & Urban Greening*, **41**, 354-363.

Huang K., Dai W.Y., Huang W.L., Ou H., H H. X., (2019), Impacts of land use change evaluation on habitat quality based on CA-Markov and InVEST model, *Bulletin of Soil and Water Conservation*, **39**, 155-162.

Irman F., Wayan B., Chaterina A.P., Dede A.R., Tatan S., Erwin H., Nama C., (2023). Ecosystem services and environmental benefit values on Komodo Island and Padar Island in Komodo National Park, Indonesia, *Environmental Engineering and Management Journal*, **22**, 1245-1257.

Yang J., Wu Y., (2023), An emprical study on the role of new energy transformation and upgrading in promoting China's economy, *Environmental Engineering and Management Journal*, **22**, 157-166.

Yu W., Ji R., Han X., Chen L., Feng R., Wu J., Zhang Y., (2020), Evaluation of the biodiversity conservation function in Liaohe Delta Wetland, Northeastern China, *Journal of Meteorological Research*, **34**, 798-805.

Johnson M.D., (2007), Measuring habitat quality: a review, *The Condor*, **109**, 489-504.

Junwen C., Yuxin X., (2023), Research on regional ecological composition in China： A focus on carbon equality, *Environmental Engineering and Management Journal*, **22**, 1283-1292.

Kar S., Gupta R., (2023), Efficiency of a glass fiber-reinforced polymer (GFRP) tank in pursuit of reliable water resources through rainwater harvesting, *Environmental Engineering and Management Journal*, **22**, 85-96.

Lang Y., Yang X., Cai H., (2023), Quantifying anthropogenic soil erosion at a regional scale - The case of Jiangxi Province, China, *Catena*, **226**, 107081, https://doi.org/10.1016/j.catena.2023.107081.

Li, Y., Duo, L., Zhang, M., Wu, Z., & Guan, Y., (2021), Assessment and estimation of the spatial and temporal evolution of landscape patterns and their impact on habitat quality in Nanchang, China. *Land*, **10**, 1073.

Liccari F., Boscutti F., Bacaro G., Sigura M., (2022), Connectivity, landscape structure, and plant diversity across agricultural landscapes: novel insight into effective ecological network planning, *Journal of Environmental Management*, **317**, 115358, https://doi.org/10.1016/j.jenvman.2022.115358.

Liu G.X., Wang X.J., Xiang A.C., Wang X.R., Wang B.X., Xiao S.M., (2021), Spatial heterogeneity and driving factors of land use change in the middle and upper reaches of Ganjiang River, southern China, *The Journal of Applied Ecology*, **32**, 2545-2554.

Liu Y., Zhou Y., Du Y., (2019), Study on the spatio-temporal patterns of habitat quality and its terrain gradient effects of the middle of the Yangtze River Economic Belt based on InVEST model, *Resources and Environment in the Yangtze Basin*, **28**, 2429-2440.

Liu W., Tsai S.B., Wu C.H., Shao X., Wacławek M., (2022), Corporate environmental management and sustainable operation: Theory and application, *Ecological Chemistry and Engineering*, **29**, 283-285.

Miserendino M.L., Casaux R., Archangelsky M., Di Prinzio C.Y., Brand C., Kutschker A.M., (2011), Assessing land-use effects on water quality, in-stream habitat, riparian ecosystems and biodiversity in Patagonian northwest streams., *Science of the Total Environment*, **409**, 612-624.

Mortelliti A., Amori G., Boitani L., (2010), The role of habitat quality in fragmented landscapes: a conceptual overview and prospectus for future research, *Oecologia*, **163**, 535-547.

Nematollahi S., Fakheran S., Kienast F., Jafari A., (2020), 16Application of InVEST habitat quality module in spatially vulnerability assessment of natural habitats (case study: Chaharmahal and Bakhtiari province, Iran), *Environmental Monitoring and Assessment*, **192**, 1–17.

Sallustio L., De Toni A., Strollo A., Di Febbraro M., Gissi E., Casella L., Geneletti D., Munafo M., Vizzari M., Marchetti M., (2017), Assessing habitat quality in relation to the spatial distribution of protected areas in Italy. *Journal of Environmental Management*, **201**, 129-137.

Shu T., Lachun W., Xiaogen W., Zilin X., Lingling C., (2019), Dynamic evaluation and spatial mapping of wetland ecosystem services value - a case study on Nanjing JIangbei New Area, *Environmental Engineering and Management Journal*, **18**. 2519-2532.

Stanford University, (2023), InVEST User's Guide, InVEST-Natural capital project, On line at: https://naturalcapitalproject.stanford.edu/software/invest

Tang Y., Zhu W.P., Zhang H., Song Y., (2015), A review on principle and application of the InVEST model, *Ecological Science*, **34**, 204-208.

Terrado M., Sabater S., Chaplin-Kramer B., Mandle L., Ziv G., Acuña V., (2016), Model development for the assessment of terrestrial and aquatic habitat quality in conservation planning, *Science of the Total Environment*, **540**, 63-70.

Wang B., Cheng W., (2022), Effects of land use/cover on regional habitat quality under different geomorphic types based on InVEST model, *Remote Sensing*, **14**, 1279, http://dx.doi.org/10.3390/rs14051279.

Wang H., Qin F., Zhu J., Zhang C., (2017), The effects of land use structure and landscape pattern change on ecosystem service values., *Acta Ecologica Sinica*, **37**, 1286-1296.

Wang J.F., Xu C.D., (2017), Geodetector: Principle and prospective, *Acta Geographica Sinica*, **72**, 116-134.

Wei L., Zhou L., Sun D., Yuan B., Hu F., (2022), Evaluating the impact of urban expansion on the habitat quality and constructing ecological security patterns: A case study of Jiziwan in the Yellow River Basin, China, *Ecological Indicators*, **145**, 109544, https://doi.org/10.1016/j.ecolind.2022.109544.

Wei Q., Abudureheman M., Halike A., Yao K., Yao L., Tang H., Tuheti B., (2022), Temporal and spatial variation analysis of habitat quality on the PLUS-InVEST model for Ebinur Lake Basin, China, *Ecological Indicators*, **145**, 109632, https://doi.org/10.1016/j.ecolind.2022.109632.

Wu C.H., (2021), An empirical study on discussion and evaluation of green university, *Ecological Chemistry and Engineering*, **28**, 75-85.

Xinge W., Jianchao X., Dongyang Y., Tian C., (2016), Spatial differentiation of rural touristization and its determinants in China: A Geo-Detector-Based Case Study of Yesanpo Scenic Area, *Journal of Resources and Ecology*, **7**, 464-471.

Xu L., Chen S.S., Xu Y., Li G., Su W., (2019), Impacts of land-use change on habitat quality during 1985-2015 in the Taihu Lake Basin, *Sustainability*, **11**, 3513, https://doi.org/10.3390/su11133513.

Xu Q., Wang P., Wang T., Shu W., Zhang H., Qi S., (2020), Investigation of the impacts of land use structure and landscape pattern on water quality in the Ganjiang River, Lake Poyang Basin, *Journal of Lake Sciences*, **32**, 1008-1019.

Zeng W., Tang H., Liang X., Hu Z., Yang Z., Guan Q., (2023), Using ecological security pattern to identify priority protected areas: A case study in the Wuhan Metropolitan Area, China, *Ecological Indicators*, **148**, 110121, https://doi.org/10.1016/j.ecolind.2023.110121.

Zhang Y., McAreavey K., Liu W., (2022), *Developing and Experimenting on Approaches to Explainability in AI Systems*, Proceedings of the 14th International Conference on Agents and Artificial Intelligence (ICAART'22), Rocha A.P., Steels L., van den Herik J. (Eds.), Vol. 2, 518-527, https://doi.org/10.5220/0010900300003116

Zhang H., Zhang C., Hu T., Zhang M., Ren X., Hou L., (2020), Exploration of roadway factors and habitat quality using InVEST, *Transport and Environment*, **87**, 102551, https://doi.org/10.1016/j.trd.2020.102551.

Zhu C., Zhang X., Zhou M., He S., Gan M., Yang L., Wang K., (2020), Impacts of urbanization and landscape pattern on habitat quality using OLS and GWR models in Hangzhou, China, *Ecological Indicators*, **117**, 106654, https://doi.org/10.1016/j.ecolind.2020.106654.

Zlinszky A., Heilmeier H., Balzter H., Czúcz B., Pfeifer N., (2015), Remote sensing and GIS for habitat quality monitoring: new approaches and future research, *Remote Sensing*, **7**, 7987-7994.