**Continuous artificial activity** **has threatened wetland ecological environment changes in the Poyang Lake region since 2000**

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**Abstract:**

Poyang Lake is an essential natural wetland in the Yangtze River basin and plays a vital role in maintaining the ecosystem function and ecological security in the middle and lower reaches of the Yangtze River. However, the relative importance and spatial heterogeneity of the impacts of human activities and land use changes on ecological security needs to be further explored. Here, we analyzed the habitat quality level around Poyang Lake in 2022 and explored the factors of habitat quality change from a geographical perspective. The land use structure changes around the Poyang Lake basin from 2000 to 2022 were quantitatively analyzed, and then the relative importance and spatial heterogeneity of each factor on ecological security changes were investigated using geographic probes. The results show that (1) The worst quality habitat (0–0.1) consists mainly of construction land (1624.9 km2) with an area of 1634.64 km2; (2) Construction land continues to increase with the most significant change, and the dynamic land use attitude is 0.47. Grassland and mudflats have the greatest decrease. The increase in cultivated land in different periods is mainly due to the shift of water surface and forest land; (3) Wetland land use change drivers are more influenced by the interaction of socioeconomic factors. The explanatory degrees of the interaction between population density and total year-end population and population density and administrative area are greater than 0.84. The data are greater than the explanatory degrees of every single factor, indicating that the land use change is mainly coupled with population density, total year-end population, and administrative area. These results reveal that human activities influence the degradation of wetlands around the Poyang Lake area. This study has significant reference value for coordinating human–land relationships in Poyang Lake, optimizing land management policy, and improving the sustainable development of cities.

**Keywords:** Wetland ecological environment, Spatial heterogeneity, Geodetectors, Artificial activity, Poyang Lake

1. Introduction

Wetlands, which evolved over billions of years of soil, water, and life development on Earth, are one of nature’s most biodiverse ecological landscapes and the most important environment for human survival (Song et al., 2021). Wetland systems often provide critical ecosystem functions, i.e., flood reduction, fish production, carbon storage, and biodiversity conservation (Ye et al., 2019; Fluet-Chouinard et al., 2023). The size, morphology, and ecology of many of the world’s natural wetlands have changed dramatically due to increased human activities over the past century (Awange et al., 2008). Accelerated urbanization and human activities have shown negative impacts on wetland changes, and shifts in land use types have led to changes in wetland distribution areas, with shifts in towns and cropland having a more significant impact on changes in wetland areas (An et al., 2022). Therefore, identifying the evolutionary trends of wetland alteration by human activities and discussing the drivers of wetland habitat quality change and degradation can help rational development and environmental protection of wetlands.

The Poyang Lake area has decreased from 4200 km2 in the 1990s to less than 2000 km2 (Han et al., 2015), while the lake water level has fallen below the warning level in 2003. The degradation and pollution of the lake ecosystem have also become a major problem for local government and society (Yang et al., 2020; Zhang et al., 2023). This trend has brought tremendous impact and challenge to the ecosystem of Poyang Lake and local people’s livelihood and has also attracted wide attention from researchers (Mei et al., 2016).

Previous studies have shown (Feng et al., 2016; Li et al., 2020,2021) that human activities, climate change, and other factors all have noticeable controlling effects on the ecological impact of Poyang Lake. Among them, the wastewater discharge (Guo et al., 2008) and the increase in fertilizer use (Lu et al., 2011) brought by the activities of agriculture and farming have seriously affected the ecological environment of the lake. In addition to the global climate change intensification, the decrease in rainfall and the increase in evaporation in the Poyang Lake area also directly impact the lake’s water level and distribution area. The outbreak of green algae is also one of the reasons for the rapid degradation of Poyang Lake’s ecological environment (Lei et al., 2011; Yang et al., 2018; Mu et al., 2020)

In the past 20 years, most studies have focused on exploring the spatial and temporal patterns and influencing factors of Poyang Lake’s water level and area changes (Chen et al., 2014; Guo et al., 2008). Remote sensing technology and GIS methods have been utilized for lake ecological and environmental evaluation (Yan et al., 2013). The construction of mathematical models and hydrological simulation has provided rich information (Zhong et al., 2022). The changes in the Poyang Lake distribution area during the past 20 years and the driving factors are still-lack a systematic understanding. It is imperative to systematically study the changes in the wetland area of Poyang Lake and the driving factors to actively respond to the national ecological civilization construction of mountains, water, forests, fields, lakes, and grasses.

This study examines the indicators of land use type, dynamic attitude, and land use transfer type in the basin around Poyang Lake from 2000 to 2022 based on the problem analysis discussed above. The study uses a land use transfer matrix, geographic probes, and other techniques to examine the impact of each factor and how it interacts with the land use structure, explore how the quality of wetland habitat has changed, and investigate how the natural environment and human activities have an impact on the long-term evolution of wetlands. A better knowledge of the geographic distribution of wetlands in Poyang Lake is made possible by this study. With the help of this study, ecological conservation and sustainable development will be strengthened via a deeper understanding of the ecological environment and resource use in the Poyang Lake region.

2. Materials and methods

2.1. Study areas

Poyang Lake is located in the north of Jiangxi Province and is the largest freshwater lake in China (Figure 1). It plays a vital role in water storage, irrigation, and flood regulation. The lake is an important throughput shallow lake in the Yangtze River basin (Sjögersten et al., 2014). Poyang Lake National Nature Reserve, located in the northwest corner of Poyang Lake, with geographical coordinates 115°47′E–116°45′E, 28°22′N–29°45′N, straddles Yongxiu and Xingzi counties and is centered on the town of Wu in Yongxiu County.

The population density of Nanchang City and its surrounding areas in the southwest of Poyang Lake can reach a maximum of 600 persons/km2 (Liu et al., 2022). The study includes 15 administrative areas in Jiujiang, Ruichang, [Hukou](https://baike.baidu.com/item/%E6%B9%96%E5%8F%A3%E5%8E%BF?fromModule=lemma_inlink), Pengze, [De’an](https://baike.baidu.com/item/%E5%BE%B7%E5%AE%89%E5%8E%BF?fromModule=lemma_inlink), Lushan, [Duchang](https://baike.baidu.com/item/%E9%83%BD%E6%98%8C%E5%8E%BF?fromModule=lemma_inlink), [Gongqingcheng](https://baike.baidu.com/item/%E5%85%B1%E9%9D%92%E5%9F%8E%E5%B8%82?fromModule=lemma_inlink), [Yongxiu](https://baike.baidu.com/item/%E6%B0%B8%E4%BF%AE%E5%8E%BF?fromModule=lemma_inlink), Poyang, Anyi, Xinjian, Nanchang, [Yugan](https://baike.baidu.com/item/%E4%BD%99%E5%B9%B2%E5%8E%BF?fromModule=lemma_inlink), [Nanchang](https://baike.baidu.com/item/%E5%8D%97%E6%98%8C%E5%8E%BF?fromModule=lemma_inlink), and Jinxian counties (Zhu, 1983).

The population expansion of cities and counties around Poyang Lake seriously threatens the wetlands. Reconciling economic and social development with the ecological health of wetlands is a necessary and comprehensive task. Analyzing the main drivers and impacts of wetland change is important to achieving this goal (Wang et al., 2022).



FIGURE 1 The location of Poyang Lake and the local scenery

2.2. Data sources

The data used in this study mainly include Landsat remote sensing images, a digital elevation model, and socioeconomic data of the Poyang Lake area. Landsat remote sensing images were taken from the United States Geological Survey (USGS), 2000–2020, with a spatial resolution of 30 m. Socioeconomic statistics are obtained from the Statistical Yearbook of Jiangxi Province ([jiangxi.gov.cn](http://www.jiangxi.gov.cn/col/col424/index.html)) from 2000 to 2022.

2.3. Methods

2.3.1. Evaluation of habitat quality

Habitat quality is the ability of an ecosystem to provide sustainable conditions for organisms and is a prerequisite and basis for ecosystem functions and services (Moreira et al., 2018). It reflects the suitability of the environment for human survival, reproduction, and productivity. It is also an important indicator of the ecosystem’s health (Tang et al., 2022). Habitat quality indices can be used to characterize habitat quality and evaluate biodiversity levels in the study area, reflecting species’ genetic variation and potential during reproduction (Sharp et al., 2018).

In this paper, the habitat quality module of the InVEST model is used to assess the habitat quality of the study area for the period 2000–2020. Habitat quality is considered a continuous variable, considering the distance and spatial weight of stressors, the degree of legal protection of the land, and the effects of changes in land cover patterns and land cover patterns on habitat quality. The index values range between 0 and 1 (Tang et al., 2020) and are calculated as follows:

, (1)

where Dｘｊ is the degree of habitat degradation of raster x in habitat type j; R is the number of threat sources; Wｒ is the weight of threat source r; Yｒ is the number of rasters of the threat element; rｙ is the coercion value of raster y; βｘ is the accessibility of the threat element to raster x (the value of βｘ is determined between 0 and 1 depending on its level of legal protection); Sｊｒ is the sensitivity of habitat type j to threat source r; iｒｘｙ is the coercion value of rｙ to raster x of raster y levels of threat, divided into linear and exponential decay:

Linear decay:, (2)

Exponential decay:, (3)

where dｘｙ is the linear distance between grid x and grid y; dｒｍａｘ is the maximum stress distance of the threat source r. Habitat quality is calculated as

, (4)

where Qxj is the habitat quality index for raster x in habitat type j; Hj is the habitat suitability of habitat type j (0 ≤ Hj ≤ 1); k is the half-saturation constant, taken as half of the maximum habitat degradation, generally set to 0.5; z is the normalization constant, generally taken as 2.5.

In this paper, we applied InVEST version 3.12.0 for habitat quality model operation. We carried out a series of processing such as vectorization, reclassification, raster calculation, and data aggregation on the land use cover data of the Poyang Lake watershed in Jiangxi Province in the ArcMap 10.8 platform, assigning a value of 1 to selected land types and 0 to the rest. There are two key issues when running the InVEST model to assess habitat quality. The first is the selection of stressors. Poyang Lake flows through Nanchang, an important transportation hub in Jiangxi Province in the middle and lower reaches of the Yangtze River in China. The expansion of construction land and human activities are the main threats to habitat patches in the context of rapid urbanization and industrialization (Zhu, 1983). Based on the actual situation of Poyang Lake in Jiangxi Province, five types of land, namely Paddy field, Dryland, Urban land, Rural residential land, and Industrial and traffic land, were extracted as threat sources (Moreira et al., 2018; Tang et al., 2022). The five land types, Dryland, Urban land, Rural residential land, and Industrial and traffic land, are sources of threat (Moreira et al., 2018; Tang et al., 2022).

Second, the parameters were determined. Model parameters were identified with reference to relevant studies (He et al., 2017; Tang et al., 2020) to determine the relevant maximum stress distances, weights, and attenuation types (see Table 1). The remaining habitat suitability and sensitivity to stressors for different types are shown in Table 2.

**TABLE 1** Attributes of the stressors.

|  |  |  |  |
| --- | --- | --- | --- |
| Stressors | Maximum distance | Weight | Spatial decay type |
| Paddy field | 6 | 0.6 | Exponential |
| Dry land | 6 | 0.6 | Exponential |
| Urban land | 10 | 0.9 | Exponential |
| Rural residential land | 8 | 0.7 | Exponential |
| Industrial and traffic land | 12 | 1 | Linear |

**TABLE 2** Habitat suitability and sensitivity of land use type to each stressor.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Land use type | Habitat suitability | Paddy field | Dry land | Urban land | Rural residential land | Industrial and traffic land |
| Paddy | 0.3 | 0 | 0.2 | 0.6 | 0.4 | 0.5 |
| Dry land | 0.3 | 0.2 | 0 | 0.6 | 0.4 | 0.5 |
| Forestland | l | 0.8 | 0.8 | 0.9 | 0.8 | 0.9 |
| Shrubland | 0.9 | 0.5 | 0.5 | 0.8 | 0.7 | 0.8 |
| grassland | 0.8 | 0.5 | 0.5 | 0.6 | 0.5 | 0.6 |
| Water body | 1 | 0.8 | 0.7 | 0.9 | 0.8 | 0.9 |
| Urban | 0 | 0 | 0 | 0 | 0 | 0 |
| Bare land | 0.1 | 0.1 | 0.1 | 0.2 | 0.2 | 0.1 |

2.3.2. Land use

This paper combines the remote sensing monitoring database of China’s land use status in 2000, 2010, and 2020. It uses the single and the integrated land use type dynamic attitude to conduct the analysis.

(1) Single land use type dynamic attitude

The single land use type dynamic attitude refers to the change in a land use type in the study area over a certain period. It is used to characterize the spatial and temporal changes in different land use types over a certain period. The expression is (Wang et al., 1999):

, (5)

where Ki is the dynamic attitude of land use type i in period a~b; Uia and Uib are the areas of land typei at times a and b, respectively (hm2); Ta and Tb refer to the early stage of the study a and the end of study b, respectively.

A higher value of Ki indicates a more significant conversion from other types of land to this type of land and a more significant relative change over the study period; conversely, a lower value of Ki indicates a smaller change.

(2) Integrated land-use types move attitudes

The integrated land use dynamic attitude indicates the land use change rate in the study area over a certain period. The specific expression is (Wang et al., 1999):

, (6)

where LC denotes the combined land use dynamics in the study area; n is the number of land use types in the study area; ΔLUi-j is the area of the study area in the study period where type i land use is converted to a non-type i land use type; LUi is the initial area of type i land use in the study area; T is the length of the study period.

A higher K value indicates a more significant change in land use in the region; conversely, a lower K value indicates a smaller change.

(3) Land use transfer matrix

To see the transfer between land use types more intuitively and understand the trend and direction of land use change, the land use transfer moment was applied to analyze the land use change in Poyang Lake wetland and visualize the area change in each land use type in Poyang Lake wetland using 20 years of data. The land use transfer matrix was mainly used to analyze the rate and direction of transfer between land use types in different periods and the inner correlation and change trend between land use types. The transfer matrix equation is as follows (Liu et al., 2010):

*P =ij* , (7)

where P represents the area of land use type transfer; n represents the number of land use types classified in the study area; i, j (i, j are integers of 1, 2, 3..... n integers) denote the area before and after the transfer of a land use type; Pij denotes the number of land use types in category i that have been transferred to category j.

The land use data of different periods were fused and overlaid by ArcGIS software to obtain two periods of land use transfer matrices. In this study, the 22 years from 2002 to 2022 were divided into two time periods, 2002–2012 and 2012–2022, and the land use transfer matrices for the two periods were established.

2.3.3. Geodetectors

Geodetector is a saliency method oriented toward spatial data that reveal the influence of driving variables on geographical phenomena and detect heterogeneity of geographical elements of the same criteria in spatial layer clouds. The geodetector model does not contain linearity assumptions, so the covariance of multiple variables does not influence the results. In addition, the geodetector can detect the joint influence of two drivers. As a result, it has been widely used in ecology (Hu et al., 2020), public health (Zhang et al., 2020), regional economics (Wang et al., 2012), and other fields (Zhang et al., 2020).

The core idea of the geodetector is based on the assumption that if an independent variable has a high weight on the dependent variable, i.e., there is a significant influence, then the spatial distribution of the two should have some similarity, i.e., there is a statistical correlation. By detecting the spatial analytic properties of regions through geodetectors, we can reflect the similarity of physical phenomena in the same region and the difference between different regions and then analyze the driving forces that form the spatial variation of geographical phenomena (Wu et al., 2022; Hua et al., 2021).

Factor detection is used to detect the spatial heterogeneity of y and the extent to which factor x explains the spatial heterogeneity of attribute y. Factor detection is used to investigate the extent to which factor x explains the dependent variable y, measured by the value of q. The expression is as follows (Wang et al., 2012):

, (8)

, (9)

, (10)

where 𝑇𝑇𝑈 is the Total Sum of Squares for the whole area, 𝑇𝑇𝑊 is the Within Sum of Squares, q is the degree of interpretation of factor x to the dependent variable y, the value range is 0–1, the larger the value, the more pronounced the spatial heterogeneity, and vice versa.

Interaction detection is used to analyze the interaction between different risk factors and whether two or more factors, when acting together, can increase or decrease the degree of explanation of the dependent variable. A two-by-two comparison between the factors makes the determination. First, the q-values of the two factors x1 and x2 on the dependent variable y, denoted q(x1) and q(x2), respectively, and the q-values of the superimposed factor x1 ∩ x2, denoted q(x1 ∩ x2), are calculated. The type of interaction between the two independent variables on the dependent variable can be determined by comparing the values of q(x1), q(x2), and q(x1 ∩ x2).

Ecological probes were used to compare whether the effects of the two factors x1 and x2 on the spatial distribution of attribute y were significantly different, as measured by the F-statistic:

, (11)

, (12)

where 𝑁 x1, 𝑁 x2 denote the number of samples for factors x1, x2, respectively; 𝑇𝑇𝑊 x1, 𝑇𝑇𝑊 x 2 denote the sum of intra-stratum variance. 𝑙1 and 𝑙2 denote the number of stratifications of samples with factors x1 and x2, respectively. The null hypothesis 𝐻 0 is that 𝑇𝑇𝑊x1 = 𝑇𝑇𝑊x2, and if 𝛼 rejects the original hypothesis at a significant level, it means that x1 and x2 have a significant difference in their effect on the spatial distribution of the dependent variable.

Land use change results from the combined effect of physical and socioeconomic constraints (Zhu et al., 2022). The topography and geomorphology of the Poyang Lake basin are the background environmental constraints on spatial and temporal land use changes. The geographical differentiation characteristics of natural elements such as elevation, slope, slope direction, and temperature control the land use type changes in the area (Shi et al., 2023). In the context of economic construction, the urban fringe of the study area has expanded, the industrial structure has been optimized, and uneven urban development differences still objectively exist (Chen et al., 2022). Based on the results of theoretical and empirical analyses of existing research on land use change factors and considering the availability of socioeconomic data and the quantitative nature of natural factors in the study area, nine influencing factors were selected from the topography, climatic conditions, soil type, population distribution and structure, and economic level elements, with factors and descriptions (Table 3).

**TABLE 3** Impact factors and description of land use change

|  |  |  |  |
| --- | --- | --- | --- |
| Type | Key elements | Factor | Description |
| Physical Geography | Terrain | X1:Elevation | Elevation of the study area (m) |
| X2:Slope | Slope of the study area (°) |
| X3:Slope direction | Slope orientation of the study area |
| Climatic conditions | X4:Precipitation | Average annual precipitation in the study area (mm) |
| X5:Temperature | Average annual temperature in the study area (°C) |
| Socio-economic |  | X6:Population density | Population distribution in the study area (persons/km2) |
| X7: Total population at the end of the year | Total population of the study area at the end of the year (million) |
| X8:Gross Domestic Product | Study area GDP (million) |
| X9: Area of the district | Area of the administrative area of the study region (km2 ) |

3. Results

3.1. Habitat quality

The model output maps of habitat quality and relative degradation, which offered qualitative analysis on a 0–1 scale, and these maps were classified into 10 equal numerical classes in our study, with an additional class to represent the highest quality class that could be achieved (1). The watershed habitat quality was classified into five groups based on a quantitative examination of the number of square cells in each class, expressed in square kilometers: excellent (0.8–1.0), good (0.7–0.8), fair (0.5–0.7), poor (0.1–0.5), and awful (0–0.1).

The five categories of habitat degradation are as follows: mild (0–0.01), low (0.01–0.05), moderate (0.05–0.10), high (0.10–0.15), and severe (0.15–0.20). Table 4 displays the area and proportion of each type of habitat quality and habitat deterioration.

**TABLE 4** Proportion and index of habitat quality and habitat degradation area at different levels in Poyang Lake basin

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Grade | Excellent | Good | General | Poor | Difference |
| Habitat quality index  Area share | 0.8 - 1.0 | 0.7 - 0.8 | 0.5 - 0.7 | 0.1 - 0.5 | 0-0.1 |
| 16.56 | 13.19 | 1.23 | 61.37 | 7.65 |
| Habitat degradation Index of area (%) | 0-0.01 | 0.01 - 0.05 | 0.05 - 0.10 | 0.10 - 0.15 | 0.15 - 0.20 |
| 3.26 | 10.51 | 78.32 | 6.36 | 1.55 |

3.1.1. Habitat quality levels

The maps obtained in this study show the values for all quality levels (Figure. 2; Table 2). The highest quality levels represent habitats without any threats. Each habitat structure varies depending on the species and geographical location it sustains. Therefore, the threats considered and their associated pressures also differed depending on these factors.

The total area assessed by the model is 24,715 km2 and includes the seven different land use types being studied. The agricultural land surrounding Poyang Lake corresponds to 50.6% (12,524.3 km2) of the total area assessed and is mainly found in the plains on the periphery of the Poyang Lake water body. The water bodies of Poyang Lake account for 15% (3720 km2) of the total assessed area, and the forests account for 27.6% (6829 km2) of the total assessed area. While grassland, submerged vegetation

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**Fig. 2.** Habitat quality classes around Poyang Lake, 1 being the highest class

(6.25 km2), bare ground (9.74 km2), shrubs (0.07 km2), and building land (1624.9 km2) together correspond to 6.6% of all habitats assessed.

The lowest habitat quality (0–0.1) has 1634.64 km2 and consists mainly of built-up land (1624.9 km2). Most are located in urban-based areas, including Jiujiang and Nanchang, with a continuing trend toward outward expansion (Chen et al., 2020).

As the economic development zone in Nanchang began to expand around 2003 (Yan et al., 2013), Nanchang County expanded to the west and north from 2004 to 2009 following the onset of widespread urbanization. In addition, the economic development plan issued by the Jiangxi Provincial Development and Reform Commission (http://drc.jiangxi.gov.cn/) has led to rapid urbanization in Nanchang and surrounding counties. The counties in the study are all distributed in small pockets, and the habitat quality around building sites may correlate with their size.

The highest habitat quality levels (0.9–1) exist around Mount Lushan and some hills around Poyang Lake, with 98% of the habitat area in the Mount Lushan region showing the highest quality levels. This fact is explained by the altitude of this natural habitat, which is 1000 m above sea level on Mount Lushan, where human habitats are considered the most significant threat. Tourism can have a negative impact on the habitat (Yang et al., 2020).

In addition, native scrub habitat quality is located in the first three categories, distributed around the mudflats around Poyang Lake, with wetland cover types exhibiting vegetation, mudflats, and water bodies along an elevation gradient from the boundary to the center of the Poyang Lake water body. During the dry season, the vegetation type is mainly meadows (Sheng et al., 2011), distributed in the southern and eastern parts of Poyang Lake. The water bodies are located in the central, eastern, and southern parts, with a small area of sand distributed northwards from the central water body around a narrow channel that empties into the Yangtze River. In near-lake areas, longer dry seasons may result in lower soil moisture due to increased evaporation, which limits the growth of wetland vegetation in these areas (Mu et al., 2020).

Water bodies are exceptional types, with Poyang Lake water bodies showing a quality rating of 0.7–0.8. The Poyang Lake Ecological Reserve covers an area of 224.4 km2, and the wetlands of Poyang Lake are mainly in the basin and plain, with a small area in the mountains. The reserve consists of nine lakes: Beng Lake, Dacha Lake, Dahu Pond, Sha Lake, Changhu Pond, Zhonghu Pond, Xiang Lake, Meixi Lake, and Zhushi Lake, and includes a dozen of nearby lakes and grassland. The central water bodies all have a habitat quality of 0.75 or above. Except for the land, the whole area of the highest quality class is inside Poyang Lake (Figure 2). Outside the boundary of Poyang Lake, large areas of agricultural land with the lowest quality levels occur, enclosing the water body. This result can be used to delineate the Poyang Lake area boundary, allowing for management improvements and potentially indicating practical management actions.

Using ArcGIS software, the raster map of habitat degradation was overlaid with the land use map to calculate the distribution of differences in habitat quality by land use type (Figure 3). The reason why grassland, bare ground, and shrubs are not shown is probably because the flooding period of Poyang Lake covered the lower elevation grassland and mudflats and some low shrubs around Poyang Lake (Feng et al., 2012). The above results show that habitat degradation in the watershed is closely related to



**FIGURE 3** Effects of different land use types on habitat quality in the Poyang Lake Basin

the land use types in the watershed. It can also be found that different land use types greatly affect habitat degradation.

3.1.2. Habitat degradation level

Habitat degradation degree ranges from 0 to 1. A higher degree of habitat degradation indicates a higher level of habitat degradation and a higher potential threat to the regional ecosystem from the threat source factor. The highest level of degradation reached by the regional habitats in the output map is 0.20 (Figure 4). Since forests and water bodies far from the agricultural land of human activities are less affected, the areas further away from human activity are less threatened; the border of the study area reaches the highest possible quality level.

In this study, the agricultural land around Poyang Lake represents 50.07% of the degradation level (0.05–0.10) area, which is the single habitat reaching the maximum degradation level. The habitat degradation degree of all cities in the Poyang Lake basin has different degrees. The highest habitat degradation degree is in Nanchang City, which has a higher degradation level. The overall habitat degradation in each city shows



**FIGURE 4** Map of habitat degradation levels around Poyang Lake, with the highest level of degradation in the study area at 0.2

a trend of decreasing and then increasing. An integration with land use analysis shows that the level of habitat degradation in the watershed is mainly influenced by woodland, grassland, and cropland. The woodland and grassland habitat suitability is higher, making the water’s habitat degradation show a decreasing trend (Michishita et al., 2012).

From 2010 to 2018, habitat degradation showed a rapid increase. The analysis of land use changes during this period showed that the area of forest land with high habitat suitability in the watershed decreased significantly. On the contrary, the rapid increase in urbanization in the watershed during this period caused a surge of construction land, which is the most threatening source, and increased habitat degradation in the watershed. As of 2018, the highest degree of habitat degradation among the cities in the basin was Nanchang City, with a degree of habitat degradation of 0.035, and the degree of habitat degradation is at a high level. The tendency of habitat degradation to increase rapidly after 2010 in all cities in the basin should be noted, and effective measures should be developed to improve the ecosystem type (Dai et al., 2021).

The raster map of habitat degradation was overlaid with the land use map in ArcGIS to obtain the different distribution of habitat degradation by land use type (Figure 5). Among the various land use types, the habitat degradation degree was in the order of construction land < water body < grassland < bare land < shrub < forest < agricultural land.



**FIGURE 5** Effects of different land use types on habitat degradation in the Poyang Lake Basin

Among them, agricultural land accounted for 50.67% of the total watershed area and was the largest land use type with the highest habitat degradation. In comparison, the construction land accounted for 6.57% of the total watershed area and was the highest land use type with 0.01 habitat degradation; bare land and shrub erosion area was the smallest, accounting for only 0.04% of the watershed.

The above results show that habitat degradation in the watershed is closely related to the land use types in the watershed. It can also be found that different land use types have large differences in habitat degradation. The large area of agricultural land with high habitat degradation index has a greater influence on the degradation index of other land types, which has a specific relationship with distance.

3.2. Land use

3.2.1. Structural changes in land use

Figure 5 shows that the water area of Poyang Lake has decreased to a certain extent from 2000 to 2020. The percentage of water area declined from 34.9% in 2000 to 34.5% in 2020. Since 2000, the water area has been steadily declining, with occasional spikes in growth or decline. The overall tendency involves a constant decline, abrupt increase/decrease, and gradual stabilization.

The construction land area has shown a year-on-year increase, including a significant increase from 2016 to 2018, with the area share increasing from 2.1% to 2.7%. This increase was probably due to the release of the Jiangxi Provincial Department of Natural Resources “Jiangxi Construction Land Indicators (2018 Edition)” (http://cgw.nc.gov.cn) (hereinafter referred to as the “Indicators”), which provides qualitative and quantitative regulations on the scale of land use and land use conditions for construction projects in seven major categories and 58 industries in Jiangxi Province. Compared with the 2011 version of the standard, the average investment intensity of 28 industrial categories specified in the indicators has increased by 26%. The control index of “tax per land” of the industrial industry was added, reflecting the provincial policy guidance, and the construction land around Poyang Lake increased significantly.

The area of paddy fields in general shows a trend of “first decreasing and then increasing,” with the area changing in two phases: from 2000 to 2008, the area continued to decrease, from 1,059 to 645 ha; from 2010 to 2020, the area continued to increase. The area share also shows a trend of “decreasing first and then increasing.” The area of arable land in the study area decreased from 1059.84 ha (2.5%) in 2000 to 645.21 ha (1.58%) in 2008, and paddy fields were closely related to human production. jiangxi.gov.cn/). These data provided the basis for proposing the policy of returning farmland to forests and lakes, and large areas of paddy fields around Poyang Lake were reduced. With the population and food demand increase, the paddy field areas in Poyang Lake started to increase after 2010, from 750.42 (1.78%) to 1092.29 ha (2.59%) in 2020, recovering to the level of accounting in 2000.

Generally, the dryland region has an erratic increasing tendency, mostly as a result of population growth and rising demand for food and oil crops. The research area's dryland region makes up the tiniest portion, with a maximum contribution of less than 2%. It is mostly concentrated in the farming polders. Due to a deteriorating trend from 2002 to 2006, the largest sudden shift in dryland occurred in 2002. Additionally, from 2008 to 2020, the government strengthened forest land management, increased citizens' awareness of environmental protection, and introduced policies to restore farmland to forests and lakes. These factors all contributed to the continuous growth of the dryland region. In 2020, the dryland area reached 858.15 hm 2, accounting for 2.03% of the total area. Although the loss of forests increases the potential for flooding, it also increases the impact of drought (Guo et al., 2008). However, it is not a cause of the drought. In the same period (2006–2014), the forested area of Poyang Lake continued to increase, but not as a result of the increase in dryland area. In addition, climate change and increased anthropogenic activities have led to reduced precipitation in the dry season basin of Poyang Lake. Human activities may have contributed to the 5.4–56.3 mm decrease in runoff in the 21st century, with human activities (e.g., irrigation of farmland, river regulation, and deforestation) being the main controls that altered hydrological processes (Ye et al., 2013). The main control on hydrological processes is human activities (e.g., irrigation, river regulation, and deforestation).

In 2000, there were 955.26 ha of woodland, accounting for 2.26% of the watershed's area. From 2000 to 2014, the woodland area increased yearly as a result of the protection of woodland in mountainous regions and the planting of forests. After 2014, the demand for arable land and construction space increased. The forest area has been varied and altered, and the development of dams and flood control infrastructure has also had an influence on the woodland area's reduction due to floods.

The grassland area generally showed irregular changes, with large fluctuations from 2000 to 2010 and a stable area from 2010 to 2020. The large fluctuation of the grassland area was mainly caused by the fact that Poyang Lake is a seasonal river, and most of the grassland is gathered around the water body of Poyang Lake. The satellite image interpretation during the dry and abundant water periods (Han et al., 2015) suggests that in the dry period, the grassland area accounts for a larger proportion due to the exposure of a large area of grassland at the bottom of the lake, while in the abundant period, the water body floods most of the grassland, reducing its proportion. In 2008, the water area accounted for a maximum of 38.28% of the whole period inundating most of the grass flats, resulting in a decrease in the area of grass flats (Figure 6). The main changes in the area of grass flats are due to changes in water level. The duration, magnitude, and frequency of water level fluctuations or when inundation recedes determine the seed germination of wetland jerkin, floating leaf, and submerged plants. Prolonged inundation or flooding can result in submerged plants (bamboo-leaved eyebright and bittercress), floating leaves (Fan et al., 2018), floating-leaved plants (Nymphaea peltata), and even some water-holding plants, such as broad-leaved balsamroot and water peanut, can significantly reduce population density and biomass, affecting population renewal and recovery (Alireza et al., 2021).

From 2000 to 2020, the average annual proportion of reedbeds was 3.08%, with two main types of reedbeds, planted and natural, mainly in Beng Lake, Dasha Lake, and Grassland. The reedbeds were mainly found in Beng Lake, Dasha Lake, and the Grassland. From 2000 to 2020, the average annual percentage of mudflats was 4.86%, mainly in the shallow areas around lakes.

In the 20 years from 2000 to 2020, the average annual proportion of grassland was 48.72%, the average annual proportion of water was 35.13%, the average annual proportion of mudflat was 4.86%, the average annual proportion of reedbed was 3.08%, the average annual proportion of forest land was 2.65%, the average annual proportion of paddy field was 2.11%, the average annual proportion of construction land was 1.98%, and the average annual proportion of dry land was 1.47%. The proportion of the area of the same period shows that the grassland> water > mud land > reed land > forest land > paddy land > construction land > dry land. The main reason for this phenomenon is that in January, the Poyang Lake basin, interpreted by satellite image, is in the dry



**FIGURE 6** Changes in the structure of land use types in the Poyang Lake Rim watershed

season, the water level is the lowest of the year, and a large area of the grass beach is exposed. The grass beach land is mainly distributed around the nine lakes in the study area, which is the largest and most widely distributed type. A part of the grass beach is in the low of Poyang Lake and cannot be seen.

3.2.2. Analysis of land use dynamic attitude and transfer matrix

As shown in previous studies, humans indirectly affect habitat quality through their effects on land use types (Gao et al., 2014; Ye et al., 2013). That is, the land type change is related to ecological quality. In this study, we analyze the characteristics of land use change in the area around Poyang Lake for over two decades, from 2000 to 2022, in terms of land use structure, dynamic attitude (Table 5), and type shift. We found the following characteristics.

**TABLE 5** Land use dynamic attitude

|  |  |  |  |
| --- | --- | --- | --- |
| Type | Time | | |
| 2000-2010 | 2010-2020 | 2000-2020 |
| Water area | -0.006 | 0.006 | -0.001 |
| Building sites | 0.021 | 0.060 | 0.047 |
| Paddy field | -0.029 | 0.046 | 0.002 |
| Dryland | -0.028 | 0.076 | 0.013 |
| Woodland | 0.022 | -0.001 | 0.010 |
| Grassland | 0.004 | -0.009 | -0.003 |
| reedbeds | 0.039 | 0.005 | 0.023 |
| Mudflats | -0.004 | -0.005 | -0.004 |
| Integrated dynamic attitude | 0.004 | 0.005 | 0.003 |

(1) On the land type of anthropogenic elements: arable land is the land type with the most apparent change in the Poyang Lake basin; the construction land area increases yearly. The expansion of construction land is the most significant (Table 6). The main

**TABLE 6** Land use transfer matrix from 2002 to 2012 (km2)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 2002 | 2012 | | | | | | | |
| Arable land | Woodland | Shrubs | Grassland | Water area | bare ground | Building sites | Total and |
| Arable land | 11860.1 | 495.88 | 0 | 3.7 | 169.4 | 0.2 | 0.02 | 12529.3 |
| Woodland | 418.3 | 6394.5 | 0 | 0.6 | 3.0 | 0 | 0.03 | 6816.4 |
| Shrubs | 0.1 | 0.2 | 0.1 | 0.02 | 0 | 0 | 0.03 | 0.5 |
| Grassland | 2.8 | 0.2 | 0 | 7.6 | 4.6 | 4.4 | 0.04 | 19.6 |
| Water area | 692.6 | 24.3 | 0 | 1.4 | 3332.8 | 2.1 | 0.05 | 4053.3 |
| Bare ground | 0.4 | 0 | 0 | 1.7 | 4.0 | 8.5 | 0.07 | 14.8 |
| Building sites | 1.1 | 0 | 0 | 0.01 | 15.9 | 0 | 0.08 | 17.1 |
| Total and | 12975.3 | 6915.1 | 0.1 | 15.2 | 3529.8 | 15.2 | 0.32 | 23451 |

reason is related to the increase in population number, accelerated urbanization in the Poyang Lake basin, and the increase in infrastructure construction scale in the Poyang

Lake wetland (Michishita et al., 2012; Yao et al., 2019).

(2) Land use type changes are closely related to policies. For example, the continuous rise of forest land until 2014 (Figure 6) and the significant expansion of construction land are influenced by related policies (<http://drc.jiangxi.gov.cn/>).

(3) According to the role of urbanization: 2000–2005, the counties and districts in the Poyang Lake area were in a primary development stage of urbanization with a slow development rate (Michishita et al., 2012). The arable land and other land types, such as unused land, were converted into construction land on a large scale (Table 7).

**TABLE 7** Land use transfer matrix from 2012 to 2022 (km2)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 2012 |  |  |  |  | 2022 |  |  |  |
| Arable land | Woodland | Shrubs | Grassland | Water area | bare  ground | Building sites | Total and |
| Arable land | 7568.3 | 1264.3 | 0.1 | 402.8 | 1325.8 | 14.6 | 2219.9 | 12795.7 |
| Woodland | 254.0 | 6336.4 | 0.1 | 96.5 | 86.8 | 6.0 | 104.1 | 6883.7 |
| Shrubs | 0 | 0.1 | 0 | 0.1 | 0 | 0 | 0 | 0.1 |
| Grassland | 2.1 | 0.41 | 0 | 4.9 | 3.0 | 2.3 | 2.4 | 15.1 |
| Water area | 88.9 | 2.71 | 0 | 37.3 | 3314.7 | 16.7 | 33.0 | 3493.3 |
| bare ground | 0.2 | 0.11 | 0 | 6.3 | 3.0 | 5.3 | 0.2 | 15.1 |
| Building sites | 108.4 | 30.2 | 0 | 45.8 | 93.7 | 11.3 | 974.0 | 1263.3 |
| Total and | 8021.8 | 7634.1 | 0.2 | 593.6 | 4827.0 | 56.1 | 3333.6 | 24466.3 |

The reasons for the decrease in arable land were twofold: on the one hand, due to the imbalance of socioeconomic development, many young people went out to work, resulting in the conversion of arable land to grassland or unused land; on the other hand, due to the continuous urbanization, the sharp expansion of development and construction projects and the increasing occupation of arable and forest land by other non-agricultural projects resulted in the shrinkage of arable and forest land (Vallecillo et al., 2016).

3.3. Driving force analysis

3.3.1. Factor detection results and analysis

A geographic probe is an important tool for measuring and mining stratified spatial heterogeneity and spatial pattern attributes, detecting the consistency of spatial distribution patterns between the dependent and independent variables through spatial heterogeneity. The explanatory degree of the independent variable to the dependent variable is measured (Wall et al., 2021), i.e., q value.

Equation (7) was used to determine the contribution of each factor to the change in land use in 2020(Figure 7). The q value presented in the figure represents the amount of independent variable explanation on the dependent variable at the 95% confidence level, and it indicates that all factors for each period passed the hypothesis test at the 5% level. The factor probing findings demonstrate that the factors X1 (elevation), X2 (slope), X3 (slope direction), and X6 (population density) have substantial explanatory power and have q-values greater than 0.40.



**FIGURE 7** Results of land use change factor detection in the county around Poyang Lake

The population density and total population at the end of the year can provide an overview of the demographic characteristics and regional population distribution; the q-values of these variables, which affect the spatial pattern of land use change, are 0.545437 and 0.114285, respectively. The indicator of the level of regional economic development is the gross domestic product. In 2020, the q-value in the Poyang Lake County area reached 0.189686. The primary factors affecting land use change are the population density and economic development level. The natural geography elements X1 (elevation), X2 (slope), and X3 (slope direction) all have substantial explanatory degrees (over 0.66) for land use change. The land use shift is best explained by the socioeconomic variables X6 (population density) and X9 (administrative area). For understanding changes in land use, the natural geography element is more important than the socioeconomic factor.

3.3.2. Interaction detection results and analysis

In the counties near Poyang Lake, the factors influencing land use change varied. The findings of interaction detection demonstrate that interactions between factors have a larger explanatory power on land use change than a single component (Figure 8).



**Fig. 8.** Interaction detection results of land use change factors around Poyang Lake

The explanatory degree of interaction between X6 (population density) and X7 (total population at the end of the year), excluding the non-natural components, is 0.8491. Population density (X6) and administrative district area (X9) interact with an explanatory degree of 0.8534. The statistics show that the land use change is mostly driven by population density, total population at the end of the year, and administrative district area as the common driving variables, which are more significant than the level of explanation for each individual element.

3.3.3. Ecological sounding results and analysis

Ecological probing is used to assess the relationship between two factors for variations in the dependent variables, i.e., to determine if there are variations in the impacts of soil type and elevation on the dependent variables in the counties around Poyang Lake (Figure 9). There are variations in the effects of precipitation, elevation, slope,



**FIGURE 9** Ecological survey results around Poyang Lake

and slope direction, as well as in the effects of population density and slope orientation, on land use change. Additionally, there are variances in the height, slope, and aspect of land use change, as well as in the total population, GDP, and year-end GDP. Administrative area, elevation, and slope orientation all have different effects on land use change. There are no appreciable variations in how other factors affect land use change.

In summary, the following points can be highlighted: ① The influence of three factors, namely elevation, slope, and slope direction, on the spatial pattern of land use change is stable. ② Non-natural factors: population density, total population at the end of the year, gross domestic product, and administrative district area do not differ significantly in their influence on the spatial pattern of land use change.

4. Discussion

4.1. Human activities put pressure on habitat quality

In this study, the InVEST model was used to analyze the effects of human activities on habitat quality regarding both habitat quality and habitat degradation levels. The results showed that there was a relationship between the quality of habitat and the extent of human activities; the closer the habitat was to the human activity area, the lower the value of habitat quality (Figure 2). This phenomenon is evident in cities with concentrated population, such as Nanchang and Jiujiang, where the habitat quality of construction land is below 0.1; on the other hand, the habitat quality of sites with less human activity is high, such as forest land, where the habitat quality level is above 0.8, and cultivated land, as a buffer zone between forest land and construction land, where the habitat quality is around 0.5. The habitat quality can also be used as an indicator to measure the ecological environment and the impact of human activities, i.e., forest land that is not fully subjected or weakly affected by human activities, arable land that is affected to some extent, and construction land that is fully affected by human activities (Lei et al., 2022; Tang et al., 2022; Wang et al., 2022).

Habitat deterioration is evident in the city of Nanchang, which is at the center of the Poyang Lake basin, and the extent of degradation increases as one approaches the built-up region. Rivers, lakes, and mountains tend to have low levels of habitat degradation, and habitat quality in these regions is excellent due to the lesser impact of human activities (Figure 2).

In conclusion, human activities have an indirect influence on ecosystems by affecting land use types (Figures 3 and 5). Additionally, geographical patterns in regional habitat quality are influenced by the interaction of natural and socioeconomic variables (Sun et al., 2019; Zhang et al., 2020). According to Zhao et al. (2018), socioeconomic variables such as population density, which are directly tied to human activities, pose a danger to habitat quality and can result in habitat loss and degradation. Nanchang, the central city of the Poyang Lake basin, is a good example of this.

4.2. Continued population growth

One of the primary causes of land use change in the wetlands around Poyang Lake is population increase. Policy has a significant impact on land use (Zhen et al., 2011), particularly in the wake of the floods of 1998. In the middle and lower portions of the Yangtze River basin, China started to put wetland restoration strategies into practice (Yan et al., 2013). The demand for arable and building land that can be exploited as land resources necessarily rises as the population grows. Humans' predatory use of the land degrades its resources and environment, which has an impact on how sustainably those resources may be used (Chen et al., 2014).

Population density is the most driving influence factor in the Poyang Lake basin’s ecological and environmental quality change, which is increasingly influenced by urbanization development (Shi et al., 2023). Our results (Figures 7–9) suggest that

population density and administrative area as essential factors of land use change. The interaction of three factors, population density, total population at the end of the year, and administrative area, is stronger.

According to Liu et al. (2010), population expansion has a major influence on the change in carbon emissions in the eco-city cluster surrounding Poyang Lake. This could compound the harm done to Poyang Lake's wetlands.

5. Conclusions

The InVEST model and geographic probes are used in this work to describe the role of human activities in wetland alteration and their effects. Analysis of the land-use patterns of wetlands surrounding the Poyang Lake basin from 2000 to 2022, as well as an examination of the relationships between the driving forces, were conducted. The study's findings suggest the following:

(1) Human activities alter the forms of land use, which in turn affects habitat quality. The cities with concentrated populations form the center of the low-quality habitat region in the Poyang Lake basin, and habitat quality gradually improves as one moves outside of these cities.

(2) According to the study of land use structure change, urbanization has likely had the greatest influence on the wetlands near Poyang Lake during the past two decades, and its effects have accelerated the shift in land use type. The expansion in population density is reflected in the increase in urbanization. The biological habitat of the wetlands is directly negatively impacted by population increases.

(3) The geodetector investigations reveal that the three primary variables impacting the habitat quality of Poyang Lake are population density, total population at the end of the year, and administrative area, and particularly the relationship between interaction between population density and administrative area.

**CRediT authorship contribution statement**

**Wenrui Yuan**: Conceptualization, Methodology, Writing – original draft. **Lingkang Chen**: Conceptualization, Writing – review & editing, Supervision,Funding acquisition. **Haixia Chen**: Methodology, Writing –review & editing. **Shaofu Deng**: Software, Data curation, Visualization.**Hong Ji**: Resources, Supervision.**Fenshuo Liang**: Software.

**Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Data availability**

The authors do not have permission to share data.

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