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Original Research

Spatio-Temporal Changes in Habitat Quality and Linkage with Landscape Characteristics Using InVEST-Habitat Quality Model: A Case Study at Changdang Lake National Wetland, Changzhou, China

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Abstract

Clarifying the spatio-temporal habitat quality changes caused by land use and associated landscape structural changes can provide scientific references for ecological conservation and landscape management. This study investigated spatio-temporal changes in habitat quality associated with land-use change and landscape characteristics in the Changdang Lake National Wetland from 2010 to 2019. The Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model was used to assess the habitat quality and partial least squares regression analysis was employed to evaluate the contribution of landscape characteristic changes to habitat quality changes caused by the land-use conversion. The results showed that the mean habitat quality value of the study area increased from 0.7 to 0.73. Meanwhile, the areas with high and low habitat quality values increased by approximately

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11.6% and 1.9%, respectively, while the areas with moderate habitat quality values decreased by 13.5%; this indicated that the wetland experienced a slight habitat quality improvement. The most important landscape structure variable that accounted for habitat quality change for all land-use types including habitat, semi-habitat and non-habitat was percentage of landscape (PLAND). These findings suggested that strengthening ecological environment management, reducing habitat modifications and restoring degraded natural habitats are crucial to maintaining biodiversity.

Keywords: habitat quality, InVEST model, landscape pattern, land use change, Changdang Lake National wetland

Introduction

Wetlands, as unique ecosystems formed by the interaction of land and water, play an important role in maintaining regional habitat security, ecological balance and biodiversity [1-2]. However, the superimposition of human activities such as industrialization, agricultural activities, urbanization and anthropogenic climate change on these natural processes is destroying these valuable ecosystems more rapidly than any other activity [3]. Combined with stress factors, such as the increasing frequency and intensity of extreme climate events, human activities have become a severe challenge for wetland ecosystems [4].

Habitat quality is an important index of the ecological environment. It refers to the ability of an ecosystem to provide suitable living conditions for the sustainable individual- and population-level development within a certain temporal and spatial range [5-7]. Due to the close association between habitat quality and land use/cover change (LUCC), the extensive LUCC currently underway is changing the habitat quality of wetlands on multiple scales. Wetland habitat quality, as an important indicator of wetland biodiversity, reflects the ability of wetlands to provide a suitable basis for the sustainable development of individuals and populations. Therefore, research on wetland habitat quality is of great significance for regional biodiversity protection, ecological security pattern construction and maintaining the balance of the ecosystem. [8]. Furthermore, improving the understanding of the relationship between habitat quality and landscape patterns can help to reveal the effect of landscape ecological processes on habitat quality, thereby deepening understanding of the spatio-temporal process of habitat quality change.

There are two approaches for assessing ecosystem quality and service capacity: mathematical models based on field survey data of animals and vegetation, and habitat assessment models that integrate landscape patterns and threat source distribution. The former approach was used to establish a habitat quality evaluation index system, including the biological abundance index, vegetation coverage index and other evaluation criteria; these are used to measure habitat quality and to carry out static research. Many studies have used this method based on animal and vegetation field survey data but few have been involved in the spatio-temporal process of threat sources [9-11], especially in dynamic environments in which resources change daily as a result of land use. While experiments can reveal habitat quality by observing resources at the species level, preference in the assessment of habitat quality settings must be inferred from patterns of observed use in environments while accounting for changing resource levels.

However, due to the limitations of data accumulation, it is difficult to determine detailed spatio-temporal changes by only the implementation of a static study in a region or community. In these cases, habitat quality assessment models can be misleading or have limited predictive power [12-13]. Although the mechanism by which landscape patterns affect habitat quality has been revealed on the theoretical level [14-15], this approach has failed to quantitatively characterize the specific spatio-temporal process underpinning the correlation between landscape and habitat quality. Therefore, it is necessary to analyze the correlation between landscape pattern change and habitat quality and to reveal their spatial correlation characteristics. Thus, there is much impetus to assess habitat quality by connecting shifting patterns of landscape change and spatio-temporal changes to measures of the landscape.

Modeling is a suitable and cost-effective technique to assess spatio-temporal dynamics of biodiversity and habitat quality. In recent years, detailed explanations of habitat spatio-temporal processes have been achieved using models such as the multiscale integrated models of ecosystem services (MIMES) [16], the ecological niche model (ENM) [17-19], the habitat suitability index model (HSIM) [20-22] and the Integrated Valuation of Ecosystem Services and Tradeoffs model (InVEST) [23-28]; these have been widely used in assessing the quality of ecosystems. These models provide a rapid route for assessing the impacts of different threats and land-use changes on an ecosystem. Commonly, they are used for habitat conservation planning, managing landscapes, assessing the extent of habitat quality and predicting habitat quality under different scenarios [29].

As a derivative part of the Tai Lake water system, Changdang Lake National Wetland is a typical wetland with rich floral, faunal and microbial diversity. Selecting this national park as a typical area, the land-use changes, landscape patterns and habitat quality

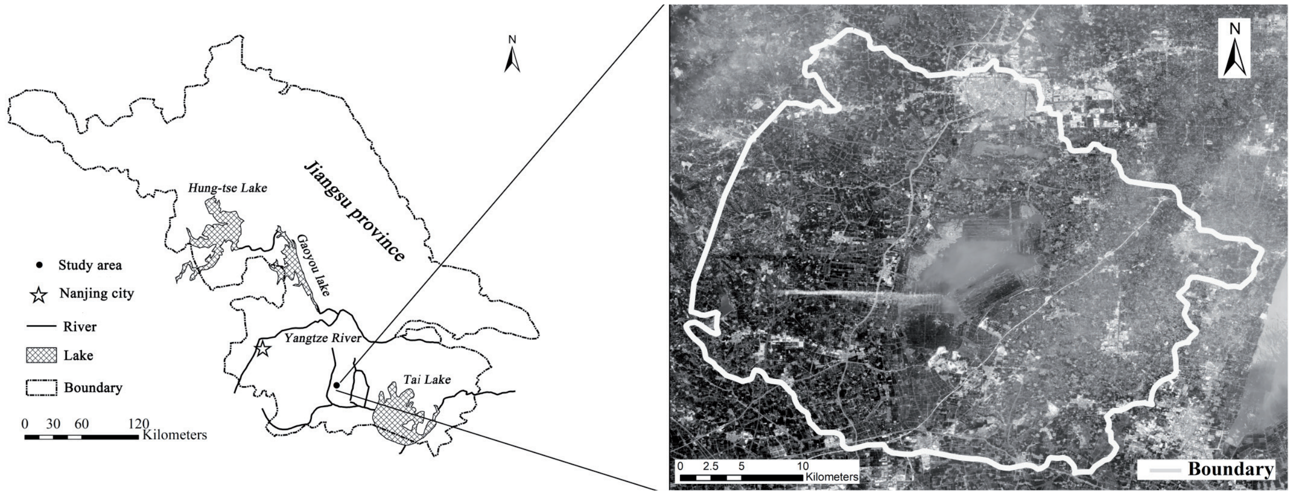

Fig. 1. Location of the Changdang Lake National wetland, Changzhou City, China.

from Landsat images were analysed to determine the relationship between landscape and habitat quality. The objectives of this study were: (1) to quantitatively evaluate the spatio-temporal changes in the landscape pattern and habitat quality of Changdang Lake National Wetland Park in China; (2) to explore the relationship between habitat quality and landscape pattern index, thereby revealing the correlation between habitat quality responses to different landscape structural changes.

Materials and Methods

Study Area

The study area, Changdang Lake National Wetland Park (31°33'-31°53'N, 119°17'-119°44'E) is in the southeast of Changzhou City, China (Fig. 1). As a derivative of the Tai Lake system, it covers an area of approximately 7969 ha and provides ecological services for surrounding areas. It is in a subtropical monsoon climate zone with an annual mean temperature of 17.5ºC, a maximum of 39.4ºC in August and a minimum of 3.2ºC in January. The average annual precipitation ranges from 900 to 1100 mm and there are approximately 2047 sunshine hours on average per year. The topography gradually tilts from west to east, with hills in the west and plains in the east.

Data Sources

Multi-date satellite images were obtained from the United States Geological Survey (USGS; http://earthexplorer.usgs.gov). From these, the spatio-temporal changes in land use/cover and landscape were analyzed (Table 1). All images were captured in the middle of the growing season in August during good weather with clear skies (cloud cover of less than 10%). All images were subjected to radiation calibration, ortho-rectification and geo-correction, with the projection of the UTM Zone 50 North and the WGS 84 coordinate. To provide training and test samples for classification, the land use/cover types in the study area were investigated by hand-held GPS (Garmin MAP 62CS; accuracy: ±3 m).

The InVEST Habitat Quality Model and Workflow

Habitat quality can be calculated by analyzing land-use and land-cover maps and the degree of threat to biodiversity can be determined using the Habitat Quality module of the InVEST model (v 3.9). This model was developed by Stanford University, the Nature Conservancy (TNC) and the World Wildlife Fund for Nature (WWF) for ecosystem service function assessment [30]. The habitat quality ranges from 0 to 1, with 1 indicating high quality and 0 denoting no habitat quality.

Table 1. Remote sensing image lists in the study.

Satellite	Sensor	Data number	Acquisition time	Spatial resolution (m)
Landsat 5	TM	LT51200382010231BJC00	2010-08-19	30
Landsat 8	ETM+	LC81200382013223LGN01	2013-08-11	
Landsat 8	ETM+	LC81190382016241LGN00	2016-08-28	
Landsat 8	ETM+	LC81190382019233LGN00	2019-08-21	

In the model, the habitat quality can be calculated in multiple ways: by using the stress factor sensitivity, external threat intensity of different land-cover types, the influence distance of stress factors, spatial weight and land protection. The model uses the running environment of ArcGIS to spatially express the habitat quality. The data to be input into the model include LUCC data for each period, stress factor layer data for each period, the stress factor table (including stress intensity and maximum stress distance) and the habitat sensitivity table for each stress factor.

The distance between the threat source and habitat which describes the impact of the threat on the habitat in the model can be calculated by the linear or exponential distance decay function (Equations 1 and 2). The degree of threat decreases with increasing distance between the habitat and threat source.

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{r\max}}\right) \text{ if linear} \quad (1)$$

$$i_{rxy} = \exp\left(\frac{-2.99 d_{xy}}{d_{r\max}}\right) \text{ if exponential} \quad (2)$$

Here, d_{xy} is the linear distance between grid cells x and y, and dram x is the maximum effective distance of threat r across space. The total threat level to land use/cover or habitat type j is calculated by Equation (3):

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{Y_r} (W_r / \sum_{r=1}^{R} W_r) r_y i_{rxy} \beta_x S_{jr} \quad (3)$$

Here, R is the number of threat factors, y_r is the set of grid cells on the r,s map, ω_r is the relative effect of each threat, β_x is the level of accessibility to grid cell x, and S_{jr} is the relative sensitivity of each habitat type to each threat.

Based on land use/cover data, in combination with habitat suitability, impact distance, the weight of stress factors and the sensitivity of each habitat type to stress factors, habitat quality was calculated using Equation (4):

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

Here, H_j is the habitat suitability of land use/cover type j, z is the normalized constant and k is the half-saturation constant.

In the model, the maximum impact distance, stress factors weightings and sensitivity of each land use/cover type to habitat stress factors need to be adjusted according to the conditions of the study area. The design and methodological details of this study are shown in Fig. 2.

Data Preparation for the InVEST-Habitat Quality Model

Extraction of Land Use Type

All Landsat data were subjected to image pre-processing including radiometric calibration, atmospheric correction and geometric correction using ENVI software. Combined with field survey data and

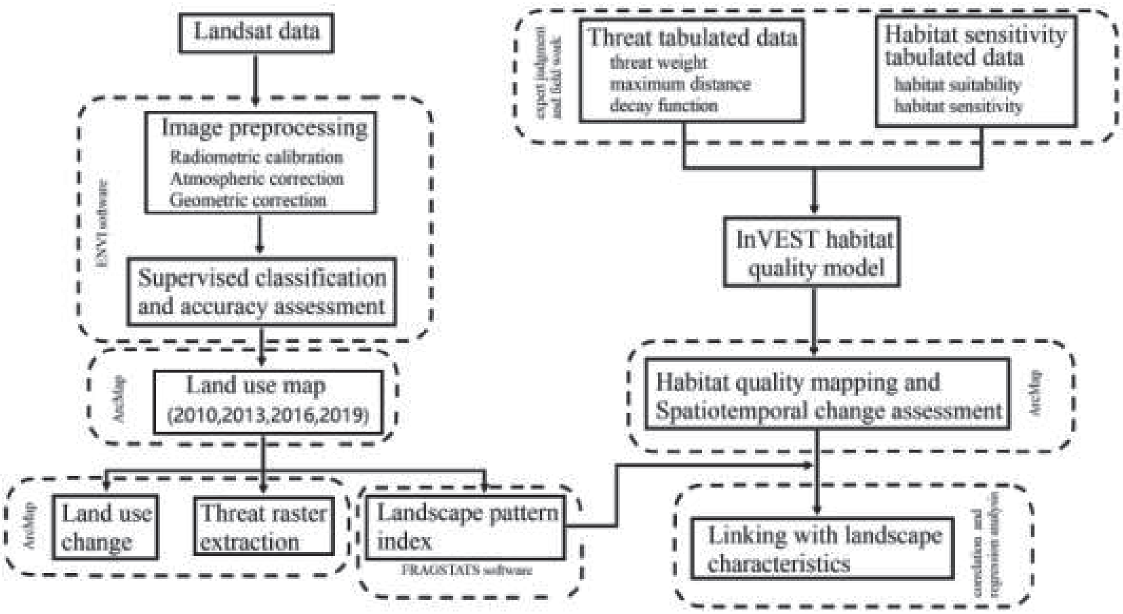

Fig. 2. Flowchart showing methodological steps followed in the study.

references such as Google Earth images, thematic maps and photos, Landsat images were classified into water, forest, grassland, farmland, construction land and bare land using the radial basis function of the Support Vector Machine (SVM) classifier with a gamma value of 0.021 and a penalty parameter of 100.

The spectral features of each land-use type were collected from Landsat images using a region of interest (ROI). Using 30% of the field survey samples, we examined and evaluated the classification precision. The classification results were also assessed based on the confusion matrix, overall accuracy, user accuracy, producer accuracy and Kappa coefficient [31]. Additionally, the land-use change transfer matrix was used to quantitatively analyze the conversion between different land-use types; this was calculated using Equation (5):

$$U_{ij} = \begin{Bmatrix} U_{11}U_{21}U_{31}...U_{1n} \\ U_{21}U_{22}U_{23}...U_{2n} \\ ... \\ U_{n1}U_{n2}U_{n3}...U_{nn} \end{Bmatrix} \tag{5}$$

Here, U_{ij} is the area of land-use type i that was transformed into land-use type j, n is the number of land-use types, i is the original land-use type and j is the land-use type after transformation.

Threat Source to Habitat Quality

The threat sensitivity of habitat types was set according to the general principles of biodiversity conservation in landscape ecology [32]. The natural environment is most sensitive to external threat factors, followed by the semi-artificial environment, while the artificial environment was almost unaffected. Based on previous research [25, 33], field observations and interviews with relevant experts, the semi-artificial environment and artificial environment were selected as habitat threat sources, which included farmland, bare land and construction land (Table 2). In the model, various land types were divided into natural and artificial environments. Combined with the ecological importance of various types, the range of ecological threat factor sensitivity was set from 0 to 1.

Calculation of Landscape Pattern Index

In this study, all landscape characteristic indexes were calculated based on the results of land-use classification using Fragstats 4.2 software. The characteristic indexes of the landscape pattern were then normalized (ranging from 0 to 1) and transformed into a unified scale. For metric landscape patterns, the characteristic indexes comprised the largest patch index (LPI), number of patches (NP), aggregation index (AI), mean patch area (MPS; the spatial arrangement of the habitat) and percentage of landscape (PLAND) [34-36] (Table 3).

Spatial Analyze Method

Based on land use and habitat quality, zonal statistics were used to analyze the changes in habitat sources. This helped assess the relationship between land-use changes and habitat quality evolution. Additionally, to analyze the spatio-temporal changes in habitat quality during 2010-2019 in the study area, map algebra was utilized for calculating the changes using habitat quality maps from the adjacent year.

Partial Least Squares Regression

Partial least squares regression was applied to assess the correlation between habitat quality and landscape metrics. Habitat quality was the dependent variable and landscape index was the independent variable. This approach is the extension of multiple linear regressions to investigate the relationship between the dependent variable and independent variables [37].

The partial least squares regression model was established using IBM SPSS software. The model performance was determined by the coefficient of determination (R^2) value an index of fitting accuracy and the cross-validated model quality index (Q^2). The variable influence on the projection (VIP) indicates

Table 2. The threats and sensitivity data were used for the habitat quality model.

Threats	Maximum distance (km)	Weight (0-1)	LULC considered as habitat			
			Water	Forest	Grassland	Farmland
			Habitat suitability			
			1	0.9	0.8	0.6
			Habitat sensitivity for threats			
Farmland	0.6	0.5	0.4	0.8	0.5	0
Construction land	3	0.6	0.5	0.5	0.6	0.7
Bare land	6	1	0.6	0.7	0.6	0.5

Table 3. The characteristic index and ecological meanings of the landscape pattern.

Name	formula	variable description	Ecological significance
Largest patch index (LPI)	$LPI = \frac{\max(a1, a2, ...an)}{A}$	a: the area of each patch, A: the total area of a certain landscape type	Reflect the dominant types of landscape
Number of patches (NP)	$NP = n$	n: the total number of landscape type ij patches	Represents the spatial pattern and heterogeneity of landscape
Aggregation index (AI)	$AI = \left[\frac{g_{ij}}{\max \to g_{ij}}\right] \times 100$	g_{ij} is number of similar adjacent patches of landscape type ij	Reflects the aggregation degree of patch types in the landscape.
Mean patch area (MPS)	$MPS = \frac{A}{n}$	A is the total area of landscape type n is the total number of patches	Represents the degree of fragmentation of landscape and the complexity of spatial structure
Percent of landscape (PLAND)	$PLAND = \frac{n_i}{A}$	n_i:the number of landscape type i patches A: the total area	

the importance of independent variables to the dependent variables in the projection. A large VIP value (VIP>1) indicates that there is significant relevance between a dependent variable and independent variable, a VIP value of >0.8 shows a significant correlation with the dependent variable and a VIP value of <0.5 indicates a weak correlation [38, 39].

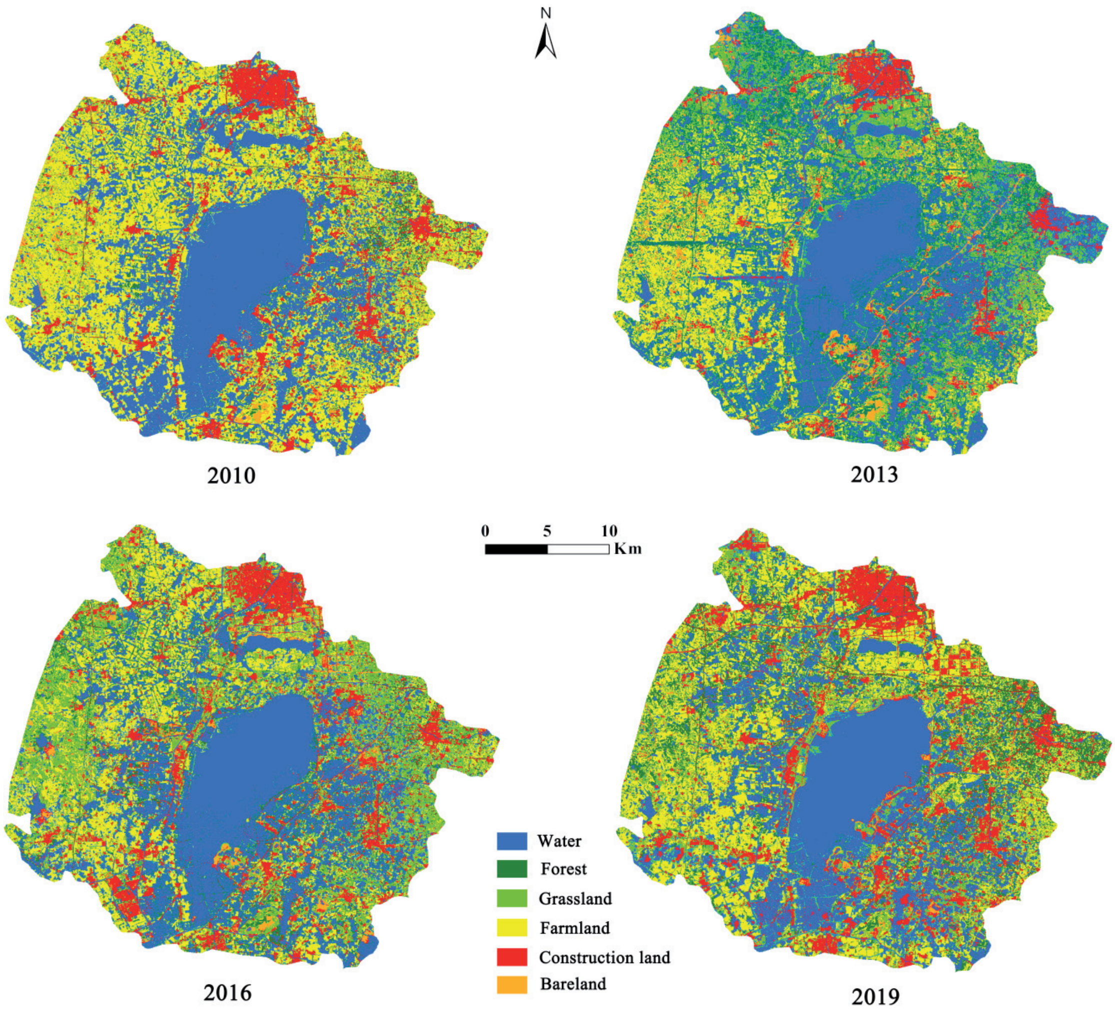

Fig. 3. Land-use type distribution in Changdang Lake National wetland from 2010 to 2019.

Results and Discussions

Land-Use Change

The classification results are shown in Fig. 3, including water, forest, grassland, farmland, construction land and bare land. The overall accuracy values and Kappa coefficients derived from the confusion matrix for 2010, 2013, 2016 and 2019 were 92.4% and 0.89, 93.2% and 0.91, 93.8% and 0.92, and 93.6% and 0.9, respectively.

Water was mainly distributed in the central parts and farmland was distributed in the west. Construction land and bare land were observed in the northern and southern parts, respectively, while the forest was distributed in the eastern parts. Grassland only occupied a small area and was scattered around construction land. The area of farmland, water and construction land decreased by 689.19 ha, 227.78 ha and 258.61 ha, respectively, between 2010 and 2019 (Table 4). The dominant artificial forest increased by 748.05 ha from 2010 to 2019, while grassland and bare land increased by 2359.3 ha and 18.15 ha, respectively.

Based on the land-use classification results, the LUCC was assessed among the different land-use types. The area and conversion of each type in 2010, 2013, 2016

Table 4. Area coverage and changes in each land use type from 2010 to 2019.

Type	Area(ha)				2010-22010-2019	
	2010	2013	2016	2019	Change (ha)	Annual change (ha yr^{-1})
Water	2866.05	2786.1	3045.66	2638.27	-227.78	-25.31
Forest	686.05	1436.2	1031.79	1431.1	682.05	75.78
Grassland	463.88	1136.8	1244.879	954.08	487.20	54.13
Farmland	2553.42	1256.6	1526.39	1855.22	-698.19	-77.58
Construction land	955.56	486.47	676.18	696.97	-258.61	-28.73
Bare land	243.95	666.59	236.54	259.10	15.15	1.68

Table 5. Land-use transfer matrix in Changdang Lake National wetland from 2010 to 2019.

Time	Land use	Water (ha)	Forest (ha)	Grassland (ha)	Farmland (ha)	Construction land (ha)	Bare land (ha)
2010-2013	Water (ha)	23117.85	93.21	51.96	809.10	1788.30	208.44
	Forest (ha)	730.26	5267.52	884.33	763.83	773.91	391.41
	Grassland (ha)	1117.79	883.08	7016.22	2287.98	417.24	603.54
	Farmland (ha)	330.66	403.29	571.77	11650.14	33.57	201.06
	Construction land (ha)	307.44	63.45	224.91	108.72	4299.48	74.79
	Bare land (ha)	416.16	240.39	136.41	791.82	294.63	985.41
2013-2016	Water (ha)	17638.56	104.60	47.74	1644.84	3170.70	416.97
	Forest (ha)	220.32	5126.40	131.42	1338.30	186.12	536.04
	Grassland (ha)	260.01	311.91	2676.87	440.49	278.10	211.86
	Farmland (ha)	330.57	332.95	670.75	5619.69	56.61	508.05
	Construction land (ha)	105.21	18.17	61.65	118.73	4034.88	2401.38
	Bare land (ha)	163.35	439.11	377.82	192.33	487.80	743.76
2016-2019	Water (ha)	18061.92	1355.40	78.94	207.09	2940.39	99.72
	Forest (ha)	454.32	11790.27	556.20	267.57	186.03	40.05
	Grassland (ha)	337.23	222.12	2657.61	954.63	159.12	195.57
	Farmland (ha)	792.13	6336.36	6235.92	11962.53	1614.69	619.02
	Construction land (ha)	2736.72	2302.38	1887.84	4221.18	9903.69	1284.21
	Bare land (ha)	162.32	83.67	48.19	75.94	47.16	338.04

and 2019 were extracted and calculated based on the classification results (Table 5). The results indicated that the most drastic change was the reduction in grassland. This was converted to water and farmland with areas of 1117.79 and 2287.98 ha from 2010 to 2013, respectively (Table 5). There was also a dramatic conversion from forest to other land types, with an area of 3543.74 ha converted to other types from 2010 to 2013. From 2013 to 2016, 2412.20 ha of forest was converted to other types, of which 1338.3 ha was converted into farmland. Additionally, about 2951.01 ha of water was transformed into other types. And, from 2016 to 2019, due to the conversion of farmland to natural vegetation, about 6336.36 ha of forest and 6235.92 ha of grassland were converted from farmland. Overall, from 2010 to 2019, the conversion of land use was mainly from water, forest and grassland into construction land, with conversion areas of 3879.03, 1815.86 and 542.03 ha, respectively. This expansion mainly occurred around cities and water and resulted in habitat destruction by occupying agricultural and ecological land for economic construction.

The land-use changes indicated that the water and construction land decreased, while forest and grassland increased from 2010 to 2019. Conversion to farmland (5193.00 ha) was the significant process, followed by forest expansion (by 3769.10 ha). Significant vegetation growth was observed in the eastern and western parts, while farmland decreased (by 698.19 ha) from 2010 to 2019 (Fig. 2). Construction land decreased by 258 ha from 2010 to 2019. The conversion of construction land to water, led by a landscape rebuilding program and the demolition of illegal tourist facilities, played a significant role in the land-use dynamics [40]. Above all, sustained land-use changes, especially to important natural- and semi-natural land-use types, indicate that the pressure of human activities is affecting the functionality of the landscape.

Landscape Pattern Analysis and Change

The landscape pattern indexes were calculated from 2010 to 2019 (Table 6). LPI increased from 15.88 to 16.28. This indicated that the landscape heterogeneity had increased to form a landscape spatial pattern in which various landscape elements coexisted. Landscape structural changes were measured by NP, AI and MPS, which increased from 5136 to 5841 ha, 62.15 to 64.19 ha and 27.88 ha to 28.93 ha at the landscape level, respectively. The increase in these indicators was ascribed to the progressive clustering of patches, leading to an increase in parcels of land. As a result, the overall heterogeneity of the landscape improved over time.

Furthermore, landscape structural changes were measured AI, LPI and MPS at the patch level. The AI and MPS values increased for water (by 13.6% and 60.2%, respectively), grassland (by 371.7% and

Table 6. Landscape index change at type levels in Changdang Lake National wetland from 2010 to 2019.

Time	2010					2013					2016					2019				
Type	LPI	NP	AI	MPS	PLAND	LPI	NP	AI	MPS	PLAND	LPI	NP	AI	MPS	PLAND	LPI	NP	AI	MPS	PLAND
Water	5.30	33690	54.92	21.98	22.80	4.55	28538	56.98	29.77	20.06	6.46	35272	61.56	36.27	20.99	5.60	24794	62.43	35.21	19.20
Forest	0.05	28541	17.41	8.18	5.68	0.20	30514	19.98	25.14	6.28	0.05	37259	35.11	9.30	7.83	0.34	24339	35.39	17.78	10.32
Farmland	1.94	10273	51.25	65.88	21.38	0.72	8283	42.50	24.40	9.20	0.36	14413	39.82	21.93	11.69	0.49	12532	44.33	28.82	13.28
Grassland	0.01	23338	6.16	6.48	3.72	0.14	24744	28.38	12.34	8.66	0.18	22782	31.13	15.47	9.67	0.05	27167	23.51	10.02	6.95
Construction land	1.06	9236	49.37	13.11	7.15	0.41	5974	40.36	13.56	3.54	0.78	15700	38.20	14.20	8.51	1.47	15174	41.81	15.74	9.54
Bareland	0.08	6601.00	27.79	7.34	1.72	0.08	13173	21.16	8.25	4.70	0.05	6309	20.71	7.48	1.73	0.02	4794	12.49	5.89	1.15

54.5%, respectively), forest (by 103.2% and 117.5%, respectively) and construction land (by 836.9% and19.9%, respectively). These results showed that the spatial distribution of water, grassland, forest and construction land patches tended to aggregate over time in response to the conversion of land-use patterns. In contrast, LPI decreased for farmland (by 74.8%) and bare land (by 60.1%). These decreasing trends indicated fragmentation of these land-use types.

Landscape structural changes showed that the AI and MPS values increased for forest (by 103.2% and 117.5%, respectively) and grassland (by 281.7% and 54.5%, respectively). Except for bare land, the increase in MPS was ascribed to the progressive clustering of patches, leading to an increase in parcels. As a result, the patches were amplified over time. On the other hand, the decrease in NP in water, forest and bare land were indicative of landscape fragmentation, which was accompanied by the increase in NP in grassland, farmland and construction land. The NP decreased for water, forest and bare land but increased for farmland, grassland and construction land. The total NP decreased by 28.7% from 2010 to 2019, which had similar implications to the increase in MPS; that is, the patches were progressively clustering. It appeared that forest, farmland and construction land patches expanded over time in response to socioeconomic development and the high demand for available resources. The increase in semi-natural habitat patches (grassland and farmland) indicated that the patch fragmentation was due to the high demand for farmland, settlement and plantations. Furthermore, the decrease in NP in forest and water revealed substantial habitat loss associated with human activities; these water and forest patches merged to form larger ones, as evidenced by the increase in and high values of MPS and AI.

The analysis of landscape metrics showed that LPI and MPS increased for all land-use types except for farmland and bare land. The peak value of LPI change was observed for water, and the patch LPI increased for all land-use types from 2010 to 2019, except for farmland and bare land. Because of the amalgamation of patches, the NP of water, forest and construction land decreased. Sustained human activities result in the increasing homogenization of a landscape [41]. The increase in AI for all land-use types indicated that adjoining landscape patches could coalesce and form large patches, particularly for natural and semi-natural habitats.

Habitat Quality Change

Habitat quality maps were produced using the InVEST habitat quality model, which combines data on land use and threats to biodiversity. The habitat quality in the study area was divided into three classes (low: 0-0.33, moderate: 0.33-0.67 and high: 0.67-1) using the equal interval breakpoint method (Table 7). The mean habitat quality values were 0.7, 0.78, 0.73 and

Table 7. Area and ratio of each habitat quality level and changes in Changdang Lake National wetland from 2010 to 2019.

Habitat Quality level	2010		2013		2016		2019		2010-2019	
	Area (ha)	Percentage (%)	Area (ha)	Percentage (%)	Area (ha)	Percentage (%)	Area (ha)	Percentage (%)	Area (ha)	Percentage (%)
Low	12723.39	13.90	13822.94	15.10	15266.16	16.68	14475.42	15.81	1752.03	1.91
Moderate	30650.67	33.48	15190.49	14.41	18294.31	19.98	18320.32	20.01	-12330.35	-13.47
High	48176.12	52.62	64536.75	70.49	57989.71	63.34	58754.44	64.18	10578.32	11.55
Mean	0.70		0.78		0.73		0.72			

0.72 from 2010 to 2019. The highest value was 1, which related predominantly to water and grassland.

The maps were generated using ArcGIS (Fig. 4). The grassland with high values was mainly distributed around the periphery. From the perspective of spatial patterns, the regions with high value were located in the middle and central south. The lowest value was 0, which is related to construction land and bare land. Moderate habitat quality is mainly related to farmland, and its area was reduced significantly by an area of 12330.35 ha from 2010 to 2019. Furthermore, the areas of low and high habitat quality increased by 1752.03 and 10578.32 ha from 2010 to 2019, respectively. These results showed that the major improvement was mainly due to the transformation of forest with moderate habitat quality to high habitat quality. High-quality habitat accounted for the largest proportion of habitat quality by area, at 52.62%, 70.49%, 63.34% and 64.18% of the whole region, while the area of moderate-quality habitat decreased from 33.48% to 20.01% from 2010 to 2019. The area of low-quality habitat increased only slightly from 13.9% to 15.81%, a change of only 1.91%. This indicated that, although most of the moderate-quality habitats areas transformed into high-quality habitat areas, some small areas still changed to become low quality.

The spatial distribution of habitat quality changes from 2010 to 2019 is shown in Fig. 5. From the temporal point of views, there was improvement at first and then deterioration. Less than 20% of the areas remained unchanged; these were mainly distributed in the central region, which was covered by water. From 2010 to 2013, the area of habitat quality deterioration surrounding the lake and town increased slightly. In contrast, due to the transformation of farmland into grassland and forest, there was a significant increase in the area of habitat quality improvement in the northern and eastern parts. The area of habitat quality deterioration

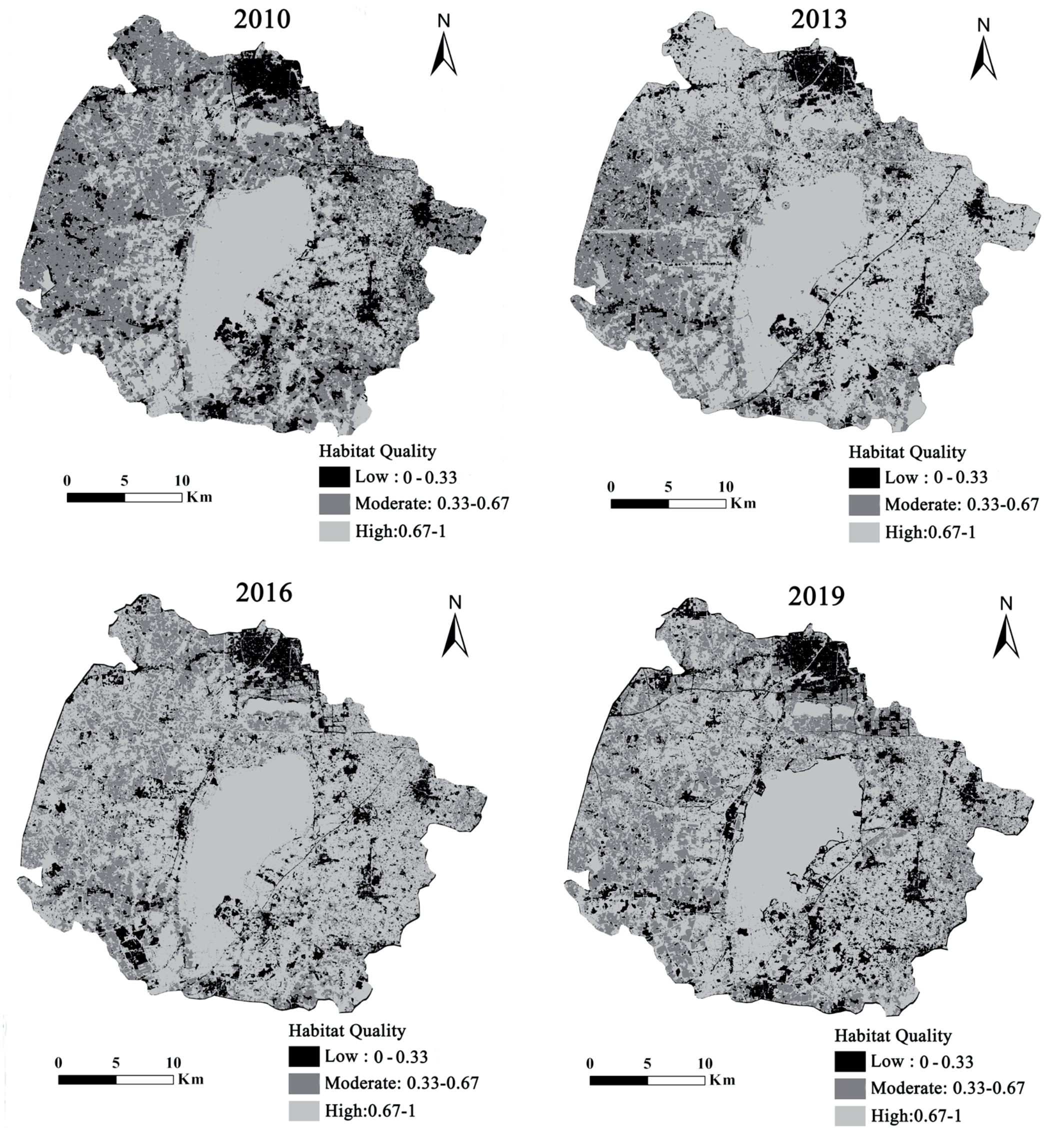

Fig. 4. Spatial distribution of habitat quality in the Changdang Lake National wetland from 2010 to 2019.

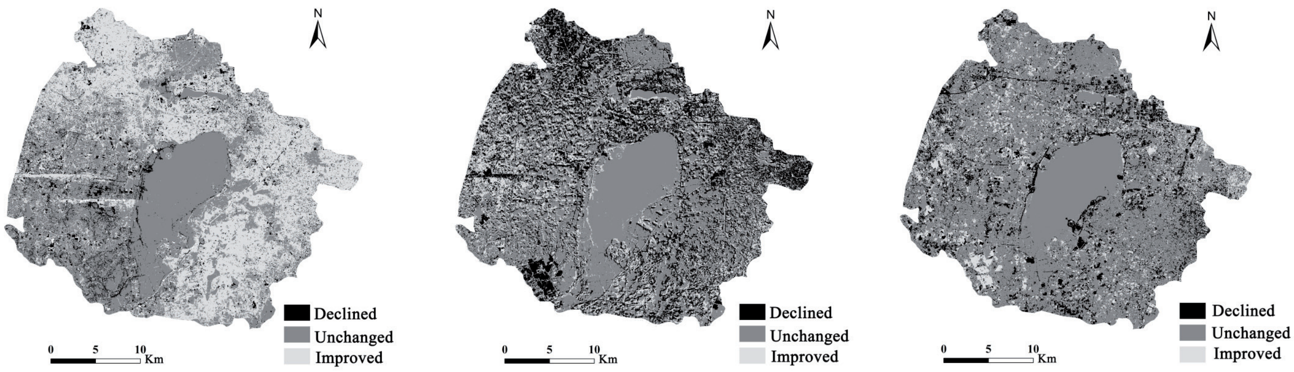

Fig. 5. Spatial distribution of habitat quality changes in Changdang lake National wetland from 2010 to 2019.

increased significantly near towns from 2013 to 2016, where the continuous expansion of construction land resulted in the clearance of large areas of forest and grassland. The areas with poor habitat quality gradually expanded to the periphery of the urban centre and the extent of the impact of ecological threat factors increased, leading to the most significant degree of habitat quality degradation. Compared with the change from 2013 to 2016, there was no significant change in the habitat degradation region which was mainly near the lake and construction land from 2016 to 2019. In the southwestern part, the habitat quality improved due to the conversion of farmland to forest.

The results revealed that the habitat quality changed rapidly and dramatically from 2010 to 2019. This was mainly due to human activity and the implementation of policies. The progressive expansion of human activities has led to over-exploitation of natural resources and environmental pollution, resulting in the loss of vegetation and habitat quality, and degradation of the pristine environment. Some studies have shown that the water quality of Changdang Lake has deteriorated due to various human activities, such as freshwater aquaculture, tourism development and wastewater discharge [42-44]. Ecosystem services and the ability of the landscape to support biodiversity decreased with the progressive pollution of the environment. In addition, road systems can be considered a threat source as they can represent anthropogenic disturbance and exploitation of the environment [45]. The habitat was degraded due to the development of access to infrastructure development, including roads, from 2010 to 2013. From 2013 to 2019, the habitat continuously improved with the restoration and reconstruction of the wetland ecosystem; for example, the area along the road was transformed into woodland and grassland in the eastern area of the wetland [46]. To protect the ecological environment, some policies were enacted in China to increase habitat sources; these include the Grain to Green program, Pastureland to Grassland program and Lake Rescue program [47]. The implementation of these policies in the Changdang Lake National wetland contributed significantly to alleviating the decline in habitat quality [40, 48].

From the spatial point of views, the central part had better habitat quality than the western and eastern parts. In the wetland, due to Changdang Lake connecting to the Taihu Lake Basin, the water cycle promoted biodiversity and environmental regulation in the watershed. However, the booming population, agricultural expansion and tourism development have threatened habitat quality [49] and led to a decline in habitat quality around the wetland. The areas with low habitat quality gradually aggregated and were mainly distributed in the north and east, where construction land and the river network are dense. These areas are mainly agricultural production areas and cities; accordingly, they have frequent human activity, large populations and low vegetation coverage. The habitat quality in the northern part did not improve from 2010 to 2019. This region is mainly construction land for highly populated residential areas. Due to population pressure, threats to habitat quality such as urbanization, pollution and agricultural expansion increased. Thus, the sources of these threats were more severe in the northern part of the wetland than in the southern part. Agricultural expansion, which particularly affected the western part, can decrease biodiversity; therefore, the habitat quality deteriorated in the western part compared to the eastern part.

Relationship Among Habitat Quality Evolution, Land Use and Landscape Metrics

Based on land use and habitat source types, zonal statistics were used to analyze the factors for habitat quality change (Table 8). The mean value of habitat quality in grassland ranged from 0.67 to 0.81 which is at a high habitat level as one of the main habitat sources and increased with the area. As similar to grassland, the mean habitat quality in forest areas ranged from 0.71 to 0.82 during 2010-2019. However, the mean value in the farmland area was located at the moderate habitat quality level (0.51-0.65).

The influence of each landscape structural variable on habitat quality was extracted from partial least squares regression (Table 9). For the habitat quality, the highest VIP value for PLAND of 1.38 was obtained

Table 8. Zonal statistics of habitat quality changes for habitat type levels in Changdang Lake National wetland from 2010 to 2019.

Habitat	Time	Area (ha)	Minimum value	Maximum value	Mean value
Grassland	2010	5333.22	0.77	0.79	0.78
	2013	12425.85	0.79	0.81	0.80
	2016	14348.79	0.62	0.84	0.81
	2019	4526.37	0.30	1.00	0.68
Farmland	2010	30650.67	0.52	0.60	0.65
	2013	13190.49	0.53	0.60	0.56
	2016	17345.16	0.58	0.66	0.62
	2019	8152.65	0.60	0.80	0.51
Forest	2010	8150.94	0.69	1.00	0.78
	2013	23342.04	0.68	0.92	0.82
	2016	11608.83	0.74	0.86	0.80
	2019	2458.71	0.70	0.76	0.71

for forest (R^2 = 0.89) while the AI of grassland had a VIP value of 1.31 (R^2 = 0.81). LPI had the highest VIP value of 1.16 and the VIP value of MPS for farmland was 0.77 (R^2 = 0.72). The VIP value of PLAND and NP for water was 1.09 and 1.19 respectively. The PLAND of construction land was 1.06 (R^2 = 0.63). These results indicated that some landscape metrics significantly contributed to the changes in habitat quality, including the high LPI and AI for grassland and forest, as well as the high PLAND for construction land.

In fact, changes to habitat accompany the transformation of land use, affecting the regional ecological environment. The relative impact of threats to habitat, the distance between the threat sources and the habitat, as well as sensitivities of specific habitats to any possible threats were considered using the InVEST model [20]. The increase in the area of high-quality habitat was greater than that of low-quality habitat, indicating that habitat quality improved from 2010 to 2019 (Table 6). This was due to increases in the area of habitat sources as a result of human intervention, such as the Grain to Green program, Pastureland to Grassland program and Lake Rescue program [47]. The low-quality habitats areas were concentrated in urban areas and along roads and became gradually connected in the degraded areas around construction land with the increasing density of roads. The increase in the area of low-quality habitat was due to the increase in anthropogenic land use, including farmland, construction land and bare land, which were considered threat sources. With the rapid development of urbanization, all kinds of anthropogenic land use have increased rapidly, greatly increasing the threat and their proximity to habitats. Additionally, due to the impact of human activities and the over-exploitation of natural resources, the area of low-quality habitats around the lake also increased.

The land-use changes were primarily attributed to anthropogenic activities and would inevitably affect landscape patterns and habitat quality. Based on the results of the partial least squares analysis, the VIP value indicated that the greatest contribution to habitat quality change was PLAND. The factors with low VIP values of close to 0 suggested slight or insignificant associations between habitat quality change and landscape patterns such as NP and AI

Table 9. PLSR variable importance and weights of the first component and regression coefficient for habitat quality model.

Land use type	Landscape metrics influence					Response variable	
	LPI	NP	AI	MPS	PLAND	R^2	Q^2
Water	0.67	1.19	0.52	0.9	1.03	0.8	0.81
Forest	0.9	1.05	0.79	0.93	1.38	0.89	0.75
Grassland	1.16	0.86	1.31	0.84	1.06	0.83	0.83
Farmland	0.98	0.51	0.79	0.77	1.18	0.72	0.81
Construction land	0.89	0.79	0.46	1.18	1.06	0.53	0.26
Bare land	0.69	0.11	0.31	0.36	1.14	0.81	0.76

(see Table 8). Frequent land-use changes lead to landscape fragmentation, such as when continuous forests and grasslands become occupied by farmland and construction land and are then artificially restored in a piecemeal fashion. Landscape fragmentation leads to the loss and fragmentation of habitats and in turn results in the reduction of biodiversity, landscape functions and various important services. In the study area, there were many small patches of fragmented landscape. As separate habitats, these are too small to satisfy the demands of individual species or populations. Due to the landscape fragmentation caused by land-use change, some species that cannot cross the non-habitat areas will be confined in the small patches, which will eventually reduce the biodiversity and species survival probability across the whole habitat. Additionally, landscape fragmentation caused by human activities leads to poor connectivity, which increases the possibility of individuals moving from habitat to non-habitat; this in turn increases the mortality probability of species that determine habitat quality, such as vegetation [25-28]. Furthermore, semi-habitat expansion cannot support the original habitat quality level, leading to the degradation of large areas of native vegetation and the fragmentation of habitat and landscape. Similar situations of habitat quality reduction have been reported in related studies [27, 49, 50].

Limitations of Assessment Habitat Quality Using InVEST Model

The InVEST habitat quality model is an important tool that assists landscape managers to protect biodiversity, but it is still limited for practical applications [30]. A land-use type data source with high precision is an important foundation for assessing the habitat quality of the model. However, there is not enough long-term quantitative data about habitat quality and its threat factors in practical applications. Furthermore, this type of habitat quality research generally depends on InVEST model dataset parameters and expert knowledge or opinions [51-53]. Thus, the model may be severely affected by the expert's judgment, which is one of its limitations and with the potential for future improvement. Using time-series data might result in some errors and uncertainty in habitat quality assessment and mapping. For example, the same spatial threat data for bare land, construction land and farmland were used for the reference years (2013, 2016, and 2019).

The deficiencies in the species distribution are another limitation of the InVEST model. Consequently, there is little information about the biotic environment, such as faunal, floral and insect biodiversity, etc., for the assessment results. Thus, using satellite images alone is inadequate; other data sources should be included in future research [54-58]. To overcome this shortcoming, the biodiversity component of the whole landscape can be predicted by combining the sample information with remote sensing technology based on a statistical model [59].

Conclusions

This study investigated the changes in habitat quality associated with land-use changes and landscape characteristics using the InVEST model between 2010 and 2019 in the Changdang Lake National Wetland of Changzhou, China. The main conclusions were as follows:

(1) The land use changed substantially, with an increase in forest and grassland and a decrease in farmland, water and construction land.

(2) The areas with low habitat quality aggregated gradually and were mainly distributed in the north and east where construction land and river networks were relatively dense. The areas with moderate habitat quality decreased significantly and were mainly distributed in farmland. The decrease in moderate habitat quality was mainly due to the transferral of farmland to forest, the latter being of high habitat quality.

(3) The drastic conversion of land use led to a decrease in landscape connectivity and an increase in landscape fragmentation. The PLAND had the greatest impact on changes in habitat quality, with changes in other landscape composition metrics (LPI and MPS) also associated with anthropogenic land cover in the wetland. The areas with high habitat quality values were primarily far from human activity centres and had abundant natural habitat resources such as vegetation and water. Land-use changes caused by anthropogenic activities such as urban area expansion, deforestation and farming practices adversely impacted habitat quality and disrupted the regional ecological balance and processes.

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Conflict of Interest

The authors declare no conflict of interest.

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