Pol. J. Environ. Stud. Vol. 33, No. 3 (2024), 2831-2846
DOI: 10.15244/pjoes/175304 ONLINE PUBLICATION DATE: 2024-02-23

Original Research

Landscape Ecological Risk Assessment of the Chaohu Lake Region Based on Dynamic Evolution of Landscape Patterns

Mimi Wang[1, 2]*, Zhenyong Niu[1], Zixun Zhong[1], Jiahao Li[3], Haiyang Liu[1]

[1]School of Architecture & Urban Planning, Anhui Jianzhu University, Hefei, PR China
[2]Anhui Provincial Institute of Land Spatial Planning and Ecology Research, Anhui Jianzhu University, Hefei, PR China
[3]School of Environment and Energy Engineering, Anhui Jianzhu University, Hefei, PR China

Received: 16 October 2023
Accepted: 15 November 2023

Abstract

In order to maintain the regional landscape ecological security, satellite remote sensing image data in 2011, 2016 and 2021 were utilized to analyze the landscape ecological risk in the Chaohu Lake Region. The ecological restoration project yielded initial results, as construction land area decreased in the later period. Waters emerged as the dominant land type, while grassland area increased over the 10-year period. Conversely, the area of cultivated land, forestland, and waters decreased, with the most significant decrease observed in cultivated land. The dynamic change in landscape patterns exhibited increasing complexity. Waters dominated the landscape, and the patch density (PD) and landscape shape index (LSI) of cultivated land, forestland, waters, and grassland tended to increase. The controlling role of dominant landscape types decreased, while landscape heterogeneity increased. The Shannon's diversity index (SHDI) and evenness index (SHEI) values increased, indicating diversification and equalization in the compositional structure of landscape types. The landscape division index (DIVISION) initially increased and then decreased, whereas the landscape aggregation degree showed an initial decrease followed by an increase. The contagion index (CONTAG) decreased continuously, indicating a decrease in the aggregation density of different land type patches. The highest-risk area increased, while higher-risk and medium-risk areas initially increased and then decreased. The lower-risk area exhibited less change, and the lowest-risk area showed a decreasing trend followed by an increasing trend. The spatial distribution pattern of the landscape ecological risk index displayed a "low on all sides and high in the middle" pattern. These research findings provide scientific references for optimizing land use structure, achieving sustainable landscape management, and maintaining regional ecological balance.

Keywords: land use, landscape pattern, landscape ecological risk assessment, Chaohu Lake Region

*e-mail: mmwang@ahjzu.edu.cn

Introduction

In recent decades, climate change and human activities have expanded globally, leading to increased environmental crises and challenges [1]. In response to these impacts on a larger scale, there is a clear trend to expand the scope of ecological risk assessment. However, as the scale increases, addressing compound risks and their spatial heterogeneity becomes more challenging. In this context, the concept of Landscape Ecological Risk Assessment (LERA) has emerged. LERA is based on landscape ecology theory and encompasses integrated information on natural and anthropogenic factors that contribute to land disturbance. It considers the heterogeneity of landscape elements, the regularity of landscape pattern evolution, and the response of the ecological environment to external risk sources [2]. Unlike regional ecological risk assessment, which focuses on the integrated assessment of multiple risks and quantification of overall ecological risk, LERA emphasizes the impact of landscape patterns on ecological environments and functions [3]. The study of ecological risk assessment gained momentum in the 1970s, with the United States being one of the early adopters of ecological risk research. As early as the 1990s, the U.S. Environmental Protection Agency proposed a framework for ecological risk assessment, outlining the fundamental concepts of ecological risk [4]. LERA, as a significant branch of ecological risk assessment, is primarily influenced by factors such as urbanization and agriculture. Since landscapes consist of various heterogeneous elements, their overall structure and dynamic processes change relatively slowly. However, when disturbances occur, the spatial components of the landscape can change at different rates and intensities [5].

Natural factors and human activities have increasingly influenced landscape patterns [6]. These high-intensity perturbations have altered the structure and function of regional landscape ecosystems, leading to ecological degradation phenomena and disaster events [7]. Consequently, LERA has emerged as a popular topics, drawing from the fields of geography, ecology, land science, and risk management science. Landscape ecology integrates the horizontal spatial heterogeneity of geography with the vertical correlation of ecology. Through the analysis of internal risk sources and external disturbances, LERA examines landscape mosaics, landscape pattern evolution, and landscape ecological processes [8, 9]. There are generally two approaches to LERA evaluation methods: the “source-to-sink” analysis method and the landscape pattern method [10-12]. The former follows the principle of “identifying risk sources and major stressors-analyzing risk receptors-establishing ecological endpoints-assessing exposure and hazards”. This approach is suitable for evaluating objects with clear regional ecological stressors [13]. The latter expands the risk receptor from a single ecological element to overall ecological indicators, considering changes in land use/cover as the causal factor for ecological risk changes. By analyzing the spatial structure and dynamic change patterns of land use/cover, it explores the changing patterns of ecological risk in the landscape [14]. LERA can be applied to various study areas such as towns, lakes, wetlands, habitats, mining areas, and mountains. Additionally, current research on LERA focuses on understanding its drivers, utilizing methods such as Boosted Regression Tree [15, 16], correlation analysis [17, 18], and geographically weighted regression [19, 20]. Landscape indexes are often used to measure landscape patterns on a regional scale and are an important component of constructing an LERA framework [21]. In recent years, the disorder and pressure on landscape patterns have increased, making watershed-scale LERA another focal point in understanding the “landscape pattern - ecological process” mechanism [22]. Therefore, in-depth research on the spatial and temporal evolution of land use and landscape patterns, as well as LERA based on landscape ecology theory, is strategically important for the ecological protection and sustainable development of the Chaohu Lake Region (CLR). It also contributes to the rational allocation and utilization of land resources [23, 24].

Chaohu Lake, one of the five largest freshwater lakes in China, is situated in the central part of Anhui Province, adjacent to Hefei City. It serves as a crucial ecosystem providing various ecological services to the region, including climate regulation, flood control and water storage, biological habitat, and tourism. However, the rapid socio-economic development and substantial population increase in the CLR have led to detrimental human activities such as deforestation, farmland reclamation, and unregulated urban expansion. These activities have caused significant damage to the landscape and ecology of the CLR due to a lack of awareness regarding environmental protection [25]. Therefore, protecting, restoring, and promoting sustainable development of terrestrial ecosystems, biodiversity, and sustainable forest management have become imperative measures for achieving regional sustainable development during the urbanization process. The application of geospatial technology in LERA can enhance our understanding of the spatial and temporal distribution of landscape ecological risk dynamics in the CLR. Geographic information science (GIS), remote sensing (RS), and landscape ecology have been widely employed in analyzing spatial and temporal changes in ecological risks [26]. Satellite imagery-derived land use data provides detailed spatial information [27], GIS can analyze and visualize land use and ecological features using various spatial techniques, and landscape ecology theories and methods can quantitatively describe land use change patterns and the relationship between land use structure and ecological processes [28]. For example, Zang et al. [29] employed RS data to empirically analyze the spatial and temporal patterns of landscape types, ecological vulnerability, and changes in ecosystem services in Yancheng Nature Reserve from 1987 to 2013. Scientific analysis of dynamic landscape pattern changes and assessment of landscape ecological risks serve as effective foundations for regional ecological protection and construction. They are also current research hotspots in ecological restoration and biodiversity conservation in the CLR [30-32]. Previous studies have revealed the following findings: (1) From 1995 to 2013, significant land use changes occurred around Chaohu Lake, with shrinking watershed and cultivated land areas, increased patch density, and fragmented landscapes [33]. (2) Using Landsat TM/ETM RS images from 1989 to 2009, it was observed that construction land in the CLR increased by 38,380 hm^2, cultivated land decreased by 34,230 hm^2, and the water body area remained relatively stable [34]. Evergreen forestland increased by 40,350 hm^2, deciduous forestland decreased by 6,760 hm^2, and the expansion of urban construction land primarily resulted from the conversion of cultivated and other land types [35]. In recent years, with growing concerns about the ecological and environmental issues in the CLR, the government had introduced a series of relevant policies to protect the region's ecological environment. After sustained protection and management efforts, significant milestones had been achieved in the integrated ecological management around CLR [36]. Additionally, the rapid development of RS technology had greatly improved the automation and intelligence level of accurate and fast processing of high-resolution multi-source RS satellite imagery. It had addressed theoretical and technical challenges related to simultaneous detection of target geometric position, physical attributes, semantic information, and temporal changes, meeting the demand for accurate and efficient intelligent processing of multi-source RS imagery in the era of big data and intelligent surveying and mapping [37].

To assess the current ecological condition of the CLR, we formulated a hypothesis that there exists significant spatial and temporal heterogeneity of landscape ecological risk in the CLR due to human activities and associated environmental changes. To test this hypothesis, we utilized RS techniques to develop a LERA model covering the period from 2011 to 2021. Subsequently, we calculated the landscape ecological risk index to analyze the changes in landscape risk around the CLR over the past decade, considering both spatial and temporal factors. Based on our findings, we propose targeted recommendations and identify key areas for future risk management. These recommendations aim to optimize land use practices and promote sustainable landscape management in the CLR. Such measures are crucial for maintaining regional ecological balance, safeguarding ecological security, establishing an ecological security pattern, addressing global climate change, and providing scientific references to support the construction of an ecological civilization.

Experimental and Methods

Study Area

The study area under investigation was situated in the southern region of the Jianghuai Hills, located in central Anhui Province. It covered a total area of 2650.5 km^2, ranging from 31°17′57″ to 31°51′53″ N and from 117°03′53″ to 117°57′09″ E (Fig. 1). The study area was surrounded by neighboring regions, including Xiage Town to the north, Huailin Town to the south, Yinping Town to the east, and Shangpai Town to the west. The central region of the study area was primarily occupied by Chaohu Lake, which stretches approximately 61.7 km from east to west and 20.8 km from north to south. The water surface area of the lake covered about 780 km^2 and spans multiple administrative regions, including Chaohu City, Baohe District of Hefei City, Lujiang County, Feixi County, and Feidong County. To the west, the lake was bounded by the Xiapai River, while the eastern boundary extended towards the main urban area of Chaohu City. The northern boundary of the lake was adjacent to the Tangxi-Changlin River-Zhongmiao-Huatang-Hekou Zhang line, and the southern boundary was demarcated by the Sanbing-Huailin-Miaozuizi line.

Data Resources and Preprocessing

To obtain the necessary data for this study, Landsat satellite images from 2011, 2016, and June and August of 2021 were acquired through the USGS Earth Explorer website (https://earthexplorer.usgs.gov/). Landsat 8 images were used for 2016 and 2021, while Landsat 7 images were used for 2011 due to the unavailability of Landsat 8 data that year [38]. The acquired images underwent radiometric and atmospheric corrections, as well as geometric correction using ENVI software, to obtain standardized images. The multispectral and panchromatic images of 2016 and 2021 were fused to produce images with a resolution of 10 m, ensuring the accuracy of land use classification. To incorporate 14 spectral data information, images from different months of the same year were merged and imported into eCognition software. The decision tree method [39] was employed for classifying land use types [40, 41]. The resulting land use classification map was then imported into Fragstats software to calculate landscape pattern indices. The changes in landscape patterns in the CLR over the past decade were analyzed using Fragstats [42].

Classification Method

Cultivated land in the CLR was primarily used for growing rice, wheat, cotton, rapeseed, and peanuts. By analyzing image data from multiple months within a year, it was observed that there was a consistent pattern of summer harvesting behavior by farmers between early June and early August each year.

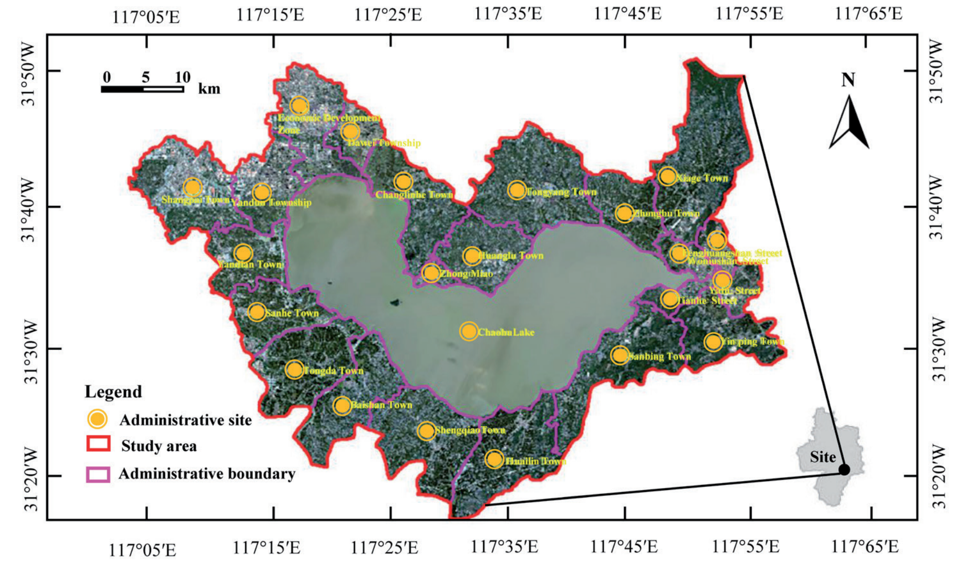

Fig. 1. Location map of Chaohu Lake Region.

This behavior led to significant changes in the spectral data reflected by the land. Based on this characteristic, the multi-scale segmentation algorithm [43] in eCognition 9.0 software was utilized for segmentation. After conducting multiple tests (Fig. 2), the image was segmented using a scale of 60, a shape factor parameter of 0.4, and a compactness parameter of 0.5 to achieve more accurate parcel segmentation. This segmentation process effectively distinguished rivers, reservoirs, and other small water bodies [44]. To classify the land in the study area around CLR, a decision tree rule was established based on spectral variability [45] (Fig. 3). The land was categorized into five classes: waters, cultivated land, forestland, grassland, and construction land [46]. Additionally, field surveys were conducted, and photographs were taken to compare the classified land with historical land imagery available at https://livingatlas.arcgis.com/wayback/ in order to manually correct misclassifications. For example, instances where building shadows were wrongly classified as water bodies were manually corrected to improve the overall accuracy of the classification [47].

Calculation of Landscape Ecological Risk Index

Landscape pattern indices are quantitative indicators that capture specific aspects of structural composition and spatial configuration by condensing landscape pattern information. These indices include commonly used metrics such as the number of patches, density, landscape shape index, landscape division index, Shannon's diversity index, and others (Table 1).

The resilience of the ecosystem to external environmental factors determines the level of ecological risk, and changes in the landscape pattern were a specific manifestation of the ecosystem [48, 49]. Landscape disturbance degree index (S_i), the landscape loss degree index (R_i) and the landscape ecological risk index (ERI_k) were calculated as follows:

$$S_i = aC_i + bN_i + cD_i \tag{1}$$

Where S_i was the disturbance index of the i-th landscape type. The weights assigned to each landscape

June 5, 2021 August 7, 2021

Fig. 2. Images of spectral data changes in cultivated land.

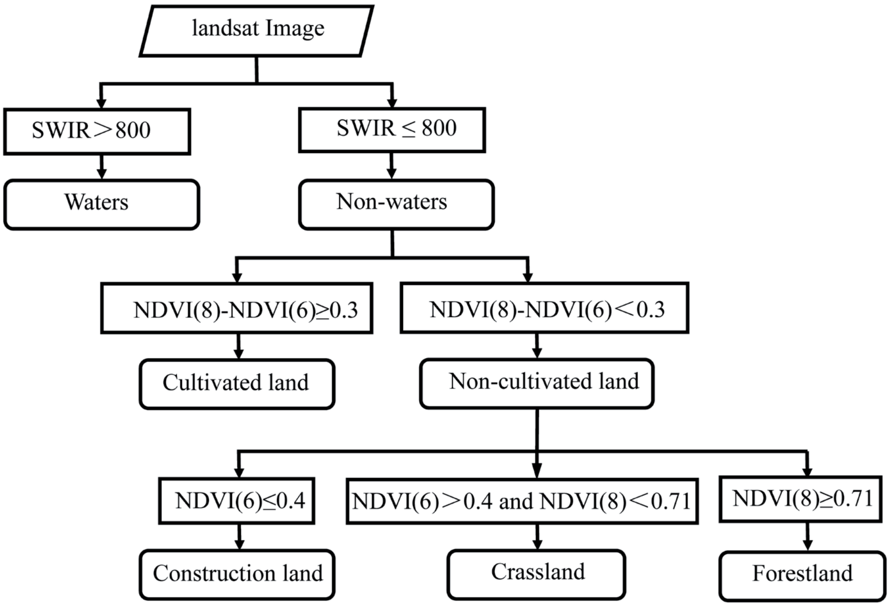

Fig. 3. Decision trees-Land use type classification.

index are a + b + c = 1, where they were assigned values of 0.5, 0.3, and 0.2, respectively [50].

$$R_i = S_i \times V_i \tag{2}$$

Where landscape vulnerability index (V_i) was obtained through expert consultation and normalization. The vulnerability of different landscape types was assigned with values as follows: forestland = 1, grassland = 2, waters = 3, construction land = 4, and cultivated land = 5 [51]. The normalization of these values resulted in the V_i for each type.

$$ERI_k = \sum_{i=1}^{N} \frac{A_{ki}}{A_k} \times R_i \tag{3}$$

Where ERI_k was the landscape ecological risk index of the *k*-th evaluation unit, and its value reflects the degree of ecological risk of the unit. A_{ki} was the area of the *i*-th landscape type in the *k*-th evaluation unit, A_k was the area of the *k*-th evaluation unit.

The construction of a landscape ecological risk index aimed to assess the level of external disturbance and restoration capacity of regional ecosystems [52]. Using the geostatistical analysis module in ArcGIS 10.8, the study area was divided into 3 km×3 km square grid cells. The ecological risk value at the center of each evaluation cell was taken as the evaluation value for that cell, and the landscape ecological risk index was calculated for each evaluation grid cell. The spherical model was employed to fit the semivariogram function [53]. Subsequently, the Kriging interpolation method [54] was then utilized to spatially interpolate the landscape ecological risk index of each evaluation unit, resulting in a spatial distribution map of landscape ecological risk. To depict the characteristics of landscape ecological risk distribution clearly, the landscape ecological risk evaluation values were divided into five risk levels using the natural breakpoint method [55]. These risk levels were categorized as follows: lowest risk (ERI<0.021), lower risk (0.021≤ERI≤0.041), medium risk (0.041≤ERI≤0.068), higher risk (0.068≤ERI≤0.097), and highest risk (ERI>0.097). The areas corresponding to each level of the ecological risk index were calculated, and the resulting information was used to complete the visualization of the spatial distribution map of landscape ecological risk. Subsequently, the "networkD3" package in R software was used to generate an interactive Sankey diagram visualizing the landscape ecological risk levels [56].

Results and Discussion

Land Use Changes

From 2011 to 2021, significant changes occurred in the distribution and area of land use types in the CLR. The dominant land type shifted from cultivated land to waters, with waters accounting for 32.33% of the total area, which was 21.96% higher than the smallest proportion occupied by grassland (Fig. 4, Table 2). Between 2011 and 2016, the land use types showed a trend of "two increases and three decreases", grassland and construction land areas increased by 89.22 km² and 230.65 km², respectively, while cultivated land, forestland, and waters areas decreased by 213.71 km², 89.66 km², and 16.37 km². The significant increase in grassland was directly linked to the illegal construction of the "Anshang grassland" project in Binhu New District, Hefei City, in 2014. This project led to an increase of 89.22 km² in grassland area between 2011 and 2016. In 2015, Chaohu Lake water bloom reached a peak area, and in order to address water pollution in the lake, a large number of residents in the surrounding areas relocated, resulting in a decrease of 213.71 km² in cultivated land area. Between 2016 and 2021, the land types in the CLR exhibited a trend of "three increases and two decreases". Forestland, waters, and grassland areas increased by 76.01 km², 14.43 km², and 104.51 km²,

Table 1. Calculation of landscape pattern indices.

Landscape Pattern Index	Computational Method	Ecological Meaning
The number of patches (*NP*)	$NP = \Sigma(Pi)$	***NP*** denotes the spatial pattern of the landscape and describe the heterogeneity of the entire landscape. ***Pi*** is the number of patches of the i-th category, and Σ(Pi) is the sum of the number of patches across all categories.
Patch density (*PD*) (*NP*/100ha)	$PD = NP/A$	***PD*** denotes the degree of landscape fragmentation and differences in patch spatial distribution. ***NP*** is the number of patches, and ***A*** is the total area of the study area.
Largest patch index (*LPI*) (%)	$LPI = \frac{Max(Pi)}{A} \times 100\%$	reflects the dominance of the landscap by indicating the proportion of the landscape occupied by the largest patch. ***Max(Pi)*** is the maximum patch area among all classes, and ***A*** is the total area of the study area.
Landscape shape index (*LSI*)	$LSI = \frac{0.25E}{\sqrt{A}}$	***LSI*** reflects the overall complexity of the landscape. ***E*** is the sum of the perimeters of all the patches, and ***A*** is the total area of the study area.
Percentage of Landscape (*PLAND*) (%)	$PLAND = \frac{\sum_{j=1}^{n} \alpha_{ij}}{A} \times 100\%$	***PLAND*** denotes one of the bases for determining the dominant landscape elements in the landscape. is the area of Patch ***ij***, ***A*** represents the total area of the study area.
Landscape division index (*DIVISION*)	$DIVISION = \left[1 - \sum_{j=1}^{n} \frac{\alpha_j}{A}\right]$	***DIVISION*** reflects the severity of landscape fragmentation, with higher values indicating a greater degree of fragmentation and a more complex overall landscape pattern due to smaller patch sizes. ***n*** is the number of patch categories, is the proportion of the area of the j-th patch to the total area of the study area, and ***A*** is the total area of the study area.
Shannon's diversity index (*SHDI*)	$SHDI = -\sum_{I=1}^{m} (P_i \times ln\, P_i)$	***SHDI*** measures the diversity of the landscape by reflecting changes in the proportion of different patch types, with higher values indicating greater patch diversity. is the proportion of the area of the i-th patch to the total area of the study area, and ***ln*** is the natural logarithm function.
Shannon's evenness index (*SHEI*)	$SHDI = SHDI\ /\ ln(S)$	***SHEI*** is used to measure the evenness of the distribution of different species in the entire landscape. ***S*** represents the number of different species, and ***ln*** is the natural logarithm function.
Contagion index (*CONTAG*) (%)	$CONTAG = 1 + \frac{\sum_{i=1}^{m}\sum_{k=1}^{m}\left[(P_i)(\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}})\, ln(P_i)(\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}})\right]}{2\, ln(m)} \times 100$	***CONTAG*** represents the degree of aggregation and contagion tendency between different patches in the landscape. ***m*** is the total number of patch types, is the number of adjacent patches between patch type ***i*** and patch type ***k***, and ***Pi*** is the proportion of patch type ***i*** in the total landscape area.
Landscape fragmentation index (C_i)	$C_i = \frac{n_i}{A_i}$	represents the process of landscape types transitioning from a single continuous entity towards complex and discontinuous patches. is the number of patches of the i-th landscape type, and is the area of the i-th landscape type.
Landscape isolation index (N_i)	$N_i = l_i \times \frac{A}{A_i}$ $l_i = \frac{1}{2}\sqrt{\frac{n}{A}}$	$\boldsymbol{N_i}$ reflects the degree of separation between different patches within a landscape. $\boldsymbol{l_i}$ is the distance index of the i-th landscape type, $\boldsymbol{A_i}$ is the area of the i-th patch, and ***A*** is the total area of the landscape.
Landscape fractal dimension index (D_i)	$D_i = \frac{2ln\,(\frac{P_i}{4})}{lnA_i}$	$\boldsymbol{D_i}$ represents the complexity and variability of landscape spatial structure. $\boldsymbol{P_i}$ is the perimeter of the i-th patch, and $\boldsymbol{A_i}$ is the area of the i-th patch.

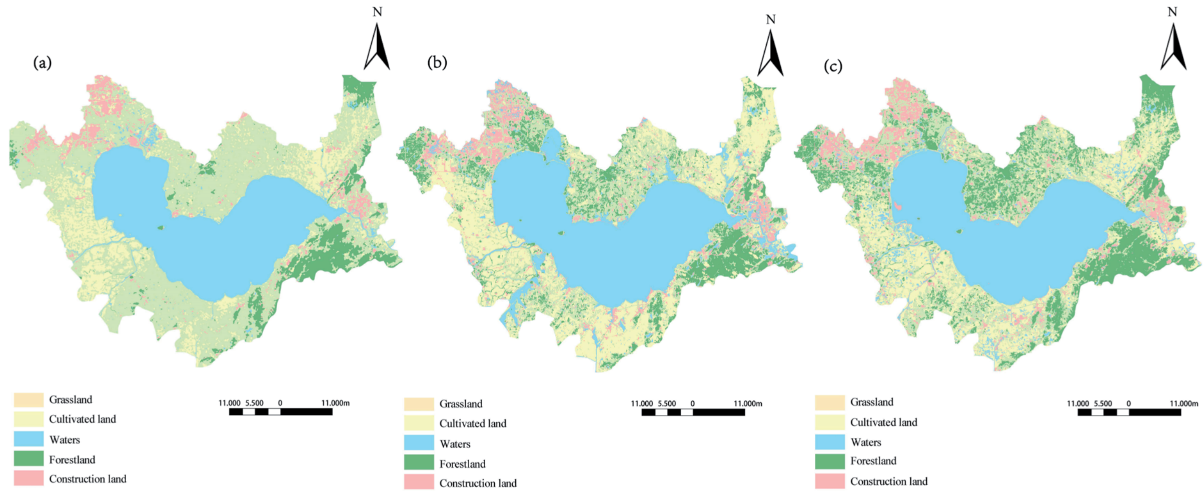

Fig. 4. Spatial distribution of landscape types in Chaohu Lake Region during 2011-2021. a) Land use types around Chaohu Lake in 2011, b) Land use types around Chaohu Lake in 2016, c) Land use types around Chaohu Lake in 2021.

respectively, while cultivated land and construction land decreased by 174.65 km² and 20.09 km², respectively. The spatiotemporal dynamic evolution of land use types was closely linked to the protection and governance policies implemented by the local government for Chaohu Lake. In 2019, the General Office of Anhui Province issued the "Chaohu Lake Comprehensive Governance Tackling Implementation Program", aiming to enhance the comprehensive governance of Chaohu Lake and expedite the dynamic changes in land types [57]. This program encompassed a range of initiatives, including water pollution control, ecological restoration, and land use optimization. It significantly impacted land use patterns, with stricter regulations reducing construction land and efforts towards ecological restoration increasing forestland and grassland. This program played a pivotal role in improving the ecological integrity and sustainability of the CLR.

From 2011 to 2021, the area of land use types around Chaohu Lake underwent dynamic changes, indicating positive growth in construction land and grassland, while cultivated land, forestland, and waters exhibited a decreasing trend (Table 2). Specifically, the area of construction land increased by 210.56 km², with a change rate of 7.93%, reflecting the rapid urbanization and population density increase in Hefei. The most significant decrease was observed in cultivated land, with an area reduction of 388.36 km² and a change rate of -5.64%, indicating encroachment on cultivated land due to urban expansion (Table 3). Between 2016 and 2021, a negative growth in construction land was observed, suggesting a slowdown in the urbanization process of Hefei. This indicates more efficient allocation of land and spatial resources, reflecting the city's high-quality development. Forestland and waters showed a decreasing trend from 2011 to 2016, with change rates of -3.39% and -0.60%, respectively. However, between 2016 and 2021, both land use types exhibited an increasing trend, with change rates of 2.76% and 0.53%, respectively. Overall, the area of these two land use types slightly decreased during the 10-year period, with decreases of 13.65 km² and 1.94 km² and change rates of -0.63% and -0.07%, respectively. The trend of land use change reflected the increasing value placed on advantageous ecological resources such as forestland and waters during urban development.

Table 2. Area of different landscape types in the Chaohu Lake region during three periods.

Landscape type	2011		2016		2021	
	Area (km²)	Proportion (%)	Area (km²)	Proportion (%)	Area (km²)	Proportion (%)
Cultivated land	1090.26	41.12	876.55	33.08	701.90	26.48
Forestland	389.77	14.71	300.11	11.32	376.12	14.18
Waters	859.06	32.40	842.69	31.80	857.12	32.33
Grassland	80.80	3.06	170.02	6.41	274.53	10.37
Construction land	230.56	8.71	461.21	17.39	441.12	16.64

Table 3. Rate of change in area of various landscape types in the Chaohu Lake region, 2011-2021.

Landscape type	Change rate (%)		
	2011-2016	2016-2021	2011-2021
Cultivated land	-8.04	-7.60	-15.64
Forestland	-3.39	2.76	-0.63
waters	-0.60	0.53	-0.07
Grassland	3.35	3.96	7.31
Construction land	8.68	-0.75	7.93

Table 4. Landscape type transfer matrix in Chaohu Lake Region from 2011 to 2016.

Landscape type		2016					
		Grassland (km²)	Cultivated Land (km²)	Construction Land (km²)	Forestland (km²)	Waters (km²)	Total (km²)
2011	Grassland	18.86	18.28	24.27	17.07	2.22	80.7
	Cultivated land	70.12	710.11	206.09	72.47	31.46	1090.25
	Construction land	22.70	34.84	153.64	13.09	6.08	230.35
	Forestland	48.92	87.45	56.68	189.76	6.28	389.10
	Waters	9.18	25.76	20.14	7.31	796.47	858.87
	Total	169.78	876.44	460.82	299.71	842.51	2649.26

The change detection function of the ENVI software was utilized to generate land use type transfer matrices for the periods 2011-2016 and 2016-2021. The results revealed notable changes in land types during these periods, particularly in construction land and cultivated land. Construction land primarily underwent transformations from cultivated land and forestland, with areas of transformation measuring 206.09 km² and 56.68 km², respectively (Table 4, Fig. 5). Additionally, 72.47 km² of cultivated land was converted into forestland, while 70.12 km² was transformed into grassland, with the remaining area largely transitioning into construction land. This 5-year period witnessed urbanization projects encroaching upon forestland,

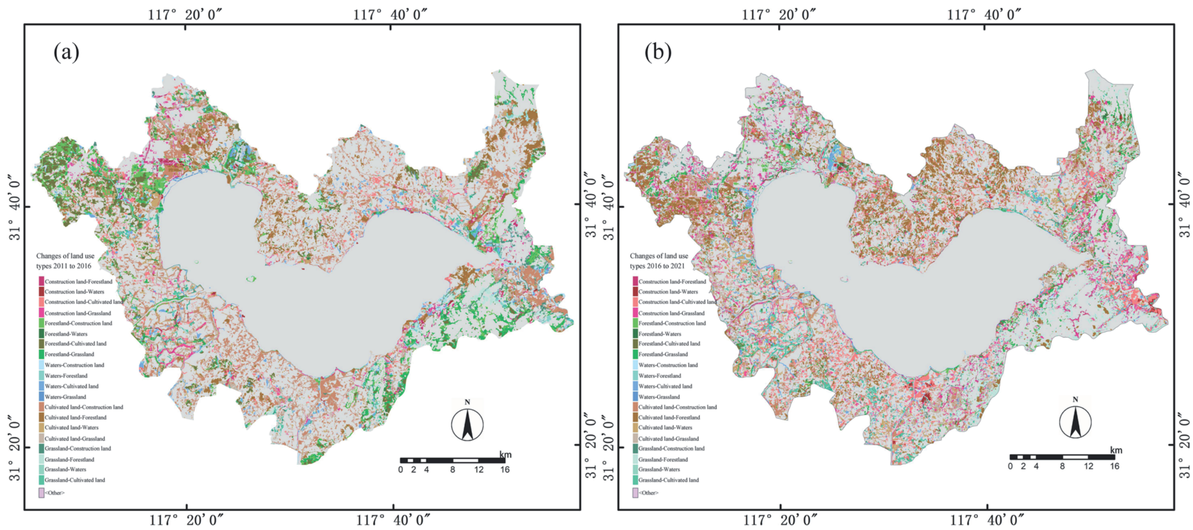

Fig. 5. Dynamic changes of different land use types in the Chaohu Lake Region from 2011 to 2021. a) Changes of land use types from 2011 to 2016, b) Changes of land use types from 2016 to 2021.

Table 5. Landscape type transfer matrix in Chaohu Lake Region from 2016 to 2021.

Landscape type		2021					
		Grassland (km²)	Cultivated land (km²)	Construction land (km²)	Forestland (km²)	Waters (km²)	Total (km²)
2016	Grassland	55.42	41.77	23.90	43.66	5.30	170.05
	Cultivated land	108.98	497.52	86.76	143.64	40.22	877.12
	Construction land	72.03	116.83	242.33	17.17	12.82	461.18
	Forestland	29.36	21.37	77.25	254.47	2.88	385.33
	Waters	8.75	24.42	10.86	3.05	795.57	842.65
	Total	274.54	701.91	441.1	461.99	856.79	2736.33

cultivated land, grassland, and waters, resulting in significant conversions of grassland and cultivated land, and to a lesser extent, forestland and waters, into construction land. Between 2016 and 2021, the key changes in land types were observed in cultivated land and grassland. Cultivated land experienced a decrease in area, primarily transforming into forestland and grassland, with conversion areas measuring 143.64 km² and 108.98 km², respectively (Table 5, Fig. 5). The cultivated land area continued to decline throughout this 10-year period, while the area of constructed land initially increased and then decreased, resulting in an overall net increase in total area, mainly transforming into cultivated land and grassland, with transformation areas of 116.83 km² and 72.03 km², respectively. The ecological restoration efforts around CLR involved targeted initiatives, including reforestation, wetland restoration, and soil erosion control, and more. Significantly, there was a notable increase in the area of grassland, indicating the initial success of ecological restoration efforts around CLR.

The results of our study revealed significant changes in the distribution and area of land use types in the CLR from 2011 to 2021. These changes reflected the dynamic nature of land use patterns and the impact of various factors such as urban expansion, ecological restoration efforts, and governance policies [58]. From 2011 to 2021, the ecological restoration project in the CLR had yielded initial results, leading to effective allocation of land and spatial resources. However, from 2011 to 2016, human activities, including urban expansion and the continuous increase in construction land, posed ecological risks to the surrounding area [59, 60]. The area of construction land exhibited positive growth throughout the study period, reflecting rapid urbanization and population density increase in Hefei. However, between 2016 and 2021, construction land experienced negative growth, indicating a slowdown in the urbanization process and more efficient allocation of land resources [61]. This shift highlighted the growing emphasis on recognizing and conserving dominant ecological resources such as forestland and waters [62, 63].

The changes in forestland and waters exhibited a mixed pattern. From 2011 to 2016, both land use types showed a decreasing trend, but between 2016 and 2021, they exhibited an increasing trend. Overall, the area of forestland and waters slightly decreased during the 10-year period, indicating the challenges posed by urban development [64]. Nonetheless, the increasing trend in recent years suggests a growing recognition of the value of ecological resources and the success of ecological restoration efforts [65]. The significant increase in grassland area and the success of ecological restoration efforts around the CLR indicated the positive outcomes of constructing an ecological civilization. These findings highlighted the importance of continued ecological restoration and sustainable land use practices in promoting the conservation of valuable ecological resources [66]. The land use change analysis revealed notable transformations between different land use types, particularly in construction land and cultivated land. Construction land primarily converted from cultivated land and forestland, while cultivated land transformed into forestland and grassland. These changes reflect the encroachment of urbanization projects on various land types and the need for effective land management strategies [67].

Changes in Landscape Patterns

From 2011 to 2021, the PD values of cultivated land, forestland, waters, and grassland exhibited a gradual increasing trend, indicating an increasing degree of fragmentation and a more complex landscape pattern for these land types (Fig. 6, Table 6). Notably, grassland had the highest PD value of 1.14. The PD value of construction land displayed an increasing and then decreasing trend, implying that the fragmentation of construction land in the CLR initially increased from 2011 to 2016 before gradually declining. Throughout the study period, waters consistently maintained the maximum LPI values, with the highest value recorded as 29.80. Between 2011 and 2016, cultivated land dominated the landscape types but exhibited a decreasing trend in terms of the proportion of the landscape (PLAND).

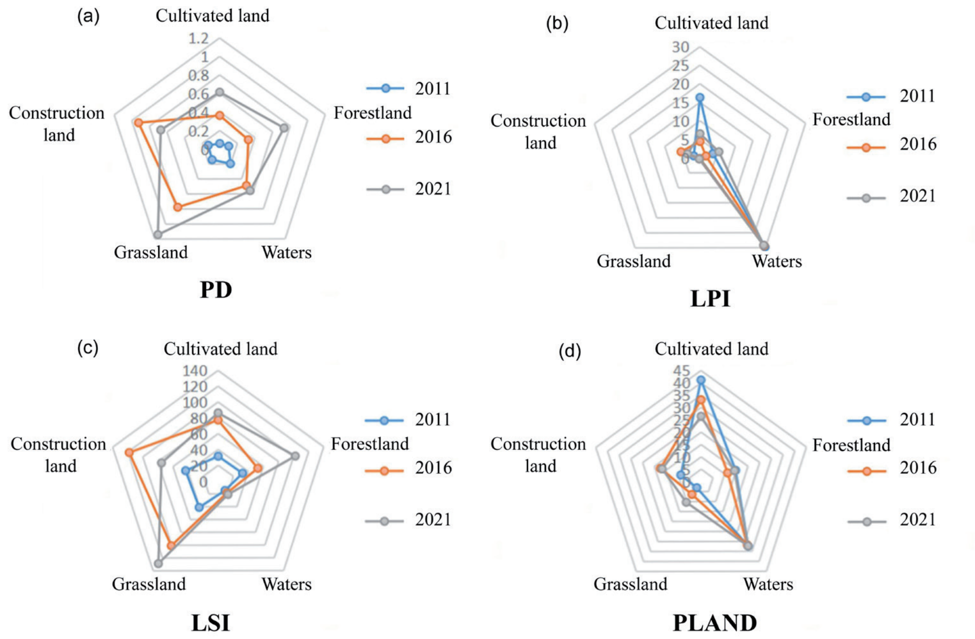

Fig. 6. Changes in landscape pattern indexes of different land use types. a) Patch density (PD), b) Largest patch index (LPI), c) Landscape shape index (LSI), d) Percentage of Landscape (PLAND).

Table 6. The landscape pattern index of the Chaohu Lake Region from 2011 to 2021.

Years	NP	DIVISION	SHDI	SHEI	CONTAG (%)
2011	1668.00	0.87	1.33	0.83	57.59
2016	7622.00	0.90	1.46	0.91	52.50
2021	9849.00	0.90	1.53	0.95	50.03

Waters had a higher PLAND value, fluctuating around 32.17. By 2021, waters became the dominant landscape type, with a PLAND value of 32.32. From 2011 to 2021, the LSI values of cultivated land, forestland, waters, and grassland displayed an upward trend, indicating a tendency towards complex and irregular shapes for these land types. This suggests a decreasing influence of human disturbances and a notable effect of ecological restoration. The LSI value of construction land showed an initial increase followed by a decrease, indicating a gradual transition from irregular to more regular shapes.

The NP, PD, SHDI and SHEI indices exhibited a continuous increasing trend. The DIVISION values initially increased and then decreased, with a DIVISION value of 0.9040 in 2016. Additionally, the CONTAG value showed a consistent decrease (Table 6). From 2011 to 2021, the PD value in the CLR area continuously increased, reaching 3.7143 in 2021. This indicates a growing landscape complexity and an ongoing increase in landscape fragmentation within the region. The DIVISION value initially increased and then decreased, suggesting a decreasing trend in landscape aggregation followed by an increase. The CONTAG value continued to decrease, indicating a gradual reduction in the aggregation density of different land type patches. The SHDI value steadily increased, reflecting an increasing landscape diversity and a tendency for the composition structure of landscape types to become more diversified. Moreover, the rising SHDI value indicated a tendency towards equalization in the proportions of each landscape type, reducing the control of dominant landscape types over the entire landscape and increasing landscape heterogeneity. The SHEI value reflected the level of landscape homogeneity, and its trend was consistent with the SHDI value, indicating a gradual increase. However, there was still a considerable gap from reaching the maximum value of 1.

During the study period, the landscape pattern in the CLR, an important lake wetland in the middle and lower reaches of the Yangtze River and a crucial ecological barrier in the Yangtze River Delta, exhibited increasing complexity. The PD values of cultivated land, forestland, waters, and grassland showed an upward trend, indicating a gradual fragmentation and a more complex landscape pattern for these land types, which aligned with the findings of Wang et al. [35]. Specifically, grassland exhibited the highest PD value, suggesting a high degree of fragmentation within this land type. This landscape fragmentation could have significant implications for biodiversity, habitat connectivity, and ecosystem functioning [68]. In the case of construction land, which had a significant impact on ecological risk, the landscape fragmentation initially increased and then decreased, transitioning from irregularity to regularity, which was consistent with the observations made by Liu et al. [69]. The PD value of construction land displayed an increasing and then decreasing trend, indicating more efficient land use practices and a shift towards a more regular and organized distribution of construction activities. It was worth noting that construction land's impact on ecological risk necessitates careful management and planning to minimize environmental degradation and ensure sustainable development. Throughout the study period, the waters maintained the highest degree of landscape dominance, underscoring their crucial role in maintaining regional ecological balance and ecological security. The preservation and proper management of water resources were essential for sustaining the overall health and functionality of the ecosystem [70].

The increasing LSI values for cultivated land, forestland, waters, and grassland demonstrated an increasing trend, indicating that the shapes of these land types became more complex. This complexity contributed to the overall stability of the ecosystems in the region [71]. The transition from irregular to more regular shapes observed in construction land implied a gradual improvement in land use planning and design, potentially enhancing the connectivity and functional integrity of the landscape [72]. Furthermore, the landscape pattern indices revealed that the values of the SHDI and SHEI exhibited a continuous upward trend. This indicated that the landscape types became more diverse and balanced in their compositional structure, reducing the control exerted by dominant landscape types on the overall landscape. The increased landscape heterogeneity resulting from this trend enhanced ecosystem stability and resilience to disturbances [73, 74]. Conversely, the DIVISION showed an increasing and then decreasing trend, suggesting that landscape aggregation initially decreased and then increased. This reflected the optimization of the landscape structure, which enhanced landscape connectivity and integrity [75]. The CONTAG exhibited a continuous decline, indicating a reduction in the aggregation density of patches of different land types. This reflected the positive impact of land use optimization and ecological restoration projects, which reduced boundary interlacing and mutual intrusion between different land types. These efforts contributed to enhanced ecosystem stability and the healthy development of ecosystems [76, 77].

Landscape Ecological Risk Assessment

The result indicated that from 2011 to 2021, the highest-risk area gradually increased, primarily concentrated in the central of CLR. Meanwhile, the higher-risk area exhibited an initial increase followed by a decrease, also mainly distributed in the Chaohu Lake waters (Fig. 7). The medium-risk areas displayed a similar increasing and decreasing trend, primarily distributed in peripheral locations of the Chaohu Lake waters, with the remaining areas concentrated in the east and south. The lower-risk areas showed minimal change, with a slight increase observed in 2016 compared to 2011, followed by a slight decrease in 2021 compared to 2016. Overall, the lower-risk areas, primarily consisting of cultivated land and grassland around the CLR, exhibited a decreasing trend. In contrast, the lowest-risk areas displayed a pattern of initially decreasing risk followed by an increase. These areas were distributed around the periphery of the Chaohu Lake waters, with a notable concentration in forestland and cultivated land. This spatial distribution pattern demonstrated a characteristic of "large aggregation and small dispersion". Notably, the landscape ecological risk index showed a consistent decreasing trend from the

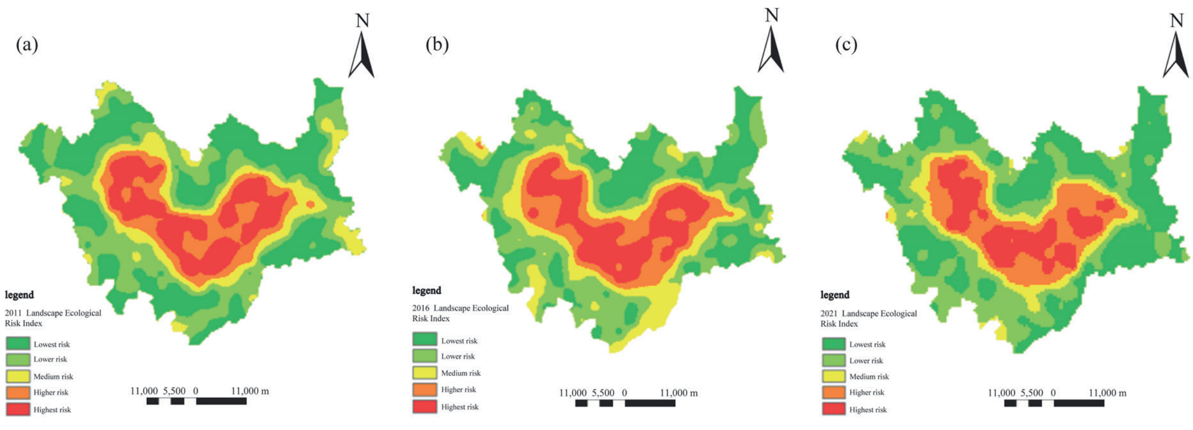

Fig. 7. Spatial distribution of landscape ecological risk in Chaohu Lake Region during 2011-2021.(a) landscape ecological risk in 2011, b) landscape ecological risk in 2016, c) landscape ecological risk in 2021.

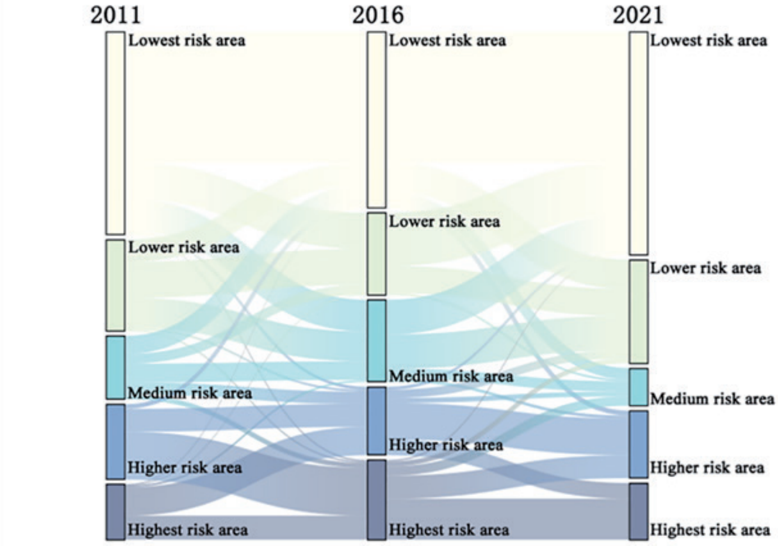

Fig. 8. Sankey diagram of different landscape ecological risk areas in 2011, 2016 and 2021.

center towards the surrounding areas, creating a spatial distribution pattern characterized by "low on all sides and high in the middle". Given that high-risk areas are primarily concentrated in the central part of the Chaohu Lake waters and occupy a larger area, these observations suggest an overall unfavorable landscape ecological risk situation in the CLR.

The main trends of ecological risk areas in each landscape indicated that between 2011 and 2016, the proportion of lowest-risk areas decreased from 41.6% to 36.1%, with 7.4% of them transitioning into lower-risk areas (Fig. 8). The proportion of lower-risk areas decreased from 18.7% to 16.8%, with 6.1% shifting to medium-risk areas. In contrast, the proportion of medium-risk areas increased from 13.0% to 16.8%, with 3.7% transitioning to lowest-risk areas. The share of higher-risk areas increased from 11.3% to 14.0%, with 4.9% shifting to highest-risk areas. Additionally, the share of highest-risk areas increased from 15.4% to 16.3%, with 4.7% transitioning to higher-risk areas. From 2016 to 2021, the share of lowest-risk regions increased from 36.1% to 45.7%, with 6.0% transitioning to lower-risk regions. The share of lower-risk regions increased from 16.8% to 21.2%, with 10.9% transitioning to lower-risk regions. Conversely, the share of medium-risk regions declined from 16.8% to 7.7%, with some transitioning to lowest-risk and lower-risk regions, accounting for 7.1% and 7.0%, respectively. The share of higher-risk areas decreased from 14.0% to 13.8%, with 3.2% transitioning to highest-risk areas. Similarly, the share of highest-risk areas decreased from 16.3% to 11.6%, with 4.7% transitioning to higher-risk areas. The Sankey diagram illustrated the trend from 2011 to 2021 (Fig. 8), revealing a 4.1% increase in the proportion of lowest-risk areas, a 2.5% increase in the proportion of lower-risk areas, a 5.3% decrease in the proportion of medium-risk areas, a 2.5% increase in the proportion of higher-risk areas, a 3.8% decrease in the proportion of highest-risk areas, and significant changes in the proportions of lowest-risk and medium-risk areas overall.

These findings suggested potential improvements in environmental conditions and ecological management practices within the CLR, as evidenced by the reduction in the highest-risk area. However, it is important to note that the higher-risk zone exhibited a gradual increase, which could be attributed to the rise in human activities and the intensification of environmental pressures in recent years [78]. Furthermore, both the higher-risk and medium-risk zones initially experienced an increase followed by a decrease, primarily located in the Chaohu Lake watershed and its adjacent areas. This pattern reflected the influence of policy interventions and environmental protection measures on ecological risk, which could be partially mitigated through measures such as enhancing pollution control in Chaohu Lake and implementing sustainable land management strategies [79]. In contrast, the lower-risk areas demonstrated minimal change. These areas were primarily located in cultivated land and grassland surrounding the CLR, indicating relative stability and lesser impacts from human activities [80]. On the other hand, the lowest-risk areas exhibited a trend initially decreasing followed by increasing, with a spatial distribution primarily in forestland and cultivated land surrounding the Chaohu Lake waters. The "large aggregation and small dispersion" pattern observed in the lowest-risk areas signified their spatial arrangement. Notably, the landscape ecological risk index displayed a decreasing trend from the center towards the surrounding regions, indicating that the ecosystems around Chaohu Lake were facing environmental pressures originating from the center, such as pollutant diffusion or biological invasions [81, 82]. These findings highlighted the need for targeted interventions and management strategies to mitigate the ecological risks in the central region and prevent the spread of these risks to the surrounding areas.

Finally, waters, forestland, and cultivated land contributed the most to the improvement of landscape ecological security in CLR, while the improvement of ecological risks of the central part of Chaohu Lake was not obvious (Fig. 7). The average ecological risk index of the waters was the highest, which was consistent with the research results of Huang et al. [83]. Considering the current situation and challenges regarding ecological risk in CLR, it was crucial to prioritize ecological principles in the process of social and economic development and land use. Protection of vital ecological lands such as water areas and forestland should be prioritized, and the uncontrolled expansion of construction land should be limited [84]. The Government should actively promote the ecological restoration of wetlands, strengthen the protection of lake water area, and halt the shrinking trend of water areas. Additionally, it was important to reserve ecological buffer zones,including wetlands, during the construction process to mitigate the deterioration of the ecological environment in high-risk areas like lake regions [85]. In the compilation of territorial spatial planning, it is necessary to consider the regional ecological risk pattern and establish a linkage between spatial divisions and ecological factors. This will enable the scientific and orderly arrangement of functional spaces such as ecological, agricultural, and urban areas. Furthermore, the requirements for ecological environment management and control should be implemented in medium and high ecological risk spaces to prevent environmental risks and enhance the environmental rationality and coordination of territorial spatial planning.

Conclusions

The study adopted land use change as its focal point and utilizes RS technology to obtain accurate and visualized data. It provided a comprehensive and quantitative assessment of landscape ecological risk in the CLR, including the analysis of land change patterns, landscape pattern changes, and landscape ecological risk index. The results indicated an overall unfavorable landscape ecological risk situation, and the dynamic changes in landscape patterns tended to be complex. These findings offered an important foundation for the development of effective ecological protection and management strategies in the CLR.

Future research can explore the potential relationship between land type transformations and the transfer of ecological risk areas. This exploration aims to implement optimal mitigation measures to control the transfer of highest-risk and higher-risk areas before the ecological risk level escalates. This proactive approach maximizes the coordination between ecology and the economy, achieving a mutually beneficial scenario of sustainable ecological development and steady economic improvement. However, it is crucial to acknowledge the limitations regarding the time span and study area. To overcome these limitations, future research should focus on improving the temporal data chain, exclude data from exceptional years (e.g., years with climatic anomalies like severe droughts or floods), and expand the study scope. These efforts will contribute to establishing a more comprehensive and sustainable dateset, which will serve as a scientific foundation and provide technical support for ecological security protection, engineering construction, and spatial planning.

Acknowledgments

This study was supported by the Natural Science Research Project of Anhui Educational Committee (No: KJ2021A0614). Science and Technology Program for Housing and Urban-Rural Development in Anhui Province (No: 2022-YF081).

Conflict of Interest

The authors declare no conflict of interest.

References

1. LAL P., SHEKHAR A., KUMAR A. Quantifying temperature and precipitation change caused by land cover change: a case study of India Using the WRF Model. Frontiers in Environmental Science, **9**, 766328, **2021**.
2. WANG B.B., DING M.J., LI S.C., AI J.H. Assessment of landscape ecological risk for a cross-border basin: a case study of the Koshi River Basin, central Himalayas. Ecologiclal Indicators, **117**, 106621, **2020**.
3. TIAN P., LI J.L., GONG H.B., PU R.L., CAO L.D., SHAO S.Y., SHI Z.Q., FENG X.L., WANG L.J., LIU R.Q. Research on land use changes and ecological risk assessment in Yongjiang river basin in Zhejiang province, China. Sustainability, **11** (10), 2817, **2019**.
4. YANG Y.P., CHEN J.J., LAN Y.P., ZHOU G.Q., YOU H.T., HAN X.W., WANG Y., SHI X. Landscape pattern and ecological risk assessment in Guangxi based on land use change. International Journal of Environmental Research and Public Health, **19** (3), 1595, **2022**.
5. TURNER M.G., COLLINS S.L., LUGO A.L., MAGNUSON J.J., RUPP T.S., SWANSON F.J. Disturbance Dynamics and Ecological Response: The Contribution of Long-Term Ecological Research. BioScience, **53** (1), 46, **2003**.
6. LI S.K., HE W.X., WANG L., ZHANG Z., CHEN X.Q., LEI T.C., WANG S.J., WANG Z.Z. Optimization of landscape pattern in China Luojiang Xiaoxi basin based on landscape ecological risk assessment. Ecological Indicators, **146**, 109887, **2023**.
7. WANG K.G., ZHENG H.H., ZHAO X.Y., SANG Z.T., YAN W.ZZ., CAI Z.Y., XU Y., and ZHANG F.R. Landscape ecological risk assessment of the Hailar River basin based on ecosystem services in China. Ecologiclal Indicators, **147**, 109795, **2023**.

8. PAN J.H., LIU X. Landscape ecological risk assessment and ecological security pattern optimization construction in the Shule River Basin. Chinese Journal of Ecology, **35** (3), 791, **2016**.
9. ZHANG Y., ZHANG F., WANG J., REN Y., GHULAM A., KUNG H. Research on ecological risk assessment and prediction of Lake Aibi based on LUCC. China Environmental Science, **36** (11), 3465, **2016**.
10. WANG H.F., RAO E.M., XIAO Y., YAN Y., LU H.T., ZHU J.Y. Ecological risk assessment in southwest China based on multi-risk source stress. China Environmental Science, **38** (24), 8992, **2018** .
11. GONG J., CAO E.J., XIE Y.C., XU C.X., LI H.Y., YAN L.L. Integrating ecosystem services and landscape ecological risk into adaptive management: Insights from a western mountain-basin area, China. Journal of Environmental Management, **281**, 111817, **2021**.
12. YAN J.X., LI G., QI G.P., QIAO H.Q., NIE Z.G., HUANG C.X., KANG Y.X., SUN D.Y., ZHANG M.H., KANG X.,YAO X.D. Landscape ecological risk assessment of farming-pastoral ecotone in China based on terrain gradients. Human and Ecological Risk Assessment, **27** (3), 1-18, **2021**.
13. SHIRVANI Z., ABDI O., BUCHROITHNER M. A synergetic analysis of sentinel-1 and -2 for mapping historical landslides using object-oriented random forest in the hyrcanian forests. Remote Sensing, **11**, 300, **2019**.
14. KARIMIAN H., ZOU W.M., CHEN Y.L., XIA J.Q., WANG Z.R. Landscape ecological risk assessment and driving factor analysis in Dongjiang river watershed. Chemosphere, **307**, 135835, **2022**.
15. LUO F.H., LIU Y.X., PENG J., WU J.S. Assessing urban landscape ecological risk through an adaptive cycle framework. Landscape and Urban Planning, **180**, 125, **2018**.
16. MO Y.Q., LI Q., KARIMIAN H., ZHANG S.T., KONG X.Y., FANG S.W., TANG B.Y. Daily spatiotemporal prediction of surface ozone at the national level in China: an improvement of CAMS ozone product. Atmospheric Pollution Research, **12** (1), 391, **2021**.
17. DING Q., SHI X., ZHUANG D.F., WANG Y. Temporal and spatial distributions of ecological vulnerability under the influence of natural and anthropogenic factors in an eco-province under construction in China. Sustainability, **10** (9), 3087, **2018**.
18. KARIMIAN H., CHEN Y.L., TAO T.H., LI Y.Q. Spatiotemporal analysis of air quality and its relationship with meteorological factors in the Yangtze River Delta. Journal of Elementology, **25** (3), 1059, **2020**.
19. KARIMIAN H., LI Q., CHEN H.F. Assessing Urban Sustainable Development in Isfahan. Applied Mechanics and Materials. **253-255**, 244, **2013**.
20. YU T., BAO A.M., XU W.Q., GUO H., JIANG L.L., ZHENG G.X., YUAN Y., NZABARINDA V. Exploring variability in landscape ecological risk and quantifying its driving factors in the Amu Darya Delta. International Journal of Environmental Research and Public Health, **17** (1), 79, **2019**.
21. LI J.L., PU R.L., GONG H.B., LUO X. YE M.Y., FENG B.X. Evolution Characteristics of Landscape Ecological Risk Patterns in Coastal Zones in Zhejiang Province, China. Sustainability, **9** (4), 584, **2017**.
22. ZHANG S.H., ZHONG Q.L., CHENG D.L., XU C.B., CHANG Y.N., LIN Y.Y., LI B.Y. Landscape ecological risk projection based on the PLUS model under the localized shared socioeconomic pathways in the Fujian Delta region. Ecological Indicators, **136**, 108642, **2022**.
23. PENG J., ZHAO M.Y., GUO X.N., PAN Y.J., LIU Y.X. Spatial-temporal dynamics and associated driving forces of urban ecologicalland: A case study in Shenzhen City, China. Habitat International, **60**, 81, **2017**.
24. SARKODIE S.A. Environmental performance, biocapacity, carbon & ecological footprint of nations: Drivers, trends and mitigation options. Science of The Total Environment, **751**, 141912, **2020**.
25. WEN M.X., ZHANG T., LI L., CHEN L.Q., HU S., WANG J., LIU W.Q., ZHANG Y., YUAN L. Assessment of Land Ecological Security and Analysis of Influencing Factors in Chaohu Lake Basin, China from 1998-2018. Sustainability, **13** (1), 358, **2021**.
26. YUAN L., GONG W.F., DANG Y.F., LONG Z.X. Study on ecological risk of land use in urbanization watershed based on RS and GIS: a case study of Songhua River watershed in Harbin Section. Asian Agricultural Research Asian Agricultural Research, USA-China Science and Culture Media Corporation, **5** (3), 1, **2013**.
27. BLASCHKE T., HAY G.J., WENG Q.H., RESCH B. Collective sensing: integrating geospatial technologies to understand urban systems-an overview. Remote Sensing, **3** (8), 1743, **2011**.
28. KUPFER J.A. Landscape ecology and biogeography: Rethinking landscape metrics in a post-FRAGSTATS landscape.Progress in Physical Geography, **36** (3), 400, **2012**.
29. ZANG Z., ZOUB X.Q., ZUO P., SONG Q.C. Impact of landscape patterns on ecological vulnerability and ecosystem service values: an empirical analysis of Yancheng Nature Reserve in China. Ecological Indicators, **72**, 142, **2017**.
30. LI M.Q. The Effect and Enlightenment of the Construction of Chaohu Ecological Civilization Demonstration Area. Journal of The Party College of C.P.C Hefei Municipal Committee, **1**, 25, **2019**.
31. KONG L.G. On the Concept of Ecological Civilization Construction and Mechanism Innovation: Research on Chaohu Ecological Civilization Demonstration Area Construction. Journal of Hefei University (Social Science), **32** (4), 3, **2015**.
32. YUAN B.X., WU N., CHENG P. Analysis on Spatial Temporal Variation Characteristics and Driving Forces Of Ecosystem Types in Chaohu Lake Basin from 2010 to 2020. Anhui Agriculture Science, **50** (7), 59, **2022**.
33. CHENG Z.Y. The Study on Ecological Restoration Modes of Wetland Landscape Based on the Natural System: A Case Study in Chaohu Lake Region. Journal of Shenyang Jianzhu University (Social Science), **17** (2),122, **2015**.
34. WANG Q.Q. Study on Dynamic Trend of Wetland Eco-environment around Chaohu Lake Watershed. Hefei: Anhui Agriculture University, **2017**.
35. WANG C.H., GUO Z.Y., GAO C., XIE C.F. Changes of Landscape Pattern in the Chaohu Lake Basin Based on Remote Sensing. Resources and Environment in the Yangtze Basin, **22** (12), 1586, **2013**.
36. www.rmh.com.cn. https://rmh.pdnews.cn/Pc/ArtInfoApi/article?id=29847325 (accessed on 11 November2022)
37. ZHANG Y.J., WAN Y., SHI W.Z., ZHAGN Z.X. LI Y.S., JI S.P., GUO H.Y., LI L. Technical framework and preliminary practices of photogrammetric remote sensing intelligent processing of multi-source satellite images. Acta Geodaetica et Cartographica Sinica, **50** (8), 1068, **2021**.
38. HU Y.J., DONG X., LI Y.J. Dynamic analysis of landscape pattern in Nanchong City based on remote sensing and GIS. Sichuan Environment, **40** (6), 81, **2021**.

39. DAI N. Research on classification method based on decision Tree. Master's Theses. Nanjing Normal University, **2003.**
40. HUANG L., QUAN S.X., WANG Z.X. Application research of the third land survey based on eCognition. Land & Resources Herald, **18** (1), 21, **2021**.
41. HOMER C., DEWITZ J., JIN S., XIAN G., COSTELLO C., DANIELSOND P., GASS L., FUNK M., WICKHAM J., STEHMAN S., AUCH R., RIITTERS K. Conterminous United States land cover change patterns 2001-2016 from the 2016 National Land Cover Database. ISPRS Journal of Photogrammetry and Remote Sensing, **162**, 184, **2020**.
42. YANG Y.L., CAO F.X. Dynamic changes of land use and landscape pattern in Nanshan national park from 1990 to 2019. Journal of Shandong Forestry Science and Technology, **51** (6), 21, **2021**.
43. ZHANG X.L. An RS Quantitative Research of Vegetation Landscape in Scenic Environment Based on eCognition Image Interpretation Technology: A Case Study of Jizu Mountain, Yunnan Province. Chinese Landscape Architecture, **36** (10), 81, **2020**.
44. SUN B.Z. Muti-scale Segmentation Technique in High Resolution Image Information Extraction Application Research. Xi'an: Xi'an University of Science and Technology, **2011**.
45. CAO J.S., YANG Y.Q., DENG Z.Y. Spatial and temporal evolution of ecological vulnerability based on vulnerability scoring diagram model in Shennongjia, China. Scientific Reports, **12** (1), 5168, **2022**.
46. GUO P.F., ZHANG F.F., WANG H.Y. The response of ecosystem service value to land use change in the middle and lower Yellow River: A case study of the Henan section. Ecological Indicators, **140**, 109019, **2022**.
47. HUANG L.X., XU D.D. Dynamic Monitoring of the Production Layout of Guangxi's Sericulture Based on eCognition and Study on the Influential Factors of Its Spatial Distribution:A Case Study of Yichou District of Hechi City. NanFang ZiRan ZiYuan, **8**, 40, **2020**.
48. TIAN L.L., WANG S.S., MU Z.P. Construction of Ecological Security Patterns in Urumqi Based on Multi-Temporal Remote Sensing Data. Arid Land Geography, **46** (7), 1155, **2023**.
49. WANG J., CUI B.S., YAO H.R., LIU S.L. TheTemporal and Spatial Characteristic of Landscape Ecological Security at Lancang River Watershed of Longitudinal Range Gorge Region in Southwest China. Acta Ecologica Sinica, **28** (4), 1681, **2008**.
50. YU T., BAO A.M., XU, W.Q., GUO, H., JIANG, L.L, ZHENG, G.X., YUAN Y., NZABARINDA V. Exploring variability in landscape ecological risk and quantifying its driving factors in the Amu Darya delta. International Journal of Environmental Research and Public Health, **17** (1), 79, **2020**.
51. YIN D.Y., LI X.S., LI G.E., ZHANG J., YU H.C. Spatio-Temporal Evolution of Land Use Transition and Its Eco-Environmental Effects: A Case Study of the Yellow River Basin, China. Land, **9**, 514, **2020**.
52. XIE H.L., WEN J.M., CHEN Q.R., WU Q. Evaluating the landscape ecological risk based on GIS: A case-study in the Poyang Lake region of China. Land Degradation & Development, **32**, 2762, **2021**.
53. AI J.W., YU K.Y., ZENG Z., YANG L.Q., LIU Y.F., LIU J. Assessing the dynamic landscape ecological risk and its driving forces in an island city based on optimal spatial scales: Haitan Island, China. Ecological Indicators, **137**, 108771, **2022**.
54. LI J., HEAP A.D. A review of comparative studies of spatial interpolation methods in environmental sciences: Performance and impact factors. Ecological Informatics, **6** (3-4), 228, **2011**.
55. WANG J., BAI W.Q., TIAN G.X. Spatiotemporal characteristics of landscape ecological risks on the Tibetan Plateau. Resources Science, **42** (9), 1739, **2020**.
56. ZHAO Z., ZUCKNICK M., AITTOKALLIO T. Enrich Intersect: an R package for custom set enrichment analysis and interactive visualization of intersecting sets. Bioinformatics Advances, **2** (1), vbac073, **2022**.
57. www.ahnews.com.cn. http://www.ahnews.com.cn/hefei/pc/con/2022-09/16/565_671847.html (accessed on 9 September 2022)
58. YANG D., LOU Y.Y., ZHANG P.Y., JIANG L. Spillover Effects of Built-Up Land Expansion Under Ecological Security Constraint at Multiple Spatial Scales. Frontiers in Ecology and Evolution, **10**, 907691, **2022**.
59. YU J., TANG B., CHEN Y.H., ZHANG L., NIE Y., DENG W.S. Landscape Ecological Risk Assessment and Ecological Security Pattern Construction in Landscape Resource-based City: A Case Study of Zhangjiajie City. Acta Ecologica Sinica, **42** (4), 1290, **2022**.
60. HUANG M.Y., FANG B., YUE W.Z., FENG S.R. Spatial Differentiation of Ecosystem Service Values and Its Geographical Detection in Chaohu Basin during 1995-2017. Geographical Research, **38** (11), 2790, **2019**.
61. MOEIN M., ASGARIAN A., SAKIEH Y., SOFFIANIAN A. Scenario-based analysis of land-use competition in central Iran: Finding the trade-off between urban growth patterns and agricultural productivity. Sustainable Cities and Society, **39**, 557, **2018**.
62. YANG Y.L., CAO F.X. Dynamic Changes of Land Use and Landscape Pattern in Nanshan National Park from 1990 to 2019. Journal of Shandong Forestry Science and Technology, **51** (6), 21, **2021**.
63. LU Q.P., ZHAO C.W., WANG J., YANG X.Y. Research on the Temporal and Spatial Evolution of Landscape Pattern Vulnerability in Guizhou Karst Mountains in the Past 30 Years. Resources and Environment in the Yangtze Basin, **31** (3), 634, **2022**.
64. CAMARE M., JAMILN.R., ABDULLAH A.F.B. Impact of land uses on water quality in Malaysia: a review. Ecological Processes, **8**, 10, **2019**.
65. ROHR J.R., BERNHARDT E.S., CADOTTE M.W., CLEMENTS W.H. The ecology and economics of restoration: when, what, where, and how to restore ecosystems. Ecology and Society, **23** (2), 15, **2018**.
66. GANN G.D., MCDONALD T., WALDER B., ARONSON J., NELSON C.R., JONSON J., HALLETT J.G., EISENBERG C., GUARIGUATA M.R., LIU J., HUA F.Y, ECHEVERRÍA C., GONZALES E., SHAW N., DECLEER K., DIXON K.W. International principles and standards for the practice of ecological restoration. Second edition. Restoration Ecology, **27** (S1), S1, **2019**.
67. ZHANG T.ZZ., GAO Y., LI C., XIE Z., CHANG Y.Y., ZHANG B. L. How Human Activity Has Changed the Regional Habitat Quality in an Eco-Economic Zone: Evidence from Poyang Lake Eco-Economic Zone, China. International Journal of Environmental Research and Public Health, **17** (17), 6253, **2020**.
68. WILSON M.C., CHEN X.Y., CORLETT R.T., DIDHAM R.K., DING P., HOLT R.D., HOLYOAK M., HU G., HUGHES A.C., JIANG L., LAURANCE W.F., LIU J.J., PIMM S.L., ROBINSONG S.K., RUSSO S.E., SI X.F., WILCOVE D.S., WU J.G., YU M.J. Habitat fragmentation

and biodiversity conservation: key findings and future challenges. Landscape Ecology, **31**, 219, **2016**.
69. LIU X., REN C.Q., DONG B., LU Z.P., WEI Z.Z. Driving Forces of Land Use Landscape Pattern Around Chaohu Lake Based on TM Image. Journal of Yunnan Agricultural University (Social Science), **17** (3), 110, **2023**.
70. COSGROVE W.J., LOUCKS D.P. Water management: Current and future challenges and research directions. Water Resources Research, **51** (6), 4823, **2015**.
71. HUANG F., OCHOA G.G., JARVIES W.T., ZHONG R.S., GUO L.D. Evolution of landscape pattern and the association with ecosystem services in the Ili-Balkhash Basin. Environmental Monitoring and Assessment, **194**, 171, **2022**.
72. BENNETT A.F. Linkages in the Landscape:The Role of Corridors and Connectivity in Wildlife Conservation. IUCN, Gland, Switzerland and Cambridge, UK. 1-254, **2003**.
73. YU L., DANG X.H., JI C., LI Z.B., XU X.L. Analysis on the Evolvement and Driving Force of Wetland Landscape Pattern in Zhuhai City.Geospatial Information, **9** (11), 48, **2021**.
74. LIU K., YANG Y.Y., SHI R.G., LI Q. WU B., ZHEGN H.Y., MI C.H. Spatiotemporal Changes in Forces Driving Landscape Patterns in the Yuqiao Reservoir Watershed during 1990-2020. Journal of Agricultural Resources and Environment, **40** (1), 154, **2022**.
75. LEI Z.X., FU J.Y., LUO J.J., CAO L. Attribution analysis of runoff changes in the Sanchuan River Basin of Shanxi Province from the perspective of landscape patterns [J]. Acta Ecologica Sinica, **42** (12), 4946, **2022**.
76. LIANG J.L., CHEN W.X., LI J.F., DONG M.J., ZHOU T., PAN S.P. Spatiotemporal patterns of landscape fragmentation andcauses in the Yellow River Basin. Acta Ecologica Sinica, **42** (5), 1993, **2022**.
77. GUO J.Q., PAN J. Dynamic Study on the Heat Island Effect and Landscape Pattern in Nanjing. Forest Resources Management, **3**, 139, **2019**.
78. ZHANG R.Y., LI S.N., WEI B.J., ZHOU X. Characterizing Production-Living-Ecological Space Evolution and Its Driving Factors: A Case Study of the Chaohu Lake Basin in China from 2000 to 2020. Internatinal Journal of Geo-Information, **11** (8), 447, **2022**.
79. GUO B.B., FANG Y.L., JIN X.B., ZHOU Y.K. Monitoring the effects of land consolidation on the ecological environmental quality based on remote sensing: A case study of Chaohu Lake Basin, China. Land Use Policy, **95**, 104569, **2020**.
80. CHENG C.Y., ZHANG F., SHI J.C., KUNG H.T. What is the relationship between land use and surface water quality? A review and prospects from remote sensing perspective. Environmental Science and Pollution Research, **29**, 56887, **2022**.
81. CHENG Z.Y., ZHANG X.F. Exploring the Habitat Restoration and Landscape Construction of the Wetland Lakeside Zone in the Lujiang Section on the Southern Bank of the Chaohu Lake. Earth and Environmental Science, **598**, 012037, **2020**.
82. LIU J.Y., LU C.S. Study on the Landscape Pattern Change and Driving Mechanism of Land Use in Hefei City. Journal of Anhui Agricultural Sciences, **49** (24), 88-92, **2021**.
83. HUANG M.Y., HE X. Landscape ecological risk assessment and its mechanism in Chaohu Basin during the past almost 20 years. Journal of Lake Sciences, **28** (4), 785, **2016**.
84. ZHOU T., QI J.L., XU Z.H., ZHOU D. Damage or recovery? Assessing ecological land change and its driving factors: A case of the Yangtze River Economic Belt, China. Journal of Resources and Ecology, **12** (2), 175, **2021**.
85. KAYASTHA N., THOMS V., GALBRAITH J., BANSKOTA A. Monitoring wetland change using inter-annual Landsat time-series data. Wetlands, **32**, 1149, **2012**.