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

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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

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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 topic, 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 concepts 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 hm², but cultivated land decreased by 34,230 hm², and the water body area remained relatively stable [34]. Evergreen forestland increased by 40,350 hm², deciduous forestland decreased by 6,760 hm², 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 supported 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 km², 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, Yinpeng 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 km² and spans multiple administrative regions, including Chaohu City, Baohu District of Hefei City, Luijiang 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 Yangxi-Changlin River-Zhongmiao-Huatai River, 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.
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:

$$S_i = aC_i + bN_i + cD_i$$ (1)

Where $S_i$ was the disturbance index of the $i$-th landscape type. The weights assigned to each landscape type need to be determined based on expert knowledge or empirical studies.
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>
<thead>
<tr>
<th>Landscape Pattern Index</th>
<th>Computational Method</th>
<th>Ecological Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>The number of patches (NP)</td>
<td>$NP = \Sigma(P_i)$</td>
<td>$NP$ denotes the spatial pattern of the landscape and describe the heterogeneity of the entire landscape. $P_i$ is the number of patches of the i-th category, and $\Sigma(P_i)$ is the sum of the number of patches across all categories.</td>
</tr>
<tr>
<td>Patch density (PD) (NP/100ha)</td>
<td>$PD = NP/A$</td>
<td>$PD$ 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.</td>
</tr>
<tr>
<td>Largest patch index (LPI) (%)</td>
<td>$LPI = \frac{\text{Max}(P_i)}{A} \times 100%$</td>
<td>reflects the dominance of the landscape by indicating the proportion of the landscape occupied by the largest patch. $\text{Max}(P_i)$ is the maximum patch area among all classes, and $A$ is the total area of the study area.</td>
</tr>
<tr>
<td>Landscape shape index (LSI)</td>
<td>$LSI = \frac{0.25E}{\sqrt{A}}$</td>
<td>$LSI$ 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.</td>
</tr>
<tr>
<td>Percentage of Landscape (PLAND) (%)</td>
<td>$\text{PLAND} = \frac{\sum_{i=1}^{n} a_i}{A} \times 100%$</td>
<td>$\text{PLAND}$ denotes one of the bases for determining the dominant landscape elements in the landscape. $a_i$ is the area of Patch $i$, and $A$ represents the total area of the study area.</td>
</tr>
<tr>
<td>Landscape division index (DIVISION)</td>
<td>$\text{DIVISION} = \left[1 - \sum_{j=1}^{n} \frac{a_i}{A}\right]$</td>
<td>$\text{DIVISION}$ 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.</td>
</tr>
<tr>
<td>Shannon’s diversity index (SHDI)</td>
<td>$\text{SHDI} = -\sum_{i=1}^{m} (P_i \times \ln P_i)$</td>
<td>$\text{SHDI}$ measures the diversity of the landscape by reflecting changes in the proportion of different patch types, with higher values indicating greater patch diversity. $P_i$ 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.</td>
</tr>
<tr>
<td>Shannon’s evenness index (SHEI)</td>
<td>$\text{SHEI} = \text{SHDI} / \ln(S)$</td>
<td>$\text{SHEI}$ is used to measure the evenness of the distribution of different species in the entire landscape. $\ln$ represents the number of different species, and $\ln$ is the natural logarithm function.</td>
</tr>
<tr>
<td>Contagion index (CONTAG) (%)</td>
<td>$\text{CONTAG} = \frac{1 + \sum_{i=1}^{m} \sum_{j=1}^{n} \left(\frac{P_i}{P_{ij}} \cdot \frac{P_{ij}}{P_k} \ln(P_i) \left(\frac{P_{ij}}{P_k} \cdot \frac{P_{ij}}{P_k}\right)\right)}{2 \ln(m)} \times 100%$</td>
<td>$\text{CONTAG}$ represents the degree of aggregation and contagion tendency between different patches in the landscape. $m$ is the total number of patch types, $n$ is the number of adjacent patches between patch type $i$ and patch type $k$, and $P_i$ is the proportion of patch type $i$ in the total landscape area.</td>
</tr>
<tr>
<td>Landscape fragmentation index ($C_i$)</td>
<td>$C_i = \frac{n_i}{A_i}$</td>
<td>represents the process of landscape types transitioning from a single continuous entity towards complex and discontinuous patches. $n_i$ is the number of patches of the i-th landscape type, and $A_i$ is the area of the i-th landscape type.</td>
</tr>
<tr>
<td>Landscape isolation index ($N_i$)</td>
<td>$N_i = l_i \times \frac{A}{A_i}$</td>
<td>$N_i$ reflects the degree of separation between different patches within a landscape. $l_i$ is the distance index of the i-th landscape type, $A$ is the area of the i-th patch, and $A_i$ is the total area of the landscape.</td>
</tr>
<tr>
<td>Landscape fractal dimension index ($D_i$)</td>
<td>$D_i = \frac{2 \ln(p_i)}{\ln A_i}$</td>
<td>$D_i$ represents the complexity and variability of landscape spatial structure. $p_i$ is the perimeter of the i-th patch, and $A_i$ is the area of the i-th patch.</td>
</tr>
</tbody>
</table>
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.

<table>
<thead>
<tr>
<th>Landscape type</th>
<th>2011</th>
<th>2016</th>
<th>2021</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Area (km²)</td>
<td>Proportion (%)</td>
<td>Area (km²)</td>
</tr>
<tr>
<td>Cultivated land</td>
<td>1090.26</td>
<td>41.12</td>
<td>876.55</td>
</tr>
<tr>
<td>Forestland</td>
<td>389.77</td>
<td>14.71</td>
<td>300.11</td>
</tr>
<tr>
<td>Waters</td>
<td>859.06</td>
<td>32.40</td>
<td>842.69</td>
</tr>
<tr>
<td>Grassland</td>
<td>80.80</td>
<td>3.06</td>
<td>170.02</td>
</tr>
<tr>
<td>Construction land</td>
<td>230.56</td>
<td>8.71</td>
<td>461.21</td>
</tr>
</tbody>
</table>
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,

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

<table>
<thead>
<tr>
<th>Landscape type</th>
<th>Change rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2011-2016</td>
</tr>
<tr>
<td>Cultivated land</td>
<td>-8.04</td>
</tr>
<tr>
<td>Forestland</td>
<td>-3.39</td>
</tr>
<tr>
<td>Waters</td>
<td>-0.60</td>
</tr>
<tr>
<td>Grassland</td>
<td>3.35</td>
</tr>
<tr>
<td>Construction land</td>
<td>8.68</td>
</tr>
</tbody>
</table>

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

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

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.
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).

<table>
<thead>
<tr>
<th>Landscape type</th>
<th>Grassland (km²)</th>
<th>Cultivated land (km²)</th>
<th>Construction land (km²)</th>
<th>Forestland (km²)</th>
<th>Waters (km²)</th>
<th>Total (km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016</td>
<td>55.42</td>
<td>41.77</td>
<td>23.90</td>
<td>43.66</td>
<td>5.30</td>
<td>170.05</td>
</tr>
<tr>
<td>Grassland</td>
<td>108.98</td>
<td>497.52</td>
<td>86.76</td>
<td>143.64</td>
<td>40.22</td>
<td>877.12</td>
</tr>
<tr>
<td>Cultivated land</td>
<td>72.03</td>
<td>116.83</td>
<td>242.33</td>
<td>17.17</td>
<td>12.82</td>
<td>461.18</td>
</tr>
<tr>
<td>Construction land</td>
<td>29.36</td>
<td>21.37</td>
<td>77.25</td>
<td>254.47</td>
<td>2.88</td>
<td>385.33</td>
</tr>
<tr>
<td>Forestland</td>
<td>8.75</td>
<td>24.42</td>
<td>10.86</td>
<td>3.05</td>
<td>795.57</td>
<td>842.65</td>
</tr>
<tr>
<td>Waters</td>
<td>274.54</td>
<td>701.91</td>
<td>441.1</td>
<td>461.99</td>
<td>856.79</td>
<td>2736.33</td>
</tr>
<tr>
<td>Total</td>
<td>242.33</td>
<td>856.79</td>
<td>40.22</td>
<td>242.33</td>
<td>12.82</td>
<td>877.12</td>
</tr>
</tbody>
</table>
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...
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 16.8%, 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, and 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 dataset, which will serve as a scientific foundation and provide technical support for ecological security protection, engineering construction, and spatial planning.

Acknowledgments

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Conflict of Interest

The authors declare no conflict of interest.

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