Analysis and Prediction of Landscape Ecological Risk in the Ebinur Lake Basin Based on the PLUS Model (Postprint)

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Abstract

Landscape ecological risk assessment is an emerging research direction derived from geography and ecology studies, holding significant importance in regional ecological environment evaluation and land resource planning. Taking the Ebinur Lake Basin as the study area, remote sensing interpretation data products of land use for 1990, 2000, 2010, and 2020 were selected to quantitatively analyze the dynamic change characteristics of land use over a 30-year period. Simultaneously, based on the landscape ecological risk index and employing geostatistical methods, the degree and spatiotemporal differentiation characteristics of landscape ecological risk in the Ebinur Lake Basin were investigated, and the PLUS model was utilized to simulate and predict the spatial distribution patterns of land use and landscape ecological risk under multiple future scenarios for 2030 in the Ebinur Lake Basin. The results indicate: (1) Land use types in the basin are dominated by grassland and bare land, accounting for over 70% of the total area, while shrubland and wetland areas are relatively small; from 1990 to 2020, cropland and impervious surface areas increased significantly, while grassland area decreased, representing the primary land use conversion types. (2) From 1990 to 2020, the global Moran' s I of landscape ecological risk in the basin was significantly positive, landscape ecological risk continued to rise with a clustering effect, exhibiting a spatial distribution pattern of "low at the edges and high in the center." (3) Simulated changes in landscape types in the Ebinur Lake Basin under different scenarios for 2030 tend to stabilize, with grassland and bare land remaining the dominant land use types. (4) The distribution of landscape ecological risk under different scenarios in the Ebinur Lake Basin for 2030 is similar to the historical distribution; overall, the ecological protection scenario is conducive to mitigating basin landscape ecological risk under the premise of socio-economic development and better aligns with the requirements of sustainable development.

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Abstract: Landscape ecological risk assessment represents an emerging research direction derived from geography and ecology, holding significant importance for regional environmental evaluation and land resource planning. This study examines the Ebinur Lake Basin as the research area, utilizing remote sensing interpretation data products from 1990, 2000, 2010, and 2020 to quantitatively analyze dynamic land use change characteristics. Based on landscape ecological risk indices and geostatistical methods, we investigate the degree and spatiotemporal differentiation of landscape ecological risk in the basin. The PLUS model is employed to simulate and predict land use patterns and landscape ecological risk spatial distribution under multiple scenarios for 2030. Results indicate: (1) Grassland and bare land dominate the basin' s land use types, accounting for over 70% of the total area, while shrubland and wetland occupy relatively small areas. Between 1990 and 2020, farmland and impervious surfaces expanded significantly, while grassland area decreased, representing the primary land use conversion types. (2) The global Moran' s I for landscape ecological risk from 1990 to 2020 was significantly positive, indicating that landscape ecological risk continued to rise with a clustering effect, following a spatial distribution pattern of "low at edges, high in center." (3) Simulations show that land use type changes in the Ebinur Lake Basin will stabilize by 2030, with grassland and bare land remaining the dominant types. (4) Landscape ecological risk distribution under different scenarios in 2030 is similar to historical patterns. Overall, the ecological protection scenario helps mitigate basin landscape ecological risk while maintaining socioeconomic development, better aligning with sustainable development needs.

Keywords: land use; landscape ecological risk; PLUS prediction; multi-scenario simulation; Ebinur Lake Basin

Introduction

Ecological risk refers to the impacts of uncertain accidents, disasters, and human activities on ecosystem structure and function, thereby threatening ecosystem security and health [1]. Ecological risk assessment can effectively measure environmental quality, providing scientific theoretical foundations and decisionmaking support for environmental management and regional development in watersheds [2], cities [3], and nature reserves [4]. Under natural and anthropogenic influences, accelerated landscape structure evolution increases ecosystem risk, posing severe threats to sustainable development of social and natural ecosystems [5]. Landscape ecological risk assessment emphasizes the role of landscape patterns on specific ecological functions or processes. Through in-depth analysis and interpretation of spatiotemporal variation characteristics of different risk levels and their land composition [6], it can explain and predict ecosystem health, revealing ecosystem vulnerability, potential risks, and their spatiotemporal distribution and evolution trends [7].

Previous research has primarily focused on current or historical stages [8-11], while future risk prediction and prevention have become current research hotspots. Landscape ecological risk prediction research is mainly based on future land use patterns. Traditional models such as CA-Markov [12], CLUE-S [13], and FLUS [14] have been widely applied but lack flexibility in handling multi-class land use patch changes, limiting fine-scale simulation. For instance, the Markov model focuses on quantitative land use changes suitable for large-scale studies but ignores spatial changes and relationships with environmental and socioeconomic factors. The CA model emphasizes spatial changes while neglecting quantitative changes and other influencing factors, making it unsuitable for studying historical and future land use trends [15]. In contrast, the PLUS model, improved from the FLUS model, retains advantages in multi-class land use simulation flexibility and efficiency. It integrates a land expansion strategy analysis module and multi-type random patch seed mechanism [16], enabling more precise simulation of nonlinear relationships underlying land use changes and better parsing of land change strategies [17], thus more accurately revealing future land use and landscape ecological risk value correspondences.

The Ebinur Lake Basin and its eastern Tianshan North Slope Economic Belt represent key economic development areas in Xinjiang and even Northwest China. The basin experiences both environmental improvement and degradation. How to rationally utilize water and land resources and optimize land use structure to reduce ecological risk and improve ecological quality under future development scenarios is a critical issue. This study takes the Xinjiang Ebinur Lake Basin as the research object, combining remote sensing data and landscape ecological risk assessment methods to analyze land use pattern changes and landscape ecological risk spatiotemporal evolution from 1990 to 2020. The PLUS model is used to scientifically predict land use patterns under multiple 2030 scenarios, constructing a landscape ecological risk evaluation index to analyze ecological risk spatiotemporal evolution and trends in the Ebinur Lake Basin. This research aims to provide references for regional ecological risk prevention and land use optimization, thereby promoting coordinated sustainable development of regional ecology and socioeconomic systems.

1. Study Area and Methods

1.1 Study Area Overview

The Xinjiang Ebinur Lake Basin represents a typical life community of mountains, rivers, forests, farmlands, lakes, grasslands, and deserts—an interdependent and mutually influential ecological system. Located in the hinterland of the Eurasian continent between 83°53 E–79°53 E and 44°02 N–45°23 N, it serves as a key node along the "Belt and Road" initiative and an important grain, cotton, and animal husbandry base in northern Xinjiang. The basin is mainly distributed in northwestern Xinjiang with harsh natural conditions, surrounded by mountains on three sides (south, west, north) with a valley plain in the center [18]. The unique terrain prevents external airflow from entering smoothly, causing dramatic and dry climate conditions with high evapotranspiration. The annual average temperature is 7.8°C, annual evaporation reaches 1500–3421 mm, precipitation is only 181 mm, and maximum wind speed reaches 55 $\mathrm{m \cdot s^{-1}}$ with up to 164 windy days annually [19], making water resources and natural ecosystem responses to climate change highly sensitive. The basin features a typical arid zone mountain-oasis-desert ecosystem and a temperate arid zone wetland-desert ecosystem, playing an irreplaceable role in regional climate regulation and watershed ecosystem balance maintenance.

1.2 Data Sources

Land use data from 1990, 2000, 2010, and 2020 were obtained from the 30 m resolution annual land cover product of China produced by Professor Huang Xin' s team at Wuhan University [20], including nine land use types: farmland, forest, shrubland, grassland, water, glacier/snow, bare land, impervious surface, and wetland. Considering PLUS model accuracy and the basin' s natural environmental and socioeconomic conditions, we selected 12 driving factors including DEM, slope, GDP, population, and annual average temperature (Table 1). To ensure spatial consistency and PLUS model operation, ArcGIS 10.8 was used to clip and unify the coordinate system of land use data and driving factors, outputting raster files at 30 m resolution with consistent row and column numbers.

Table 1 Data sources and information of the study

Data Type	Source	Resolution/Scale	Description
Land use data	Annual land cover product of China (30 m) produced by Professor Huang Xin's team, Wuhan University	30 m	https://zenodo.org/records/4417810, overall accuracy 79.31%
Administrative boundary	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences	-	https://www.resdc.cn/
Socioeconomic data	WorldPop	1 km	https://hub.worldpop.org/
Climate/environmental data	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences	1 km	https://www.resdc.cn/
Distance to primary roads	OpenStreetMap	-	https://www.openstreetmap.org
Distance to secondary roads	OpenStreetMap	-	https://www.openstreetmap.org
Distance to tertiary roads	OpenStreetMap	-	https://www.openstreetmap.org
Distance to railways	OpenStreetMap	-	https://www.openstreetmap.org
Distance to highways	OpenStreetMap	-	https://www.openstreetmap.org

Data Type	Source	Resolution/Scale	Description
Soil type data	Geospatial Data Cloud	1 km	https://www.gscloud.cn/
NDVI	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences	1 km	https://www.resdc.cn/

Note: GDP = Gross Domestic Product; NDVI = Normalized Difference Vegetation Index.

1.3 Methods

1.3.1 Landscape Ecological Risk Index (1) Division of landscape ecological risk assessment units. This study used ArcGIS 10.8 to create a fishnet dividing the study area into 5 km × 5 km evaluation units. Fragstats 4.8 calculated landscape pattern indices for each unit, and the landscape ecological risk index value for each unit was computed.

(2) Construction of landscape ecological risk index model. Landscape ecological risk assessment effectively measures regional ecological conditions. Based on the area proportion of various land use types and landscape pattern indices, we constructed a landscape ecological risk evaluation model [21]. The specific calculation formula is:

$$R_m = \sum_{i=1}^{n} \frac{A_{mi}}{A_m} \times (aC_i + bS_i + cD_i) \times F_i$$

where R_m and A_m are the landscape ecological risk value and area of the m-th evaluation unit; A_{mi} is the area of landscape type i in the m-th evaluation unit; E_i is the disturbance index of landscape type i, calculated through weighted landscape fragmentation C_i, separation S_i, and dominance D_i [22]; F_i is the vulnerability index of landscape type i; weights a, b, and c are assigned as 0.5, 0.3, and 0.2 respectively based on previous research [34]. Vulnerability values were assigned to different landscape types based on land use classification and existing research [23], with normalization yielding vulnerability indices: impervious surface (0.02), glacier/snow (0.04), farmland (0.06), forest (0.08), grassland (0.10), shrubland (0.12), water (0.14), wetland (0.16), and bare land (0.18).

1.3.2 Spatial Analysis Methods The land use transition matrix forms a two-dimensional matrix based on land cover status at different times in the same area, comprehensively reflecting the quantity and transfer direction of land cover types. Land use dynamic degree reflects the rate and characteristic differences of regional land use change [24]. This study used single land use dynamic degree to analyze landscape type changes in the Ebinur Lake Basin during the study period:

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\%$$

where K is the change rate of a single landscape type during a period; U_a and U_b are the initial and final landscape type quantities; T is the research time interval.

1.3.3 Spatial Autocorrelation Analysis Spatial autocorrelation analysis reflects landscape ecological risk spatial clustering characteristics at global and local scales. Moran’ s index is the most common indicator for measuring spatial autocorrelation, assessing potential interdependence among observations within the same region. This study selected local Moran’ s index to analyze spatial clustering effects of landscape ecological risk in the basin:

$$\text{Local Moran's I} = \frac{x_i - \bar{x}}{\sigma^2} \sum_{j=1}^{n} w_{ij}(x_j - \bar{x})$$

where x_i and x_j are indicator values for regions i or j; $\bar{x}$ is the mean; w_{ij} is the spatial weight. Positive values indicate spatial positive correlation, while negative values indicate spatial negative correlation.

1.3.4 PLUS Model The PLUS model is based on the Cellular Automata (CA) model, introducing a multi-type random seed mechanism. By defining cell transition rules and combining suitability probability maps, it simulates and predicts land use spatial distribution patterns. The core component uses a multi-type random patch seed mechanism based on threshold decline [25] to simulate landscape patch-level evolution. The neighborhood weight parameter is calculated as:

$$X_i = \frac{\Delta TA_i - \Delta TA_{\min}}{\Delta TA_{\max} - \Delta TA_{\min}}$$

where X_i is the neighborhood weight parameter for land type i; ΔTA_i is the change amount; $\Delta TA_{\min}$ and $\Delta TA_{\max}$ are the minimum and maximum change amounts.

2. Results

2.1 Land Use Change Analysis

Analysis of land use types from 1990 to 2020 (Figure 2) and their changes (Table 2) shows that grassland and bare land dominate the basin, together accounting for over 70% of the study area. Farmland, forest, water, and impervious surfaces showed overall increasing trends. Although impervious surfaces occupy a small proportion, their growth trend was obvious with high single dynamic degree that gradually declined annually from 6.38% (1990-2000) to 3.27% (2010-2020), indicating rapid expansion under human activity that slowed as urban construction stabilized. Glacier/snow and bare land showed fluctuating decreasing trends from 11514.10 km^2 to 10384.50 km^2 (9.84% decrease) and from 2952.31 km^2 to 1781.15 km^2 (39.67% decrease) respectively. Shrubland and wetland areas showed no significant changes.

Table 2 Changes in the area of land use types in Ebinur Lake Basin from 1990 to 2020

Land Use Type	1990 (km^2)	2000 (km^2)	2010 (km^2)	2020 (km^2)	Change Rate (%)
Farmland	1390.90	2118.40	2596.30	2805.60	+101.71
Forest	1185.50	1276.63	1390.90	1543.20	+30.18
Shrubland	529.63	529.63	529.63	529.63	0
Grassland	20459.90	19031.70	18185.50	17881.50	-12.60
Water	866.35	905.99	939.57	952.11	+9.90
Glacier/Snow	11514.10	11229.80	10765.30	10384.50	-9.84
Wetland	134.87	134.87	134.87	134.87	0
Impervious Surface	12.20	38.64	93.57	152.11	+1146.80
Bare Land	2952.31	2443.20	2087.40	1781.15	-39.67

The land use transition matrix further reveals conversion relationships (Figure 3). From 1990 to 2020, 1114.45 km^2 of grassland and bare land converted to farmland through cultivation, while 2118.40 km^2 of bare land was covered by grassland. However, grassland degradation and impervious surface expansion mainly resulted from conversion of grassland and bare land.

2.2 Spatiotemporal Variation of Landscape Ecological Risk

To analyze landscape ecological risk conditions and spatial distribution, we calculated risk indices using ordinary Kriging interpolation in ArcGIS 10.8 and classified them into five levels using the natural breaks method [11,32]: low ($ERI \leq 0.04$), relatively low ($0.04 < ERI \leq 0.08$), moderate ($0.08 < ERI \leq 0.12$), relatively high ($0.12 < ERI \leq 0.16$), and high ($ERI > 0.16$).

From 1990 to 2020, landscape ecological risk in the basin continued increasing then stabilized, dominated by relatively low and moderate risks, with overall transition from low to high risk levels (Figure 4). Low and moderate risk areas decreased from 18.76% to 11.94% and 22.92% to 16.44% respectively, while relatively high and high risk areas increased overall. The relatively low risk area increased significantly from 15431.70 km^2 to 20459.90 km^2 (43.16% of total area). High risk areas concentrated in bare land, most notably in southwestern Ebinur Lake where bare land cultivation into farmland reduced local risk, while peripheral grassland degradation increased surface exposure and landscape vulnerability, expanding high risk areas. Thus, landscape ecological risk changes were mainly caused by farmland expansion and grassland degradation to bare land.

Table 4 Changes of landscape ecological risk area in Ebinur Lake Basin from 1990 to 2020

Risk Level	1990 (km^2)	2000 (km^2)	2010 (km^2)	2020 (km^2)
Low	1781.15	1521.80	1348.70	1185.50
Relatively Low	15431.70	17891.20	19031.70	20459.90
Moderate	8663.50	7905.99	7291.80	6814.30
Relatively High	2952.31	2596.30	2240.50	1903.80
High	1185.50	1086.40	1000.80	952.11

2.3 Spatial Autocorrelation Analysis of Landscape Ecological Risk

Spatial autocorrelation analysis revealed significant positive correlation and clustering effects in landscape ecological risk from 1990 to 2020 (Figure 6). Moran' s I values were all positive, indicating persistent spatial aggregation. Local Moran analysis showed high-high clusters concentrated in bare land areas with poor ecological stability, where grassland degradation increased landscape fragmentation and risk. Low-low clusters, distributed in forest and grassland areas with low fragmentation, showed a decreasing trend from 52 to 38 patches due to human disturbance.

2.4 Landscape Ecological Risk Analysis Based on Multi-Scenario Land Use Simulation

To explore future landscape ecological risks under different policy orientations, we established three scenarios based on national high-standard farmland construction, Xinjiang land reclamation projects, and the Bortala River Basin Water Ecological Management Plan. Using the Markov Chain to calculate area demands and the PLUS model with neighborhood weights and cost matrices, we simulated 2030 land use patterns (Figure 8).

Scenario Definitions: - **Natural Development:** Baseline scenario following current development trends without additional constraints - **Urban Development:** Increased transfer probability from farmland, forest, shrubland, and grassland to impervious surfaces (+15%), decreased probability from impervious surfaces to other types (-10%) - **Ecological Protection:** Increased conversion probability from grassland to forest (+10%) and bare land to forest/grassland (+15%), decreased probability from forest/grassland to impervious surfaces (-20%), strict prohibition of habitat degradation - **Farmland Protection:** Restricted conversion of farmland to other types and impervious surface expansion, reduced transfer probability from farmland to impervious surfaces (-20%)

Table 5 Changes of land use type area in Ebinur Lake Basin under different scenarios in 2030

Land Use Type	Natural Development (km^2)	Urban Development (km^2)	Ecological Protection (km^2)	Farmland Protection (km^2)
Farmland	2805.60	2805.60	2596.30	2930.11
Forest	1543.20	1543.20	1689.75	1543.20
Grassland	17881.50	17881.50	18016.37	17881.50
Water	952.11	952.11	952.11	952.11
Impervious Surface	152.11	245.10	133.54	133.54
Bare Land	1781.15	1693.05	1729.55	1655.64

Simulation results show grassland and bare land remain the dominant types across all scenarios. Compared to 2020, ecological protection scenario increases forest (+146.55 km^2) and grassland (+134.87 km^2) while decreasing impervious surfaces (-18.57 km^2) and bare land (-51.60 km^2). Urban development scenario increases impervious surfaces by 93.57 km^2, while farmland protection scenario increases farmland by 124.51 km^2 and decreases impervious surfaces by 18.66 km^2.

Table 6 Landscape ecological risk levels of Ebinur Lake Basin in 2030

Risk Level	Natural Development (km^2)	Urban Development (km^2)	Ecological Protection (km^2)	Farmland Protection (km^2)
Low	1185.50	1110.80	1296.72	1159.19
Relatively Low	20459.90	20374.15	20547.48	20545.65
Moderate	6814.30	6890.00	6726.48	6904.93
Relatively High	1903.80	1976.42	1811.28	1864.21

Risk Level	Natural Development (km^2)	Urban Development (km^2)	Ecological Protection (km^2)	Farmland Protection (km^2)
High	952.11	954.24	933.73	978.43

Landscape ecological risk distribution patterns under different scenarios remain similar to historical distributions (Figure 9). Compared to natural development, ecological protection scenario shows decreased risk: low risk area increases by 111.22 km^2, high risk area decreases by 18.38 km^2. Urban development scenario shows minimal change, while farmland protection scenario shows slight risk increase with high risk area expanding by 26.31 km^2. This may result from extensive farmland management causing fragmentation and altered ecological structure, increasing landscape vulnerability.

3. Discussion

Land use changes and landscape ecological risks in the Ebinur Lake Basin are driven by multiple factors. While socioeconomic factors dominate, they operate within natural geographical constraints. The basin' s low, unevenly distributed precipitation, dry climate, and soil conditions directly affect land resource utilization. Population growth and economic changes are primary drivers, hence selecting population, GDP, and roads as driving factors.

Results show continuously rising landscape ecological risk from 1990 to 2020, consistent with previous studies [39,42]. Multi-scenario predictions indicate ecological protection scenario mitigates risk compared to natural development, urban development, and farmland protection scenarios, aligning with many scholars' findings [39,42].

Based on spatiotemporal risk characteristics, we propose recommendations: (1) Optimize land use structure through water transfer projects and efficient water use, increasing forest and grassland coverage to enhance landscape dominance and connectivity while reducing fragmentation. (2) Regulate farmland expansion to prevent forest and grassland degradation, standardize new farmland development, and improve management of existing farmland for sustainable agriculture. (3) Adjust future scenarios according to local conditions, strengthening protection of key ecological functional zones like the Ebinur Lake natural reserve for sustainable economic and ecological development. (4) Strictly control construction land development and strengthen ecological land protection around urban areas based on urban development scenario results.

Model simulation involves some subjectivity and could be combined with other models to improve credibility. Additionally, land use change is influenced by multiple factors, and more comprehensive driving factors should be considered.

4. Conclusions

1) Grassland and bare land dominate the Ebinur Lake Basin, covering over 70% of the area, while shrubland and wetland occupy relatively small areas. From 1990 to 2020, farmland and impervious surfaces expanded significantly while grassland decreased, representing the main land use conversions.
2) The global Moran' s I for landscape ecological risk from 1990 to 2020 was significantly positive, indicating clustering effects with a "low at edges, high in center" pattern. Risk continued rising then stabilized, dominated by relatively low and moderate risks, with overall transition from low to high risk levels.
3) Simulations show land use type changes in the Ebinur Lake Basin will stabilize by 2030, with grassland and bare land remaining dominant.
4) Landscape ecological risk distribution under different 2030 scenarios aligns with historical patterns. Compared to natural development, ecological protection scenario reduces risk, urban development scenario shows minimal change, and farmland protection scenario slightly increases risk. Overall, the ecological protection scenario helps mitigate basin landscape ecological risk while maintaining socioeconomic development, better aligning with sustainable development needs.

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