Multi-scenario Landscape Ecological Risk Assessment and Prediction Based on the FLUS-Markov Model: A Case Study of Kezhou, Southern Xinjiang (Postprint)

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Abstract

Taking Kizilsu Kirghiz Autonomous Prefecture (Kizhou) in Xinjiang as a case study, this research predicted the land use patterns in 2025 using the FLUS-Markov hybrid model based on spatial pattern changes of land use from 2005 to 2015. The CRITIC (Criteria Importance Through Intercriteria Correlation) weighting method was employed to construct landscape ecological risk indices under natural growth and ecological protection scenarios, which were then classified into five levels from low to high (Risk , Risk , Risk , Risk , and Risk) using the natural breaks method. The risk index centroid and standard deviation ellipse were utilized to evaluate spatiotemporal patterns and variation characteristics of landscape ecological risk across different years and multiple scenarios, and to investigate the driving factors influencing its evolution. The results indicate that: (1) Under the natural growth scenario, the areas of cultivated land, water bodies, and construction land continuously increased, while those of forest land, grassland, desert, and bare land gradually decreased; under the ecological protection scenario, grassland area increased by 51 km^2 compared with the natural growth scenario. (2) From 2005 to 2025, the overall landscape ecological risk in Kizhou exhibited a decreasing trend. Compared with the natural growth scenario, the areas of Risk , Risk , and Risk under the ecological protection scenario increased by 34 km^2, 1240 km^2, and 66 km^2, respectively, whereas the areas of Risk and Risk decreased by 695 km^2 and 645 km^2, respectively. (3) From 2005 to 2025, under the natural growth scenario, Risk , Risk , Risk , and Risk in Kizhou displayed a diffused distribution pattern, while Risk demonstrated a compact contraction pattern. (4) The primary factor driving the evolution of landscape ecological risk is topographic and climatic factors (with explanatory power exceeding 85%), followed by population (with explanatory power exceeding 59%) as another important driving factor, while

the contribution of GDP to landscape ecological risk change diminished.

Full Text

FLUS-Markov Model-Based Multiscenario Evaluation and Prediction of Landscape Ecological Risk in Kezhou, South Xinjiang

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Abstract

Taking the Kirgiz Autonomous Prefecture of Kizilsu (Kezhou) in Xinjiang as a case study, this research employs an FLUS-Markov composite model based on land use spatial pattern changes from 2005 to 2015 to predict land use conditions in 2025. The Criteria Importance Through Intercriteria Correlation (CRITIC) weight method was used to construct landscape ecological risk indices under natural growth and ecological protection scenarios, with risk levels divided into five grades (Risk I–V from low to high) using the natural breakpoint method. Risk index centroids and standard deviation ellipses were applied to evaluate spatiotemporal patterns and variation characteristics of landscape ecological risk across different years and scenarios, and to explore the driving factors influencing these evolutionary characteristics.

Results indicate that: (1) Under the natural growth scenario, areas of cultivated land, water bodies, and construction land continuously increase, while woodland, grassland, desert, and bare land gradually decrease. Under the ecological protection scenario, grassland area increases by 51 km^2 compared with the natural growth scenario. (2) From 2005 to 2025, the overall landscape ecological risk in Kezhou shows a decreasing trend. Compared with the natural growth scenario, the ecological protection scenario shows increases of 34 km^2, 1240 km^2, and 66 km^2 in Risk I, II, and IV areas respectively, and decreases of 695 km^2 and 645 km^2 in Risk III and V areas respectively. (3) From 2005 to 2025, Risk I, II, IV, and V in Kezhou exhibit a diffused distribution pattern, while Risk III shows a compact contraction pattern. (4) The primary factors influencing landscape ecological risk evolution are topographic and climatic factors (interpretive power >85%), followed by population (interpretive power >59%) as another important driving factor, while the contribution of GDP to landscape ecological risk changes has decreased.

Keywords: land use; FLUS-Markov model; landscape ecological risk index; scenario simulation; driving force; Xinjiang

Introduction

With accelerating urbanization and intensifying human activities, landscape patterns face increasing stress and disturbance, exerting nearly irreversible impacts on the structure, quality, and function of native ecosystems. Landscape ecological risk assessment can select indicators from natural foundations and ecological landscape perspectives as evaluation factors for regional landscape ecological risk, establishing comprehensive evaluation models at the most appropriate scales to quantitatively assess the adverse ecological impacts arising from interactions between landscape patterns and ecological processes. Land use impacts on ecosystems exhibit cumulative and regional characteristics, directly reflected in ecosystem structure and composition, and indicating the manner and degree of human influence on natural ecosystems.

Currently, Future Land Use Simulation (FLUS) is a land use prediction model based on cellular automata that can effectively simulate land use under different years and scenarios according to transformation rules and quantitative relationships between various driving factors and land use types, using roulette wheel selection algorithms. However, this model lacks simulation of land use quantity requirements. The Markov model focuses on temporal dimension analysis of land use change prediction, offering advantages in long-term quantity prediction efficiency. Combining the FLUS and Markov models can improve both the accuracy of land use quantity demand prediction and the simulation of spatial distribution under multiple scenarios, fully leveraging the strengths of both models in quantity prediction and spatial distribution to achieve dual simulation of land use in both space and quantity.

Weight assignment for landscape ecological risk indicators is an indispensable component of evaluation, where inappropriate methods can directly influence results and increase uncertainty. Most current studies assign weights based on expert experience and judgment, but objective assignment methods determined by actual regional data calculations remain underexplored. While weight assignment methods have no inherent superiority in terms of universality, appropriate methods must be selected according to research objectives. However, many landscape ecological risk evaluations focus on calculating landscape pattern indices while ignoring correlations among indices, affecting the applicability of risk assessment results. Therefore, to screen and construct optimal landscape pattern indices and effectively reduce subjective human influence, this study employs the CRITIC weight method for objective assignment of multiple indicators based on research objectives and the ecological significance of landscape indices, combined with study area characteristics.

This research uses 2005, 2010, and 2015 land use data as a foundation to predict land use changes in 2025 under natural growth and ecological protection scenarios using the FLUS-Markov composite model. The CRITIC method is applied to construct landscape ecological risk indices, and spatial interpolation is performed using the inverse distance weighting method to evaluate spatiotemporal patterns and variation characteristics of landscape ecological risk under different years and scenarios. Geodetector is used to analyze the contribution of different driving factors to landscape ecological risk changes. This study provides theoretical and methodological references for landscape ecological risk assessment and offers scientific foundations for territorial spatial planning and decision-making in Xinjiang, contributing to sustainable development of Xinjiang' s ecological environment.

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1. Study Area and Data Sources

1.1 Study Area Overview Kezhou is located in southwestern Xinjiang Uygur Autonomous Region (Fig. 1), spanning the southwestern Tianshan Mountains, eastern Pamir Plateau, northern slopes of the Kunlun Mountains, and the northwestern margin of the Tarim Basin. With relatively backward economic development and prominent ecological problems, Kezhou' s ecological environment index is lower than Xinjiang' s overall level. The prefecture borders Kyrgyzstan and Tajikistan to the north and west with a borderline of 1,195 km, connects to Aksu Prefecture in the east, and adjoins Kashgar Prefecture in the south. The prefecture extends 500 km from east to west and 140 km from north to south, covering approximately 72,500 km^2. The climate is typical temperate continental, characterized by abundant sunlight, aridity, cold winters, hot summers, short spring and autumn seasons, and variable temperatures. Climate differences are extreme with obvious vertical responses and relative temperature variations of 16.6°C.

This study selects Kezhou as the research area due to its diverse topography, varied landforms, rich landscape types, but relatively fragmented overall landscape patterns with low stability, poor resilience, and fragile ecological environment that changes rapidly and significantly under human activities and natural disturbances.

1.2 Data Sources and Processing All data used in this study (Table 1) were obtained from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/). Based on the "Current Land Use Classification Standard" (GBT 21010-2017) and considering Kezhou' s natural environment characteristics and research requirements, land use types were reclassified. Unused land was divided into desert and bare land, resulting in seven final categories: cultivated land, woodland, grassland, water bodies, construction land, desert, and bare land.

Selected driving factors for simulating land use change include topographic, climatic, and socioeconomic factors. Topographic factors include elevation and slope; climatic factors include temperature and precipitation; socioeconomic factors include population and GDP. All data were resampled to 30 m × 30 m resolution and projected to the Albers coordinate system.

2. Methods

2.1 FLUS-Markov Model Configuration

2.1.1 Land Use Scenario Settings According to Xinjiang' s territorial spatial planning requirements, this study simulated two scenarios: natural growth and ecological protection. By modifying the input parameters of the FLUS-Markov model, the spatial distribution of various land use types in 2025 under both scenarios was estimated. The natural growth scenario allows land use types to evolve naturally under current conditions without deliberate intervention. The ecological protection scenario designates ecological protection areas, strengthens conservation of ecological land such as woodland, grassland, and water bodies, and reduces the expansion capacity of other land use types.

The FLUS-Markov model operates through the following steps: (1) Set restricted areas. Based on actual conditions, this study sets no restricted areas, allowing land use conversion. (2) Calculate future land use areas. Using 2005 and 2015 data as base periods, the Markov model calculates the area of each land use type in 2025. (3) Input land use change driving data. Selected driving factors include topographic, climatic, and socioeconomic aspects totaling six factors. (4) Set transition matrix and neighborhood factor parameters. The transition matrix indicates whether conversion between land use types is prohibited (0) or allowed (1). Neighborhood factor parameters represent the difficulty of converting a land use type to others, with parameter ranges of 0–1; higher values indicate stronger expansion capacity. This study focuses on two scenarios with identical parameter settings as control variables.

Model accuracy was verified using Overall Accuracy and Kappa coefficient. The simulation results achieved Overall Accuracy of 97.70% and Kappa coefficient of 96.48%, meeting research requirements.

2.2 Construction of Landscape Ecological Risk Index Landscape indices highly concentrate landscape pattern information and can be used to analyze various ecological processes at different scales, reflecting ecological landscape structure characteristics and evolution. Building upon previous landscape ecological risk assessment research and considering study area characteristics and the ecological significance of landscape indices, this study reconstructed the landscape fragmentation index, landscape separation index, and landscape dominance index through repeated experimental calculations, eliminating duplicate and minor values (Table 2).

Using landscape ecology methods, landscape structure indices (landscape fragmentation index, landscape separation index, landscape dominance index), landscape vulnerability index, and landscape loss index were selected to construct the landscape ecological risk index (ERI) as a risk evaluation indicator, characterizing spatial differentiation and pattern changes of landscape ecological risk in Kezhou. Field surveys and comparisons with concurrent land use change data confirm that selected indices effectively reflect actual conditions. Based on the distribution characteristics of landscape ecological risk index values, the natural breakpoint method was used to divide landscape ecological risk into five levels: low ecological risk (Risk I), relatively low ecological risk (Risk II), medium ecological risk (Risk III), relatively high ecological risk (Risk IV), and high ecological risk (Risk V).

Since the constructed landscape ecological risk index is a spatial variable, to compensate for the limitation of using averages to express regional landscape distribution, spatial interpolation was performed using the inverse distance weighting method to 绘制生态风险级别图. Referencing the national grid standard "Geographic Grid" (GB12409—2009), grids should adopt 2-5 times the average patch area. Based on Kezhou' s land use type area, coverage, workload, and spatial information integrity, creating a 5 km × 5 km fishnet dividing the study area into 2,900 evaluation units effectively distinguished spatial homogeneity and heterogeneity.

2.3 Landscape Ecological Risk Centroid and Standard Deviation Ellipse The centroid is an important indicator describing the spatial distribution of geographic phenomena. Changes in landscape ecological risk centroid migration can effectively describe spatiotemporal evolution characteristics from a spatial perspective. By understanding the distribution of centroids for different risk levels in various periods, the changing trends of landscape ecological risk can be identified. The standard deviation ellipse method is a classic approach for analyzing spatial distribution directionality, where the ellipse size reflects the concentration degree of overall spatial pattern elements, and the long semi-axis reflects the dominant direction of the pattern. This study uses centroid offset to determine the expansion direction of landscape ecological risk in Kezhou and verifies the expansion direction through the standard deviation ellipse method.

2.4 Driving Force Analysis of Landscape Ecological Risk Evolution Geodetector can detect spatial stratified heterogeneity and examine the consistency of spatial distributions between variables, serving as a statistical method to reveal underlying driving forces. The factor detector in Geodetector can use factor interpretation power to determine the influence degree of certain factors on landscape ecological risk evolution. This study uses landscape ecological risk index as the dependent variable and driving factors as independent variables, employing the factor detector to obtain contribution values (PD values) of each driving factor to explore their influence degrees. Driving factors include natural factors (climate: temperature, precipitation; topography: elevation, slope) and socioeconomic factors (population, GDP). To avoid spatial autocorrelation and human influence, random sampling was used to generate 2,900 sample points across the study area, extracting landscape ecological risk values and driving factor values at each point for analysis.

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3. Results and Analysis

3.1 Analysis of Current Land Use Change Characteristics From 2005 to 2015, Kezhou' s land use pattern change characteristics were similar to those from 2010 to 2015, with continuously increasing areas of cultivated land, water bodies, and construction land, and gradually decreasing areas of other land use types (Table 4). Specifically, cultivated land, water bodies, and construction land increased by 203 km^2, 10 km^2, and 17 km^2 respectively, while woodland, grassland, desert, and bare land decreased by 2 km^2, 78 km^2, 135 km^2, and 15 km^2 respectively. The study area is dominated by grassland and bare land, accounting for 53.29% and 22.98% of total area respectively, with desert and water bodies comprising 13.22% and 7.94%, and cultivated land, woodland, and construction land occupying extremely small proportions of 1.75%, 0.72%, and 0.09% respectively. This indicates that with continuous urbanization and development of border defense and reclamation in Kezhou, farmland reclamation and urbanization processes persist, desert and bare land areas have declined, water areas have increased, playing a positive role in socio-economic development, yet human activities may have negatively impacted ecological land such as woodland and grassland.

3.2 Landscape Ecological Risk Based on Multiscenario Land Use Change Simulation From 2005 to 2015, landscape ecological risk indices in Kezhou ranged between 12.55–18.64, with a mean value of 15.38. Under the 2025 natural growth scenario, landscape ecological risk indices range between 12.12–19.27 with a mean of 15.24; under the ecological protection scenario, indices range between 12.30–19.27 with a mean of 15.12. From the perspective of maximum, minimum, and mean values, the maximum landscape ecological risk index is increasing while the mean is decreasing, indicating that overall landscape ecological risk in Kezhou declined from 2005 to 2025, though local areas experienced surging risk.

Overall, Kezhou is dominated by Risk III, accounting for 33.31% and 32.87% of total area in natural growth and ecological protection scenarios respectively, with Risk V occupying the smallest relative proportions of 2.09% and 2.32% respectively. Compared with the 2015 natural growth scenario, the ecological protection scenario shows increasing trends in Risk I, II, and IV areas (34 km^2, 1240 km^2, and 66 km^2 respectively) and decreasing trends in Risk III and V areas (-695 km^2 and -645 km^2 respectively). This demonstrates that ecological protection can effectively reduce landscape ecological risk.

3.3 Ecological Risk Centroid and Standard Deviation Ellipse Analysis From 2005 to 2025, the spatial distribution pattern of landscape ecological risk in Kezhou continuously changes (Fig. 4). Risk I, II, IV, and V show expansion trends with more dispersed distribution, while Risk III shows contraction trends with more compact distribution. Specifically, compared with 2015, Risk I and II centroids shifted northeast by 80.53 km and 116.60 km respectively, Risk IV centroid shifted southeast by 51.91 km, and Risk V centroid shifted northwest by 95.35 km. Standard deviation ellipse areas for Risk I, II, IV, and V increased by 25.61 km^2, 16,628.17 km^2, 22,214.74 km^2, and 11,089.56 km^2 respectively, while Risk III standard deviation ellipse area decreased by 3,839.85 km^2.

Compared with the 2025 natural growth scenario, the ecological protection scenario shows Risk I and II centroids shifting southwest by 22.87 km and northwest by 123.77 km respectively, Risk III and V centroids shifting east by 109.88 km and 24.66 km respectively, and Risk IV centroid shifting south by 21.61 km. Standard deviation ellipse areas for Risk I, II, and V increased by 33,031.41 km^2, 25,581.25 km^2, and 19,227.57 km^2 respectively, while Risk III and IV areas decreased by 24,007.07 km^2 and 2,803.68 km^2 respectively. This indicates that the ecological protection scenario can make Risk I, II, and V areas more dispersed and Risk III and IV areas more aggregated.

3.4 Driving Force Analysis of Landscape Ecological Risk Evolution Kezhou' s landscape ecological risk evolution is influenced by natural, economic, and social factors. Using Geodetector software, factor detection analysis was conducted on driving factors of landscape ecological risk evolution from 2005 to 2025 (Table 6). Regarding the influence of each factor on landscape ecological risk values, natural factors' PD values range 0.917-0.941, and socioeconomic factors' PD values range 0.859-0.894. Specifically, temperature (0.938-0.941), elevation (0.925-0.894), and slope (0.917-0.909) all show interpretation power above 85%, indicating that topographic and climatic factors are the primary drivers of landscape ecological risk evolution. Population (0.859-0.894) is also an important factor with interpretation power above 59%, showing that population drives landscape ecological risk evolution. GDP (0.538-0.521) shows interpretation power below 60%, indicating its contribution to landscape ecological risk changes has decreased.

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4. Discussion

The application of the FLUS-Markov composite model achieves dual simulation of land use in both space and quantity, fully leveraging the advantages of both models in spatial distribution and quantity prediction, overcoming the limitations of single models and improving prediction accuracy. However, several key points warrant further exploration:

1) Regarding result accuracy, compared with Zhang Yue et al.' s study using the Markov model to predict land use changes in Ebinur Lake region and research on land use change simulation in Guangzhou, this study fully

considers multiple natural and social factors, thereby improving simulation accuracy. For land use simulation in the same study area, this study' s accuracy is also higher than Yu Tao et al.' s simulation of Kezhou land use in 2025.

2) Regarding research methodology, the selection of driving factors significantly affects model accuracy in multiscenario simulation of future land use. This study analyzes natural and socioeconomic factors, while future land use changes are also deeply influenced by local policies, which could be incorporated in future research to improve FLUS-Markov model simulation accuracy and result interpretability.

3) This study uses the objective CRITIC weighting method to assign values to landscape fragmentation index, landscape separation index, and landscape dominance index. Evaluation results were validated through field surveys and comparison with concurrent land use change data, showing reasonable accuracy. However, future research should further explore the specific impacts of objective versus expert scoring weighting methods on landscape ecological risk assessment results to optimize evaluation outcomes.

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5. Conclusions

This study uses the FLUS-Markov composite model and CRITIC weight method to construct a landscape ecological risk evaluation system, analyzing spatiotemporal evolution characteristics and driving factors of landscape ecological risk in Kezhou from 2005 to 2025. Main conclusions are:

1) From 2005 to 2015, land use pattern changes in Kezhou were similar to those from 2010 to 2015, with continuously increasing areas of cultivated land, water bodies, and construction land, and gradually decreasing areas of other land use types. Under the ecological protection scenario, grassland received effective protection, increasing by 51 km^2 compared with the natural growth scenario.

2) From 2005 to 2025, the overall landscape ecological risk in Kezhou shows a decreasing trend, with ecological protection playing a role in reducing risk. Compared with the 2025 natural growth scenario, the ecological protection scenario shows increases in Risk I, II, and IV areas and decreases in Risk III and V areas.

3) From 2005 to 2025, Risk I, II, IV, and V in Kezhou show diffused distribution patterns, while Risk III shows compact contraction patterns. The ecological protection scenario can make Risk I, II, and V areas more dispersed and Risk III and IV areas more aggregated.

4) Driving force analysis based on Geodetector shows that temperature, precipitation, elevation, and slope have significant effects on landscape eco-

logical risk changes, population is also an important factor affecting landscape ecological risk evolution, while the impact of GDP has not reached a significant level.

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Note: Figure translations are in progress. See original paper for figures.