Multi-scenario landscape ecological risk assessment based on Markov–FLUS composite model

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\textbf{ABSTRACT}

This study analysed the spatial pattern change of land use from 2005 to 2015 in Xinjiang and proposed a Markov–Future Land Use Simulation composite model to predict land-use change by 2025 under natural growth and ecological protection scenarios. The Criteria Importance Through Intercriteria Correlation method was proposed to construct the landscape ecological risk index based on land-use data. By calculating the risk index centroid and standard deviation ellipses, the spatio-temporal patterns and changing characteristics of landscape ecological risk in different scenarios in 2005, 2015, and 2025 were evaluated, and the driving forces of their evolution were also analysed. The results indicated that: (1) The characteristics of land use pattern change under the natural growth scenario from 2015 to 2025 are similar to those from 2005 to 2015. Under an ecological protection scenario, restricting the expansion of construction land, forest land, and grassland, which are the central ecological lands, can be effectively protected. Compared to the natural growth scenario, these areas increased by 507 and 724 km\textsuperscript{2}, respectively. (2) From 2005 to 2015, landscape ecological risk in Xinjiang generally showed a decreasing trend. Compared to the natural growth scenario in 2025, ecological protection can effectively reduce the ecological risk of the landscape. The highest, higher, and medium ecological risks were reduced by 0.39\%, 3.11\%, and 4.43\%, respectively, while the areas with the lowest and lower ecological risks increased by 0.16\% and 7.77\%, respectively. (3) Under the natural growth scenario from 2005 to 2025, the centroid of landscape ecological risk in Xinjiang generally shifted to the southwest. To some extent, the ecological protection scenario can make the distribution of the highest, the higher, and the medium ecological risk areas more dispersed and the distribution of the lower ecological risk areas more concentrated. (4) Temperature is positively correlated with landscape ecological risk, while rainfall, Digital Elevation Model, slope, and aspect are negatively correlated with landscape ecological risk. There is also a correlation between soil types and landscape ecological risk. This research can reference the theory and method of landscape ecological risk and provide decision support for the sustainable development of the ecological environment of Xinjiang.

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1. Introduction

Landscape ecological risk refers to the adverse effects of the interaction between landscape patterns and ecological processes under the influence of natural or human factors (Li et al. 2019). With the constant change in the global climate and the increasing intensity and scope of human activities, landscape patterns are increasingly subject to stress and interference. Thus, landscape ecological risk assessment has received more and more attention as an essential means to assess and predict the adverse effects of natural and human activities on the ecological environment (Satir et al. 2016; Yang et al. 2016; Cao et al. 2018). The impact of land use on ecology is cumulative and regional, which can be directly reflected in the structure and composition of the ecosystem to reflect how and the degree to which human activities impact the natural ecosystem (Xu et al. 2011). In recent years, concentrating on different regions and research purposes, many scholars have selected relevant indicators, methods, and models to carry out a large number of practical studies on landscape ecological risk assessment (Sun and Liu 2011; Xie et al. 2014; Liu et al. 2015; Shi et al. 2015; Pan and Liu 2016; Li et al. 2017; Mo et al. 2017). However, few studies on using the model to simulate the future multi-scenario land-use change and evaluate its landscape ecological risk consider the time and space scales. Meanwhile, the weight assignment of the landscape ecological risk index is a vital link in the evaluation process. Improper application of the method may directly affect the distribution characteristics of the evaluation results and thus may significantly increase the uncertainty of the evaluation results (Peng et al. 2015). At present, most research is based on the experience and judgment of scholars to assign weight subjectively. At the same time, there are relatively few studies on objective assignment methods according to the results of the calculation of specific regional data. The weight assignment method is neither absolutely good nor bad in terms of universality. However, it is necessary to choose an appropriate way according to the research purpose. At present, some landscape ecological risk assessments have become a simple calculation and accumulation of the landscape pattern index (Liu et al. 2014; Huang and He 2016; Zhang et al. 2016; Xie et al. 2017; Liu et al. 2018; Lv et al. 2018; Xie et al. 2018; Lou et al. 2020), which directly leads to a decrease in the applicability and credibility of the risk assessment results.

At present, landscape ecological risk assessment can be divided into two evaluation methods: risk sources and sink and those on landscape patterns. The latter, to some extent, breaks the inherent mode of traditional ecosystem evaluation and directly evaluates landscape ecological risk from the perspective of spatial patterns on a regional scale. The research focus of this system is to carry out an ecological risk assessment with land-use change as the incentive (Peng et al. 2015). The Future Land Use Simulation (FLUS) model (Liu et al. 2017) is a land-use prediction model based on cellular automata, which uses a roulette selection algorithm. The FLUS model can effectively simulate the spatial pattern of land use in different years and under scenarios according to the quantitative relationship and transformation rules between various driving factors and land use types and can carry out the spatial distribution of simulated land use (Cao et al. 2019; Qin et al. 2019; Wang et al. 2019). However, this model lacks the simulation of land use quantity, and so this needs to be
calculated by other models or methods. For instance, the Markov model can effectively predict the amount of land use. Combining the Markov and FLUS models can improve the prediction accuracy of land use quantity and effectively simulate the spatial change of land use under multiple scenarios (Zhu et al. 2019). The advantages of the two models in terms of quantity prediction and spatial distribution enable us to realize the dual simulation of land use in space and quantity. This study uses the Criteria Importance Though Intercriteria Correlation (CRITIC) (Wang and Song 2003) method to objectively assign values to multiple indicators, according to the purpose of the study and the ecological significance of the landscape index through repeated experiments, to construct the landscape ecological risk index.

This article chooses Xinjiang, China, as the research area. This area has a sizeable topographic fluctuation and diverse landform and landscape types, but the overall landscape pattern is relatively broken, with poor stability and resilience. Its ecological environment is fragile and changes rapidly and obviously under human activities and natural disturbance. Thus, it is a hotspot for studying geography (Li et al. 2006; Sun et al. 2006; Gao et al. 2010; Yu et al. 2011; Chen et al. 2015). Because of this, this study uses the Markov–FLUS composite model to predict land-use change under the natural growth and ecological protection scenarios in 2025 based on the land use data of Xinjiang in 2005 and 2015. Furthermore, we use the CRITIC method to construct landscape ecological risk index. By calculating the risk index centroid and standard deviation ellipses, the spatial and temporal pattern and change characteristics of landscape ecological risk in different scenarios from 2005 to 2025 are evaluated. The driving forces of their evolution are analysed. This study can provide some reference for the theory and method of landscape ecological risk assessment. It can also provide a scientific basis for land use planning and decision-making in Xinjiang to help realize the sustainable development of Xinjiang’s ecological environment.

2. Study area and data

2.1. Study area overview

Xinjiang is located between longitude 73°40′–96°18′ east and latitude 34°25′–48°10′ north (Figure 1). Mountains and basins alternate in Xinjiang. The Tianshan mountains lie in Xinjiang, dividing the region between the north and the south. The Altai Mountains and the Tarim Basin area in the north, while the Kunlun mountains and the Junggar Basin area in the south. People are accustomed to calling the area south of the Tianshan Mountains in Xinjiang as Southern Xinjiang and north of the Tianshan Mountains as Northern Xinjiang. Aiding Lake in Turpan, the lowest point in Xinjiang is 155 m below sea level. The highest point, K2, on the Kashmir border, is 8611 m above sea level. The Gurbantunggut Desert in Xinjiang Province is the farthest point on land from the ocean, at 2648 km from the nearest coastline. Xinjiang is far from the sea, surrounded by high mountains; therefore, it is difficult for ocean airflow to reach Xinjiang, forming a temperate continental climate. Xinjiang has a significant temperature difference, low precipitation (150 mm per year), and sufficient sunshine time (2500–3500 h per year). However, there is a big difference between the
north and the south areas of Xinjiang. The temperature in the south is higher than that in the north, and the precipitation in the north is higher than that in the south. In the coldest month (January), the average temperature in Junggar Basin is below minus 20 °C, and the absolute lowest temperature in Fuyun County on the northern edge of the basin has reached −50.15 °C, which is one of the coldest regions in China. In the hottest month (July), the average temperature in Turpan is above 33 °C, and the absolute highest temperature has reached 49.6 °C, ranking the highest in the country. Xinjiang is rich in biological types, but the ecological environment is relatively fragile, and the landscape pattern is complex.

Xinjiang is China’s largest provincial-level administrative region, with a total area of 1.66 million km². Furthermore, Xinjiang borders Russia, Kazakhstan, Kyrgyzstan, Tajikistan, Pakistan, Mongolia, India, and Afghanistan, with more than 5000 km. Historically, Xinjiang was an essential passage along the ancient silk road and is now the only place to pass the second Eurasian land bridge. With the development of China’s “One Belt and One Road,” its strategic position is very prominent.

2.2. Data source and processing

All of the data in this article are from the Resource and Environment Data Cloud Platform (http://www.resdc.cn/). According to the classification standard of land use and the actual situation in Xinjiang, this article divided the land into nine categories: arable land, forest land, grassland, water, glaciers, construction land, sandy, Gobi, and other unused lands. The spatial resolution of the land use data is 1 km.
The selected land-use change drivers include topographic, meteorological, soil, and socio-economic factors. Topographic factors include elevation, slope, and aspect, extracted from Digital Elevation Model (DEM) data; meteorological factors include temperature and precipitation; soil factors include soil types, and socio-economic factors include population distribution and Gross Domestic Product (GDP). The above data were all resized to 1 km, and the projection method was uniformly transformed to Albers. This adjustment was to standardize the input parameters of the model without any other adverse effects. A detailed description of the data can be seen in Table 1.

| Data type             | Data content                          | Time of data | Data resolution | Data use          |
|-----------------------|---------------------------------------|--------------|-----------------|-------------------|
| Land use data         | Land-use type                         | 2005, 2015   | 1 × 1 km        | Model base input data |
| Topographic data      | Elevation                             | 2005, 2015   | 30 × 30 m       | Driving factor    |
|                       | Slope                                 |              |                 |                   |
|                       | Aspect                                |              |                 |                   |
| Meteorological data   | Temperature                            | 2005, 2015   | 1 × 1 km        | Driving factor    |
|                       | Precipitation                         |              |                 |                   |
| Soil data             | Soil type                             |              |                 | Driving factor    |
| Socio-economic factors| Population distribution               | 2005, 2015   | 1 × 1 km        | Driving factor    |
|                       | Gross domestic product (GDP)          |              |                 |                   |

3. Methods

3.1. Land use change prediction based on Markov–FLUS composite model

By modifying the input parameters of the FLUS model, this study estimated the land type area under the natural growth and ecological protection scenario of Xinjiang in 2025. The natural growth scenario refers to the genuine change of land use type according to the actual conditions without deliberate change. The ecological protection scenario refers to strengthening forest land, grassland, water, glaciers, and other ecological lands while weakening the expansion capacity of the other land types.

The running of the Markov–FLUS composite model includes the following aspects:

a. Setting of restricted areas. According to the actual situation of the research area, some ecological function protection areas were chosen as the restricted area, and the conversion of land use was forbidden.

b. Calculating future land use area. Based on 2005 and 2015, this study used the Markov model to calculate land use in Xinjiang in 2025.

c. Inputting land use change-driven data. The selected driving factors include terrain, meteorology, soil, and social economy.

d. Setting the transition matrix and weight of the neighbourhood. The transition matrix is represented by 0 and 1. When one land type is not allowed to be converted to another, we set the corresponding value of the matrix to 0, and when the conversion is allowed, it was set to 1. The weight of the neighbourhood was used to indicate how easy it is for one class to convert to another. Its parameter range 0–1, and the larger the value, the stronger the expansion capacity of the land. Based on the simulation results and the actual situation in Xinjiang, the
transfer matrix and weight of the neighbourhood of natural growth and ecological protection were set as follows (Tables 2 and 3) in this study through multiple experiments.

e. Verifying model accuracy. This study used the model to simulate the land use situation in 2015 based on the land use data in 2005 and compared it with the actual situation. The Overall Accuracy, Kappa coefficient, and Figure of Merit (FoM) values were used to verify the accuracy of the simulation results. The larger the Overall Accuracy and the Kappa coefficient, the higher the simulation accuracy. FoM is the matching rate, and the smaller the value, the more accurate it is. The Overall Accuracy and Kappa coefficient of the simulation results were 89.4% and 88.1%, respectively, and the FoM was only 0.03, which met the research needs.

3.2. Construction of the landscape ecological risk index based on the CRITIC weight method

The landscape index highly condenses landscape pattern information and can analyse various ecological processes at different scales to reflect the structural characteristics and evolution of ecological landscape (Achilleos 2011). According to the purpose of the study and the ecological significance of the landscape index, the following

Table 2. The transition matrix and weight of the neighbourhood in the natural growth scenario.

| Name            | Arable land | Forest land | Grassland | Water | Glaciers | Construction land | Sandy land | Gobi | Other unused lands |
|-----------------|-------------|-------------|-----------|-------|----------|--------------------|------------|------|-------------------|
| Arable land     | 1           | 1           | 1         | 1     | 1        | 1                  | 1          |      |                   |
| Forest land     | 1           | 1           | 1         | 1     | 1        | 1                  | 1          |      |                   |
| Grassland       | 1           | 1           | 1         | 1     | 1        | 1                  | 1          |      |                   |
| Water           | 1           | 1           | 1         | 1     | 1        | 1                  | 1          |      |                   |
| Glaciers        | 1           | 1           | 1         | 1     | 1        | 1                  | 1          |      |                   |
| Construction land| 1         | 1           | 1         | 1     | 1        | 1                  | 1          |      |                   |
| Sandy land      | 1           | 1           | 1         | 1     | 1        | 1                  | 1          |      |                   |
| Gobi            | 1           | 1           | 1         | 1     | 1        | 1                  | 1          |      |                   |
| Other unused lands | 1        | 1           | 1         | 1     | 1        | 1                  | 1          |      |                   |
| Weight of the neighbourhood | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

Table 3. The transition matrix and weight of the neighbourhood in the ecological protection scenario.

| Name            | Arable land | Forest land | Grassland | Water | Glaciers | Construction land | Sandy land | Gobi | Other unused lands |
|-----------------|-------------|-------------|-----------|-------|----------|--------------------|------------|------|-------------------|
| Arable land     | 1           | 1           | 1         | 1     | 1        | 0                  | 0          | 0    |                   |
| Forest land     | 1           | 1           | 1         | 1     | 1        | 0                  | 0          | 0    |                   |
| Grassland       | 1           | 1           | 1         | 1     | 1        | 0                  | 0          | 0    |                   |
| Water           | 1           | 1           | 1         | 1     | 1        | 0                  | 0          | 0    |                   |
| Glaciers        | 1           | 1           | 1         | 1     | 1        | 0                  | 0          | 0    |                   |
| Construction land| 1         | 1           | 1         | 1     | 0        | 1                  | 1          | 1    |                   |
| Sandy land      | 1           | 1           | 1         | 1     | 1        | 1                  | 1          | 1    |                   |
| Gobi            | 1           | 1           | 1         | 1     | 1        | 1                  | 1          | 1    |                   |
| Other unused lands | 1        | 1           | 1         | 1     | 1        | 1                  | 1          | 1    |                   |
| Weight of the neighbourhood | 1 | 1 | 1 | 1 | 0.1 | 0.1 | 0.1 | 0.1 | 1 |

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Table 4. Calculation methods of landscape pattern indexes.

| Name                           | Landscape indexes                                      | Ecological meaning                                                                                                                                 |
|--------------------------------|--------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------|
| Landscape fragmentation index | Edge density (ED); area-weighted mean shape index (AWMSI) | ED is used to reveal the extent of landscape segmentation, a direct reflection of landscape fragmentation. AWMSI is one of the critical indexes used to measure the complexity of landscape spatial patterns. It also has another significant ecological significance in terms of the shape analysis of natural landscapes, i.e. the edge effect. |
| Landscape isolation index (Ni)| Patch cohesion index (COHESION); aggregation index (AI); interspersion juxtaposition index (UI) | COHESION describes the reunion degree or extending trend in different landscape patches. AI is derived from the calculation of the adjacent matrix at the level of patch type, which is one of the essential indexes used to reflect the degree of landscape aggregation and separation. UI reflects the distribution characteristics of those ecosystems that are severely restricted by certain natural conditions. |
| Landscape dominance index (Di)| Largest patch index (LPI)                              | LPI helps to determine the dominant type of landscape. Its value determines the ecological characteristics, such as the abundance of dominant and internal species in the landscape. A change in its value can change the intensity and frequency of disturbance and reflect the direction and strength of human activities. |
| Landscape structure index      | $S_i = a(ED) + b(AWMSI) + c(COHESION) + d(AI) + e(UI) + f(LPI)$ | This reflects the loss of disturbance to the ecosystem represented by different landscapes, where $a, b, c, d, e,$ and $f$ are the weights of the corresponding landscape index. |
| Landscape vulnerability index   | Score by expert                                         | This represents the sensitivity of different landscape types to external disturbance. The greater the value, the greater the ecological risk. The fragility of a landscape is related to its stage in the natural succession of landscapes. Based on the characteristics of the research area, this article assigned values of nine landscape types from high to low in the order of their vulnerability: 9, other unused lands; 8, Gobi; 7, sandy land; 6, water areas; 5, glaciers; 4, arable land; 3, grassland; 2, forest land; and 1, construction land. |
| Landscape loss index (Ri)      | $R_i = \sqrt{S_i} \times F_i$                          | This shows the extent to which different ecosystems lose their natural attributes when they are disturbed by the outside world. |
| Landscape ecological risk index| $ER_i = \sum_{i=1}^{n} \frac{A_k}{A_k} R_i$           | This represents the relative magnitude of ecological loss within an evaluation unit, where $ER_i$ is the landscape ecological risk index of the $i$ evaluation unit; $A_k$ is the area of landscape type $i$ in the $k$ evaluation unit, and $A_k$ is the area of the $k$ evaluation unit. |
indicators were selected to construct the landscape ecological risk index (as shown in Table 4). When constructing the landscape ecological risk index, to effectively reduce subjective factors, the CRITIC weight method was used to assign values to multiple indicators. The CRITIC weight method is objective, and its idea is to use two indicators, i.e. the comparison intensity and the conflicting index. The comparison intensity is expressed by standard deviation, and the larger the standard deviation, the higher the weight. The correlation coefficient represents conflict. The higher the correlation value between indicators, the smaller the conflict and the lower the weight. After the weight was calculated, the contrast intensity and the conflicting index were multiplied and normalized to obtain the final weight (Table 5).

The constructed landscape ecological risk index is a spatial variable. In order to better study temporal and spatial evolution, the study area was divided into 100 evaluation units by creating a 10-row × 10-column fishing net. The ecological risk index of each evaluation unit was then calculated, and spatial interpolation was carried out using the inverse distance weight method to draw the ecological risk level map.

### 3.3. Landscape ecological risk centre of mass and standard deviation ellipse

The centroid is a crucial index to describe the spatial distribution of geographical phenomena. The mass centre migration of landscape ecological risk can describe its spatial and temporal evolution. By understanding the centroid distribution of different ecological risk levels in different periods, the variation trend of landscape ecological risk can be found. The standard deviation ellipse method is one of the classical methods to analyse the directivity of spatial distribution. The size of the ellipse reflects the concentration of the overall elements of the spatial pattern, and the deviation angle reflects the dominant direction of the pattern. In order to better describe the spatial characteristics of ecological risk, we use the standard deviation ellipse to summarize them, including its major trend, dispersion degree, and direction trend. Therefore, centroid and standard deviation ellipse analyses were applied to the study of landscape ecological risk to explore their evolution characteristics.

### 3.4. Analysis of the driving force of landscape ecological risk evolution

In this article, the Xinjiang landscape ecological risk index was taken as the dependent variable and the driving factor as the independent variable. Linear regression analysis was performed on each variable, and the correlation index was calculated to
explore the driving factors of landscape ecological risk in Xinjiang. The selection of driving factors includes natural factors and social and economic factors, with natural factors including meteorology (i.e. temperature and rainfall), topography (i.e. DEM, slope, and aspect), and soil (i.e. soil type), while social and economic factors include population and GDP. In order to avoid the influence of data space autocorrelation and human factors, we use a random sampling method to generate 1000 sample points in the research area, and the ecological risk and driving factor values of each point were extracted for regression analysis and correlation calculation.

4. Results and analyses

4.1. Analyses of the characteristics of land use change

Table 6 is the land-use area table of Xinjiang from 2005 to 2025. As shown in Table 6, the land use types in Xinjiang in 2015 were mainly grassland, sandy land, Gobi, and other unused lands, with area proportions of 28.57%, 21.20%, 17.42%, and 22.22%, respectively. Arable land, forest land, and glaciers followed (with 4.74%, 2.27%, and 2.35%, respectively), while water and construction land accounted for a tiny proportion (i.e. 0.82% and 0.41%, respectively). On the whole, arable land, glaciers, and construction land in Xinjiang increased by 16.13%, 0.19%, and 41.01%, respectively, from 2005 to 2015. However, forest land, grassland, water, sandy land, Gobi, and other unused land areas showed a decreasing trend (i.e. −2.13%, −1.29%, −0.11%, −0.28%, −0.80%, and −0.70%, respectively). Thus, in the past 10 years, from 2005 to 2015, with the continuous development of urbanization and border areas, Xinjiang has cultivated farmland and thus accelerated the urbanization process, which has played a positive role in promoting Xinjiang’s social and economic development. At the same time, the harsh ecological environment in Xinjiang has been improved to some extent as the area of sandy land, and Gobi desert has decreased. However, under the influence of global warming and drought, Xinjiang’s water area has been shrinking. Human activities also harm forest land and grassland.

Figure 2 shows the simulation results of land use under different scenarios in Xinjiang in 2025. As shown in Figure 2 and Table 5, the arable land area in 2025 did not change under the natural growth and ecological protection scenarios. However, the total area increased by 10,409 km² (13.49%) compared to that in 2015. As the
main ecological land types, forest land and grassland showed a declining trend from 2015 to 2025. However, under the scenario of ecological protection, the areas were effectively protected, increasing by 507 (1.40%) and 724 km² (0.16%), respectively, compared to the natural growth scenario. Under the natural growth scenario, construction land showed an apparent increasing trend, increasing by 1991 km² (29.98%), while under the ecological protection scenario, the expansion rate slowed down, only increasing by 760 km² (11.45%). However, water, glaciers, sand, Gobi, and other unused areas did not change significantly in either scenario, but all areas except glaciers declined compared to 2015. Thus, land use pattern changes from 2015 to 2025 are similar to those from 2005 to 2015. Arable land, glaciers, and construction land show an increasing trend, while the other types of land show a decreasing trend. In the context of environmental protection, forest land and grassland can be effectively protected by restricting the expansion of construction land.

4.2. Assessment of landscape ecological risk

The ecological risk index of 100 evaluation units in the research area was calculated under the natural growth scenario in 2005, 2015, and 2025 and the ecological protection scenario. The results show that the ecological risk index of Xinjiang in 2005 ranged from 0 to 22.47, with an average value of 14.46. In 2015, the ecological risk index was between 0 and 41.77, with an average value of 13.17. In 2025, the ecological risk index under the natural growth scenario was between 0.83 and 42.75,
with an average value of 17.18. In 2025, the ecological risk index under the ecological protection scenario was 1.02 and 41.76, with an average value of 16.98. From the perspective of the maximum and mean values, the maximum value of the ecological risk index in 2015 was on the rise, and the mean value was on the decline compared to that in 2005, indicating that the overall ecological risk in the study area was on the decline in 2015; however, there was a sharp increase in the ecological risk in some local areas. Under the natural growth and ecological protection scenarios, the mean value of ecological risk in 2025 was greater than that in 2015. The maximum value did not significantly change, indicating a rise in the ecological risk in the research area from 2015 to 2025. However, the mean and maximum values of the ecological risk in the ecological protection scenario were smaller than those in the natural growth scenario, indicating that ecological protection in the research area can be an effective measure to reduce its ecological risk.

In order to compare the spatial variation of ecological risk in different years in the study area, the landscape ecological risk value of the evaluation unit was taken as its central point value, and the spatial distribution of ecological risk was obtained by using the inverse distance weighting method (Figure 3). According to previous studies and the actual situation of the research area, combined with the interpolation results, the natural breakpoint method was used to divide the landscape ecological risk into five levels: lowest ecological risk, lower ecological risk, medium ecological risk, higher ecological risk, and highest ecological risk.
ecological risk, and highest ecological risk. For convenience, they are expressed as risk I, risk II, risk III, risk IV, and risk V. At the same time, the study areas of different ecological risk levels each year were statistically analysed (Table 7).

As can be seen from Table 6, risk III dominated in 2015, accounting for 36.41% of the total area. This was followed by risk I, risk II, and risk IV (12.98%, 26.53%, and 22.11%, respectively). The area of risk IV was the lowest (1.97%). On the whole, from 2005 to 2015, the areas of risk I, risk II, and risk III in Xinjiang increased by 5.53%, 14.57%, and 17.43%, respectively, while the areas of risk IV and risk V showed a decreasing trend (i.e. -12.19% and -25.34%). Thus, during the 10 years from 2005 to 2015, the overall ecological risk situation in the study area showed a decreasing trend. Under the natural growth and ecological protection scenarios in Xinjiang in 2025, risk III became the dominant factor with area proportions of 55.26% and 50.83%, respectively, followed by risk II (with 30.40% and 38.17%), while the areas of risk I, risk IV, and risk V were relatively small. On the whole, compared to 2015, under the natural growth scenario, the areas of risk II, risk III, and risk V in 2025 showed an upward trend, increasing by 3.87%, 18.85%, and 0.23%, respectively, while the areas of the risk I and risk IV regions showed a downward trend (i.e. -9.8% and -13.15%). Compared to the natural growth scenario in 2025, the areas of risk III, risk IV, and risk V under the ecological protection scenario all showed a decreasing trend, with a decrease of 0.39%, 3.11%, and 4.43%, respectively, while the areas of risk I and risk II increased by 0.16% and 7.77%, respectively. Thus, ecological protection can effectively play a role in reducing ecological risk.

### 4.3. Analyses of the centre of mass and standard deviation ellipse of ecological risk

As shown in Figure 4, in the natural growth scenario from 2005 to 2025, the mass centre of ecological risk in Xinjiang generally presents a spatial pattern of shifting to the southwest. The centre of mass transfer distances of risk I, risk II, risk III, risk IV, and risk V was 300.18, 67.12, 387.51, 365.76, and 822.13 km, respectively. Furthermore, the standard deviation ellipse of risk IV and risk V decreased obviously on the long axis, while the short axis to the long axis increased gradually. However, there was no significant change in the size of the ellipse of risk III. Meanwhile, the short and long axes of the standard deviation ellipse of risk I and risk II both showed a decreasing trend, which indicates that landscape ecological risk in the research area
is in a contracting state in the east-west direction. The south-north direction and the contraction trend of the long axis are more vital than that of the short axis. Under different conditions, the centre of mass and the standard deviation ellipse are also different. In 2025, compared to the natural growth scenario, the centroids of risk V and risk II shifted to the northwest by 26.27 and 188.10 km, respectively; the centre of mass of risk IV and risk III shifted to the southwest by 75.74 and 342.55 km, respectively; and the centre of mass with the risk I shifted 24.55 km to the north. Meanwhile, the standard deviation ellipse of risk I, risk III, risk IV, and risk V increased by 2117.47, 108,528.42, 891,821.11, and 18,257.17 km², respectively, while the standard deviation ellipse area of risk II reduced by 27,976.96 km², which shows that the ecological protection scenario makes the distribution of regions with risk III, risk IV, and risk V more dispersed and the distribution of regions with the risk I more concentrated.

4.4. Analyses of driving forces of ecological risk evolution

In order to facilitate analysis of the results, all driving factors and ecological risk indexes were normalized in 2005 and 2015, respectively (Figures 5 and 6). From the meteorology perspective, the correlation index between the ecological risk value and the temperature in Xinjiang in 2005 and 2015 was 0.49 and 0.28, and the correlation
index between the ecological risk value and rainfall was $-0.45$ and $-0.16$, respectively. Thus, it can be seen that temperature is positively correlated with ecological risk, while rainfall is negatively correlated with ecological risk. In other words, with the continuous rise of temperature, the ecological risk also increases, and with the continuous increase of rainfall, the ecological risk gradually decreases. Xinjiang’s dry climate, low rainfall, extensive deserts, and small lakes may have contributed to this phenomenon. However, the influence of meteorological factors on ecological risk changed over time. In 2005, the ecological risk was more influenced by meteorological factors than in 2015. From the perspective of topography, the correlation indexes between the ecological risk value and DEM, slope, and aspect were $-0.39$, $-0.23$, and $-0.07$ in 2005, and $-0.30$, $-0.15$, and $-0.05$ in 2015, respectively. It can be seen that the topographic factors are all negatively correlated with ecological risk, but the aspect is less correlated with ecological risk. In other words, with the increase of DEM and slope, the ecological risk gradually decreases. The reason for this may be that as the terrain rises, the landscape becomes more stable and less susceptible to other creatures. So the topographic factors are all negatively correlated with ecological risk. With regards to soil, there is also a correlation between soil types and ecological risk. The correlation indexes in 2005 and 2015 were $-0.16$ and $-0.11$, respectively. This may be related to the structure and nature of the soil. From the social economy

**Figure 5.** Correlation diagram of each driving factor to landscape ecological risk in 2005.

**Figure 6.** Correlation diagram of each driving factor to landscape ecological risk in 2015.
perspective, the correlation indexes of ecological risk value and population distribution in Xinjiang in 2005 and 2015 were $-0.07$ and $-0.03$, respectively. The correlation indexes of ecological risk value and GDP were 0 and $-0.02$, respectively. Perhaps because of the highly uneven spatial distribution of the population and the randomness of sampling in the study area, the correlation between social and economic factors and ecological risk is not high.

5. Discussion

1. Choice of driving factor: The selection of driving factors significantly influences the model’s accuracy in the multi-scenario simulation of future land use. However, the chosen socio-economic drivers are not comprehensive. Local policies also influence future land-use change. Due to the highly uneven spatial distribution of the population in the study area, the interpretation of the results of social and economic factors is lacking. Therefore, future research should focus on how to select the driving factors of the social economy. In order to improve the simulation accuracy of the Markov–FLUS composite model and the interpretability of results, local policies should be fully integrated, spatialized, and quantified.

2. Choice of landscape index: The composite model contains multiple parameters, and the simulation results are different due to the different settings of the model parameters. Based on the research objective and the characteristics of the research area, the model parameters in this article were determined through repeated experiments. Therefore, the key to future research is to find the best model parameters for different research purposes and research areas. The choice of landscape pattern index is also the key to constructing an ecological risk index. Based on the ecological meaning of the landscape pattern index and the experimental results, we chose edge density, the area-weighted mean shape index, the most extensive patch index, the interspersion juxtaposition index, the aggregation index, and the patch cohesion index as the landscape pattern index. However, there was no comparison with other risk assessment models, so this is not absolute. Therefore, to improve the applicability of the evaluation model, the choice of landscape pattern index is also a key idea for future research.

3. Choice of segmentation scale: The research area was divided into 100 grid units using fishing nets. However, the scale effect is inevitable in the study of geography. This article did not explore whether there were differences in the results of landscape ecological risk under different segmentation scales. Therefore, different scales or methods can be further explored to segment the landscape in the future. It is necessary to select a reasonable evaluation unit and pay attention to its geographical significance to optimize the evaluation results.

6. Conclusion

This study analysed the spatial pattern change of land use from 2005 to 2015 in Xinjiang, using the Markov–FLUS composite model to predict land-use change under natural growth and ecological protection scenarios. We used the CRITIC weight
method to construct the landscape ecological risk index. By calculating the risk index centroid and standard deviation ellipses, the spatial and temporal patterns and changing characteristics of landscape ecological risk in different scenarios in 2005, 2015, and 2025 were evaluated.

The results showed that arable land, glaciers, and construction land in Xinjiang increased from 2005 to 2015, while forest land, grassland, water, sandy land, Gobi, and other unused land areas showed a decreasing trend. Furthermore, the characteristics of land use pattern change under the natural growth scenario from 2015 to 2025 were similar to those from 2005 to 2015. Under an ecological protection scenario, by restricting the expansion of construction land, the central ecological lands (forest land and grassland) can be effectively protected. Compared to the natural growth scenario, the areas increased by 507 and 724 km², respectively. Under the natural growth scenario from 2005 to 2025, the centroid of landscape ecological risk in Xinjiang generally shifted to the southwest. Under different conditions, the centre of mass and the standard deviation ellipse were also different. To some extent, the ecological protection scenario can make the distribution of the highest, higher, and medium ecological risk areas more dispersed and the distribution of the lower ecological risk areas more concentrated. Furthermore, from 2005 to 2015, landscape ecological risk in Xinjiang generally showed a decreasing trend. The areas of risk I, risk II, and risk III in Xinjiang increased while risk IV and risk V decreased. Compared to 2015, under the natural growth scenario, the areas of risk II, risk III, and risk V in 2025 showed an upward trend, while the areas of risk I and risk IV showed a downward trend. Compared to the natural growth scenario in 2025, ecological protection can effectively reduce the ecological risk of the landscape. The highest, higher, and medium ecological risks were reduced, while the lowest and lower ecological risks were increased.

Regarding meteorology, the temperature is positively correlated with ecological risk, while rainfall is negatively correlated with ecological risk. However, the influence of meteorological factors on ecological risk changed over time. Regarding topography, the topographic factors are all negatively correlated with ecological risk, but the aspect is less correlated with ecological risk. With regards to soil, there is also a specific correlation between soil types and ecological risk.

This study can reference the theory and method of landscape ecological risk and provide decision support for the sustainable development of the ecological environment of Xinjiang.

**Disclosure statement**

No potential conflict of interest was reported by the authors.

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