

Simulation Study for Constructing Ecological Security Pattern: A Couple d InVEST-PLUS Model Approach

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Abstract

Establishing ecological security patterns (ESP) effectively sustains regional ecosystem service stability and boosts sustainable development. This study selects the Mu Us Sandy Land (MUS) as the research area. Guided by the ESP-land use simulation integrated framework, it employs the Patch-Generating Land Use Simulation (PLUS) model to conduct multi-scenario land use simulation for the year 2030. The outcomes of this simulation support the subsequent development of the MUS's future ESP. In the process of ecological source identification, the study obtains two key assessment results: one from the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model, and the other from the groundwater vulnerability assessment. These two sets of results are then synthesized to accurately determine the spatial extent of ecological sources. Ecological nodes are detected through circuit theory to build MUS's future ESP. The findings indicate that: (1) Land use varies by scenario—natural development (ND) sees sharp construction land decline; economic development (ED) has the least construction land reduction, largest area, and more cultivated land loss; ecological protection (EP) has the biggest grassland increase and smallest forest loss. (2) Under 2030 ND, 5 ecological sources (13.20% of the area, concentrated in west/east/north margins), 6 corridors (314.23 km), 120 pinch points, and 605 km² barrier areas are identified. The study suggests balancing economic-ecological development, strengthening source protection, corridor construction and node optimization. These measures are intended to provide scientific reference for promoting the high-quality development of the Yellow River Basin (YRB) and advancing ecological restoration in desertified areas.

1 Introduction

Against the background of rapid economic and social development and intensified climate change, the interference of human activities on ecosystems has been increasingly growing, leading to significant changes in ecological processes. This is particularly prominent in the arid and semi-arid regions of northwest China, posing a serious threat to regional ecological security and sustainable development (S. Li et al., 2025). Relevant studies have shown that the construction of ecological security patterns (ESP) can effectively address the ecological and environmental problems caused by economic development, and also enable refined management and regulation of ecological processes (Chen et al., 2022). The ESP refers to a spatially connected functional system formed by the organic coupling of ecological sources, ecological corridors, and ecological nodes. By optimizing the spatial configuration of key ecological elements, it promotes the efficient and rational use of land resources, thereby maximizing the supply capacity of regional ecological services. This pattern is widely recognized as a scientific approach to safeguarding ecological security and coordinating regional development contradictions (Xu et al., 2023).

Research related to ESPs originated in the international field of landscape ecology. Initially, it focused on the analysis of single ecological elements. With the continuous deepening of theories and technologies, the research content has gradually shifted to a comprehensive model of multi-element synergy and multi-scale linkage (Niu et al., 2025). Current studies are mostly built on the theoretical framework of "source-resistance-corridor". By identifying core habitats, quantifying species diffusion resistance and key ecological elements, multi-level ESPs are constructed (Liu et al., 2024a). At present, there are certain limitations in the research on ESPs, especially in the regional identification of ecological sources (W. Li et al., 2025). Ecological sources are specific areas with high ecological value or in need of protection, and they are the foundation and key for the construction of ESP (Xue et al., 2024). When determining ecological sources, some studies usually directly designate specific areas such as nature reserves, scenic spots, and ecological protection red lines as ecological sources. This method ignores the impact of human activities and patch connectivity (Liu et al., 2023a). On this basis, scholars have gradually enriched the methods for ecological source screening. For instance, Li et al. (2025) used the Morphological Spatial Pattern Analysis (MSPA) model, and delimited ecological source areas by using the patch importance index (dPC); Liu et al. (2023b) comprehensively considered the geographical environment characteristics of the study area and the impact of human activities to conduct ecological sensitivity evaluation, and proposed the "ecosystem service trade-off and ecological sensitivity" evaluation system to identify ecological sources. The above studies fully consider the interactions between

different ecological processes from different aspects, and provide new ideas for the effective screening of ecological sources.

In the selection of ecological sources, establishing an ESP solely based on ecosystem services lacks a holistic ecological perspective. Pan et al. (2022) argued that an ecosystem is secure only when the ecological sources are of high health status and low risk, and ecological security assessment needs to integrate information such as ecosystem service functions and vulnerability. Since the beginning of the 21st century, the frequency of extreme climate events has increased significantly, exerting a major impact on water resource systems (Han et al., 2024). Currently, the Mu Us Sandy Land (MUS) is also facing problems such as declining groundwater levels, water resource shortages, and soil erosion (Gao et al., 2024). Groundwater has become a key limiting factor for ecosystem services, and this study innovatively adopts groundwater vulnerability and the significance of ecosystem services as dual indicators to select ecological sources. Common methods for groundwater vulnerability assessment include the overlay index method, process-based mathematical simulation, and statistical methods, among which the DRASTIC model is the most widely used both domestically and internationally (Jang et al., 2025). This study comprehensively considers various factors such as the actual conditions of the MUS, geological conditions, and the impact of human activities, and improves the original model to make the modified model more practical and accurate (Petpongpan et al., 2025). In addition, regarding the selection of ecosystem service assessment models, common ones mainly include the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model (Mukhopadhyay et al., 2025), the Multiscale Integrated Models of Ecosystem Services (MIMES) (Boumans et al., 2015), and the Social Values for Ecosystem Services (SoVES) model (Obateru et al., 2025). Among them, the InVEST model features the integration of multiple ecosystem sub-models by utilizing Land Use Cover Change (LUCC) data, physical environment data, and socio-economic data. It is widely used due to advantages such as flexible parameter adjustment and easy spatial visualization of evaluation results (Z. Wang et al., 2022). Cao et al. (2024) adopted multi-tool synergy approach: they used the InVEST model to quantify ecosystem service importance and Conefor software to analyze landscape connectivity, then integrated these two types of assessment results to determine the spatial scope of ecological sources.; Wei et al. (2025) optimized the model's application by selecting key functional modules of the InVEST model to evaluate ecosystem service importance. They also coupled this with ecological sensitivity analysis to form a comprehensive screening index system for ecological sources. This research confirmed the InVEST model's high adaptability in multi-indicator integration assessments.

Nevertheless, at the current research stage, ESP construction mostly adopts a "status-quo-oriented" approach, it takes existing ecological resources as the core basis for pattern design. While this static construction paradigm plays a role in safeguarding the integrity of existing ecological patches, it has two critical limitations: first, it fails to achieve the dynamic coordination between regional ESP evolution and socio-ecological system development; second, it neglects the cumulative impact of LUCC on the future spatial structure of landscape patterns (Luo and Fu, 2023). Taking into account the dynamic evolution characteristics of land use types can not only effectively optimize the adjustment strategies for ecological sources and ecological corridors but also further enhance the resilience of the study area to respond to external environmental changes. For example, Wu et al. (2025) proposed to comprehensively consider ecosystem service trade-offs and priority protected areas under different decision-making risks through the Ordered Weighted Averaging (OWA)-ESP-Patch-Generating Land Use Simulation (PLUS) framework, select the optimal scenario, and construct ESPs. At present, research on the dynamic coupling of LUCC simulation and ESP construction remains relatively scarce, and they are quite subjective, this method can comprehensively consider the complexity and uncertainty of LUCC, provide a scientific basis for the sustainable management of land, and at the same time offer a new perspective for scenario simulation of future ESPs.

Traditional methods for predicting LUCC mainly include quantitative prediction and spatial prediction. Quantitative prediction models mainly include logistic regression model, Markov model, and system dynamics (SD) model, while spatial prediction models mainly include cellular automaton (CA) model, Conversion of Land Use and its Effects at Small regional extent (CLUE-S) model, Geographical Simulation and Optimization System (Geo-SOS) model, Future Land Use Simulation (FLUS) model, and PLUS model (H. Li et al., 2025; Rong et al., 2025). The CA model, first proposed by von Neumann, has been widely applied in fields such as urban development, land use transformation, and habitat protection (J. Zhang et al., 2025a). Later, researchers combined the CA model with the Markov chain prediction model (Markov-CA) to calculate land use transition

probabilities, aiming to improve prediction accuracy (Taloor et al., 2024). However, such models perform poorly in revealing the potential driving factors of LUCC and cannot capture the evolution of multiple land use patches in time and space. Therefore, Liang et al. (2021) proposed a PLUS model based on the Random Forest (RF) algorithm on the basis of traditional models. This model integrates data on human activities, environmental factors, and accessibility, and can effectively simulate the contribution of land expansion driving factors to the development probability of various land types. It overcomes the limitation that traditional models cannot effectively simulate the evolution of multiple land types and has been verified to show better performance in land use simulation. For instance, Zhao et al. (2024a) compared the ecological security indices of ESPs under different scenarios based on the projected LUCC in 2035, and found that the scenario restricting the transfer of source areas had the highest ecological security index (with a Kappa coefficient of 0.898 and an overall accuracy of 93.7% in the verification stage). The simulation and prediction effect of this study is good with high overall accuracy, indicating that the model has universality.

The MUS, one of China's four major sandy lands, its ecological management is not only associated with the ecological security stability in northern China, but also forms an essential part of the initiative to advance the sustainable development of the Yellow River Basin (YRB). Driven by both economic development and policy implementation, the MUS is undergoing drastic economic and social transformation and LUCC (Liu et al., 2020). However, the existing ecological restoration work has insufficient prediction of future LUCC trends and ignores the systematic construction of regional-scale ESPs, making it difficult to cope with complex and changeable environmental challenges and not conducive to comprehensively improving regional ecological security and stability (Z. Xu et al., 2025). How to scientifically predict future land use scenarios, construct and optimize forward-looking and adaptive ESPs accordingly, and implement targeted management measures are the core difficulties that need to be broken through urgently at present. Guided by the classic "source-resistance-corridor" theoretical framework, this study adopts a multi-model synergy approach for ESP construction: first, it applies the InVEST model and the improved DRASTIC model to conduct a comprehensive identification of ecological sources. Second, it couples the ecological source with the PLUS model to construct the MUS's future ESP. Finally, it clarifies key restoration areas and formulates targeted optimization measures. Its objectives are as follows: (1) Use the PLUS model to simulate the 2030 spatial distribution of land use in the MUS under three typical scenarios—natural development (ND), economic development (ED), and ecological protection (EP). (2) Integrate the assessment results of the InVEST model and the DRASTIC model to achieve multi-criteria identification of ecological sources. Then, apply circuit theory to identify ecological nodes and further integrate these elements to obtain the complete future ESP of the MUS; (3) Conduct modular governance according to the constructed ESP and propose targeted ecological restoration measures. This study integrates multi-model methods to construct a more comprehensive evaluation framework for ESPs, laying a scientific basis for ecological restoration efforts. Meanwhile, it contributes to the high-quality development of the YRB and offers theoretical references for the construction of ESPs in similar desertified areas.

2 Study area and material

2.1 Study area

The MUS is geographically positioned between 37°27'-39°22'N and 107°20'-111°30'E, lies in the central section of the farming-pastoral ecotone in northern China, at the transition zone connecting the Ordos Plateau and the Loess Plateau. It functions as a key ecological barrier in the YRB of northern China, characterized by significant ecological vulnerability and spatial heterogeneity, with an area of approximately 42,200 km². Climatically, it features a typical continental monsoon climate, the region's annual average temperature falls within the range of 6.5°C to 10.3°C, while its annual average precipitation varies between 150 mm and 500 mm (Liu et al., 2025). At present, although ecological management in the MUS has achieved remarkable results, large-scale afforestation has led to a reduction in runoff and groundwater storage, altering regional water cycle processes and water resource distribution (Cheng et al., 2023). Inappropriate restoration models can cause soil nutrient loss and accelerated decomposition of soil carbon pools, which increases the potential risk of "secondary desertification" in the MUS and exerts a significant impact on the ecological restoration process (Yu et al., 2024). The

geographical location of the study area, as well as the spatial distribution of land use types and groundwater level observation points, are shown in Fig. 1.

Note

CL, FL, GL, WA, CTL, and UL stand for cultivated land, forest land, grassland, water area, construction land, and unused land respectively.

2.2 Data source and pre-processing

All data employed in this study are comprehensively detailed in Table 1. To ensure data consistency and applicability for subsequent spatial analysis, all data underwent preprocessing in ArcGIS 10.7. The coordinate system was uniformly adopted as Asia_North_Albers_WGS84_LCR. Meanwhile, the spatial resolution of all raster data was standardized to 1000 m × 1000 m.

Table 1
Types and Sources of Data.

Name	Type	Resolution	Source
LUCC	Grid	1km	Chinese Academy of Sciences Data Center for Resources and Environmental Sciences (http://www.resdc.cn)
Digital Elevation Model (DEM)	Grid	30m	Geospatial data cloud (http://www.gscloud.cn/)
Precipitation / Temperature	Grid	1km	National Oceanic and Atmospheric Administration - National Centers for Environmental Information (https://www.ncei.noaa.gov/data/global-summary-of-the-day/archive/)
Potential Evapotranspiration	Grid	1km	National Science and Technology Infrastructure Platform - National Earth System Science Data Center - Loess Plateau Sub-center (http://loess.geodata.cn/)
Future climate data	Grid	1km	Science Data Bank (https://www.scidb.cn/en/detail?dataSetId=cece16f1863b4ebd839894f6df26f8ac&version=V5)
Road	Vector	—	Open Street Ma (https://www.openstreetmap.org/)
Soil	Grid	1km	The National Glacier Desert Science Data Center has established a Chinese soil dataset based on the World Soil Database (HWSD) (v1.1) (http://www.ncdc.ac.cn)
Depth of bedrock	Grid	1km	China's bedrock depth map (http://globalchange.bnu.edu.cn/research/cdtb.jsp)
Underground water level	Text	—	China Geological Environment Monitoring Annual Report on Groundwater Levels
Fractional Vegetation Cover (FVC)	Grid	250m	National Qinghai-Tibet Plateau Data Center —China Regional Vegetation Coverage Dataset (https://doi.org/10.11888/Terre.tpd.300330 .)
Soil type	Grid	1km	Resource and Environment Science Data Platform — Spatial Distribution Data of Soil Types in China (Resource and Environment Science and Data Platform)
Nighttime lights	Grid	1km	https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/GIYGJU
Density of population	Grid	1km	WorldPop (https://dx.doi.org/10.5258/SOTON/WP00674)
Gross Domestic Product	Vector	—	Assembled from yearbooks and statistical bulletins of provinces and cities
Net Primary Productivity (NPP)	Grid	500m	Chinese Academy of Sciences Data Center for Resources and Environmental Sciences (http://www.resdc.cn)
Normalized Difference Vegetation Index	Grid	1km	MODIS dataset under the MOD13A3 data (https://search.earthdata.nasa.gov/search)

3 Methodology

To develop an ESP that achieves a balance between economic development and ecological protection, this study adopts an InVEST-PLUS coupled model framework, which serves as the core technical support for analyzing future land use dynamics and ESP construction. Specifically, The PLUS model is employed to simulate the spatial distribution of land use in the MUS

under multiple scenarios for 2030; Subsequently, the InVEST model and improved DRASTIC model are combined to identify high-value ecological area, which are defined as potential future ecological sources of the MUS. Hot spot analysis is further used to verify and confirm the final ecological source areas; Then, an ecological resistance surface is constructed by integrating key factors from ecological and anthropogenic dimensions. On this basis, circuit theory is applied to identify ecological nodes, and the study area's ESP is finally formed by spatially overlaying ecological sources and nodes; Finally, differentiated ecological restoration and protection measures are proposed based on the constructed ESP. The overall technical roadmap and research procedure of this study are illustrated in Fig. 2.

3.1 PLUS model

The PLUS model is composed of two key modules: the Land Expansion Analysis Strategy (LEAS) module and the Competitive Adaptive Reweighted Sampling (CARS) module. Within the LEAS module, the PLUS model utilizes a RF algorithm to derive the expansion probability of each land use type, drawing on land use data from two periods and driving factor data. Furthermore, the PLUS model introduces a decreasing threshold rule, which constrains the patch growth of various land use types through iteration. Units with higher total probabilities are more likely to be prioritized for expansion by applying this decreasing threshold (Zhang et al., 2024).

The neighborhood weights in the CARS module can reflect the conversion difficulty between distinct land use types. This study employs range standardization to calculate the neighborhood weights under different development scenarios, the formula is presented as follows: $X_i = \frac{T_i - T_{min}}{T_{max} - T_{min}}$ #1

Among them, T_i denotes the quantitative variable of this land type between two periods; T_{max} and T_{min} respectively denote the maximum and minimum values among the changes of all land types (J. Zhang et al., 2025b).

The Kappa coefficient is adopted in this study to evaluate the accuracy of the simulation outcomes. When $0.8 < \text{Kappa} \leq 1$, it indicates that the predicted results are highly consistent with the actual values, and its expression is as follows (Lin et al., 2024a):

$$\text{Kappa} = \frac{P_0 - P_c}{P_p - P_c} \quad \#2$$

Among them, P_0 denotes the consistency rate between actual results and simulated results; P_c represents the expected correct simulation ratio under random conditions; P_p is the correct simulation ratio under ideal conditions, typically set to 1.

3.2 InVEST model

This study comprehensively considers relevant references and regional characteristics, and selects four key indicators—water yield, carbon sequestration, habitat quality, and soil conservation—to assess the importance of ecosystem services. The aim is to enhance the diversity and integrity of ecological source identification (Wang et al., 2025; X. Xu et al., 2025). The specific evaluation methods are presented in Table 2.

Table 2
Assessment Method for Ecosystem Services.

Ecosystem service	Computational process
Water yield	$Y(x) = \left(1 - \frac{AET(x)}{P(x)}\right)P(x) \quad \#3$ Among them, $Y(x)$ is the annual water yield of grid x; $AET(x)$ is the actual evapotranspiration of grid x; $P(x)$ is the annual precipitation of grid x (Liu et al., 2024b).
Carbon sequestration	$C_{xj} = C_{soil} + C_{abovej} + C_{belowj} + C_{deadj} \quad \#4$ Among them, C_{xj} represents the annual carbon capacity of grid x for land use type j; C_{soil}, C_{abovej}, C_{belowj} and C_{deadj} respectively denote the densities of soil organic carbon, aboveground organic carbon, underground organic carbon and dead organic carbon corresponding to land use type j (Zhao et al., 2022).
Habitat quality	$Q_{xj} = H_j \left[1 - \left(\frac{D_{xj}}{D_{xj}^Z}\right)^{\frac{1}{k}}\right] \quad \#5$ Among them, Q_{xj} denotes the habitat quality index of grid x for land type j; H_j represents the habitat suitability of land type j; D_{xj} is the habitat degradation degree of grid x for land type j; k stands for the half-saturation constant; Z is the default parameter of the model (He et al., 2017).
Soil conservation	$SR = RKLS - USLE = R \times K \times LS \times C \times P - R \times K \times LS \quad \#6$ Among them, SR is the soil conservation amount; $RKLS$ is the potential soil erosion amount; $USLE$ is the actual soil erosion amount; R is the rainfall erosivity factor; K is the soil erodibility factor; LS is the slope length factor; C is the vegetation cover and crop management factor; P is the soil and water conservation factor (Guo et al., 2023).

3.3 Improved DRASTIC model

This study comprehensively selects six evaluation factors, namely Fractional Vegetation Cover (FVC), topographic slope, soil type, groundwater level depth, groundwater recharge modulus, and land use type, to construct a groundwater vulnerability evaluation system (Table 3). With reference to relevant literature, the weights of each indicator are determined as 0.0333, 0.1453, 0.0679, 0.1664, 0.2907, and 0.2964 respectively (Loganathan and Sathiyamoorthy, 2024; Seraiche et al., 2025). The comprehensive evaluation result of groundwater vulnerability is obtained after superposition.

Table 3
Groundwater Vulnerability Assessment System.

FVC		Slope		Soil type	
Classification/%	Score	Classification/°	Score	Classification	Score
[0, 20)	10	[0, 2)	10	Saltern	1
[20, 30)	9	[2, 6)	9	Anthrosol	2
[30, 40)	7	[6, 12)	5	Saline—alkali soil	3
[40, 50)	5			Aquatic soil	4
[50, 80)	3			Hydromorphic soil formation	5
[80, 100]	1			First crop of soil	6
				Pedocal	7
				Xerosol	8
Underground water level		Groundwater recharge modulus		Land use	
Classification/m	Score	Classification/mm	Score	Classification	Score
[0, 10)	10	[0, 50)	1	CL	10
[10, 50)	9	[50, 70)	2	FL	1
[50, 100)	7	[70, 90)	3	GL	1
		[90, 120)	4	WA	3
		[120, 150)	5	CTL	10
				UL	1

3.4 Construction of ecological resistance surface

As a core basis for the accurate identification of ecological corridors, the ecological resistance surface quantifies the obstruction intensity of different regions to the progression of ecological processes. Combining existing studies and the ecological status of the MUS, this study selects land use type, Normalized Difference Vegetation Index (NDVI), elevation, slope, aspect, undulation, and distance to roads as basic resistance factors (Kong et al., 2025). The resistance value ranges from 1 to 5, and a weighted summation method is applied to construct the resistance surface evaluation system. Considering that basic factors may underestimate human activity impacts, nighttime light data is further introduced for modification—this data can effectively characterize human activity intensity by reflecting indicators such as regional economic development level and energy consumption, thereby improving the accuracy of the resistance surface (Yang et al., 2025).

3.5 Ecological element identification

The Linkage Pathways tool in Linkage Mapper is employed to identify the minimum cost distance between ecological source areas:

$$NLCC_{AB} = CWD_A + CWD_B - LCD_{AB} \# (7)$$

In the formula, $NLCC_{AB}$ is the normalized least-cost path length between core area A and core area B; CWD_A denotes the cost-weighted distance for core area A; CWD_B stands for the cost-weighted distance for core area B; LCD_{AB} refers to the cost-weighted distance along the least-cost path. In addition, the Pinch Point Mapper tool and Barrier Mapper tool in the Linkage Mapper module can be used to identify pinch points and barrier areas in corridors (Huang et al., 2024).

4 Analysis of results

4.1 Model configuration and accuracy verification

This study utilizes the 2000 and 2010 land use datasets of the MUS, this study first overlaid the land use data from these two periods to extract raster units with changes, which were then input into the LEAS module. The Root Mean Square Errors (RMSE) of CL, FL, GL, WA, CTL, and UL obtained are 0.1246, 0.0880, 0.1460, 0.0670, 0.0659, and 0.0570 respectively, indicating that the data are relatively reliable. The development probability maps of various land types are shown in Fig. 3.

1. Setting of land type conversion cost matrix parameters

The conversion cost matrix denotes the conversion rules of various land types and is used to reflect whether various land types can be converted into one another. When one land type is convertible to another, the corresponding matrix value is 1; otherwise, it is 0 (Cai et al., 2023). The transfer cost settings in the accuracy verification stage are shown in Table 4.

Table 4
Settings of Land Type Conversion Cost Matrix.

LUCC	CL	FL	GL	WA	CTL	UL
CL	1	1	1	1	1	0
FL	1	1	0	0	0	0
GL	1	0	1	0	0	0
WA	1	1	1	1	0	1
CTL	1	0	1	0	1	1
UL	0	0	0	0	0	1

2. Analysis of Land Use Demand

In this study, a basic assumption is made regarding land use change in the MUS: the change patterns during 2010–2020 period are assumed to be consistent with those observed in the preceding periods. Using the 2000–2010 land use data of the MUS, the Markov chain in PLUS software is employed to predict the demand for each land use type in the MUS in 2020 (Table 5).

Table 5
Prediction of Land Use Demand in the MUS in 2020 (1 pixel = 900 m²).

LUCC	CL	FL	GL	WA	CTL	UL
2000 (Actual)	4201959	1450220	30350146	393235	144842	8991937
2010 (Actual)	3439747	1202506	33028527	301345	207020	7353194
2020 (Actual)	3444724	1181822	33131096	320833	118928	7334936
2020 (Predicted)	3443819	1204477	33037145	289530	202378	7354989

As shown in Table 5, the predicted number of grids for the six land use types in 2020 is relatively close to the actual number of grids in 2020, indicating that the reliability of the land use demand for the target year prediction. The comparison between the 2020 simulation results and actual status is presented in Fig. 4. The accuracy verification results show that the Kappa coefficient is 0.962, and the overall simulation accuracy is 0.983. This indicates that the PLUS model has high simulation accuracy and is suitable for simulating the future land use status of the MUS.

4.2 2030 Land Use Multi-scenario Simulation

Taking the actual land use status of the MUS as the research basis, this study designs three scenarios for future land use spatial changes: the ND scenario, the ED scenario, and the EP scenario. The conversion cost matrix (Table 6) and demand quantity (Table 7) are modified to realize the simulation of different scenarios.

- (1) ND scenario: This scenario assumes that the land use spatial pattern of the MUS follows a linear development path consistent with its historical evolution trajectory, serving as the reference basis for other scenarios.
- (2) ED scenario: In this scenario, the transfer probability of CTL to CL, FL, GL, WA, and UL is reduced by 30%, and the probability of CL, FL, and GL to CTL is increased by 20%.
- (3) EP scenario: This scenario increases the transfer probability of CL, GL, and UL to FL by 20%, reduces the transfer probability of CL, FL, and GL to CTL by 30%, and raises the transfer probability of CL, CTL, and UL to GL by 20%.

Table 6
Settings of Land Type Conversion Cost Matrix Under Different Scenarios.

LUCC	ND						ED						EP					
	CL	FL	GL	WA	CTL	UL	CL	FL	GL	WA	CTL	UL	CL	FL	GL	WA	CTL	UL
CL	1	0	1	1	0	0	1	0	1	1	1	0	1	0	1	1	0	0
FL	1	1	0	1	0	0	1	1	0	1	0	0	1	1	0	1	0	0
GL	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0
WA	1	1	1	1	0	0	1	1	1	1	0	0	1	1	1	1	0	0
CTL	1	1	1	0	1	1	1	0	1	0	1	1	1	1	1	0	1	1
UL	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1

Table 7
Land Type Demands Under Different Scenarios (Number of Pixels: 1 pixel = 900 m²).

Scenario	CL	FL	GL	WA	CTL	UL
ND	3433435	1161380	33208862	333231	80135	7315296
ED	3423803	1161169	33193751	333238	105583	7314795
EP	3398797	1163067	33256406	332766	69242	7312061

The spatial distribution of various types of land in the three scenarios is shown in Fig. 5. In addition, the changes in area have also been statistically analyzed (Table 8).

Under the ND scenario, various land types transfer and change according to the original probability. Compared with 2020, CTL sees the most significant area reduction (11,002 hm²), and GL the most notable increase (12,893 hm²). Additionally, FL, UL, and CL decrease by 3,089 hm², 1,801 hm², and 935 hm² respectively, while water bodies increase by 3,933 hm². Among the three scenarios, the ED scenario features the smallest reduction in CTL area (8,712 hm²), with its total area reaching the highest among the three (9,502 hm²). CL decreases more than in the ND scenario, by 1,801 hm². GL still has the largest area increase, though slightly lower than in the ND scenario (11,426 hm²). Under the EP scenario, CTL has the largest reduction (11,982 hm²) and CL the greatest decrease (4,052 hm²) among the three scenarios; FL has the smallest reduction (2,843 hm²), while GL achieves the largest area increase (16,780 hm²) across all scenarios.

Figure 5 Simulated Maps of in the MUS Under Different Scenarios in 2030.

Note

(a) Natural-development scenario (ND); (b) Economic-development scenario (ED); (c) Ecological-protection scenario (EP); A1-A3, B1-B3, and C1-C3 denote partial enlarged views of typical regions for ND, ED, and EP scenarios.

Table 8
Area Changes of Various Land Use Types Under Different Scenarios in 2030 (hm²).

LU CC	2020	2030			Variation		
		ND	ED	EP	ND	ED	EP
CL	309944	309009	308142	305892	-935	-1801	-4052
FL	108403	105314	105360	105560	-3089	-3043	-2843
GL	2973343	2986236	2984770	2990123	12893	11426	16780
WA	26058	29991	29991	29949	3933	3934	3891
CTL	18214	7212	9502	6232	-11002	-8712	-11982
UL	661949	660148	660144	660155	-1801	-1805	-1794

4.3 Analysis of Future Spatiotemporal Changes in the ESP

(1) Identification of Ecological Sources.

Based on the single ecosystem evaluation results and the OWA algorithm, the weight superposition corresponding to the maximum trade-off degree was selected to obtain comprehensive ecosystem services (Fig. 6(a)). Under the 2030 ND scenario, the high-importance regions for ecosystem services cover 4,985 km², accounting for 12.50%, which are primarily concentrated on the eastern edge and scattered in the southeast, and show a clear trend of gradual decrease from the periphery toward the interior. For the groundwater vulnerability assessment, the corresponding results are illustrated in Fig. 6 (b). It indicates that under the 2030 ND scenario, high vulnerability regions occupy 2,405 km², accounting for 6.02%, which are concentrated in the south and east. Dominated by CL, this area is highly susceptible to human disturbance and chemical pollution. Low vulnerability regions are primarily distributed along the western, northern, and southern edges (10.59%). Given that most groundwater in the study area is at medium vulnerability or below, identifying low vulnerability areas as potential ecological sources has become an urgent task. Through equal-weight superposition of the ecosystem service importance evaluation results and groundwater vulnerability, high-importance regions and low vulnerability regions were selected as potential ecological sources. Through hotspot analysis, patches with a confidence level exceeding 90% were chosen as the final ecological sources. Under the 2030 ND scenario, a total of 5 ecological sources were identified, covering an area of 5,409 km², spatially concentrated in the western, eastern, and northern edge regions.

(2) Spatial Distribution of Ecological Resistance Surface.

The comprehensive resistance surface was obtained by weighting the analysis results of various resistance factors; subsequently, the Natural Breaks method was applied to classify it into high resistance areas, medium resistance areas, and low resistance areas (Fig. 6(c)). Under the 2030 ND scenario, the comprehensive resistance surface demonstrates notable spatial differentiation, showing a gradual decreasing trend from north to south. High resistance areas are mainly concentrated in the northern section of the northwestern part and scattered in small patches along the southeastern edge (accounts for 23.08%).

(3) Construction of ESP.

Drawing on circuit theory, this study integrated the identified ecological sources and comprehensive resistance surface to identify the ecological corridors and ecological nodes in the study area, thereby constructing a comprehensive ESP for the

region. As illustrated in Fig. 6(d), a total of 6 ecological corridors were identified, with a combined length of 314.23 km, realizing effective connectivity between ecological sources. A total of 120 ecological pinch points were detected, which are spatially distributed around shorter ecological corridors and at the connections between corridors and sources.

5 Discussion

5.1 Analysis of Driving Forces of Land Use

By overlaying the maps of newly added areas of various land types (2000–2010) with the driving factors that have the highest contribution to them, the impact of driving factors on changes in each land use type can be visually analyzed (Fig. 7).

Figure 7(c) presents the influence of different driving factors on the expansion of CL. Population density has the highest contribution degree, exceeding 0.16; NPP ranks second, with a contribution degree of 0.15. Areas with high population density are primarily distributed at the study area's edge, especially in the northern, southern, and southeastern edges (Fig. 7(a)), while NPP shows a spatial distribution trend of gradual increase from northwest to southeast (Fig. 7(b)). Under the combined influence of these two factors, newly added CL is mainly distributed in a point-like pattern along areas with high population density and high NPP values. From the perspective of population density, high population density directly generates greater demand for crop yields, making other land types in this region more likely to be converted into CL (Liu et al., 2021). Meanwhile, NPP refers to the organic carbon fixed by vegetation after accounting for its respiratory consumption; regions with high NPP mean more remaining energy for plant growth, making these areas more suitable for farming and thus more conducive to the expansion of CL (Xue et al., 2023). Zheng et al. (2023) studied the temporal and spatial patterns of biomass and driving mechanisms during the rice growing period in China and found a strong correlation between crop biomass and NPP. Biomass roughly reflects crop yield, indicating that NPP can be effectively used to characterize the degree of CL expansion. Figure 7(f) illustrates the influence of GL expansion. Among these factors, population density still has the highest contribution degree, while DEM ranks second with a contribution degree of 0.14. It is worth noting that the spatial distribution pattern of DEM is opposite to that of NPP: specifically, high DEM values are primarily concentrated in the northwestern region (Fig. 7(e)). Therefore, under the synergistic effect of these two driving factors, the distribution of newly added GL breaks the previous limitation of being only in the edge areas; instead, it begins to expand toward the central region, with a more obvious spreading trend in the south-central region. Regarding population density, due to the demand for ecological restoration, the single effect of human activities plays an important role in GL restoration (Sun et al., 2017). Especially in arid and semi-arid transition zones, accompanied by the implementation of multiple ecological restoration projects and desertification control measures, large-scale greening and the trend of reverse desertification have been promoted, and human activities have gradually become dominant (Jiazheng Li et al., 2025; Z. Wang et al., 2023). From the perspective of DEM, GL ecosystems have important soil and water conservation capabilities, making them more adaptable to high-altitude areas; the expansion of GL in these regions is more conducive to ecological protection. Lv et al. (2024) found that the phenomenon of shrub encroachment on GLs in arid and semi-arid regions mainly occurs in low-to-medium altitude areas, which is consistent with the results of our study. In addition, Yang et al. (2024) conducted a study on the driving factors influencing aboveground biomass in the Inner Mongolia GL ecosystem. Their analysis results showed that alpine meadows exhibit the highest level of average aboveground biomass. This indicator—providing the basic material for GL ecosystem animals and microorganisms—effectively reflects GL ecological status, further confirming that high-altitude areas are more favorable for GL expansion. Figure 7(i) shows the influence of various driving factors on the expansion of CTL is presented. The top two factors with relatively higher contribution degrees are consistent with those identified for CL. Notably, the contribution degree of population density here reaches a maximum value of 0.28—this value is higher than the contribution degrees of population density for both CL and GL. In contrast, the contribution degree of NPP is significantly lower than that of population density, with a value of only 0.12. With population density contributing dominantly, the expansion area of CTL is far smaller than that of CL, basically concentrated only in areas with high population density. Population density directly reflects the agglomeration degree and demand of human social and economic activities, thereby significantly affecting the degree of CTL expansion (Wu et al., 2024).

5.2 Land Use Spatial Management and Planning under Multi-scenario Prediction

Differences in land type changes across three scenarios have distinct impacts on the study area's development trajectory. Under the ND scenario, CTL area experienced the most notable reduction, with most of it converted to GL. This transformation is primarily driven by ecological restoration initiatives and policies (Gao et al., 2024); For the ED scenario, the likelihood of CTL expansion increased, which further enhanced the regional economic level. However, this expansion poses risks to agricultural land and ecological land, creating obstacles to long-term sustainable development. This conclusion matches the research findings of J. Zhang et al. (2025b), who identified economic development as the main factor contributing to the reduction of CL and GL; In the EP scenario, CL, FL, and GL—all possessing high ecological value—were afforded certain protective measures. Additionally, the encroachment of CTL on adjacent agricultural land was reduced, resulting in a partial improvement in the ecosystem's condition. That said, the maximum potential of various land types has not been fully tapped (Lin et al., 2024b).

It is necessary to comprehensively consider multiple factors, including economic development and ecological protection, and develop balanced land use policies. This approach helps avoid adverse outcomes stemming from a single-minded focus on one goal (B. Xu et al., 2025). Taking into account the current development characteristics of the MUS, two key aspects should be prioritized: on the one hand, implement ecological environment protection policies, strictly adhere to the CL protection red line, enhance the production efficiency of CL, and emphasize the protection and restoration of FL in key ecological zones; on the other hand, rationally plan the expansion of CTL, minimize its encroachment on agricultural and ecological land, and adjust the direction of land use conversion. By formulating sound policies and ensuring their effective implementation, the sustainable development of land use can be achieved (Ma et al., 2023).

5.3 Construction and Protection Strategies of Ecological Security Pattern Coupled with Land Use Simulation

After years of development, the construction methods for the ESP are still being continuously innovated and improved, with increasingly diverse indicators used (Shu et al., 2024). At present, some scholars have incorporated groundwater into the influencing factors for constructing ESPs. For example, from the perspective of groundwater transformation, Wang et al. (2023) studied the evolution of landscape ecological patterns in arid riparian zones and proposed that groundwater, as a critical water source in arid areas, should be given full consideration in relevant academic studies to ensure the accuracy of ecological pattern analysis. Against this background, this study adopts the improved DRASTIC model and selects six indicators representing the study area's groundwater status to conduct a comprehensive assessment of groundwater vulnerability. The traditional DRASTIC model includes seven parameters: Depth to groundwater (D), Recharge (R), Aquifer media (A), Soil media (S), Topography (T), Impact of vadose zone (I), and Hydraulic conductivity (C) (Baalousha, 2025). Although this model is widely used, it needs to be modified based on the study area according to the characteristics of aquifers and pollutants, which limits its further application (Bordbar et al., 2025). Therefore, relevant existing studies have attempted to replace or add new parameters to the DRASTIC model to enhance the applicability of this framework. For instance, Singh et al. (2015) incorporated human impacts into the improved DRASTIC model using nighttime light data and land use data; Ashagrie et al. (2025) introduced land use changes into the DRASTIC model to better assess groundwater vulnerability under different land management scenarios. In view of this, based on the study area's ecological environment conditions, when applying the DRASTIC model to assess the MUS's groundwater vulnerability, this study optimized and improved the model considering that the characteristics of vadose zone media and aquifer hydraulic conductivity are difficult to obtain, while the depth of groundwater level can reflect the vadose zone's impact to a certain extent. Specifically, the indicators related to the vadose zone and aquifer in the original model were eliminated, and indicators of FVC and land use type were added. The improved model is more consistent with the study area's actual conditions and still has high scientificity, practicality, and accuracy when data is limited.

By comparing the research results with relevant studies in the region, it is found that the results are reasonable. For example, the results of this study show that the junction between northern Shaanxi and Inner Mongolia is mostly in the medium-high vulnerability zone. This may be because with the large-scale mining of coal resources in this area, a large number of serious pollutants pose a serious threat to the groundwater environment (Yang et al., 2018). As a densely populated area, northern Shaanxi is also an important region for agricultural and animal husbandry activities and energy development in China. Extensive energy mining has caused ecological damage, and human activities have greatly disrupted the local ecological environment (Kong et al., 2024), this observation aligns with the research results obtained from the Shaanxi section of the study area in the present research.

Besides, most current studies focus on ESPs at specific time points, with less attention paid to changes in future ESPs (Luo et al., 2024). As an important factor affecting the formation and development of ESPs (C. Wang et al., 2023), LUCC has led some scholars to begin studying future ESPs by simulating land use changes. For example, Guo et al. (2025) took the Loess Plateau, another arid and semi-arid region, as the study area, assessed ecological risks under different scenarios, and established an ESP, providing substantial advantages for addressing the uncertainties of future development. Zhao et al. (2024b) used the PLUS model to carry out multi-scenario simulations of LUCC in Hubei Province by 2035, and combined landscape patterns and the InVEST model to evaluate future ESPs. Based on the aforementioned research, this study adopts the approach of integrating land use simulation to construct the future ESP. Taking the land use distribution under the 2030 baseline scenario (ND scenario) as the foundation, ecological sources were identified by combining the InVEST model and the DRASTIC model. Furthermore, the ESP was established based on circuit theory, and protection strategies were proposed. This research provides an important basis for the dynamic construction of the ESP.

(1) Strengthening the protection of ecological sources.

Ecological sources, as the foundation of the ESP, play a crucial role in sustaining regional ecological security and ensuring the stability of ecosystems (Fu et al., 2020). Within the study area, the spatial distribution of ecological sources shows a relatively concentrated pattern; however, their available area is limited, which makes it challenging to generate significant ecological advantages. Although some regions have connecting ecological corridors, they are far apart and lack sources for connectivity. Stepping stones can be established between the eastern and western ecological sources to expand the core areas of ecological sources and strengthen corridor construction between them, which will facilitate species migration and energy exchange (Y. Li et al., 2025).

(2) Emphasizing the construction of ecological corridors.

Ecological corridors are important channels for material exchange, energy flow, and biological migration between sources (L. Zhang et al., 2025). Ecological restoration work should be based on the expansibility of material exchange and biological migration, adding suitable habitat corridors and appropriately widening narrow sections of the corridors to reduce external interference. At the same time, they should be organically integrated with ecological isolation zones to form an overall ecological framework (Y. Wang et al., 2022). Furthermore, the connectivity of different ecological corridors varies. Ecological corridors with a large number of ecological nodes, cross-regional coverage, and long distances have more critical ecological service value. A more complete formulation of the ecological corridor system helps to rationally plan the spatial configuration of corridors, thereby facilitating the efficiency of energy flow and realizing the optimal circulation of ecological resources (Nie et al., 2024).

(3) Restoring and optimizing ecological nodes.

For regions with high corridor resistance, optimizing ecological pinch points and removing or repairing barrier areas are crucial for restoring the ecological attributes of corridors and enhancing the connectivity between source areas (Gong et al., 2025). Ecological nodes in the MUS are mostly located around corridors and at their junctions with ecological sources. The restoration and optimization of these nodes are difficult and time-consuming. Scientific dynamic supervision and ecological restoration should be implemented to continuously protect key nodes and their surrounding environments. Additionally,

branch corridors and stepping stone patches should be established to strengthen connectivity within the ecological network (Wang et al., 2024).

5.4 Research limitations and future research directions

In this study, a future ESP of the MUS was constructed using the "PLUS-InVEST" coupled model. The PLUS model was employed to predict the development trends of land use types in the region in 2030, and ecological sources were identified by integrating ecosystem service importance and groundwater vulnerability. Through this process, an ESP consistent with the MUS's land use development trends was established. Nevertheless, this study has certain limitations. Firstly, parameters such as neighborhood size and RF involved in the PLUS model are susceptible to subjectivity and limited data availability. Even when multiple natural and anthropogenic factors are selected, it is still difficult to comprehensively analyze the causes of land use changes (Zhao et al., 2024b). For future research, it is recommended to establish a quantitative spatial coupling model through the integration of the SD model. Specifically, various influencing factors should be integrated into the driving mechanism system, which will enable more scientific simulation of the nonlinear and dynamic properties inherent in the LUCC process (Diao et al., 2025). In addition, regarding the selection of the ecosystem service importance evaluation model, the InVEST model relies too heavily on historical data and is insufficient in predicting system mutations caused by sudden disturbances and policy-driven factors. In the future, attempts should be made to compare data results using multiple models and integrate multi-source real-time data to improve prediction sensitivity (Lin et al., 2025).

6 Conclusions

To explore the future ESP of the MUS, this study employed the PLUS model to simulate the region's land use conditions in 2030. Subsequently, the InVEST model was coupled with the improved DRASTIC model for ecological source identification. On this basis, circuit theory was adopted to recognize key ecological elements, and the future ESP was further constructed. Finally, targeted and differentiated ecological restoration measures were proposed, which are intended to provide technical support for the implementation of regional ecological protection work. The specific research results are outlined below:

(1) Under the ND scenario, as ecological restoration policies advanced, CTL saw the most significant area reduction, with most of it converted into GL; under the ED scenario, the decrease in CTL area was the smallest, and its area reached the maximum among the three scenarios, while CL decreased more than that under the ND scenario; under the EP scenario, GL had the largest area increase, and FL had the smallest area decrease.

(2) Under the 2030 ND scenario, 5 ecological sources were identified, covering an area of 5,409 km² (13.20%), spatially mainly distributed in the western, eastern, and northern edge regions. Additionally, 6 ecological corridors were identified (314.23 km), and 120 ecological pinch points and 605 km² of ecological barrier areas were determined. Based on the LUCC trends under multiple scenarios and the constructed future ESP, it is proposed to take the integration of economic development and ecological protection as the goal orientation, and carry out ecological restoration measures focusing on source protection, corridor construction, and node optimization respectively.

Declarations

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Author Contribution

Data Availability

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

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Figures

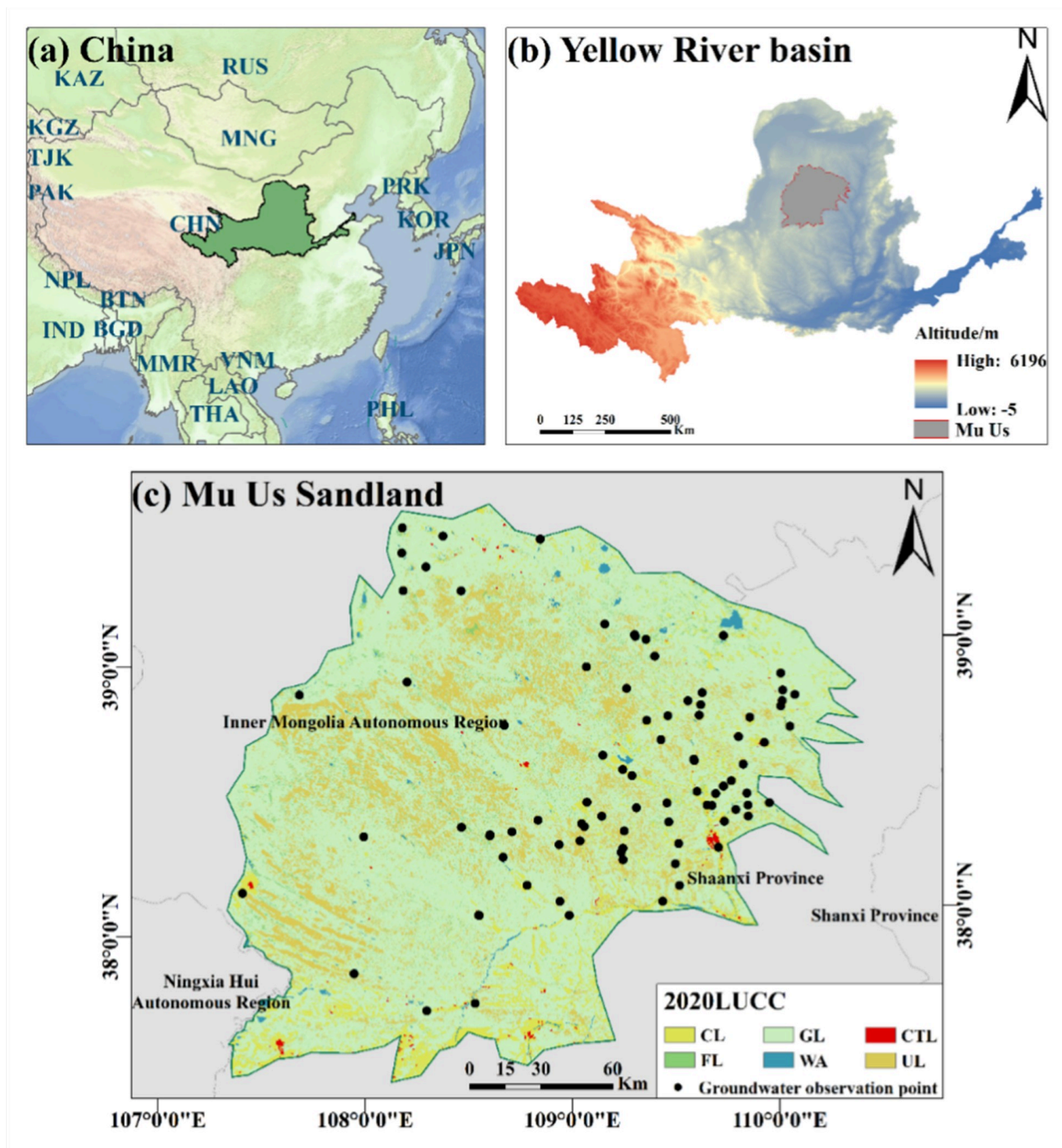


Figure 1

a) Location of the YRB, (b) Location of the MUS, (c) Spatial Distribution of Land Use Types and Groundwater Level Observation Points in 2020.

Note: CL, FL, GL, WA, CTL, and UL stand for cultivated land, forest land, grassland, water area, construction land, and unused land respectively.

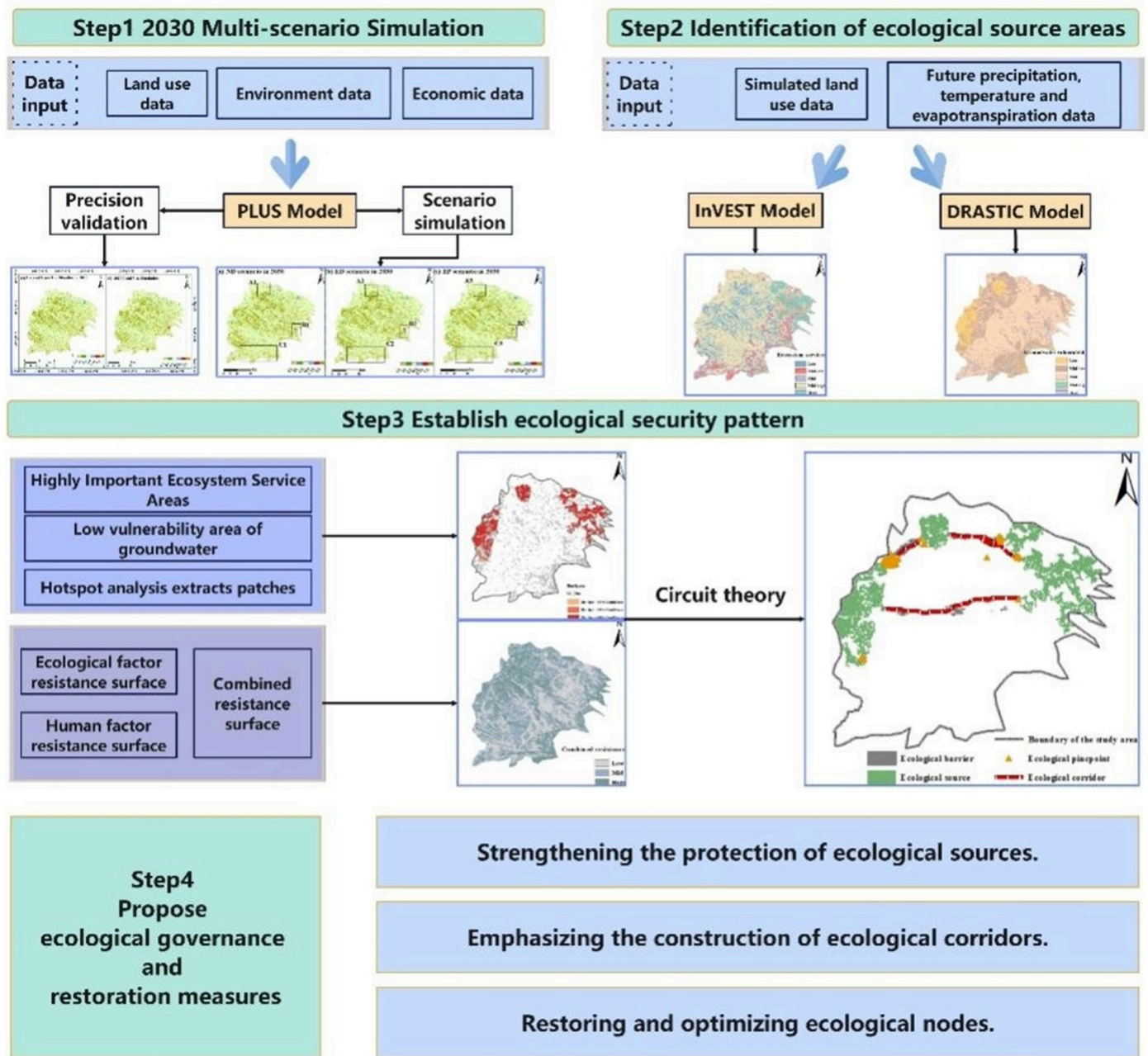


Figure 2

Technology roadmap.

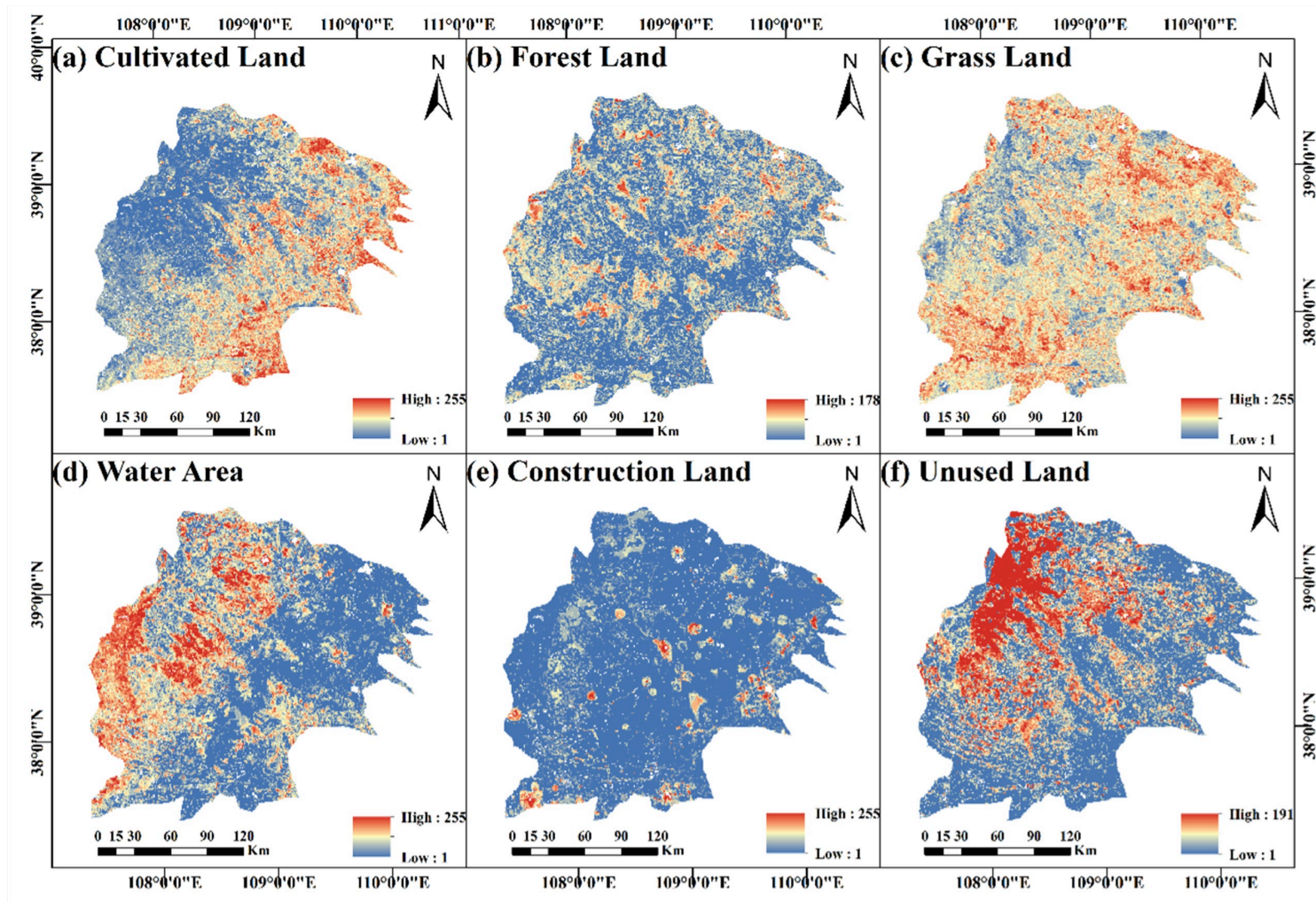


Figure 3

Maps of Land Development Probabilities for Different Land Use Types.

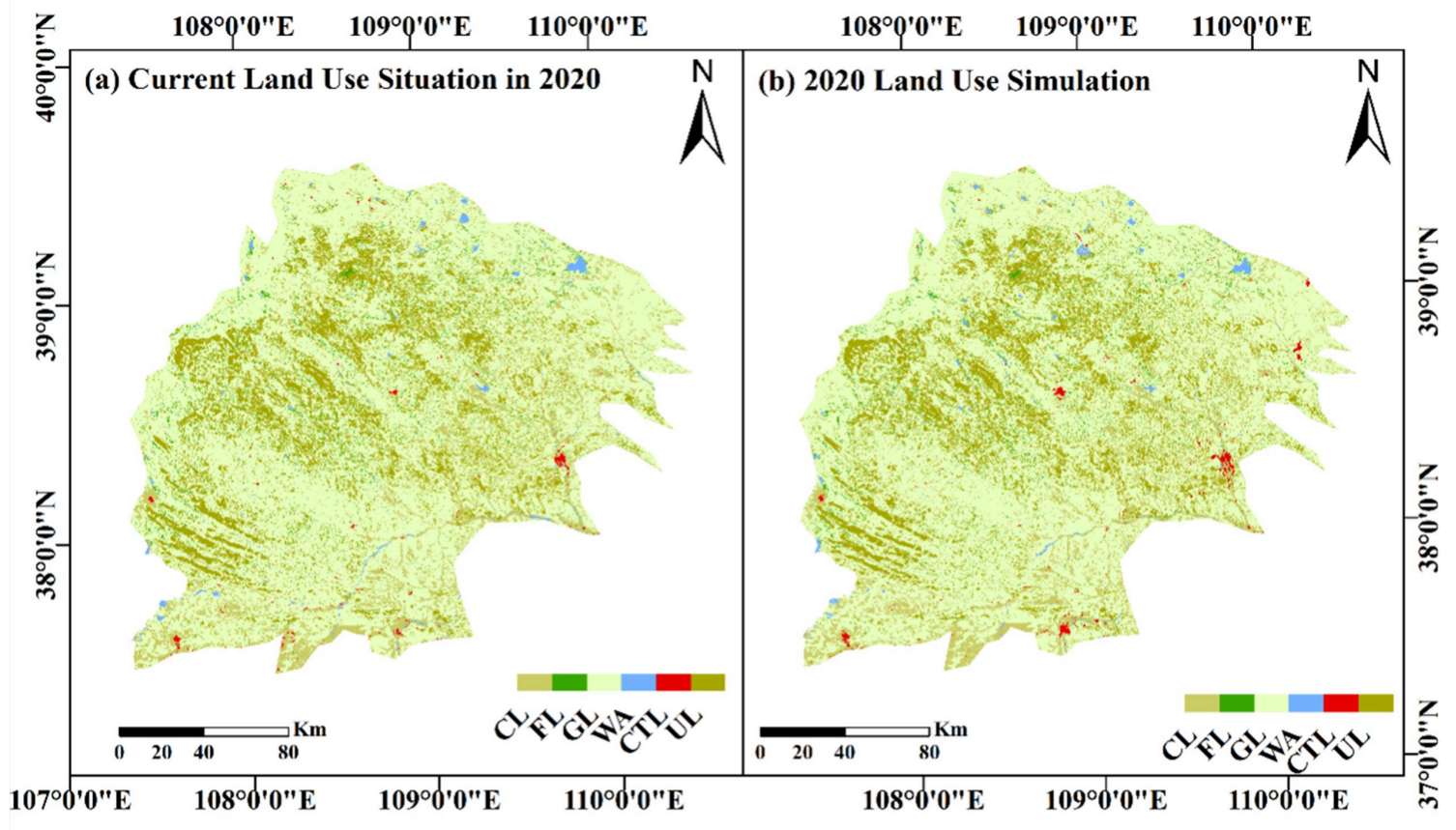


Figure 4

Comparison Between Actual Land Use Status and Simulation Results in 2020.

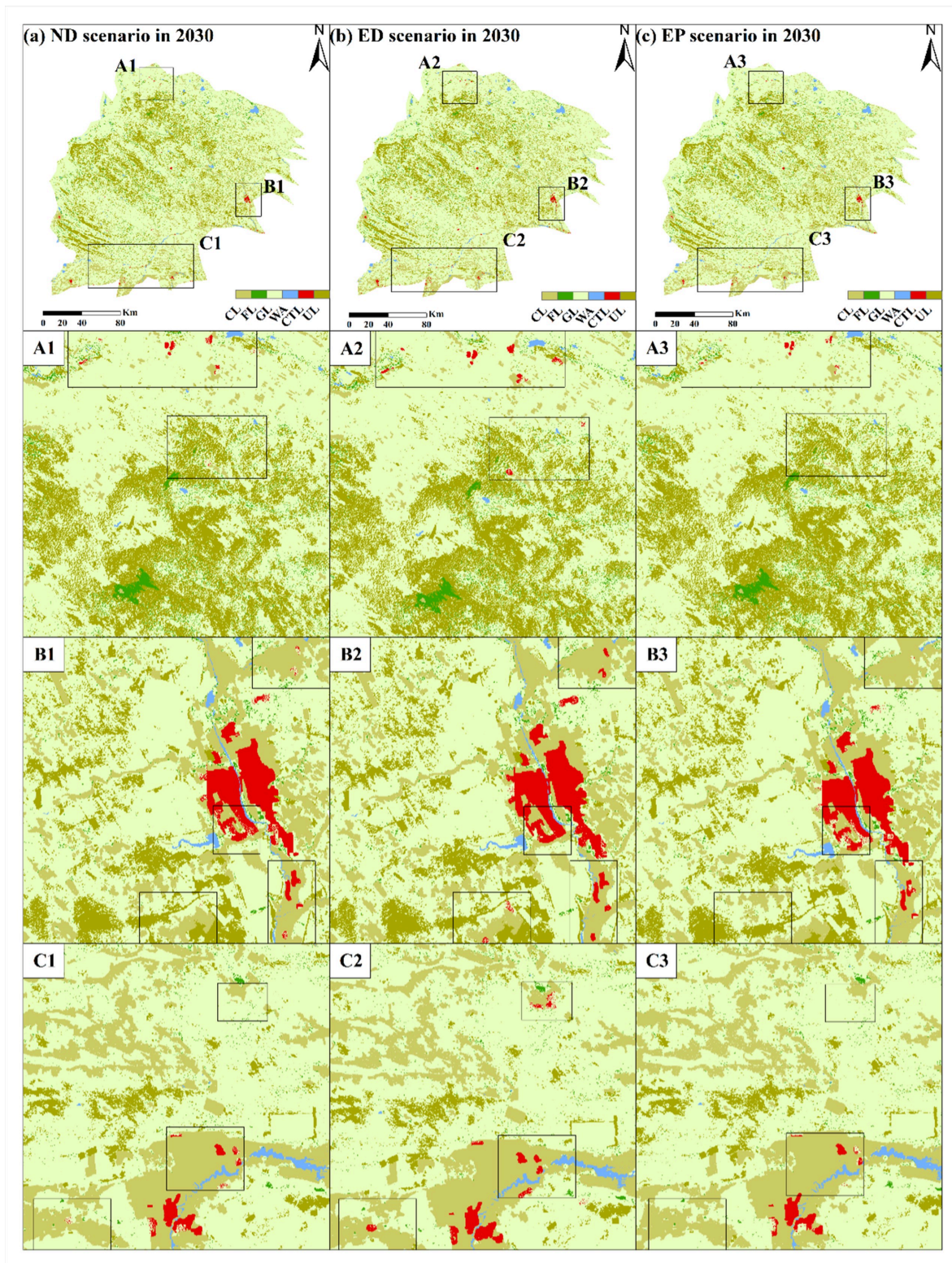


Figure 5

Simulated Maps of in the MUS Under Different Scenarios in 2030.

Note: (a) Natural-development scenario (ND); (b) Economic-development scenario (ED); (c) Ecological-protection scenario (EP); A1-A3, B1-B3, and C1-C3 denote partial enlarged views of typical regions for ND, ED, and EP scenarios.

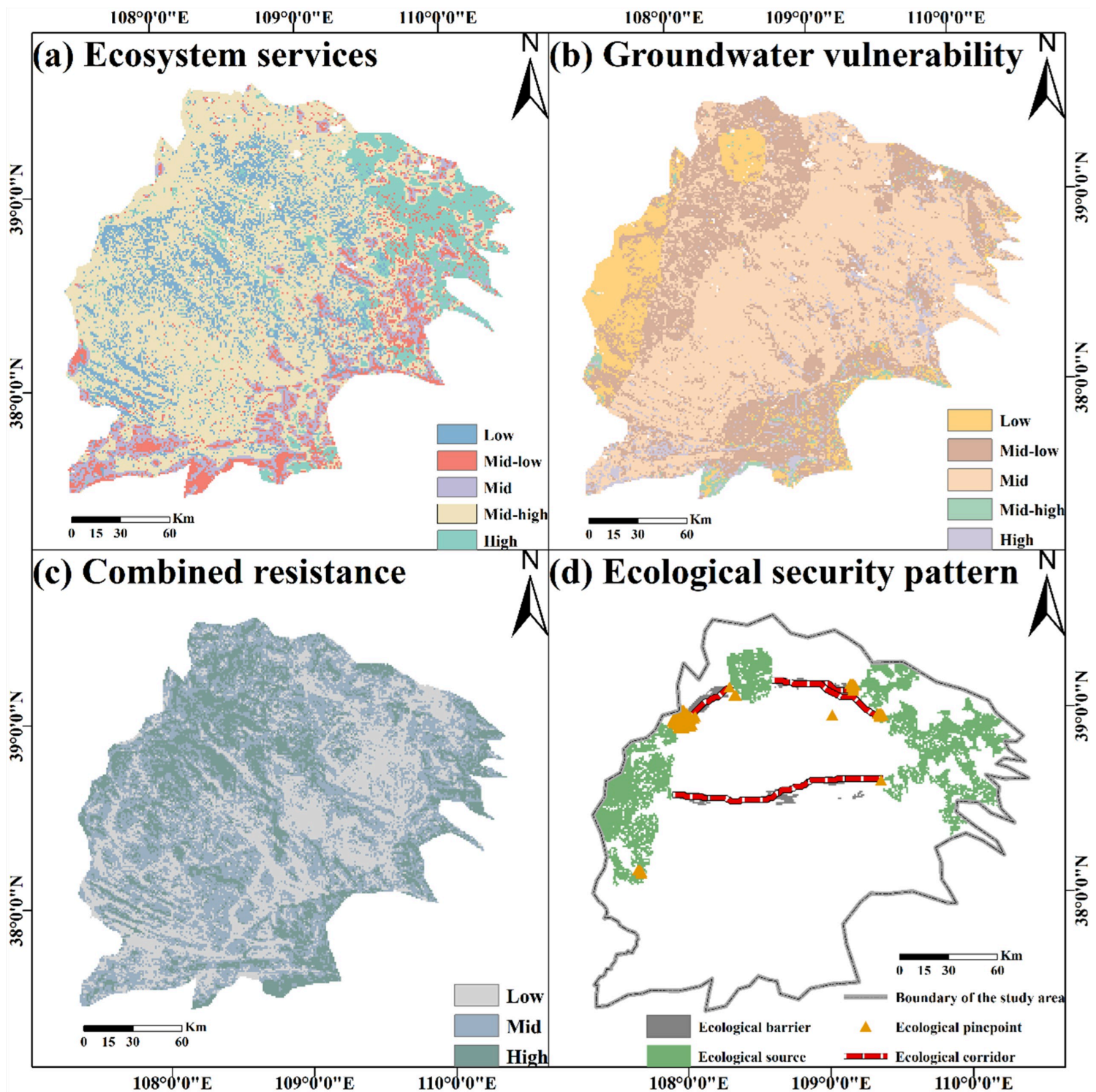


Figure 6

ESP of the MUS Under the ND Scenario.

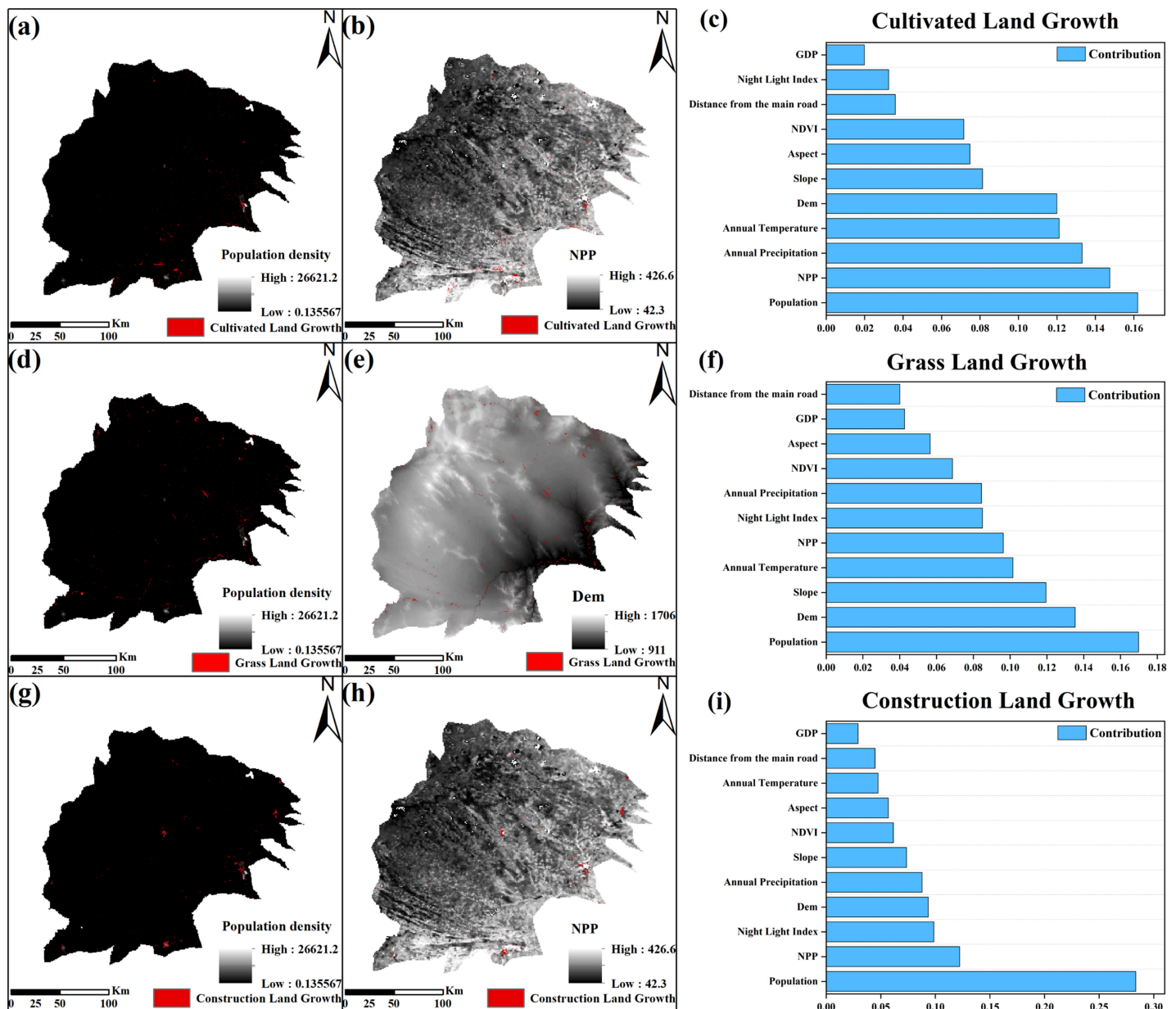


Figure 7

Importance of Driving Factors in Contributing for the Growth of Three Land Use Types.