

Article

Future Scenario Simulation and Optimization of Ecological Security Patterns Under Policy Drivers: A Case Study of the Henan Section of the Yellow River Basin, China

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Highlights

What are the main findings?

- Explicit policy constraints enable policy-informed simulations of future LUCC and ecological security patterns.
- The High-Quality Development Scenario (HQDS) produced a different simulated configuration ecological sources, corridors, and ecological security than the Natural Growth Scenario (NGS).

What are the implications of the main findings?

- The proposed framework provides a practical tool for policy-informed ecological security assessment.
- The findings support ecological network optimization and sustainable territorial spatial planning.

Abstract

Understanding the spatiotemporal dynamics of land-use and cover change (LUCC) and ecosystem service (ES) responses is essential for assessing ecological functions in regional landscapes. However, conventional LUCC simulations often rely on historical trends and inadequately represent the spatially heterogeneous effects of top-down policy constraints. Taking the Henan section of the Yellow River Basin (HYRB) as a case study, we developed a policy-to-rule framework that translated ecological redlines, urban development boundaries, and restoration requirements into explicit spatial constraints and land-use transition rules in the PLUS model. A policy-constrained High-Quality Development Scenario (HQDS) was established, with the Natural Growth Scenario (NGS) as a reference. Five ESs were assessed using InVEST from 1985 to 2050, and the results were integrated with the Minimum Cumulative Resistance (MCR) model and circuit theory to construct an

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ecological security pattern (ESP). Historical reconstruction of the 2022 land-use pattern achieved an overall accuracy of 90.18% and a Kappa coefficient of 86.39%. The five ESs remained relatively stable overall: water yield, soil conservation, and the sediment-related indicator increased, whereas habitat quality and carbon storage declined slightly. Ecological source areas expanded from 7140.54 km² in 1985 to 12,039.17 km² under the HQDS in 2050, a 68.6% increase. Compared with the NGS, the HQDS increased source areas by 562.42 km² (4.9%), reduced ecological corridors from 26 to 24, and increased their total length from 1068.89 to 1099.61 km. These differences represent the projected, scenario-conditioned consequences of the specified policy constraints and provide quantitative decision support for future ecological management.

Keywords: ecosystem services; ecological security patterns; policy-constrained simulation; multi-scenario simulation; Yellow River Basin

1. Introduction

Dynamic assessment of the Ecological Security Pattern (ESP) at national and regional scales, coupled with future scenario simulations, is essential for enhancing ecological early-warning capacity, promoting spatial optimization, and supporting regional sustainable development [1,2]. In China, intensive human activities and large-scale development strategies have profoundly reshaped regional land-use structures, exacerbating the spatial conflict between urban expansion and ecosystem conservation [3]. To mitigate these conflicts and achieve adaptive environmental governance, quantitatively modeling and optimizing the spatial topology of ecosystems is crucial. ESP, which represents the potential spatial network of ecosystems shaped by the distribution and interactions of key ecological elements across the landscape, has become an important basis for decision support in regional ecological management and spatial planning [4–6].

In recent years, as the concept of ecosystem services (ES) has been increasingly incorporated into ESP research, ESP research has gradually shifted from structure-oriented analyses to function-oriented assessments [7–9]. Early ES research was largely centered on monetary valuation and macro-level natural capital accounting, primarily to enhance public and policymakers' recognition of ecological value [10]. However, growing evidence suggests that uniform approaches based on static estimates often obscure the spatial heterogeneity of ecological processes in complex geographical settings, thereby constraining their applicability to land-use optimization and meso- and micro-scale spatial management [11]. Recent advances in geospatial analysis have shifted ES research from conventional economic valuation toward dynamic, multidimensional analyses of spatial trade-offs. This methodological shift helps overcome the limitations of traditional approaches that rely on static land-cover patterns and provide limited insight into underlying driving mechanisms. It also creates new opportunities to integrate ESs into ESP research. By combining ecosystem service assessment with ESP analysis, researchers can identify key geographical factors that support regional ecosystem stability and provide a scientific basis for refined, cross-regional ecological conservation policies.

As research on this coupled framework has advanced, ESP construction has shifted from subjective, qualitative approaches to more objective, quantitative methods. This transition has contributed to a research paradigm centered on the identification of ecological sources, the delineation of ecological barriers, and the construction of ecological corridors [12]. The identification of ecological sources is fundamental to understanding landscape dynamics and constructing ESP. Two main approaches are commonly used to identify ecological sources. The first approach is based on Morphological Spatial Pattern

Analysis (MSPA). This approach applies morphological operations to land-use/land-cover change (LUCC) data to extract core landscape areas, which are then identified as ecological sources [13,14]. However, MSPA is primarily suited to spatial-structure analysis and has limited applicability to policy-oriented tasks, such as delineating ecological conservation redlines or functional zones [15]. The second approach identifies ecological sources by assessing ES using the Integrated Valuation of ESs and Tradeoffs (InVEST) model. This approach quantitatively identifies hotspots of multiple ESs as ecological source areas. The InVEST model is well aligned with contemporary goals of ecological civilization construction, and its outputs have been widely applied in ecological compensation and spatial decision-support systems [16,17]. For ecological corridor identification, an integrated approach combining the Minimum Cumulative Resistance (MCR) model and Circuit Theory (CT) has become increasingly common [18,19]. The MCR model identifies potential corridors by calculating least-cost paths between ecological sources, whereas circuit theory simulates ecological flows as random walks across a resistance surface [20]. CT uses current-density patterns to identify multiple potential pathways and ecological pinch points while accounting for landscape permeability and corridor width [21]. This combined approach more realistically captures dispersal barriers in heterogeneous landscapes and helps overcome the limitation of the standalone MCR model, which tends to represent connectivity through a single optimal pathway [22]. Although the research framework for ESP has become increasingly sophisticated, its application remains largely limited to static evaluation, with gaps still existing in dynamic simulation and prediction.

In response to increasingly complex regional environmental changes, scholars have recognized that static assessments of ESs are no longer sufficient to meet the needs of sustainable development. Accordingly, dynamic modeling and prediction of regional ecosystem service trajectories under multi-scenario frameworks have become increasingly important [23]. LUCC strongly shapes interactions between human activities and the natural environment, thereby influencing regional development patterns and ecosystem evolution [24]. Therefore, accurate simulation of LUCC under different development scenarios is essential for effectively managing future regional ESP. Commonly used models for LUCC simulation include traditional Cellular Automata (CA) [25], Conversion of Land Use and its Effects at Small Regional Extent (CLUE-S), and the Future Land Use Simulation (FLUS) model [26]. However, these models remain limited in simulating complex land-surface processes. As a result, they may not fully capture the nonlinear evolution of land-use patches or the competition between natural vegetation and artificial landscapes under multiple drivers.

To address these technical challenges, the Patch-generating Land Use Simulation (PLUS) model has been developed. By integrating the Land Expansion Analysis Strategy (LEAS) with a cellular automata model based on multi-type random patch seeds (CARS), PLUS improves the simulation of patch-level changes across multiple land-use types. Therefore, it has been widely used to predict future land-use scenarios and support the optimization of regional ecological spaces [27]. Despite its advantages in patch-based spatial simulation, several limitations remain in the application of PLUS to policy-informed LUCC simulation and subsequent ecosystem-service and ecological-security assessments [28]. Policy constraints, including ecological conservation redlines, protected areas, permanent basic farmland, and urban development boundaries, have increasingly been incorporated into land-use scenario simulations through restricted-conversion zones or land-transition rules. These approaches are effective in preventing ecologically important areas from being converted into incompatible land-use types. However, many existing ecological conservation scenarios still represent policy intervention primarily through static spatial masks or generalized adjustments to future land-use demand.

Region-specific policy objectives are therefore not always systematically translated into coordinated adjustments to land-use demand, conversion direction, transition probability, and spatial allocation.

The Henan section of the Yellow River Basin (HYRB) is both an important national grain-producing region and a major development area of the Central Plains Urban Agglomeration. It is characterized by distinctive water–sediment interactions and pronounced ecological fragility, while facing increasing pressures from water scarcity, soil erosion, and urban expansion [29]. In 2019, ecological protection and high-quality development in the Yellow River Basin were elevated to a major national strategy, providing an overarching framework for coordinating ecological conservation and regional development. Against this background, 2035 corresponds to China’s national objective of basically achieving socialist modernization and coincides with the planning horizon of the Henan Provincial Territorial Spatial Plan (2021–2035) [30], whereas 2050 represents the mid-century vision of building a strong modern socialist country and provides a long-term horizon for evaluating policy effects [31]. Accordingly, this study translated HYRB-specific policy mechanisms into spatial constraints and land-use transition rules within the PLUS model, established a High-Quality Development Scenario (HQDS), and compared it with a Natural Growth Scenario (NGS). Historical LUCC from 1985 to 2022 and future projections for 2035 and 2050 were simulated to assess the spatiotemporal responses of multiple ESs and construct ESP. The specific objectives are as follows: (1) develop a spatial modeling framework that translates macro-level policy objectives into explicit land-use constraints and transition rules; (2) simulate the spatiotemporal dynamics of multiple ESs and compare the spatially heterogeneous effects of the HQDS and NGS; and (3) construct an ecological network optimization framework to support policy-responsive ecological management and territorial spatial planning in the basin.

2. Materials and Methods

2.1. Study Area

The HYRB is located between 110 and 116°E and 33–36°N, covering approximately 66,800 km² (Figure 1). Situated in the transitional zone between the middle and lower reaches of the Yellow River, the region is characterized by mountainous, hilly, and plain terrain. It has a warm temperate continental monsoon climate, with a mean annual temperature of 12.7–15.5 °C and annual precipitation of 349.2–970.1 mm. The study area is a major grain-producing region in China and is characterized by high population density, intensive land development, and acute land-use conflicts.

Owing to its complex topography and rich biodiversity, the region is highly sensitive to climate change and anthropogenic disturbances. Furthermore, intensified development activities have increased the intensity of human–land interactions and aggravated the conflict between resource exploitation and ecological conservation. These pressures are reflected in water scarcity and uneven water distribution, severe soil erosion, and habitat fragmentation. As a core area for implementing the national strategy for ecological conservation and high-quality development in the Yellow River Basin, the study area provides a representative case for examining policy-driven changes in ecological security patterns and simulating future development trajectories under multiple scenarios.

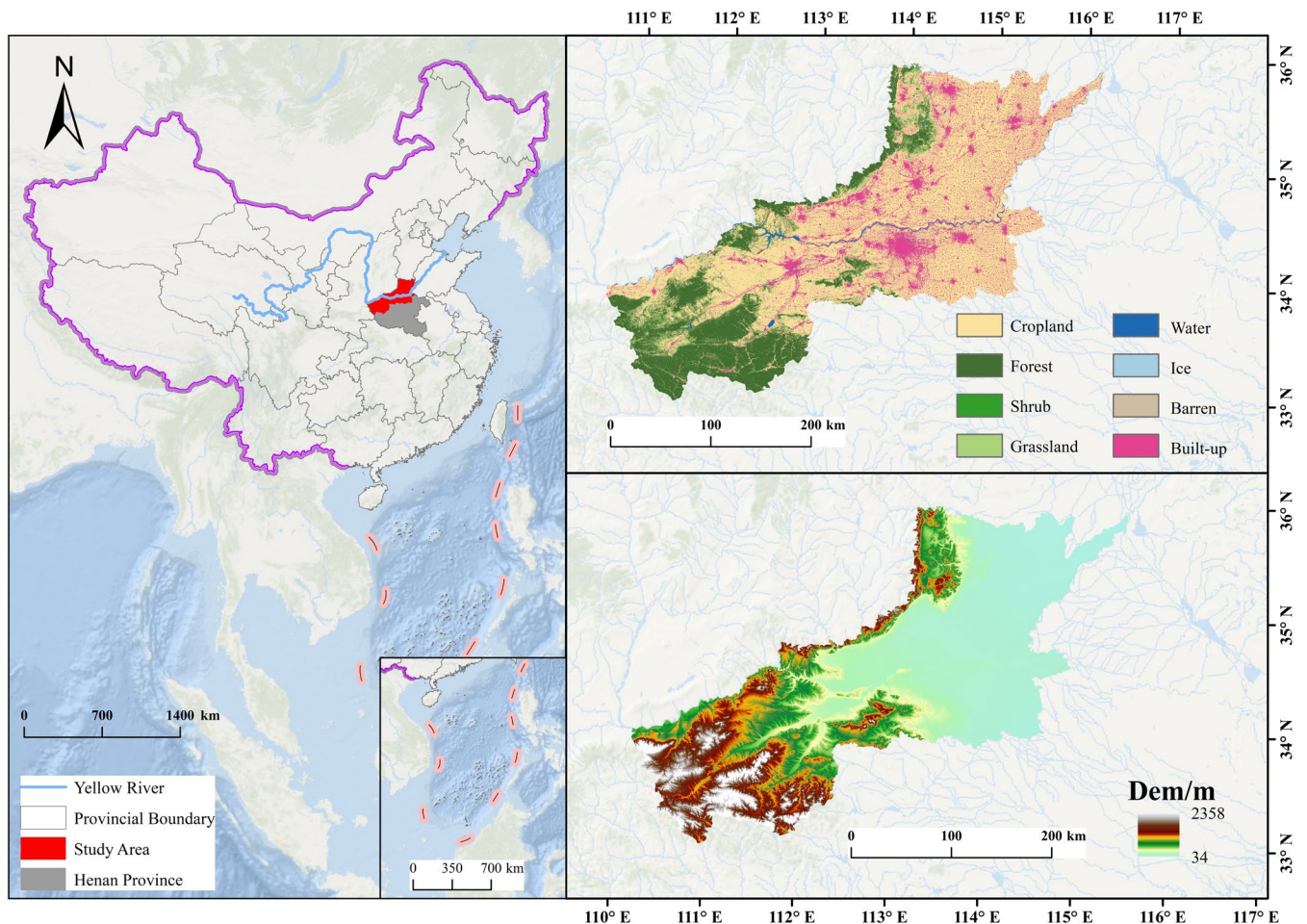


Figure 1. Location of the Henan section of the Yellow River Basin, China.

2.2. Data Sources

Considering the performance, availability, relevance, and temporal accuracy of the PLUS model, this study integrated LUCC data from 1985 to 2022 along with 17 related driving factors to predict future LUCC (Table 1), comprising (1) administrative boundaries, protected areas, wetlands, and river networks from the National Earth System Science Data Center; (2) elevation, slope, river systems, precipitation, temperature, soil types, population density, gross domestic product, and human footprint data from the Resource and Environmental Science and Data Center; and (3) road networks—including urban roads, railways, and national, provincial, and county roads—from OpenStreetMap. The LUCC data were provided by a research group led by Xin Huang at Wuhan University [32]. (4) Future meteorological data were obtained from CMIP6 climate projections generated by the MRI-ESM2-0 model under the SSP245 scenario. Annual precipitation, annual mean temperature, and potential evapotranspiration data for 2035 and 2050 were extracted.

This study employed land use data from nine periods (1985, 1990, 1995, 2000, 2005, 2010, 2015, 2020, and 2022) to calculate the corresponding ES and ESP for each year. Due to space limitations, only the results for 1985 and 2022 are presented in the main text, while the full series of temporal maps and statistical analyses are provided in the Supplementary Materials (Figures S1–S9).

Table 1. Sources of the data used in this study.

Type	Name	Resolution (m)	Data Source
Basic data	LUCC	30	Zenodo repository (https://zenodo.org/records/12779975 , accessed on 20 March 2026)
	Administrative divisions	—	NESSDC (https://www.geodata.cn/ , accessed on 20 March 2026)
	Elevation	30	RESDC
	Slope	30	Derived from elevation data
	River systems	—	RESDC
	Historical precipitation	1000	RESDC
Climatic and environmental data	Historical temperature	1000	RESDC
	Future precipitation	1000	CMIP6 MRI-ESM2-0, SSP245
	Future temperature	1000	CMIP6 MRI-ESM2-0, SSP245
	Future potential evapotranspiration (PET)	1000	CMIP6 MRI-ESM2-0, SSP245
Socio-economic data	Soil types	—	RESDC
	Population density	1000	RESDC
	Gross domestic product	1000	RESDC
	Human footprint	1000	RESDC
	Road networks	—	OpenStreetMap
Policy-constraint data	County government points	—	OpenStreetMap
	Protected areas	—	NESSDC
	Wetlands	30	NESSDC
	River protection zones	30	Georeferenced data
	Built-up land	30	Derived from LUCC
	Urban development boundary	30	Henan Territorial Spatial Plan

2.3. Research Framework

The methodological framework comprised three main components (Figure 2). First, data collection (detailed in Section 2.2) was conducted, which served as the foundation for all subsequent analyses. Second, the land-use scenario prediction component projected future land-use types using the PLUS model. The PLUS model comprised three modules: suitability probability estimated using a random forest algorithm, adaptive inertia integrated with competitive CA, and demand calculations [33]. Using the PLUS model, the ESP was simulated under both the NGS and HQDS. Finally, regional ESP was constructed by identifying ecological sources based on multiple ESs and extracting ecological corridors using the MCR model.

2.4. Methods

2.4.1. PLUS Model

The PLUS model, a grid-based CA framework specifically designed for simulating land use changes at the patch scale, was used to simulate future land use patterns in the HYRB. The model integrates historical land use data with regional policy directives, including afforestation areas under the Grain-for-Green Program, ecological protection zones, and projected urban development, along with anthropogenic activity data and other driving factors (Table 1).

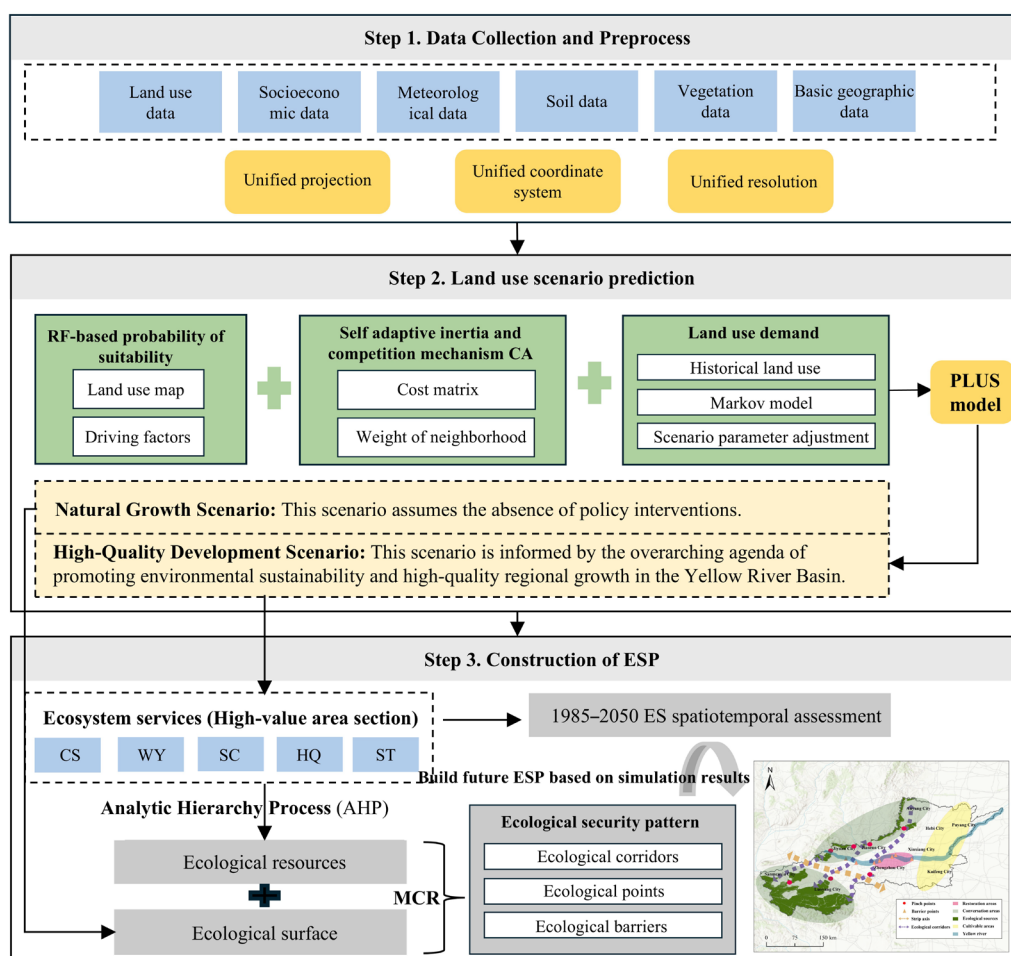


Figure 2. Schematic of the employed research framework.

To ensure the reliability of the simulation, the overall accuracy and kappa coefficient were used as quantitative metrics to assess the performance of the PLUS simulation. The formulations are as follows:

$$Kappa = (K_0 - K_c) / (K_d - K_c) \quad (1)$$

where K_0 represents the proportion of correctly simulated values, K_c denotes the expected proportion of simulated values, and K_d is the ideal simulation value, which is typically set to 1.

For historical hindcast validation, the observed 2022 LUCC data were withheld from model calibration and used only as an independent validation reference. The simulated 2022 LUCC pattern was compared with the observed 2022 LUCC data, yielding an overall accuracy of 90.18% and a Kappa coefficient of 0.8639 (86.39%). These results indicate that the model reproduced the recent historical LUCC pattern with a high level of agreement. For 2035, the land-use transition probability matrix was derived from the observed LUCC changes between 2005 and 2020 and used to estimate land-use demand for the subsequent 15-year period from 2020 to 2035. Because both the transition-calibration interval and the projection interval spanned 15 years, no additional temporal rescaling was required. For 2050, a new transition probability matrix was derived from the LUCC transition structure between 2020 and 2035, with the 2035 LUCC pattern obtained from the preceding simulation. This matrix was then used to estimate land-use demand for the subsequent 15-year period from 2035 to 2050. (Detailed parameter settings are provided in the Supplementary Materials).

2.4.2. ESs Evaluation

This study used the InVEST model to quantify the key ESs associated with LUCC. InVEST provides spatially explicit models for simulating ecosystem functions and service flows by integrating biophysical processes with land-use/land-cover data under different scenarios. Four ESs were selected based on their relevance to the ecological security pattern of the HYRB: water yield (WY), soil conservation (SC), carbon storage (CS), and habitat quality (HQ). WY, SC, CS, and HQ were quantified using the InVEST Water Yield, Sediment Delivery Ratio, Carbon Storage, and Habitat Quality modules, respectively. The input data, model parameters, and detailed calculation procedures are provided in the Supplementary Materials.

To characterize the water–sediment relationship in the HYRB, the InVEST Sediment Delivery Ratio (SDR) model was also used to derive a sediment transport regulation indicator (ST). The raw `sed_export.tif` output was first defined as sediment export (SE), rather than as direct sediment transport or sediment retention [34]. At the pixel level, SE was calculated as:

$$SE_i = USLE_i \times SDR_i \quad (2)$$

where SE_i is the sediment export from pixel i , $USLE_i$ is the soil loss estimated by the $USLE$ component, and SDR_i is the sediment delivery ratio. Thus, SE represents the amount of eroded sediment delivered from a pixel to the stream network. It does not represent sediment transport, deposition, or erosion processes within the river channel.

Because SE is a negative indicator, with higher values indicating greater sediment delivery pressure and weaker sediment regulation, it was transformed into a positive sediment transport regulation indicator (ST) using inverse min–max normalization

$$ST_i = \frac{SE_{\max} - SE_i}{SE_{\max} - SE_{\min}} \quad (3)$$

where $SE_{\max}$ and $SE_{\min}$ represent the maximum and minimum SE values within the corresponding assessment raster, respectively. After normalization, higher ST values indicate lower modeled sediment export pressure and stronger regulation of overland sediment delivery.

2.4.3. Multi-Scenario Simulation Scheme

Drawing on previous research and the region's unique environmental context [35], this study designed two scenarios: a Natural Growth Scenario (NGS) and a High-Quality Development Scenario (HQDS).

Scenario I, NGS: The NGS assumes that no additional policy-specific constraints are imposed beyond the baseline land-use conversion rules. Land-use demand for 2035 was estimated using transition probabilities derived from the 2005–2020 LUCC data. For the 2050 projection, the transition structure derived from the 2020–2035 NGS simulation was used to estimate land-use demand for 2035–2050. The binary conversion matrix used values of 1 and 0 to indicate permitted and prohibited land-use transitions, respectively.

Scenario II, HQDS: The HQDS translates regional ecological conservation and territorial spatial planning policies into spatial constraints and quantitative transition parameters. Ecological conservation redline areas, including river systems, wetlands, protected areas, and other designated ecological zones, were converted into raster constraint layers. Land-use conversions prohibited within these areas were assigned a value of 0 in the conversion matrix. The urban development boundary obtained from the Henan Provincial Territorial Spatial Plan (2021–2035) was georeferenced and rasterized. Outside this boundary, conversions from non-built-up land to built-up land were prohibited, whereas such conversions were permitted within the boundary according to the baseline transition rules. In addition, guided by the Notice on Territorial Ecological Restoration and Forest Henan Construction, cropland cells with

slopes greater than 25° were identified as priority areas for Grain for Green restoration, and cropland-to-forest transitions were prioritized in these areas.

For quantitative land-use demand estimation, baseline transition probabilities for 2005–2020 were first obtained using the Markov model. Under the HQDS, the probabilities of cropland conversion to forest, grassland, water bodies, and unused land, as well as those of built-up land conversion to water bodies and unused land, were multiplied by 1.20. The adjusted probabilities were then normalized so that each row summed to 1, while policy-prohibited transitions remained fixed at 0. For the 2050 projection, the scenario-specific 2020–2035 transition structure was used, with the corresponding HQDS policy constraints applied. The complete transition matrices and policy parameters are provided in the Supplementary Tables.

2.4.4. Identification of Ecological Sources

As critical areas for maintaining ecosystem stability and landscape coherence, ecological source areas play a key role in enhancing regional ecological resilience and safeguarding biodiversity protection [36]. This study normalized five key ecosystem service indicators (SC, WY, CS, HQ, and ST) derived from the InVEST model. Areas with high ecosystem service functionality were then identified to delineate ecological conservation redlines. Subsequently, the five ESs were weighted using expert judgment through the analytic hierarchy process (AHP) [37]. The weighted indicators were aggregated to produce an Ecosystem Service Index (ESI). The resulting ESI layers were classified into five categories using the natural break method, with the highest-value areas identified as ecological sources [38]. Considering that excessively small patches may compromise ecological connectivity, patches smaller than 10 km² were excluded based on prior studies and connectivity analyses, whereas the remaining patches were retained as the final ecological sources [39]. (Specific design details are provided in the Table S9).

2.4.5. Construction of Comprehensive Resistance Surface

The resistance surface serves as a crucial tool for analyzing how species overcome ecological barriers to expand their distribution ranges [40]. In this study, six indicators were selected as resistance factors for constructing the overall resistance surface: land cover type, topographic conditions (elevation and slope), and ecological stress factors (distance from roads, built-up areas, and water bodies) (Table 2). Based on previous research and the natural environmental characteristics of the area, as well as differences in habitat suitability and distance decay principles, values were assigned to these resistance factors. Each resistance factor was then weighted based on its relative importance, as determined using the AHP method.

Table 2. Weights and coefficients of various resistance factors.

Factor	Weight	Indicator	Coefficient	Factor	Weight	Indicator	Coefficient
Land type	0.4585	Forest	1	Distance from Road	0.081	>35,000	1
		Water	10			25,000–35,000	100
		Grassland	50			10,000–25,000	300
		Cropland	100			3000–10,000	500
		Barren	500			<3000	800
DEM	0.0495	Built-up land	1000	Distance from Water	0.2469	0–3000	1
		<200	1			3000–7000	5
		200–500	100			7000–15,000	100
		500–800	200			15,000–20,000	200
		800–1000	300			>20,000	300
Slope	0.0639	>1000	500	Distance from Built-up Land	0.1002	>4000	1
		<6	1			3000–4000	100
		6–15	100				

15–25	200	2000–3000	200
25–35	500	1000–2000	500
>35	1000	<1000	1000

2.4.6. Extraction of Ecological Corridors

The maintenance of ecological processes and the enhancement of landscape connectivity rely heavily upon ecological corridors [41,42]. Circuit theory is widely applied to identify ecological corridors because it can effectively model multiple dispersal pathways across heterogeneous landscapes [43]. The formula is as follows:

$$I = V / R_{ef} \quad (4)$$

Ecologically, I represents the aggregate likelihood of species movement, V denotes the probability of directional movement from a source to a target, and R_{ef} measures the resistance of the landscape to movement or energy flow.

Ecological corridors were delineated by integrating ecological source areas with a resistance surface utilizing circuit theory and the Linkage Mapper tool. Five resistance classes were derived from the integrated resistance surface using quantile-based classification [44]: high ecological security (HES), sub-high ecological security (SHES), moderate ecological security (MES), sub-low ecological security (SLES), and low ecological security (LES). Linkage Mapper was implemented to connect ecological sources with resistance surface data, calculating the cost-weighted distance (CWD) and least-cost path (LCP) between sources based on a connectivity model grounded in circuit theory.

3. Results

3.1. Spatiotemporal Evolution of LUCC During 1985–2050

In summary, under both scenarios, cropland is projected to decline continuously from 1985 to 2050, whereas built-up land is expected to expand steadily, with most converted cropland transitioning into built-up land. Spatially, the study area is dominated by cropland, followed by forest and built-up land (Figure 3). Cropland is predominantly distributed across the central and eastern plains, where abundant solar radiation and favorable hydrothermal conditions support intensive agricultural production. Forest is mainly distributed in the southern Funiu Mountains and northern Taihang Mountains, where relatively humid conditions and stable precipitation support montane forest ecosystems.

Historical LUCC data indicate that from 1985 to 2022, land-cover change in the region was primarily driven by urbanization and followed a clear pattern of “three increases and two decreases”—namely, increases in built-up land, forest, and water bodies, and decreases in cropland and grassland (Table 3). During this period, cropland area declined steadily, with most cropland converted to built-up land (6643.34 km²), followed by grassland (1536.11 km²). Grassland area also declined overall, decreasing by 1271.57 km², mainly due to forest conversion (1128.54 km²). Forest area fluctuated but increased overall, expanding by 1427.95 km², primarily through cropland conversion. The area of water bodies increased slightly by 110.91 km². Built-up land expanded steadily under continuous urbanization and became the land-cover type with the largest absolute change, increasing by 6162.03 km² over the 37 years. The expansion of built-up land was primarily driven by conversion from cropland (6643.34 km²). Notably, a small portion of built-up land (618.99 km²) was also converted back to cropland, indicating limited land-use reversals. Barren land accounted for only a marginal proportion of the study area and had limited influence on the overall land-use structure. Although barren land showed a relatively high rate of change, its absolute area remained minimal. Due to initial reclamation for forest and grassland, followed by rapid conversion to built-up land, barren land increased by only 0.61 km² during the study period. Under the HQDS, projected LUCC

changes include losses of 3102.44 km² of cropland and 175.64 km² of grassland. Most converted cropland is expected to transition to built-up land (2596.81 km²), whereas grassland is projected to be primarily converted to forest (193.40 km²). No substantial changes are projected for water bodies or barren land.

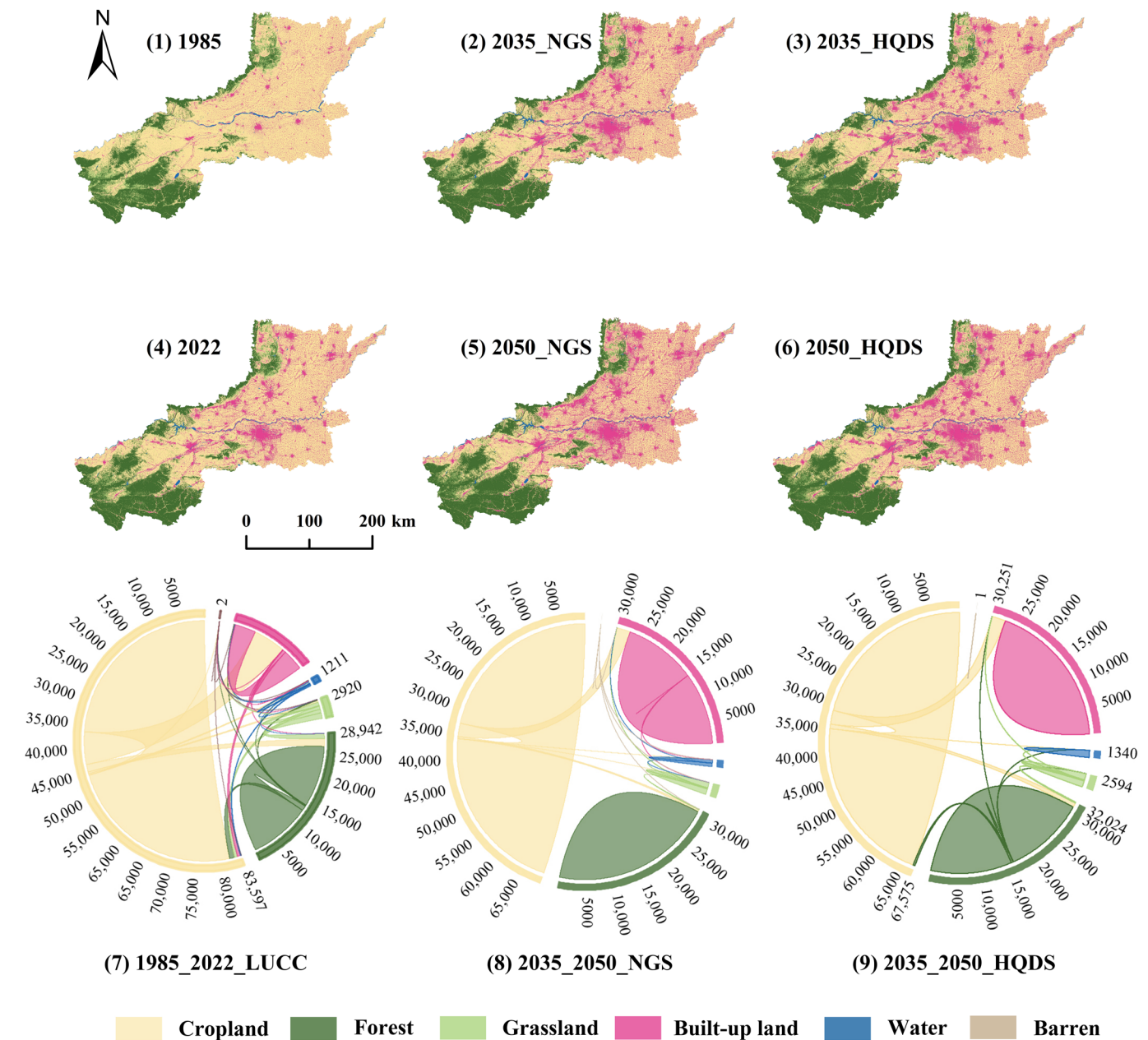


Figure 3. Spatial distribution and transformation of LUCC in the study area.

Table 3. LUCC (km²) from 1985 to 2050.

LUCC	1985	2022	1985–2022	2035		2050		2035–2050 (NGS)	2035–2050 (HQDS)
				NGS	HQDS	NGS	HQDS		
Crop land	45,013.34	38,583.41	−6429.93	35,530.80	35,338.63	32,569.71	32,236.19	−2961.1	−3102.44
Forest	13,748.07	15,176.02	1427.95	15,546.98	15,687.49	16,060.73	16,336.80	513.75	649.31
Grass land	2596.01	1324.44	−1271.57	1288.77	1384.90	1064.35	1209.26	−224.42	−175.64
Water	550.06	660.97	110.91	678.36	666.73	686.16	673.45	7.8	6.72
Built-up land	4984.46	11,146.49	6162.03	13,847.64	13,814.44	16,511.71	16,436.50	2664.07	2622.06
Barren	0.82	1.43	0.61	0.21	0.57	0.10	0.57	−0.11	0
Total	66,892.76	66,892.76		66,892.76	66,892.76	66,892.76	66,892.76		

3.2. Spatiotemporal Evolution of ESs During 1985–2050

Overall, the four ESs and the raw sediment export output (SE) exhibited pronounced spatial heterogeneity during 1985–2050 (Figure 4). WY showed a clear southwest–north–east gradient, with relatively low values in the southwest and progressively higher values toward the northeast. SC, HQ, and CS were generally higher in the mountainous and forested areas, particularly in the southwestern Funiu Mountains and the northern mountainous region, and lower in the central and eastern plains. These spatial patterns were consistent with the effects of topography, vegetation cover, and land-use structure. In contrast, SE was mainly concentrated in mountainous areas with relatively high erosion and sediment-delivery potential, whereas lower values were generally observed in the plain areas.

The temporal changes differed among the indicators and periods. From 1985 to 2022, WY, SC, HQ, and CS decreased to varying degrees, while SE also declined. During 2035–2050, WY and SC increased under both the NGS and HQDS, with WY showing the most pronounced increase. In contrast, HQ and CS decreased slightly under both scenarios. SE increased during the same period under both scenarios, but the magnitude of the increase was slightly lower under the HQDS than under the NGS.

3.3. Ecological Source Area Identification and Modeling

Overall, the area of the ecological source regions in the HYRB demonstrated a steadily increasing trend from 1985 to 2050, reaching a maximum in 2050 (Figure 5). The ecological source area increased from 7140.54 km² in 1985 to 7821.99 km² in 2022, corresponding to a growth of 681.45 km². The scenario simulations further projected that the ecological source area would reach its highest value within the study period by 2050, reflecting the continuous spatial expansion of regional ecological functions. Under the future scenarios, the ecological source area is projected to reach 8691.76 km² under the NGS and 8857.68 km² under the HQDS by 2035. Compared with 2022, these values represent increases of 869.77 km² under the NGS and 1035.69 km² under the HQDS. By 2050, the ecological source area is projected to reach its peak. Specifically, the ecological source area is projected to reach 11,476.75 km² under the NGS and 12,039.17 km² under the HQDS (Table 4). The number of ecological source patches decreases steadily over the study period, from 38 in 1985 to 35 in 2022 and further to 15 by 2050.

Spatially, ecological source areas were primarily concentrated in the southwestern Funiu Mountains and northern Taihang Mountains. Newly added ecological source areas were largely situated near the northern Taihang Mountains, whereas ecological connectivity in the southwestern Funiu Mountains continued to improve. This pattern suggests that high ecological quality in these regions extends into surrounding areas, thereby enhancing overall regional ecological functions.

Table 4. Areas and number changes in ecological sources.

	Number of Ecological Sources	Area of Ecological Sources (km ²)	Change Relative to 1985 (km ²)	Change Relative to 1985 (%)	Change Relative to 2022 (km ²)	Change Relative to 2022 (%)
1985	38	7140.54				
2022	35	7821.99	+681.45	+9.54		
2035_NGS	32	8691.76	+1551.22	+21.72	+869.77	+11.12
2035_HQDS	31	8857.68	+1717.14	+24.05	+1035.69	+13.24
2050_NGS	15	11,476.75	+4336.21	+60.73	+3654.76	+46.72
2050_HQDS	15	12,039.17	+4898.66	+68.60	+4217.18	+53.91

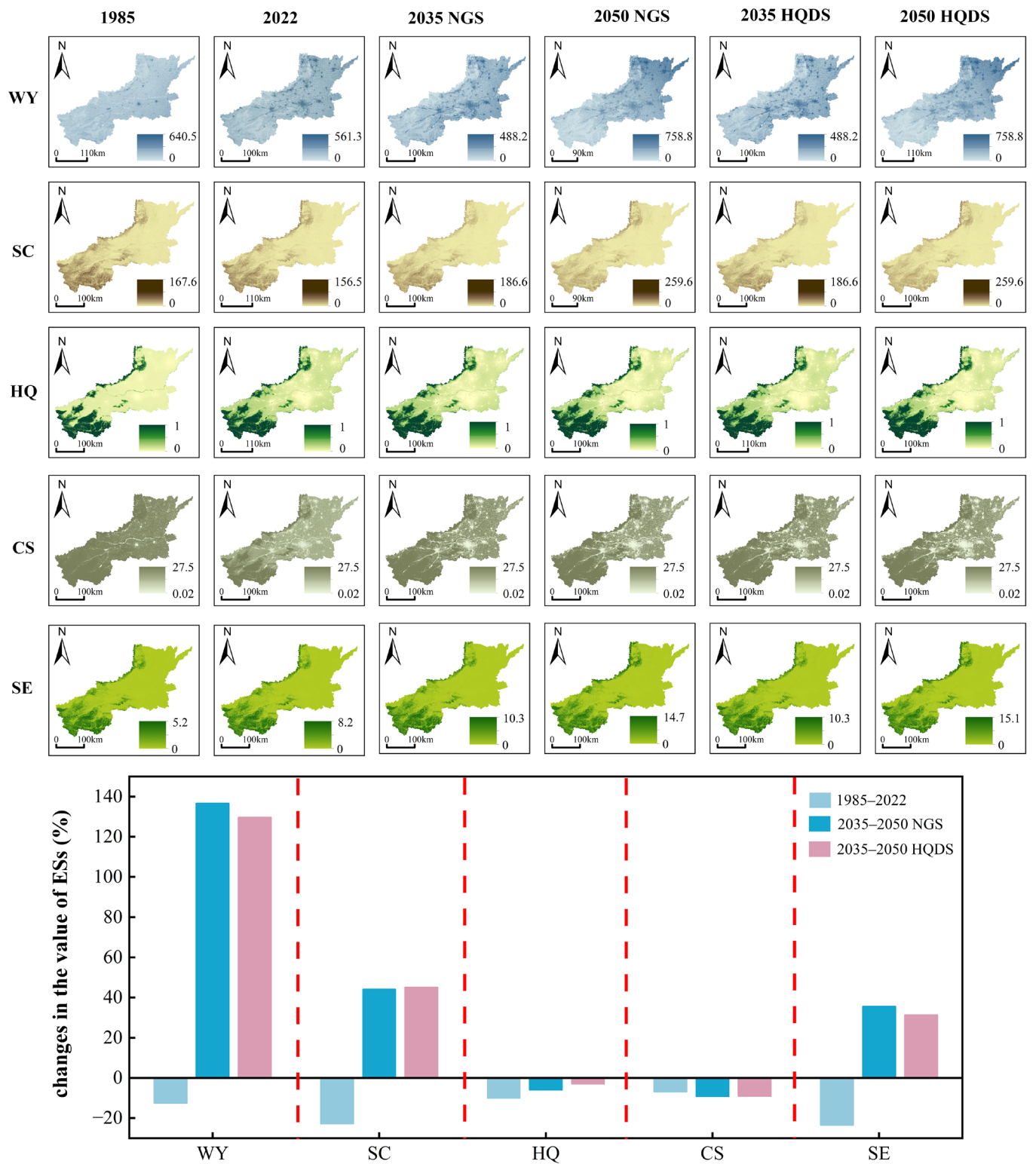


Figure 4. Spatial distribution and temporal variation of the ES.

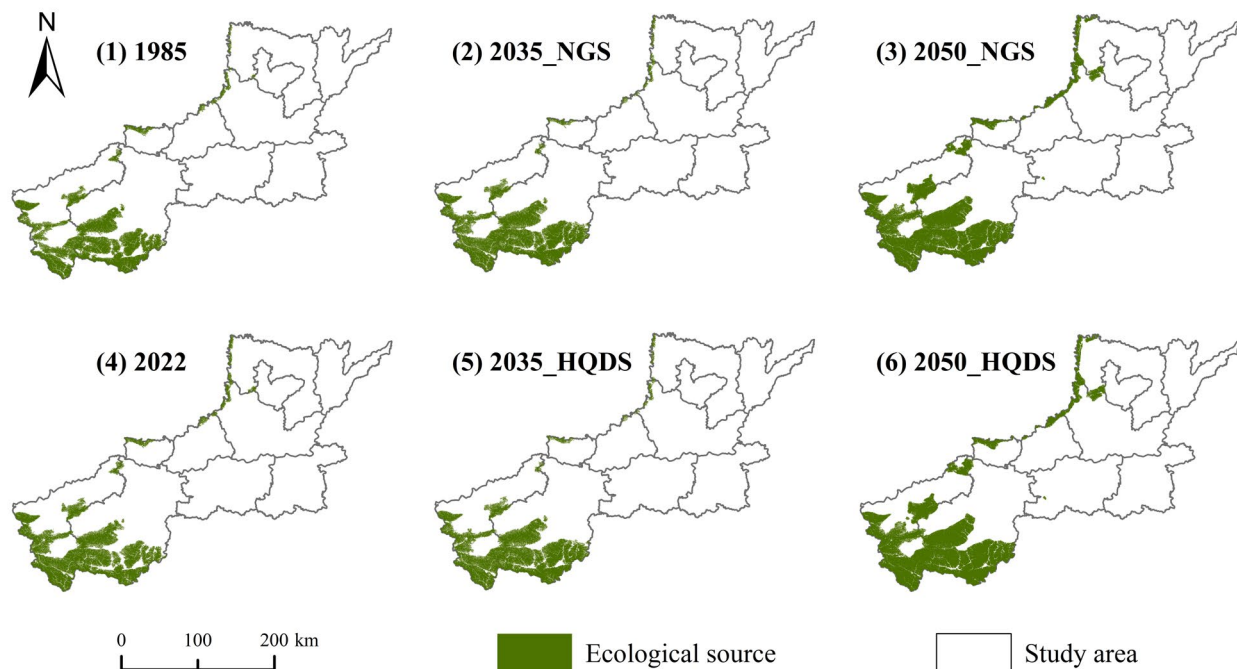


Figure 5. Spatiotemporal distribution of the ecological sources.

3.4. Resistance Surface Construction and Modeling

Overall, the regional resistance surface exhibited pronounced spatial heterogeneity (Figure 6). Low-resistance areas were concentrated in the southwestern Funiu Mountains, whereas high-resistance areas were mainly clustered around built-up areas in the central, eastern, and northern parts of the study area. Over time, these high-resistance zones gradually expanded outward from urban centers. Specifically, the regional resistance values extended from 13.67 up to 786.22. Under the NGS, the average resistance was lowest in 1985 (245.61) and highest in 2050 (318.65) (Table 5). From 1985 to 2050, the mean resistance increased steadily under both scenarios.

Spatially, resistance values showed marked heterogeneity. Low resistance zones were predominantly distributed in the southwestern Funiu Mountains, where abundant rainfall, dense vegetation, and high biodiversity support species migration and ecological processes, leading to reduced ecological resistance. The areas with higher resistance levels were mainly located in various cities, and they have gradually spread to nearby regions over time.

Table 5. Descriptive statistics of resistance-surface values from 1985 to 2050.

	Minimum	Maximum	Mean	Standard Deviation
1985	16.79	786.22	245.61	118.97
2022	13.92	786.22	286.30	162.00
2035_NGS	13.67	786.22	302.43	175.99
2035_HQDS	13.67	786.22	302.12	175.89
2050_NGS	13.67	786.22	318.65	187.24
2050_HQDS	13.67	786.22	317.96	187.18

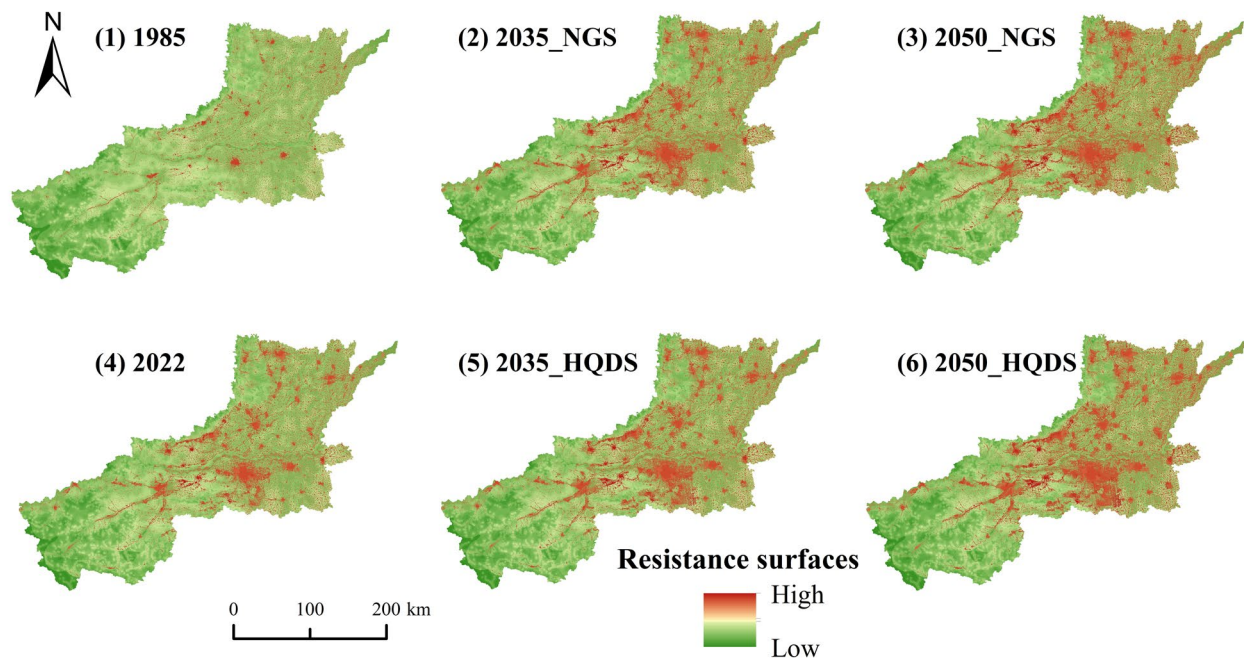


Figure 6. Spatiotemporal distribution of the resistance surfaces.

3.5. Ecological Corridor Construction

Based on the identified ecological sources and barriers, an ecological corridor network was constructed. The results showed that the ecological corridors in the HYRB region display clear spatial clustering and directionality (Figure 7). These corridors were primarily located between concentrated ecological sources in the southwest and the ecological patches in the north, extending along low-resistance zones, river valleys, and mountain edges. This configuration formed an ecological network centered on the source areas in the southwest, linking to the ecological patches in the north and center.

Between 1985 and 2022, the ecological safety rating of HYRB declined. The area classified as HES decreased from 13,741.30 km² to 13,529.23 km², while the area classified as SHES decreased from 15,668.62 km² to 13,612.02 km² (Table 6). In contrast, the area categorized as LES increased from 10,913.37 km² to 12,668.46 km². Future scenario simulations revealed that different development pathways significantly impacted the structure of ecological security levels. By 2035, under the HQDS, the areas of HES and SHES were projected to be 13,552.68 km² and 15,692.59 km², respectively, which were slightly higher than those under the NGS. By 2050, the areas of HES and SHES under the HQDS were projected to reach 13,529.84 km² and 14,501.30 km², respectively, remaining higher than the corresponding NGS values of 13,391.30 km² and 14,447.47 km².

In terms of ecological network characteristics, 62 ecological corridors were identified in 1985, with a total length of 909.15 km. By 2022, the number of ecological corridors had decreased to 56, while their total length had increased to 1457.43 km. Under the NGS, the number of ecological corridors is projected to decrease to 50 by 2035 and further to 26 by 2050. Under the HQDS, 47 corridors are projected by 2035, with a total length of 1186.31 km. By 2050, the number of corridors is projected to decrease to 24, with a total length of 1099.61 km.

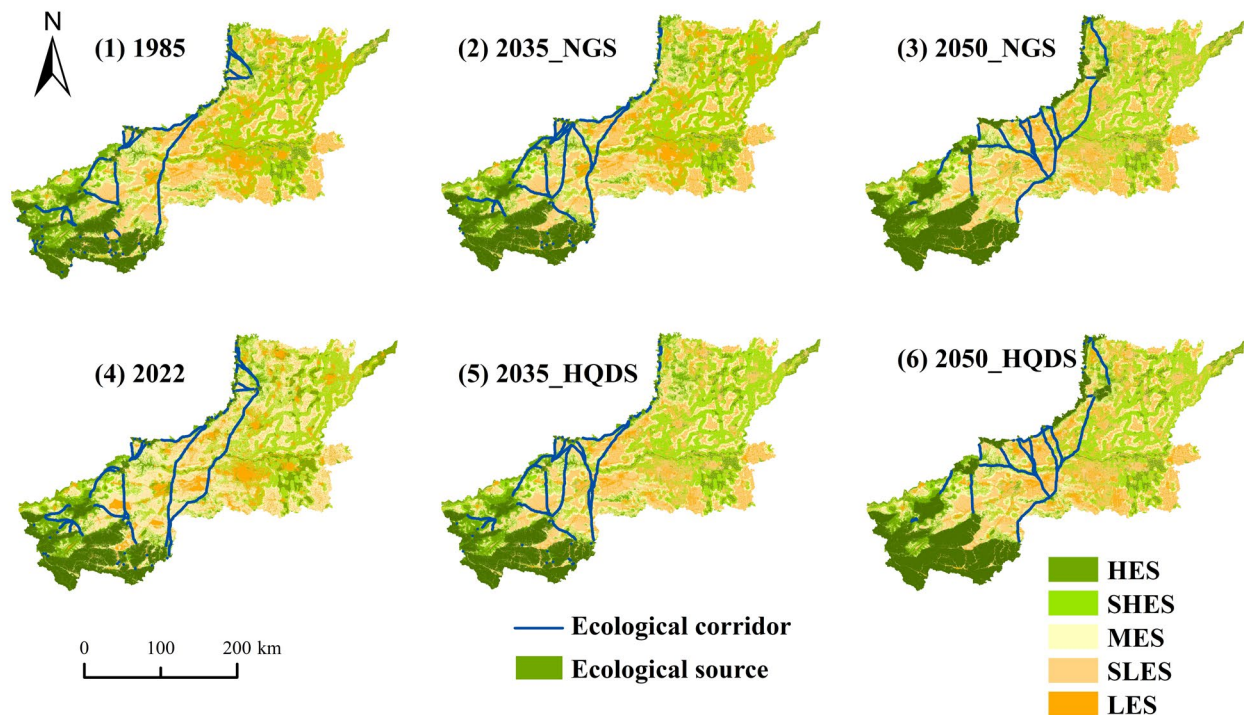


Figure 7. Spatiotemporal distribution of ecological security patterns. HES: High ecological security; SHES: Sub-high ecological security; MES: Moderate ecological security; SLES: Sub-low ecological security; LES: Low ecological security.

Table 6. Areas of change in ecological security levels.

	HES (km ²)	SHES (km ²)	MES (km ²)	SLES (km ²)	LES (km ²)
1985	13,741.30	15,668.62	14,715.05	11,854.43	10,913.37
2022	13,529.23	13,612.02	13,789.51	13,293.55	12,668.46
2035_NGS	13,531.57	15,622.63	13,130.71	12,315.22	12,292.64
2035_HQDS	13,552.68	15,692.59	13,163.83	16,597.96	7885.71
2050_NGS	13,391.30	14,447.47	13,038.41	16,466.35	9549.23
2050_HQDS	13,529.84	14,501.30	12,996.03	16,336.53	9529.06

4. Discussion

4.1. Innovative Application of HQDS in ESP Construction

The main contribution of this study is the development of a policy-to-rule framework that translates regional ecological conservation and territorial spatial planning objectives into explicit spatial constraints and land-use transition rules within the PLUS model. This approach provides quantitative evidence that implementing a series of policies, including the Yellow River Basin ecological protection policy, has positively contributed to ecological conservation in the HYRB region. In contrast, previous studies have primarily relied on Shared Socioeconomic Pathways (SSPs) or historical trends to simulate LUCC, assuming that land-use change follows a gradual and linear process driven by natural and economic factors, while overlooking the strong intervention effects of national and regional macro-policies on LUCC dynamics [45]. In regions subject to strict planning and management controls, LUCC is driven not only by natural and economic factors but also strongly regulated by policy constraints. Traditional LUCC simulation methods fail to capture the large-scale structural land transformations induced by policy interventions, thereby limiting the policy relevance and practical applicability of the resulting assessments [46,47]. Our approach was specifically designed to address this gap. We explicitly and

quantitatively incorporated policy constraints relevant to the HYRB into the LUCC transition rules of the PLUS model. For instance, we imposed strict limits on urban expansion within designated urban development boundaries and incorporated policy-driven ecological restoration measures (e.g., the conversion of steep-slope cropland to forestland) as key controls on spatial dynamics. This approach transforms LUCC simulation from a purely predictive model into a spatially explicit policy assessment framework, enabling the quantification of the long-term cumulative environmental benefits of the HQDS relative to the NGS under explicit policy interventions.

Under these assumptions, the modeled ecological source area under the HQDS was 562.42 km² larger than that under the NGS by 2050. The mean raw sediment export under the HQDS was also 11.9% lower than that under the NGS over the simulated period. These differences reflect the modeled ecological implications of the specified policy constraints and indicate how policy-oriented land-use regulation may affect ecological sources, sediment-delivery pressure, and landscape connectivity. At the LUCC level, the HQDS–NGS contrast also suggests a reallocation of land-use transitions rather than a uniform improvement in all ecological indicators. During 2035–2050, forest area increased by 649.31 km² under the HQDS, compared with 513.75 km² under the NGS, while built-up land expanded by 2622.06 km² under the HQDS, compared with 2664.07 km² under the NGS. However, cropland declined by 3102.44 km² under the HQDS, compared with 2961.10 km² under the NGS.

These results suggest that the specified policy rules redirected part of the projected land-use change toward ecological restoration and moderately constrained built-up expansion, but they also involved potential trade-offs related to cropland retention and socioeconomic development. Accordingly, the HQDS should be interpreted as an ecology-prioritized development pathway under the specified assumptions rather than as a universally optimal development scenario. In this conditional sense, the framework provides a useful tool for ex ante policy screening, spatial prioritization, and comparison of alternative policy pathways.

4.2. Attribution of Ecological Differences Under Policy-Driven Spatial Regulation

This study designed two scenarios—the NGS and the HQDS—and constructed ESP for two key milestone years in China’s modernization process: 2035 and 2050. The results indicate that the ecological source area under the HQDS reaches 8857.68 km² in 2035 and 12,039.17 km² in 2050. These values are higher than the corresponding NGS values of 8691.76 km² in 2035 and 11,476.75 km² in 2050. In addition, the areas classified as HES and SHES under the HQDS are larger than those under the NGS. These results indicate that HQDS produced larger ecological source areas and higher modeled HES and SHES areas than the NGS.

The fundamental reason for the difference lies in the mandatory policy interventions and the spatial restructuring of regional LUCC under the HQDS. This is primarily reflected in two aspects. First, there is the mandatory restriction on built-up land expansion. Under the NGS, built-up land expansion is mainly driven by economic growth and historical inertia, leading to uncontrolled urban sprawl that encroaches on high-quality farmland and potential ecological source areas. In contrast, under the HQDS, macro-level policy constraints, such as urban planning regulations, are explicitly embedded and enforced within the PLUS model’s transition probability matrix (transition rules). This top-down spatial regulation effectively suppresses urban expansion into core ecological sources and corridors, thereby mitigating the risks of habitat fragmentation and ecological network degradation. Second, policy-driven ecological land transformation plays a critical role. Under the HQDS, mandatory ecological restoration projects, such as the conversion of cropland to forest or grassland, are explicitly implemented, particularly for croplands

with slopes exceeding 25°. In the model, this intervention was represented by increasing the transition probability from cropland to forestland/grassland while reducing the probability of conversion from cropland to built-up land, thereby simulating policy-enforced land-use transformation. These rules altered the projected land-use composition and spatial configuration, which subsequently affected the InVEST-derived ES indicators, ESI, ecological-source identification, and ecological-security classification.

Therefore, the comparison demonstrates the sensitivity of the modeled ecological system to policy-oriented land-use constraints and quantifies their projected spatial implications relative to the NGS. In this conditional sense, the HQDS generated a more conservation-oriented projected configuration than the NGS.

4.3. Future ESP Planning Strategies Under the HQDS Framework

Based on the future ESP simulations, this study proposes a scenario-based framework comprising “four zones, one ecological belt, three ecological corridors, and multiple nodes.” (Figure 8) The framework was developed by weighting the five ESs using AHP, identifying ecological sources from the resulting ESI, and integrating the sources with the resistance surface through the MCR and circuit-theory approaches.

Because expert-derived AHP weights introduce uncertainty into the ESI and ecological-source identification, an equal-weight sensitivity analysis was conducted. The five ESs were assigned equal weights of 0.20, while the normalization procedure, source-identification threshold, minimum patch-area criterion, and other processing steps were kept unchanged (Figure S10). Under the equal-weight scheme, ecological sources remained mainly concentrated in the southwestern Funiu Mountains and northern Taihang Mountains, broadly consistent with the baseline AHP-weighted result. This result suggests that the broad regional distribution of the main ecological sources is not solely determined by the higher weights assigned to HQ and SC. However, differences may occur along source boundaries and in peripheral patches.

The conservation zones are mainly located in the southwestern and northern forested regions, where multiple ESs show relatively high modeled values. These areas may be considered candidate priority areas for ecological conservation. Restoration zones are concentrated in the built-up areas surrounding Zhengzhou, where ecological restoration and functional recovery could be prioritized after field verification and detailed planning assessment. Cultivable zones are mainly distributed across the low-elevation eastern plains and could be managed in coordination with permanent basic farmland protection and ecological buffer measures. The ecological belt along the Yellow River represents a modeled regional ecological axis. The three ecological corridors indicate potential pathways connecting major ecological sources, while the multiple nodes identify potential ecological bottlenecks and barrier locations. These features may provide useful references for ecological management, but their detailed spatial boundaries and connectivity functions may vary under alternative weighting schemes.

Corresponding planning recommendations were developed based on the proposed future ESP framework. First, relevant planning authorities should identify and delineate ecological source areas and core conservation zones prior to policy formulation, incorporating them into the regional planning system and designating them as “no-development zones.” For example, protected areas should be established in the southwestern and northern forest regions of the HYRB, where land development activities should be strictly restricted. This mechanism ensures strict protection of ecologically important areas, reflecting a development strategy that prioritizes ecological integrity. Second, ecological corridors and ecological nodes should be designated as environmentally sensitive areas. Any project that may pose threats to these areas should be subject to strict spatial regulation, with the implementation of mandatory ecological compensation measures. Such

measures help maintain the integrity and connectivity of the ecological network while preventing disruption caused by localized development activities. Finally, areas along the Zhengzhou section of the Yellow River, characterized by dense ecological barriers and high sediment output risks, should be prioritized for ecological restoration investment and spatial governance, ensuring the efficient allocation of limited management resources.

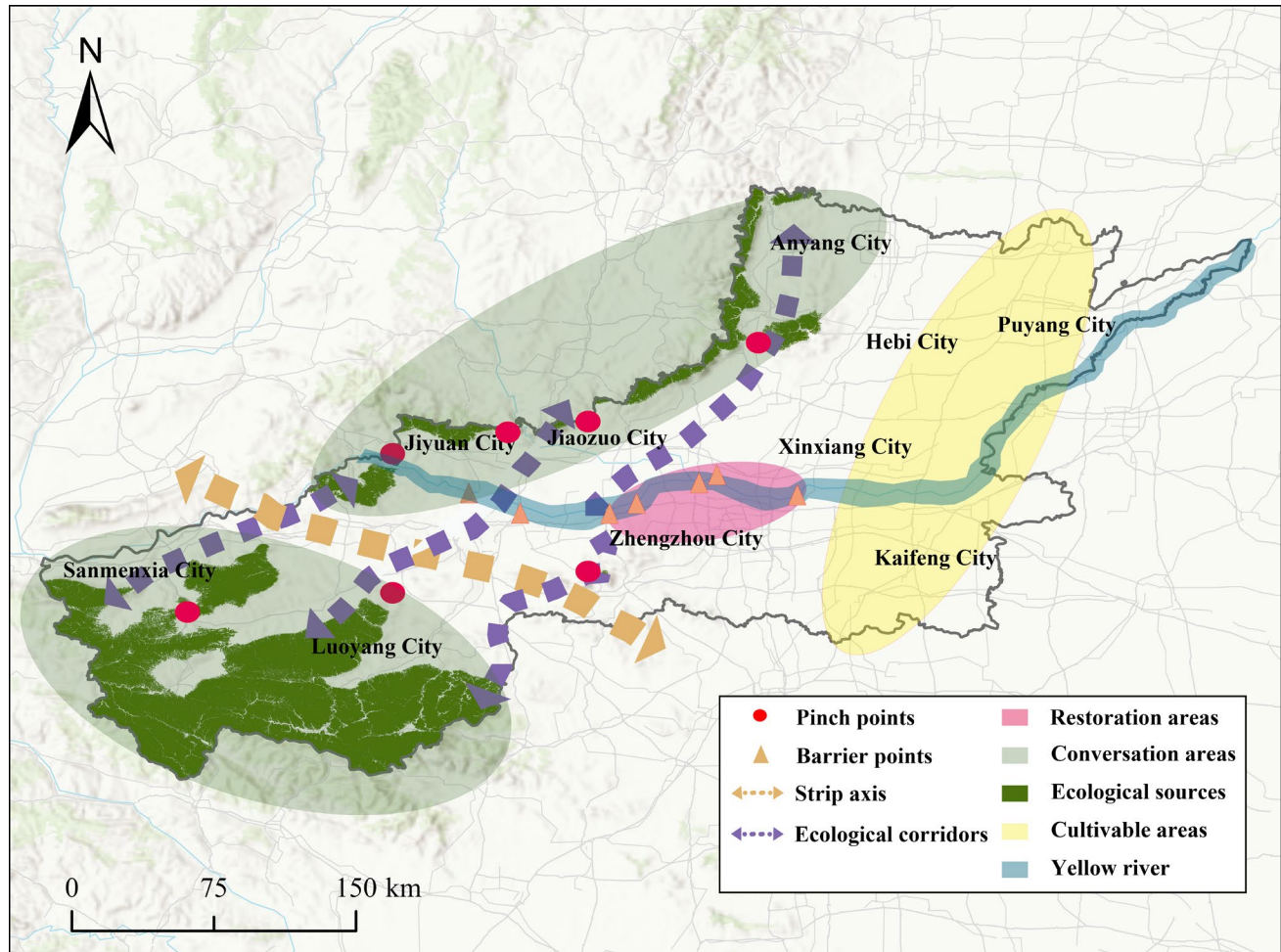


Figure 8. Proposed regional ecological security pattern planning map.

4.4. Limitations and Prospects

Although this study provides a scenario-based geospatial assessment of future ecological dynamics in the HYRB, several limitations should be acknowledged. First, the selection of ESs was primarily oriented toward the core objectives of the Ecological Protection and High-Quality Development Strategy. Accordingly, this study focused on five regulating services (WY, CS, SC, ST, and HQ) that are highly relevant to ecological vulnerability in the HYRB. Although provisioning services, such as grain production, were not explicitly quantified in the ES assessment, the HQDS constrained urban expansion on high-quality arable land in plain areas. However, this constraint does not quantitatively evaluate the trade-off between ecological restoration, farmland quality, food production, and economic costs. Future research should integrate crop-yield and economic models to further quantify these trade-offs. Second, the construction of resistance surfaces and the weighting of ESs partly relied on expert knowledge and literature-based parameterization. Although this approach is widely adopted in regional ecological assessments, it inevitably introduces uncertainty and subjectivity into the modeling process. An equal-weight sensitivity analysis was conducted by assigning a weight of 0.20 to each ecosystem

service. The resulting ecological sources remained broadly concentrated in the southwestern Funiu Mountains and northern Taihang Mountains, consistent with the baseline AHP-weighted result. However, this analysis included only one alternative weighting scheme and was conducted mainly at the ecological-source identification stage. The complete ecological-corridor network was not reconstructed under all possible weighting combinations. Future research should incorporate multiple expert panels, one-at-a-time weight perturbations, or Monte Carlo sampling of weight distributions to further evaluate the robustness of the complete ESP. Finally, constrained by the 30 m resolution of the LUCC data, this study prioritized macro-scale ecological patterns and excluded patches smaller than 10 km² to maintain computational efficiency. Consequently, certain micro-scale ecological processes and small but critical stepping stones may have been omitted. Future studies are encouraged to employ higher-resolution remote-sensing datasets and multi-scale analytical frameworks to better represent fine-scale ecological connectivity and spatial heterogeneity.

5. Conclusions

Based on relevant policies for ecological conservation and high-quality development in the HYRB, this study developed HQDS and used NGS as the reference scenario to evaluate the effects of policy interventions on regional ecosystems. The spatiotemporal evolution of multiple ESs from 1985 to 2050 was subsequently simulated, and ESPs were constructed to systematically characterize their evolutionary dynamics in the HYRB. The main conclusions are as follows: (1) From 1985 to 2050, LUCC in the region remained relatively stable. Built-up, cropland, and forest were the dominant land cover types, showing pronounced spatial heterogeneity. The primary land use transitions occurred between cropland and built-up areas. (2) Across the HYRB, various ESs remained relatively stable from 1985 to 2050. Specifically, SC, HQ, and CS generally showed higher values in mountainous and forested areas and lower values in the central and eastern plains. The SE was mainly concentrated in areas with relatively high erosion and sediment-delivery potential, whereas lower SE values were generally observed in the plain areas. In contrast, WY showed a distinct spatial distribution, with lower values in the southwestern region and higher values in the northeastern region. Based on the simulations for 2035 and 2050, WY and SC were projected to increase under both future scenarios, whereas HQ and CS exhibited slight declines. SE increased from 2035 to 2050 under both scenarios, although the magnitude of the increase was slightly lower under the HQDS than under the NGS. Moreover, the mean SE under the HQDS was 11.9% lower than that under the NGS over the 1985–2050 simulation period, indicating reduced modeled overland sediment-delivery pressure. (3) The regional ESP exhibits pronounced spatial heterogeneity. Ecological sources are primarily concentrated in the southwestern Qinling–Funiu mountains, where ecosystem service provision is relatively high. This region plays a key role in maintaining regional ecological stability and landscape connectivity. Scenario comparisons indicate that the HQDS produces more favorable ecological conservation outcomes than the NGS. Compared with the NGS, the HQDS results in a larger total ecological source area and fewer ecological source patches and corridors, indicating greater aggregation of ecological sources and improved ecological network connectivity. This framework provides a robust computational ecology methodology and spatial decision-support system for future adaptive ecosystem management, enabling the effective algorithmic translation of macro-level conservation policies into quantifiable ecological strategies. These findings provide a scientific foundation for future regional ecological protection and spatial management efforts.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs18152554/s1>, Figure S1: Land Use Distribution Pattern from 1985 to 2022; Figure S2: Spatiotemporal distribution of CS service from 1985 to 2022; Figure S3: Spatiotemporal distribution of HQ service from 1985 to 2022; Figure S4: Spatiotemporal distribution of SC service from 1985 to 2022; Figure S5: Spatiotemporal distribution of ST service from 1985 to 2022; Figure S6: Spatiotemporal distribution of WY service from 1985 to 2022; Figure S7: Spatiotemporal distribution of ecological sources from 1985 to 2022; Figure S8: Spatiotemporal distribution of ecological resistance surfaces from 1985 to 2022; Figure S9: Spatiotemporal distribution of ESP from 1985 to 2022; Figure S10: Ecological source identification under equal weights; Figure S11: Ecological security patterns under different ecological source patch thresholds; Table S1: Table of data sources required for each ecosystem service; Table S2: Domain weight parameters (NGS); Table S3: Transition matrix (NGS); Table S4: Domain weight parameters (HQDS); Table S5: Transition matrix (HQDS); Table S6: Observed land-use transition probabilities during 2005–2020; Table S7: Transition probabilities applied under the NGS during 2020–2035; Table S8: Transition probabilities applied under the HQDS during 2020–2035; Table S9: Comparison of Different Ecological Patch Thresholds.

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Data Availability Statement: LUCC data from <https://zenodo.org/records/12779975> (accessed on 2 June 2026). Administrative boundaries, protected areas, wetlands, and river networks from the National Earth System Science Data Center (<https://www.geodata.cn/>) (accessed on 2 June 2026), elevation, slope, river systems, precipitation, temperature, soil types, population density, gross domestic product, and human footprint data from the Resource and Environmental Science and Data Center (<https://www.resdc.cn/>) (accessed on 2 June 2026), road networks from OpenStreetMap <https://www.openstreetmap.org/> (accessed on 2 June 2026).

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Abbreviations

The following abbreviations are used in this manuscript:

HYRB	The Henan section of the Yellow River Basin
ESP	Ecological Security Pattern
ES	Ecosystem Services
LUCC	Land-use/land-cover change
MSPA	Morphological Spatial Pattern Analysis
InVEST	Integrated Valuation of Ecosystem Services and Tradeoffs
MCR	Minimum Cumulative Resistance
CT	Circuit Theory
CA	Cellular Automata
CLUE-S	Conversion of Land Use and Its Effects at Small Regional Extent
FLUS	Future Land Use Simulation
LEAS	Land Expansion Analysis Strategy
PLUS	Patch-generating Land Use Simulation
HQDS	High-Quality Development Scenario

NGS	Natural Growth Scenario
WY	Water Yield
SC	Soil Conservation
CS	Carbon Storage
HQ	Habitat Quality
SE	Sediment export
ST	Sediment Transport
HES	High Ecological Security
SHES	Sub-high Ecological Security
MES	Moderate Ecological Security
SLES	Sub-low Ecological Security
LES	Low Ecological Security
CWD	Cost-weighted Distance
LCP	Least-cost Path

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