

Article

Risk-Informed Ecological Network Optimization in a Semi-Arid Coal Mining Landscape

Wenting Zhang, Pinlin Li, Jiaxian Jiang and Di Wang *

Department of Landscape Architecture, School of Architecture, Chang'an University, Xi'an 710061, China; zwt@chd.edu.cn (W.Z.)

* Correspondence: jzxywd@chd.edu.cn

Abstract

Coal mining landscapes require restoration strategies that account not only for where ecological risk is concentrated but also for how risk constrains landscape connectivity. However, landscape ecological risk assessment is still commonly used as a zoning tool, with weak links to resistance surface parameterization and node-level restoration. Using the Shenmu coal mining area in northern China as a case study, we developed a risk-informed ecological network framework based on multi-source spatial data from 1995 to 2020. The framework combined landscape ecological risk assessment, GeoDetector-based driver analysis, ecological source screening, resistance surface construction, minimum cumulative resistance modeling, a gravity model, and circuit theory-based node diagnosis. Landscape dominance showed the highest explanatory power within the tested factor set ($q = 0.06083$), followed by land use type, water body proximity, and landscape fragmentation, while most factor interactions showed bivariate or nonlinear enhancement. Risk zoning delineated ecological conservation (467.62 km²), enhancement (1434.86 km²), and restoration areas (2566.49 km²). The framework identified 10 ecological sources; 18 potential corridors with a total length of 213.18 km; and 89 key nodes, including 52 pinch points, 4 barrier points, and 33 fracture points. The main contribution of this framework lies not in combining established ecological network tools, but in transferring ecological risk information into resistance surface parameterization and linking different types of critical nodes to differentiated restoration priorities. These outputs should be interpreted as model-based structural and potential functional connectivity priorities, rather than as direct evidence of realized species movement.

Keywords: landscape ecological risk; ecological network; coal mining landscape; connectivity modeling; ecological restoration; Shenmu

Academic Editors: Shicheng Li,
Lanhui Li and Mingjie Song

Received: 18 July 2026

Revised: 4 August 2026

Accepted: 6 August 2026

Published: 7 August 2026

Copyright: © 2026 by the authors.
Licensee MDPI, Basel, Switzerland.
This article is an open access article
distributed under the terms and con-
ditions of the [Creative Commons At-
tribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Mining landscapes are among the most intensively disturbed social–ecological systems. Coal extraction, associated infrastructure, and land use conversion can fragment habitat patches, alter vegetation and hydrological conditions, and increase the spatial concentration of ecological risk [1]. These effects are particularly pronounced in semi-arid mining regions, where limited water availability, sparse vegetation cover, and continuing resource development jointly constrain ecological recovery [2–4]. For landscape planning in such regions, the central challenge is not only to map where risk is high but also to

translate risk information into spatial decisions that maintain ecological connectivity and prioritize restoration [5–7].

Landscape ecological risk assessment provides a way to integrate natural background conditions, land use change, and human disturbance into a spatially explicit evaluation of ecological instability [8]. This type of risk assessment has been widely applied in urban regions, protected areas, river basins, ecological function zones, and resource development areas [9,10]. Existing studies have developed a range of assessment approaches, including landscape index methods, source–sink risk models, pressure–state–response frameworks, multi-source spatial data, and GeoDetector-based attribution analysis [11]. In mining landscapes, these approaches are valuable for identifying risk hotspots and explaining spatial heterogeneity. However, many applications remain diagnostic and do not, by themselves, indicate how ecological risk should affect source screening, corridor routing, or node-level restoration decisions [12].

Ecological network construction offers a complementary planning framework because it links ecological sources, corridors, and key nodes into a connected spatial system that can support landscape connectivity and potential ecological flow [13,14]. Morphological spatial pattern analysis, landscape connectivity indices, minimum cumulative resistance models, gravity models, and circuit theory have been widely used to identify source patches, least-cost paths, corridor hierarchies, pinch points, and barriers. The reliability of these outputs depends strongly on how the resistance surface is parameterized [15,16]. Conventional resistance surfaces are often based on land cover type, topography, or habitat suitability, whereas mining-related ecological degradation may also involve subsidence, geological hazards, groundwater vulnerability, waste accumulation, and infrastructure fragmentation [17,18]. A network that ignores these risk gradients may connect apparently suitable patches through areas where ecological flow is likely to be constrained or disrupted [19,20].

Recent studies have begun to integrate ecological risk assessment with ecological security patterns or network construction [21]. This shift is important because it moves risk assessment from descriptive mapping toward planning support: low-risk and high-quality patches can be screened as ecological sources, risk gradients can be embedded in resistance surfaces, and corridors can be routed to avoid or mitigate areas where ecological flow is likely to be constrained [10,22,23]. Evidence from semi-arid and mining regions further suggests that mine clustering and surface mining effects can reshape landscape ecological risk and network configuration [24,25]. Nevertheless, two gaps remain for coal mining landscapes in semi-arid regions. First, the pathway from risk drivers to resistance surface parameterization is often weak or implicit, which makes it difficult to evaluate how risk information changes source selection and corridor configuration [26]. Second, node-level restoration strategies remain less developed than source and corridor identification, even though pinch points, barriers, and fracture points can determine whether a planned network remains connected under continuing disturbance [27]. Accordingly, the contribution of this study lies in establishing an explicit risk-driver-to-resistance pathway and a node-specific restoration logic, rather than in introducing new ecological network algorithms [28].

Here, we address these gaps by developing a risk-informed ecological network framework for the Shenmu coal mining area in northern China. We first assess landscape ecological risk from 1995 to 2020 using indicators of ecological sensitivity, landscape loss, and mining disturbance, and then analyze the relative explanatory power and interactions of risk drivers with GeoDetector. We then embed the resulting risk index into an ecological resistance surface and combine minimum cumulative resistance modeling, a gravity model, and circuit theory to identify ecological sources, potential corridors, and key nodes [29,30]. This study asks the following three linked questions:

- (1) How is ecological risk distributed and driven in a semi-arid coal mining landscape?
- (2) How can ecological risk drivers be transferred into resistance surface parameterization and ecological network construction?
- (3) How can different types of critical ecological nodes support differentiated restoration priorities?

Importantly, this study constructs a model-based structural and potential functional connectivity framework for planning under mining disturbance, and its conclusions should be interpreted within that boundary.

The remainder of this study is organized as follows. Section 2 describes the study area, data sources, and methodological workflow for risk assessment, driver detection, resistance surface construction, and ecological network extraction. Section 3 presents the spatial pattern and drivers of ecological risk, the ecological baseline, ecological sources, potential corridors, and key nodes. Section 4 discusses how risk gradients can inform ecological network optimization, node-level restoration, and planning in semi-arid coal mining landscapes, while also outlining uncertainty and model limitations. Section 5 summarizes the main conclusions and management implications.

2. Materials and Methods

2.1. Study Area and Data Preparation

2.1.1. Study Area

The study area is the contiguous coal mining landscape in northwestern Shenmu City, Shaanxi Province, China (Figure 1). This coal mining area lies in the transitional zone between the Loess Plateau and the Mu Us Sandy Land and represents a typical energy development region in the middle of the Yellow River Basin. The analyzed area covers approximately 4670 km² and contains 117 coal mine units, including the Dabaodang, Jinjie, Daliuta, Sunjiacha, Dianta, and Zhongji mining districts. The region has a semi-arid continental monsoon climate, with a mean annual temperature of approximately 8.9 °C and a mean annual precipitation of approximately 440 mm, most of which falls in summer. Sparse vegetation, uneven precipitation, and intensive mining make the area sensitive to soil erosion, runoff disturbance, and landscape fragmentation.

Ecologically, the regional landscape is characterized by a mosaic of grassland, sandy vegetation, cropland, riparian habitats, and inland wetlands located within the transitional zone between the Mu Us Sandy Land and the Loess Plateau. The broader northwestern Shenmu region includes the Hongjiannao National Nature Reserve, which is also recognized as a nationally important wetland. The principal conservation targets of the Hongjiannao National Nature Reserve include the composite wetland ecosystem and associated biodiversity, particularly the relict gull (*Ichthyaeetus relictus*), a species under first-class national protection in China. These ecological characteristics indicate that regional connectivity is jointly constrained by vegetation continuity, water availability, soil stability, land use disturbance, and mining pressure, thereby supporting the inclusion of vegetation coverage, water body proximity, soil erosion sensitivity, desertification, land use, and mining-related factors in the ecological risk and resistance models.

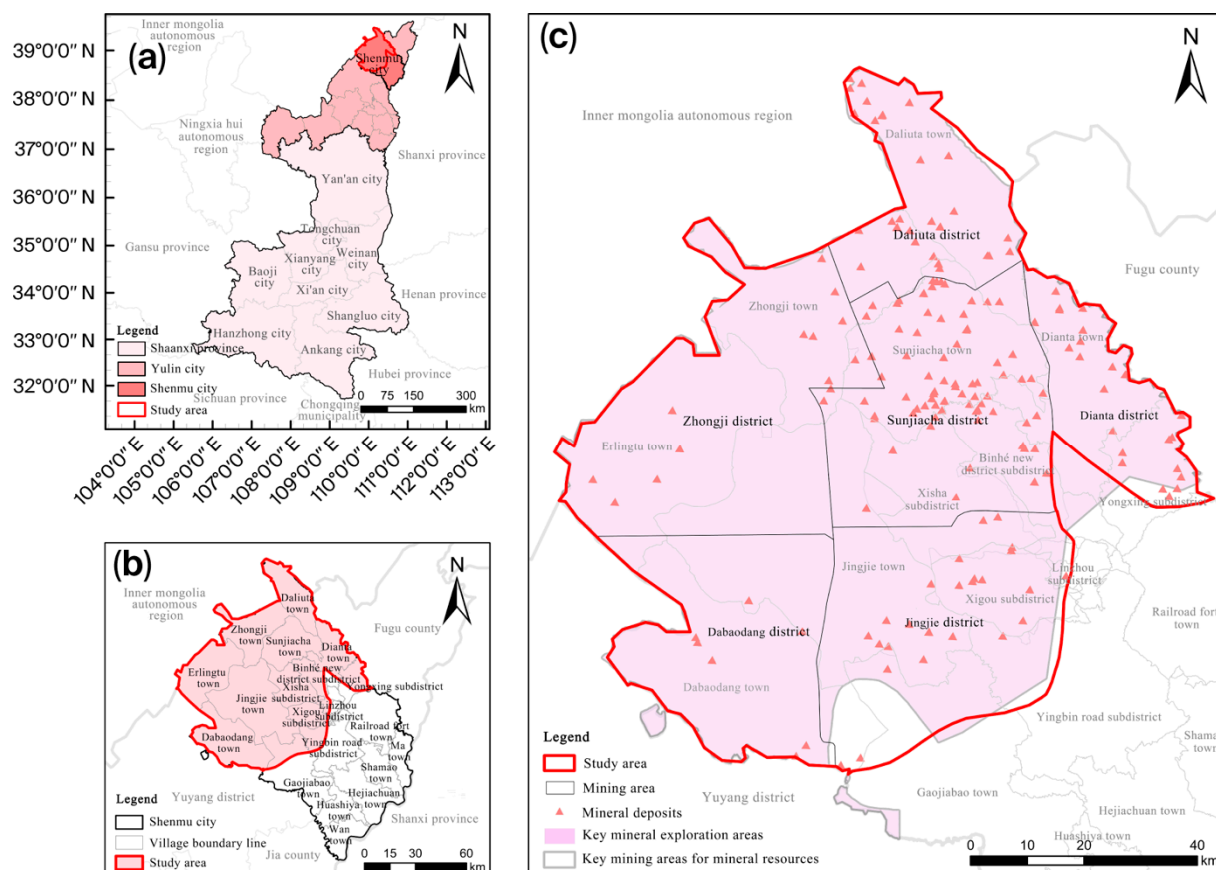


Figure 1. Location of the Shenmu coal mining area in Shaanxi Province, China. (a) Location of the study area in Shaanxi Province; (b) location of the study area in Shenmu City; and (c) mining districts, mineral deposits, and key mineral resource zones. Source: Authors' compilation based on the datasets listed in Table 1.

The study area was selected because it combines long-term coal extraction and the rapid expansion of industrial and mining land with ecologically sensitive grassland, sandy land, riparian, and wetland systems. This combination makes Shenmu an appropriate test case for landscapes characterized by intensive mining disturbance, semi-arid conditions, fragile vegetation, water constraints, and pronounced landscape fragmentation. Accordingly, the proposed framework is expected to be most relevant to mining-disturbed, semi-arid, or ecologically fragile landscapes for which comparable multi-source spatial data are available.

Table 1. Data sources and preprocessing used for ecological risk assessment and ecological network modeling.

Data Type	Years	Resolution/Format	Source	Main Use	Preprocessing
Landsat imagery	1995, 2000, 2005, 2010, 2015, 2020	30 m	Geospatial Data Cloud; Landsat 4 and Landsat 8 OLI/TIRS	NDVI, albedo, vegetation coverage and desertification difference indices	Radiometric calibration, atmospheric correction, and clipping in ENVI 5.3; NDVI/albedo calculated with Band Math; exported to GeoTIFF; projected to GCS_WGS_1984 and WGS_1984_World_Mercator.
DEM	2021	30 m	GDEM V2 30 m digital elevation data	Elevation, slope, and terrain factors	Mosaicking, mask extraction, projection unification, and derivation of elevation and slope.

Soil data	Not year-specific	1 km	Harmonized World Soil Database v1.2; 1:1,000,000 soil data for China	Soil erosion sensitivity and RUSLE-related parameters	Mask extraction, projection unification, and resampling to 30 m.
Soil erosion data	Not year-specific	1 km	Classification Standard for Soil Erosion (SL190-96)	Soil erosion sensitivity assessment	Mask extraction, resampling, and standardization.
Land use data	1995, 2000, 2005, 2010, 2015, 2020	30 m	Resource and Environment Science and Data Center, Chinese Academy of Sciences	Land use change, landscape pattern, ecological space dynamic degree, factor X1, and source identification	Reclassified into cropland, forestland, grassland, water, rural settlements, industrial and mining land, unused land, and urban land; projection and clipping unified.
Annual precipitation	1995, 2000, 2005, 2010, 2015, 2020	1 km	National Tibetan Plateau Data Center, China 1 km annual precipitation dataset	Rainfall erosivity in RUSLE and auxiliary ecological sensitivity factor	Converted to millimeters, clipped, projected, and resampled to 30 m.
Evapotranspiration	2000, 2005, 2010, 2015, 2020	1 km	National Tibetan Plateau Data Center	Auxiliary analysis of regional hydrothermal conditions	Mask extraction, projection unification, and resampling.
Groundwater level	2005, 2010, 2015, 2020	Dataset	China Geological Environment Monitoring Groundwater Level Yearbook	Groundwater pollution risk and DRAVM model	Ordinary kriging interpolation, clipping, projection unification, and resampling to 30 m.
Roads, railways, and water systems	1995, 2000, 2005, 2010	Vector	National Platform for Common Geospatial Information Services	Road, railway, and water buffer factors; fracture point identification; resistance surface construction	Clipping, projection unification, Euclidean distance/buffer analysis, and rasterization.
Roads, railways, and water systems	2015, 2020	Vector	OpenStreetMap	Same as above	Same as above.
Geological hazard points	2020	Vector	Resource and Environment Science and Data Center, Chinese Academy of Sciences	Kernel density estimation of collapse, landslide, and ground collapse risks	Year checking, clipping, projection unification, kernel density estimation, and 30 m output.
Administrative boundary	2021	Vector	National Platform for Common Geospatial Information Services	Study area boundary and clipping mask	Projection unification and clipping.
Geological map	2021	Vector	China Geological Survey, 1:200,000 regional hydrogeological map spatial database	Groundwater pollution risk and geological/aquifer conditions	Clipping, projection unification, and spatial overlay.
Hydrogeological map	2021	Vector	China Geological Survey, 1:200,000 regional hydrogeological map spatial database	DRAVM groundwater pollution risk parameters	Clipping, projection unification, and attribute processing.
Mineral resource data	2021	Vector	National mineral resource database	Mining development intensity and mining risk	Clipping, projection unification, and year/attribute checking.
Key mineral exploration zones	Not year-specific	Vector	National natural resource and geospatial-information database	Auxiliary factor for mining risk and resistance surface	Clipping and projection unification.

2.1.2. Data Sources and Preprocessing

The analysis used multi-source spatial datasets for six time points: 1995, 2000, 2005, 2010, 2015, and 2020 (Table 1). The core datasets included Landsat remote sensing images, a digital elevation model (DEM), land use data, soil and soil erosion data, precipitation data, groundwater-level data, water system layers, road and railway vectors, and geological hazard data. These datasets were used to derive vegetation, terrain, hydrological, land use, infrastructure, and mining disturbance indicators for the ecological risk and network models.

All spatial data were processed in Environment for Visualizing Images (ENVI) 5.3 and ArcGIS 10.6. Landsat images were radiometrically calibrated, atmospherically corrected, and clipped to the study boundary; the normalized difference vegetation index (NDVI) and surface albedo were then calculated. DEM data were mosaicked, clipped, and used to derive elevation and slope data. Soil, land use, precipitation, and soil erosion layers were standardized through unit conversion, spatial clipping, and resampling. Groundwater-level data were interpolated using ordinary kriging to generate a continuous raster surface. Vector layers, including roads, railways, water bodies, and geological hazards, were clipped and topologically checked before rasterization.

To ensure spatial consistency, all layers were transformed to the World Geodetic System 1984 (WGS 84) geographic coordinate system and projected to the WGS 84 / World Mercator projected coordinate system. Raster datasets were resampled to a 30 m spatial resolution. Continuous indicators were normalized to a common scale before overlay analysis, with the direction of normalization determined by whether higher values increased or reduced ecological risk. The 18 risk-driving factors and their processing rules are summarized in Table 2. This produced a harmonized raster and vector database for subsequent ecological risk assessment, driver detection, and network construction.

Table 2. Risk-driving factor system used for ecological risk assessment and GeoDetector analysis.

Dimension	Code	Indicator Meaning	Direction	Processing Method	Data Source
Ecological sensitivity: land use impact	X1	Land use effect on ecological space degradation, reflecting development intensity and habitat suitability	Positive after risk assignment	Land use reclassification, rasterization, risk-level assignment, and standardization	Land use data from CAS
Ecological sensitivity: back-ground	X2	Slope, reflecting terrain constraint, erosion, and engineering disturbance sensitivity	Positive	Slope derived from DEM and standardized/risk-classified data	GDEM V2 DEM
Ecological sensitivity: back-ground	X3	Vegetation coverage, reflecting ecological barrier function and surface stability	Negative	Vegetation coverage derived from NDVI and inversely normalized	Landsat imagery
Ecological sensitivity: back-ground	X4	Water body buffer, reflecting hydrological regulation and corridor conditions	Distance-based	Euclidean distance/buffer analysis, resampling to 30 m and risk classification	Water system vectors
Ecological sensitivity: back-ground	X5	Elevation, reflecting terrain background and ecological differentiation	Positive or classified	Elevation extracted from DEM and standardized/reclassified	GDEM V2 DEM
Ecological sensitivity: human disturbance	X6	Road buffer, reflecting habitat fragmentation and human disturbance	Negative distance	Euclidean distance and inverse standardization/risk classification	Road vectors
Ecological sensitivity: human disturbance	X7	Railway buffer, reflecting barrier and fragmentation effects	Negative distance	Euclidean distance and inverse standardization/risk classification	Railway vectors
Ecological sensitivity: human disturbance	X8	Rural settlement buffer, reflecting settlement expansion and living disturbance	Negative distance	Settlements extracted from land use; Euclidean distance and inverse standardization	Land use data
Ecological sensitivity: human disturbance	X9	Industrial and mining land buffer, reflecting direct mining construction disturbance	Negative distance	Industrial/mining land extracted from land use; Euclidean distance and inverse standardization	Land use data
Ecological sensitivity: ecological disturbance	X10	Desertification difference index, indicating vegetation cover degradation and desertification risk	Positive	NDVI and albedo feature space; DDI calculation and range standardization	Landsat imagery
Ecological sensitivity: ecological disturbance	X11	Soil erosion sensitivity, indicating material migration, erosion intensity, and land stability	Positive	RUSLE-related assessment using soil, precipitation, DEM, and land use layers; range standardization	Soil, precipitation, DEM, and land use data

Landscape loss	X12	Landscape fragmentation, indicating the shift from continuous to fragmented landscape structure	Positive	Fragstats (V4.2)/ArcGIS calculation; 100 m × 100 m grid; standardization and natural break classification	Land use data
Landscape loss	X13	Landscape separation, indicating spatial dispersion of patches	Positive	Fragstats/ArcGIS calculation; 100 m × 100 m grid; standardization and natural break classification	Land use data
Landscape loss	X14	Landscape dominance, indicating dominance and spatial control of major patch types	Positive in risk evaluation	Fragstats/ArcGIS calculation; 100 m × 100 m grid; standardization and natural break classification	Land use data
Mining risk	X15	Mining collapse risk, reflecting subsidence and surface deformation hazards	Positive	Kernel density estimation from geological hazard points and mineral resource data; 30 m output and standardization	Geological hazard and mineral resource data
Mining risk	X16	Landslide risk, reflecting mining- and terrain-related slope instability	Positive	Kernel density estimation and standardization	Geological hazard data and DEM
Mining risk	X17	Ground collapse risk, reflecting surface instability hazards under mining disturbance	Positive	Kernel density estimation and standardization	Geological hazard data and geological map
Mining risk	X18	Groundwater pollution risk, reflecting mining-related groundwater vulnerability	Positive	DRAVM model combining groundwater depth, recharge, aquifer, vadose zone, and mineral development intensity; standardization	Groundwater yearbook, hydrogeological map, and mineral resource data

2.2. Research Framework

A risk-informed ecological network optimization framework was developed to connect ecological risk diagnosis with landscape connectivity planning in semi-arid coal mining landscapes (Figure 2). The framework consists of four sequential and functionally distinct stages. First, the ecological risk index was calculated from ecological sensitivity, landscape loss, and mining risk. The resulting 2020 risk pattern provided the spatial basis for identifying low-risk candidate ecological sources. Second, GeoDetector was used to diagnose the relative explanatory power and interactions of the ecological risk factors. GeoDetector *q* values were used for mechanism interpretation and were not directly incorporated into resistance scores or weights. Third, selected natural, land use, and mining disturbance layers were standardized and combined using renormalized analytic hierarchy process (AHP)–entropy weights to construct the risk-informed resistance surface. Finally, the resistance surface and ecological sources were used in minimum cumulative resistance modeling, gravity modeling, and circuit theory analysis to identify potential corridors, corridor hierarchy, and key ecological nodes. Thus, ecological risk entered network construction through source screening and resistance representation, whereas GeoDetector provided diagnostic evidence rather than direct numerical parameters for network modeling.

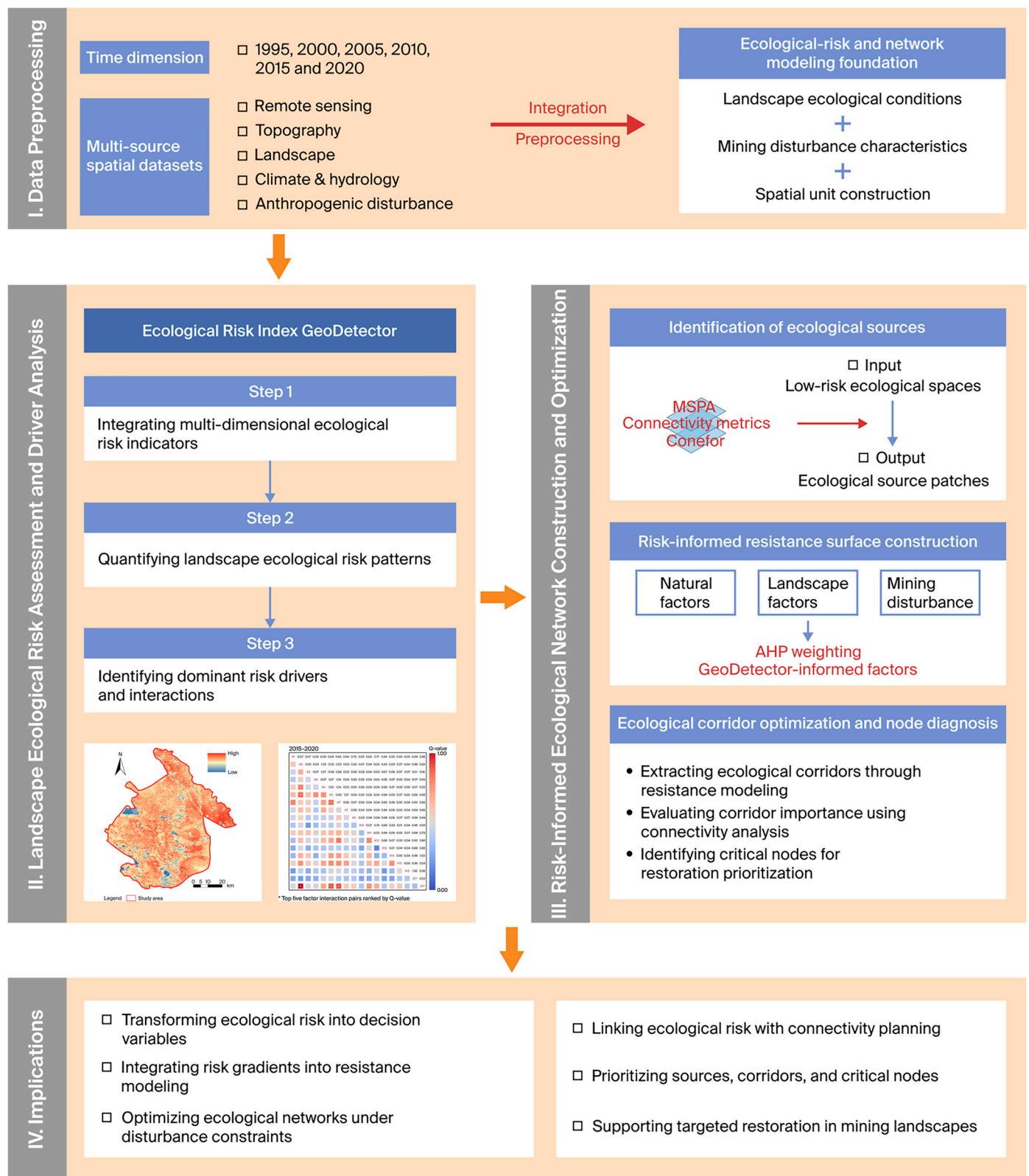


Figure 2. Analytical framework linking landscape ecological risk diagnosis with risk-informed ecological network optimization.

2.3. Landscape Ecological Risk Assessment and Driver Analysis

2.3.1. Construction of Landscape Ecological Risk Index

The landscape ecological risk assessment was designed to represent three dimensions of mining landscape disturbance: ecological sensitivity, landscape loss, and mining risk [31]. Ecological sensitivity describes environmental susceptibility and anthropogenic

pressure through land use, terrain, vegetation, hydrological conditions, infrastructure, settlements, desertification, and soil erosion indicators [32,33]. Landscape loss describes the structural degradation of the landscape mosaic through fragmentation, separation, and dominance. Mining risk represents direct mining-related disturbances, including mining collapse, landslide, ground collapse, and groundwater pollution [34].

The indicators were selected according to their ecological relevance to semi-arid mining landscapes, distinct process-based meanings, and spatial data availability [35]. Although some indicators describe related pressures, they represent different mechanisms [36]. For example, land use characterizes the ecological condition of the landscape matrix, whereas settlement, industrial/mining land, road, and railway buffers represent proximity-based disturbance. Similarly, vegetation coverage, desertification, and soil erosion sensitivity, respectively, reflect ecological condition, degradation, and susceptibility to material loss. Species-specific and fine-scale microhabitat variables were excluded because consistent regional data were unavailable and the study focused on landscape-level connectivity [37].

Ecological space change was quantified using single and comprehensive dynamic degree indices for water, forest, and grassland ecological spaces. The single dynamic degree for land use type i was calculated as follows [38]:

$$k_i = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\% \quad (1)$$

where k_i is the single dynamic degree of land use type i , U_a and U_b are the areas of that type at the beginning and end of the period, respectively, and T is the monitoring interval [39].

The comprehensive ecological space dynamic degree was calculated as follows:

$$L_c = \frac{\sum_{i=1}^n \Delta L_{U_{i-j}}}{2 \sum_{i=1}^n \Delta L U_i} \times \frac{1}{T} \times 100\% \quad (2)$$

where L_c is the comprehensive dynamic degree, $\Delta L_{U_{i-j}}$ is the area converted from ecological land use type i to other land use types, and LU_i is the area of ecological land use type i . These indices provide the response variable for identifying spatial variation in ecological space degradation [40].

The subjective weights were derived from expert consultation. Hierarchical pairwise comparison matrices were constructed based on expert judgments, and the weight coefficients were calculated using the principal eigenvector corresponding to the maximum eigenvalue [41]. Consistency tests were conducted to verify the logical consistency of the judgment matrices. The objective weights were determined using the entropy weight method, which assigns higher weights to indicators with greater information variability [42]. Finally, the subjective and objective weights were integrated according to the adopted combination weighting rule to obtain the final combined weights of the 18 ecological risk factors [43]. This combined weighting strategy was adopted to balance expert-based ecological judgment with the information variability of the spatial data, thereby reducing dependence on either a purely subjective or a purely data-driven weighting scheme [44].

The integrated ecological risk index (ERI) was calculated by weighted overlay of the three risk dimensions as follows:

$$ERI = W_1 R + W_2 S + W_3 M \quad (3)$$

where S is the ecological sensitivity; R is the landscape loss; M is the mining risk; and W_1 , W_2 , and W_3 are the corresponding dimension weights. The dimension-level and factor-level weights were determined using the combined AHP–entropy weighting procedure described above. The resulting ecological risk surface was classified into five levels

using the natural breaks method to support ecological baseline zoning and ecological source screening.

2.3.2. Identification of Ecological Risk Drivers Using GeoDetector

GeoDetector was used to quantify the explanatory power of the 18 risk-driving factors and their pairwise interactions. The method is based on the q -statistic, which measures spatial stratified heterogeneity by comparing within-stratum variance with total variance [45]. A larger q value indicates that a factor explains a greater proportion of the spatial variation in the response variable. Before detection, continuous factors were discretized into categorical strata using consistent classification rules [46]. Factor detection was used to rank individual drivers, and interaction detection was used to determine whether pairs of factors weakened, independently enhanced, bi-factor enhanced, or non-linearly enhanced the spatial pattern of ecological risk [11].

GeoDetector was used as a diagnostic and interpretive tool to evaluate the relative explanatory power and interactions of the ecological risk factors. The q values were not directly used to assign resistance scores or calculate resistance weights [5]. Quantitative resistance surface parameterization was based on the standardized factor layers and their renormalized AHP–entropy weights, as described in Section 2.4.2.

2.4. Risk-Informed Ecological Network Construction and Optimization

2.4.1. Identification of Ecological Sources

The process of ecological source identification began with the 2020 low-risk ecological space. The 2020 landscape was selected because it was the final year of the 1995–2020 assessment series and therefore represented the most recent integrated landscape condition evaluated in this study [4]. Low-risk patches were selected as preliminary candidate sources because they represented areas with relatively low ecological resistance and higher potential to support ecological flow. Morphological spatial pattern analysis (MSPA) was used to remove small and fragmented patches that could not maintain stable core ecological functions [38]. A minimum patch area threshold of 0.8 km² was then applied to retain candidate source patches [40].

The retained candidates were evaluated using landscape connectivity metrics, including the number of links (NL), the number of components (NC), the equivalent connected area based on the integral index of connectivity (EC(IIC)), the equivalent connected area based on the probability of connectivity (EC(PC)), the delta landscape coincidence probability (dLCP), the delta integral index of connectivity (dIIC), and the delta probability of connectivity (dPC). Conefor was used to calculate the contribution of each candidate patch to the overall landscape connectivity. Patches with high connectivity contribution and sufficient ecological quality were retained as final ecological sources [47].

2.4.2. Construction of Risk-Informed Resistance Surface

The ecological resistance surface was constructed by integrating natural, land use, and mining disturbance factors. All resistance factor values were standardized to a 0–100 scale, with higher values indicating greater ecological resistance [40]. These values represent relative movement costs at the landscape scale rather than empirically observed species-specific movement probabilities. Lower values indicate comparatively permeable ecological conditions, whereas higher values indicate stronger constraints associated with terrain, human disturbance, or mining-related hazards [48]. The standardized factor value represents the local intensity of resistance, while the normalized weight represents the relative contribution of that factor to the composite resistance surface [11]. GeoDetector was used as a diagnostic tool to interpret the relative explanatory power and interactions

of the ecological risk factors, and the q values were not directly incorporated into the resistance weights (Table 3). Instead, the final resistance weights were obtained by renormalizing the combined AHP–entropy weights of the factors included in the resistance surface model [12]:

$$w_i^R = \frac{w_i^C}{\sum_{j=1}^n w_j^C} \quad (4)$$

where w_i^R represents the final resistance weight of factor i , w_i^C represents its combined AHP–entropy weight, and n is the number of factors included in the resistance surface model. The standardized resistance factor layers were subsequently overlaid using the normalized weights to generate the comprehensive ecological resistance surface. This procedure maintained a clear distinction between the qualitative diagnostic role of GeoDetector and the quantitative weighting procedure used for resistance surface construction. The resulting resistance surface was subsequently used as the landscape cost layer for corridor extraction and circuit theory-based key node identification.

Table 3. Combined weights of resistance factors used to construct the ecological resistance surface.

Resistance Dimension	Resistance Factor	Combined Weight
Natural influence	Elevation	0.036
	Slope	0.051
	Vegetation coverage	0.059
	Water body buffer	0.044
Human influence	Land use	0.093
	Road buffer	0.058
	Railway buffer	0.049
	Rural settlement buffer	0.066
	Industrial/mining land buffer	0.065
Mining influence	Mining collapse	0.121
	Landslide	0.130
	Ground collapse	0.103
	Groundwater pollution	0.126

Note: Resistance weights were obtained by renormalizing the combined AHP–entropy weights of the selected factors. GeoDetector q values were not directly incorporated into the weighting

2.4.3. Ecological Corridor Extraction and Critical Node Key Node Diagnosis

Potential ecological corridors were extracted from the resistance surface using minimum cumulative resistance modeling and the Linkage Mapper toolbox [8]. Least-cost modeling identifies pathways between source patches that minimize accumulated resistance, and Linkage Mapper further calculates cost-weighted distances and mosaic pairwise corridors into a composite corridor network [14]. A gravity model was then used to estimate the interaction strength between source patches and to classify corridors into hierarchical importance levels:

$$G_{ij} = \frac{N_i N_j}{D_{ij}^2} = \frac{\left[\frac{1}{P_i} \times \ln(S_i) \right] \left[\frac{1}{P_j} \times \ln(S_j) \right]}{\left(\frac{L_{ij}}{L_{max}} \right)^2} = \frac{L_{max}^2 \ln(S_i) \ln(S_j)}{L_{ij}^2 P_i P_j} \quad (5)$$

where G_{ij} is the interaction strength between ecological sources i and j , N_i and N_j are source importance values derived from the source area and connectivity contribution, and D_{ij} is the cumulative resistance between the two sources. In this formulation, interaction strength increases with source importance and decreases with cumulative resistance.

Key ecological nodes were identified with circuit theory-based connectivity analysis [48]. Circuit theory treats the landscape as a resistance network and models potential ecological flow through multiple pathways rather than a single least-cost route [38]. Pinch-point Mapper was used to identify areas where current density was concentrated, representing potential pinch points that are sensitive to disturbance [49]. Barrier Mapper was used with a 300 m moving window to identify barrier points where local restoration would be expected to reduce cumulative resistance. Road and railway intersections with ecological corridors were overlaid in a geographic information system (GIS) to identify fracture points caused by linear infrastructure. These three node types provided the basis for differentiated restoration priorities [33].

3. Results

3.1. Spatial Patterns and Driving Mechanisms of Ecological Risk

3.1.1. Spatial Distribution of Ecological Risk

The combined AHP–entropy weighting procedure produced dimension weights of 0.3830, 0.3437, and 0.2737 for ecological sensitivity, landscape loss, and mining risk, respectively. The corresponding subjective, objective, and combined weights of the 18 ecological risk factors are presented in Table 4. These weights were subsequently used to calculate the integrated landscape ecological risk index.

Table 4. AHP-based subjective weights, entropy-based objective weights, and combined weights of the 18 ecological risk factors.

Dimension	Factor	Subjective Weight	Objective Weight	Combined Weight
Ecological sensitivity	X5 Elevation	0.017	0.025	0.020
	X2 Slope	0.025	0.036	0.029
	X3 Vegetation coverage	0.032	0.037	0.034
	X4 Water body buffer	0.029	0.018	0.025
	X1 Land use	0.035	0.080	0.053
	X6 Road buffer	0.037	0.026	0.033
	X7 Railway buffer	0.032	0.021	0.028
	X8 Rural settlement buffer	0.032	0.048	0.038
	X9 Industrial/mining land buffer	0.048	0.021	0.037
	X10 Desertification difference index	0.051	0.061	0.055
	X11 Soil erosion sensitivity	0.034	0.040	0.036
Landscape loss	X12 Landscape fragmentation	0.156	0.029	0.104
	X13 Landscape separation	0.071	0.029	0.055
	X14 Landscape dominance	0.068	0.367	0.185
Mining risk	X15 Mining collapse	0.095	0.029	0.069
	X16 Landslide	0.079	0.067	0.074
	X17 Ground collapse	0.083	0.021	0.059
	X18 Groundwater pollution	0.086	0.048	0.072

The 2020 landscape ecological risk index was classified into five levels using the natural breaks method: low, relatively low, moderate, relatively high, and high risk (Figure 3). On this basis, the study area was reorganized into three ecological management zones (Figure 4). Low and relatively low-risk areas were defined as ecological conservation areas, moderate-risk areas as ecological enhancement areas, and relatively high- and high-risk areas as ecological restoration areas.

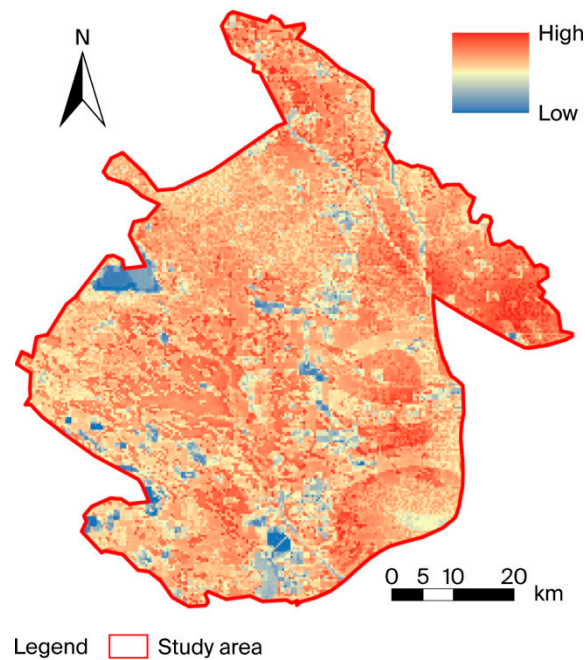


Figure 3. Spatial distribution of landscape ecological risk levels in the Shenmu coal mining area. Source: Authors' compilation based on the datasets listed in Table 1.

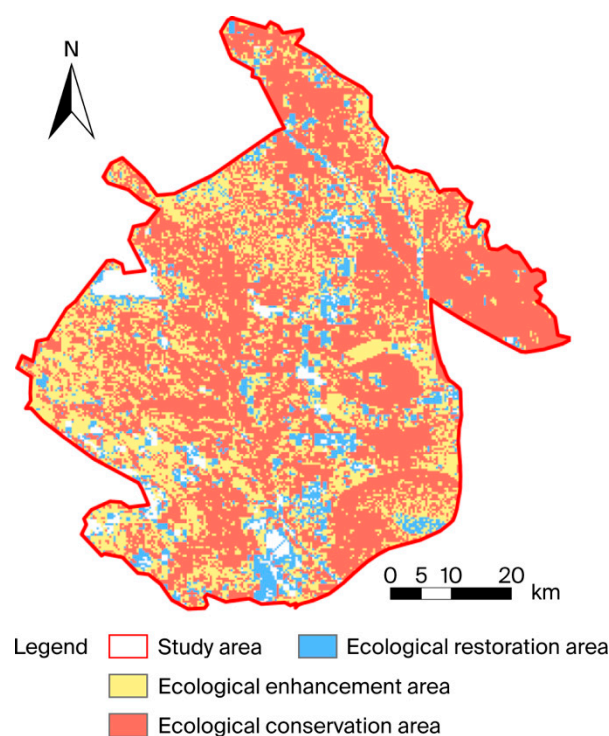


Figure 4. Ecological functional zoning of the Shenmu coal mining area. Source: Authors' compilation based on the datasets listed in Table 1.

Ecological conservation areas covered 467.62 km² and were mainly associated with water bodies, forestland, and cultivated land. Ecological enhancement areas covered 1434.86 km², which mainly included grassland and unused land where soil erosion and desertification pressure were prominent. Ecological restoration areas occupied the largest area, 2566.49 km², and included industrial and mining land, rural settlements, and unused land (Table 5). These zones provided the spatial basis for subsequent source screening, resistance surface construction, and corridor planning.

Table 5. Summary of ecological management zones in the Shenmu coal mining area.

Ecological Management Zone	Area (km ²)	Approximate Proportion	Main Spatial or Land Use Characteristics	Management Implication
Ecological restoration area	2566.49	54.96%	Industrial and mining land, rural settlements, unused land, and parts of grassland and cropland	Highest planning priority; collapse treatment, pollution prevention, and mine land reclamation may be considered following site-specific ecological and engineering assessments.
Ecological enhancement area	1434.86	30.73%	Grassland, unused land, and mining edge zones	Control of mining-derived disturbance and reduction in desertification, soil erosion, and fragmentation.
Ecological conservation area	467.62	10.01%	Water bodies, forestland, and cropland with relatively low ecological risk	Land protection as the conservation baseline for ecological network construction and restriction of additional disturbances.

3.1.2. Relative Explanatory Power and Interactions of Ecological Risk Factors

To identify the factors controlling the spatial differentiation of landscape ecological risk, GeoDetector was applied to the 18 risk driving factors across five consecutive periods and the full 1995–2020 interval (Table 6). The *q*-statistic was used to quantify relative explanatory power. Given the generally low *q* values, the results were interpreted as comparative rankings within the tested factor set rather than as evidence of strong overall explanation or causality.

For the full 1995–2020 period, landscape dominance (X14, *q* = 0.06083) showed the highest explanatory power within the tested factor set, followed by land use type (X1, *q* = 0.01278), water body buffer zone (X4, *q* = 0.00517), and landscape fragmentation (X12, *q* = 0.00514). This ranking indicates that the ecological risk pattern was primarily associated with landscape configuration and land use structure, while hydrological proximity and fragmentation provided secondary explanatory signals. Mining collapse (X15, *q* = 0.00184) had comparatively low explanatory power at the regional scale, suggesting that its influence was more localized than that of broader landscape structure variables.

Table 6. Explanatory power (*q* values) of landscape ecological risk driving factors in the Shenmu coal mining area.

Code and Risk Factor	1995–2000	2000–2005	2005–2010	2010–2015	2015–2020	1995–2020
X1 Land use type	0.00371	0.00315	0.00512	0.00454	0.00771	0.01278
X2 Slope	0.00267	0.00189	0.00359	0.00220	0.00341	0.00393
X3 Vegetation coverage	0.00235	0.00405	0.00232	0.00227	0.00351	0.00457
X4 Water body buffer zone	0.00717	0.00325	0.00228	0.00387	0.00168	0.00517
X5 Elevation	0.00368	0.00414	0.00321	0.00776	0.00238	0.00426
X6 Road buffer zone	0.00315	0.00312	0.00202	0.00301	0.00253	0.00239
X7 Railway buffer zone	0.00208	0.00280	0.00227	0.00257	0.00197	0.00298
X8 Rural residential buffer zone	0.00111	0.00275	0.00497	0.00229	0.00463	0.00226
X9 Industrial and mining land buffer zone	0.00359	0.00367	0.00257	0.00183	0.00198	0.00272
X10 Desertification index	0.00301	0.00250	0.00222	0.00155	0.00583	0.00347
X11 Soil erosion sensitivity	0.00220	0.00288	0.00341	0.00226	0.00379	0.00219
X12 Landscape fragmentation	0.00266	0.00253	0.07296	0.00222	0.00273	0.00514
X13 Landscape separation	0.11754	0.00140	0.07441	0.00159	0.00274	0.00210
X14 Landscape dominance	0.11930	0.07023	0.07485	0.05477	0.03512	0.06083
X15 Mining subsidence	0.00350	0.00306	0.00494	0.00460	0.00280	0.00184
X16 Landslide susceptibility	0.00110	0.00196	0.00101	0.00402	0.00641	0.00220
X17 Surface collapse susceptibility	0.00186	0.00341	0.00490	0.00187	0.00203	0.00415
X18 Groundwater pollution risk	0.01569	0.00320	0.00255	0.00529	0.00456	0.00457

Interaction detection indicated that most factor pairs produced either bivariate enhancement or nonlinear enhancement (Figure 5), suggesting that ecological risk was shaped by coupled natural, landscape, and mining-related processes. Interactions between elevation (X5) and landscape structure factors (X12 and X14) were particularly important, indicating that topographic conditions modulated the effect of landscape configuration on ecological vulnerability. The interaction between landslide risk (X16) and

ground collapse (X17) further suggested that geological disturbances acted synergistically in mining-affected areas. To preserve the comparability of interaction patterns across the five periods, all matrices were retained and are presented in Figure 5 at an enlarged scale.

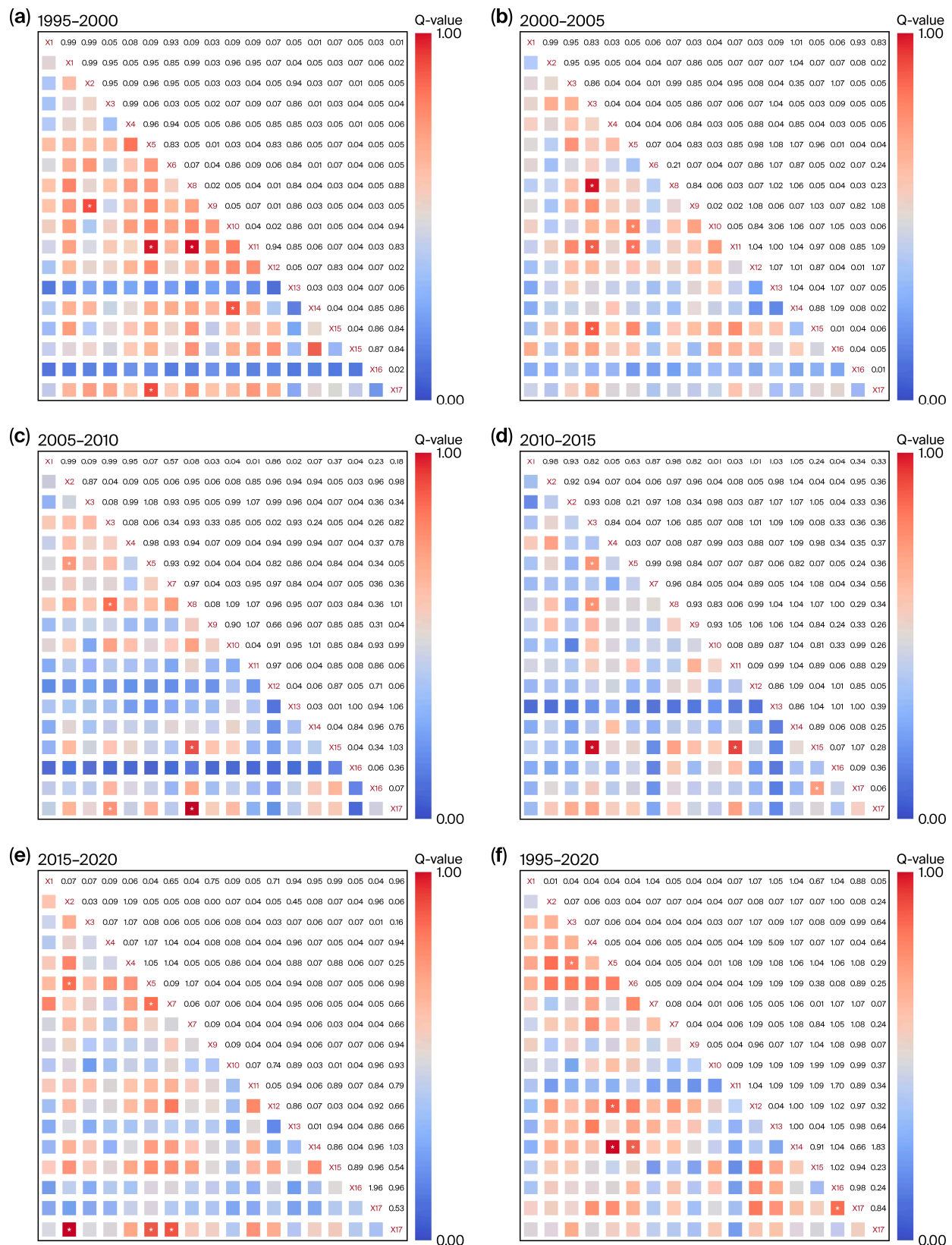


Figure 5. Interaction detection results for landscape ecological risk driving factors in the Shenmu coal mining area: (a) 1995–2000; (b) 2000–2005; (c) 2005–2010; (d) 2010–2015; (e) 2015–2020 and (f) 1995–2020. * Represents the top five factor interaction pairs ranked by Q-value.

3.2. Risk-Informed Ecological Network Configuration

3.2.1. Ecological Source Identification

Based on ecological baseline zoning and multi-criteria screening, 10 core patches were selected as ecological sources (Figure 6). The selected sources had dPC values ranging from 0.52 to 29.180, indicating substantial differences in their contributions to overall landscape connectivity. These patches met the combined requirements of relatively low ecological risk, adequate spatial scale, landscape quality, and connectivity contribution. Spatially, the sources were concentrated along a southeastern axis, where patch density was higher and relatively continuous ecological land remained. This pattern indicates that the southern and eastern parts of the mining landscape form the main structural support for the ecological network.

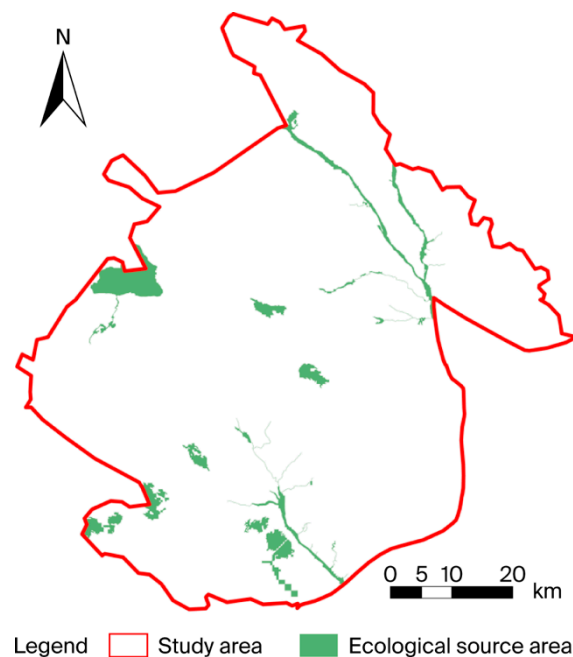


Figure 6. Ecological source areas in the Shenmu coal mining area. Source: Authors' compilation based on the datasets listed in Table 1.

3.2.2. Resistance Surface and Ecological Corridor Extraction

The risk-informed resistance surface showed marked spatial heterogeneity (Figure 7). High-resistance areas formed a north–south belt and were concentrated around industrial areas, mining construction land, and rural settlements, where intensive human activity and coal extraction increased movement cost. Moderate-resistance areas occurred mainly in mining subsidence influence zones and transitional areas between built-up land and natural patches. Low-resistance areas were associated with water bodies, forestland, and grassland, which provided the basic spatial conditions for corridor extraction.

Minimum cumulative resistance modeling identified 18 potential ecological corridors with a total length of 213.18 km (Figure 8; Table 7). Gravity model classification divided these corridors into three importance levels. Three first-level corridors connected core sources and formed the main backbone of regional connectivity. Six second-level corridors linked larger source patches and served as major ecological flow routes. Nine third-level corridors connected smaller sources and provided supplementary dispersal routes within the network.

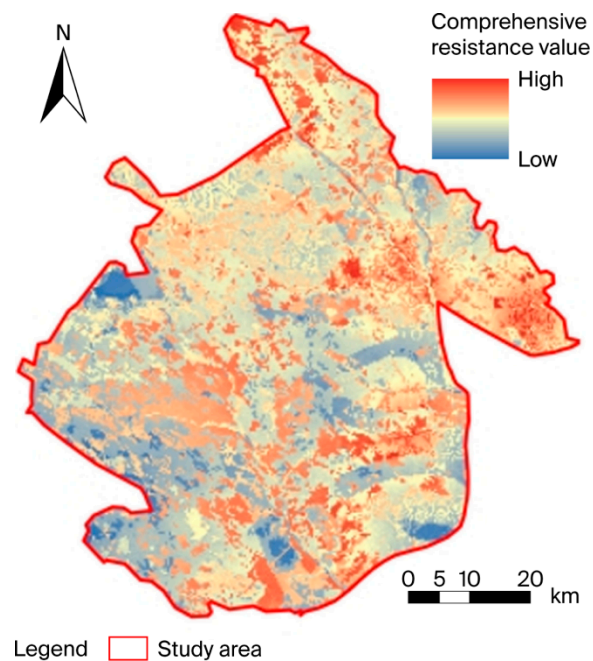


Figure 7. Comprehensive ecological resistance surface of the Shenmu coal mining area. Source: Authors' compilation based on the datasets listed in Table 1.

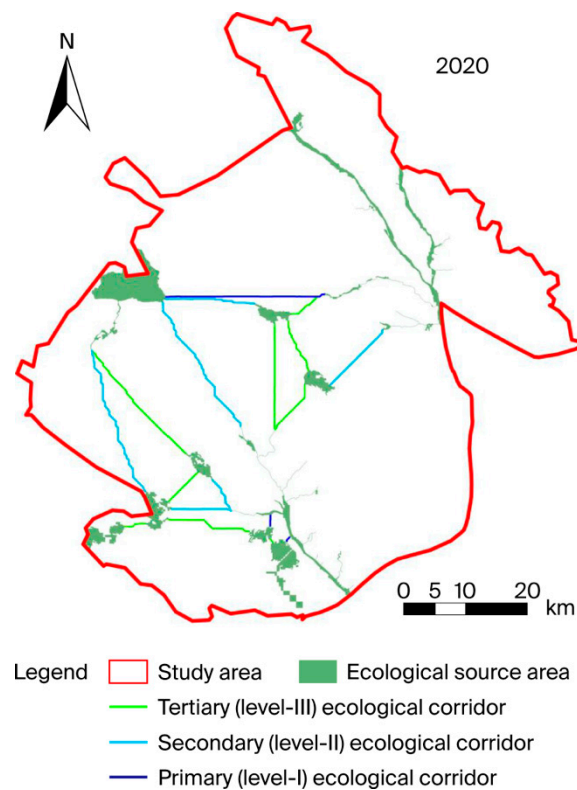


Figure 8. Hierarchical classification of potential ecological corridors in the Shenmu coal mining area. Source: Authors' compilation based on the datasets listed in Table 1.

Table 7. Summary of ecological sources, corridors, key nodes, and network effect indicators.

Result Type	Key Criterion or Method	Quantity, Area or Length	Interpretation
Candidate ecological sources	0.8 km ² patch area threshold	62 patches, 274.593 km ²	Small, isolated patches with limited network contribution.
Final ecological sources	dPC $\geq$ 0.5; 500 m distance threshold; connection probability = 0.5	10 patches, 181.240 km ²	Sources concentrated along the southeastern axis.
Potential ecological corridors	Linkage Mapper	18 corridors, 213.180 km	Risk-informed least-cost connections between sources.
First-level corridors	Gravity model and natural-break classification	3 corridors	Core corridors with the strongest source–source interaction.
Second-level corridors	Gravity model and natural-break classification	6 corridors	Major ecological flow routes linking larger source patches.
Third-level corridors	Gravity model and natural-break classification	9 corridors	Supplementary routes connecting smaller sources within the network.
Corridor length by land use type	Overlay with land use map	Grassland 129.311 km; unused land 40.415 km; cropland 25.665 km; forestland 13.418 km; water 1.193 km; industrial/mining land 1.219 km; rural settlements 0.561 km	Grassland formed the dominant corridor substrate.
Ecological pinch points	Pinchpoint Mapper/Circuitscape	52 points	Locations of concentrated modeled ecological flow that should be prioritized for protection assessment.
Ecological barrier points	Barrier Mapper, 300 m search radius	4 points	Local resistance-reduction targets.
Ecological fracture points	Road/railway corridor overlay	33 points	Traffic-related fragmentation nodes requiring connectivity restoration.
Key ecological nodes	Pinch points + barrier points + fracture points	89 points	Nodes occurred mainly in grassland, cropland, and forestland.
Network effect: IIC	Before–after comparison	1.630 to 2.054; +26.013%	Overall landscape connectivity increased.
Network effect: LCP	Before–after comparison	1.647 to 2.564; +55.668%	Landscape coincidence probability increased substantially.

3.3. Key Ecological Nodes

Circuit theory modeling and spatial overlay analysis identified 89 key ecological nodes (Figure 9). These included 52 pinch points, four barrier points, and 33 fracture points. The dominance of pinch points indicates that several corridor segments carried concentrated potential ecological flow and were therefore sensitive to additional disturbance or land use conversion.

Most key nodes were located in grassland, cropland, and forestland, while a smaller number occurred in industrial and mining land or unused land. Pinch points overlapped with high-resistance areas, barrier points were spatially associated with source–corridor intersections, and fracture points were mainly caused by built-up expansion and linear

transport infrastructure. This classification translates the ecological network into differentiated restoration targets: pinch-point protection, barrier removal or local habitat repair, and connectivity restoration at infrastructure-related fractures. For an integrated overview of the optimized ecological network, Table 7 summarizes the ecological sources, potential corridors, key ecological nodes, and overall network effect indicators.

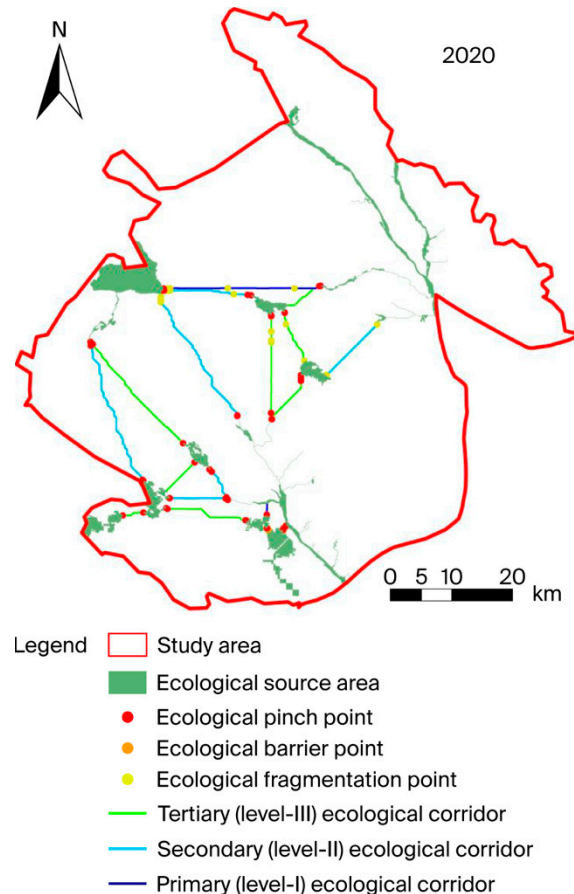


Figure 9. Spatial distribution of key ecological nodes in the Shenmu coal mining area. Source: Authors' compilation based on the datasets listed in Table 1.

4. Discussion

4.1. From Ecological Risk Assessment to Risk-Informed Ecological Network Optimization

The key contribution of this study lies in establishing an explicit risk-driver-to-resistance pathway, through which ecological risk diagnosis was transferred from a descriptive assessment outcome into ecological source screening and resistance surface parameterization [47]. In the Shenmu coal mining landscape, the resulting risk-informed resistance surface provides a risk-sensitive representation of potential ecological connectivity rather than a simple representation of land cover suitability [37].

The identified spatial configuration reflects the cumulative effects of mining disturbance [50]. Land conversion and vegetation fragmentation reduce habitat continuity, while subsidence, geological hazards, hydrological alteration, settlement expansion, and mining infrastructure constrain landscape permeability. These effects are further intensified by limited water availability and slow ecological recovery under semi-arid conditions [38,40]. Conventional ecological network approaches based mainly on land cover or topography may therefore underestimate resistance in areas that remain functionally constrained by

mining disturbance. By incorporating these disturbance processes, the proposed framework shifts resistance representation from a static land cover perspective toward disturbance-sensitive ecological network planning [36,48].

Compared with conventional ecological network studies, in which ecological sources and resistance surfaces are derived mainly from habitat quality, land cover, or topography, the present framework introduces ecological risk at three decision stages: low-risk ecological spaces inform source screening, risk-related disturbance factors constrain resistance surface parameterization, and different types of network vulnerability are linked to differentiated restoration priorities [39,51]. Therefore, the added value lies in changing the role of ecological risk from a parallel assessment layer into an operational input that affects where sources are retained, how corridors are routed, and which nodes are prioritized for intervention. Nevertheless, the resulting network represents structural and potential functional connectivity rather than verified species movement [39,51].

4.2. Risk-Sensitive Ecological Network Restoration Through Node-Level Prioritization

A second implication of the results is that ecological network optimization should extend beyond the identification of sources and corridors. The 89 key nodes identified in this study, including 52 pinch points, four barrier points, and 33 fracture points, represent different types of modeled network vulnerability [10]. Therefore, the contribution lies not merely in identifying these nodes, but in translating different types of network vulnerability into differentiated restoration priorities [52]. Pinch points indicate locations where current density is concentrated in the circuit theory model and where additional disturbance may disproportionately affect potential connectivity. Barrier points indicate local resistance accumulations that could be reduced through targeted restoration. Fracture points indicate corridor interruptions associated mainly with built-up expansion and linear transport infrastructure [25]. Accordingly, ecological sources and pinch points should be prioritized for disturbance control and habitat protection, barrier points for local substrate and vegetation restoration, and road- or railway-related fracture points for potential connectivity measures such as culverts or ecological bridges [53]. Areas affected by desertification, soil erosion, and fragmentation should focus on vegetation recovery and corridor habitat maintenance [54].

This node classification provides a basis for differentiated restoration rather than uniform intervention (Figure 10). It also clarifies how the Shenmu results relate to mining-specific disturbance processes. Studies of surface coal mining landscapes have shown that mining activity can reshape landscape ecological networks in semi-arid steppe settings, while mine agglomeration may amplify landscape ecological risk in semi-arid fragile watersheds [55,56]. In Shenmu, pinch points are most relevant to narrow corridor segments crossing high-resistance mining edges, barrier points correspond to local resistance concentrations associated with disturbed land or degraded substrates, and fracture points mainly reflect road and railway crossings [57,58]. The proposed measures, including protection of pinch points, local substrate and vegetation restoration at barriers, and engineering connectivity measures at infrastructure fractures, should be interpreted as potential planning interventions rather than direct prescriptions. Their implementation requires field verification, land tenure assessment, engineering feasibility evaluation, and subsequent ecological monitoring [59].

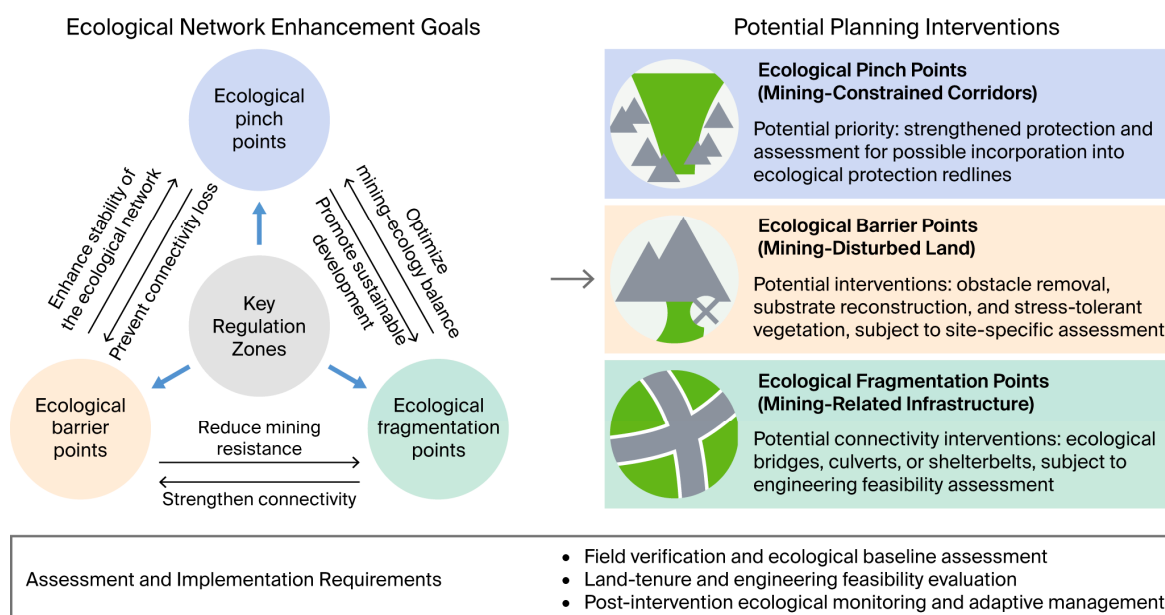


Figure 10. Strategies for enhancing ecological connectivity and resilience in mining-disturbed landscapes.

4.3. Planning Implications, Uncertainty, and Future Perspectives

4.3.1. Planning Implications for Semi-Arid Coal Mining Landscapes

The Shenmu case highlights the value of linking ecological risk, resistance, and connectivity in semi-arid coal mining landscapes, but it also shows why this linkage needs to be interpreted cautiously [60]. Previous work in Shenmu has constructed and optimized ecological spatial networks for a typical mining city of the Yellow River Basin, and broader mining restoration studies have argued for composite ecological networks that coordinate restoration objectives across territorial scales [59]. The present study extends this line of work by adding a risk-driver-to-resistance pathway and by separating restoration priorities into source protection, corridor maintenance, and node-specific intervention [28]. The transferability of the framework is most defensible for mining-disturbed, semi-arid, or ecologically fragile landscapes that exhibit comparable combinations of vegetation fragility, water limitation, landscape fragmentation, and mining-related disturbance, and for which consistent multi-source spatial data are available [4,7]. Therefore, the framework should be regarded as a context-dependent planning tool rather than a general solution for all mining regions or ecological network applications. It should not be assumed that the framework predicts species-specific movement or restoration success without additional field or monitoring evidence [49].

4.3.2. Limitations and Uncertainty

Several limitations of this study should be recognized. First, the ecological sources, corridors, and key nodes were identified through model-based spatial analyses and were not independently validated using species occurrence records, movement data, field surveys, or formal spatial comparisons with protected area and ecological planning datasets. Therefore, the outputs should be interpreted as planning hypotheses about structural and potential functional connectivity rather than as confirmed movement pathways or ecological processes. Although vegetation, land use, hydrological, and mining disturbance data were incorporated into source screening and resistance modeling, consistency with these input layers does not constitute independent validation. Future research should evaluate the predicted network using independent biodiversity observations, field-based habitat assessments, species movement data, protected area boundaries, and existing ecological

restoration or planning schemes. Second, source identification and resistance modeling relied on the 2020 risk pattern, whereas mining landscapes are dynamic. Future land use change, mining expansion, restoration projects, and climate variability may alter the stability and priority order of corridors and nodes. Third, the indicator weights, classification thresholds, and resistance values introduce parameter uncertainty. Alternative weighting schemes or resistance scenarios were not tested in the present study; therefore, the stability of ecological source selection, corridor routing, and key node identification under parameter variation remains to be quantified. In addition, this study did not construct a parallel conventional network based solely on land cover, topography, or habitat suitability. Future research should examine alternative AHP–entropy weight combinations, resistance value settings, and classification thresholds through sensitivity analysis, together with parallel conventional and risk-informed scenarios and field validation.

5. Conclusions

This study developed a risk-informed ecological network optimization framework that links ecological risk diagnosis with ecological source identification, resistance surface parameterization, corridor extraction, and key node identification. Spatially, higher ecological risk and resistance were concentrated mainly in mining disturbance zones, industrial areas, rural settlements, and fragmented transition landscapes, whereas ecological sources were concentrated along a relatively low-risk southeastern axis. Ecological zoning identified 467.62 km² of conservation areas, 1434.86 km² of enhancement areas, and 2566.49 km² of restoration areas. The resulting network comprised 10 ecological sources, 18 potential corridors with a total length of 213.18 km, and 89 key ecological nodes, including 52 pinch points, four barrier points, and 33 fracture points.

For regional land use planners and policymakers, these results provide a spatial basis for coordinating ecological protection, land use control, and mine land restoration. Conservation areas should be prioritized for ecological source protection and the control of additional disturbance, while enhancement and restoration areas require greater attention to mining-related degradation, soil erosion, desertification, and landscape fragmentation. At the network level, source protection, corridor maintenance, and node-specific interventions should be coordinated rather than implemented separately. Measures such as substrate reconstruction, mine land reclamation, ecological bridges, culverts, and shelterbelts should be regarded as potential planning interventions that require field verification, land tenure assessment, engineering feasibility evaluation, and subsequent ecological monitoring before implementation.

Methodologically, this study establishes an explicit risk-driver-to-resistance pathway and provides a context-dependent analytical framework for mining-disturbed, semi-arid, or ecologically fragile landscapes. Nevertheless, several limitations should be recognized. The resistance surface was based mainly on the 2020 ecological risk pattern and therefore represents a static landscape condition. The modeled network reflects structural and potential functional connectivity rather than verified movement pathways for particular species. Uncertainty also remains in the indicator weights, classification thresholds, and resistance values. In addition, because a parallel conventional ecological network was not constructed, the incremental effects of ecological risk information on corridor configuration, connectivity, and key node identification remain to be quantified.

Future research should develop dynamic resistance surfaces that incorporate land use change, mining expansion, ecological restoration scenarios, and climate variability. Sensitivity analysis and parallel comparisons between conventional and risk-informed networks are also needed to evaluate model robustness and the incremental contribution of ecological risk information. Species-specific or multi-species connectivity modeling, combined with field surveys, long-term ecological monitoring, and empirical validation

of predicted corridors and nodes, would further strengthen the ecological relevance of the framework. Applications in other regions should recalibrate the indicator system, resistance parameters, and validation procedures according to local ecological processes and data availability.

Author Contributions: Conceptualization, W.Z. and D.W.; methodology, W.Z., P.L. and J.J.; data curation, W.Z. and P.L.; formal analysis, W.Z. and J.J.; visualization, P.L.; writing—original draft preparation, W.Z.; writing—review and editing, P.L., J.J. and D.W.; supervision, D.W.; project administration, D.W.; funding acquisition, W.Z. and D.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Shaanxi Province Special Research Project on Philosophy and Social Sciences (Grant No. 2026YB0408), the Shaanxi Province Postdoctoral Research Project (Grant No. 2025BSHSDZZ275), and the Fundamental Research Funds for the Central Universities (Grant No. XJ2026002701).

Data Availability Statement: This study is based on publicly available datasets and data generated during the analysis. Public data sources are cited in the manuscript. Processed data supporting the conclusions are available from the corresponding author upon reasonable request.

Acknowledgments: We are grateful to the three reviewers for their valuable comments. We also thank the academic and English editors for their valuable comments on this paper. The authors thank all those who provided support and assistance during the preparation of this manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Li, Y.; Shaogang, L.; Zhao, Y.; Cao, R.; Josep, P. Vegetation dynamics and dominant driving factors in a semi-arid coal mining area under a disturbance–restoration zoning framework. *Geocarto Int.* **2026**, *41*, 2603053. <https://doi.org/10.1080/10106049.2025.2603053>.
2. Jin, W.; Dong, Z.; Bian, Z.; Zhang, X.; Wei, Z. Spatiotemporal variations in the impacts of small-to medium-scale mines agglomeration scale on landscape pattern and ecological risk in the watershed in a semi-arid ecologically fragile area. *Ecol. Indic.* **2024**, *166*, 112319. <https://doi.org/10.1016/j.ecolind.2024.112319>.
3. Hernandez-Santin, L.; Gagen, E.J.; Erskine, P.D. Setting restorative goals with a regional outlook: Mine-rehabilitation outcomes influence landscape connectivity. *J. Environ. Manag.* **2024**, *357*, 120778. <https://doi.org/10.1016/j.jenvman.2024.120778>.
4. Wu, Z.; Lei, S.; Yan, Q.; Bian, Z.; Lu, Q. Landscape ecological network construction controlling surface coal mining effect on landscape ecology: A case study of a mining city in semi-arid steppe. *Ecol. Indic.* **2021**, *133*, 108403. <https://doi.org/10.1016/j.ecolind.2021.108403>.
5. Dong, Z.; Bian, Z.; Jin, W.; Guo, X.; Zhang, Y.; Liu, X.; Wang, C.; Guan, D. An integrated approach to prioritizing ecological restoration of abandoned mine lands based on cost-benefit analysis. *Sci. Total Environ.* **2024**, *924*, 171579. <https://doi.org/10.1016/j.scitotenv.2024.171579>.
6. Zhao, J.; Yu, Q.; Xu, C.; Ma, J.; Liu, W.; Sun, W.; Miao, Y.; Nawaz, T. Integrated approach for ecological restoration and ecological spatial network optimization with multiple ecosystem functions in mining areas. *Ecol. Indic.* **2023**, *156*, 111141. <https://doi.org/10.1016/j.ecolind.2023.111141>.
7. Zheng, P.; Tang, S.; Dai, J.; Guo, C.; Zhou, Y.; Mi, M.; Liu, H.; Tian, F. Evaluating ecological restoration outcomes in historical mine sites: Landscape connectivity and ecosystem service changes in the Xiang River Basin, China. *Ecol. Model.* **2025**, *509*, 111273. <https://doi.org/10.1016/j.ecolmodel.2025.111273>.
8. Xu, W.; Yao, W.; Bai, Z.; Yang, J.; Li, L. Ecological Risk Evaluation and Ecological Restoration Model of Mining in the Source Area of the Yellow River Basin. *Land* **2023**, *12*, 933.
9. Wu, J.; Zhu, Q.; Qiao, N.; Wang, Z.; Sha, W.; Luo, K.; Wang, H.; Feng, Z. Ecological risk assessment of coal mine area based on “source-sink” landscape theory—A case study of Pingshuo mining area. *J. Clean. Prod.* **2021**, *295*, 126371. <https://doi.org/10.1016/j.jclepro.2021.126371>.

10. Yuan, Y.; Yuan, Y.; Bai, Z.; Ma, R.; Huang, Y. Ecological restoration strategies of mining areas based on composite ecological networks: A comprehensive framework and case study. *Ecol. Eng.* **2025**, *220*, 107750.
11. Wang, S.; Zhao, Y.; Wang, Q.; Ren, H.; Zhu, S.; Cao, J. Ecological network construction and optimization of typical resource-based regions, and strategies for the enhancement of multiple ecosystem services: Balancing function and structure. *Ecol. Indic.* **2025**, *170*, 112951. <https://doi.org/10.1016/j.ecolind.2024.112951>.
12. Jin, W.; Bian, Z.; Dong, Z.; Chen, D.; Zhang, X.; Wei, Z. Diagnosis of ecological security and the spatial heterogeneity of its driving factors in the mining-impacted watershed, based on ecosystem health-risk-services framework. *Ecol. Indic.* **2024**, *167*, 112683. <https://doi.org/10.1016/j.ecolind.2024.112683>.
13. Xu, W.; Wang, J.; Zhang, M.; Li, S. Construction of landscape ecological network based on landscape ecological risk assessment in a large-scale opencast coal mine area. *J. Clean. Prod.* **2021**, *286*, 125523. <https://doi.org/10.1016/j.jclepro.2020.125523>.
14. Zhu, X.; Li, P.; Wang, B.; Zhao, S.; Zhang, T.; Yao, Q. Construction of landscape eco-geological risk assessment framework in coal mining area using multi-source remote sensing data. *Ecol. Inform.* **2024**, *81*, 102635. <https://doi.org/10.1016/j.ecoinf.2024.102635>.
15. Wang, X.; Sun, Y.; Liu, Q.; Zhang, L. Construction and Optimization of Ecological Network Based on Landscape Ecological Risk Assessment: A Case Study in Jinan. *Land* **2023**, *12*, 743.
16. Pan, H.; Du, Z.; Wu, Z.; Zhang, H.; Ma, K. Building ecosystem services-based ecological networks in energy and chemical industry areas. *Ecol. Model.* **2024**, *498*, 110897. <https://doi.org/10.1016/j.ecolmodel.2024.110897>.
17. Ren, D.; Cao, A. Analysis of the heterogeneity of landscape risk evolution and driving factors based on a combined GeoDa and Geodetector model. *Ecol. Indic.* **2022**, *144*, 109568. <https://doi.org/10.1016/j.ecolind.2022.109568>.
18. Jin, B.; Geng, J.; Ding, Z.; Guo, L.; Rui, Q.; Wu, J.; Peng, S.; Jin, R.; Fu, X.; Pan, H. Construction and optimization of ecological corridors in coastal cities based on the perspective of “structure-function”. *Sci. Rep.* **2024**, *14*, 27945.
19. Wang, Y.; Hu, X.; Wei, B.; Luo, Z.; Wang, Z.; Chen, C. Assessing landscape ecological risk in the Southern Hill and Mountain Belt of China: A 30-year analysis and future projection. *Ecol. Indic.* **2024**, *166*, 112283. <https://doi.org/10.1016/j.ecolind.2024.112283>.
20. Huang, Y.; Zhang, J.; Zhang, P.; Chen, Z.; Zhang, X.; Lu, R.; Li, M.; Xing, G.; Song, Y. Construction and optimization of ecological security pattern based on landscape ecological risk assessment in the affected area of the Lower Yellow River. *Front. Ecol. Evol.* **2023**, *11*, 1271352.
21. Sun, W.; Yu, Q.; Xu, C.; Zhao, J.; Wang, Y.; Miao, Y. Construction and optimization of ecological spatial network in typical mining cities of the Yellow River Basin: The case study of Shenmu City, Shaanxi. *Ecol. Processes* **2024**, *13*, 60.
22. Lu, J.; Lu, H.; Wang, W.; Feng, S.; Lei, K. Ecological risk assessment of heavy metal contamination of mining area soil based on land type changes: An information network environ analysis. *Ecol. Model.* **2021**, *455*, 109633. <https://doi.org/10.1016/j.ecolmodel.2021.109633>.
23. Pan, N.; Du, Q.; Guan, Q.; Tan, Z.; Sun, Y.; Wang, Q. Ecological security assessment and pattern construction in arid and semi-arid areas: A case study of the Hexi Region, NW China. *Ecol. Indic.* **2022**, *138*, 108797. <https://doi.org/10.1016/j.ecolind.2022.108797>.
24. Yan, J.; Li, J.; Yao, X.; Li, Q.; Zheng, Z.; Li, G.; Qi, G.; Ma, W.; Song, M.; Gao, P. Ecological security pattern construction based on landscape ecological risk assessment in the Yellow River basin. *Front. Environ. Sci.* **2025**, *13*, 1514599.
25. Xie, W.; Li, J.; Liu, Y.; Peng, K.; Zhang, K. Evaluation of ecological buffer zone based on landscape pattern for non-point source pollution control: A case study in Hanjiang River basin, China. *J. Hydrol.* **2023**, *626*, 130341.
26. Yuan, Y.; Wang, J.; Qiao, N.; Huang, Y.; Bai, Z. Identifying ecological strategic points based on multi-functional ecological networks: A case study of Changzhi City, China. *Appl. Geogr.* **2023**, *157*, 103002.
27. Liu, Y.; Zhao, M. Linking ecosystem service supply and demand to landscape ecological risk for adaptive management: The Qinghai-Tibet Plateau case. *Ecol. Indic.* **2023**, *146*, 109796. <https://doi.org/10.1016/j.ecolind.2022.109796>.
28. Ye, K.; Zou, Q.; Wang, C.; Luo, Y.; Li, X.; Ye, R.; Luo, X.; Wang, T.; Yuan, B.; Zhao, Q.; et al. Optimal scale landscape ecological risk evaluation based on the SI-ERI model: A case study of Leshan City, Southwest China. *J. Mt. Sci.* **2025**, *22*, 4280–4297. <https://doi.org/10.1007/s11629-024-9413-2>.
29. Sui, L.; Yan, Z.; Li, K.; Wang, C.; Shi, Y.; Du, Y. Prediction of ecological security network in Northeast China based on landscape ecological risk. *Ecol. Indic.* **2024**, *160*, 111783. <https://doi.org/10.1016/j.ecolind.2024.111783>.
30. Xu, X.; Peng, Y.; Qin, W. Simulation, prediction and driving factor analysis of ecological risk in Savan District, Laos. *Front. Environ. Sci.* **2023**, *10*, 1058792. <https://doi.org/10.3389/fenvs.2022.1058792>.

31. Kervellec, M.; Couturier, T.; Bauduin, S.; Chenesseau, D.; Defos du Rau, P.; Drouet-Hoguet, N.; Duchamp, C.; Steinmetz, J.; Vandel, J.-M.; Gimenez, O. Bringing circuit theory into spatial occupancy models to assess landscape connectivity. *Methods Ecol. Evol.* **2024**, *15*, 2141–2152. <https://doi.org/10.1111/2041-210X.14418>.
32. Huang, L.; Chen, Z.; Yang, Z.; Chen, M.; Chen, X.; Zhai, T.; Qiu, T. Integrating “quality-risk-demand” framework and circuit theory to identify spatial range and priority area of ecological security pattern in a rapidly urbanizing landscape. *Ecol. Inform.* **2024**, *82*, 102673. <https://doi.org/10.1016/j.ecoinf.2024.102673>.
33. Cheng, W.; Ma, C.; Li, T.; Liu, Y. Construction of Ecological Security Patterns and Evaluation of Ecological Network Stability under Multi-Scenario Simulation: A Case Study in Desert–Oasis Area of the Yellow River Basin, China. *Land* **2024**, *13*, 1037.
34. Zhou, G.; Huan, Y.; Wang, L.; Lan, Y.; Liang, T.; Shi, B.; Zhang, Q. Linking ecosystem services and circuit theory to identify priority conservation and restoration areas from an ecological network perspective. *Sci. Total Environ.* **2023**, *873*, 162261. <https://doi.org/10.1016/j.scitotenv.2023.162261>.
35. Yang, R.; Bai, Z.; Shi, Z. Linking Morphological Spatial Pattern Analysis and Circuit Theory to Identify Ecological Security Pattern in the Loess Plateau: Taking Shuozhou City as an Example. *Land* **2021**, *10*, 907.
36. Ma, J.; Mei, Z.; Wang, X.; Li, S.; Liang, J. Ecological Security Pattern Construction and Multi-Scenario Risk Early Warning (2020–2035) in the Guangdong–Hong Kong–Macao Greater Bay Area, China. *Land* **2024**, *13*, 1267.
37. Wang, Y.; Yang, X.; Zhang, X.; Zhu, L.; Wang, X.; Li, Y.; Zhou, L.; Yu, X. Spatiotemporal dynamic characteristics and conservation strategy of ecological security pattern in a rapidly urbanizing zone. *Ecol. Indic.* **2024**, *166*, 112457. <https://doi.org/10.1016/j.ecolind.2024.112457>.
38. Zhao, C.; Wu, S.; Yang, L.; Wu, Y.; Xiao, P.; Xu, J.; Liu, Y. Evaluating ecological conservation effectiveness of security patterns under multiple scenarios: A case study of Hubei Province. *Ecol. Indic.* **2024**, *166*, 112528. <https://doi.org/10.1016/j.ecolind.2024.112528>.
39. Lao, Y.; He, X.; Liang, Y.; Tian, J.; Huang, J.; Yin, Z. Accurately uncovering the regional ecological restoration priorities: A multidimensional approach to eco-dynamic sustainable management. *Environ. Sustain. Indic.* **2024**, *24*, 100497. <https://doi.org/10.1016/j.indic.2024.100497>.
40. Guo, J.; Feng, P.; Xue, H.; Xue, S.; Fan, L. A framework of ecological security patterns in arid and semi-arid regions considering differences socioeconomic scenarios in ecological risk: Case of Loess Plateau, China. *J. Environ. Manag.* **2025**, *373*, 123923. <https://doi.org/10.1016/j.jenvman.2024.123923>.
41. Tan, L.; Luo, W.; Yang, B.; Huang, M.; Shuai, S.; Cheng, C.X.; Zhou, X.; Li, M.N.; Hu, C.W. Evaluation of landscape ecological risk in key ecological functional zone of South-to-North Water Diversion Project, China. *Ecol. Indic.* **2023**, *147*, 109934. <https://doi.org/10.1016/j.ecolind.2023.109934>.
42. Hui, J.W.; Cheng, Y.S. Integrating mining district data into ecological security pattern identification: A case study of Chenzhou. *Sci. Rep.* **2025**, *15*, 15800. <https://doi.org/10.1038/s41598-025-00883-w>.
43. Lei, C.; Phillips, M.; Li, X. Transition Characteristics and Drivers of Land Use Functions in the Resource-Based Region: A Case Study of Shenmu City, China. *Urban Sci.* **2025**, *9*, 520.
44. Pei, Y.; Wei, W.; Wei, X.; Yang, X.; Xie, B.; Zhou, J.; Zhang, Y.; Liu, C. Ecological risk assessment and ecological restoration zoning based on nature-society-landscape systems: A case study of Hexi Corridor, Northwest China. *Hum. Ecol. Risk Assess. Int. J.* **2025**, *31*, 1040–1061.
45. Wang, Z.; Wang, B.; Zhang, Y.; Sa, R.; Zhang, Q.; Hao, S. Ecological zone construction and multi-scenario simulation in Western China combining landscape ecological risk and ecosystem service value. *Sci. Rep.* **2025**, *15*, 11297.
46. Xu, H.; Xu, Q.; Gao, G.; Dou, H.; Waheed, A.; Aili, A. Advances in Ecological Restoration of Mining-Impacted Landscapes: Techniques, Case Studies, and Key Challenges. *Environ. Res.* **2026**, *290*, 123485.
47. Poor, E.E.; Scheick, B.; Cox, J.J.; Guthrie, J.M.; Mullinax, J.M. Towards robust corridors: A validation framework to improve corridor modeling. *Landsc. Ecol.* **2024**, *39*, 177. <https://doi.org/10.1007/s10980-024-01971-4>.
48. Liang, T.; Chen, Y.; Lu, X.; Zhou, Y.; Mao, Y.; Yang, F. Ecological security pattern construction of the Qinghai-Tibet Plateau: A comprehensive evaluation based on multiple sources and resistance surfaces. *Adv. Space Res.* **2025**, *76*, 4213–4234. <https://doi.org/10.1016/j.asr.2025.07.073>.
49. Luo, K.; Wang, H.; Yan, X.; Yi, S.; Wang, C.; Lei, C. Integrating CVOR and circuit theory models to construct and reconstruct ecological networks: A case study from the Tacheng-Emin Basin, China. *Ecol. Indic.* **2024**, *165*, 112170. <https://doi.org/10.1016/j.ecolind.2024.112170>.

50. Young, R.E.; Gann, G.D.; Walder, B.; Liu, J.; Cui, W.; Newton, V.; Nelson, C.R.; Tashe, N.; Jasper, D.; Silveira, F.A.O.; et al. International principles and standards for the ecological restoration and recovery of mine sites. *Restor. Ecol.* **2022**, *30*, e13771. <https://doi.org/10.1111/rec.13771>.
51. Song, Z.; Bao, Y.; Zhang, J.; Xu, J.; Bole, Y.; Fan, S.; Bao, Y.; Bao, Y. Building an implementable ecological security pattern: Ecological source identification and “element-zoning-city” governance pathway for sustainable development. *J. Clean. Prod.* **2025**, *536*, 147064. <https://doi.org/10.1016/j.jclepro.2025.147064>.
52. Li, M.; Abuduwaili, J.; Liu, W.; Feng, S.; Saparov, G.; Ma, L. Application of geographical detector and geographically weighted regression for assessing landscape ecological risk in the Irtysh River Basin, Central Asia. *Ecol. Indic.* **2024**, *158*, 111540.
53. Peng, J.; Zong, M.; Hu, Y.; Liu, Y.; Wu, J. Assessing landscape ecological risk in a mining city: A case study in Liaoyuan City, China. *Sustainability* **2015**, *7*, 8312–8334.
54. Zhang, H.; Song, Q.; Wang, S.; Zhao, J.; Gao, W. Ecological network construction and land degradation risk identification in the Yellow River source area. *iScience* **2025**, *28*, 112775. <https://doi.org/10.1016/j.isci.2025.112775>.
55. Zhang, W.; Jiang, Z.; Dai, H.; Lin, G.; Liu, K.; Yan, R.; Zhu, Y. Modelling Multi-Scenario Ecological Network Patterns and Dynamic Spatial Conservation Priorities in Mining Areas. *Land* **2024**, *13*, 1065.
56. Zeller, K.A.; Compton, B.W.; Finn, S.P.; Palm, E.C. Measuring ecological connectivity with ecological distance and dynamic resistant kernels. *Landsc. Ecol.* **2024**, *39*, 95. <https://doi.org/10.1007/s10980-024-01890-4>.
57. Xu, D.; Peng, J.; Jiang, H.; Dong, J.; Liu, M.; Chen, Y.; Wu, J.; Meersmans, J. Incorporating barriers restoration and stepping stones establishment to enhance the connectivity of watershed ecological security patterns. *Appl. Geogr.* **2024**, *170*, 103347. <https://doi.org/10.1016/j.apgeog.2024.103347>.
58. Wang, B.; Fu, S.; Hao, Z.; Zhen, Z. Ecological security pattern based on remote sensing ecological index and circuit theory in the Shanxi section of the Yellow River Basin. *Ecol. Indic.* **2024**, *166*, 112382. <https://doi.org/10.1016/j.ecolind.2024.112382>.
59. Ma, J.; Li, L.; Jiao, L.; Zhu, H.; Liu, C.; Li, F.; Li, P. Identifying Ecological Security Patterns Considering the Stability of Ecological Sources in Ecologically Fragile Areas. *Land* **2024**, *13*, 214.
60. Ma, B.; Zeng, C.; Lv, T.; Liu, W.; Yang, W. Prioritization of Ecological Conservation and Restoration Areas Through Ecological Networks: A Case Study of Nanchang City, China. *Land* **2024**, *13*, 878.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.