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Recognition of ecological security patterns based on the geographical detector model

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Abstract

Constructing a regional ecological security pattern (ESP) is essential for maintaining ecosystem health and enhancing ecosystem service functions. However, most existing ESP studies focus only on future scenarios and lack an integrated analysis of historical and future conditions. The selection of resistance factors usually depends on expert experience, which is often constrained by insufficient basic data. This study takes northeastern Chongqing as the study area and innovatively combines the geographical detector model with the patch-level land use simulation model, morphological spatial pattern analysis model, and circuit theory to establish a cross-temporal ESP from 2000 to 2030, integrating historical retrospective analysis and future scenario prediction. The geographical detector model was used to quantitatively identify the core driving factors of the comprehensive ecosystem service index (CESI), avoiding subjective factor selection and providing a scientific method for ESP construction in data-scarce regions. Coupling multi-scenario land-use simulation with ecosystem service assessment enables dynamic identification of ecological sources and objective construction of resistance surfaces, filling the research gap of integrated past–future ESP analysis. The results show that changes in forest land from 2000 to 2030 are concentrated in the central and northeastern parts, reflecting the trade-off between ecological protection and urbanization in the Three Gorges Reservoir Area. Temperature, digital elevation model, land use, and railroads are the dominant drivers of CESI, revealing the combined effects of natural and human activities. The northeast has complex ecological corridors and pinch points with high connectivity, while the southwest suffers from serious ecosystem fragmentation. This study provides a reproducible technical framework for ESP research in ecologically sensitive areas with limited data.

Keywords: Ecological security pattern; Geographical detector; Patch-level land use simulation; Land use simulation; Circuit theory; Ecological environment planning

1. Introduction

Ecological security refers to the integrity and health of an ecosystem that sustain human well-being and development.[1] Public awareness of ecological environmental issues is increasing as a result of rapid global economic expansion.[2] In the context of global warming, increasing areas of natural and agricultural land are being converted into construction land because of human activities and urban development, and existing studies have proved that land use change is an important driver of rising greenhouse gas emissions.[3-5] As a result, academics both domestically and internationally are progressively beginning to address the issue of ecological security. Since the 1980s, China's rapid economic growth has also led to several environmental problems,[6] including water shortages, biodiversity loss, solid waste accumulation, high energy consumption, and ecosystem degradation. Given this context, research has demonstrated that ESPs may help guide urban expansion and promote more balanced coordination between development and ecological protection[7,8] The ESP framework may offer a practical means of reconciling environmental protection with economic growth.[9]

Against this backdrop, the ecological security pattern (ESP) has emerged as an effective spatial planning tool, serving as a viable approach to safeguarding regional ecosystem security.[10,11] It serves as a spatial framework for maintaining ecological processes, material circulation, and energy flow within ecosystems.[12] The essence of ESP construction lies in achieving a dynamic equilibrium between ecosystem service provision and ecological security demands through spatial pattern adjustments, thereby mitigating the conflict between economic development and ecological conservation. Contemporary research has adopted a fundamental approach that involves three key steps: identifying ecological sources, constructing ecological resistance surfaces, and delineating ecological corridors as the foundational framework for ESP construction.[13-15]

Ecological sources serve as the core carriers of regional ecosystem functions, and their scientific identification is the fundamental premise for delineating ecological conservation zones and constructing stable ESPs. Existing methods for ecological source identification have formed a relatively diverse technical system, mainly including three types of approaches: first, directly taking protected areas with clear ecological protection attributes (such as national parks, natural scenic spots, and nature reserves) as ecological sources, relying on their existing protection mechanisms and relatively intact ecosystem structure;[16] second, selecting areas with high habitat quality evaluated by models such as InVEST as ecological sources, focusing on the suitability of habitats for biological survival and reproduction;[17] third, identifying key areas with significant ecosystem service functions (such as water conservation, carbon sequestration, and soil conservation) as ecological sources, emphasizing the supply capacity of ecosystems for human well-being.[11] In recent years, the morphological spatial pattern analysis (MSPA) model has been widely integrated into the process of ecological source identification. By extracting core patches, bridges, and other landscape components from forest land, grassland, and other natural landscapes, this model effectively enhances the structural connectivity and scientific robustness of ecological sources, thereby compensating for the limitations of selecting single patches.[9,18] However, existing ecological source extraction methods still exhibit significant limitations. Most studies focus on a single ecosystem type or a single ecosystem service function, neglecting the synergistic effects and integrated characteristics of multiple ecosystem services.[19] This results in extracted ecological sources failing to fully reflect the multifunctional value of regional ecosystems. Simultaneously, the identification process lacks systematic integration of regional ecological characteristics, leading to identified ecological sources exhibiting weak adaptability and explanatory power for local ecological conditions.[20]

The ecological resistance surface quantitatively describes the difficulty of species migration and material cycling between ecological sources, and its proper construction directly impacts the accuracy of ecological corridor simulations. Existing research primarily relies on expert experience or existing research findings.[21] For example, based on the findings of earlier research, Luo *et al.*[22] created an ecological resistance surface by choosing 11 anthropogenic and natural variables. Huang *et al.*[23] constructed an ecological resistance surface by using slope and road distance. To create ecological resistance surfaces, Wang *et al.*[10] considered land use, habitat quality, water distance, road distance, and landscape fragmentation. These methodologies can offer a theoretical foundation for establishing ecological resistance surfaces. However, at the initial stage of the study, we explored whether resistance factors could be selected objectively to reduce subjectivity and to better characterize migration barriers in data-scarce areas. The lack of objective, data-driven factor screening methods has become a critical bottleneck in enhancing the scientific rigor of constructing ecological resistance surfaces.

Ecological corridors are the "connecting bridges" between ecological sources, and their delineation is crucial for maintaining ecological connectivity. When establishing ecological corridors, the primary techniques employed are the minimum cumulative resistance (MCR) method and circuit theory. While the MCR model is widely utilized by researchers, it is plagued by issues such as the inability to extract corridor width and identify ecological pinch points.[24] The shortcomings of the MCR model can be compensated for using circuit theory, which is a model that can simulate species movement analogously to current flow in an electrical circuit.[25] The current ecological-corridor studies mostly concentrate on the present and the future, and few scholars have analyzed the changes in ecological corridors in the whole period from the past to the future.[23,26,27] Historical corridor evolution can provide a contextual basis for current ecological protection, while future corridor simulation can guide urban development patterns—ignoring the temporal continuity leads to disconnection between ESP construction and long-term ecological management needs.[28,29] As a result, modeling current and future ecological corridors in particular regions is required.

The geographical detector model can quantitatively calculate the q-value of each potential factor on ecological security through spatial stratified heterogeneity detection. Only factors with significant explanatory power ($p < 0.01$) are selected as core resistance factors, and the interaction between factors is further analyzed to determine their combined effects.[30] Applying the geographical detector model to ESP construction has two main advantages:

(i) The detector does not require additional assumptions on the examined data and can be evaluated directly, thus selecting the resistance factors objectively and avoiding the subjectivity of the researcher's choice.
(ii) Assuming that a region constructs an ESP with limited data, the geographical detector model can be used to conduct a multi-factor analysis, to screen and obtain the core resistance factors of the region, thus constructing an ESP.

The primary data source for creating ESPs is land use, which is crucial for ecological security.[31,32] Land-use research can effectively reflect patterns relevant to ESP construction.[33] The CA-Markov model,[34] CLUE-S model,[35] GeoSOS-FLUS model,[36] and patch-level land use simulation (PLUS) model[37] are some of the land use simulation and prediction research methodologies now in use. In contrast, the PLUS model integrates the advantages of the CA model and the random forest algorithm: it not only can quantitatively analyze the driving mechanisms of land use change through the land expansion analysis strategy but also accurately simulate the spatial distribution of land use types through the patch generation strategy, with higher simulation accuracy and results that are more consistent with the actual situation.[38]

Situated in the western part of China, Chongqing Municipality is a typical hilly metropolis that borders the Sichuan Basin.[39] Its natural environment is crucial to the safe running and well-being of the Three Gorges Project. It is also a significant national water reserve center and an important ecological barrier region in the middle reaches of the Yangtze River.[40] However, the local region may experience severe issues, including ecological deterioration due to the Three Gorges Reservoir Migration Project's effects on the surrounding ecological environment and the rapid rise of urbanization.[10,41] Nevertheless, establishing a scientifically grounded ecological conservation spatial pattern in this region holds significant practical implications for both local and national ecological security frameworks. ESP can precisely identify core ecological sources, key corridors, and vulnerable bottlenecks, providing targeted spatial guidance for ecological restoration and conservation. This approach contributes to maintaining the integrity and stability of regional ecosystems.

Therefore, to address the limitations of previous studies—including subjective selection of resistance factors, incomplete identification of ecological sources, and the absence of full-cycle corridor analysis—this research innovatively integrates the geographical detector model, PLUS model, MSPA model, and circuit theory to construct a spatiotemporal ESP model for northeastern Chongqing (2000–2030). Ecosystem services provide an important basis for maintaining ecological security. However, a single ecosystem service indicator cannot fully capture the overall status of regional ecological security. Therefore, building on previously developed CESI frameworks, this study integrated multiple ecosystem service functions into a unified assessment system.

The specific objectives were as follows:

(i) to simulate land use in 2030 under multiple scenarios using the PLUS model and analyze its spatiotemporal patterns;
(ii) to integrate multiple ecosystem services into an improved comprehensive ecosystem service index (CESI) and identify ecological sources using the MSPA model;
(iii) to identify core resistance factors using the geographical detector model and construct an ecological resistance surface; and
(iv) to delineate ecological corridors and pinch points based on circuit theory and establish a dynamic ESP that integrates historical evolution with future projections.

This study aims to provide an integrated methodological framework for ESP construction in ecologically sensitive areas and to support ecological protection and territorial spatial planning in the Three Gorges Reservoir Area.

2. Data sources

2.1. Study area

Northeastern Chongqing, also referred to here as part of the Three Gorges Reservoir Area, is situated in the northeastern part of Chongqing Municipality (107.20°–110.20°E, 29.50°–32.20°N), spanning over 33900 km^2. It acts as a strategically significant biological barrier in the Yangtze River's upper reaches (Figure 1). The terrain of the area is relatively complex, including mountains, hills, and plains. It is rich in water resources, such as Bashan Lake, Shuanggui Lake, Longxi River, and the Yangtze River. The area has a humid subtropical climate with four distinct seasons and abundant rainfall. Forested areas account for over 70% of the region's land cover, forming the core component of its ecological system. Natural forests constitute approximately 65% of this total, primarily distributed across the northeastern mountainous terrain. Facing impacts from the Three Gorges Reservoir resettlement and rapid urbanization, ecological security in this area has become an urgent priority. According to the Chongqing Overall Land Space Plan (2021–2035), the area is expected to serve as a hub for the Yangtze River Economic Belt, strengthen biodiversity conservation, and enhance the ecological functions of the Three Gorges Reservoir Area. As a result, this study is therefore of practical relevance to ecological protection and spatial planning in the region.

2.2. Data sources and preprocessing

Based on previous studies, this study compiled land-use, ecosystem, socioeconomic, transportation, and water-system data. The data preprocessing mainly used the ArcGIS 10.8 program, as shown in Table 1.

3. Methods

In this study, we constructed the ESP for northeast Chongqing from 2000 to 2030 using the PLUS, InVEST, MSPA, geographical detector, and circuit-theory approaches; Figure 2 illustrates the research framework.

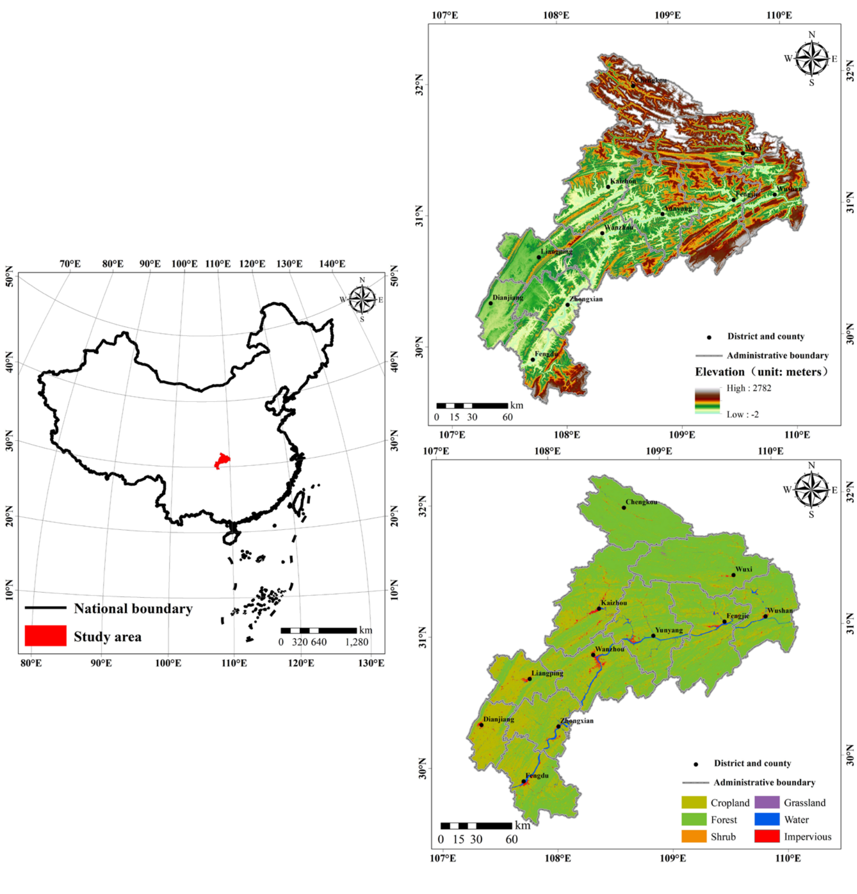

Figure 1. Study area

Table 1. Data sources

Category	Data	Resolution, m	Sources
LUCC	Land use/cover change data	30	https://zenodo.org/records/5816591#.ZAWM3BVBy5c
Ecosystem data	DEM data	30	https://www.gscloud.cn/
	Slope data	30	Extracted based on DEM data to obtain
	NPP dataset	500	https://lpdaac.usgs.gov/product_search/
	Meteorological dataset	1,000	https://data.tpdc.ac.cn/home
	Precipitation dataset	1,000	
	Evapotranspiration dataset	1,000	
Socioeconomic data	DMSP/OLS dataset	1,000	https://www.ngdc.noaa.gov/eog/dmsp.html
	NPP/VIIRS dataset	1,000	https://www.ngdc.noaa.gov/eog/viirs/index.html
	Population dataset	1,000	https://landscan.ornl.gov/
	GDP dataset	1,000	https://www.resdc.cn/
Transportation and water system data	Railroad dataset	30	Obtained using the ArcGIS10.8 Euclidean distance extraction method（source data from the https://openmaptiles.org/）
	Highway dataset	30	
	Primary road dataset	30	
	Secondary road dataset	30	
	Tertiary road dataset	30	
	Water system dataset	30	

Abbreviations: DEM: Digital elevation model; DMSP/OLS: Defense Meteorological Satellite Program/Operational Linescan System; GDP: Gross domestic product; LUCC: Land use/cover change; NPP: Net primary productivity; NPP/VIIRS: National Polar-orbiting Partnership/Visible Infrared Imaging Radiometer Suite.

The workflow consists of:

(i) simulating 2030 land use under multiple scenarios using the PLUS model;
(ii) estimating food production using the method of Liu *et al.*[32] and obtaining habitat quality, water yield, carbon storage, and soil conservation using the InVEST model;
(iii) calculating the improved CESI using the method of Wu and Fan;[42]
(iv) analyzing the influencing factors of CESI in each period using the geographical detector model, followed by interaction analysis; and
(iv) identifying ecological pinch points and constructing the ESP utilizing the MSPA model, circuit theory, and related techniques.

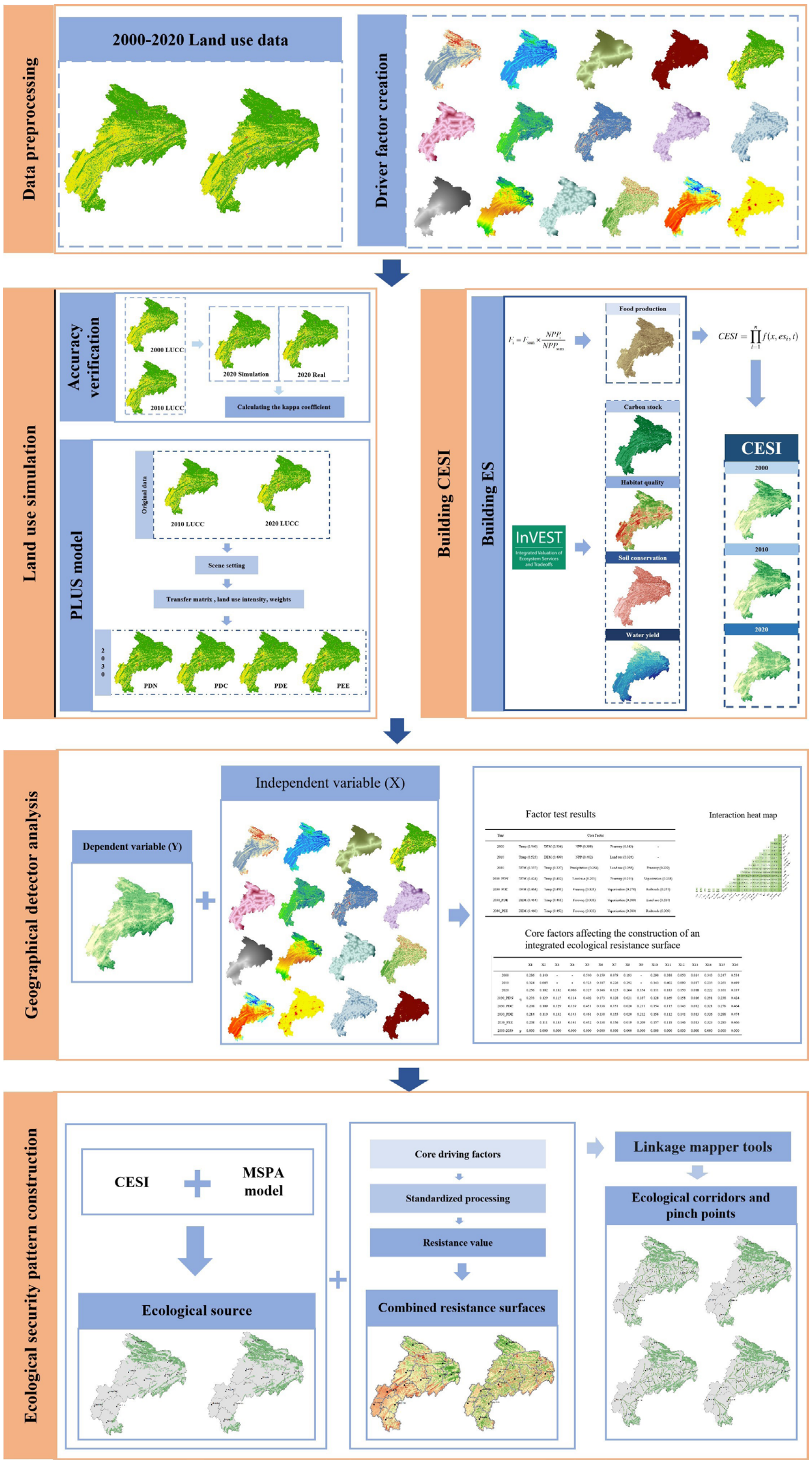

Figure 2. Technological framework of the present study

Abbreviations: CESI: Comprehensive ecosystem service index; ES: Ecosystem services; LUCC: Land use/cover change; MSPA: Morphological spatial pattern analysis; PDC: Priority development of cropland; PDE: Priority development of the economy; PDN: Priority development of nature; PEE: Priority development of the ecological environment; PLUS: Patch-level land use simulation.

3.1. Land-use simulation based on the patch-level land use simulation model

To validate the accuracy of the PLUS model, this study utilized land use data from 2000 and 2010 within the study area to simulate 2020 land use using the PLUS model. The simulated data were then compared with actual data to assess accuracy. With an overall accuracy of 90.4% and a Kappa coefficient of 0.872, the model is suitable for further research. Subsequently, based on the Chongqing Overall Territorial Space Plan (2021–2035) and the studies of Huang *et al.*[43] and Wang *et al.*,[37] four scenarios for 2030 were established: priority development of nature (PDN), priority development of cropland (PDC), priority development of the economy (PDE) and priority development of the ecological environment (PEE). This step provides continuous land use data for the subsequent calculation of ecosystem services and identification of ecological sources across the entire study period (2000–2030). The parameters for different development scenarios are shown in Table 2.

Table 2. Parameters for different development scenarios

Scenario type	Scenario description
PDN	No consideration was given to the binding effects of any policy planning on land use changes.
PDC	The probability of arable land converting to other land types has decreased by 50%, while the probability of other land types converting to arable land has increased by 30%.[44]
PDE	The probability of forest land, grassland, and farmland being converted to construction land has increased by 20%, while the probability of construction land being converted to other land use types besides farmland has decreased by 30%.[43]
PEE	The probability of forest and grassland being converted to construction land has decreased by 50%, while the probability of farmland being converted to construction land has decreased by 30%. Conversely, the probability of farmland and grassland being converted to forest land has increased by 30%.[37,45]

Abbreviations: PDC: Priority development of cropland; PDE: Priority development of the economy; PDN: Priority development of nature; PEE: Priority development of the ecological environment.

3.2. Construction of the improved comprehensive ecosystem service index

Ecosystem services are the intrinsic support of ecological security, and a single service indicator cannot fully reflect the comprehensive ecological status. Based on the United Nations' Millennium Ecosystem Assessment, ecosystem service functions are mainly composed of five components: food production, water yield, soil conservation, habitat quality, and carbon storage.[46] In this study, the water yield, habitat quality, soil conservation, and carbon storage service functions in the study area were determined by the InVEST model, and food production was computed using Liu *et al.*'s[32] technique. After that, this study combined the multiplication method proposed by Wu and Fan, and the above five ecosystem service functions were standardized in ArcGIS 10.8 software and multiplied to obtain the improved CESI.[42] The CESI is then classified into five levels using the natural breakpoint method, which not only quantifies the temporal-spatial differences in regional ecological security but also provides a direct basis for the subsequent identification of ecological sources.

3.3. Geographical detector impact factor selection

According to Wang *et al*, the geographical detector is a statistical technique that can identify geographically stratified heterogeneity and identify the primary influencing elements that cause it.[35] The geographical detector's q-value reflects the extent to which the independent variable influences the dependent variable; the higher the q-value, the greater the effect. The p-value represents the significance of the factor, and when $p < 0.01$, it indicates strong statistical significance.[47] Current applications of the geographical detectors include analyses of NDVI drivers, land degradation, watershed landscape ecological risk, and carbon dioxide emission drivers.[30,47-49] They are rarely applied to the study of ESPs. As a result, to identify the primary elements influencing CESI, this study integrated the geographical detector model with the ESP and chose 16 variables, including road, land use, and temperature. Then, the interaction detection method is used to analyze the interaction of each influencing factor on CESI.

3.4. Basic principle of circuit theory

Circuit theory, originally a branch of physics describing the flow of electric current in circuits, has been innovatively applied to ecological connectivity research in recent years.[50] Its core principle is to analogize the ecological process to an electric circuit system: ecological source areas are regarded as "nodes" with potential differences, the ecological resistance surface is equivalent to "resistors" that hinder current flow, and the migration path of species or the flow of ecological processes is analogous to the "current" flowing between nodes. Unlike the MCR model, which only simulates a single optimal path, circuit theory assumes that species migration is a random process, and there are multiple alternative paths between ecological sources. The "current intensity" in the circuit corresponds to the frequency and importance of species migration on a specific path—higher current intensity indicates that the path is more important for maintaining ecological connectivity.

3.5. Ecological security pattern construction

Ecological source identification: This study extracted ecological sources using the MSPA model (Guidos Toolbox software) based on the improved CESI dataset. In the ArcGIS 10.8 software, the CESI data set is preprocessed, CESI levels 4 and 5 are selected as the foreground and assigned as 2, CESI levels 1, 2, and 3 as the background and assigned as 1, and then the data is imported into the Guidos Toolbox software for processing. The software classifies the landscape into seven categories, and the core area is the ecological source area.[23] To remove small patches, this study used the ArcGIS 10.8 software to remove core areas with an area of less than 5 km^2.

3.5.1. Ecological resistance surface construction

In this study, 16 elements were used as independent variables, including temperature, land use, and road conditions. The improved CESI was used as the dependent variable and screened by geographical detector modeling to obtain the key drivers for each period. To make the constructed resistance surface more accurate, this study normalized all the driving factors. Subsequently, weights were assigned to each core driving factor with reference to Wei *et al.*,[17] thereby generating a comprehensive ecological resistance surface. The Linkage Mapper toolkit and corridor junctions were used to identify ecological corridors and ecological pinch points, respectively.[33]

4. Results

4.1. Analysis of land-use change

The PLUS model was used to simulate land use in 2030 based on land-use data from 2000 and 2020. According to the findings (Table 3, Figure 3–5), the study area's land use type has changed dramatically during the last 30 years. Spatial differences among the four scenarios were limited overall, although forest land exhibited the largest transfer area. Forest land accounted for more than 4,000 km^2 in each scenario, representing more than 70% of the total area. It is mostly found in the study area's central and northeastern sections. Under the PDN scenario, transfers of other land types were relatively limited and were mainly distributed in the northern, southern, and northeastern parts of the study area. The transfer area of cultivated land was 15.13 percent, mostly from forest land. The transfer area of construction land and water area was 4.87% and 3.48%, respectively. The proportions of grassland and shrubland remained low across scenarios, although they varied slightly. In the PDC scenario, cultivated land is well preserved, and its area is expanded, encompassing 17.81% of the total area, primarily converted from forest land and a portion of construction land. In this scenario, the construction land area is reduced and effectively controlled. The PDE and PEE scenarios exhibited a declining trend in both the construction land and water area, with respective decreases of 0.53% and 0.25%. The increase in water area was derived from the conversion of small areas of cropland and forest land, whereas most construction land was converted from cropland. The PEE scenario had a forest-area proportion that was 3.41 percentage points higher than that in the PDN scenario, and the ecological environment was adequately safeguarded.

4.2. Characteristics of the spatial and temporal distribution of the CESI

Level 1 represents the lowest ecological quality and level 5 the highest, as shown in the improved CESI spatial distribution maps generated using the multiplication approach (Figure 6). In this study, CESI was classified into five levels using the natural breakpoint method. The findings indicate that areas with low ecological quality were concentrated mainly in construction areas and their surrounding zones, with some also distributed along riverbanks. In contrast, areas with high ecological quality were dominated by woodland and showed a clustered spatial distribution. According to Figure 6A–C, ecological quality in the study area first improved and then declined over time. In 2000, areas with high ecological quality were

Table 3. Land-use transfers under different scenarios

Land use type	2000–2030_PDN		2000–2030_PDC		2000–2030_PDE		2000–2030_PEE	
	Area, km²	Proportion, %	Area, km²	Proportion, %	Area, km²	Proportion, %	Area, km²	Proportion, %
Cropland	985.3159	15.13%	1055.0060	17.81%	958.6121	14.85%	878.6717	12.87%
Forest	4938.1870	75.82%	4383.2860	74.01%	4929.5300	76.34%	5410.5499	79.23%
Grassland	16.2483	0.25%	19.5924	0.33%	17.5520	0.27%	17.1084	0.25%
Impervious	317.1644	4.87%	213.7616	3.61%	292.8607	4.54%	272.7562	3.99%
Shrub	29.31463	0.45%	39.1100	0.66%	34.2703	0.53%	29.0594	0.43%
Water	226.8756	3.48%	211.9179	3.58%	224.4912	3.48%	220.4235	3.23%

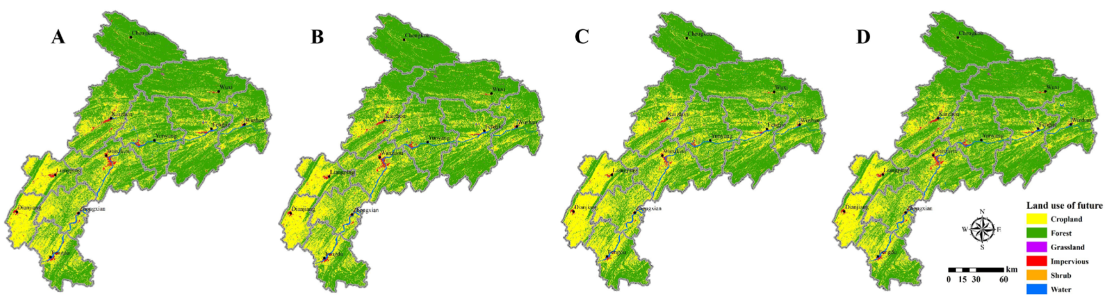

Figure 3. Land use types in 2030. (A) 2030_PDN, (B) 2030_PDC, (C) 2030_PDE, (D) 2030_PEE.

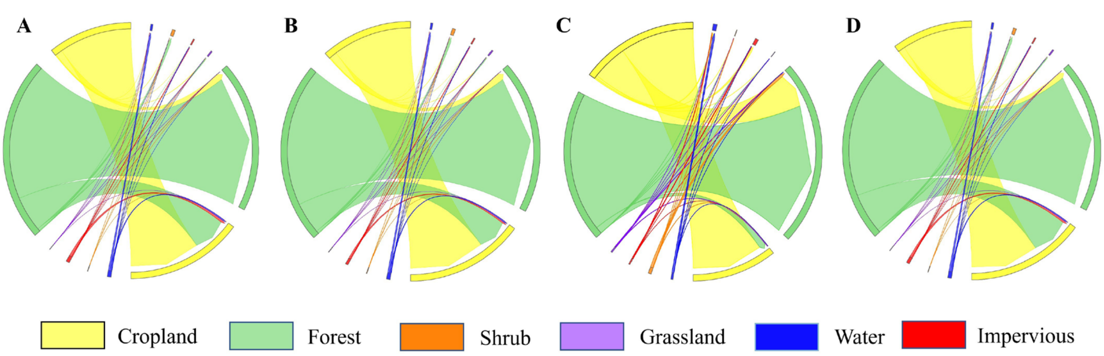

Figure 4. Land use transfers 2000–2030. (A) 2030_PDN, (B) 2030_PDC, (C) 2030_PDE, (D) 2030_PEE.

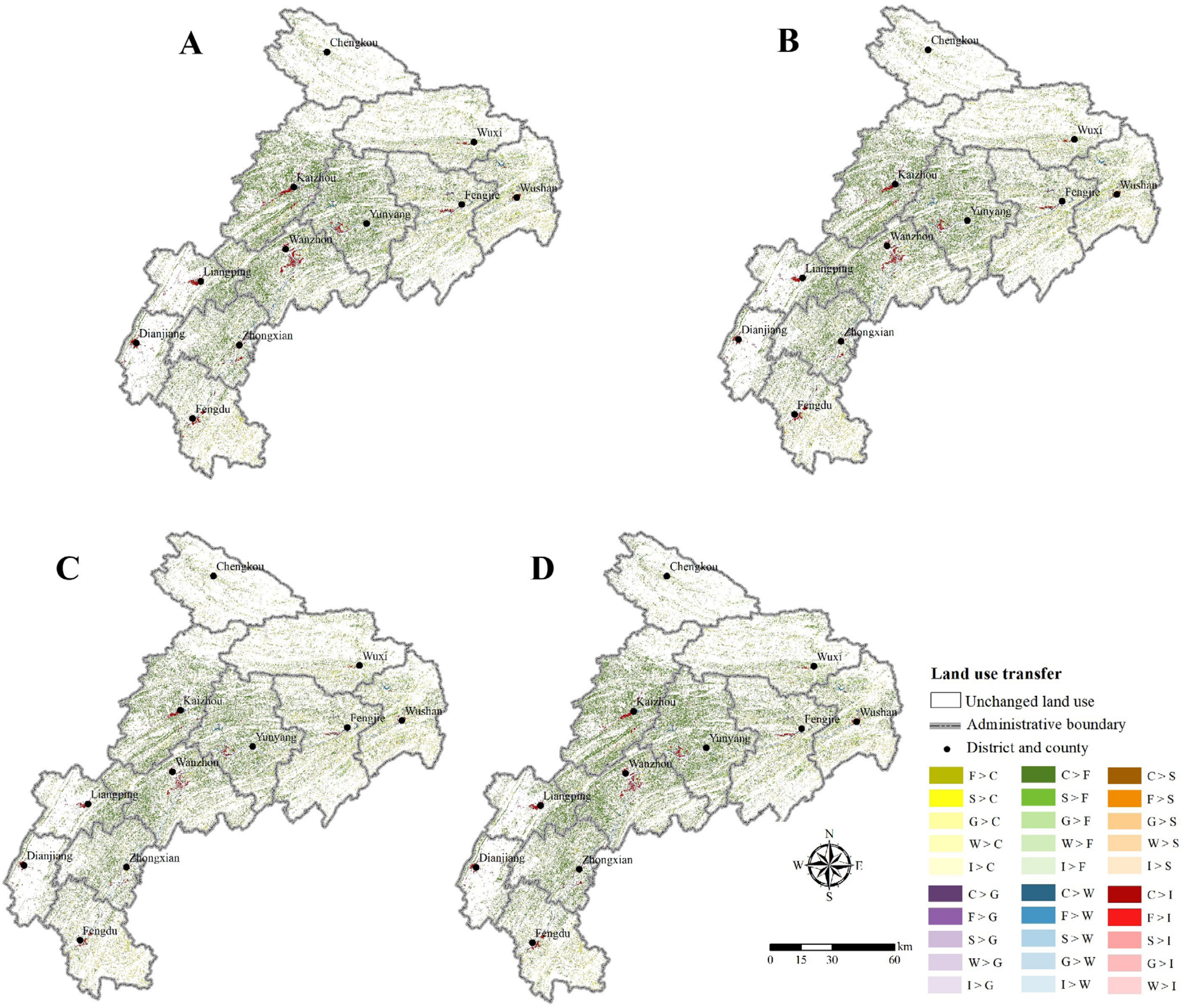

Figure 5. Spatial distribution of land-use transfers, 2000–2030. (A) 2030_PDN, (B) 2030_PDC, (C) 2030_PDE, (D) 2030_PEE.

located mainly in the northern and northeastern parts of the study area, whereas areas with low ecological quality were concentrated primarily in the central and southwestern parts. In 2010, ecological quality improved further, and the area classified as level 5 expanded. By 2020, ecological quality in the study area had declined markedly; as shown in Figure 6C, previously high-quality areas had begun to deteriorate, and only limited level 5 areas remained.

The multi-scenario projections (Figure 6D–G) suggest that ecological quality in the study area is likely to improve by 2030. Compared with 2020, the 2030 scenarios indicate that the projected ecological improvement will be concentrated mainly in the northeastern part of the study area.

4.3. Detection of factors affecting the comprehensive ecosystem service index

4.3.1. Factor detection analysis

Table 4 presents the findings of the geographical detector analysis used to quantify the explanatory power of each factor for CESI. The main results are as follows:

(i) In 2000, factors with $q > 0.2$ were temperature (0.540), digital elevation model (DEM; 0.534), net primary productivity (NPP; 0.388), expressway (0.343), first-class road (0.290), land use (0.286), and evapotranspiration (0.247).
(ii) In 2010, factors with $q > 0.2$ were temperature (0.523), DEM (0.499), NPP (0.402), land use (0.324), rainfall (0.292), evapotranspiration (0.261), expressway

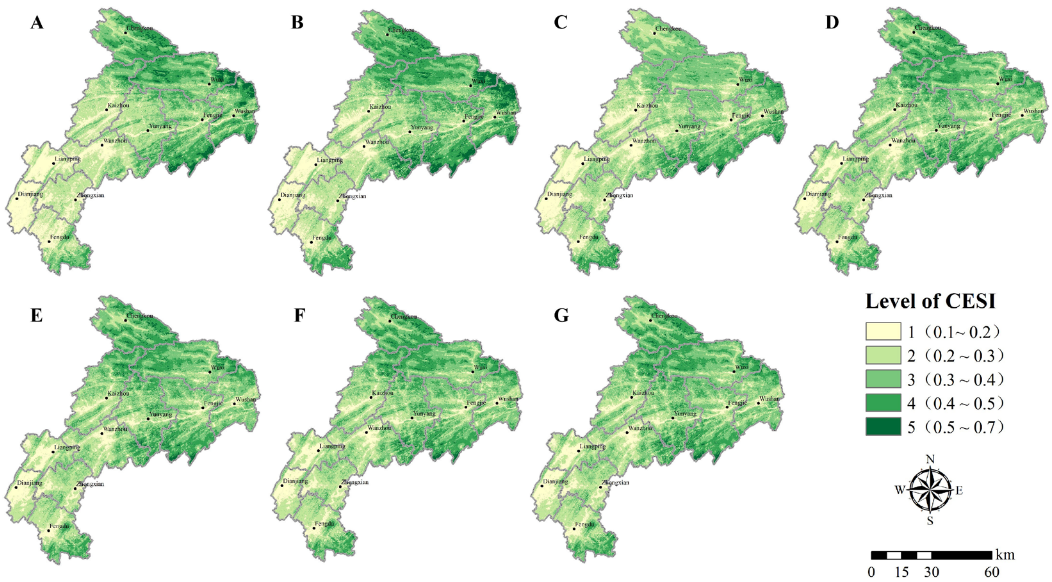

Figure 6. Improved comprehensive ecosystem service index (CESI) (A) 2000, (B) 2010, (C) 2020, (D) 2030_PDN, (E) 2030_PDC, (F) 2030_PDE, (G) 2030_PEE. CESI scale 1–5, with 1 being the poorest ecosystems and 5 the best ecosystems.

(0.233), and secondary road (0.226).

(iii) In 2020, factors with $q > 0.2$ were DEM (0.337), temperature (0.327), rainfall (0.264), land use (0.256), and highway (0.222).

(iv) Across the four 2030 scenarios, the factors that consistently showed $q > 0.2$ included temperature, DEM, highways, evapotranspiration, land use, and railways.

Overall, natural factors, particularly temperature and DEM, showed relatively strong explanatory power for CESI across the study period. Among the human-related factors, land use and railroads also contributed substantially.

4.3.2. Interaction analysis

To further characterize the interactions among explanatory factors, this study performed an interaction analysis of the variables influencing CESI. The purpose of this analysis was to determine whether the combined explanatory power of two factors on CESI was enhanced or weakened when the factors acted together. The interaction analysis results are shown in Figure 7.

In 2000, DEM and temperature showed strong interactions with 12 other factors, indicating enhanced explanatory power for CESI variation when these variables were combined with other drivers. Other factor combinations with relatively high interaction values ($q > 0.45$) included NPP with land use, primary roads, rainfall, highways, and evapotranspiration; rainfall with primary roads and highways; and evapotranspiration with highways.

In 2010, in addition to the dominant roles of temperature and DEM, several other factor combinations also showed relatively strong interaction effects ($q > 0.45$), including rainfall with land use, railway, NPP, highway, and evapotranspiration, as well as NPP with secondary roads, railways, primary roads, highways, and evapotranspiration.

In 2020, rainfall, temperature, and DEM were the factors most frequently involved in strong interactions ($q > 0.45$), indicating that these variables played major roles in explaining CESI variation. Under the multi-scenario projections for 2030, temperature and DEM remained the dominant interacting factors, while evapotranspiration and railway also contributed substantially to the combined explanatory power of the model.

Overall, the interaction analysis suggests that CESI is shaped jointly by natural factors and human activities, with temperature and DEM exerting particularly strong influences on its spatial distribution.

4.4. Evaluation of ecological security pattern construction

4.4.1. Ecological sources

Table 5 and Figure 8 present the MSPA model-based results. In 2000, 59 ecological source patches were identified, with a total area of 7,043.2695 km^2, or 20.78% of the study area. Spatially, it was mainly concentrated in most parts of Chengkou and Wuxi counties and was also distributed in

Table 4. Factor test results

Year		X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16
2000		0.286	0.140	–	–	0.540	0.159	0.079	0.193	–	0.290	0.388	0.050	0.014	0.343	0.247	0.534
2010		0.324	0.065	–	–	0.523	0.187	0.226	0.292	–	0.143	0.402	0.090	0.017	0.233	0.261	0.499
2020		0.256	0.102	0.132	0.086	0.327	0.146	0.125	0.264	0.154	0.111	0.183	0.150	0.018	0.222	0.161	0.337
2030_PDN	*q*	0.293	0.129	0.115	0.114	0.402	0.173	0.128	0.021	0.187	0.128	0.169	0.158	0.016	0.291	0.238	0.424
2030_PDC		0.208	0.109	0.129	0.139	0.451	0.138	0.151	0.020	0.211	0.154	0.115	0.143	0.012	0.321	0.278	0.464
2030_PDE		0.214	0.110	0.132	0.143	0.461	0.138	0.155	0.020	0.212	0.156	0.112	0.141	0.013	0.326	0.288	0.474
2030_PEE		0.208	0.111	0.133	0.141	0.452	0.138	0.156	0.019	0.209	0.157	0.118	0.146	0.013	0.323	0.280	0.466
2000–2030	*p*	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Note: X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13, X14, X15, X16 denote land use, populations, water, tertiary roads, temperature, slope, secondary roads, precipitation, railroads, primary roads, net primary productivity, nighttime light, gross domestic product, freeway, vaporization, and digital elevation model, respectively.

Fengjie, Wushan, and Fengdu counties (Figure 8A). There were 62 ecological sources in 2010; their combined size was 7,925.0265 km^2 or 23.38% of the research area. The area of the ecological source patches exhibited an increasing tendency, growing by 881.757 km^2 compared to 2000. The spatial distribution was similar to that in 2000 (Figure 8B). In 2020, there were 91 ecological source patches, up from 2010; nonetheless, the overall area exhibited a declining tendency, with a drop of about 1,386.9342 km^2, or 19.29% of the studied area, in comparison. Only in the intersections of Wushan County and Wuxi County, Chengkou County and Wuxi County, and the southern portions of certain districts and counties did spatial data reveal a declining trend (Figure 8C). Across the four 2030 scenarios, the number of ecological sources ranged from 79 to 88. The PDN scenario showed the source land area's greatest value, whereas the PEE scenario showed the lowest value. The four scenarios' spatial distribution (Figure 8D–G) stayed mostly unchanged, with Chengkou and Wuxi counties serving as the primary ecological source areas.

4.4.2. Ecological resistance surfaces

The core factors impacting CESI (Table 6) were determined based on the geographical detector's calculation findings, and a thorough resistance surface was built, as seen in Figure 9. The distribution pattern was generally low in the north and high in the south. Because natural factors dominated in 2000 and 2010, the resistance surface during

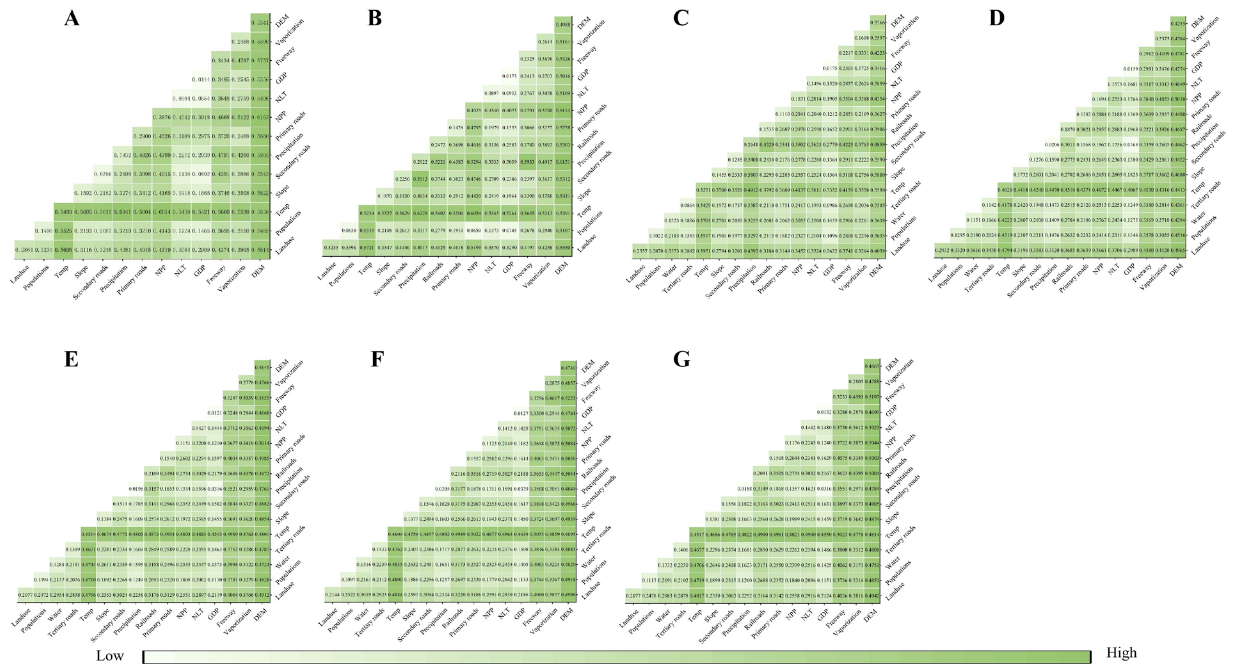

Figure 7. Heat map of interactions among multiple factors influencing the comprehensive ecosystem service index. (A) 2000, (B) 2010, (C) 2020, (D) 2030_PDN, (E) 2030_PDC, (F) 2030_PDE, (G) 2030_PEE.

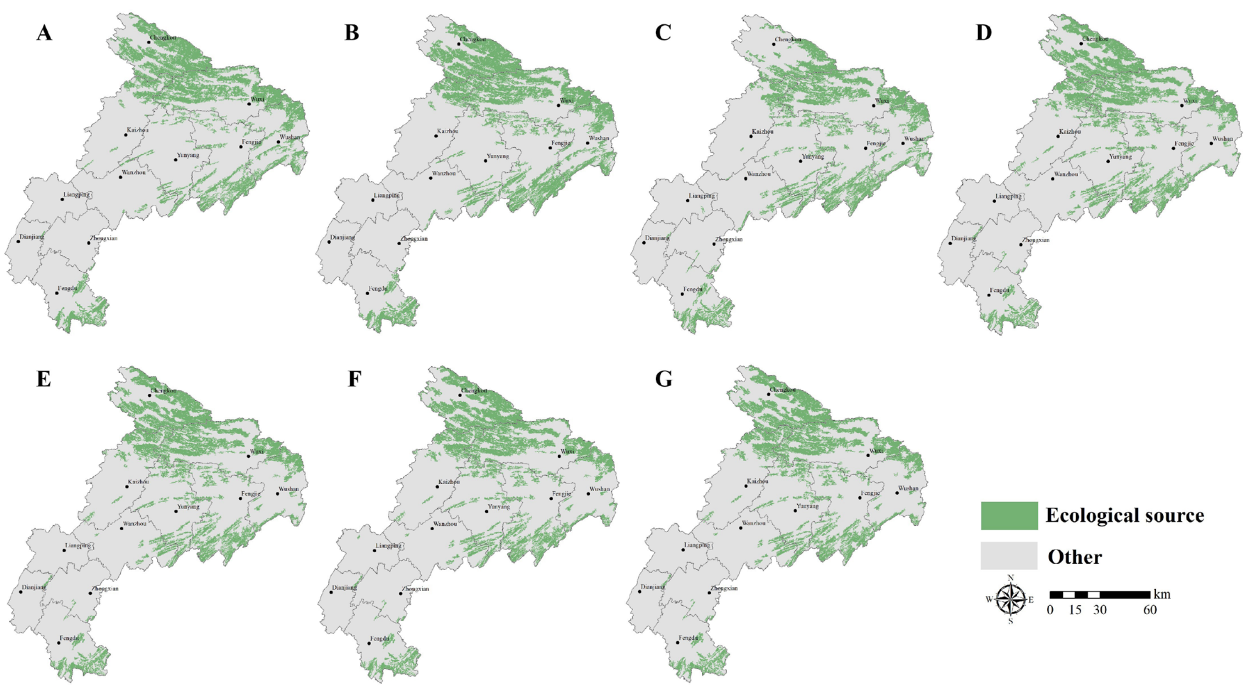

Figure 8. Ecological source patches. (A) 2000, (B) 2010, (C) 2020, (D) 2030_PDN, (E) 2030_PDC, (F) 2030_PDE, (G) 2030_PEE.

Table 5. Ecological source area statistics by period

	2000	2010	2020	2030_PDN	2030_PDC	2030_PDE	2030_PEE
Ecological source	59	62	91	85	88	84	79
Area, km^2	7,043.2695	7,925.0265	6,538.0923	7,300.5435	7,252.5177	7,189.4826	7,061.7078
Proportion, %	20.78	23.38	19.29	21.54	21.39	21.21	20.83

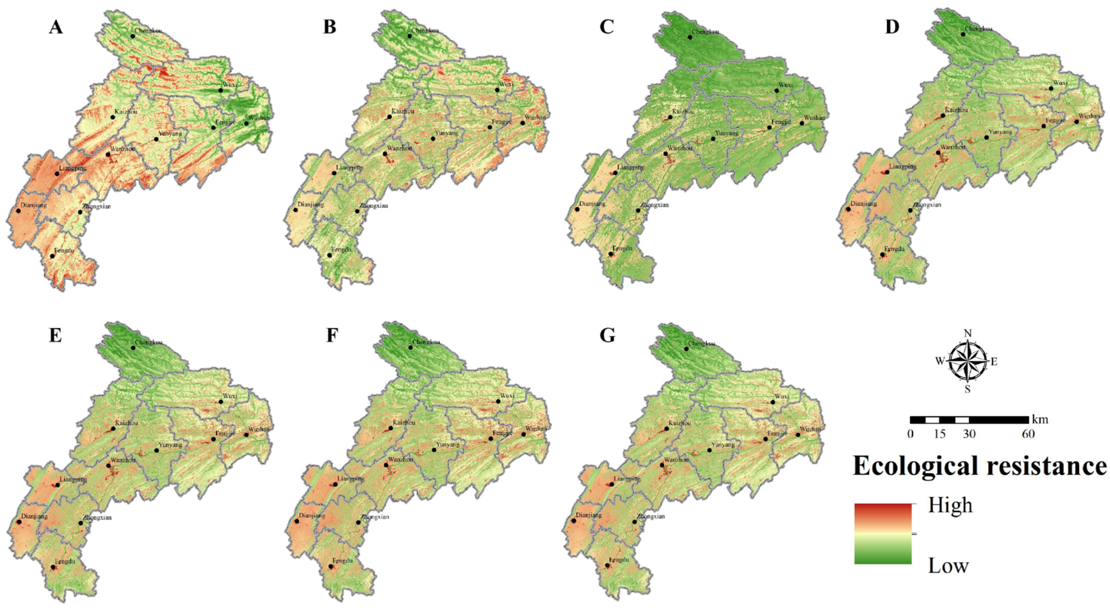

Figure 9. Integrated ecological resistance surfaces (A) 2000, (B) 2010, (C) 2020, (D) 2030_PDN, (E) 2030_PDC, (F) 2030_PDE, (G) 2030_PEE.

these periods was driven mainly by topographic and climatic variables. Figure 9A shows that low-resistance areas were concentrated mainly in Wushan County, Wuxi County, and Chengkou County. Figure 9B indicates that resistance decreased in some parts of the study area. In 2020, a relatively large low-resistance area was observed in the spatial distribution of the resistance surface. This pattern may be related to changes in the explanatory power of the key factors, whose q-values were lower in 2020 than in the earlier periods. In the multi-scenario prediction, the coupling of natural factors and social factors makes the resistance surface unstable, and the majority of the places with high development land density, a large volume of human activity, and intricate transportation networks are those with high resistance values. However, regions characterized by low resistance values are identified as forest land in terms of land use classification (Figure 3), aligning with areas exhibiting robust ecosystems based on CESI spatial distribution (Figure 6).

4.4.3. Ecological corridors and pinch points

Based on circuit theory, ecological corridors were identified in this study (Figure 10, Figure 11, and Table 7). In 2000, 152 ecological corridors were identified, with a total length of 1830.6429 km, along with 19 pinch points. With a total length of 1228.8199 km and 9 pinch points, there were 146 ecological corridors in 2010. In 2020, 23 pinch points and 225 ecological corridors were identified,

Table 6. Core factors affecting the construction of an integrated ecological resistance surface

Year	Core factor				
2000	Temp (0.540)	DEM (0.534)	NPP (0.388)	Freeway (0.343)	–
2010	Temp (0.523)	DEM (0.499)	NPP (0.402)	Land use (0.324)	–
2020	DEM (0.337)	Temp (0.327)	Precipitation (0.264)	Land use (0.256)	Freeway (0.222)
2030_PDN	DEM (0.424)	Temp (0.402)	Land use (0.293)	Freeway (0.291)	Vaporization (0.238)
2030_PDC	DEM (0.464)	Temp (0.451)	Freeway (0.321)	Vaporization (0.278)	Railroads (0.211)
2030_PDE	DEM (0.464)	Temp (0.461)	Freeway (0.326)	Vaporization (0.288)	Land use (0.214)
2030_PEE	DEM (0.466)	Temp (0.452)	Freeway (0.323)	Vaporization (0.280)	Railroads (0.209)

Note: "–" indicates that no additional core factor was retained for that period under the selected screening criterion.
Abbreviations: DEM: Digital elevation model; NPP: Net primary productivity; Temp: Temperature.

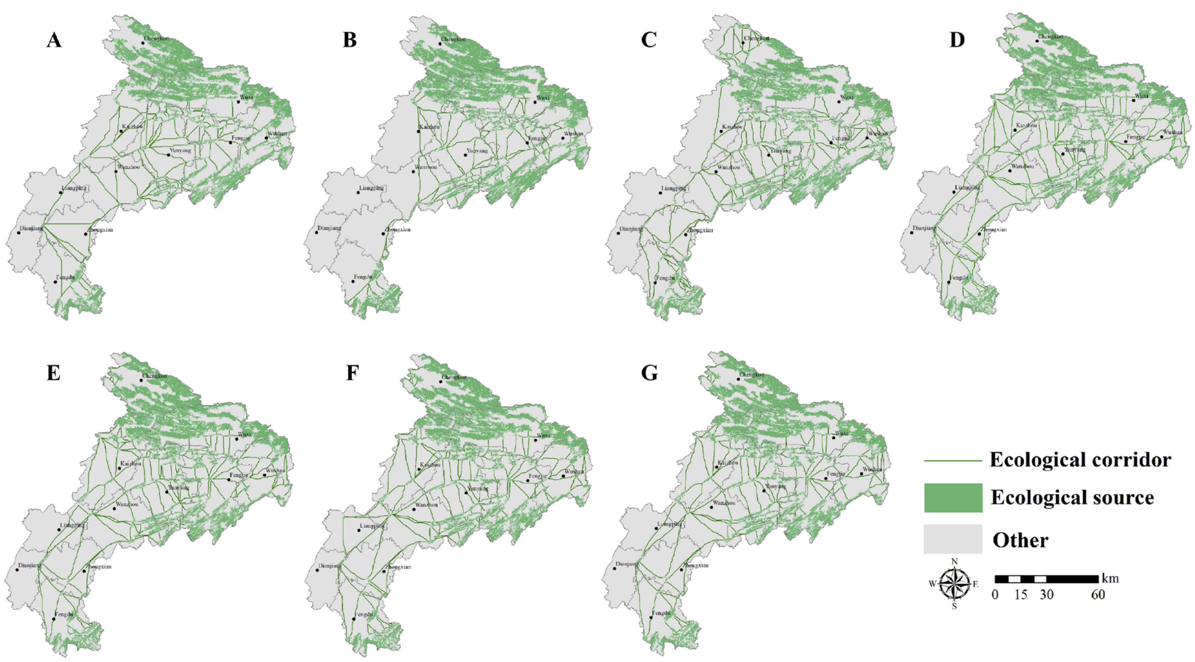

Figure 10. Ecological corridors (A) 2000, (B) 2010, (C) 2020, (D) 2030_PDN, (E) 2030_PDC, (F) 2030_PDE, (G) 2030_PEE.

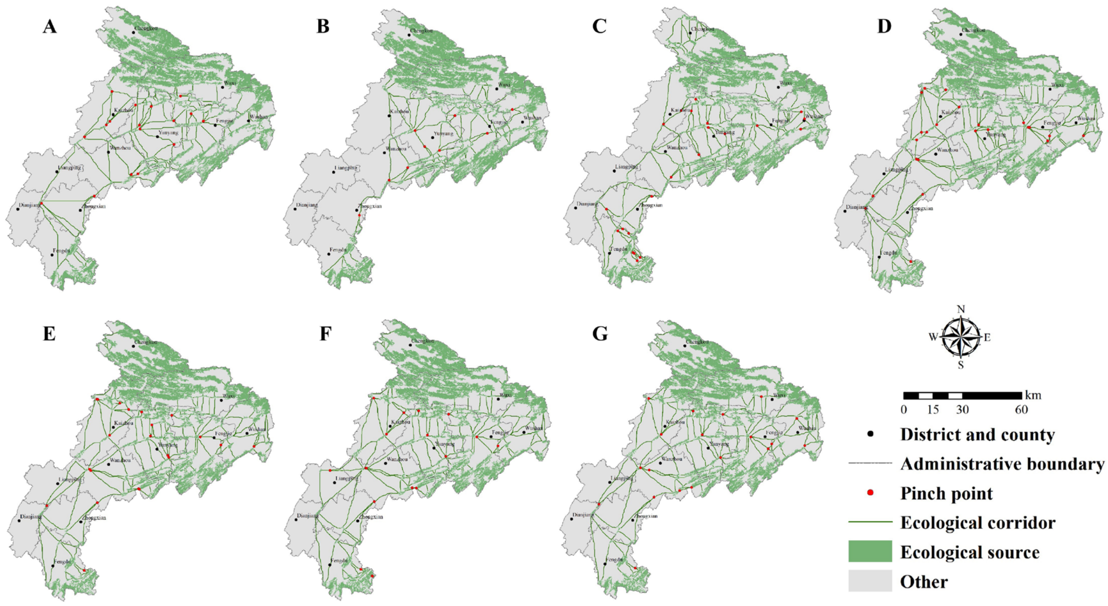

Figure 11. Ecological pinch points (A) 2000, (B) 2010, (C) 2020, (D) 2030_PDN, (E) 2030_PDC, (F) 2030_PDE, (G) 2030_PEE.

totaling 2115.1020 km in length. In the multi-scenario predictions, the highest count of ecological corridors was observed in the PDC scenario, while the lowest count was noted in the PEE scenario. Additionally, the maximum and minimum lengths of ecological corridors were recorded in the PDE and PEE scenarios, respectively. Over the study period, ecological connectivity first declined and then improved. The ecological corridors and pinch points in Kaizhou District, Chengkou County, Wuxi County, Wushan County, Fengjie County, and Yunyang County are dense, as can be observed from the spatial distribution, and these areas can offer conducive circumstances for species movement. In Wanzhou District, Zhongxian County, and Fengdu County, there are few ecological corridors and pinch points, while in Liangping District and Dianjiang County, ecological corridors and pinch points were limited to border areas, indicating detrimental effects to the ecosystem's stability.

5. Discussion

5.1. Mechanism of ecological security pattern evolution: The role of land use change and policy regulation

Ecosystem services are crucial for human socio-ecological systems' trade-offs and harmony.[51] Exploring multiple ecosystem services can address the singularity and complexity of ecosystem services, and rational land use is an important factor in socio-environmental services.[42] Land use change serves as the direct driver: the transfer of forest land to construction land (4.87% in the 2000–2030 PDN scenario) led to the fragmentation of ecological sources and an increase in resistance, while the recovery of forest land (a 3.41% increase in the PEE scenario) promoted the connectivity of corridors and the stability of pinch points, which aligns with the conclusion that land use transfer is the core factor affecting ecological security.[33] In this study, we used the InVEST model and multiplication approach to produce the geographical distribution map of CESI in each period based on land use data (Figure 6). We discovered a strong correlation between the geographical distribution of ecosystem services and CESI, indicating that ecosystem services influenced the latter's spatial distribution. The results are consistent with Wu and Fan.[42]

Notably, the number of ecological source areas increased from 62 in 2010 to 91 in 2020, but the total area decreased by approximately 1386.93 km^2, a phenomenon that directly reflects the severe fragmentation of ecological sources during this period. This fragmentation has profound negative impacts on regional ecological security: ecologically, fragmented source patches are difficult to form a contiguous ecological network, which weakens the material circulation and energy exchange between ecosystems, reduces the carrying capacity of biodiversity, and limits the migration and diffusion of species—especially for large terrestrial animals with high habitat connectivity requirements, fragmented patches increase

Table 7. Statistics on ecological corridors and pinch points by time period

	2000	2010	2020	2030_PDN	2030_PDC	2030_PDE	2030_PEE
Ecological corridor	152	146	225	209	221	208	197
Length, km	1830.6429	1228.8199	2115.1020	2344.2500	2309.3781	2348.4972	2254.3845
Pinch point	19	9	23	25	22	20	20

the risk of population isolation and genetic degradation. In terms of ecological connectivity, the fragmentation of sources leads to the discontinuity of ecological corridors, increases the resistance of species migration paths, and even forms "ecological islands" that are difficult to connect, further reducing the overall stability and resilience of the regional ecosystem.

Policy regulation acts as an indirect driver: the Chongqing Overall Land Space Plan (2021–2035) has guided the differentiation of ESP patterns under multiple scenarios. The emphasis on ecological protection in the PEE scenario has optimized the structure of ecological networks, while the economic priority in the PDE scenario has led to ecological risks, indicating that scientific territorial spatial planning can effectively reconcile the conflict between development and protection and mitigate the negative effects of ecological fragmentation.

5.2. Addressing key deficiencies of traditional ecological security pattern research

This study's integration of the geographical detector, PLUS model, and circuit theory has solved three key problems in traditional ESP research: first, the objective selection of resistance factors—using the geographical detector's q-value and interaction analysis to avoid the subjectivity of expert experience, identifying temperature, DEM, land use, and railroads as core factors, which is more scientific than traditional methods.[21] For data-scarce regions, this method can screen core factors through limited variables, improving the applicability of ESP construction. Second, cross-temporal dynamic analysis—the construction of ESP from 2,000 to 2,030 makes up for the deficiency of traditional single-period research, reveals the historical evolution and future trend of ecological security, and clarifies the process and mechanism of ecological source fragmentation, providing a contextual basis for current ecological protection. Third, multi-scenario optimization—the PLUS model's multi-scenario simulation predicts the ESP pattern under different development strategies, identifies the PEE scenario as the optimal option, and provides a quantitative tool for decision-makers to balance economic development and ecological protection, especially offering targeted solutions for mitigating ecological fragmentation.

5.3. Practical implications for ecological protection in the Three Gorges Reservoir area

Based on the results, targeted recommendations for ESP optimization are proposed: for key protection areas (northeast), such as Chengkou and Wuxi counties with dense ecological sources and corridors, it is necessary to strengthen the protection of forest ecosystems, prohibit the occupation of ecological land, focus on protecting pinch points at the junctions of forest land and roads, and establish ecological buffer zones to reduce human disturbance, thereby preventing further fragmentation of existing contiguous ecological sources. For ecological restoration areas (southwest), such as Wanzhou and Liangping districts with fragmented ecological sources, efforts should be made to expand ecological source areas by restoring degraded land and building urban green spaces, constructing artificial ecological corridors to connect scattered ecological patches, and improving the connectivity of the ecological network to reverse the fragmentation trend. In terms of policy coordination, promote the integration of ESP into territorial spatial planning, delineate ecological protection red lines based on ecological sources and corridors, restrict urban expansion and transportation construction in high-resistance areas, and, for the PDC scenario, optimize the layout of cropland to avoid conflicts with ecological corridors, ensuring the integrity and connectivity of ecological sources.

5.4. Limitations and prospects

The ESP developed in this study, utilizing a combination of geographical detectors, effectively addresses areas with missing data. However, it still exhibits certain limitations that need to be acknowledged. In this study, in the PLUS model, most of the multi-scenario prediction parameters are derived from existing studies, which may have problems such as regional differences. The identification of ecological source areas primarily relies on the improved CESI raster data. However, the accuracy of the CESI data is heavily dependent on the quality of the underlying data sources for ecosystem services. If the spatial resolution of these basic data sources is low, it can result in issues such as reduced accuracy in the constructed CESI. Secondly, this study combined the geographical detector model mainly to improve the resistance surface, and we did not conduct an in-depth study on the width and division type of the constructed ecological corridor. Future studies should use higher-resolution input data to improve CESI accuracy and adopt a finer spatial scale to provide more locally actionable guidance for ecosystem management.

6. Conclusion

The accelerating pace of global urbanization has brought ecosystem security increasingly into the research focus of scholars. An ecological security framework constructed solely on the basis of a single ecosystem service may struggle to comprehensively reflect local ecosystem security. Multi-ecosystem services have thus emerged as a current research trend. However, how to objectively construct an ecological security framework remains a persistent challenge for many scholars. This study applies the geographical detector model to construct an ESP, objectively analyzing the primary drivers influencing integrated ecosystem services. It offers a novel research perspective for constructing ecosystem patterns and holds significant reference value. Key findings include:

(i) Under multi-scenario projections, forest land exhibits the most pronounced land-use conversion within the study area, accounting for over 70% of the total area. This conversion is primarily concentrated in the central and northeastern regions;
(ii) Areas with poorer ecosystems are primarily distributed in construction land and its surrounding regions, with some occurring along riverbanks. Areas with better ecosystems are mainly located in the northeastern part of the study area, where forest land dominates the land use types;
(iii) Core natural factors influencing the spatial distribution of CESI are temperature and DEM; key social factors are land use and railway networks;
(iv) Extracted ecological source areas are concentrated in the northeastern part of the study area; regions with higher resistance values include Dianjiang County, Fengdu County, Liangping District, Wanzhou District, Fengjie County, Wushan County, and Wuxi County.
(iv) Ecological corridors and nodes are relatively concentrated in the northeastern region, which should be prioritized for ecological conservation and management. Ecological corridor structures in Wanzhou District, Liangping District, Zhong County, Dianjiang County, and Fengdu County are simple with sparse nodes, necessitating focused ecological restoration efforts.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study. Zhuangzhuang Hou is affiliated with Shanxi Coal Geology 144th Exploration Institute Co., Ltd; however, this affiliation did not influence the study design, data collection, data analysis, interpretation of results, manuscript preparation, or the decision to publish.

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Availability of data

Data will be made available upon reasonable request to the corresponding author.

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