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Ecological space delineation and security analysis in the hilly areas of chongqing, China

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The appropriate delineation of ecological space is crucial for ensuring ecological security, enhancing the regional environmental carrying capacity, and fostering sustainable economic and social development. For hilly and mountainous areas, there are few studies on ecological security pattern analysis combined with land use types. Taking Chongqing, China as a case study, this paper systematically developed an special evaluation system for ecosystem sensitivity (ES) and ecosystem service function (ESF) in hilly and mountainous areas, utilizing various sources of data from the year 2022 to support the delineation of ecological space types (EST), and analyzing ecological pattern security issues in conjunction with the current land use status. The results were as follows: (1) The ES was predominantly classified as extremely sensitive, comprising 47.54% (39,171.12 km^2) of the area, characterized by high terrain and abundant forest resources, with a spatial trend of increasing from west to east. (2) The comprehensive ESF was primarily of general importance, accounting for 48.06% (39,603.89 km^2), characterized by flat terrain and associated with areas of intensive development and construction, exhibiting a spatial trend of lower values in the northwest and higher values in the southeast. (3) Based on ES and ESF, we classified the EST into core, auxiliary, transitional, and development-friendly, representing 53.83% (44,360.12 km^2), 9.15% (7,538.51 km^2), 19.96% (16,450.80 km^2), and 17.06% (14,052.57 km^2), respectively, with 39.50% (13,574.00 km^2) of the cultivated land located within the core-auxiliary ecological space, indicating a certain ecological security conflict. These findings lay the foundation for implementing scientifically effective management strategies in the study area, provide valuable insights for optimizing the national land use pattern in the hilly and mountainous areas of Southwest China, and assist management authorities in optimizing the spatial pattern of land.

KEYWORDS

ecosystem sensitivity, ecosystem service function, ecological space type, ecological security conflict, hilly and mountainous

1 Introduction

With the development of the economy and society, the increasing demand for production and living space has led to the continuous encroachment on ecological space, resulting in significant ecological degradation (Hou et al., 2022; Liu et al., 2017; Liu Y. et al., 2024; Liu and Zhong, 2024). This issue is particularly prominent in Chongqing, a key ecological barrier of the Yangtze River, where rapid urban expansion and agricultural land use intensification have heightened the contradiction between cultivated land protection and ecological security. The balance between economic growth and ecological conservation has become a critical challenge for sustainable development in this region. China has implemented a series of ecological civilization construction plans, which explicitly call for optimizing the national land use pattern and enhancing ecological land protection. Ecological space is vital for maintaining the ecological security pattern, enhancing regional environmental carrying capacity, and promoting the sustainable development of the economy and society (Liang et al., 2023; Zhao et al., 2022a; Chakraborti et al., 2018). In Chongqing, as the last ecological barrier of the Yangtze River before it enters the densely populated eastern regions, the protection and rational allocation of ecological space are of particular importance. The region's ecological security directly influences water resource conservation, biodiversity protection, and disaster prevention along the Yangtze River Basin. The appropriate delineation of ecological space has thus become a key research issue, requiring careful consideration of trade-offs between land resource utilization and ecological sustainability (Wang et al., 2022; Liu and Ding, 2022). Ecological space is generally defined as the area that ensures regional ecological security, provides essential ecological services, and fulfills important ecological functions. The classification and delineation methods for ecological space are still under exploration. Currently, the division of EST based on their role in supporting ecosystem health is a prominent topic of scholarly research (Chen et al., 2021; Ngom et al., 2016; Zhang et al., 2022). Among these, ES and ESF are critical indicators that reflect ecosystem health (Liu et al., 2023; Luo Q. et al., 2023). ESF maintains the dynamic balance of the ecosystem and plays an important supporting role within it (Yu et al., 2021). ES indicates the degree of the ecosystem's response to external disturbances and is essential for maintaining ecological stability (Liu T. et al., 2024; Ye and Wang, 2024).

Numerous studies have delineated ecological space, with a focus on mesoscopic and macro scales, including national, provincial, urban agglomeration, and municipal levels (Ouyang et al., 2022; Ban et al., 2022; Gupta et al., 2012). Domestic and international studies have employed various methods and integrated diverse datasets to comprehensively analyze ecological space-related issues. Internationally, various methods have been used to analyze ecological space. For example, Manob Das et al. analyzed the correlation between ecological space quality and land use in Delhi, India, based on land cover changes (Das et al., 2024). They employed the Entropy Method (EM) and geospatial techniques to assess the ecological space quality of the Delhi metropolitan area (India). Their findings contribute to spatial landscape planning and sustainable ecological space management. Additionally, some studies have utilized statistical methods to analyze ecological spaces. For instance, Shmakova et al. assessed the characteristics of ecological spaces in Russian regions using various official statistical data (Shmakova and Kuznetsova, 2023). Some studies have integrated ecological space data with other relevant factors to jointly analyze ecological issues. For example, Bekisoglu et al. explored the relationship between urban green spaces and ecological zones, using data on urban green spaces and ecological space boundaries (Bekisoglu and Keyis, 2023). Their study highlights the role of urban green spaces in maintaining ecological functions and their interaction with broader ecological space frameworks. In China, Zhao et al. applied and extended the methodological approach of ecological function zoning to urban spaces in Taizhou, China (Zhao et al., 2022b). They combined ecological environmental sensitivity, the importance of ecosystem service functions, and socio-economic stress assessments to analyze both ecological and economic conditions comprehensively. Li et al. constructed an ecological resistance surface based on factors such as land use types, topographic position index, and soil erosion intensity, and analyzed the ecological space pattern in Shaanxi, China (Li et al., 2022). Chen et al. delineated the ecological security space of the Guanzhong Plain urban agglomeration in China using ecological importance and sensitivity data (Chen et al., 2022). Furthermore, they incorporated ecological source points to analyze ecological corridors, providing insights into regional ecological connectivity and spatial optimization strategies.

While numerous studies have explored EST assessment and the integration of ES and ESF, research focusing on hilly and mountainous areas remains limited. Taking Chongqing as the study area, and considering its unique "Mountain City" characteristics and environmental risk factors, this study, utilizing the 2022 dataset, constructs an ES evaluation system and an ESF evaluation system by integrating key ecological factors such as soil and water loss sensitivity, desertification sensitivity, geological disasters sensitivity, habitat sensitivity, water resource conservation function, soil and water conservation function, and biodiversity function. Traditional ES evaluations often rely on methods such as the Analytic Hierarchy Process (AHP) and maximum value method, which may lead to the dominance of a single factor and fail to reflect the multidimensional nature of ecological sensitivity (He et al., 2021). To overcome this limitation, this study employs a back propagation (BP) neural network for ES factor evaluation. This approach enhances the objectivity and accuracy of ecological sensitivity assessments by mitigating biases caused by subjective weighting. Differing from other studies, by incorporating land use data, we jointly explore the direct relationship between ecological security and land use patterns. This integration of ES, ESF, and EST enables us to analyze ecological space patterns, providing new insights into ecological pattern security and offering guidance for sustainable land management in hilly and mountainous regions.

2 Study area and materials

2.1 Study area

Chongqing, located in the southwest of China, extends from 105°11′ to 110°11′ east longitude and from 28°10′ to 32°13′ north latitude. It consists of 26 districts, 8 counties, and 4 autonomous counties, covering a total area of 82,402 km^2. Serving as a crucial link between the "Belt and Road" initiative and the "Yangtze River Economic Belt," Chongqing functions as an inland open highland (Luo L. et al., 2023). Chongqing's 2024 regional GDP reached 3,219.315 billion yuan, with *per capita* GDP exceeding

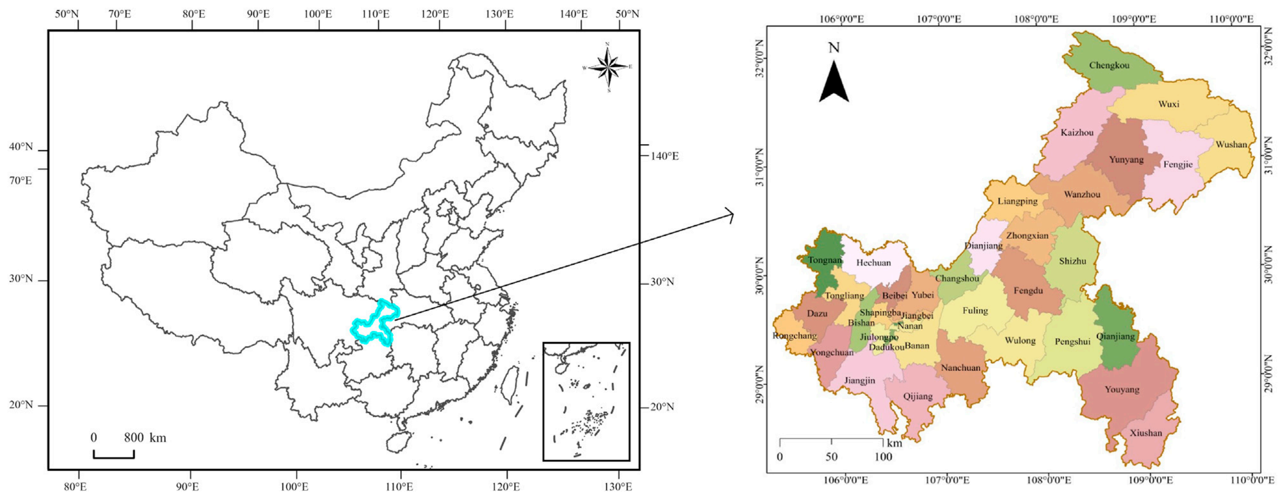

FIGURE 1
Overview of the study area.

TABLE 1 Basic dataset.

Data	Period	Spatial resolution	Source
Precipitation	2015–2022	1 km	China Meteorological Data Network
NPP (Net primary productivity)	2015–2022	500 m	NASA Earthdata
FVC (Fractional vegetation cover)	2015–2022	250 m	
Land use pattern	2022	1 km	Resources and Environmental Science Data Platform, China
Road Network	2022	—	
Nature Reserve	2022	—	
DEM (Digital elevation model)	2022	90 m	Geospatial Data Cloud
Soil properties	2022	—	Institute of Tibetan Plateau Research Chinese Academy of Sciences
Survey of geological disaster risk points	2022	—	Geographic Remote Sensing Ecological Network
Fault zone distribution	2022	—	
Stratigraphic lithology	2022	—	China HWSD Attribute Database

100,000 yuan, ranking it as the fourth-largest GDP city in China. The region is characterized by mountainous terrain and valleys, with an altitude difference of 2,723.7 m, making it prone to landslides and collapses. Chongqing's topography is marked by significant undulations, with lower elevations in the west and higher elevations in the east and southeast. The predominant landform type is mountainous, accounting for 76% of the area, earning the city its nickname, "Mountain City." Situated at the heart of the Three Gorges Reservoir area, it serves as the last gateway of the ecological barrier in the upper reaches of the Yangtze River. As a vital ecological barrier in the upper reaches of the Yangtze River, Chongqing plays an irreplaceable role in maintaining the ecological security of the Yangtze River Basin and promoting national ecological civilization construction, as shown in Figure 1.

2.2 Dataset

This study utilized various basic datasets, including precipitation, net primary productivity (NPP) of vegetation, fractional vegetation cover (FVC), land use patterns, road networks, digital elevation model (DEM), fault zone datasets, and stratigraphic lithology, among others, as outlined in Table 1. For example, NPP data was obtained from the MOD17A3 NPP product, with a spatial resolution of 500m, covering the period from 2015 to 2022. FVC data was sourced from the China 250 m FVC dataset, with a spatial resolution of 250 m. The land use data was derived from the Resources and Environmental Science Data Platform, China. Using these datasets, we calculated key parameters such as rainfall erosivity, slope length, slope, degree of relief, soil erodibility, and regional carbonate

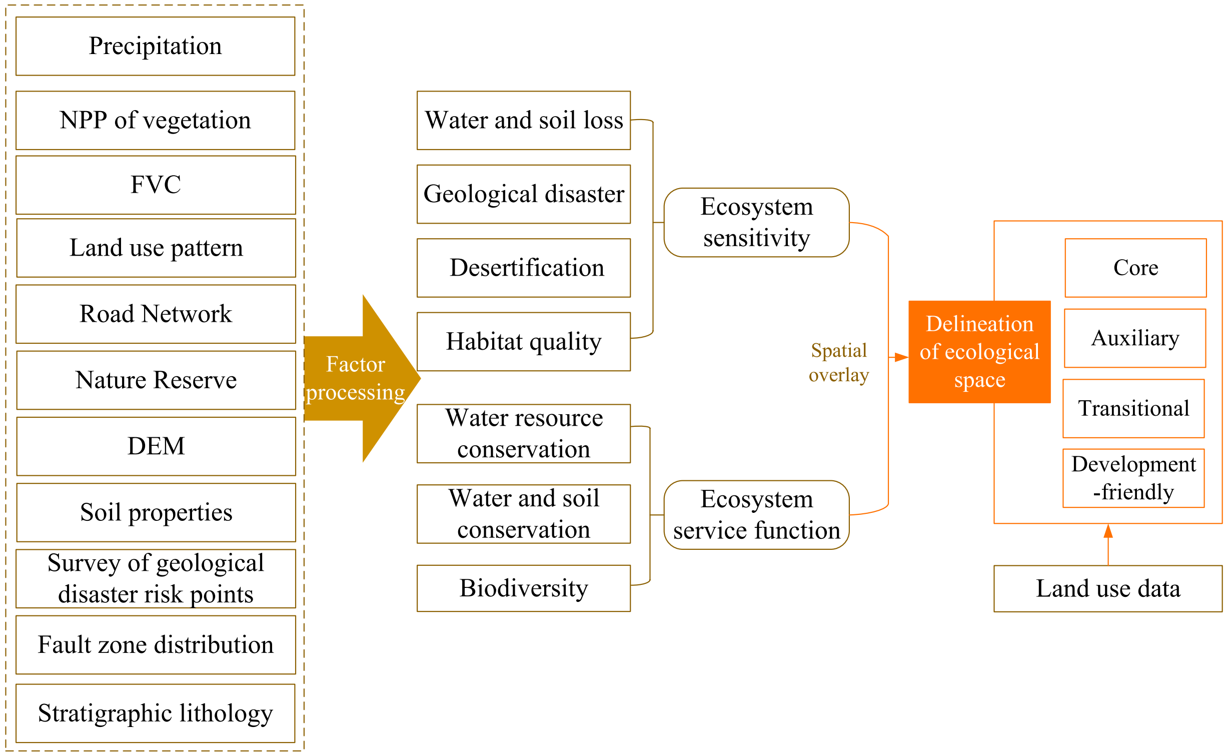

FIGURE 2
Overall technical route (The first column represents the fundamental data, from which the relevant factors in the second column are derived. These factors are further processed to obtain the ecological factors in the third column. Finally, ecological space is delineated.).

exposure percentage. Rainfall erosivity was calculated from precipitation data (Wang et al., 2023; Xie et al., 2024), which was obtained from the China Meteorological Data Network for the period 2015–2022. Slope length, slope, and degree of relief were derived from DEM data (Zhang et al., 2012; Zhu and Chen, 2024), which was provided by the SRTM data from the Geospatial Data Cloud, with a resolution of 90 m. Soil erodibility and regional carbonate exposure percentage were calculated using the Chinese HWSD attribute database (Kabolizadeh et al., 2023; Zhang et al., 2021). All data were resampled to a resolution of 250 m.

3 Methods

3.1 Overview

In alignment with the related works of (Yi et al., 2020; Xu et al., 2023; Tang et al., 2018; Lai et al., 2023) and considering the mountainous terrain and elevation fluctuations in the study area, we developed an ES evaluation model that incorporates factors such as soil and water loss sensitivity, desertification sensitivity, geological disasters sensitivity, and habitat sensitivity. Additionally, taking into account the local ecology, we included factors related to water resource conservation function, soil and water conservation function, and biodiversity function to develop the ESF evaluation model. We applied Principal Component Analysis (PCA) (He et al., 2010), the BP neural network (Chen et al., 2017), and other methods to separately determine the weights of ES-related factors. Furthermore, we referenced existing ecological space delineation methods (Zhao et al., 2022c; Zhang et al., 2023) and classified the study area into four categories: core, auxiliary, transitional, and development-friendly ecological spaces to evaluate ecological pattern security. Based on the ecological space results, we analyzed ecological pattern security issues in conjunction with the current land use status. The specific technical approach of this paper is shown in Figure 2.

3.2 Ecosystem sensitivity

3.2.1 Soil and water loss sensitivity

Our study primarily evaluated soil and water loss sensitivity by considering water dynamics. Based on the principle of soil and water loss equation (Xie et al., 2018; Equation 1), rainfall erosivity, soil erodibility, slope, slope length, and FVC were selected for GIS product calculation. The natural breaks method (Jenks, 1967) was used to divide the sensitivity into five levels. The formula of soil and water loss sensitivity is as follows:

$$S_i = \sqrt[4]{R_i \times K_i \times LS_i \times C_i} \tag{1}$$

where S_i is the soil and water loss sensitivity index of spatial unit i, R_i, K_i, LS_i, C_i are rainfall erosivity, soil erodibility, slope length and slope, and FVC, respectively.

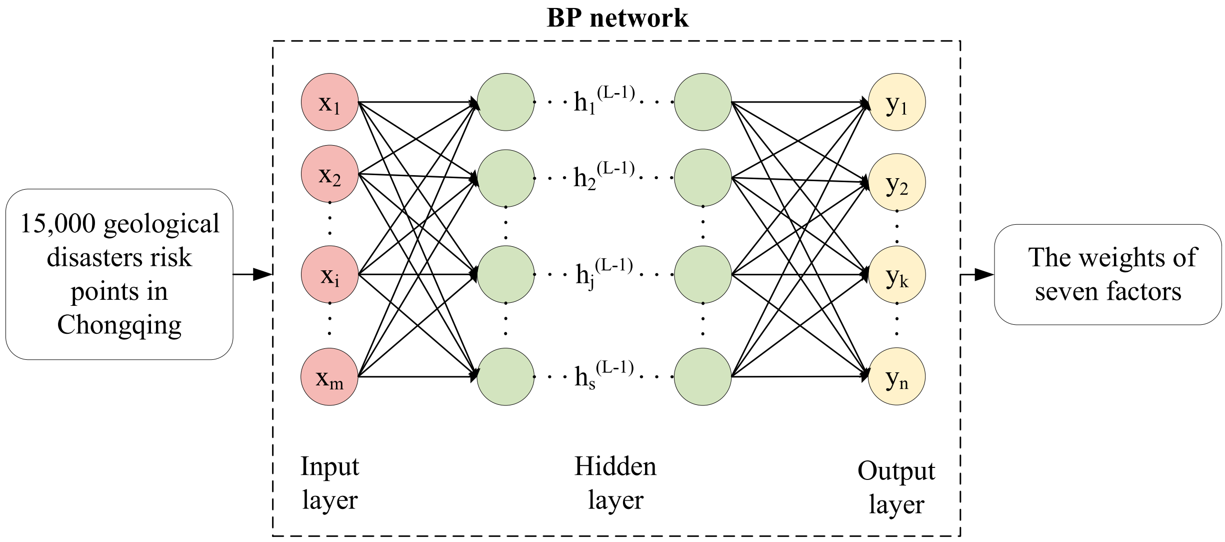

FIGURE 3
BP network model.

3.2.2 Desertification sensitivity

Based on the formation mechanism of desertification, regional carbonate exposure percentage, slope and FVC factors were selected to construct an evaluation system (Equation 2). After GIS product calculation (Gu et al., 2021), the natural breaks method (Jenks, 1967) was again used to divide the sensitivity into five levels. The formula of desertification sensitivity is as follows:

$$S_i = \sqrt[3]{D_i \times P_i \times C_i} \tag{2}$$

where S_i is the desertification sensitivity index of the evaluation area i, D_i, P_i, C_i are regional carbonate exposure percentage, slope and FVC in the evaluation area i, respectively.

3.2.3 Geological disaster sensitivity

In line with relevant studies (Hongtao, 2020), we selected factors such as stratigraphic lithology, distance from fault zone, degree of relief, slope, rainfall erosivity, soil erodibility and FVC to construct an evaluation system of geological disaster sensitivity. The structure of the BP neural network is illustrated in Figure 3.

As shown in Equations 3, 4, the factors influencing geological disasters are set as the input $X = \{X_1, X_2, \ldots, X_I\}$, the system presets the hidden layer $V = \{V_1, V_2, \ldots, V_j\}$, and the probability of potential geological disasters is the output layer $Y = \{Y_1, Y_2, \ldots, Y_k\}$. The expected output layer is $Y' = \{Y_1', Y_2', \ldots, Y_k'\}$. The weights $w_1, w_2, \ldots, w_j$ of the hidden layer adjust the proportion of each vector in the input layer, connecting the input layer to the output layer. The specific functional relationships are as follows:

$$v_j = f_1\left(\sum_{i=1}^{I} w_{ij} \times x_i - \theta_j\right), \quad j = (1, 2, \ldots, J) \tag{3}$$

$$y_k = f_2\left(\sum_{j=1}^{I} w_{jk} \times v_j - \varphi_k\right), \quad k = (1, 2, \ldots, K) \tag{4}$$

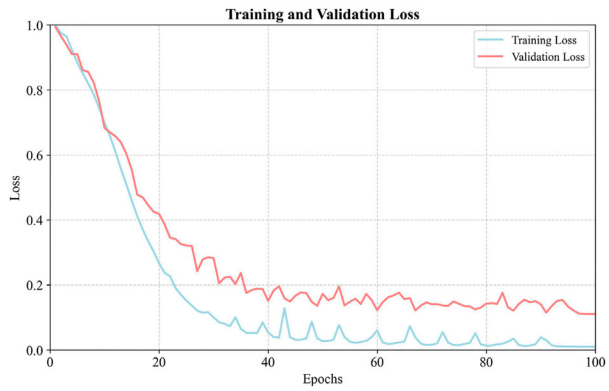

FIGURE 4
Training and validation loss.

where w_{ij} and w_{jk} are the weights between the input layer and the hidden layer, and between the hidden layer and the output layer, respectively. θ_j and φ_k are the thresholds, and f_1 and f_2 are the activation functions. The BP neural network employs the steepest descent method to continuously adjust the weights and thresholds, minimizing the model error and achieving the best fitting effect (Wolfe, 1969).

Our study input the field survey data of 15,000 geological disaster risk points in Chongqing from 2022 into the BP neural network. The dataset was initially divided into training and testing sets at an 8:2 ratio, with 10% of the training set further allocated as a validation set. A learning rate of 0.01 was adopted to ensure stable convergence during the training process. Through multiple iterations, we determined that the optimal configuration consisted of 7 nodes in the first hidden layer and 5 nodes in the second hidden layer. The training and validation loss curves indicate that the model achieved stable convergence, with both losses

TABLE 2 Geological disasters sensitivity levels.

Factors	Geological disasters sensitivity level					Weight
	Insensitive	Mildly sensitive	Moderately sensitive	Severely sensitive	Extremely sensitive	
Stratigraphic lithology	Gabbro, quartzite, marble, diorite porphyry, quartz monzonite	Diorite, granite, granodiorite, calcareous, granite porphyry, carbonate rock, dolomite	Gravel, metamorphic carbonate, coal seams	Limestone, mudstone, siltstone, conglomerate, sandstone, mortar-sand, ice and snow, modern glaciers	Loess, sand, sand, sandy soil, rock debris, sand mud, boulder	0.14
Distance from fault zone (m)	<500	500–1,000	1,000–2,000	2,000–3,000	>3,000	0.17
FVC(Fractional vegetation cover)	>0.75	0.55~0.75	0.35~0.55	0.25~0.35	<0.25	0.14
Rainfall erosivity	<25	25–100	100–400	400–600	>600	0.14
Degree of relief	0–25	20–50	50–100	100–300	>300	0.13
Soil erodibility	<0.25	0.25–0.4	0.4–0.5	0.5–0.65	>0.65	0.15
Slope	<5	5–15	15–25	25–35	>35	0.14

TABLE 3 Habitat sensitivity level table.

Factors	Habitat sensitivity level					Weight
	Insensitive	Mildly sensitive	Moderately sensitive	Severely sensitive	Extremely sensitive	
Vegetation coverage	<0.2	<0.35	<0.50	<0.65	>0.65	0.34
Land use	Architecture	Arable land	Grassland	Garden shrubs	Woodland	0.28
Distance from nature reserve (km)	<8	<18	<28	<40	<60	0.22
Distance from main road (m)	<500	<1,000	<1,500	<2000	>2000	0.16

decreasing significantly over 100 epochs, reflecting effective learning and generalization, as shown in Figure 4. The importance and weights of each factor were determined through the BP neural network training and testing process, as shown in Table 2. The overall accuracy of the model reached 0.87, demonstrating its reliability in predicting geological disaster sensitivity.

Using the weights of factors to calculate geological disaster sensitivity (Equation 5), the formula of geological disaster sensitivity is as follows:

$$S_i = \sum_{i=1}^{n} (C_i * w_i) \tag{5}$$

where S_i is the geological disasters sensitivity index of spatial units i, C_i is the factor sensitivity level, w_i is the factor weight. As shown in Table 2, the results were divided into 5 sensitivity levels.

3.2.4 Habitat sensitivity

Land use, vegetation coverage, distance from main roads, and distance from nature reserves were selected to construct a Habitat Sensitivity evaluation system. As shown in Table 3, five levels were divided according to relevant research (Yi et al., 2020). To determine the relative importance of each factor, Principal Component Analysis (PCA) was employed. PCA is a statistical method used to reduce the dimensionality of the data while retaining the most important variance information. By applying PCA, the weight of each factor was extracted based on its contribution to the principal components, which represent the most significant patterns of variation in the data. Factors with larger coefficients in the principal components are considered more important and thus assigned higher weights in the habitat sensitivity evaluation system. This approach allows for a more objective and comprehensive assessment of habitat sensitivity, considering the interrelationships between different factors (Equation 6). The formula for habitat sensitivity is as follows:

$$S_i = \sum_{i=1}^{n} (C_i * w_i) \tag{6}$$

where S_i is the spatial habitat sensitivity index, C_i is the factor sensitivity level, and w_i is the factor weight.

3.2.5 Ecosystem sensitivity

Referring to previous studies (Zhao Z. et al., 2022), the evaluation results of the above four sensitivity factors were spatially superimposed using the mean value method to obtain a comprehensive evaluation result map of ES. This study divided comprehensive ES into three sensitivity levels: general sensitivity, sensitive, and extremely sensitive, using the natural breaks method (Jenks, 1967). By using this method, we can better capture the natural thresholds in ecological sensitivity, leading to more precise and actionable insights for ecological conservation and management.

Areas classified as general sensitivity exhibit low to moderate levels of sensitivity across the evaluated factors, indicating relatively stable conditions with minimal vulnerability to soil erosion, desertification, geological hazards, and habitat degradation. These regions are generally suitable for development with appropriate mitigation measures. Areas categorized as sensitive demonstrate moderate to high levels of sensitivity in at least one or more factors, reflecting a heightened vulnerability to environmental stressors. These regions require careful management to balance ecological conservation and development needs, as they are more prone to degradation under external pressures. Areas identified as extremely sensitive show high to very high levels of sensitivity across multiple factors, representing regions with critical ecological vulnerability. These areas are highly susceptible to severe soil erosion, desertification, geological disasters, and habitat loss, necessitating stringent protection measures to maintain ecological stability and prevent irreversible damage. This classification provides a clear framework for understanding the spatial distribution of ecological sensitivity and supports targeted strategies for sustainable land use and ecological conservation.

3.3 Ecosystem service function

3.3.1 Water resource conservation function

Using the NPP quantitative indicator evaluation method (Lv et al., 2022), the ecosystem water source service capacity index was adopted as evaluation indicator (Equation 7). The formula of water resource conservation function is as follows:

$$S_{WR} = NPP_{\text{mean}} \times F_{\text{sic}} \times F_{\text{pre}} \times (1 - F_{\text{slo}}) \tag{7}$$

where S_{WR} is the ecosystem water resource conservation function index, NPP_{mean} is the average value of NPP over many years, F_{sic} is soil seepage, F_{pre} is the average precipitation over many years, and F_{slo} is slope.

3.3.2 Soil and water conservation function

The soil and water conservation function model, based on the Revised Universal Soil and Water Loss Equation (RUSLE) (Feng and Zhao, 2014), was used to assess importance of soil and water conservation (Equation 8). The formula of soil and water conservation function is as follows:

$$S_{SW} = S_p - S_r = R \times K \times L \times S \times (1 - C) \tag{8}$$

where S_{SW} is the soil and water conservation function index, S_p is the potential amount of soil erodibility, S_r is the reality amount of soil erodibility, R is rainfall erosivity, K is soil erodibility, L is slope length, S is slope, and C is FVC for different ecosystem types.

3.3.3 Biodiversity function

For assessing biodiversity importance (Ma et al., 2019), we utilized the biodiversity maintenance service capacity index as the evaluation indicator (Equation 9). The formula of biodiversity function is as follows:

$$S_{\text{BIO}} = NPP_{\text{mean}} \times F_{\text{pre}} \times F_{\text{tem}} \times (1 - F_{\text{alt}}) \tag{9}$$

where S_{BIO} is the biodiversity function index, NPP_{mean} is the multi-year NPP of vegetation, F_{pre} is the multi-year average precipitation, F_{tem} is the multi-year average temperature, and F_{alt} is the altitude.

3.3.4 Ecosystem service function

Referring to previous studies (Niu et al., 2022), we used 50% and 80% of the three service function factors as evaluation threshold values. Each service function factor was classified into three levels: extremely important, important, and generally important. The results of the three factors were then overlaid, and the maximum value was taken to obtain the comprehensive evaluation of the importance of ESF (Equation 10). The formula of ESF is as follows:

$$E = \text{Max}\{S_{WR}, S_{SW}, S_{BIO}\} \tag{10}$$

where S_{WR}, S_{SW}, and S_{BIO} represent the results of the water resource conservation function, soil and water conservation function, and biodiversity function, respectively.

Areas classified as generally important exhibit relatively lower levels of contribution to water resource conservation, soil and water conservation, and biodiversity maintenance compared to other regions. While these areas still provide valuable ecosystem services, their functional importance is less pronounced in the broader context of regional ecological balance. Areas categorized as important demonstrate moderate to high levels of contribution to at least one or more ecosystem service functions, reflecting their significant role in supporting water resources, soil stability, or biodiversity. These regions are key to maintaining ecological functionality and require thoughtful management to ensure their continued contribution. Areas identified as extremely important show high to very high levels of contribution across multiple ecosystem service functions, representing regions that are critical for water resource conservation, soil and water retention, and biodiversity preservation. These areas play an indispensable role in sustaining regional ecological health and resilience. This classification provides a nuanced understanding of the spatial distribution of ecosystem service function importance, highlighting the varying degrees of contribution across different regions. It supports targeted strategies for sustainable land use planning and ecological conservation, ensuring the protection and enhancement of ecosystem services where they are most needed.

3.4 Ecological space division

Referring to established ecological space delineation methods (Zhao et al., 2022c; Zhang et al., 2023), we employed the spatial overlay method to classify ecological space into four categories based on the results of ESF and ES: core, auxiliary, transitional, and development-friendly. This classification was further examined in conjunction with current land use data to evaluate ecological pattern

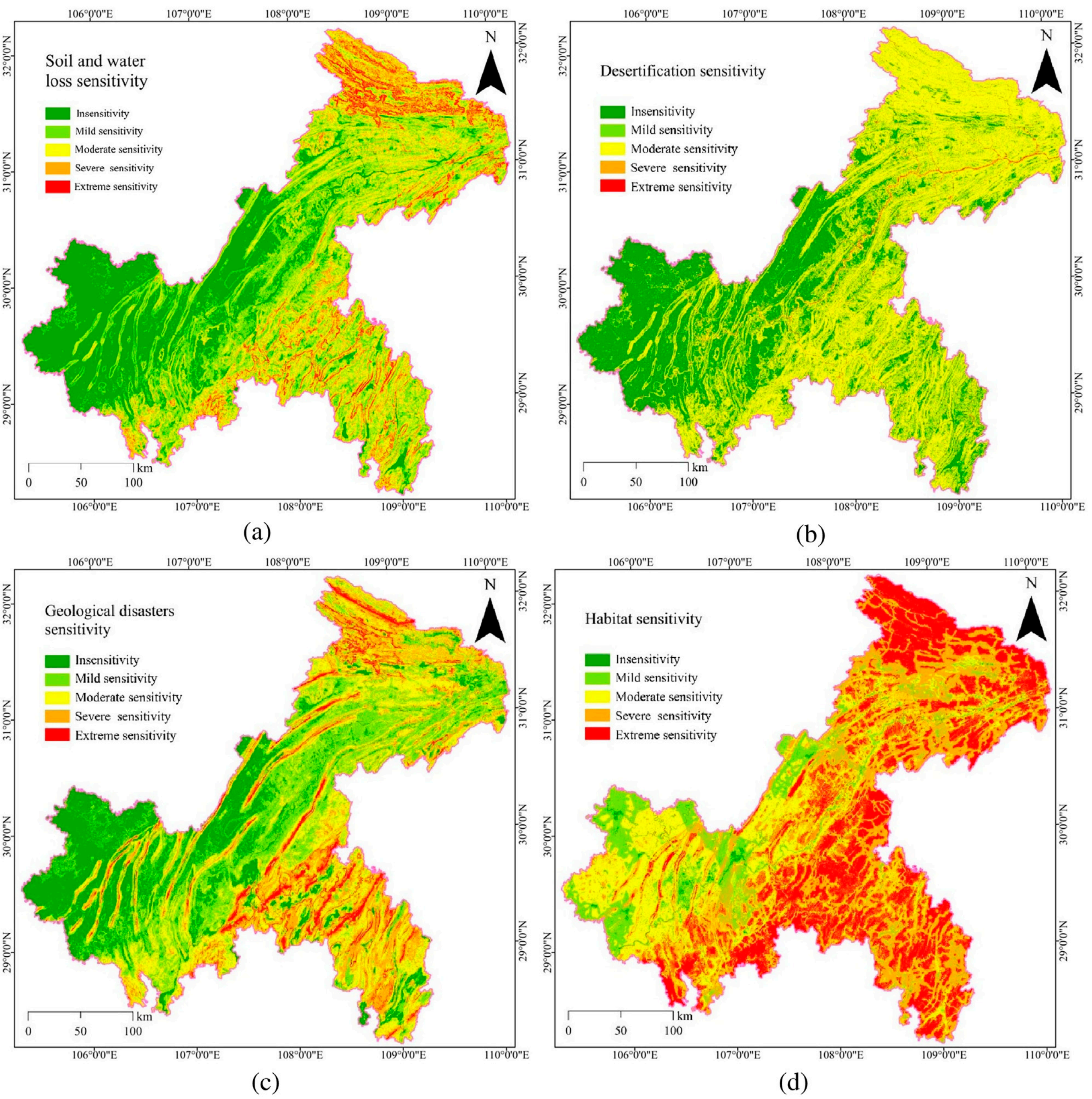

FIGURE 5
Ecosystem sensitivity evaluation. **(a)** Soil and water loss sensitivity **(b)** Desertification sensitivity **(c)** Geological disasters sensitivity **(d)** Habitat sensitivity.

security. Ecological space was subsequently grouped into important and non-important types, where core and auxiliary ecological spaces constituted the important category, while transitional and development-friendly ecological spaces were classified as non-important.

Core ecological space encompasses areas characterized by either extremely important ESF or extremely sensitive ES, playing a critical role in maintaining ecological balance and biodiversity. Auxiliary ecological space consists of areas with important ESF and sensitive ES, serving as a supportive buffer to core ecological spaces and contributing to overall ecological stability. Transitional ecological space includes regions exhibiting either important ESF or sensitive ES, functioning as an intermediate zone between core/auxiliary spaces and development-friendly areas. Development-friendly ecological space comprises areas with generally important ESF and generally sensitive ES, making them suitable for development activities with minimal ecological impact.

This structured classification framework facilitates a comprehensive understanding of ecological patterns and provides a scientific basis for sustainable land use planning. By integrating ecological conservation objectives with development requirements, this approach ensures a balanced and informed decision-making process in land resource management.

TABLE 4 Results of ecosystem sensitivity evaluation.

Ecosystem sensitivity	Sensitivity level	Size (km^2)	Proportion (%)	Proportion (Cumulative) (%)
Soil and water loss sensitivity	Insensitivity	2,492.20	3.02	3.02
	Mild sensitivity	15,776.91	19.15	22.17
	Moderate sensitivity	20,598.78	25.00	47.17
	Severe sensitivity	28,942.00	35.12	82.29
	Extreme sensitivity	14,592.11	17.71	100.00
Desertification sensitivity	Insensitivity	35,011.59	42.50	42.50
	Mild sensitivity	0.00	0.00	42.50
	Moderate sensitivity	46,766.70	56.75	99.25
	Severe sensitivity	61.30	0.07	99.32
	Extreme sensitivity	562.40	0.68	100.00
Geological disasters sensitivity	Insensitivity	18,408.80	22.34	22.34
	Mild sensitivity	24,801.48	30.10	52.44
	Moderate sensitivity	20,804.18	25.25	77.69
	Severe sensitivity	13,833.25	16.79	94.48
	Extreme sensitivity	4,554.30	5.52	100.00
Habitat sensitivity	Insensitivity	1,369.52	1.66	1.66
	Mild sensitivity	10,259.70	12.45	14.11
	Moderate sensitivity	23,084.19	28.01	42.12
	Severe sensitivity	22,573.85	27.40	69.52
	Extreme sensitivity	25,114.74	30.48	100.00
Comprehensive ecosystem sensitivity	General sensitivity	18,401.50	22.33	22.33
	Sensitivity	24,829.38	30.13	52.46
	Extreme sensitivity	39,171.12	47.54	100.00

4 Results and analysis

4.1 Ecosystem sensitivity

We selected Chongqing as the study area and conducted an analysis of its ecosystem sensitivity based on data from 2022, including factors such as soil and water loss sensitivity, desertification sensitivity, geological disasters sensitivity, and habitat sensitivity. In the study area, the soil and water loss sensitivity types were primarily classified as moderately and severely sensitive, with areas of 25.00% (20,598.78 km^2) and 35.12% (28,942.00 km^2), respectively (Figure 5a; Table 4). Among these, the moderately sensitive areas were mostly scattered, while the severely sensitive areas were distributed between the extremely sensitive and moderately sensitive areas. The severely sensitive areas were predominantly located in the southeast and northeast of the study area. The insensitive and slightly sensitive areas, accounting for 3.02% (2,492.20 km^2) and 19.15% (15,776.91 km^2), respectively, were mainly located in the low mountains and hilly regions in the western part of the study area. The extremely sensitive areas, accounting for 17.71% (14,592.11 km^2), were distributed in strips in Qianjiang, Youyang, Pengshui, Shizhu, Wuxi, Kaizhou, and other areas, characterized by strong precipitation erosion, high mountains, and deep valleys.

Figure 5b and Table 4 indicate that the desertification sensitivity of the study area was predominantly insensitive and moderately sensitive, accounting for 42.50% (35,011.59 km^2) and 56.75% (46,766.70 km^2), respectively. The western part of the study area was largely insensitive. In contrast, the southeast and northeast areas, which were predominantly moderately sensitive.

Figure 5c and Table 4 describe the geological disasters sensitivity in the study area, which was predominantly moderate and mild. Insensitive areas were mainly distributed in low mountains and hilly regions such as Tongnan District, Hechuan, and Dazu in the west of Chongqing, accounting for 22.34% (18, 408, 80 km^2). Mildly sensitive areas were located in Zhongxian and Wanzhou in the central part of Chongqing, accounting for 30.10% (24,801.48 km^2). The moderately sensitive areas spanned 20,804.18 km^2, accounting for 25.25%. Severely sensitive and extremely sensitive areas were mostly distributed in strips in Wulong, Pengshui, Qianjiang, and

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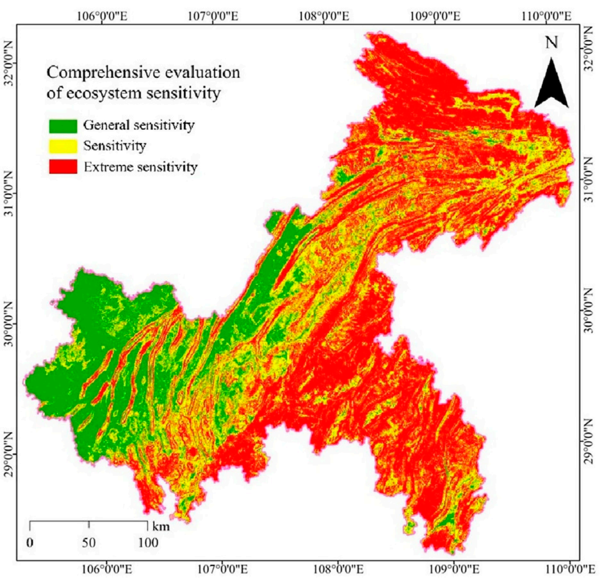

FIGURE 6
Comprehensive evaluation of ecosystem sensitivity.

Chengkou, accounting for 16.79% (13,833.25 km^2) and 5.52% (4,554.30 km^2), respectively.

From Figure 5d and Table 4, with a large proportion of nature reserves and ecological sources, the habitat sensitivity of the study area was predominantly classified as sensitive. Among these, the extremely sensitive areas were located in national nature reserves such as Daba Mountain, Jinfo Mountain, and Jinyun Mountain, accounting for 30.48% (25,114.74 km^2). Severely sensitive areas were found in Wulong, Fengdu, Shizhu, Youyang, Xiushan, Qianjiang, and Chengkou, accounting for 27.40% (22,573.85 km^2). Moderately sensitive areas were distributed in Hechuan, Dazu, Bishan, Tongliang, and Jiangji, accounting for 28.01% (23,084.19 km^2). Mildly sensitive areas were mainly located in the main urban area, as well as in Tongnan and Tongliang, where the proportion of cultivated land was relatively large, accounting for 12.45% (10,259.70 km^2).

As shown in Figure 6 and Table 4, the ES areas were predominantly classified as extremely sensitive, accounting for 47.54% (39,171.12 km^2), and were distributed in the east, where the terrain was high and forest resources were abundant. The sensitive areas were scattered and closely connected to the general sensitivity areas, accounting for 30.13% (24,829.38 km^2). The generally sensitive areas were mainly distributed in the southwest of the study area, accounting for 22.33% (18,401.50 km^2).

4.2 Ecosystem service function

We analyzed the ecosystem service functions of Chongqing based on 2022 data for water resource conservation function, soil and water conservation function, and biodiversity function. As shown in Figure 7a and Table 5, the results indicated that water resource conservation function was predominantly of general importance, accounting for 70.46% (58,061.33 km^2), and was primarily distributed in the eastern, central, and northeastern parts of the study area. The water resource conservation function area of importance, accounting for 20.15% (16,603.02 km^2), was mainly located around the general importance areas. The extremely important water resource conservation function areas, accounting for 9.39% (7,737.65 km^2), were mainly concentrated in Pengshui, Qianjiang, Youyang, and Xiushan counties.

As shown in Figure 7b and Table 5, the soil and water conservation function was primarily of general importance, accounting for 77.14% (63,569.27 km^2), and was mainly distributed in the eastern, central, and northeastern parts of the study area. The extremely important soil and water conservation function areas, distributed in strips around the mountains of Qianjiang District, Pengshui County, and Youyang County, accounted for 7.59% (6,253.90 km^2). The areas of importance were mainly located around the extremely important regions, accounting for 15.27% (12,578.84 km^2).

As shown in Figure 7c and Table 5, the biodiversity function was mainly of general importance, accounting for 67.42% (55,559.44 km^2). The important areas of biodiversity function were located in Jiangjin, Qijiang, Wansheng, Nanchuan, Kaizhou, and Fengjie, accounting for 21.68% (17,864.36 km^2). The extremely important biodiversity function areas, located in Pengshui, Qianjiang, Youyang, and Xiushan, accounted for 10.9% (8,978.20 km^2).

As shown in Figure 8 and Table 5, the results indicated that the comprehensive ecosystem service function was primarily of general importance, distributed in the central, western, and northeastern parts of the study area, accounting for 48.06% (39,603.89 km^2). The important areas covered 21,283.54 km^2, accounting for 25.83%. The extremely important areas, characterized by high altitudes and rich forest resources, accounted for 26.11% (21,514.57 km^2).

4.3 Ecological space division

As shown in Figure 9 and Table 6, the area of important ecological space was 51,898.62 km^2, accounting for 62.98%. Among these, the core ecological space refers to areas with extremely important ecological service functions or extremely fragile and sensitive ecosystems. The core ecological space was primarily distributed in the southeast and northeast of the study area, accounting for 53.83% (44,360.12 km^2), and was largely composed of nature and ecological conservation areas. The auxiliary ecological space refers to areas that play an important service function and are also ecologically sensitive. These areas were located around the core ecological space, accounting for 9.15% (7,538.51 km^2).

The area of non-important ecological space was 30,503.37 km^2. Among these, the development-friendly ecological space refers to areas with general ecological function importance and general ES, mainly concentrated in the main urban area and Tongnan District in the western part, accounting for 17.06% (14,052.57 km^2). Transitional ecological space refers to areas where ecological space plays an important service function or is ecologically sensitive, accounting for 19.96% (16,450.8 km^2).

To analyze the ecological space security pattern, construction and cultivated lands were overlaid with ecological land. As shown in Table 7, 91.24% (1,524 km^2) of construction land was distributed in traditional-developmental ecological spaces, where security conflicts

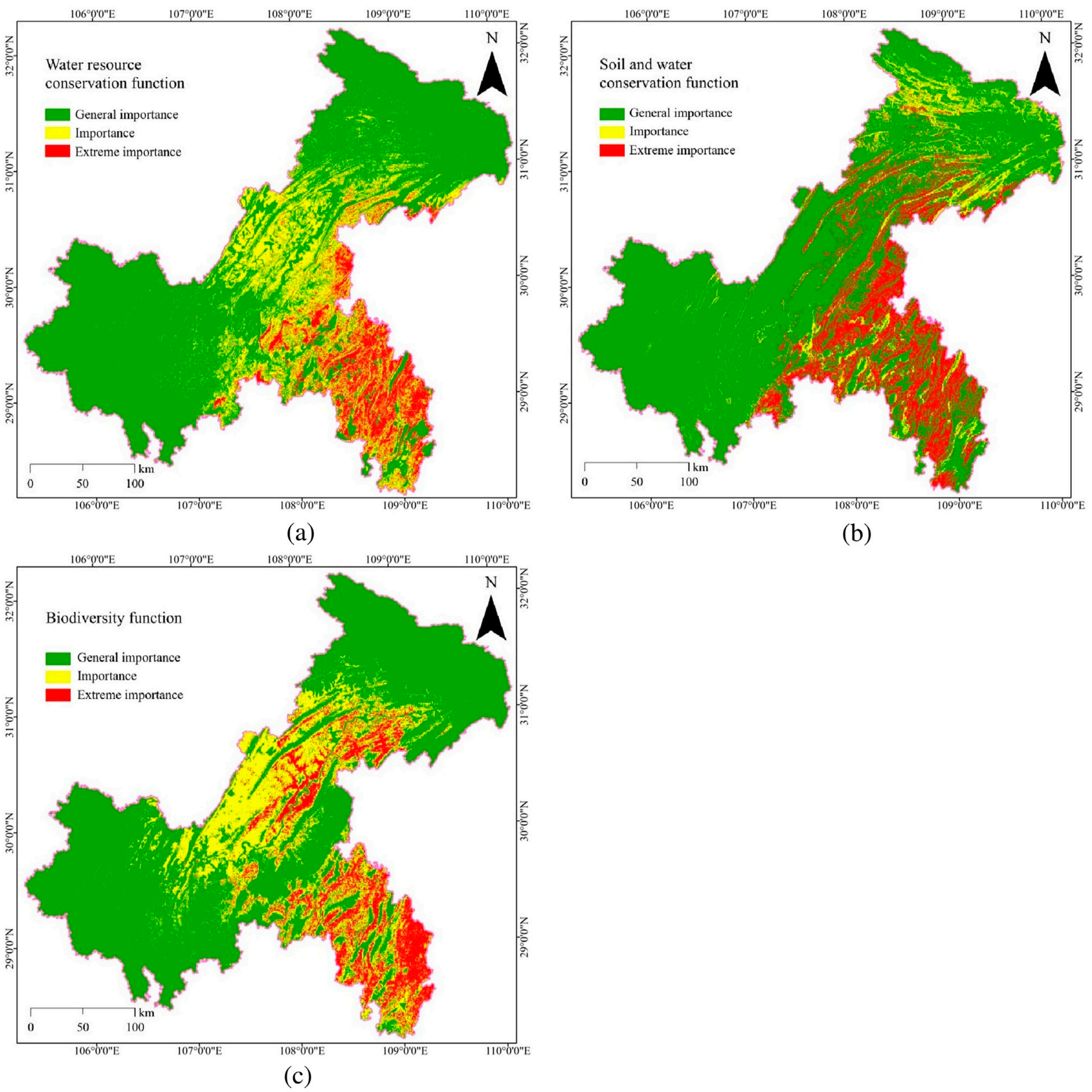

FIGURE 7
Ecosystem service function evaluation. **(a)** Water resource conservation function **(b)** Soil and water conservation function **(c)** Biodiversity function.

with core ecological space were minimal. However, 39.50% (13,574.00 km^2) of cultivated land was located in core-auxiliary ecological spaces, where ecological security conflicts existed, sometimes resulting in ecological risks.

5 Discussion

5.1 Ecosystem sensitivity

In the study area, the analysis of desertification sensitivity revealed that carbonate rock is prone to leaching and slow soil formation, which provides the material basis for desertification. However, carbonate rock leakage in the study area was not prominent, and the high coverage of forest and grass vegetation effectively mitigated erosion forces and dissolution conditions, limiting desertification processes. The western part of the study area exhibited predominantly insensitive characteristics. In contrast, the southeastern and northeastern regions, characterized by high mountains, steep slopes, and intense summer rainfall, created favorable conditions for erosion, resulting in predominantly moderate sensitivity. For habitat sensitivity, severely sensitive areas, which are rich in forest resources, exhibit high vegetation coverage and abundant precipitation, making them critical

TABLE 5 Statistical results of ecosystem service function evaluation.

Service function	Importance rating	Size (km^2)	Proportion (%)	Proportion (Cumulative) (%)
Water resource conservation	General importance	58,061.33	70.46	70.46
	Importance	16,603.02	20.15	90.61
	Extreme importance	7,737.65	9.39	100.00
Soil and water conservation	General importance	63,569.27	77.14	77.14
	Importance	6,253.90	7.59	84.73
	Extreme importance	12,578.84	15.27	100.00
Biodiversity	General importance	55,559.44	67.42	67.42
	Importance	17,864.36	21.68	89.10
	Extreme importance	8,978.20	10.90	100.00
Comprehensive ecosystem service	General importance	39,603.89	48.06	48.06
	Importance	21,283.54	25.83	73.89
	Extreme importance	21,514.57	26.11	100.00

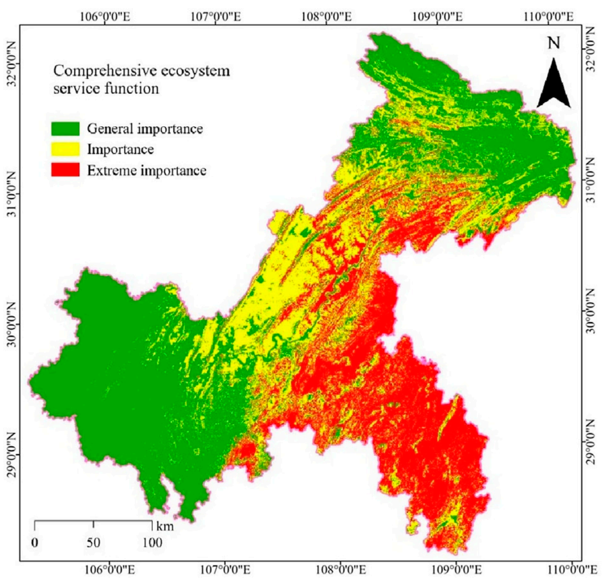

FIGURE 8
Comprehensive ecosystem service function.

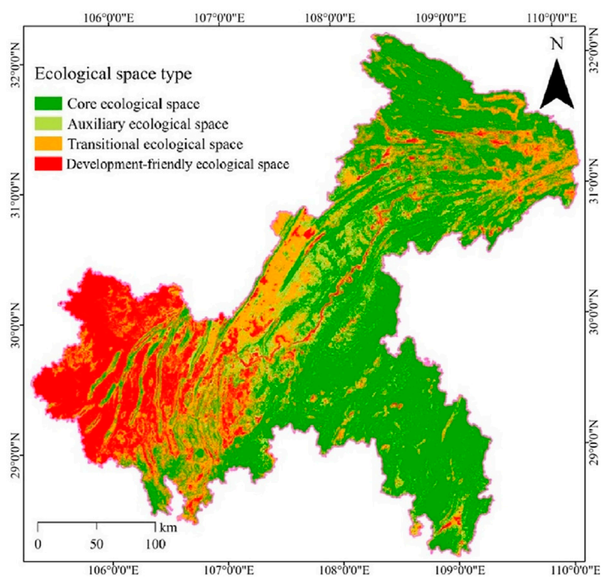

FIGURE 9
Ecological space type division.

ecological conservation zones. The ES was primarily classified as extremely sensitive, and was mainly concentrated in the east region, where the terrain is elevated, and forest resources are abundant. In terms of spatial distribution, ES generally followed a west-to-east increasing trend, with lower sensitivity in the west and higher sensitivity in the east. The dominant influencing factors were soil and water loss sensitivity and habitat sensitivity. Given the varying ecological sensitivity conditions across the study area, it is essential to adopt differentiated land-use management and ecological protection strategies to enhance regional sustainability.

The primary factor weight determination methods used in this study include the BP neural network and PCA. The weighting of geological disasters sensitivity factors was determined using a BP neural network, which provides a relatively objective analytical approach. Additionally, for habitat sensitivity, we employed PCA to calculate the weights of relevant factors. This method minimizes subjectivity by extracting the most significant features from the dataset, ensuring a more data-driven and unbiased assessment. Therefore, this approach is feasible and reliable for determining factor weights in ecological studies.

5.2 Ecosystem service function

The comprehensive ESF of the study area was primarily classified as generally important, which had flat terrain and were

TABLE 6 Statistical results of ecological space classification.

Ecological space type		Size (km^2)	Proportion (%)	Proportion (Cumulative) (%)
Important ecological space	Core ecological space	44,360.12	53.83	53.83
	Auxiliary ecological space	7,538.51	9.15	62.98
Non-important ecological space	Transitional ecological space	16,450.80	19.96	82.94
	Development-friendly ecological space	14,052.57	17.06	100.00

TABLE 7 Statistics on the current status of ecological space construction land.

Ecological space type	Construction land		Cultivated land	
	Size(km^2)	Proportion (%)	Size(km^2)	Proportion (%)
Core ecological space	89.63	5.37	9,523.44	27.70
Auxiliary ecological space	56.69	3.40	4,050.56	11.80
Transitional ecological space	360.56	21.59	9,516.94	27.73
Development-friendly ecological space	1,163.44	69.65	11,234.63	32.73
Total	1,670.30	100.00	34,325.56	100.00

located in densely developed regions. The dominant factor was water resource conservation function. The extremely important water resource conservation function areas, were mainly concentrated in Pengshui, Qianjiang, Youyang, and Xiushan counties, where there was abundant precipitation, high forest coverage, and strong water resource conservation capacity. In terms of spatial distribution, the ESF in the study area exhibited a trend of lower values in the northwest and higher values in the southeast. Based on the ESF distribution results and facing the complex ecological and environmental risk problems in the study area, it is recommended to strengthen water resource management, focus on vegetation protection and natural restoration, rationally develop and utilize land resources to enhance land use efficiency, and improve the ecological compensation mechanism. These measures aim to promote the coordinated and sustainable development of the regional ecological environment and socio-economic systems.

5.3 Ecological space division

This paper divided EST into core, auxiliary, transitional, and development-friendly categories. Among them, the core ecological space was largely composed of nature and ecological conservation areas. However, these areas were also fragile and sensitive, significantly impacted by human activities. Therefore, it is essential to develop policies for their reasonable development and protection. The auxiliary ecological space, serving as a supplementary area to the core ecological space, should impose restrictions on large-scale urban development activities. The development-friendly ecological space has abundant arable land resources and is extensively urbanized. The transitional ecological space, acting as a buffer zone for ecological space, possesses a relatively high environmental carrying capacity and can supplement important and development-friendly ecological spaces for further development.

As shown in Table 7, 91.24% (1,524 km^2) of construction land was distributed in traditional-developmental ecological spaces, where security conflicts with core ecological space were minimal. The spatial distribution of construction land was reasonable and conducive to urban economic development. However, a small portion of construction land still occupied core ecological spaces, which should be gradually reduced in an orderly manner. Simultaneously, the connectivity between green ecological spaces and areas outside urban regions should be strengthened to establish a comprehensive green ecological network.

In contrast, 39.50% (13,574.00 km^2) of cultivated land was distributed in core-auxiliary ecological spaces, posing certain ecological security risks. To optimize the spatial pattern of cultivated land, it is necessary to enhance national guidance and control over the “balance between occupation and compensation” of cultivated land, implement differentiated protection policies, and effectively improve the suitability of cultivated land. Given the ecological security risks associated with cultivated land in core-auxiliary ecological spaces, it is recommended to convert important water-source cultivated land, steep-slope cultivated land, and severely polluted cultivated land into forested areas.

Furthermore, efforts should be made to enhance the protection of core ecological spaces and issue warnings against human interference. Since core ecological spaces are key ecologically sensitive areas, it is essential to strengthen the monitoring of soil erosion and desertification, increase forest and grass vegetation coverage, maintain the integrity of forests, wetlands, and urban green spaces, halt commercial logging of natural forests, establish a biodiversity monitoring network, and improve habitat quality. These measures are crucial to maintaining ecological security and promoting sustainable land use management.

6 Conclusion

Chongqing is located in the heart of the Three Gorges Reservoir area and has typical mountainous and hilly geomorphological characteristics. We selected Chongqing as the study area and analyzed the ecological space patterns based on various ecological factors from the 2022 data. Additionally, land use data was incorporated to further examine the associated relationships. In contrast to prior research, our study constructed a special ES-ESF-EST ecological space pattern security issue research framework, tailored to the environmental characteristics of hilly and mountainous areas. First, to construct an ES evaluation model, our study selected soil and water loss sensitivity, desertification sensitivity, geological disasters sensitivity, and habitat sensitivity factors, utilized BP neural network methods to determine the indicator weights, and also incorporated relevant factors such as geology, vegetation, roads, climate, and others to build the evaluation system. Secondly, to construct the ESF evaluation model, we selected water resource conservation function, soil and water conservation function, and biodiversity function factors, and obtained the comprehensive ESF results based on the maximum value method. Finally, the spatial distribution structure of EST was mapped based on the results of ES and ESF and using spatial overlay methods. Unlike previous studies, the ecological pattern division results for each land use type were obtained, and the spatial security pattern issues for each land use type were analyzed by incorporating land use data. In the context of implementing the ecological civilization strategy and maintaining national ecological security, this study can support the construction of a natural ecological spatial pattern and optimize the delineation of national land space development patterns, which is of great significance to ecological protection and construction.

Production space, living space, and ecological space together constitute the national land space planning pattern. The topography of Chongqing is complex, and the ecological space delineated in this paper slightly conflicts with the agricultural space of the production space. In subsequent research, other spaces should be considered to explore more scientific and practical methods for dividing ecological space. Moreover, this study primarily focuses on ecological data to delineate the ecological spatial pattern, without incorporating economic, demographic, or policy-related data. Future research will integrate these additional factors to analyze the ecological configuration of Chongqing in comparison with other cities in China, providing a more comprehensive understanding of regional differences in ecological spatial planning.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

WH: Conceptualization, Data curation, Project administration, Writing – original draft, Writing – review and editing. JL: Data curation, Formal Analysis, Methodology, Project administration, Writing – original draft, Writing – review and editing. WW: Methodology, Writing – original draft. RG: Methodology, Writing – original draft. JT: Visualization, Writing – original draft. JW: Formal Analysis, Writing – original draft.

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Conflict of interest

Authors WH, JL, WW, RG, JT, and JW were employed by Chongqing Huadi Resource and Environment Technology Co.,LTD.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

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