ASSESSMENT OF REGIONAL DEVELOPMENT VULNERABILITY IN GUIZHOU PROVINCE OF CHINA BASED ON THE BP NEURAL NETWORK

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Abstract. Regional development often exhibits imbalances among environmental, economic, and social dimensions. Previous studies have frequently equated regional development solely with economic growth or land expansion, neglecting its interconnected effects on environmental and social systems. To address this gap, this study assesses nine regions in Guizhou Province, China, through the construction of an integrated Environmental—Economic—Social (EES) evaluation model. Using the entropy method and the BP neural network modeling, we quantify the vulnerability of regional development from 2014 to 2023, examining its spatiotemporal evolution. Principal component analysis (PCA) is further employed to identify key factors influencing regional vulnerability. The results reveal significant disparities in economic and social vulnerabilities across regions, while environmental vulnerability remains relatively balanced. PCA indicates that the centralized urban sewage treatment rate, the proportion of tertiary industry in GDP, the value-added of secondary industry, and urbanization rate positively contribute to vulnerability reduction. In contrast, energy consumption per unit of GDP and the regional GDP growth rate exhibit the most negative correlations with vulnerability. These findings highlight the diverse factors shaping regional development and provide critical insights for policy-making aimed at promoting balanced and sustainable regional growth.
Keywords: *regional development, vulnerabilities, spatiotemporal evolution, BP neural network, PCA*

Introduction

The level of regional development has become a key indicator for measuring the comprehensive competitiveness of a region. As a basis for assessing the development status and formulating future development plans (Yang et al., 2019), vulnerability evaluation can systematically reveal a region’s response capacity to disturbances and provide scientific support for designing differentiated development strategies (Wang, 2025), which is of great significance for achieving regional sustainable development. However, amid the process of rapid urbanization and regional integration, regions are increasingly confronted with prominent issues such as ecological degradation, excessive focus on short-term benefits, and homogeneous competition (Shi et al., 2018)—these problems have significantly intensified the vulnerability and instability of regional development. Located in Southwest China, Guizhou Province is characterized by high

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forest coverage, yet its ecological environment is highly sensitive and fragile, making addressing of its development vulnerability an urgent priority.

Vulnerability is a conceptual framework encompassing three core elements: sensitivity, exposure, and adaptability (Tian et al., 2013). Based on the theory of urban resilience, the vulnerability of regional development involves multi-dimensional factors, including the environment, society, economy, and governance (Li et al., 2025), and is primarily reflected in aspects such as economic vulnerability, ecological vulnerability, and livelihood vulnerability (Wang, 2025). The study of "vulnerability" originally originated in the field of natural disasters (Janssena et al., 2006) and has gradually expanded to disciplines including ecology, management, economics, and engineering. It has now become a key focus of research in the field of sustainable development. Scholars have explored this topic from diverse perspectives: the research scope has evolved from early studies on ecological vulnerability to investigations in the economic domain (Shan, 2019; Li and Zhu, 2020) and social domain shifting from single-system analysis to comprehensive evaluation of complex systems. Research objects mainly focus on specific regions, such as urban areas (Fang et al., 2016; Chen et al., 2022), rural areas (Yang and Pan, 2021), ecologically sensitive zones (Su et al., 2024), poverty-stricken areas, and other human-environment systems. For evaluation methods, static analysis is commonly adopted using statistical approaches, such as the Vulnerability Scoping Diagram (VSD) model (Lu et al., 2020), the Pressure-Driver-Response (PDR) model (Prata, 2024), the Analytic Hierarchy Process (AHP) (Diao et al., 2018), and the entropy weight method (Hao and Zhang, 2021). Vulnerability evaluation is widely applied in multi-system coupling theory, including studies on the coupling coordination between ecological vulnerability and economic development (Fan et al., 2022; Wang et al., 2023) and the coupling coordination of social-ecological systems (Wei et al., 2023). Additionally, machine learning has been extensively introduced in geographical research, with applications in climate studies (Zhang et al., 2022; Gong et al., 2022), forestry (Zheng et al., 2024), water resources (Zuo et al., 2024), and thermal environment analysis (Qiao and Tian, 2014).

The core of vulnerability in Guizhou Province lies in the interactive effects of environmental constraints (Gao et al., 2024), economic growth, and social demands during regional development (Fan et al., 2022). For instance, energy-intensive industries intensify environmental pressure (Zhou et al., 2021), and various types of pollution exert comprehensive stress on the environment (Chen et al., 2023) — these issues further affect social stability. Additionally, karst areas face constraints from topographic pressure (Wang and Zhao, 2022), and as an underdeveloped province located in western China (Zhu and Yu, 2025), Guizhou epitomizes the conflict between ecological protection and economic catch-up. Consequently, the research findings are generalizable to Southwest China. Despite substantial achievements in vulnerability research, existing studies still have three limitations: first, most rely on cross-sectional data for static spatial analysis, with insufficient attention paid to the dynamic evolution laws of vulnerability (Wang and

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Fang, 2014); second, research perspectives often focus on a single dimension, resulting in few comprehensive studies on the vulnerability of complex regional development systems; third, traditional statistical methods have limitations in handling non-linear relationships and complex systems (Huang et al., 2019). In recent years, the Back Propagation (BP) neural network has been applied to regional development research, demonstrating significant advantages in adaptability and prediction accuracy. It does not require preset linear relationships and can capture non-linear correlations between indicators (Wang et al., 2025). When combined with Principal Component Analysis (PCA), it forms a closed loop of "evaluation-verification-driving mechanism analysis," which not only enables quantitative assessment but also reveals driving mechanisms, thereby addressing the limitations of traditional static analysis.

In view of this, this study constructs a regional development vulnerability evaluation system covering three dimensions—"environmental system-economic system-social system"—and selects 15 specific indicators. It employs the entropy weight method and the Back Propagation (BP) neural network model to measure the vulnerability levels and spatiotemporal evolution trends of 9 prefecture-level cities in Guizhou Province from 2014 to 2023, and uses PCA to explore the key influencing factors. This research focuses on addressing three scientific questions: (1) How did the vulnerability of the 9 prefecture-level cities/autonomous prefectures in Guizhou Province fluctuate temporally and differentiate spatially from 2014 to 2023? (2) How does the interaction between the environmental, economic, and social systems affect overall vulnerability? (3) Through what pathways do key indicators (e.g., urbanization rate, industrial structure) drive changes in vulnerability? Given the uniqueness of Guizhou's karst landform and ecological sensitivity, the research results can provide precise policy support for the sustainable development of ecologically fragile areas in Southwest China.

Materials and methods

Study area

Guizhou Province is located in the hinterland of Southwest China, bordering Sichuan and Chongqing to the north, Guangxi to the south, Yunnan to the west, and Hunan to the east. Geographically situated on the Yunnan-Guizhou Plateau, it is characterized by numerous mountain ranges, spanning longitudes from 103°36′E to 109°35′E and latitudes from 24°37′N to 29°13′N (*Fig. 1*). The province straddles two major river basins—the Yangtze River and the Pearl River—and serves as a critical ecological barrier for the upper reaches of these two rivers. Severe rocky desertification not only restricts the sustainable development of Guizhou's ecological economy but also poses a threat to the ecological security of the Yangtze and Pearl River basins (Fan et al., 2022). As a major tourist destination in China, Guizhou is situated in a concentrated karst area, where its tourism industry primarily relies on advantages of the natural environment. Notably, karst landforms account for 61.9% of Guizhou's total land area (Guo et al., 2023). The

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contradiction between its ecological vulnerability and underdeveloped economy makes Guizhou a typical case for studying regional development vulnerability. Administratively, Guizhou is divided into nine prefecture-level units: six cities (Guiyang, Zunyi, Bijie, Anshun, Liupanshui, and Tongren) and three autonomous prefectures (Qiandongnan, Qiannan, and Qianxinan).

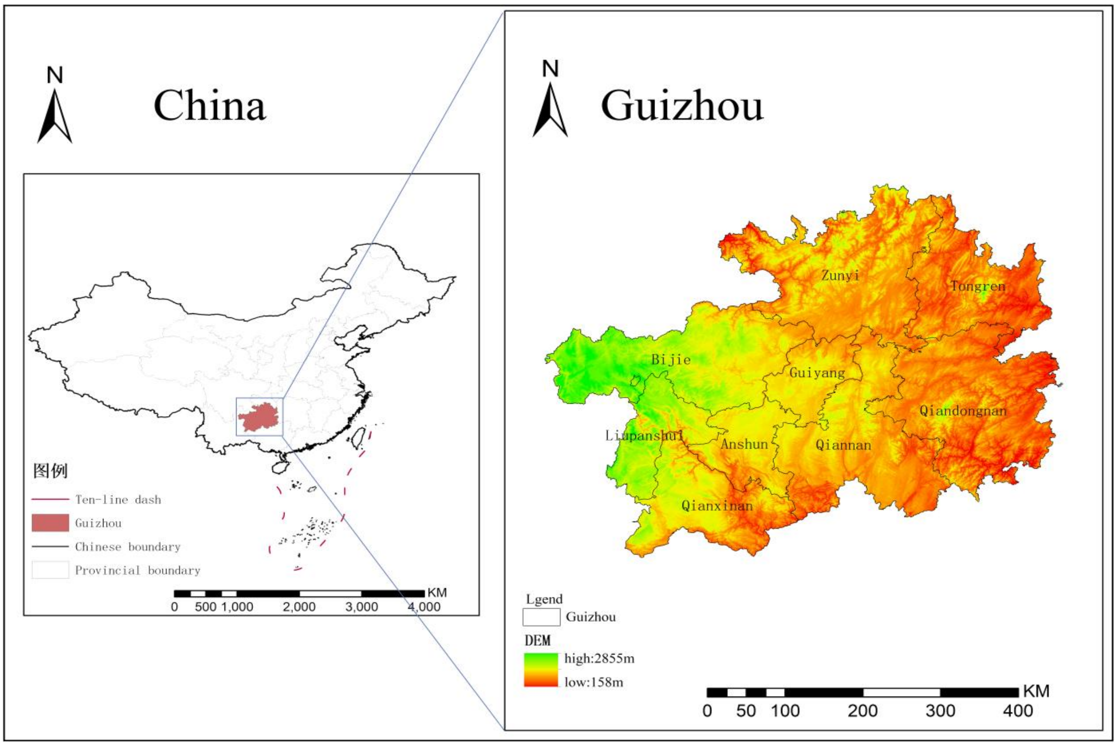

***Figure 1.** The research area*

Data source and processing

To ensure the accuracy and reliability of the data, this study primarily utilizes a ten-year panel dataset (2014–2023). The data were sourced from the China Urban Construction Statistical Yearbook, the China Statistical Yearbook, the Guizhou Statistical Yearbook, the Guiyang Statistical Yearbook, as well as from the statistical yearbooks, statistical bulletins, and natural resources bulletins of each prefecture-level city and autonomous prefecture in Guizhou (*Table 1*). Some indicators were calculated from the raw data. Data from different sources were cross-validated, with any discrepancy maintained below a 5% threshold to ensure consistency. For missing values, linear interpolation was applied to maintain a complete and consistent dataset for analysis.

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***Table 1.** Data sources*

Data Type	Specific indicators	Indicator meaning	Data Source
Direct indicator data	X_1:Per capita park green space area	Residential Greening Environment	《China Statistical Yearbook》 《China Urban Construction Statistical Yearbook》 《Guizhou Provincial Statistical Yearbook》 《Guiyang Statistical Yearbook》 《Anshun Statistical Yearbook》 《Zunyi Statistical Yearbook》 《Bijie Statistical Yearbook》 《Qiannan Statistical Yearbook》 《Statistical Yearbook of Qiandongnan》 《Qianxinan Statistical Yearbook》 《Tongren Statistical Yearbook》 《Liupanshui Statistical Yearbook》
	X_2:Forest coverage rate	Urban Greening Level	
	X_3:Percentage of days with good air quality	Urban Air Environment	
	X_4:Urban sewage centralized treatment rate	Urban wastewater intensity	
	X_5:Natural Population Growth Rate	Urban Energy Intensity	
	X_6:Urbanization rate	Economic Structure	
	X_7:Per capita disposable income of urban residents	Economic growth rate	
	X_8:Per capita disposable income of rural residents	Industrialization Intensity	
Derived Indicator Data	X_9:Energy consumption per unit of GDP	Total economic output	
	X_{10}:Value added of the tertiary industry as a percentage of GDP	Industrial production value	
	X_{11}:Regional GDP Growth Rate	Population growth	
	X_{12}:Value Added of the Secondary Industry	Traffic Road Capacity	
	X_{13}:GDP per capita	Traffic Road Capacity	
	X_{14}:Industrial Value Added	Urban and Rural Residents' Income	
	X_{15}:Road area per capita	Income of Rural Residents	

Research methods

Establishment of vulnerability indicators

Commonly cited vulnerability indicator frameworks include risk-hazard (RH) models, such as the Vulnerability Scoping Diagram (VSD) and Pressure-State-Response (PSR) models. These models clarify the relationship between exposure to natural hazards and the resulting losses. From a systematic theoretical perspective, combined with the actual conditions of Guizhou Province and with reference to relevant studies, 15 indicators were selected under three dimensions—environmental system vulnerability, economic system vulnerability, and social system vulnerability—to construct an urban vulnerability assessment indicator system for Guizhou Province.

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Urban Environmental System Vulnerability (UESV): This dimension uses indicators characterizing the urban environment to explain the outcomes of interactions between urban development and the environment when the city is exposed to external environmental disturbances. The selected indicators include per capita park green space (X_1), forest coverage rate (X_2), proportion of days with good air quality (X_3), centralized urban sewage treatment rate (X_4), and energy consumption per unit of GDP (X_5).

Urban Economic System Vulnerability (UECSVI): This dimension uses indicators reflecting disturbances to the economic system (focusing on the secondary and tertiary industries). The selected indicators include the proportion of the added value of the tertiary industry in GDP (X_6), regional GDP growth rate (X_7), added value of the secondary industry (X_8), per capita GDP (X_9), and industrial added value (X_{10}).

Urban Social System Vulnerability (USSV): This dimension uses indicators characterizing human-related factors in urban society to explain the impact of basic urban development on the city. The selected indicators include natural population growth rate (X_{11}), per capita road area (X_{12}), urbanization rate (X_{13}), per capita disposable income of urban residents (X_{14}), and per capita disposable income of rural residents (X_{15}) (*Table 2*).

Data standardization

For positive indicators of the target layer, *formula (1)* is applied; for negative indicators, *formula (2)* is applied.

$$Y_{ij} = \frac{X_{ij} - \mathrm{Min}(X_{ij}))}{\mathrm{Max}(X_{ij}) - \mathrm{Man}(X_{ij})} + 0.001 \quad \text{(Eq.1)}$$

$$Y_{ij} = \frac{\mathrm{Max}(X_{ij}) - (X_{ij})}{\mathrm{Max}(X_{ij}) - \mathrm{Man}(X_{ij})} + 0.001 \quad \text{(Eq.2)}$$

In the formula, Y_{ij}, X_{ij}, $\mathrm{Max}(X_{ij})$, $\mathrm{Min}(X_{ij})$ are the normalized value of original index data, the original value of the index data, the maximum and minimum values of the j_{th} indicator in the ith sample village, respectively.

$$P_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{m} Y_{ij}} \quad \text{(Eq.3)}$$

Calculate the entropy value e_j for the j_{th} indicator.

$$e_j = -k \sum_{i=1}^{m} P_{ij} \ln(p_{ij}), \quad k > 0, 0 \le e_{ij} \le 1 \quad \text{(Eq.4)}$$

In the formula: k=1/lnn, where $e_j \geq 0$.

Calculate the information entropy redundancy g_j of the j_{th} indicator.

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$$g_j = 1 - e_j \qquad \text{(Eq.5)}$$

Calculate the weights w_j for each indicator.

$$w_j = \frac{g_j}{\sum_{i=1}^{m} g_j} \qquad \text{(Eq.6)}$$

Table 2. *Vulnerability study indicators*

Target layer	System layer	Index layer	Nature	Unit	Consultation
Regional Development Vulnerability Evaluation Indicators for Guizhou Province	Vulnerability of environmental systems	X_1:Per capita park green space area	-	m^2	(Xu et al., 2023)
		X_2:Forest coverage rate	-	%	(Gao et al., 2024)
		X_3:Percentage of days with good air quality	+	%	(Fan et al., 2022)
		X_4:Urban sewage centralized treatment rate	-	%	(Bai et al., 2018)
		X_5:Energy consumption per unit of GDP	+	$T/10^4$yuan	(Gao et al., 2024)
	Vulnerability of economic systems	X_6:Value added of the tertiary industry as a percentage of GDP	-	%	(Guo et al., 2009)
		X_7:Regional GDP Growth Rate	-	%	(Fan et al., 2022)
		X_8:Value Added of the Secondary Industry	-	10^8yuan	(Tao, 2020)
		X_9:GDP per capita	-	10^4yuan	(Fan et al., 2022)
		X_{10}:Industrial Value Added	-	10^8yuan	(Bai et al., 2018)
	Vulnerability of social systems	X_{11}:Natural Population Growth Rate	+	‰	(Guo, 2022)
		X_{12}:Road area per capita	+	m^2	(Huang et al., 2020)
		X_{13}:Urbanization rate	-	%	(Shen, 2014)
		X_{14}:Per capita disposable income of urban residents	-	yuan	(Fan et al., 2022)
		X_{15}:Per capita disposable income of rural residents	-	yuan	(Liu, 2018)

BP neural network model construction

The BP Neural Network consists of three layers: an input layer, a hidden layer, and output layer. Neurons within the same layer are mutually independent, while neurons across different layers are interconnected, with weights assigned to these inter-layer connections for calculation (Li et al., 2016; Zhou et al., 2017). Structurally inspired by

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the neural network of the human brain, it is a multi-layer network architecture that operates based on error backpropagation, with continuous weight correction and model training. The working mechanism is as follows: first, sample data is fed into the input layer to initiate the training process. Subsequently, the error generated between the model output (from the output layer) and the actual target value is propagated backward through the network. During this backpropagation, the connection weights between neurons are dynamically adjusted to minimize the error iteratively. Through such repeated training and weight optimization, the BP Neural Network is capable of approximating a complex nonlinear function with high accuracy, ultimately outputting the corresponding predicted values (Lu and Zhang, 2016). Eventually, these predicted values can achieve a high degree of proximity to the real target values (*Figure 2*).

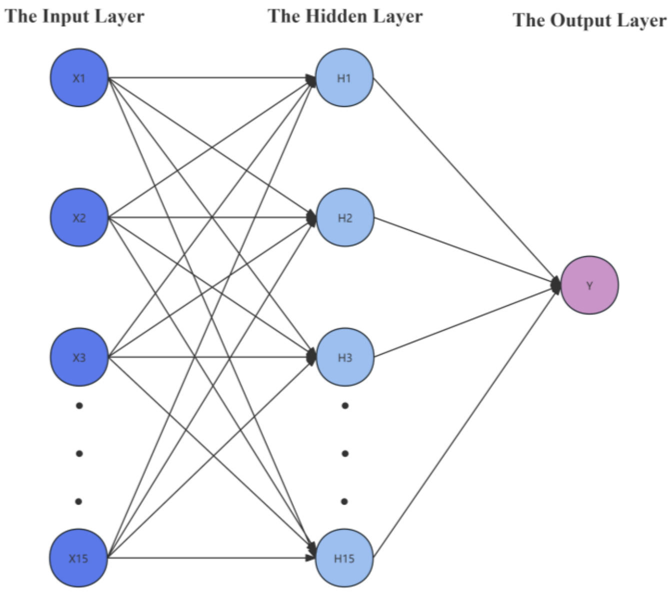

Figure 2. *BP neural network topology of regional development vulnerability evaluation model in Guizhou province*

In this study, the BP neural network was constructed using the MLPRegressor module from the Scikit-learn library in Python, with subsequent optimization and computation performed in PyCharm 2025.1. The Python-implemented BP neural network model includes built-in functions for weight initialization, model learning, and training. After modification, the model allows flexible configuration of the input layer, hidden layer, and output layer structures. For this research, a total of 15 indicators from the three systems ("environment-economy-society") were designated as input layer variables, while the vulnerability scores of the three subsystems and the overall regional development vulnerability served as output variables. Following model training and optimization, the vulnerability levels of each subsystem and the comprehensive regional development vulnerability were derived and subjected to integrated evaluation.

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Currently, there is no unified standard for defining the optimal range of regional vulnerability evaluation, nor is there a fixed assessment criterion for evaluating development vulnerability using BP neural networks. To address this gap, this study adopted the natural breaks classification method to categorize the evaluation results generated by the BP neural network. Regional vulnerability was divided into 4 levels, denoted as low vulnerability (Grade I), relatively low vulnerability (Grade II), relatively high vulnerability (Grade III), and high vulnerability (Grade IV), respectively. First, the weights of each evaluation indicator are calculated using the entropy method to construct a comprehensive evaluation indicator system based on the BP neural network. Second, a three-layer BP neural network model is constructed:

Input Layer: Contains 15 indicators (X_1—X_{15}) representing regional vulnerability.

Hidden Layer: N nodes (optimal value determined experimentally).

Output Layer: Contains 1 node (Y), corresponding to regional vulnerability level.

Network model parameters are set as follows:

- Learning rate: 0.01
- Maximum training iterations: 2000
- Training objective accuracy: 0.005
- Other parameters: Default

Model training was terminated when either the target accuracy was achieved or the maximum number of training epochs was reached—this marked the successful construction of the artificial neural network model. Finally, the standardized indicator data were input into the trained BP neural network model, which automatically output the corresponding regional vulnerability grade. The output values ranged between [0, 1].

Principal component analysis (PCA)

Principal Component Analysis (PCA) is a crucial step in examining the composition of regional development vulnerability. As one of the fundamental methods in multivariate statistical analysis, PCA can reduce the dimensionality of multiple datasets and identify the primary factors influencing regional vulnerability (Gong et al., 2014). The specific steps are as follows: (1) Incorporate standardized data into the correlation coefficient matrix (R) to compute the vulnerability correlation matrix based on standardized data; (2) Calculate eigenvalues and eigenvectors, selecting principal components with eigenvalues greater than 1 for analysis (Wu et al., 2025); (3) Compute the cumulative sum of principal variance and contribution rates to identify principal components; (4) Calculate principal component loadings to determine the primary indicators influencing overall regional vulnerability.

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Results

Indicator weighting and model fitting

Indicator weight calculation

The weights for each indicator in Guizhou Province over the 10-year period from 2014 to 2023 were calculated using the entropy method. The average values of each indicator over the 10-year period were then taken to ultimately obtain the weights for the regional development vulnerability assessment indicators of Guizhou Province (*Table 3*).

Table 3. *Weighting of indicators for vulnerability assessment of regional development in Guizhou Province*

Secondary Indicators	Weight	Level 3 Indicators	Weight
Environmental System	0.2313	X_1:Per capita park green space area	0.0724
		X_2:Forest coverage rate	0.0449
		X_3:Percentage of days with good air quality	0.0624
		X_4:Urban sewage centralized treatment rate	0.0287
		X_5:Energy consumption per unit of GDP	0.0227
Economic System	0.3996	X_6:Value added of the tertiary industry as a percentage of GDP	0.0447
		X_7:Regional GDP Growth Rate	0.0427
		X_8:Value Added of the Secondary Industry	0.1043
		X_9:GDP per capita	0.1132
		X_{10}:Industrial Value Added	0.0944
Social System	0.3691	X_{11}:Natural Population Growth Rate	0.0446
		X_{12}:Road area per capita	0.0341
		X_{13}:Urbanization rate	0.0699
		X_{14}:Per capita disposable income of urban residents	0.0873
		X_{15}:Per capita disposable income of rural residents	0.1330

It can be concluded that the weight of the economic system is higher than that of the social system and environmental system. According to the calculation results of the entropy weight method, this phenomenon is attributed to the relatively high weights of three core indicators in the economic system: per capita GDP (X_9), added value of the secondary industry (X_8), and industrial added value (X_{10}). These three indicators exhibit a high degree of variation, meaning there are significant differences in their values across different years and regions in Guizhou Province. This finding reveals two key insights: On one hand, it reflects that the economic system is the most prominent dimension of Guizhou's regional development achievements. On the other hand, it indicates that the development gap among cities in Guizhou is most obvious in the economic system

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(weight = 0.3966), followed by the social system (weight = 0.3691), and finally the environmental system (weight = 0.2313). Specifically, Guizhou's economic growth mainly relies on the secondary industry within the economic system—among which, the added value of the secondary industry (X_8, weight = 0.1043) and industrial added value (X_{10}, weight = 0.0944) together account for nearly 50% of the total weight of the economic system. This further confirms the dominant role of fluctuations in the economic system in driving the overall regional development dynamics of Guizhou Province.

BP neural network model fitting

A critical challenge in the modeling of BP networks lies in determining the optimal number of hidden layer neurons. To address this, iterative training was conducted to identify the optimal number of hidden layer neurons for the pre-constructed BP neural network model. Specifically, a stepwise testing approach was adopted: the number of hidden layer neurons was varied incrementally, and the model was retrained for each configuration. The coefficient of determination R^2 was used as the key metric to evaluate model fit, with higher R^2 values indicating better agreement between predicted and actual vulnerability grades. The optimal number of hidden layer neurons was determined as the configuration that yielded the maximum R^2 value. Results of this optimization process are presented in *Table 4*.

Table 4. *Implicit neuron number test effect*

Neuron	6	7	8	9	10	11	12
R^2	0.6040	0.6631	0.8291	0.9866	0.8949	0.9806	0.8639
MSE	0.0018	0.0016	0.0008	0.0001	0.0005	0.0002	0.0006

As shown in *Table 4*, when the number of hidden layer neurons was set to 9, the coefficient of determination R^2 reached its maximum value (0.9866) while the mean squared error (MSE) was minimized (0.0001). These metrics indicate that the BP neural network model achieved the best training fit for the sample data and the highest prediction accuracy under this configuration. Based on these results, the optimal structure of the BP neural network was determined as 15×9×1, where the input layer contains 1 neurons, the hidden layer contains 9 neurons, and the output layer contains 1 neuron.

Indicator data for each region were processed using the optimized BP neural network (*Table 5*). Each subsystem (environmental, economic, social) was categorized into four vulnerability grades. After data normalization, the natural breaks method was applied to define the classification thresholds for each vulnerability grade: the minimum normalized value (0) corresponded to the lowest vulnerability grade, while the maximum normalized value (1) corresponded to the highest vulnerability grade. The model training was terminated after 13 iterations, as the error fell below 5×10^{-3} (*Fig. 3*), meeting the target

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training accuracy. The final performance metrics were as follows: mean squared error (MSE) = 0.1×10^{-3}, mean absolute error (MAE) = 6.1×10^{-3}, root mean squared error (RMSE) = 7.9×10^{-3}, and coefficient of determination (R^2) = 0.9866. These results indicate excellent agreement between the model predictions and actual vulnerability levels.

Table 5. *Level of vulnerability*

Level	I	II	III	IV
Regional Development Vulnerability	＜0.294	0.295~0.348	0.349~0.389	＞0.390
Environmental System Vulnerability	＜0.171	0.172~0.224	0.225~0.317	＞0.318
Economic System Vulnerability	＜0.315	0.316~0.363	0.364~0.507	＞0.508
Social System Vulnerability	＜0.358	0.359~0.407	0.408~0.458	＞0.459

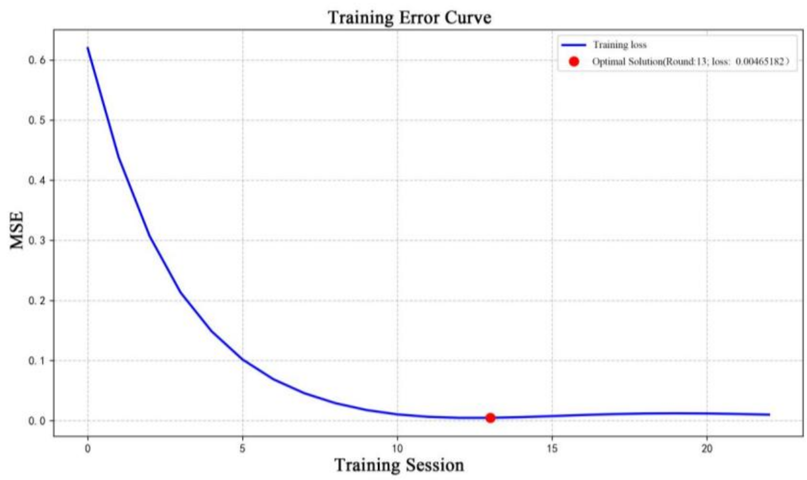

Figure 3. *Deviation curve of BP neural network*

Spatiotemporal evolution analysis of regional development vulnerability

Using the aforementioned indicator system, the normalized data were input into the BP neural network, with indicator weights determined by the entropy weight method. After model operation, four sets of vulnerability indices were obtained for the 9 prefecture-level cities/autonomous prefectures in Guizhou Province from 2014 to 2023: comprehensive development vulnerability, environmental vulnerability, economic vulnerability, and social vulnerability. To visualize the temporal dynamics of these indices, time-series plots were constructed. For each plot, the horizontal axis (X-axis) represented the time period (2014–2023), while the vertical axis (Y-axis) represented the corresponding vulnerability index value. These plots collectively illustrate the annual fluctuations and long-term trends of each vulnerability dimension across Guizhou's administrative regions over the 10-year study period.

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Trends in vulnerability dynamics

(1) Overall regional vulnerability and subsystem interactions (*Fig. 4a*)

Based on the vulnerability indices of each subsystem (environmental, economic, social) for Guizhou Province derived from the BP neural network (*Fig. 4a*), the overall development vulnerability of each administrative region in Guizhou was further calculated. Owing to the inherent complexity of regional systems, the three subsystems are inherently interconnected and mutually influential:

First, a region's resource and ecological environment serves as a fundamental prerequisite for economic and social development—neither economic growth nor social progress can be sustained independently of stable environmental conditions. Conversely, human activities driving regional expansion (e.g., urban sprawl, resource exploitation) often exert pressure on the environment, potentially causing degradation. This reciprocal relationship—where each subsystem both supports and constrains the others—was particularly evident in Guizhou's development during 2014–2017.

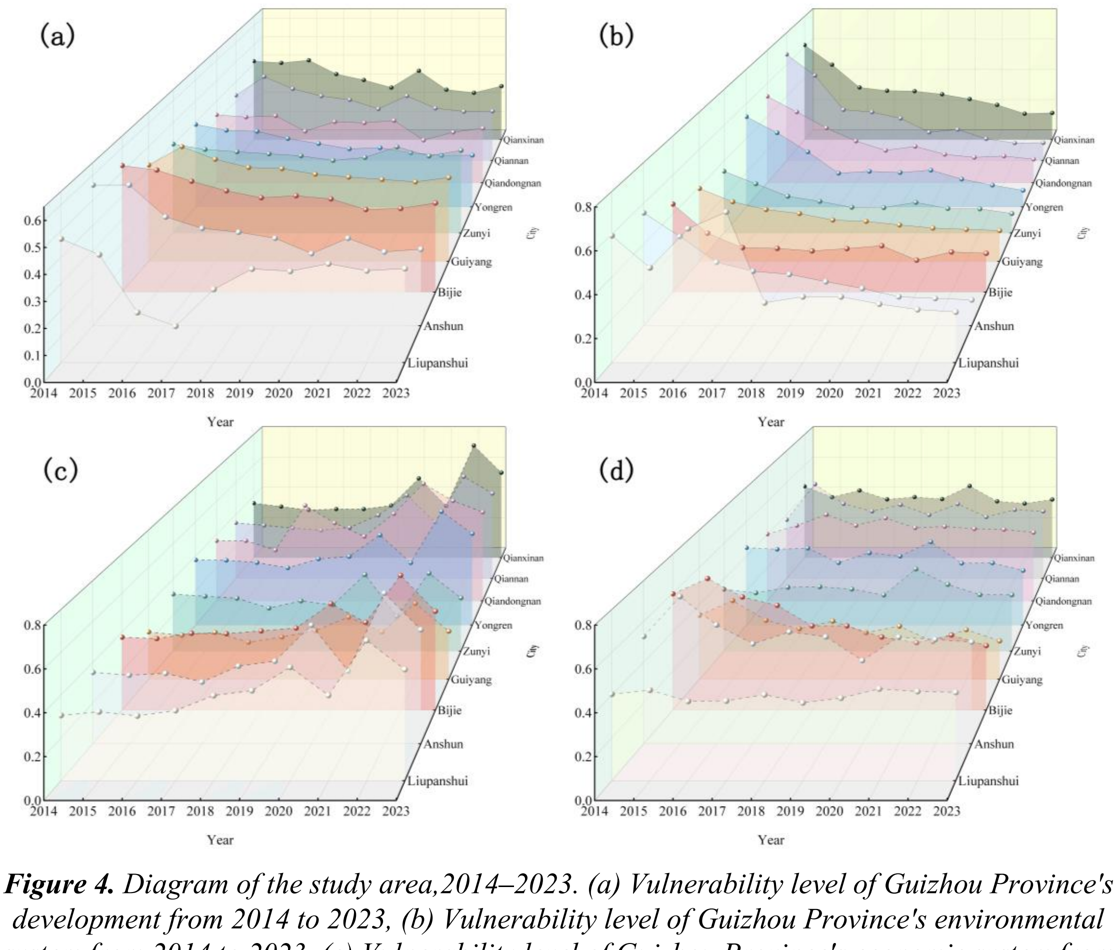

Figure 4. *Diagram of the study area,2014–2023. (a) Vulnerability level of Guizhou Province's development from 2014 to 2023, (b) Vulnerability level of Guizhou Province's environmental system from 2014 to 2023, (c) Vulnerability level of Guizhou Province's economic system from 2014 to 2023, (d) Vulnerability level of Guizhou Province's social system from 2014 to 2023*

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During this period, guided by national policy directives, Guizhou's overall regional vulnerability exhibited a downward trend, with all cities except Guiyang and Qiannan Buyi and Miao Autonomous Prefecture (Qiannan) experiencing reductions in vulnerability. This trend directly reflects the effectiveness of Guizhou's environmental protection initiatives during this phase. In contrast, over the entire 10-year study period (2014–2023), the economic system vulnerability showed a fluctuating upward pattern, while the social system vulnerability displayed a fluctuating downward trajectory—highlighting the divergent dynamics of the three subsystems.

(2) Environmental system vulnerability trends (*Fig. 4b*)

All 9 prefecture-level administrative units (hereafter referred to as "regional clusters") in Guizhou exhibited temporal fluctuations in environmental vulnerability. Liupanshui, a typical resource-based city, saw its environmental vulnerability first increase and then decrease, peaking in 2017 as the highest among all 9 clusters. This peak indicates that Liupanshui's environmental protection efforts were insufficient to keep pace with its economic development during this period.

Notably, Liupanshui's environmental vulnerability index declined sharply after 2017, dropping from 0.70 in 2017 to 0.28 in 2018. This dramatic reduction was closely tied to improvements in environmental governance: Liupanshui's centralized urban sewage treatment rate had fallen to 65.36% in 2017 (down from 72.36% in 2016), but targeted remediation measures implemented in 2018 significantly restored sewage treatment capacity, leading to the steep decline in vulnerability.

In contrast, the remaining 8 regional clusters maintained a steady downward trend in environmental vulnerability from 2014 to 2023, with the lowest values recorded in 2023. This consistent reduction underscores Guizhou's commitment to balancing regional development with ecological conservation, ensuring that economic expansion did not come at the expense of environmental quality.

(3) Economic system vulnerability trends (*Fig. 4c*)

The economic vulnerability of Guizhou's 9 regional clusters showed substantial variability, with Qiandongnan Miao and Dong Autonomous Prefecture (Qiandongnan) exhibiting the most pronounced fluctuations. Qiandongnan's economic vulnerability reached two distinct peaks: the first (0.57) in 2017 and the second (0.70) in 2021.

The 2017 peak was primarily driven by a sharp decline in key economic indicators: the regional GDP growth rate plummeted to 3.8% in 2017 (compared to 11.8% in 2016 and 6.4% in 2018), while industrial added value fell to 141.88×10^8 yuan (down from 180.74×10^8 yuan in 2016 and only slightly recovering to 142.48×10^8 yuan in 2018).

The 2021 peak, by contrast, stemmed from a drop in the proportion of tertiary industry added value in GDP—this ratio fell from 57.4% in 2020 to 51.6% in 2021—even as other economic indicators continued to rise steadily.

For the remaining 8 regional clusters, economic vulnerability decreased sharply in 2021 due to proportional growth across most economic metrics. A slight decline in indicators was observed in 2022, followed by a recovery in 2023. This pattern suggests

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that Guizhou’s regional economy was disrupted by the global COVID-19 pandemic in 2020; however, the post-pandemic resumption of production enabled a gradual return to the high-growth trajectory seen before the pandemic.

(4) Social system vulnerability trends (*Fig. 4d*)

The regional vulnerability of all nine urban clusters in Guizhou Province showed an average development trend. However, Anshun City experienced a significant increase from 0.52 in 2014 to 0.72 in 2015, Bijie City (0.59 in 2014 to 0.67 in 2015), and Qiannan Prefecture (0.36 in 2014 to 0.59 in 2015) all experienced vulnerability increases in 2015. The remaining clusters saw vulnerability decreases in 2016, though these declines were modest. This indicates that alongside economic development, local clusters across Guizhou Province are simultaneously addressing social needs, refining social systems, and enhancing the quality of life for its people. As the provincial capital, Guiyang leads the province, followed by Zunyi and Tongren. Anshun, with its relatively late start in social development, currently has the highest vulnerability rating in the province.

Over the past decade, the regional development vulnerability index for some cities in Guizhou Province first declined and then rose, with all regions ultimately maintaining vulnerability below Level IV. Guiyang and Zunyi saw their regional vulnerability gradually increase to Level III urban vulnerability. Guizhou's regional development still requires attention: Liupanshui must prioritize environmental system vulnerability alongside development, Qiannan should focus on economic system vulnerability, while Anshun, Bijie, and Qiannan should pay attention to social system vulnerability. From a holistic perspective, Guiyang City experienced a decline in environmental vulnerability (0.39-0.16) between 2014 and 2023, while its economic system vulnerability remained stable (0.25-0.25) and its social system vulnerability decreased (0.34-0.20). This reflects Guiyang's concurrent efforts to protect its environmental system and influence its social system while developing its economy. Zunyi City saw its environmental vulnerability decrease (0.34–0.10) from 2014 to 2023, accompanied by declines in both economic vulnerability (0.31–0.29) and social vulnerability (0.34–0.31), indicating a trade-off between economic growth and ecological conservation. Anshun City experienced a decline in its environmental system (0.55–0.12) and social system (0.52–0.49) from 2014 to 2023, while its economic system improved (0.34–0.55). This highlights Anshun's prioritization of environmental protection, yet as the city with the lowest regional GDP, it faces challenges in achieving robust economic development. Bijie City, Tongren City, Qiandongnan Prefecture, Qiannan Prefecture, and Qianxinan Prefecture mirrored Anshun's trajectory, with their environmental systems ultimately declining to (0.19, 0.09, 0.14, 0.11, 0.17) while their economic systems rose to (0.50, 0.53, 0.53, 0.53, 0.55).

Geographically, Guiyang as the provincial capital and Zunyi bordering Chongqing represent Guizhou's two largest economies. These cities receive the province's strongest policy and economic support and cultural tourism resources (*Fig. 5*), with their unique developmental conditions enabling them to significantly outperform other regions in Guizhou.

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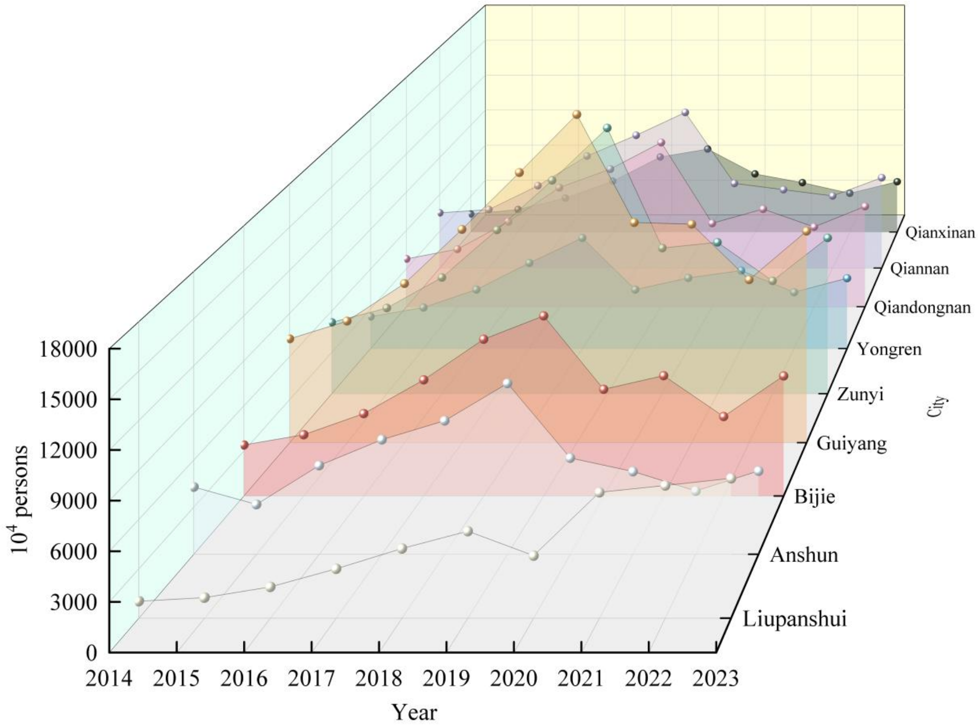

Figure 5. *To assess temporal trends in tourist arrivals from 2014 to 2023*

Evolutionary patterns of vulnerability spaces

(1) Based on the annual vulnerability indicator characteristics calculated in the preceding sections, spatial distribution maps of environmental vulnerability were generated using ArcMap 10.8 (*Fig. 6*). These maps reveal a dramatic spatial-temporal transformation of environmental vulnerability in Guizhou Province from 2014 to 2023, with the following key stages. 2014 *(Fig. 6a*): The entire study area was classified as Grade IV (high environmental vulnerability), indicating that Guizhou's regional environment was under widespread pressure at the start of the study period. 2017 (*Fig. 6b*): A clear spatial differentiation emerged: 3 administrative units reached Grade II (relatively low vulnerability), 4 units remained at Grade III (relatively high vulnerability), and 2 units persisted at Grade IV (high vulnerability). This transition reflects the initial effectiveness of targeted environmental governance measures in some regions. 2020 (*Fig. 6c*): Environmental vulnerability across all regions fell below Grade IV, marking a provincial-scale breakthrough in environmental quality improvement—no area remained in the "high vulnerability" category. 2023 (*Fig. 6d*): The optimization of environmental vulnerability reached its peak: 6 administrative units achieved Grade I (low vulnerability), 2 units maintained Grade II (relatively low vulnerability), and only 1 unit remained at Grade III (relatively high vulnerability).

Notably, Guiyang and Zunyi—Guizhou's key development hubs—also attained Grade I environmental vulnerability by 2023. This outcome demonstrates that these two regions

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successfully balanced economic development with environmental protection, avoiding the trade-off between growth and ecological degradation often observed in rapidly developing areas.

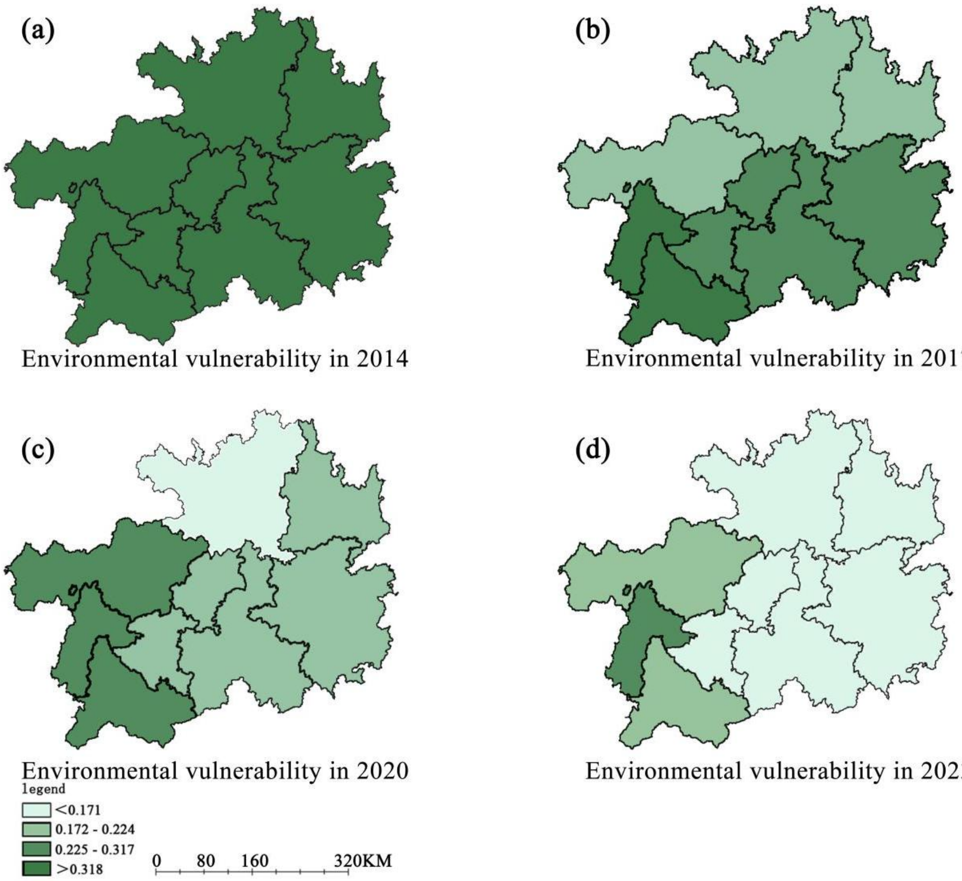

Figure 6. *Spatial evolution of regional development environmental vulnerability in Guizhou Province, 2014–2023*

(2) Spatial dynamics of economic system vulnerability

Spatial distribution maps of economic vulnerability (*Fig. 7*) reveal a contrasting pattern to environmental vulnerability, with a growing concentration of high vulnerability in non-core regions over the study period: 2014 (*Fig. 7a*): The economic vulnerability exhibited relatively balanced spatial distribution: 2 administrative units were classified as Grade I (low vulnerability), 5 units as Grade II (relatively low vulnerability), and 2 units as Grade III (relatively high vulnerability). No region reached Grade IV (high vulnerability) at this stage. 2017 (*Fig. 7b*): A clear hierarchical gap emerged: Guiyang (the provincial capital) remained at Grade I, Zunyi (the second-largest economic hub) at Grade II, while all other regions fell into Grade III or IV. This marked the initial formation of an economic vulnerability gradient centered on Guiyang and Zunyi. 2020 (*Fig. 7c*): Driven by the radiative effects of Guiyang and Zunyi, the economic

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vulnerability of surrounding regions decreased, with no area exceeding Grade IV. This reflects the role of core cities in driving the economic stability of neighboring regions. 2023 (*Fig. 7d*): The spatial polarization of economic vulnerability intensified: Only Guiyang and Zunyi maintained Grade I (low vulnerability), while the remaining 7 prefecture-level units regressed to Grade IV (high vulnerability). This pattern clearly manifests a "core-periphery" structure in Guizhou's economic development—core cities (Guiyang, Zunyi) enjoy stable, low-vulnerability growth, while peripheral regions face persistent economic instability.

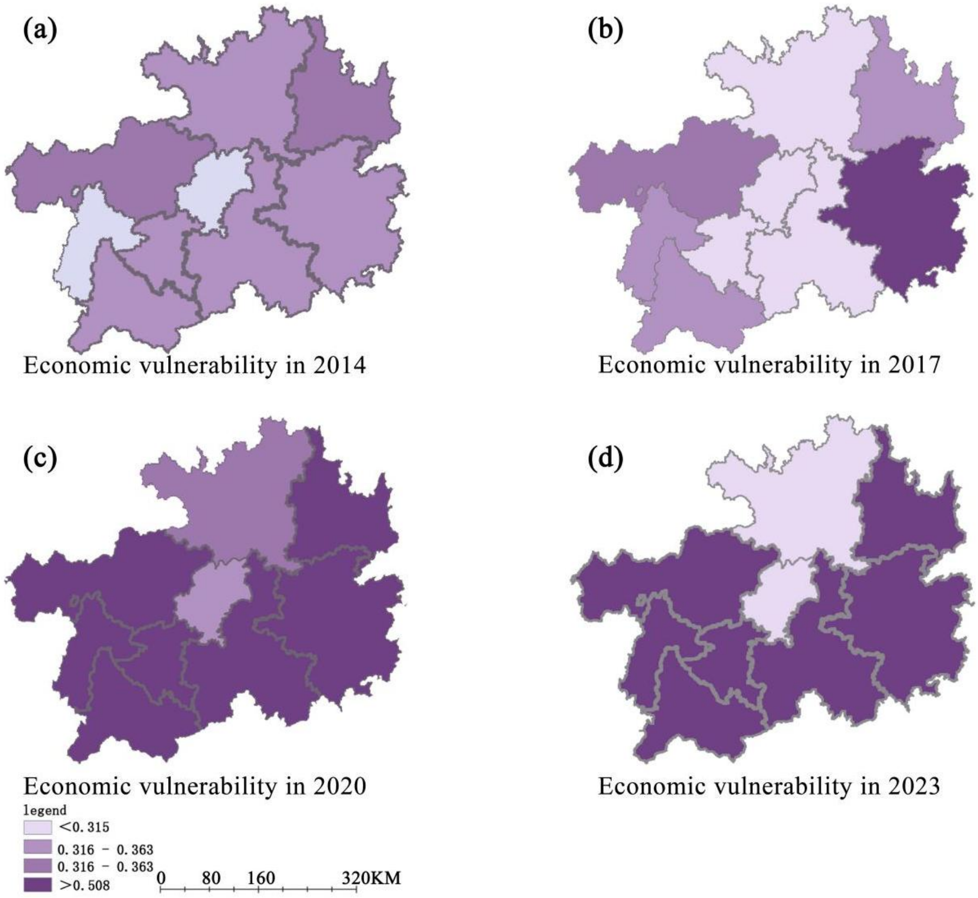

Figure 7. *Spatial evolution of regional economic vulnerability in Guizhou Province, 2014–2023*

(3) Spatial dynamics of social system vulnerability (2014–2023)

Based on the spatial distribution maps of social system vulnerability (*Fig. 8*), a general trend of progressive improvement was observed across Guizhou Province over the 10-year period, with significant inter-regional variations in the pace and magnitude of improvement:

Guiyang: Maintained consistently low social vulnerability throughout the study period, fluctuating between Grade II (relatively low) and Grade I (low). This stability reflects Guiyang's advanced social infrastructure, mature public service systems, and

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continuous investments in social welfare—advantages inherent to its role as the provincial capital.

Zunyi: Exhibited a volatile but overall downward trajectory: social vulnerability initially rose from Grade III (relatively high) to Grade IV (high) in the early stage, before declining steadily to Grade I (low) by 2023. This pattern suggests a period of social adjustment (e.g., addressing gaps in public services amid rapid economic growth) followed by targeted policy interventions that restored social stability.

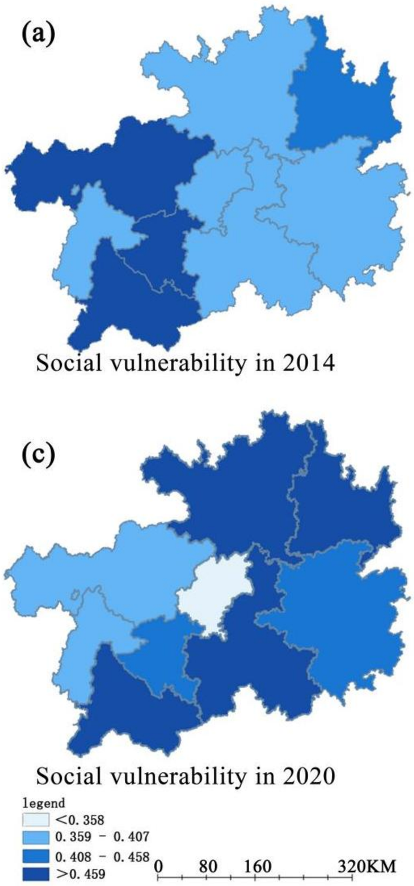

Figure 8. *Spatial evolution of regional development social vulnerability in Guizhou Province, 2014–2023*

Bijie: Achieved the most dramatic reduction in social vulnerability, transitioning from Grade IV (high) to Grade II (relatively low) and ultimately to Grade I (low) by 2023. This progress is closely linked to Bijie's economic development: economic growth has facilitated increased investments in social sectors (e.g., education, healthcare, and poverty alleviation) and environmental governance, forming a positive synergistic relationship between economic advancement, social improvement, and ecological protection.

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By 2023, the spatial differentiation of social system vulnerability in Guizhou had become clear, with the following grade distribution:

Grade I (low vulnerability): Guiyang, Zunyi, Bijie, and Tongren—these regions represent the leading areas of social development in Guizhou, supported by robust economic foundations or targeted social policies.

Grade II (relatively low vulnerability): Qianxinan Buyi and Miao Autonomous Prefecture—this region showed moderate improvement but still lags slightly behind the Grade I group, likely due to slower progress in social infrastructure upgrades.

Grade III (relatively high vulnerability): Qiandongnan Miao and Dong Autonomous Prefecture, Qiannan Buyi and Miao Autonomous Prefecture, and Liupanshui—these regions face persistent challenges such as uneven distribution of public services or lagging social welfare coverage.

Grade IV (high vulnerability): Anshun—uniquely remaining in the highest vulnerability grade, this outcome underscores the strong link between Anshun's underdeveloped economic base and its lagging social development. Unlike regions where economic growth drove social progress (e.g., Bijie), Anshun's limited economic capacity has constrained investments in social sectors, resulting in slower improvement in social vulnerability.

(4) Spatial dynamics of overall regional vulnerability (2014–2023)

Spatial distribution maps of overall regional vulnerability (*Fig. 9*) reveal a profound transformation in Guizhou's regional development resilience over the 10-year period, with a clear shift from widespread high vulnerability to differentiated but generally reduced risk:

2014 (Initial State): Guizhou's overall regional vulnerability was highly concentrated at high grades: only 2 administrative units were classified as Grade II (relatively low vulnerability), while all remaining regions fell into Grade IV (high vulnerability). This pattern reflected the province's limited development resilience and widespread challenges across environmental, economic, and social systems at the start of the study period.

2023 (Final State): A balanced and differentiated spatial pattern emerged after a decade of development:

Grade III (relatively high vulnerability): Guiyang, Zunyi, Bijie, and Liupanshui;

Grade II (relatively low vulnerability): Anshun;

Grade I (low vulnerability): Qianxinan Buyi and Miao Autonomous Prefecture, Qiannan Buyi and Miao Autonomous Prefecture, Qiandongnan Miao and Dong Autonomous Prefecture, and Tongren.

A notable counterintuitive trend emerged in the 2023 data: Regions with higher economic and social vulnerability tended to exhibit lower overall vulnerability, while regions with lower economic vulnerability showed higher overall vulnerability. This pattern is quantified by the 2023 overall vulnerability indices:

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Low overall vulnerability (Grade I regions): Tongren (0.24), Qiandongnan (0.26), Qiannan (0.25), and Qianxinan (0.28)—these regions, despite facing higher economic and social subsystem risks, achieved balanced performance across environmental, economic, and social dimensions (e.g., strong environmental protection offsetting economic instability), leading to lower integrated vulnerability.

Higher overall vulnerability (Grade III core regions): Guiyang (0.36) and Zunyi (0.37)—as Guizhou's economic hubs, these regions maintained low economic vulnerability but faced lingering pressures in other subsystems (e.g., social service gaps amid rapid urbanization or environmental stress from industrial expansion), resulting in higher integrated vulnerability than their peripheral counterparts.

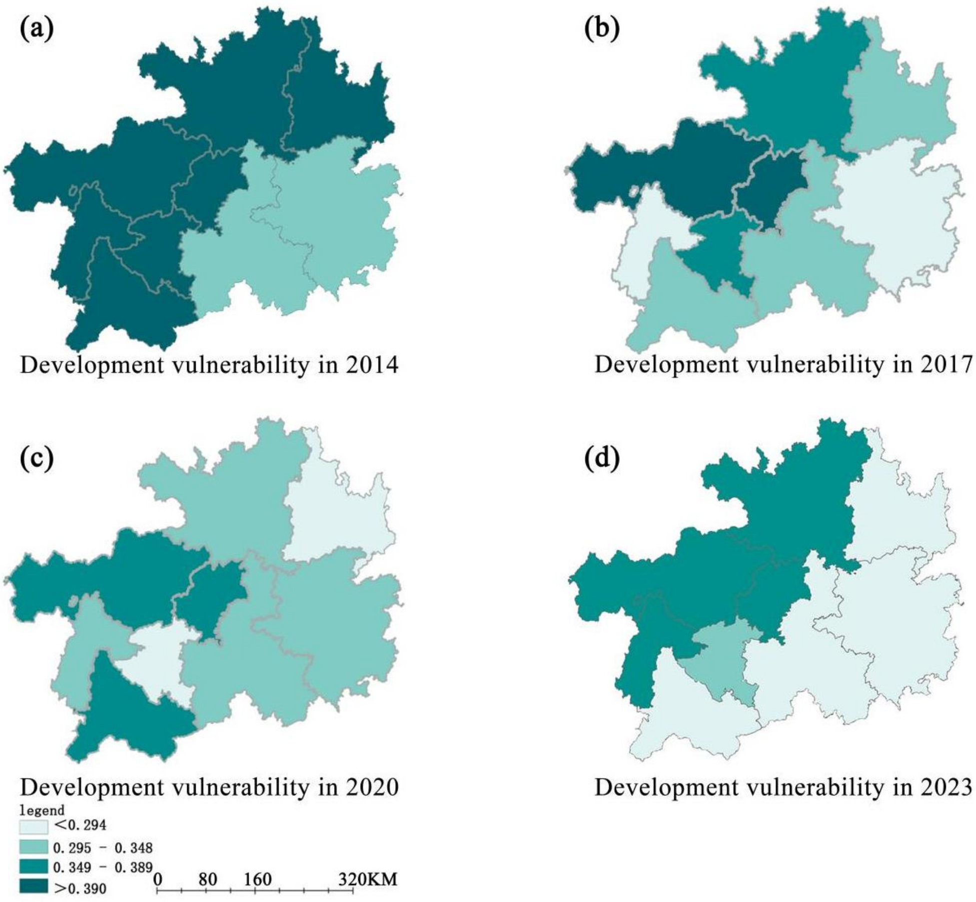

Figure 9. *Spatial evolution of overall regional development vulnerability in Guizhou Province, 2014–2023*

Factors influencing overall regional development vulnerability

Data were processed using IBM SPSS Statistics 26 to derive factor loading matrices and rotated factor scores. Principal component scores were calculated based on the relationship between principal component scores and unrotated factor scores. Scores for

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each principal component factor were weighted by their variance contribution rates and summed to obtain the composite scores for each indicator.

Factor contribution analysis in principal component analysis (PCA)

To extract the impact of key factors on regional development vulnerability, a principal component analysis (PCA) was conducted on the 15 current influencing factors, yielding five principal components with a cumulative contribution rate of 80.7%. It is generally accepted that data with a Kaiser-Meyer-Olkin (KMO) measure threshold greater than 0.5 are suitable for PCA. Although the current cumulative contribution rate is not exceptionally high, the data demonstrate a certain common structure among the current factors, making them suitable for principal component analysis. The p-value (sig.) is significantly less than 0.05, indicating that the current independent variables exhibit significant correlations among the factors, thus supporting the application of principal component analysis (*Table 6*).

Table 6. *Total variance explained by principal components*

PCA	Extract the sum-of-squares load			Rotational Square Sum Load		
	Total (Eigenvalue)	Variance %	Cumulative%	Total (Eigenvalue)	Variance %	Cumulative%
PC1	5.706	38.038	38.038	4.281	28.537	28.537
PC2	2.906	19.375	57.413	4.192	27.947	56.484
PC3	1.322	8.815	66.228	1.375	9.166	65.651
PC4	1.157	7.711	73.939	1.221	8.138	73.789
PC5	1.026	6.838	80.776	1.048	6.988	80.776
Ksiser-Meyer-Olkin(KMO)Sufficient sampling inspection				0.729		
Bartlett's Sphericity Test				X^2=1294.262 df=105 p=0.00		

Principal component analysis (PCA) factor analysis

The principal component loadings matrix for the 15 indicators is shown in *Figure 4*. The development of the first principal component (PC1) is closely related to economic growth. The second principal component (PC2) is associated with environmental and urban social development. PC3 is related to population growth. PC4 is associated with the development of the tertiary industry. PC5 is related to environmental governance.

In *Figure 10*, it can be seen that in the principal component analysis, PC1 contributes 38.038%. The loadings for secondary industry value-added (X_8), per capita GDP (X_9), industrial value-added (X_{10}), urbanization rate (X_{13}) have loadings of 0.948, 0.846, 0.884, 0.889, and 0.748, respectively. This indicates that industrialization is the core driver of economic vulnerability in PC1. While high-value-added industries (Zunyi equipment

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manufacturing) do not significantly impact the natural environment, resource-based industries (Liupanshui coal) cause environmental pollution during production. PC2 contributes 19.375% to variance. Regional GDP growth rate (X_7), per capita road area (X_{12}), and per capita disposable income of urban residents (X_{14}) have loadings of -0.789, 0.819, and 0.812 respectively. This indicates that regional economic factors are direct contributors to PC2, while GDP growth rate exerts a negative influence. In PC3, the load factor for per capita park green space area (X_1) is 0.803, indicating environmental factors are direct contributors. In PC4, the load factor for tertiary industry value-added as a percentage of GDP (X_6) is 0.931, confirming economic factors remain the primary contributor. In PC5, the load factor for centralized urban sewage treatment rate (X_4) is 0.983, indicating that pollution treatment in the region is a direct influencing factor for PC5.

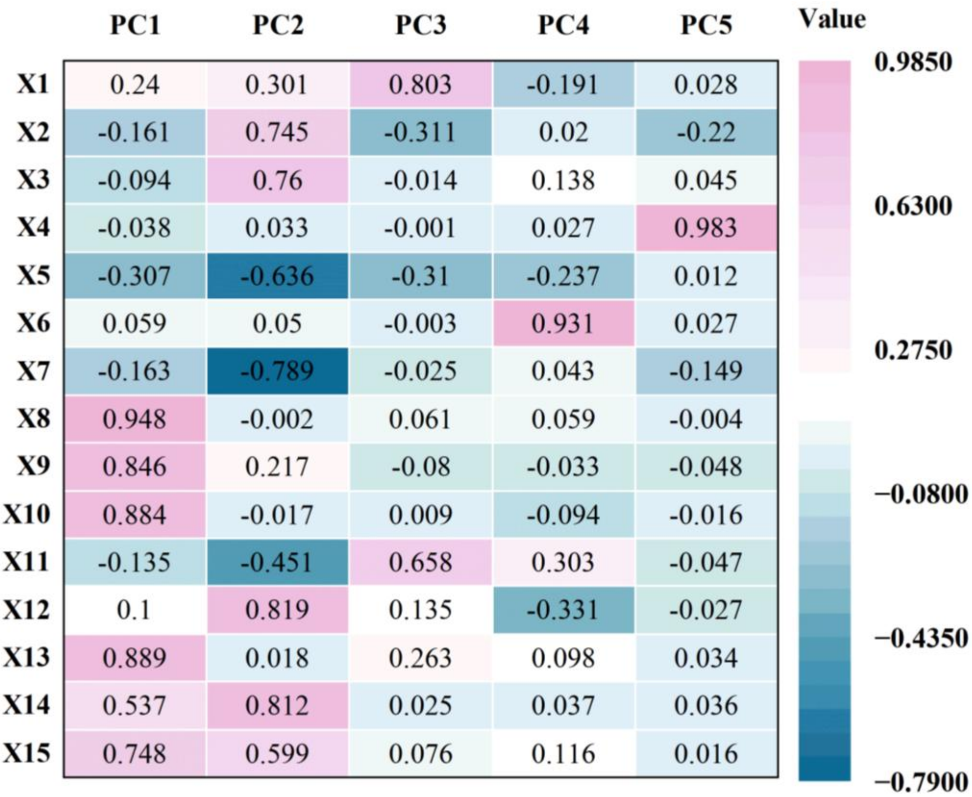

Figure 10. *Principal component matrix*

Based on the above analysis, it is evident that in calculating environmental vulnerability, indicator X_4 exhibits the strongest positive correlation, while X_5 shows the strongest negative correlation. When calculating economic vulnerability, indicators X_6 and X_8 demonstrate the strongest positive correlations, and X_7 exhibits the strongest negative correlation. In assessing social vulnerability, all indicators show positive correlations, but X_{13} is most strongly associated with social vulnerability.

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Discussion

Comparison with existing research

Existing research has achieved significant progress in regional development studies. For instance, neural networks have been employed to interpret various regional vulnerability factors such as marine economic systems, tourism economic systems, ecological systems, and gas pipeline networks (Peng et al., 2015; Ma et al., 2019). As environmental systems represent the most sensitive dimension of regional development (Iwanaga et al., 2022), their development process must adhere to sustainability principles. This study adopts a macro-level perspective to analyze the role of regional environmental socio-economic systems in regional development (Li et al., 2022), seeking a balance between regional growth and environmental conservation (Kang et al., 2021; Deng et al., 2022).

The research contributes to the expansion of vulnerability theory. While the existing Vulnerability Scoping Diagram (VSD) model emphasizes the "Exposure-Sensitivity-Adaptive Capacity" framework, this study proposes a "multi-system coupling framework" that reveals a closed-loop mechanistic pathway of "environmental constraints-economic vitality-social response". This approach more accurately captures the transmission mechanism of "economic growth (X_9)—urbanization (X_{13})—reduction in social vulnerability", thereby better reflecting the realities of regional development.

Furthermore, Principal Component Analysis (PCA) was applied to validate the results derived from Backpropagation (BP) neural network analysis (Sequeira and Borges, 2024). This methodology not only identifies the influence of individual components on overall regional vulnerability development (Giri et al., 2021), but also provides deeper insights into the complex synergistic and antagonistic interactions among factors within these components. Consequently, it enables more effective formulation of targeted strategies for addressing regional development vulnerabilities. The findings offer governmental agencies evidence-based policy recommendations tailored to regional transformations.

While previous studies have emphasized the varying importance of climate change (Kemp et al., 2022), environmental shifts, economic poverty (Chen et al., 2021), and energy shortages (Cao and Nguea, 2025) in regional environmental, economic, and social development (Singh et al., 2021), this study employs Principal Component Analysis (PCA) to demonstrate that value-added of the secondary industry, per capita GDP, industrial value-added, urbanization rate, per capita disposable income of urban residents, and disposable income of rural residents are key factors in achieving coordinated regional development.

Although prior research exhibits considerable diversity (Kurniawan et al., 2022; Rakuasa and Latue, 2023), the resulting policy recommendations tend to be broad and span multiple domains. In contrast, the recommendations of this study are more specific

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and readily implementable. Whereas earlier studies often relied on models such as RH, VSD, and PSR to calculate vulnerability indices, this research introduces a Backpropagation (BP) neural network model. This model is a multi-layer feedforward network trained according to the error backpropagation algorithm. Its advantage lies in not requiring a predefined mathematical equation describing the mapping relationship; instead, it can directly learn and store extensive input-output mapping relationships, thereby facilitating a more efficient computation of vulnerability indices

Limitations and future prospects

Although this study quantified the vulnerability index of regional development in Guizhou Province using BP neural network, several limitations should be acknowledged.

First, the analysis was conducted at the prefecture level or above. Future work should prioritize the use of county-level data to refine the spatial accuracy of regional indicators and enhance the specificity of the vulnerability assessment. We must also recognize a key methodological limitation: the BP neural network was trained on only ten years of data. Due to missing records for certain years in Guizhou's urban datasets, the training and test sets—though split in an 80%-20% ratio—were ultimately based on a limited number of instances, with only two years of data available for testing. This constrained the model's ability to robustly predict vulnerability. Although the neural network produced a quantifiable output, it converged before reaching the maximum number of training iterations, resulting in suboptimal adaptability and generalizability. Future studies should focus on improving vulnerability predictions for Guizhou by incorporating more comprehensive datasets, thereby supporting development strategies that reduce environmental, economic, and social vulnerabilities.

Furthermore, while the selected indicators covered representative aspects of environmental, economic, and social dimensions, the framework did not include emerging indicators such as "technological innovation" or "digital economy." Future assessments would benefit from incorporating metrics like "ecosystem service value," "R&D investment intensity," and "digital economy scale" to better capture the dynamics of high-quality development.

Finally, we recommend extending the model to other provinces in southwestern China to construct an "Ecologically Sensitive Regional Vulnerability Database." This would provide a quantitative foundation for national ecological compensation policies and support regional resilience planning.

Conclusions

Key findings

This study constructs a vulnerability evaluation framework based on the "environmental system–economic system–social system" triad from a regional

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perspective. Taking specific regions within Guizhou Province as the study object, a Backpropagation (BP) neural network was applied to calculate various vulnerability indices, enabling an evolution analysis of vulnerability characteristics over time. Principal Component Analysis (PCA) was further employed to examine the contribution of each evaluation indicator to the overall vulnerability.

The results reveal that the spatiotemporal pattern of vulnerability in Guizhou Province is characterized by "economic dominance and regional divergence". In 2023, four prefectures reached Grade I (low vulnerability), while Guiyang and Zunyi were classified as Grade III due to industrial agglomeration and urbanization pressures. In contrast, ecologically advantaged areas such as Qiandongnan, Qiannan, and Qianxinan exhibited lower vulnerability, reflecting disparities in development quality. PCA identified indicators X_4, X_6, X_8, and X_{13} as major positive driving factors, whereas X_5 and X_7 were key negative factors influencing vulnerability.

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