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Yusen Lin, Yong Xiang, Hao Yin & Zeyou Chen

Selection of Emergency Logistics Facility Locations Considering Major Natural Disasters in Mountainous Cities Based on GIS-MCDM

Yusen Lin [a], Yong Xiang [a], Hao Yin [a], Zeyou Chen [a*]

a. School of Architecture and Civil Engineering, Xihua University, Chengdu, 610039, China

*Corresponding author:

Zeyou Chen

Postal address: School of Architecture and Civil Engineering, Xihua University, Chengdu, 610039, China.

Tel/Fax: +8613982007880

E-mail address: 0119940033@xhu.edu.cn

Abstract : The rising frequency of extreme natural disasters under global climate change presents significant uncertainty and safety challenges for emergency logistics facility planning, particularly in mountainous regions. Addressing the limitations of traditional location studies that often overlook terrain complexity and disaster risks, this study proposes an integrated framework for mountainous emergency logistics site selection, combining Geographic Information Systems (GIS) spatial analysis with Multi-Criteria Decision-Making (MCDM) methods. Using 88 counties and districts in Guizhou Province as a case study, the framework incorporates four criterion-level dimensions and eight indicator-level factors, and employs GIS spatial analysis alongside a hybrid BWM–EWM weighting scheme and an improved TOPSIS evaluation to generate a suitability map. Sensitivity analysis confirms the robustness of the model. The results reveal an east-strong–west-weak spatial pattern of suitability, with population density and transportation accessibility as dominant factors, terrain imposing fundamental constraints, and natural disaster risk providing critical differentiation for decision-making.

Keyword : Emergency logistics; Natural disasters in mountainous areas; Facility siting; Site selection; Multi-criteria decision-making（MCDM）

1. Introduction

Under the background of global climate change, the frequency and intensity of extreme natural disasters have shown a sustained upward trend. According to statistics from the Centre for Research on the Epidemiology of Disasters (CRED), more than 9,000 natural disaster events were recorded globally between 2000 and 2024 **Error! Reference source not found.**, resulting in over 1.7 million deaths **Error! Reference source not found.** Data Source: **Statista**and **Error! Reference source not found.**. Research indicates that, in many disaster events, casualties and economic losses are not solely caused by the disaster itself, but are often closely associated with delayed emergency logistics response, imbalanced resource allocation, and inefficient information transmission. For example, during Typhoon Haiyan in the Philippines in 2013, the Nepal earthquake in 2015, and the Indonesia earthquake in 2018, relief supplies failed to reach affected areas within critical time windows, significantly amplifying disaster losses.

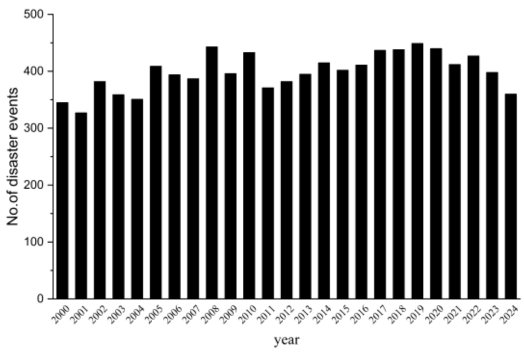

Fig. 1Global number of natural disasters events 2000–2024.

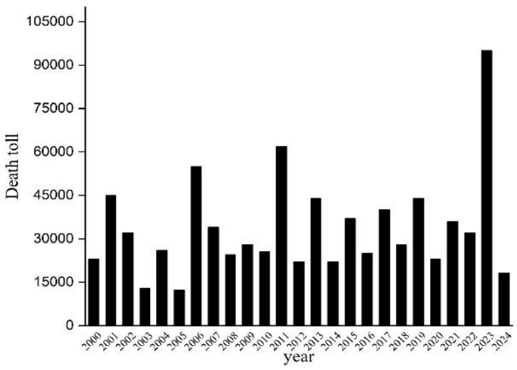

Fig. 2Global natural disaster deaths from 2000 to 2024.

Data Source: Statista

This problem is particularly pronounced in mountainous cities [3]. Mountainous regions are characterized by rugged terrain, fragile transportation networks, dispersed populations, and complex climatic conditions, which collectively increase their vulnerability to extreme natural disasters. Disasters in mountainous areas often exhibit “chain” and “compound” characteristics [4]. For instance, in 2009, typhoon-induced floods, flash floods, and debris flows in southern Taiwan’s mountainous areas caused widespread paralysis of the transportation system. In 2011, the Great East Japan Earthquake and subsequent tsunami disrupted transportation networks, leaving remote mountainous areas without timely rescue support for an extended period. These events demonstrate that, under complex topographical constraints, the operational efficiency of emergency logistics systems directly determines the extent to which disaster losses escalate. Establishing an efficient emergency logistics system adapted to mountainous geographical and disaster characteristics is therefore a critical pathway to enhancing regional disaster response capacity.

Within the disaster risk management framework, disaster governance typically includes stages such as risk identification, prevention and mitigation, preparedness, response, and recovery. The preparedness stage serves as a crucial bridge between risk assessment and emergency response. Research on risk governance emphasizes that effective disaster risk reduction relies not only on infrastructure investment, but also on institutional arrangements, organizational coordination mechanisms, and systematic risk management processes [5]. As a key decision-making issue in the preparedness stage, emergency logistics facility location directly affects response efficiency, resource utilization, and social equity. The uncertainty of disaster demand, dynamic changes in transportation networks, and the complex coupling of disaster scenarios render this problem multi-objective, multi-constrained, and highly uncertain[6][7]. In response, existing research has generally formed two main methodological approaches.

The first approach is based on operations research optimization models. Relevant studies construct mathematical programming models or develop improved heuristic algorithms to minimize construction and transportation costs, reduce response time, or maximize service levels. Multi-objective optimization, uncertain demand modeling, and dynamic constraint mechanisms have gradually been incorporated to better capture disaster complexity[8][9][10][11]. Some scholars have further integrated stochastic programming, robust optimization, and intelligent algorithms to model demand fluctuations and transportation uncertainty[12][13]. However, such approaches often rely on strong modeling assumptions, have limited capacity to represent terrain complexity and spatial heterogeneity, and involve high computational complexity, which poses challenges for practical application in mountainous environments.

The second approach integrates GIS with multi-criteria decision-making (MCDM) methods to form a spatial decision-support framework. By combining GIS-based spatial analysis with MCDM-based indicator aggregation and evaluation, this approach enables multi-dimensional factor visualization and ranking, and has been widely applied in emergency facility location studies [15][14][16]. In recent years, methods such as the entropy weight method, the CRITIC method, and prospect theory have been introduced to enhance the objectivity of weight determination and improve decision stability[17][18]. Nevertheless, existing GIS-MCDM studies still show limitations in characterizing multi-hazard spatial risk coupling effects under complex disaster scenarios. Moreover, indicator weights remain to a considerable extent dependent on expert subjective judgment, and the robustness of results requires further improvement.

Some studies have examined disaster preparedness from the perspective of capacity building and training exercises, emphasizing the role of organizational coordination and institutional improvement in risk reduction, thereby expanding the behavioral and institutional dimensions of disaster governance [19]. However, these studies mainly focus on drill mechanisms and organizational processes, and have not systematically incorporated spatial geographical constraints and facility layout optimization issues.

In summary, under the context of complex mountainous geography and multi-hazard risk, how to integrate spatial distribution characteristics of disaster risk and enhance the objectivity and robustness of decision results through more scientific weight determination methods remains an issue requiring in-depth research.

Accordingly, this study selects a typical mountainous city as the research object and constructs an integrated framework for emergency logistics facility location that combines GIS spatial analysis with MCDM methods. The research includes: (1) developing a spatial indicator system suitable for complex mountainous terrain conditions, incorporating population distribution, topography, transportation infrastructure, and natural disaster factors; (2) introducing a combined BWM–EWM weighting approach to balance expert preferences while reducing subjective bias, thereby improving the objectivity and robustness of weight allocation; and (3) from the perspective of the preparedness stage in disaster risk management, proposing a spatial facility layout decision model oriented toward pre-disaster planning, to provide scientific support for the construction of emergency logistics systems in mountainous regions.

2. Research Methodology

2.1 Study area

Guizhou Province, located in the southwestern part of China, lies at the core of the Yunnan-Guizhou Plateau. Approximately 88% of its area is covered by bedrock mountains, 9.6% by hills, and 1.4% by river valley basins. The province's terrain is dominated by complex mountain ranges, hills, gorges, and karst landforms, leading to highly varied and rugged topography. Key mountain ranges include the Wuling Mountains, Wumeng Mountains, Daluo Mountains, Qiannan Mountains, and Qiandong Mountains. Most of Guizhou lies at altitudes ranging from 800 to 1500 meters, with karst topography being the most representative feature. Some areas exhibit hill-like characteristics, further complicating the region’s physical landscape.

This diverse geography makes Guizhou particularly susceptible to a wide range of natural disasters, such as flooding, earthquakes, mudslides, and landslides. The province's major river basins, including the Wujiang, Chishui River, Nanpanjiang, Beipanjiang, Duliu River, and Huangguoshu River basins, are primarily located in mountainous or hilly regions. These basins experience high precipitation, narrow river channels, and concentrated water flow, making them prone to frequent floods, particularly during the rainy season (June to September). Moreover, heavy rainfall in the mountainous areas often triggers secondary disasters, such as landslides and mudslides, exacerbating the impacts of flooding and further complicating disaster management efforts.

In addition, Guizhou lies along several fault zones, including the Songtao-Dushan, Yadu-Ziyun, Qiandong, Suining-Rongan, and Kaiyuan-Pingtang fault zones. These faults divide the province into three major seismic blocks: Qiandong, Qianxi, and Qianzhong, which cover almost the entire region. Although historical earthquakes have not reached high magnitudes [20], their sudden onset and destructive potential make them a significant threat to the region. The province’s rugged terrain and limited transportation infrastructure further complicate emergency response efforts, making it challenging to quickly mobilize resources and provide timely relief during disaster events.

Given Guizhou's diverse geography and its frequent exposure to a variety of natural disasters, this study focuses on emergency logistics site selection within the context of natural disasters in the province. The aim is to develop a framework that can be used to optimize logistics sites, improving disaster response efficiency not only for Guizhou but also for other mountainous cities facing similar challenges. The study will focus on 88 county-level administrative regions in Guizhou, with their distribution shown in Fig. 3

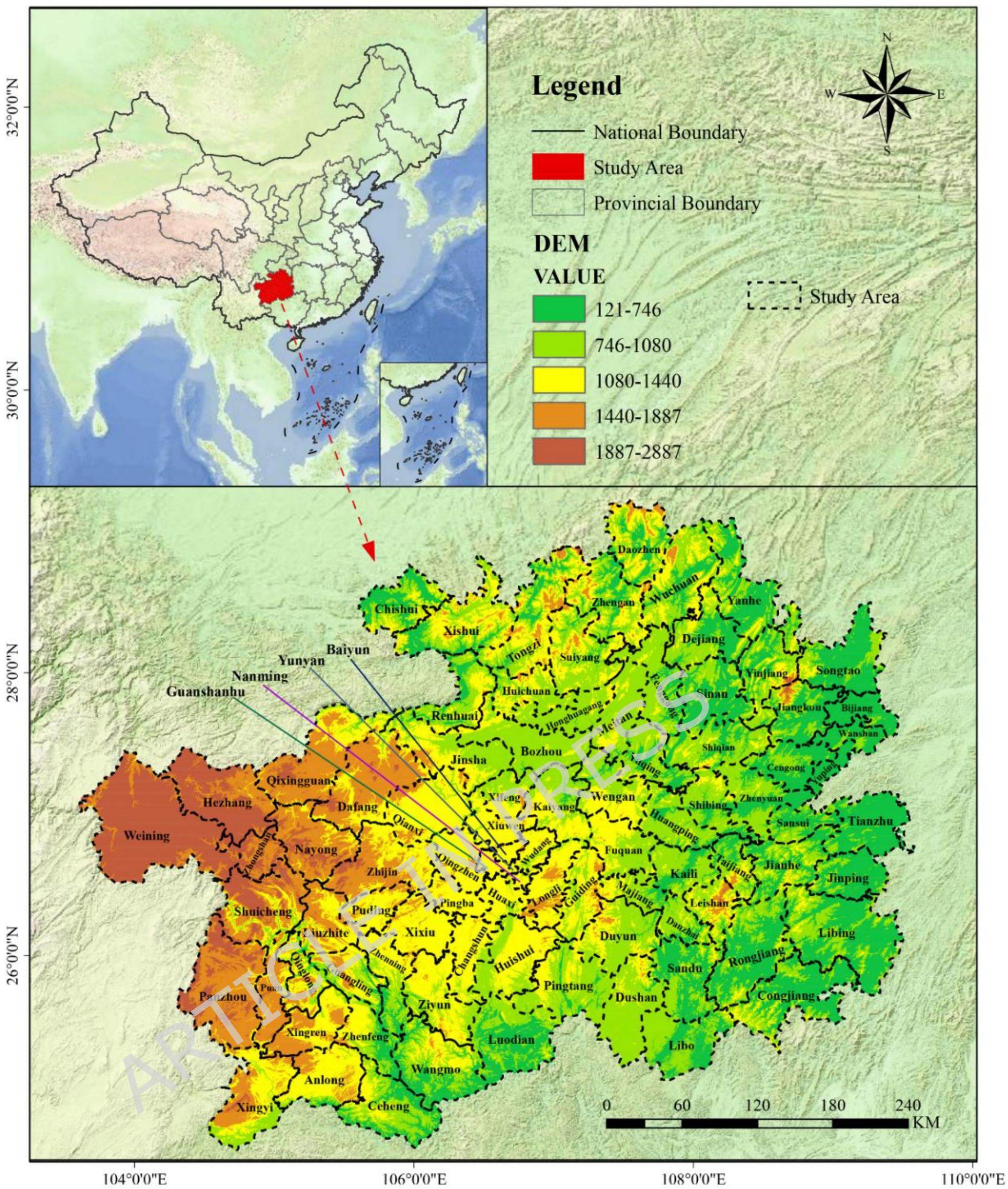

Fig. 3 Research Area

2.2 Methodology and Process

This study proposes a novel Best-worst method–Entropy Weight Method （BWM–EWM） hybrid weighting framework, integrating Geographic Information Systems (GIS) with Multi-Criteria Decision-Making (MCDM) to identify optimal emergency logistics sites in mountainous cities Fig. 4**Error! Reference source not found.**. The methodology comprises five key steps:

(1) Indicator system development: Based on a comprehensive literature review and expert consensus, a structured hierarchy was established using Analytic Hierarchy Process principles, consisting of four criterion-level dimensions and eight sub-indicators [21][22] to comprehensively evaluate site suitability (2) Spatial data analysis: All data layers were processed in ESRI ArcGIS 10.8. Euclidean distance metrics quantified point-to-point proximities to assess accessibility, while kernel

density analysis identified the spatial distribution and concentration of high-risk areas (3) Data normalization: To ensure comparability, all layers were normalized to a [0–1] scale using GIS fuzzy membership functions and raster calculator tools, eliminating differences in measurement units (4) Weight determination: Indicator weights were computed using the BWM–EWM hybrid method, integrating subjective expert judgments with objective data characteristics, thereby enhancing the objectivity and robustness of weight allocation (5)Site suitability mapping and sensitivity analysis: The EBWM–TOPSIS method was applied to generate the site suitability map, followed by sensitivity analysis to assess the robustness of the results to variations in indicator weights.)

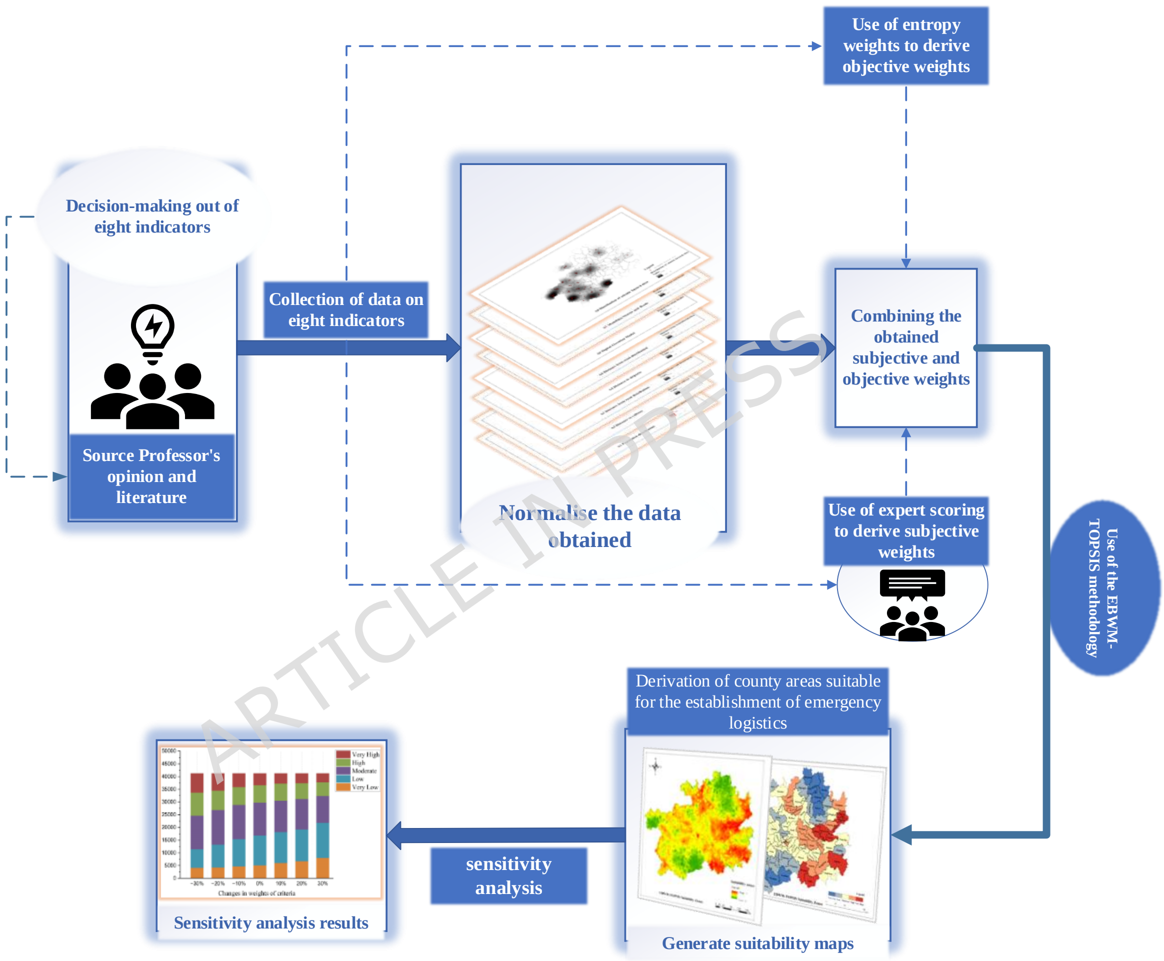

Fig. 4Research Framework

2.2.1 Best-Worst Method（BWM）

The Best–Worst Method (BWM) is a Multi-Criteria Decision-Making (MCDM) approach first introduced by Jafar Rezaei in 2015[23]. The method aims to enhance consistency in pairwise comparisons of criteria or alternatives while reducing the cognitive burden on decision-makers by simplifying the comparison process [24]. Compared with traditional techniques such as the Analytic Hierarchy Process (AHP), BWM requires significantly fewer pairwise comparisons to derive criterion weights, thereby minimizing cognitive effort during the decision-making process. Owing to these advantages, BWM has demonstrated substantial practical value in MCDM problems, particularly those involving complex indicator systems and expert judgment. The main procedural steps of the method are outlined below:

Step 1 Define the criteria for the indicators and select the best indicator U_b and the worst indicator U_w.

Step 2 The decision-maker must compare the best criterionU_b with all other criteria, and similarly compare the worst criterionU_w. with all other criteria. The comparisons are conducted using the 1–9 Saaty scale, which reflects the relative importance between two criteria: equal importance (1), slight importance (3), moderate importance (5), strong importance (7), extreme importance (9), and the intermediate values (2, 4, 6, 8). Construct a comparison matrix of the weights of the other indicators when compared to the optimal indicator.

$$A_b = (a_{b1} \quad a_{b2},,,,a_{bm}) \tag{1}$$

Constructing a comparison matrix of the weights of other indicators when compared to the worst indicators

$$A_w = (a_{1w} \quad a_{2w},,,,a_{mw}) \tag{2}$$

a_{bi} *and* $a_{iw} \in \{1.2....8,9\}$

$U_w.(w_1 \quad w_2,,,,w_n)$

$$\min_j \max\left\{\left|\frac{W_b}{W_i}-a_{bi}\right|,\left|\frac{W_i}{W_w}-a_{iw}\right|\right\} s.t, \sum_{j=1}^{n} w_j = 1, w_j \geq 0 \; \forall \in j \tag{3}$$

The original formula is more complicated; in order to simplify the calculation process, we have carried out an appropriate conversion, and the obtained formula is as follows.

$$\min\zeta\left\{\left|\frac{W_b}{W_i}-a_{bi}\right|,\left|\frac{W_i}{W_w}-a_{iw}\right|\right\} s.t, \sum_{j=1}^{n} w_j = 1, w_j \geq 0 \; \forall \in j \tag{4}$$

Parameter ζ in the equation will be used to determine the inconsistency rate for calculating the weights

Step 4 CR Determination

After obtaining the optimal weights of the indicators from BWM, the reliability of the results needs to be considered, and the reliability is calculated by calculating the Consistency Ratio (CR), which can be used for calculation by ζ The formula is as follows

$$CR = \frac{\zeta}{CI} \tag{5}$$

Consistency Index CI based on order of preference from best to worst criteria

2.2.2 Entropy Weight Method（EWM）

The Entropy Weight Method (EWM) is a widely used objective weighting technique in multi-criteria comprehensive evaluation. By computing the information entropy of each indicator, the method objectively quantifies indicator weights, thereby enhancing the scientific rigor and accuracy of the evaluation process [25]. Compared with other objective weighting approaches, EWM offers several key advantages: (1) high objectivity, effectively minimizing subjective interference; (2) computational convenience, making it well suited for processing large sets of indicators; and (3) the ability to fully reflect the intrinsic information contained in the data, ensuring a rational and data-driven allocation of weights. Owing to these strengths, the entropy method has become a commonly applied tool for determining indicator weights in multi-criteria decision-making problems. The detailed computational steps of the method are outlined below.

In the first step, all raw data are dimensionless (the calculated values are between 0 and 1) and a decision matrix Y is constructed.

For positive indicators (bigger is better)

$$y_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{6}$$

For negative indicators (smaller is better)

$$y_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{7}$$

Where x_{ij} is the original value of the i sample on the j indicator and y_{ij} is the normalised value.

The decision matrix Y

$$Y = \begin{vmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{n2} \\ \cdots & \cdots & \cdots & \cdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{vmatrix} \tag{8}$$

Step 2 Calculate the weight of each indicator.

$$p_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}} \tag{9}$$

where m is the sample size.

Step 3 Calculate the information entropy of each indicator[26]

$$e_j = -K\sum_{i=1}^{m} p_{ij} \ln p_{ij}, K > 0, 0 \le e_j \le 1 \tag{10}$$

$K = \frac{1}{\ln(n)}$, e_j is the information entropy of the j indicator.

Step 4 Calculate the coefficient of variation for each indicator.

$$m_j = 1 - e_{ij} \tag{11}$$

The coefficient of variation m_j reflects the degree of variation in the information of the indicators, the larger the coefficient of variation, the more important the indicator.

Step 5 Calculate the weights of the indicators

$$w_j = \frac{m_j}{\sum_{j=1}^{n} m_j} \tag{12}$$

where n is the number of indicators and W_j is the weight of the j indicator.

2.2.3 BWM-EWM Combined Empowerment

In multi-criteria decision-making (MCDM), indicator weight determination is a critical step that directly affects the rationality, transparency, and scientific validity of decision outcomes [27]. The BWM–EWM approach adopted in this study belongs to a hybrid subjective–objective weighting method that integrates exogenous and endogenous information. Specifically, the Best–Worst Method (BWM) reflects expert knowledge and decision preferences and is therefore classified as an exogenous weighting approach, while the Entropy Weight Method (EWM) derives weights based on the degree of dispersion in indicator data and represents an endogenous, data-driven approach. By integrating these two methods, the proposed approach effectively balances expert judgment and objective data characteristics, reducing the bias associated with purely subjective weighting while avoiding the limited interpretability often encountered in purely data-driven methods. This integration enables a coordinated use of expert knowledge and empirical evidence, thereby enhancing the robustness, effectiveness, and reliability of the overall decision-making process. Consequently, hybrid weighting methods that combine subjective and objective information are increasingly recognized as more scientific and credible approaches in complex MCDM scenarios, particularly in disaster risk management and spatial decision-making contexts[28].

Assuming that the weights given to BWM and EWM are α and 1-α (α is usually taken to be 0.5), respectively, the portfolio weights are

$$W_j^* = \alpha W_j + (1-\alpha) N_j \tag{13}$$

W_j represents the value obtained from the objective weighting method (EWM), and N_j represents the value derived from the subjective weighting method (BWM).

2.3 Combined Empowerment-Improving TOPSIS

The Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) is a multi-criteria decision-making (MCDM) method originally proposed by C. L. Hwang and K. Yoon in 1981[29][30]. By evaluating the performance of alternatives across multiple criteria, TOPSIS provides an efficient and systematic tool that assists decision-makers in identifying the most desirable option.

A key strength of TOPSIS lies in its structured decision-making process. The method simultaneously accounts for the performance of each alternative on all relevant attributes and determines the option that is closest to the ideal solution while farthest from the nadir solution. This dual consideration enables the objective identification of the most preferable alternative among competing options.

Owing to these advantages, TOPSIS has been widely applied in diverse multi-criteria decision-making contexts. The specific procedural steps of the method are detailed below.

Step 1 The first step involves multiplying the standardized decision matrix Y (Equation 8) by the combined weights computed using Formula (13).

$$V = W_j^* \times y_{ij} \tag{14}$$

W_j^* represents the combined weight of the j-th indicator.

Step 2 Find the optimal and negative solutions for each indicator in the alternative scenarios

positive ideal solution

$$V^+ = \max\left(v_{i1}, v_{i2,} v_{i3}\right) \tag{15}$$

negative ideal solution

$$V^- = \min\left(v_{i1}, v_{i2,} v_{i3}\right) \tag{16}$$

Step 3 Measure the proximity of each scenario to the ideal and negative ideal solutions (Euclidean distance)

Distance to ideal solution D_i^+:

$$D_i^+ = \sqrt{\sum_{j=1}^{m} \left(V_{ij} - V_j^+\right)^2} \tag{17}$$

Distance to negative ideal solution D_i^- :

$$D_i^- = \sqrt{\sum_{j=1}^{m} \left(V_{ij} - V_j^-\right)^2} \tag{18}$$

Step 4 Improved relative proximity formula

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{19}$$

The larger the value of C_i, the better the ranking

3 Case studies

3.1 The Construction of the Emergency Logistics Site Selection Indicator System

Based on a systematic review of relevant literature and expert consultations, this study develops an emergency logistics site selection indicator system consisting of four criterion-level dimensions and eight sub-indicators. The four criteria dimensions are as follows: population factors (C1), transportation infrastructure (C2), terrain factors (C3), and natural disaster factors (C4) [31][32][33]. Among these, population factors represent the scale of emergency demand and the spatial distribution characteristics of the population; transportation infrastructure reflects logistics transportation efficiency and accessibility; terrain factors affect the construction conditions of facilities and the operational feasibility of emergency responses; and natural disaster factors determine the region's potential disaster exposure and operational safety.

In the indicator layer, A7 is used to describe the flood and mudslide disasters induced by heavy rainfall in mountainous areas. Given the significant chain reactions and clustering effects of such disasters, they are modeled as a comprehensive disaster system [34]. A8 focuses on earthquakes with a magnitude ≥3.0 that cause casualties and property damage, reflecting the actual seismic risk in the region. The detailed definitions and data sources for each indicator are provided in **Error! Reference source not found.**.

It is important to note that existing research on emergency logistics site selection generally emphasizes factors such as cost, distance, time, and infrastructure, with relatively insufficient consideration of geographic characteristics and potential natural disasters. This gap is particularly pronounced in mountainous cities, where site suitability is influenced not only by conventional factors such as transportation and population but also by significant constraints from natural disasters such as flooding, landslides, and earthquakes. Therefore, in this study, on top of traditional site selection factors, major natural disaster data from the past decade in Guizhou Province's mountainous cities are systematically incorporated. The study evaluates emergency logistics site selection from two dimensions: geographic environmental features and disaster risk exposure. This approach helps develop more realistic and constraint-driven site selection strategies, achieving a comprehensive optimization between supply-demand balance, transportation efficiency, and disaster risk management.

Table 1 Indicator Explanation

Criterion Layer	Indicator Layer	Indicator Explanation	Attribute
Population Factors (C1)	Population Density Distribution (A1)	Areas with high population density often require more rescue supplies and larger logistics facilities.	positive
Transportation Infrastructure (C2)	Railway Distribution (A2)	Should be close to railways to increase transport efficiency	positive
	Road Distribution (A3)	Close to the dense road network to enhance transport flexibility and reduce costs.	positive
	Airport Locations (A4)	Proximity to airports for rapid response and timeliness	positive
Topography and Terrain (C3)	Water System Distribution (A5)	Stay out of the water and reduce the risk of flooding.	negative
	Elevation (A6)	increases ease of transport and reduces disaster risk	negative
Natural Disaster Factors (C4)	Flooding and Mudslide Disasters Induced by Heavy Rain (A7)	Stay away from storm-prone areas	negative
	Earthquake Disasters (A8)	Stay away from earthquake-prone areas	negative

3.3 GIS analysis

In this study, the basic geographical layers of the Guizhou study area were first loaded into the GIS software, with spatial reference unification and geographical annotation completed. The data sources for the various evaluation indicators include https://map.baidu.com; https://map.baidu.com; https://openstreetmap.org; https://www.gscloud.cn/; https://news.ceic.ac.cn/; http://www.mem.gov.cn/; https://www.ndrcc.org.cn/. After data preparation, all indicators were imported into the GIS platform for spatial quantification processing. The specific process is as follows:

(1) For railway distribution (A2), road network distribution (A3), airports (A4), and distance from water systems (A5), Euclidean distance analysis was applied to calculate the minimum distance from each cell to the corresponding feature, generating continuous raster layers. Transportation-related indicators are positively correlated with location suitability, meaning shorter distances imply higher suitability; conversely, distance from water bodies is negatively correlated, as proximity to rivers or streams increases flood risk and is therefore unfavorable for facility placement.(2) For rainfall-induced cascading disasters (A7) and seismic events (A8), Kernel Density Estimation (KDE) was used to quantify spatial intensity and reveal the clustering patterns and potential impact ranges of natural hazards. (3) Population density (A1) was derived from the World Pop 2020 population raster dataset (100-m resolution) and calibrated using the Guizhou Statistical Yearbook 2024 to improve spatial accuracy. Elevation (A6) was obtained from the GDEMV3 dataset (30-m resolution) provided by the Geospatial Data Cloud, representing terrain variation and its influence on location suitability. After completing these spatial processing steps, all raster layers were normalized to a 0–1 scale, ensuring dimensional consistency for subsequent multi-criteria evaluation. In the normalized Grid, areas with a value of 1 (white) indicate high site suitability, while areas with a value of 0 (black) indicate the lowest suitability. All normalized layers are shown in Fig.

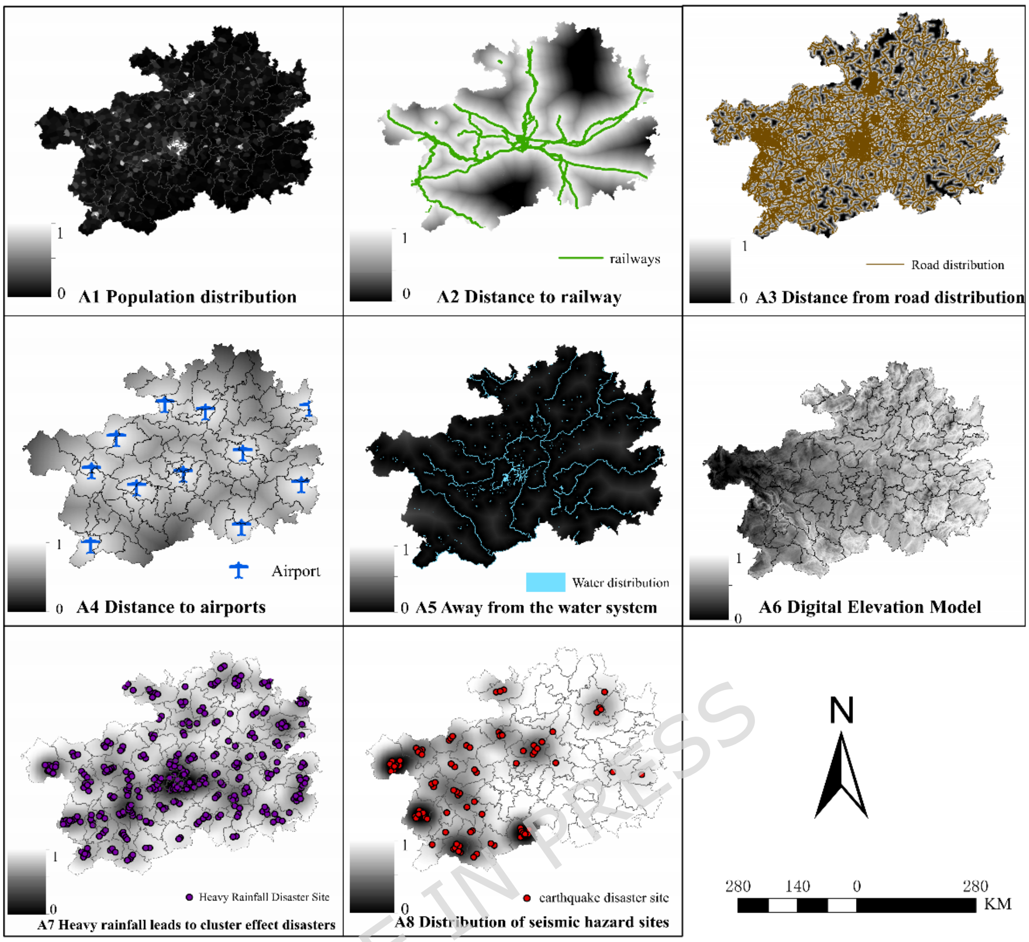

Fig. 5 Indicator data Normalization

3.3Analysis of weighting results

3.3.1 BWM weighting analysis

In the first step of the BWM, the key task is to identify the best and the worst criteria. Based on the consensus of nine experts, population density (A1) was selected as the best criterion, while earthquake disaster (A8) was identified as the worst criterion. Detailed background information of the experts is provided in.Table 2.

According to the second step of the BWM, the experts constructed two comparison vectors—the best-to-others vector (U_b) and the others-to-worst vector (U_w)—using a 1–9 scale and assigned values to each criterion based on their professional experience. Subsequently, criterion weights contributed by each expert were computed using Equation (5) in the SPSSAU environment. Table 3 presents the consistency index (CI) for each expert, and Table 4 summarizes the weight vectors obtained from all nine experts. To ensure reliability, the consistency ratio (CR) of each vector was calculated using Equation (6) and is shown in the last row of the table. In this study, all CR values are below 0.1, indicating that the derived weights are consistent and credible.

As shown in Table 4, population density (A1) has the highest weight (0.2444), whereas earthquake disaster (A8) has the lowest weight (0.066). This result highlights the dominant role of population distribution in emergency logistics facility location, while seismic factors exert relatively minor influence, reflecting the importance of population-related considerations in mountainous emergency logistics planning.

Table 2 Expert information

Expert	Field	Degree	professions	Experiences(year)
Expert 1	Disaster management	Ph.D.	university professor	16
Expert 2	Disaster management	Ph.D.	Relevant Professional Practitioners	23
Expert 3	Disaster management	Ph.D.	university professor	15
Expert 4	Disaster management	Ph.D.	Relevant Professional Practitioners	14
Expert 5	Disaster management	Ph.D.	university professor	24
Expert 6	Urban risk	Ph.D.	Relevant Professional Practitioners	18
Expert 7	Urban risk	Ph.D.	university professor	15
Expert 8	Urban risk	Ph.D.	university professor	14
Expert 9	Urban risk	Ph.D.	university professor	16

Table 3 Coherence index

	1	2	3	4	5	6	7	8	9
CI	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

Table 4 BWM weighting results

Expert	A1	A2	A3	A4	A5	A6	A7	A8
Expert 1	0.2316	0.1909	0.1405	0.1053	0.0795	0.0941	0.0988	0.0593
Expert 2	0.2598	0.1425	0.1547	0.0784	0.0949	0.0948	0.1163	0.0586
Expert 3	0.2511	0.1161	0.1261	0.1043	0.1126	0.1044	0.1157	0.0697
Expert 4	0.2124	0.1424	0.1373	0.0953	0.1207	0.1191	0.1216	0.0512
Expert 5	0.2682	0.1363	0.143	0.0981	0.1022	0.1022	0.0804	0.0696
Expert 6	0.2641	0.1594	0.1489	0.0712	0.0868	0.0751	0.1196	0.0749
Expert 7	0.2216	0.1348	0.1736	0.0788	0.0824	0.1204	0.1085	0.0799
Expert 8	0.2505	0.1255	0.1417	0.1103	0.087	0.0948	0.1173	0.0729
Expert 9	0.2411	0.1342	0.1452	0.089	0.1108	0.1112	0.1098	0.0587
N_j	0.2444	0.1424	0.1456	0.0923	0.0974	0.1017	0.1102	0.066
CR	0.025	0.044	0.034	0.026	0.041	0.027	0.02	0.023

3.3.2 Entropy weighting method weighting analysis

After importing the processed indicator data into ArcGIS, all datasets were converted to raster format, ensuring complete consistency across layers in terms of spatial reference (UTM Zone 48N), pixel resolution, and the number of rows and columns. This alignment guarantees spatial comparability for subsequent multi-criteria overlay analyses. The pixel values of each indicator raster were then exported and imported into MATLAB R2024b. When constructing the entropy-weight model, positive and negative normalization formulas were applied according to the attribute characteristics of each indicator. Population density (A1), railway distribution (A2), road distribution (A3), and airport distribution (A4) are positively correlated with suitability and were therefore processed using positive normalization. In contrast, indicators associated with risk—distance from water systems (A5), elevation (A6), rainfall-induced cascading disasters (A7), and earthquake disasters (A8)—were standardized using inverse normalization. Following the completion of spatial data normalization, the entropy-weight method was employed to quantify the information contribution of each indicator and calculate their objective weights.

The results are shown in Table 5.Population density (A1) has the highest weight (0.2427), indicating that it possesses the strongest information discriminability within the evaluation system and contributes most significantly to the suitability assessment of emergency logistics site selection. This is followed by distance from water systems (A5) with a weight of 0.1253 and road distribution (A3) with a weight of 0.118, highlighting the crucial roles of transportation accessibility and flood-related risk in regional planning. In contrast, rainfall-induced cascading disasters (A7) have the lowest weight (0.0995), suggesting limited information dispersion within the dataset and a relatively weaker impact on the comprehensive evaluation of site suitability.

Table 5 Entropy weighting method weight values

	A1	A2	A3	A4	A5	A6	A7	A8
W_j	0.2427	0.1058	0.118	0.1033	0.1253	0.1022	0.0995	0.1032

3.3.3 EBWM portfolio empowerment

To obtain more scientifically grounded and robust indicator weights, this study adopts a combined weighting strategy that couples the subjective weights derived from the BWM method with the objective weights generated using the entropy evaluation method (EWM), producing the integrated weight system EBWM. By systematically summarizing and comparing the three sets of weights (BWM, EWM, and EBWM), a solid foundation is established for the subsequent comprehensive evaluation of emergency logistics site selection. The final EBWM weights are presented in Table 6.

The results show that population density (A1) holds the highest combined weight (0.2431), highlighting its dominant influence on emergency logistics site selection. Road distribution (A3) and railway distribution (A2) follow with weights of 0.1318 and 0.1241, respectively, indicating that transportation accessibility plays a critical role in determining optimal facility locations. The weight for distance from water systems (A5) is 0.1113, reflecting the continued significance of flood-related risks in facility layout planning. The remaining indicators are ranked as follows: rainfall-induced cascading disasters (A7) at 0.1049, elevation (A6) at 0.1019, airport distribution (A4) at 0.0983, and earthquake disasters (A8) at 0.0846.

From the perspective of disaster emergency response and rescue demand, the rationality of these weight distributions becomes evident. The dominance of population density is attributed to the fact that densely populated areas are more prone to large-scale casualties during disasters, with correspondingly urgent needs for emergency supplies such as food, water, and medical resources; thus, such areas warrant higher priority in site-selection decisions [35]. The prominence of railway and road indicators reflects the essential role of well-developed transportation networks in enhancing the efficiency of material dispatch and the coverage of rescue operations [36]. Regarding topographical factors, high-altitude regions are more susceptible to geological hazards, whereas low-lying and gently sloping areas are more conducive to facility safety and transport accessibility [37]. The lowest weight assigned to earthquake disasters corresponds to the relatively low seismic activity within the study area.

As illustrated in Fig. , the BWM and EEW weights show noticeable differences, whereas the EBWM weights fall between the two distributions. This indicates that the combined weighting approach effectively integrates subjective expert knowledge with objective data-driven information, reducing the potential biases introduced by relying on a single weighting method and enhancing the stability and reliability of weight allocation. Therefore, the combined weighting model offers stronger comprehensiveness and interpretability than either subjective or objective weighting alone, and demonstrates clear application advantages in the context of this study.

Table 6 Weight Coefficients of Indicators in Weighting Methods

Indicator Layer	BWM Weight	EWM Weight	Combined Weight
A1	0.2444	0.2427	0.2431
A2	0.1424	0.1058	0.1241
A3	0.1456	0.1180	0.1318
A4	0.0923	0.1033	0.0983
A5	0.0974	0.1253	0.0918
A6	0.1017	0.1022	0.1113
A7	0.1102	0.0995	0.1019
A8	0.066	0.1032	0.0846

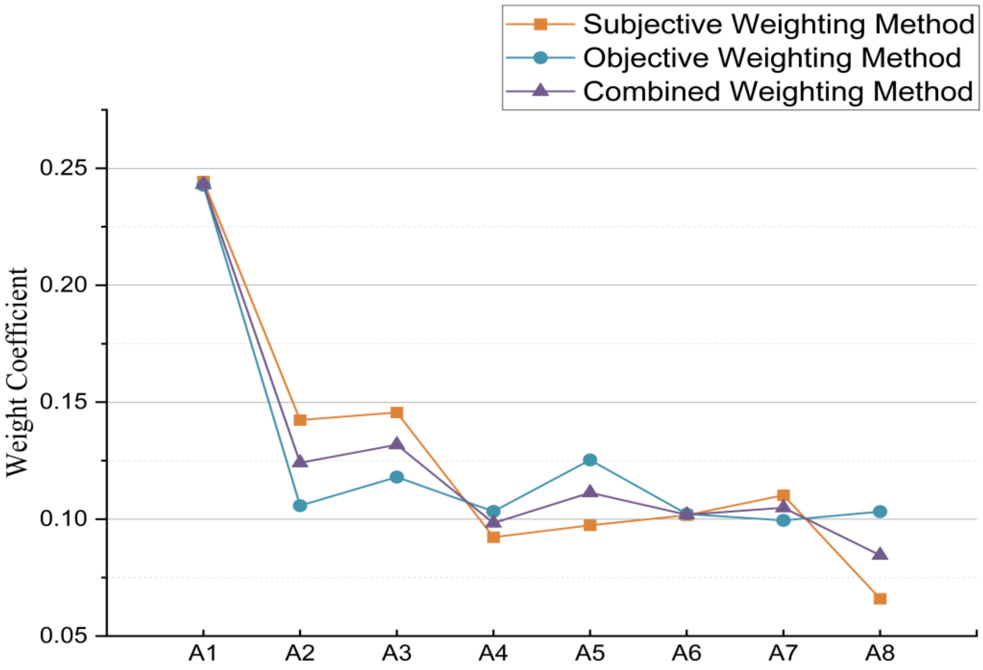

Fig. 6 Comparison of Weight Values

4 Results

The multi-criteria decision-making (MCDM) method employed in this study is an improved version of the TOPSIS method, combined with the weights obtained from BWM-EEM for comprehensive analysis. The implementation of the TOPSIS method was conducted using MATLAB R2024b software. By establishing the EBWM-TOPSIS model, an emergency logistics suitability map was generated based on GIS. The natural breaks classification method (Jenks) in ArcGIS was applied to perform a detailed five-level classification of the map, dividing it into very low, low, moderate, high, and very high suitability levels. As shown in the figure, the suitability map clearly displays the spatial distribution of each level. The Jenks classification system, commonly used in GIS, has the advantage of minimizing intra-class variance and maximizing inter-class variance by considering the natural grouping of data, thereby optimizing classification boundaries and more accurately revealing the distribution characteristics of spatial data [38].

Error! Reference source not found. provides a detailed percentage distribution of the areas in each category, with deep red representing the most suitable areas for emergency logistics and dark green representing the least suitable areas. Based on the ranking, these areas were categorized into five levels, and **Error! Reference source not found.** presents the area covered by each suitability level for emergency logistics. Specifically, the very high suitability areas account for 12.8% of the total area, high suitability areas account for 14.3%, moderate suitability areas account for 40.4%, low suitability areas account for 20.4%, and very low suitability areas cover 12.1%.

In this study, the "Zonal Statistics" tool in ArcGIS 10.8 was used (commonly applied to raster or vector data such as administrative divisions, land use classification, risk zones, and slope categories) to calculate the average suitability value of grid cells within each administrative region. The results are shown in **Error! Reference source not found.**. GIS-based spatial analysis provides a clear view of the overall suitability for emergency logistics site selection across different regions, offering a reliable basis for comparing regional differences.

From the suitability evaluation map, it is evident that there are significant spatial differences in suitability across regions. Notably, areas such as Yunyan District, BiJiang District, Wanshan District, Yuping County, Zhenyuan County, Sansui County, Shibing County, Dushan County, Liping County, and Libo County exhibit relatively high average suitability values and are thus identified as preferred zones for emergency logistics facility placement. These areas have comprehensive advantages in terms of transportation accessibility, population distribution, and geographic environment, which contributes to their higher suitability ratings in the comprehensive weight assessment.

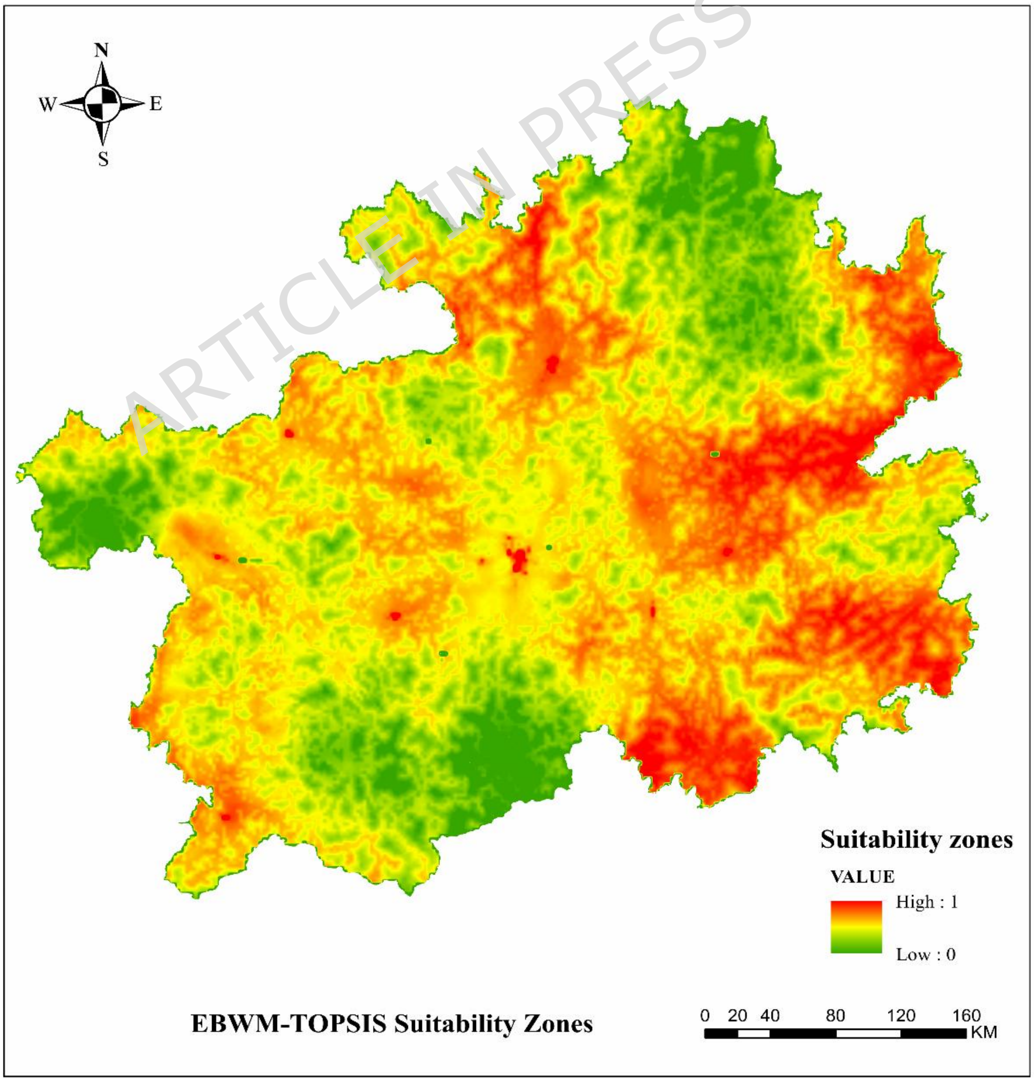

Fig. 7 Region of suitability for emergency logistics site selection in Guizhou Province

Table 7 Percentage area of each suitability for emergency logistics areas

Suitability	Area(Km^2)	Area(%)
Very Low	19730.704	12.1%
Low	35938.068	20.4%
Moderate	74694.808	40.4%
High	25896.549	14.3%
Very High	19906.871	12.8%

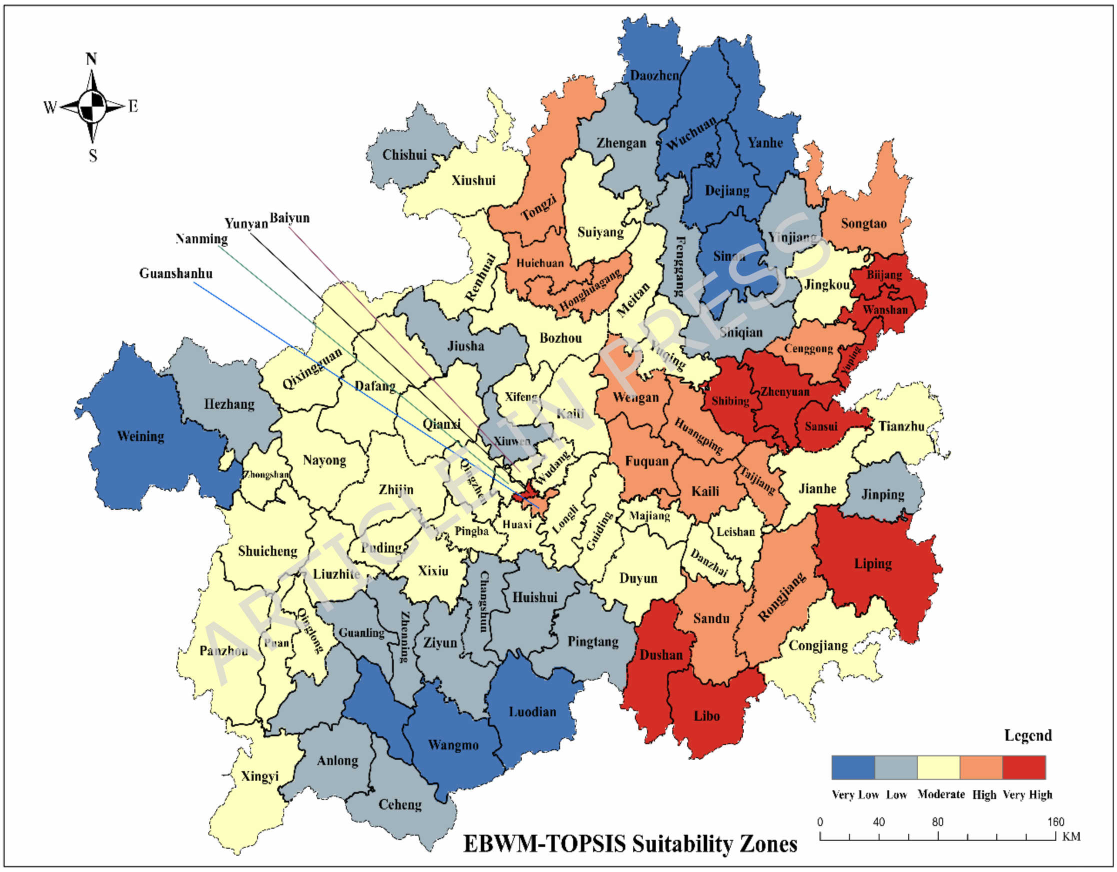

Fig. 8 Guizhou Province emergency logistics suitable for counties and districts

4.1 sensitivity analysis

The emergency logistics site selection problem is often influenced by various uncertain factors, which may fluctuate in real-world applications. To ensure the robustness of the site selection decision across different scenarios, it is necessary to conduct a sensitivity analysis on key indicators and their weights. The core method of sensitivity analysis is to adjust the input indicator weights and quantify their impact on the output result—namely, the emergency logistics site suitability map. Specifically, in this study, the weights of various indicators in the GIS layers were adjusted at predefined percentage change (PC) levels, and the effect of weight changes on the site selection results was analyzed. This process allows for the identification of the most sensitive indicators in the site selection outcome and assesses the stability of the overall site selection plan under weight fluctuations.

$$c_i = c_{io} \mp c_{io} \times pc \tag{20}$$

In this basic process, the weights of key conditions are mainly adjusted. The weights of other indicators are adjusted according to specific equations and proportionally accordingly to ensure the rationality and accuracy of the whole analysis process.

$$c_j = (1 - c_i) \times \frac{(c_{jo})}{(1 - c_{io})} \tag{21}$$

where C_j is the new weight value assigned to indicator j and is the weight of the indicator at the particular PC level. For example, when the weight value of the population density criterion (0.2431) is increased by 30 per cent, equations 20 and 21 can be used as follows.

$$c_i^{dop} = 0.2431 + 0.2431 \times 30\% = 0.3160$$

$$c_j^{dftr} = (1 - 0.3160) \times \frac{0.1241}{(1 - 0.2431)} = 0.1121$$

In this study, a “stepwise adjustment of the maximum-weight indicator” strategy was employed to assess the sensitivity of the evaluation framework to perturbations in indicator weights. Population Density Distribution (A1)—the indicator with the highest baseline weight—was selected as the core variable, and its weight was adjusted within a range of −30% to +30% in increments of 10%, forming six adjustment levels. In each iteration, the weights of all remaining indicators were proportionally rescaled to ensure that the total weight remained equal to 1. A suitability evaluation map was regenerated in each run using the improved TOPSIS model to examine how changes in weights affect spatial patterns.

Suitability levels for the study area were classified into five categories using the Jenks natural breaks method, with class boundaries kept consistent with those in **Error! Reference source not found.**. The sensitivity analysis reveals that increasing the weight of population density substantially reduces the extent of highly suitable zones, whereas decreasing the weight shifts the overall suitability distribution upward. As shown in Figure 9, among the 41,928 raster cells, a 30% increase in the population density weight reduces the proportion of “highly suitable” areas to 8.21%, while the share of “highly unsuitable” areas rises to 19.4%. Conversely, when the weight is reduced by 30%, the proportion of “highly suitable” areas increases to 18.1%, and the proportion of unsuitable areas decreases to 10%. These results indicate that the spatial heterogeneity of population density in the study area is pronounced, and changes in its weight exert a strong dominant effect on the overall evaluation, demonstrating high sensitivity to this indicator.

Fig. and Fig. show that suitability changes are concentrated primarily in the southeastern region and the central basin of Guizhou, whereas the northwestern part—characterized by poor transportation accessibility, complex terrain, and higher exposure to natural hazards—remains consistently in the “less suitable to highly unsuitable” range regardless of weight perturbation. This indicates that entrenched geographical disadvantages render this region insensitive to weight changes. Further zonal statistics reveal that under the +30% scenario, only a limited number of counties with flat terrain and favorable transportation conditions maintain high suitability. Under the −30% scenario, however, highly suitable areas expand significantly, newly appearing across multiple counties in the central and eastern regions, confirming that reducing the weight of population density weakens its restrictive effect on site-selection outcomes.

The sensitivity analysis supports three major conclusions:(1) The population density indicator exhibits the highest sensitivity and is the dominant factor shaping spatial suitability patterns(2) The overall suitability structure of the study area shows a degree of stability, but the southeastern region and central basin respond most strongly to weight variations(3) The northwestern region of Guizhou, constrained by topography and transportation limitations, shows minimal sensitivity to weight perturbations.

Table 8 Sensitivity analysis calculation results

Change	A1	A2	A3	A4	A5	A6	A7	A8
30%	0.3160	0.1121	0.1108	0.0883	0.1096	0.0921	0.0947	0.0764
20%	0.2922	0.1161	0.1139	0.0915	0.1135	0.0953	0.0984	0.0791
10%	0.2678	0.1201	0.1178	0.0951	0.1174	0.0986	0.1014	0.0818
0	0.2431	0.1241	0.1318	0.0983	0.1113	0.1019	0.1049	0.0846
-10%	0.2189	0.1282	0.1257	0.1013	0.1252	0.1052	0.1082	0.0873
-20%	0.1946	0.1321	0.1296	0.1044	0.1291	0.1085	0.1116	0.0901
-30%	0.1702	0.1362	0.1335	0.1072	0.1336	0.1117	0.1149	0.0927

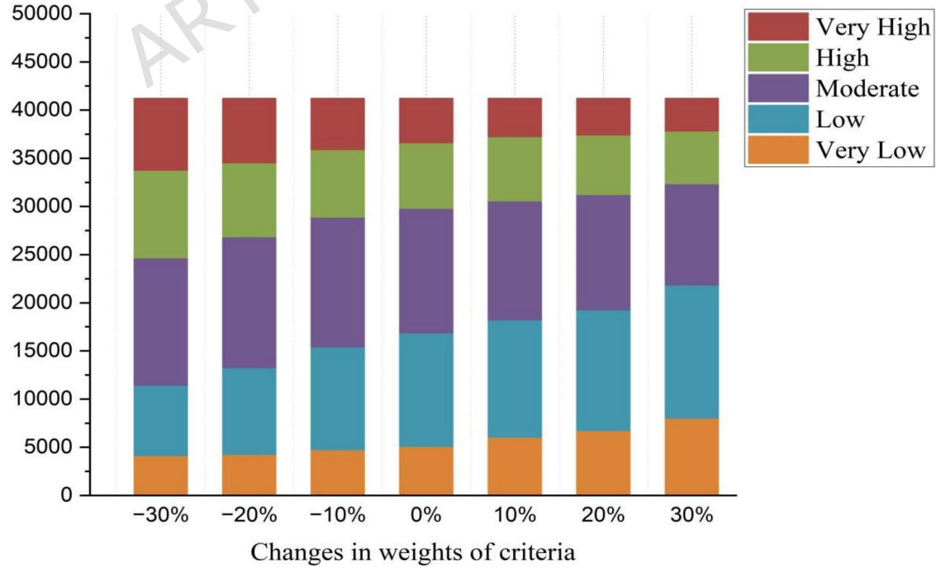

Fig. 9 Number of Grid in each percentage of sensitivity analysis

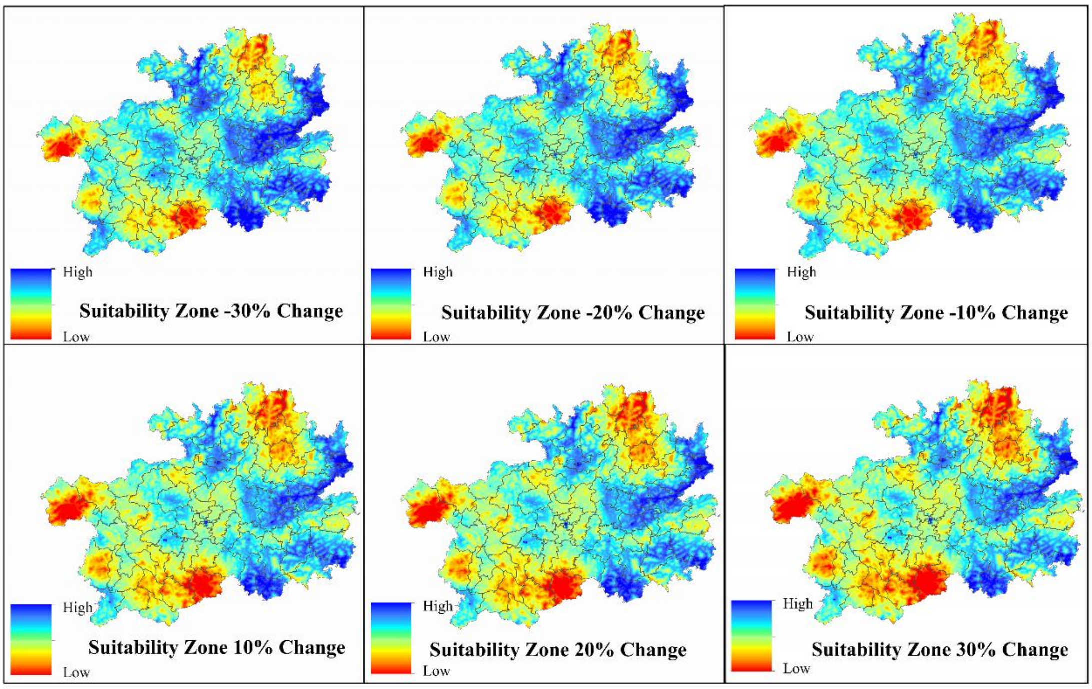

Fig. 10 Emergency Logistics Suitability Area by Percentage

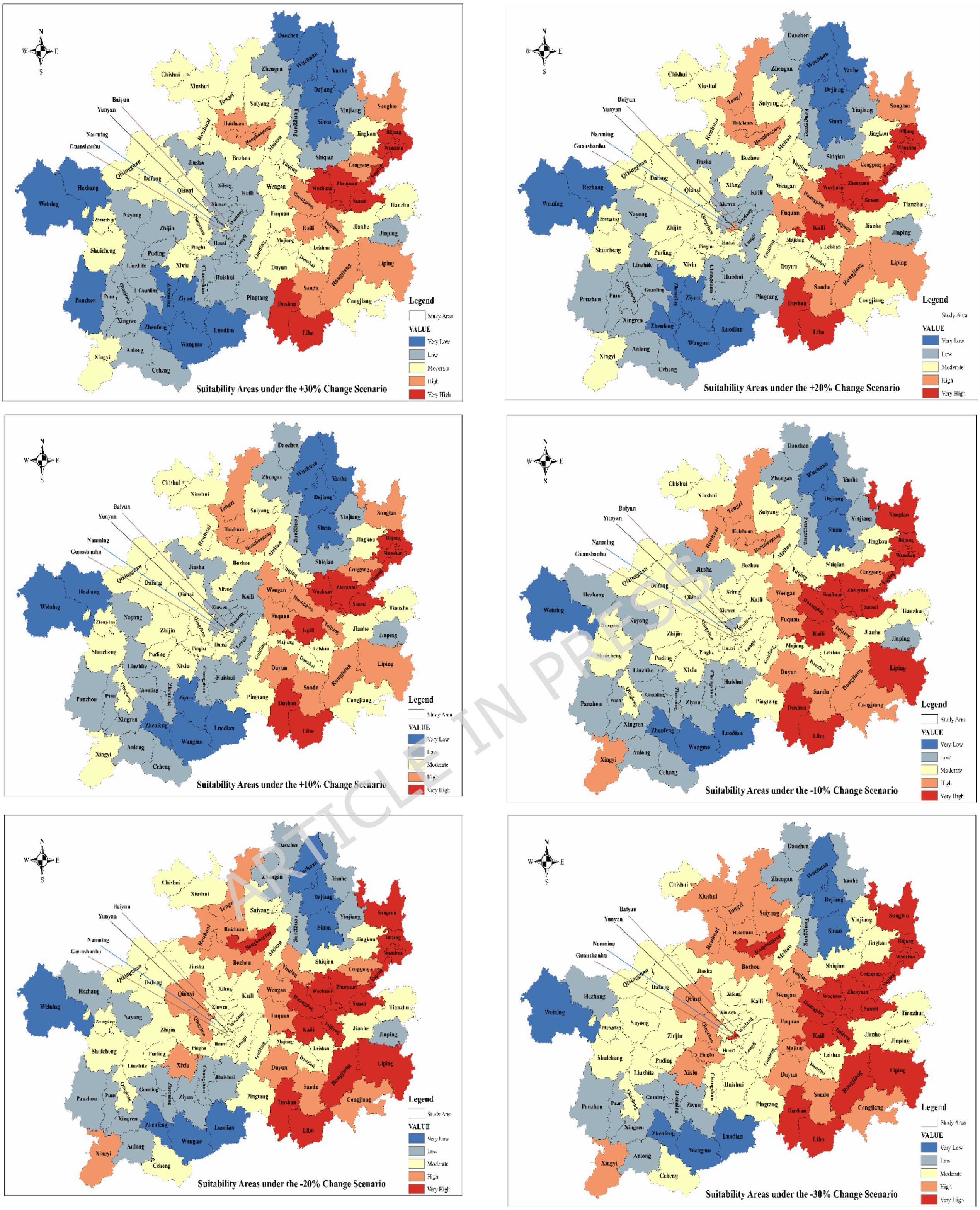

Fig. 11 Emergency Logistics Suitability Zones by Percentage

5 Discussion

The results indicate that the suitability of emergency logistics facility location in mountainous Guizhou exhibits a pronounced spatial pattern characterized by “higher suitability in the east and lower suitability in the west.” This spatial structure is not driven by a single factor but is formed through the coupling effects of demand scale, transportation efficiency, terrain constraints, and hazard exposure levels. From the perspective of population density (C1), areas with higher population concentrations receive higher comprehensive evaluation scores due to their greater emergency material demand and node importance. Central urban districts such as Yunyan District and Bijiang District become primary preferred areas because of their highly concentrated populations. This is consistent with the results of both BWM and EWM, which identify population density (A1) as the most important indicator, and is also highly consistent with the findings of [18]. Sensitivity analysis shows that even under scenarios of population weight fluctuation, densely populated areas maintain high evaluation grades, indicating that the population factor exhibits strong stability in influencing final siting results; Transportation infrastructure (C2) demonstrates a strong dominant role in the comprehensive evaluation. The presence of multiple railways, highways, and aviation hubs significantly enhances regional emergency logistics efficiency, leading to high rankings for transportation nodes such as Yunyan District, Bijiang District, Sansui County, and Yuping County. Sensitivity analysis further reveals that when the weight of transportation indicators is slightly increased, the boundaries of high-suitability areas in transportation-advantaged regions expand accordingly. This suggests that transportation accessibility constitutes an irreplaceable foundational condition for emergency logistics siting in mountainous cities; Terrain factors (C3) play a structural constraint role in the siting pattern of Guizhou Province. Basins, hills, and low mountain areas exhibit clear advantages in the model due to their relatively favorable construction conditions. Counties such as Zhenyuan County, Wanshan District, and Liping County receive high suitability evaluations because of their basin or gentle slope terrain. In contrast, western high-mountain canyon areas, characterized by steep slopes and highly fragmented surfaces, obtain significantly lower scores in the comprehensive evaluation. This further confirms the necessity of incorporating elevation, hydrological distribution, and other terrain-related indicators in mountainous siting studies; The inclusion of natural disaster factors (C4) effectively compensates for the limitation of traditional siting models that neglect risk contexts. Rainfall-induced clustered disasters and fault-zone-related seismic distribution exert substantial impacts on suitable areas. Regions such as Bijiang District, Wanshan District, and Yuping County, which experience relatively weak seismic activity and controllable flood risks, demonstrate comparative advantages. Sensitivity analysis further indicates that when the weight of natural disaster indicators increases, some areas originally classified as moderately suitable are rapidly downgraded. This suggests that natural disaster factors possess clear constraint effects and strong discriminative capacity.

Compared with existing emergency logistics siting studies, this research incorporates complex mountainous terrain into the decision constraints. Previous studies predominantly emphasize efficiency maximization logic, whereas in mountainous environments, terrain first defines the feasible decision space. This study adopts an evaluation structure of “feasibility first, efficiency optimization second,” elevating terrain to a first-level constraint condition. Such structural adjustment enhances the applicability of the model to terrain-dominated regions. Furthermore, disaster risk is directly incorporated into the evaluation system. Unlike models that treat disasters merely as background assumptions, this study conducts quantitative risk analysis and uses sensitivity analysis to reveal the significant influence of risk weight changes on decision outcomes. In addition, the study achieves integration of subjective and objective weighting. This approach maintains interpretability while reducing the influence of a single statistical distribution on the weight structure. The consistency between BWM and EWM weight results further strengthens the reliability of the weighting system.

Although this study advances structural integration, several limitations remain. (1) The model is constructed based on static spatial data and does not capture dynamic network degradation, demand fluctuations, or infrastructure functional changes during disaster events. Therefore, the framework is more suitable for pre-disaster strategic siting planning rather than real-time operational optimization during disasters. (2) Risk representation is primarily based on spatial exposure intensity and does not incorporate probabilistic models, compound disaster scenarios, or cascading failure mechanisms. Future research may combine artificial intelligence and machine learning methods to improve accuracy. (3) The model mainly focuses on structural spatial factors and does not incorporate behavioral variables such as organizational coordination capacity, personnel response efficiency, or emergency training levels.

6 Conclusions

This study takes the mountainous region of Guizhou Province as a case and constructs a comprehensive evaluation framework for emergency logistics facility location by integrating GIS-based spatial analysis with the EBWM–TOPSIS multi-criteria decision-making method. Topographic conditions, transportation accessibility, population density distribution, and multi-hazard risks are incorporated into a unified analytical system. The results demonstrate strong consistency and robustness in both spatial pattern identification and mechanism interpretation.

The findings indicate that the suitability of emergency logistics facility location in Guizhou exhibits a significant spatial differentiation characterized by "stronger in the east and weaker in the west." This pattern results from the combined coupling of demand scale, transportation efficiency, topographic constraints, and disaster exposure levels. Eastern regions are characterized by concentrated populations, well-developed transportation networks, relatively moderate terrain conditions, and comparatively controllable risk levels. In contrast, western mountainous areas are constrained by poor accessibility, steep slopes, and higher levels of hazard exposure, resulting in significantly lower suitability.

The weighting results show that population density is the most critical indicator, followed by road and railway accessibility. The ranking outcomes of BWM and EWM are largely consistent, confirming the central role of demand scale and transportation efficiency in mountainous contexts. Because transportation impedance increases nonlinearly with terrain complexity, transportation conditions not only affect service efficiency but also directly determine system responsiveness and operational resilience. Topographic factors function as foundational constraints within the decision-making system. Basin and hilly areas significantly outperform high-altitude and steep-slope regions, indicating that in mountainous environments, location selection is first a matter of feasibility and only subsequently one of efficiency optimization. This finding underscores the necessity of incorporating terrain analysis into emergency logistics planning in mountainous areas. In addition, natural disaster risk exerts a clear suppressive effect on suitability outcomes. Rainfall-induced hazards and seismic distribution effectively differentiate regional risk levels. Sensitivity analysis shows that variations in hazard-related weights significantly influence regional rankings, indicating that risk indicators play a structural moderating role.

This study also has certain limitations. First, the analysis is based on static spatial data and does not capture the dynamic evolution of demand and transportation networks during disaster events. Second, the study focuses primarily on structural spatial layout and does not incorporate non-structural factors such as personnel response capacity and organizational coordination. Future research may introduce dynamic network models and behavioral response mechanisms to achieve an integrated assessment that combines spatial location planning with emergency response capability evaluation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and materials

Original data may be obtained from the corresponding author upon reasonable request.

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