Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Operational Risk Assessment System for Landslide Mitigation Projects: Framework and Case Study

Jingqing Cheng

cheng_hbdz@163.com

Hubei Center of Geological Disaster Control

Zhen Chen

Hubei Center of Geological Disaster Control

Yongheng Sang

The 5th Geological Brigade of Sichuan, Sichuan Bureau of Geology, Chengdu 610203, China

Xin Qiu

Hubei Center of Geological Disaster Control

Liyang Wu

Hubei Center of Geological Disaster Control

Shengsheng Zhang

Hubei Center of Geological Disaster Control

Article

Keywords:

Posted Date: May 6th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9340340/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Operational Risk Assessment System for Landslide Mitigation Projects: Framework and Case Study

Jingqing Cheng[1,2,*], Zhen Chen[1,2], Yongheng Sang[3], Xin Qiu[1,2], Liyang Wu[1,2], Shengsheng Zhang[1,2]

1. *Hubei Center of Geological Disaster Control, Wuhan 430034, China*
2. *Hubei Key Laboratory of Resource and Eco-Environment Geology (Hubei Geological Bureau), Wuhan 430034, China*
3. *The 5th Geological Brigade of Sichuan, Sichuan Bureau of Geology, Chengdu 610203, China*

Abstrcat: Large-scale landslide mitigation projects face complex environmental influences and decline in service performance over their service life. To enhance the level of risk management in landslide mitigation projects, this study developed an operational risk assessment system for such projects based on the Hierarchical Holographic Model (HHM). The system comprises 18 secondary indicators across 4 dimensions: hazard source, retaining structures, environmental factors, and management factors. The Best-Worst Method (BWM) and the improved CRITIC method are used to extract subjective and objective weights, respectively, and a combined weighting scheme is implemented based on game theory. Building on this, a bivariate normal cloud model is introduced to determine the risk indicator levels. The case study results indicate that the operational risk level of the Huangtupo landslide mitigation project is Level III, which is considered a general risk. Notably, the numerical characteristics of the risk clouds regarding the probability and consequence levels for cumulative displacement and stress overload exhibit high values, specifically representing expected values of 5.80 and 6.50 for cumulative displacement, and 6.50 and 7.20 for stress overload,

*Corresponding author.
E-mail: cheng_hbdz@163.com

respectively. These two factors should be central to risk management.

Introduction

As the Three Gorges Follow-up Work Plan nears completion, geohazard prevention efforts in the Three Gorges Reservoir Area(TGRA) will transition from large-scale remediation to a long-term operation and maintenance phase[1]. To date, hundreds of landslide mitigation projects centered on anti-slide piles and lattice anchors have been completed in the TGRA [2,3]. Notably, a significant portion of these projects have been in service over 20 years, entering a critical stage of material aging and performance degradation[4]. Coupled with complex environmental factors such as periodic fluctuations in reservoir water levels and heavy rainfall, the landslide mitigation projects face increasingly severe operational safety risks[5,6]. Although no reports of failed landslide mitigation projects have been documented in the TGRA, cases of project instability caused by extreme weather events have risen annually in recent years [7,8]. To proactively address these challenges, scientifically assessing the operational safety status of landslide mitigation projects and establishing effective risk control mechanisms represent critical scientific issues that must be resolved to achieve long-term prevention and control of geological hazards in the TGRA.

Operational risk assessment for landslide mitigation projects requires consideration of accurate and comprehensive risk factors from multiple perspectives. Zhang et al. evaluated the long-term stability of the landslide-stabilizing pile system under cycles of reservoir drawdown and rainfall,

based on field monitoring data[9]. Liu et al. employed local-scale field investigation and multi-source ground monitoring data to verify the deforming states of active landslides and to evaluate the effectiveness of the landslide engineering remedial works[10]. Jiang et al. proposed a Monte Carlo simulation-based reliability approach to perform system reliability analysis of anchored rock slopes[11]. In terms of operational risk assessments, Huang et al. employed the Analytic Hierarchy Process(AHP) to systematically investigate the effectiveness of landslide mitigation projects, establishing a comprehensive evaluation model that integrates quantitative and qualitative assessments to holistically evaluate the outcomes of landslide mitigation projects[12]. Xia et al. constructed a three-tiered index system to assess slope stability and the safety of anchoring structures[13]. Li et al. introduced time-related parameters to capture evolving risk trends over project lifetimes, ensuring that the selected measures possess long-term effectiveness[14].

Although existing literature provides valuable references for assessing operational risks in landslide mitigation projects, most research predominantly focuses on the ultimate limit state of the structures-essentially answering whether the project will fail under extreme conditions. Other studies on operational risk evaluation systems for landslide mitigation projects primarily focus their assessment indicators on objective monitoring parameters (e.g., ground surface displacement, pile foundation stress) and structural physical conditions. Subjective factors, particularly those related to operational management, changes in the

surrounding environment of the project, and anthropogenic activities, are often overlooked. Given this, this study employs a hierarchical holographic model(HHM) to construct a comprehensive operational risk assessment indicator system. It systematically identifies potential risk factors in landslide mitigation projects across four dimensions: the hazard source (landslide mass), the condition of mitigation structures, surrounding ecological environment, and operation & maintenance. Crucially, the method incorporates the complex interactions of operational risk factors and the underlying mechanisms triggering system failure. Simultaneously, existing models are often limited by their inability to handle large-scale index systems characterized by high randomness and strong fuzziness. In response, we propose an operational risk assessment model for landslide mitigation projects that utilizes a combined weighting 2D cloud model. To address the uncertainty inherent in the data, this study applies Game Theory to synthesize weights derived from the Best-Worst Method(BWM) and an improved Criteria Importance Through Intercriteria Correlation (CRITIC) method, thus mitigating the bias of single weighting approaches. Furthermore, by computing the cloud parameters for each indicator across various risk levels, we generate risk cloud maps that provide an intuitive visualization for identifying the operational risk status of the mitigation structures.

Establishment of Operational Risk Evaluation Indicator System for Landslide Mitigation Projects

Analysis based on HHM

Within the HHM, "hierarchical" denotes the multi-level decomposition of the system, while "holographic" emphasizes the adoption of multiple perspectives for risk identification[15]. Fundamentally, the objective of HHM aims to characterize the inherent and extrinsic features of a system's attributes through the integration and coordination of levels, perspectives, and dimensions. This approach effectively ensures that the project risk identification is both systematic and comprehensive. Since failures in landslide mitigation projects typically evolve through the interaction of multiple factors[16], this study adopts the "human, machine, environment, management" framework from safety science as its theoretical foundation[17]. By integrating this theory with the practical realities of geological hazard mitigation engineering, the systemic elements of the framework are mapped to the specific characteristics of landslide mitigation measures, thereby establishing four evaluation dimensions: "hazard source, retaining structures, environmental factors, and management factors." These four dimensions constitute the first level of the risk assessment framework model developed in this study. Each dimension further extends into sub-dimensions, constituting the second tier of the identification framework model. Given the inherent generalizability and guidance of the framework model itself, this study did not further subdivide the sub-dimensions.

Based on national standards and specifications[18-20] and expert opinions, this study investigated the interaction mechanisms among four dimensions “hazard source, retaining structures, environmental factors, and management factors”. Furthermore, it elucidates the triggering mechanisms responsible for the progressive failure of landslide mitigation projects. Through research on the instability phenomena of mitigation structures, the primary inducements are identified as material deterioration and stress overload. Common characteristics include structural cracking and human engineering activities, which accelerate the dissipation of anti-sliding resistance and the accumulation of deformation energy. Meanwhile, indirect causes are attributed to management deficiencies, delayed maintenance, and insufficient emergency response capabilities. Fig.1 summarizes the interactions among four kinds of factors and their accident-triggering relationships, providing a basis for the sub-dimensions and the second level of the identification framework model.

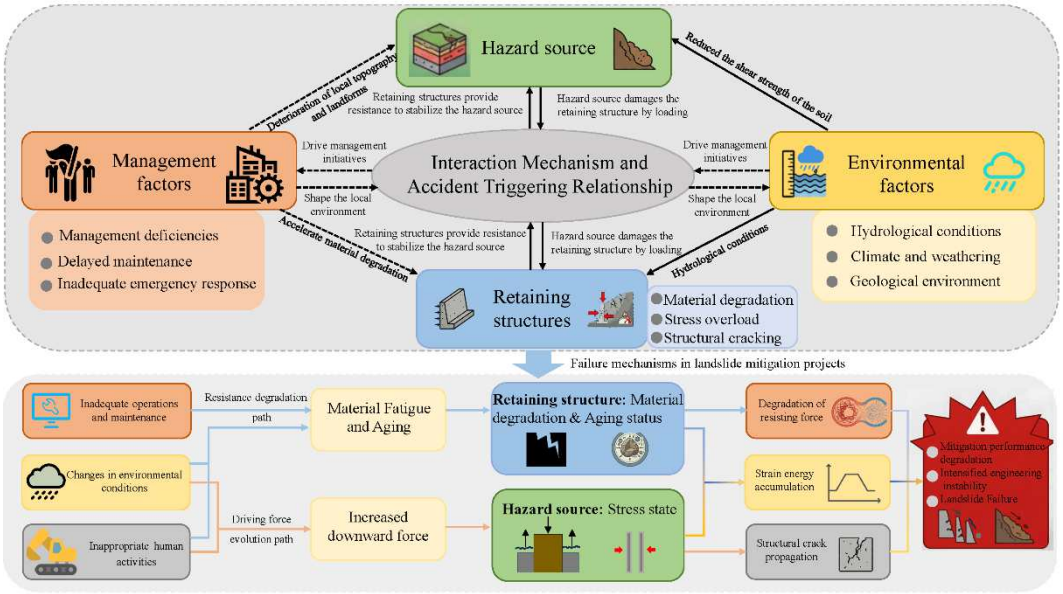


Fig.1 Causative factors of accidents and their interactive relationships in landslide mitigation

135 Establishment of the Assessment Index System

136 By identifying the specific operational risk under the sub-dimensions,
137 this study has determined 18 operational risk factors for landslide
138 mitigation projects based on HHM analysis. These factors are, namely:
139 cumulative displacement, deformation rate, macroscopic cracks,
140 geotechnical strength parameters, concrete cracking, corrosion of
141 reinforcement or anchor cables, stress overload, loss of prestress, structural
142 displacement, clogging of drainage facilities, reservoir level fluctuation,
143 heavy rainfall, inappropriate human engineering activities, agricultural
144 cultivation, monitoring equipment malfunction, irregular routine
145 maintenance, delayed release of early warning information, and deficiency
146 in emergency preparedness.

147 This study analyzed the operational risk of landslide mitigation
148 projects from four dimensions: “hazard source, retaining structures,
149 environmental factors, and management factors”. The indicators are
150 selected based on the risk factors derived from the HHM. Integrating
151 geological hazard expert consultation and adhering to the principles of
152 combining qualitative and quantitative analysis, scientificity, operability,
153 and systematicness, an operational risk assessment system for landslide
154 mitigation projects has been constructed, as shown in Fig. 2.

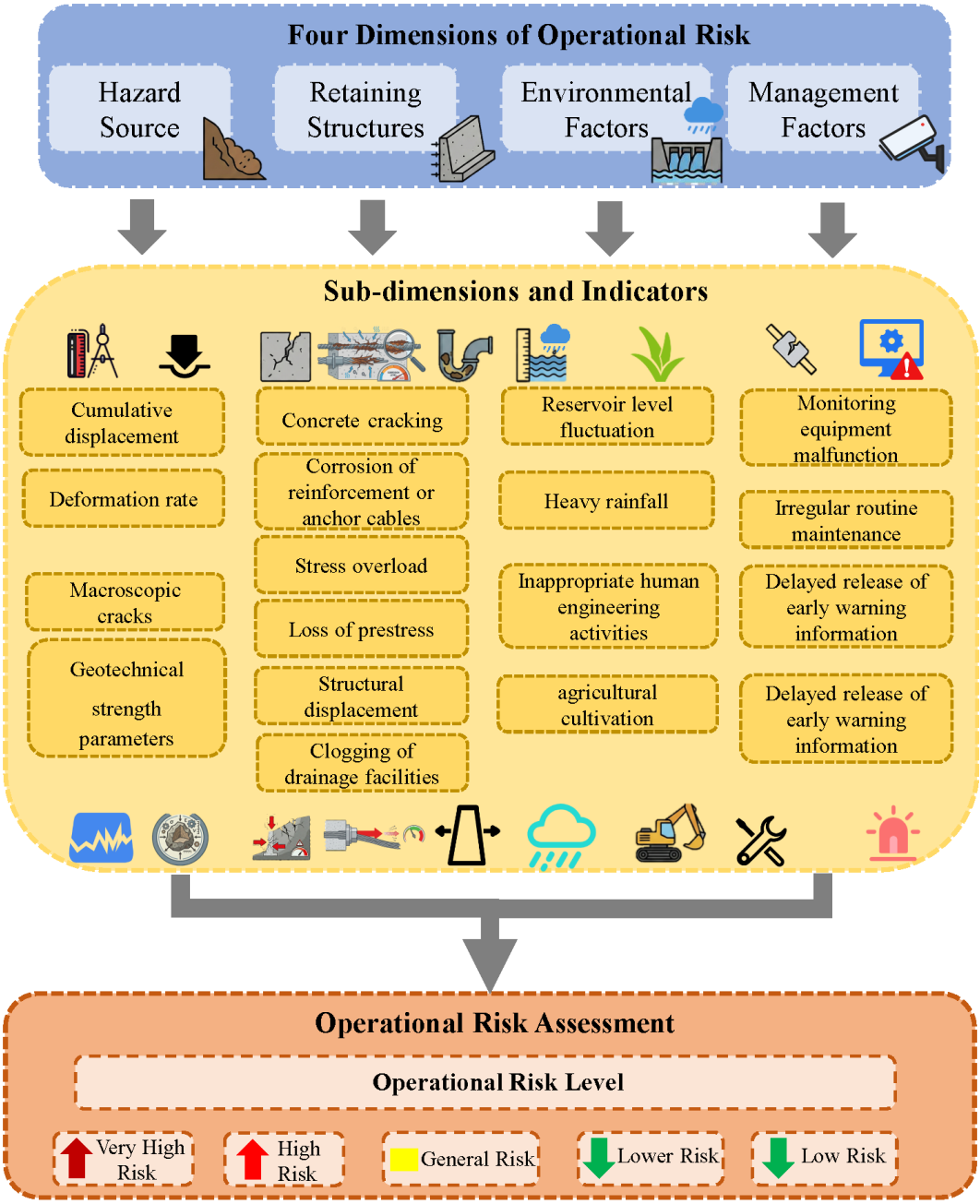


Fig.2 Evaluation indicator system for landslide mitigation projects

Comprehensive operational risk evaluation model

BWM-based improved CRITIC composite weighting method

The weighting of operational risk indicators in landslide mitigation projects reflects the importance of assessment metrics. Game-theoretic combination weighting synthesizes the strengths and weaknesses of

subjective and objective weighting methods, mitigating potential biases from single weighting approaches[21]. The BWM determines the relative importance of each indicator by having decision-makers identify the best and worst indicators and then compare all others against these two benchmarks. Compared to the AHP, BWM achieves consistent conclusions with fewer comparative inputs[22]. The CRITIC method calculates objective weights for each indicator based on the intensity of comparisons and conflicts between individual indicators. To address data conflict and discontinuity, the CRITIC method was enhanced by introducing redundancy information entropy and taking the absolute value of correlation coefficients to eliminate the influence of positive/negative signs. Therefore, this study integrates subjective and objective factors, employing Game Theory to combine the BWM method with the improved CRITIC method, thereby scientifically and reasonably assigning weights to risk parameters.

Comprehensive evaluation based on a bivariate normal cloud model

Basic theory of bivariate normal cloud model

Two-Dimensional cloud model is an evaluation tool that combines probability theory and fuzzy mathematics. It takes into account both risk probability and risk consequences on the basis of the one-dimensional cloud model, and considers the fuzziness of the boundary of the indicator risk level[23]. Points satisfying Eq.(1) become cloud droplets, and a large number of two-dimensional cloud droplets coalesce into a bivariate normal

cloud.

$$\begin{cases} (x_i, y_i) = F(E_{xx}, E_{xy}, E_{nx}, E_{ny}) \\ (P_{xi}, P_{yi}) = F(E_{nx}, E_{ny}, H_{exx}, H_{ey}) \\ \mu_i = \exp\left\{-\frac{1}{2}\left[\frac{(x_i - E_{xx})^2}{P_{xi}^2} + \frac{(y_i - E_{xy})^2}{P_{yi}^2}\right]\right\} \end{cases} \quad (1)$$

Where, F represents a two-dimensional random function with normal distribution characteristics, i is the cloud droplet serial number, x_i and y_i represent the cloud droplet coordinates, P_{xi} and P_{yi} denote the conditional cloud droplet coordinates, E_{xx} and E_{yy} represent the expectations, E_{nx} and E_{ny} are entropies, H_{ex} and H_{ey} are the hyperentropies, μ_i is the membership function of the two-dimensional cloud.

Generation of integrated risk cloud

The integrated risk cloud reflects the overall operational health status of the landslide mitigation project. Using the risk indicators identified in the HHM framework as metrics, the probability level and consequence level are selected as the fundamental variables for risk assessment. By utilizing the combination weights determined by Game Theory as coefficients, the numerical characteristics of the cloud models for secondary indicators are aggregated to generate the primary dimension risk clouds. Subsequently, these primary clouds are further integrated to form the final comprehensive risk cloud. The calculation algorithm is expressed in Eq. (2)

$$C = (w_1, w_2, \cdots w_n)\begin{pmatrix} E_{x1} & E_{n1} & H_{e1} \\ \vdots & \vdots & \vdots \\ E_{xn} & E_{nn} & H_{en} \end{pmatrix} = (E'_x, E'_n, H'_e) \quad (2)$$

Where, E'_x, E'_n, and H'_e are the expected value, entropy, and

hyperentropy of the previous level index, respectively.

Construction of standard risk clouds

Referencing the relevant risk assessment literature[21,24], the operational risk of landslide mitigation projects is classified into five hierarchical levels: Level I (Low Risk), Level II (Lower Risk), Level III (General Risk), Level IV (High Risk), and Level V (Very High Risk). The quantitative evaluation domain is defined within the interval [0, 10]. This domain is equidistantly divided into 5 sub-intervals, each representing a specific risk grade. The numerical characteristic of the standard risk cloud at the j-th risk level, denoted as $C_j\left(\overline{E_{xj}}, \overline{E_{nj}}, \overline{H_{ej}}\right)$, is calculated using Eq.(3) based on the principle of bilateral constraints:

$$\begin{cases} \overline{E_{xJ}} = \dfrac{S_j^{max} + S_j^{min}}{2} \\ \overline{E_{nJ}} = \dfrac{S_j^{max} - S_j^{min}}{6} \\ \overline{H_{eJ}} \in \left[\dfrac{E_{\mathrm{x}}}{100}, \dfrac{E_{\mathrm{n}}}{10}\right] \end{cases} \tag{3}$$

Where, S_j^{min} and S_j^{max} represent the lower and upper boundaries of the interval for the j-th risk level, respectively. The denominator 6 implies that the span of the risk level covers $6\overline{E_{nJ}}$, ensuring that 99.74% of the cloud drops fall within the effective interval according to the rule of normal distribution. $\overline{H_{eJ}}$ represents the discrete randomness of the qualitative concept. Considering the inherent uncertainty and fuzziness of geological monitoring data, $\overline{H_{eJ}}$ is set to 0.05 in this study to maintain a moderate degree of cloud atomization. The calculated parameters for the standard

227 risk clouds and their corresponding interval definitions are presented in
228 Table 1.

229 Table 1. Evaluation standards of risk level

Risk Level	Risk Description	Interval Range $[x_{min},\ x_{max}]$	Cloud Parameters (E_x, E_n, H_e)	Operational Status Description
I	Low Risk	[0,2)	(1,0.333,0.05)	Minimal harm
II	Lower Risk	[2,4)	(3,0.333,0.05)	Minor harm
III	General Risk	[4,6)	(5,0.333,0.05)	Moderate harm
IV	High Risk	[6,8)	(7,0.333,0.05)	Significant harm
V	Very High Risk	[8,10]	(9,0.333,0.05)	Extremely harmful

230 **Similarity measure calculation**

231 Since the bivariate normal cloud maps are three-dimensional views,
232 which may cause visual errors, the proximity method is used to determine
233 the operational risk level of landslide mitigation projects. The higher the
234 proximity, the closer the evaluation result is to the standard risk level
235 corresponding to that proximity.

236 Let the final integrated risk cloud of the landslide mitigation project
237 be$C_j\left(\bar{Ex}_j, \bar{En}_j, \bar{He}_j\right)$. By employing the Monte Carlo simulation method[25],
238 the calculation steps are as follows:

239 1. Generate a normal random number $En' = \mathrm{NORM}(En, He)$ using
240 the entropy En and hyperentropy H_e of the integrated risk cloud.

241 2. Generate a normal random number $x = \mathrm{NORM}(Ex, En')$ as a
242 “cloud droplet” representing the concrete manifestation of engineering risk.

3. Calculate the membership degree u_j of cloud droplet x belonging to the j-th standard risk level C_j. To ensure statistical significance, this process is repeated N times. The average effectiveness represents the similarity metric λ_j, calculated as shown in Eq.(4):

$$\lambda_j = \frac{1}{N}\sum_{i=1}^{N} \exp\left(-\frac{\left(x_i - \bar{Ex}_j\right)^2}{2\left(\bar{En}_j'\right)^2}\right) \quad (4)$$

Where, λ_j is the similarity measure between the project's risk state and the j-th risk level. x_i is the value of the i-th generated cloud drop. $\overline{E_{xj}}$ is the expectation of the j-th standard cloud. $\bar{E}n_j'$ is a normal random number generated from the standard cloud parameters $(\bar{E}n_j, \bar{H}e_j)$.

Analysis of the Huangtupo landslide mitigation project

Assessment project

This study evaluated the landslide mitigation project at Huangtupo in Badong County, located within the TGRA. The landslide complex comprises the “Biandianzhan Landslide”, “Linjiang Landslide I”, “Linjiang Landslide II” and “Yuanyichang Landslide”. Characterized by its massive volume and complex geological environment, it represents a typical case of an exceptionally large landslide within the reservoir area's geological hazard prevention projects. The mitigation system primarily comprises the following subsystems: The anti-slip retaining system, serving as the main load-bearing structure, primarily includes large-section reinforced concrete anti-slip piles and prestressed anchor cables deployed at the landslide's front edge and shear outlet to resist deep-seated

downward thrust. The drainage system, comprising a surface drainage network and deep drainage tunnels, diverts atmospheric precipitation and groundwater seepage to reduce pore water pressure. The slope protection system, including grid anchoring, retaining walls, and slope reduction works, maintains surface stability and controls soil erosion. Since completion, the project has operated for over 20 years, fully enduring the entire cycle of the Three Gorges Reservoir's 175m trial impoundment and multiple extreme rainfall events. A comprehensive monitoring network comprising GNSS displacement, deep inclinometer, and groundwater level measurements is now deployed within the landslide area. This has accumulated long-term operational monitoring data, establishing the data foundation and engineering evidence required for operational risk assessment.

Weighting analysis

The appropriateness of the indicator weights determines the accuracy of the risk assessment results[26]. The BWM-based improved CRITIC combined weighting model is adopted to integrate the subjective weight vector (w_s) derived from expert and the objective weight vector (w_0) extracted from monitoring data, and comprehensively measures various risk indicators from both subjective experience and objective data dimensions.

Subjective Weight Calculation Based on BWM

Five experts in geological disaster prevention, monitoring data analysis, and structural safety were invited to conduct pairwise

comparisons of the importance of risk indicators based on the design and construction report of the loess slope landslide control project, using the 1-9 scale method. Each expert participated voluntarily after being invited and provided informed consent after being briefed on the research objectives and the intended use of their evaluations for publication. Taking the primary indicators as an example, the experts unanimously agreed that "landslide body factor (B1)" was the best indicator, while "management factor (B4)" was the worst indicator relative to the physical state of the landslide body. A comparison vector is constructed and the BWM model is solved. To verify the logical consistency of the expert judgment, a consistency ratio K_s is introduced for testing.

$$K_s = \frac{\xi^*}{CI} \tag{5}$$

Where, ξ^* represents the consistency coefficient obtained from the model optimization solution. CI is the consistency index of the corresponding scale. Calculations show that K_s = 0.038 < 0.1, for the primary indicator, indicating a high degree of consistency and credibility in the expert scores. The calculated subjective weight vector of the primary indicator is w_s = (0.415, 0.273, 0.198, 0.114).

Objective weight calculation based on improved CRITIC

The objective weights were derived from long-term operational monitoring data of the Huangtupo landslide, including GNSS displacement, deep inclinometer data, and anchor cable stress values. The contrast intensity and conflict of 18 secondary indicators were calculated using the improved CRITIC method. By introducing redundant information entropy

and absolute correlation coefficient, this method mitigates the inherent data noise and multicollinearity in geological monitoring, effectively. Indicators such as “cumulative displacement” and “stress overload” exhibit higher contrast and information content, reflecting their sensitivity to landslide operational states.

Game Theory Combination Weighting

To mitigate the bias inherent in single-weighting methods, this study employed Game Theory to reconcile subjective and objective preferences. This method determines the optimal combined weight vector (w^*) by minimizing the bias between subjective and objective preferences. The combined weight of the j-th indicator is calculated as follows:

$$w^* = \alpha w_s + \beta w_o \quad (6)$$

where α and β are the optimal coefficients determined through the game-theoretic optimization process. The specific classification criteria for each operational risk indicator are shown in Table 2.

Table 2. Classification criteria of operational risk indicators

Category	Code	Indicator	Level I	Level II	Level III	Level IV	Level V
B1 Hazard Source	C1	Cumulative displacement (mm)	<50	[50,150)	[150,300)	[300,500)	≥500
	C2	Deformation rate (mm/d)	<0.1	[0.1,0.5)	[0.5,2.0)	[2.0,5.0)	≥5.0
	C3	Macroscopic cracks (m)	None	Small/Local	Moderate	Extensive	Penetrating

	C4	Geotechnical strength (c, ϕ)	<5%	[5%,15%)	[15%,25%)	[25%,35%)	≥35%
	C5	Concrete cracking (mm)	0	≤0.2	(0.2,1.0]	(1.0,5.0]	>5.0
	C6	Corrosion of reinforcement	None	Surface rust	Pitting	Cross-section loss	Failure
B2	C7	Stress overload (P_{act}/P_{des})	<0.70	[0.70,0.85)	[0.85,0.95)	[0.95,1.05)	≥1.05
Retaining Structures	C8	Loss of prestress	<5%	[5%,10%)	[10%,20%)	[20%,30%)	≥30%
	C9	Structural displacement (mm)	<10	[10,30)	[30,60)	[60,100)	≥100
	C10	Clogging of drainage	<5%	[5%,20%)	[20%,40%)	[40%,70%)	≥70%
	C11	Reservoir fluctuation (m/d)	≤0.5	(0.5,1.0]	(1.0,2.0]	(2.0,3.0]	>3.0
	C12	Heavy rainfall (mm/d)	<30	[30,50)	[50,100)	[100,200)	≥200
B3 Environment	C13	Human engineering activities	Minor	Local excavation	Moderate load	Large excavation	Heavy load
	C14	Agricultural cultivation	None	Shallow	Intermed.	Deep plowing	Heavy irrigat.

	C15	Monitoring malfunction	<1%	[1%,5%)	[5%,10%)	[10%,20%)	≥20%
B4 Management	C16	Routine maintenance	[90,100]	[80,90)	[70,80)	[60,70)	[0,60)
	C17	Warning info release	[90,100]	[80,90)	[70,80)	[60,70)	[0,60)
	C18	Emergency preparedness	[90,100]	[80,90)	[70,80)	[60,70)	[0,60)

Analysis of Weighting Results

The calculation results of the classification criteria and combined weights (w^*) for the safety evaluation indicators are shown in Table 2 and Table 3, respectively. The weight analysis reveals the key characteristics of the operational risks of the loess slope landslide control project. The results from the combination weights (w^*) indicate that stress overload (0.0914), cumulative displacement (0.0895), reservoir water level fluctuation (0.0754), and heavy rainfall (0.0682) carry significant weights. This indicates that the operational risks of landslide mitigation projects are primarily influenced by hazard sources, retaining structures, and environmental factors. Among the primary indicators, the disaster source carries the highest weight (0.3852), indicating that deformation of the landslide remains the fundamental driver influencing operational risk. Specifically, cumulative displacement is the most critical parameter characterizing the state of landslide movement. The retaining structure holds the second-highest weight (0.3126), with stress overload being the

most critical secondary indicator. This reflects the actual conditions of Huangtupo landslide: after over two decades of operation, the structural health of the anti-slip piles is sensitive to redistribution of deep downward thrust. The high weighting of stress monitoring underscores the necessity of preventing structural fatigue or sudden failure in reinforced concrete piles.

Furthermore, the significant weights assigned to reservoir water level fluctuations and heavy rainfall within the environmental factors highlight the influence of hydrological conditions on landslides in the TGRA. Periodic reservoir level fluctuations affect pore water pressure and effective stress within landslide mass, thereby regulating loads on retaining structures. Although management factors carry relatively low weight, the prominence of monitoring equipment malfunction underscores the importance of reliable automated monitoring networks for timely anomaly detection.

Table 3. Results of weight calculation for all 18 indicators

Primary Indicator	Subjective Weight (w_{B_S})	Objective Weight (w_{B_O})	Combined Weight w_B^*	Secondary Indicator	Subjective Weight (w_{C_S})	Objective Weight (w_{C_O})	Combined Weight w_C^*
B1 Hazard source	0.415	0.3554	0.3852	C1 Cumulative displacement	0.16	0.137	0.1485
				C2 Deformation rate	0.09	0.077	0.0835
				C3 Macroscopic cracks	0.0646	0.0554	0.0600
				C4 Geotechnical strength	0.1004	0.086	0.0932
B2 Retaining structures	0.273	0.3522	0.3126	C5 Concrete cracking	0.0393	0.0507	0.045

				C6 Corrosion of reinforcement	0.0332	0.0428	0.038
				C7 Stress overload	0.1	0.129	0.1145
				C8 Loss of prestress	0.0511	0.0659	0.0585
				C9 Structural displacement	0.0285	0.0367	0.0326
				C10 Clogging of drainage	0.0209	0.0271	0.024
				C11 Reservoir fluctuation	0.0733	0.0775	0.0754
B3 Environment	0.198	0.2096	0.2038				
				C12 Heavy rainfall	0.0663	0.0701	0.0682

				C13 Human activities	0.0311	0.0329	0.0320
				C14 Agricultural cultivation	0.0273	0.0291	0.0282
				C15 Monitoring malfunction	0.0377	0.0273	0.0325
				C16 Routine maintenance	0.029	0.021	0.0250
B4 Management	0.114	0.0828	0.0984	C17 Warning info release	0.0243	0.0177	0.0210
				C18 Emergency preparedness	0.023	0.0168	0.0199

Evaluation of operational risk levels based on bivariate normal cloud model

To evaluate the operational risk of the Huangtupo landslide mitigation project, the 18 secondary indicators identified in the HHM framework were scored according to the classification criteria in Table 2. Five experts were invited to score the probability and consequence level of each indicator, with a rating range of [0, 10]. Using the combined weights ($w*$) in Table 3, the numerical characteristics of the secondary indicators, primary dimensions, and overall risk cloud are calculated using Eq. (2). The results are shown in Table 4. A comparative visualization of the integrated risk cloud, primary risk cloud, and standard risk cloud generated using a forward cloud generator is shown in Fig.3 and Fig. 4a. A analysis of the risk levels for secondary indicators was conducted. This study selected the B2 Retaining structures factor-which exhibits the highest risk expectation value among primary indicators-and enumerated the risk levels for its five secondary indicators. A comparison cloud map between the secondary risk cloud and the standard cloud was generated, as shown in Fig. 4b.

As shown in Fig. 3, the operational risk level of the Huangtupo landslide mitigation project is between level III and level IV. Due to the potential for visual errors in three-dimensional graphics, this study substituted the characteristic values of the comprehensive risk cloud and the characteristic values of the standard risk cloud into Eq. (4) to calculate the closeness and determine the operational risk level of the Huangtupo landslide mitigation project. The calculated similarities are as follows:

$\lambda_I = 0.0008$, $\lambda_{II} = 0.0831$, $\lambda_{III} = 0.6582$, $\lambda_{IV} = 0.1245$, and $\lambda_V = 0.0021$. Based on the similarity ranking results, the operational risk level of this landslide mitigation project is determined to be Level III. Therefore, a comprehensive analysis across multiple dimensions-namely hazard sources, retaining structures, environmental factors, and management factors—is required, along with the integrated risk control measures to ensure the stable operation of the mitigation project.

As shown in Fig.4a, in the primary level risk cloud, the risk of management factor (B4) can be visually observed as close to level II risk, while the environmental factor (B3) exhibits distinct characteristics of high probability. However, the risks of the hazard source (B1) and retaining structures (B2) almost overlap on the cloud map. Similarity calculations show that both are classified as Level III. Therefore, when implementing risk control measures for Huangtupo landslide mitigation project, special attention should be paid to both the hazard source and retaining structure factors.

As shown in Fig. 4b, among the six secondary indicators of retaining structures (B2), the risk levels of structural displacement (C9) and clogging of drainage (C10) are close to Level II; concrete cracking (C5), corrosion of reinforcement (C6), and loss of prestress (C8) are all close to Level III. Among them, the probability risk level and consequence risk level of the stress overload (C7) indicator are significantly higher than those of the other five indicators in the B2 indicator, directly approaching Level IV.

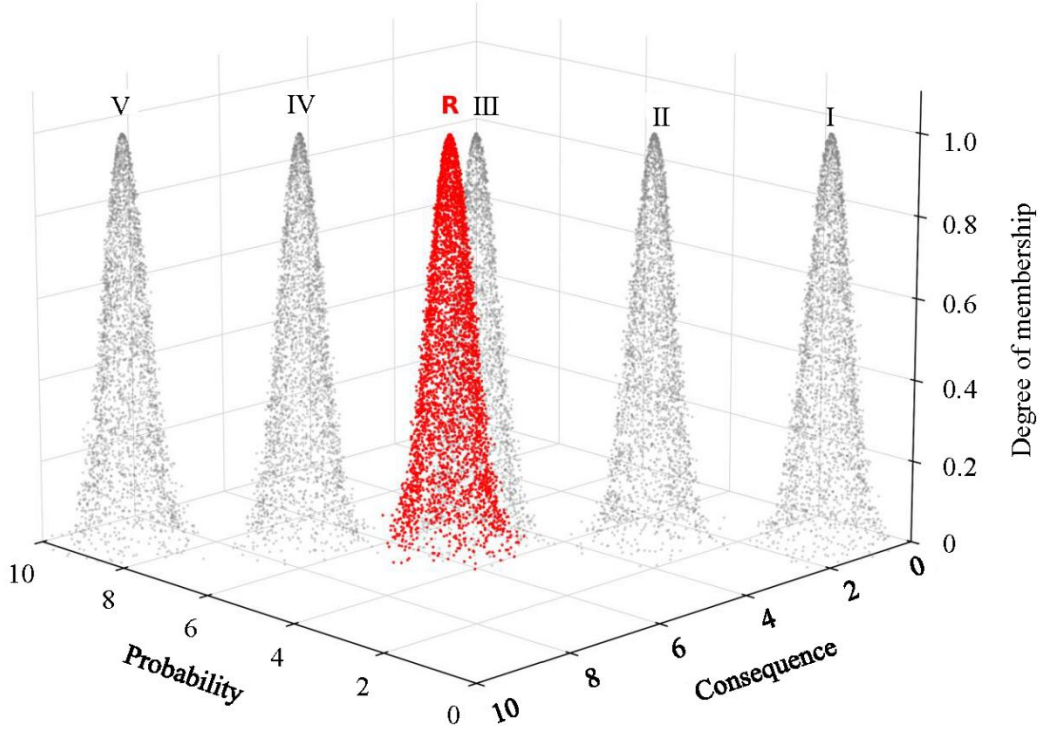


Fig.3 Integrated risk cloud

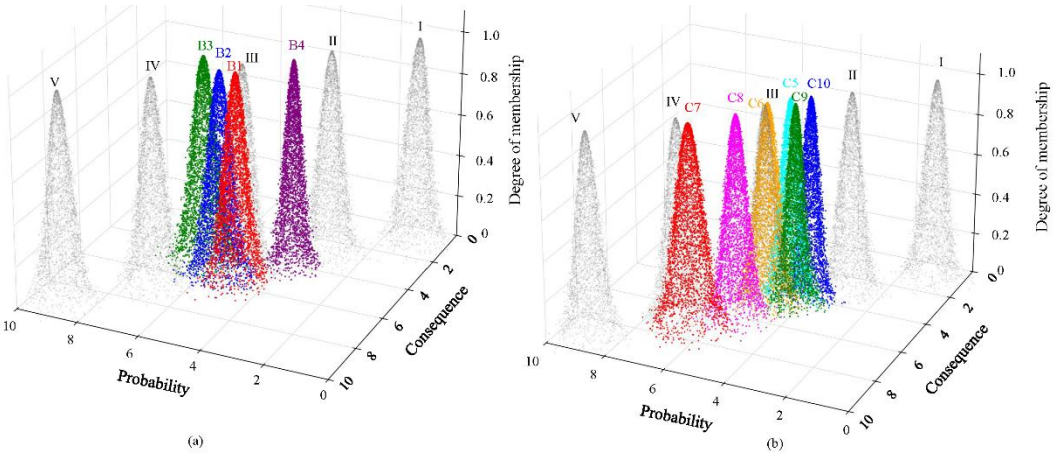


Fig.4 Level 1and level 2 risk cloud; (a) level 1 risk cloud; (b) level 2 risk cloud

In fact, since the Huangtupo landslide mitigation project has been in service for more than 20 years, the long-term periodic water level fluctuations and heavy rainfall in the TGRA may cause huge bearing pressure on the anti-slide piles, which in turn leads to the redistribution of deep-seated downward thrust and affects the stress state of the structure and the prestress of the anchor cables. Therefore, this landslide mitigation

project should monitor the stress and prestress of the deep structure in real time to ensure that the anti-slide structure is in a suitable and healthy state, thereby improving the long-term safety and operational stability of the mitigation project.

Targeted risk mitigation strategies

Based on the evaluation results of the Huangtupo landslide mitigation project using the bivariate normal cloud model mentioned above, the accelerated deterioration of local anti-slide structures(C7 stress overload and C8 prestress loss) has become a key variable constraining the long-term service performance of the project. This risk accumulation caused by the spatiotemporal evolution of deep-seated downward thrust reveals the inherent limitations of traditional passive protection systems based on macroscopic surface deformation during the long-term maintenance period. Therefore, exploring targeted mitigation strategies from a systems engineering perspective has significant theoretical and practical implications for improving the disaster resistance of large-scale landslide mitigation project.

At the mechanistic level, considering the impact of periodic water level changes in the TGRA on the stress state variation at the landslide toe, localized stress overload in the anti-slide structure can be explained as dynamic fluctuations in the landslide groundwater level caused by reservoir water level fluctuations. This, in turn, triggers redistribution of the landslide stress field and dynamic response of the displacement field[27,28]. The evaluation results of this study indicate that subsequent

control strategies should evolve towards a synergistic approach. Deploying deep-hole drainage arrays in the groundwater-rich area of the principal sliding zone can actively reduce the confined water head and weaken the additional thrust generated by groundwater accumulation.

Regarding operational status monitoring, the expected consequences of local anti-slide stress overload (C7) calculated by the model (E_x= 7.20) present a pressing need to optimize the existing monitoring and early warning network. Currently, Huangtupo landslide mitigation project has been equipped with advanced monitoring equipment, particularly multi-point distributed flexible inclinometer technology and landslide deformation coupled pipeline trajectory inertial measurement technology. Although these systems can provide high-resolution, long-term spatiotemporal deformation data, their current applications are mainly limited to isolated single-point threshold early warnings, and the diagnostic potential of the system has not yet been fully realized.

To optimize operational risk assessments, continuous strain curves and three-dimensional motion trajectories can be extracted from these sensors as dynamic input variables. These real-time physical parameters can be fed back into the proposed bivariate normal cloud model, upgrading the static risk assessment to a continuously updated model. This data-driven integration helps to identify hidden structural fatigue and guide targeted interventions, thereby effectively mitigating progressive damage caused by redistribution of deep-seated downward thrust.

Table 4. Digital characteristics of risk cloud for consequence-level and probability-level

Integrated Risk Cloud (R)	Primary Risk Cloud		Secondary Risk Cloud	
Total Indicator	Indicator	Consequence (E_X, E_n, H_e) Probability (E_X, E_n, H_e)	Indicator	Consequence (E_X, E_n, H_e) Probability (E_X, E_n, H_e)
Consequence: (5.36, 0.34, 0.05) Probability: (5.24, 0.33, 0.05)	B1	(5.63, 0.37, 0.05) (4.93, 0.32, 0.05)	C1	(6.50, 0.42, 0.05) (5.80, 0.35, 0.05)
			C2	(5.20, 0.35, 0.05) (4.50, 0.30, 0.05)
			C3	(5.80, 0.38, 0.05) (4.80, 0.32, 0.05)
			C4	(4.50, 0.30, 0.05) (4.00, 0.28, 0.05)
	B2	(5.71, 0.35, 0.05) (5.41, 0.34, 0.05)	C5	(4.20, 0.25, 0.05) (4.50, 0.30, 0.05)

			(4.80, 0.30, 0.05)
		C6	
			(5.00, 0.35, 0.05)
			(7.20, 0.45, 0.05)
		C7	
			(6.50, 0.40, 0.05)
			(6.00, 0.35, 0.05)
		C8	
			(5.50, 0.32, 0.05)
			(4.50, 0.28, 0.05)
		C9	
			(4.20, 0.25, 0.05)
			(3.80, 0.20, 0.05)
		C10	
			(4.00, 0.25, 0.05)
			(5.50, 0.35, 0.05)
		C11	
	(4.94, 0.32, 0.05)		(7.80, 0.45, 0.05)
B3			
	(6.29, 0.36, 0.05)		(5.80, 0.38, 0.05)
		C12	
			(7.50, 0.42, 0.05)

			(3.50, 0.25, 0.05)
		C13	
			(3.20, 0.20, 0.05)
			(3.00, 0.20, 0.05)
		C14	
			(2.80, 0.18, 0.05)
			(4.50, 0.28, 0.05)
		C15	
			(4.20, 0.25, 0.05)
			(3.50, 0.25, 0.05)
		C16	
	(4.08, 0.28, 0.05)		(3.80, 0.22, 0.05)
B4			
	(3.75, 0.23, 0.05)		(4.00, 0.30, 0.05)
		C17	
			(3.50, 0.25, 0.05)
			(4.20, 0.32, 0.05)
		C18	
			(3.20, 0.20, 0.05)

Validation and comparative analysis

To verify the scientific validity and applicability of the bivariate normal cloud model constructed in this study in the operational risk assessment of the landslide mitigation projects, the traditional fuzzy comprehensive evaluation method (FCE) was introduced for comparative testing of the Huangtupo landslide mitigation project. Four primary evaluation factors (B1-B4) and the fuzzy membership vector of the comprehensive operational risk were calculated. Based on the principle of maximum membership, the final risk level of each evaluation object was determined. A comparison of the calculation results of the two risk evaluation models is detailed in Table 5.

Table.5 Comparison of risk level evaluation results of different methods

Evaluation Object	FCE Maximum Membership Degree	FCE Evaluation Level	Bivariate Cloud Model Level
B1 Hazard source	0.421 (Level III)	Level III	Level III
B2 Retaining structures	0.456 (Level III)	Level III	Level III
B3 Environmental factors	0.380 (Level II)	Level II	Level II
B4 Management factors	0.410 (Level II)	Level II	Level II
Comprehensive operational risk	0.443 (Level III)	Level III	Level III

As shown in Table 5, the risk levels of the primary indicators and the overall operational risk levels calculated using the FCE method are consistent with the evaluation results of the bivariate normal cloud model constructed in this study. This agreement in risk classification fully verifies the rationality and applicability of the indicator system and combined

485 weight allocation model proposed in this study.

486 However, a comparison of the evaluation process reveals that the FCE
487 method, after linear weighting, can only output a definite and single final
488 level. In contrast, the bivariate normal cloud model constructed in this
489 study not only yields a macroscopic classification but also, by introducing
490 entropy and hyperentropy, truly maps the randomness and fuzziness of the
491 evaluation indicators into a two-dimensional space. As shown in Fi. 3 and
492 Fig. 4 above, the bivariate normal cloud model can intuitively highlight the
493 fluctuation characteristics of key indicators such as stress overload (C7)
494 approaching the level IV range. Therefore, the bivariate normal cloud
495 model, while ensuring the accuracy of the evaluation results, provides more
496 refined evaluation results and can offer a deeper level of decision-making
497 basis for the long-term management of landslide mitigation projects.

498 ## Conclusion

499 This study constructs a comprehensive evaluation model based on the
500 BRIM-CRITIC combined weighting and the bivariate normal cloud model ,
501 and conducts empirical analysis and result verification using the
502 Huangtupo landslide mitigation project as an example. The main
503 conclusions are as follows:

504 (1) Based on the constructed comprehensive evaluation model, this
505 study analyzed the potential risk factors from 4 dimensions: hazard source,
506 retaining structures, environmental factors, and management factors.
507 Finally, a single-objective, multi-level risk evaluation index system for
508 landslide mitigation projects was constructed, consisting of 4 primary

indicators and 18 indicator layers.

(2) By combining the BWM method with the improved CRITIC method, the optimal combination of subjective and objective weights was achieved using game theory, and the weights were calculated. The results show that among the primary indicators, the hazard source has the largest weight (0.3852), and among the secondary indicators, cumulative displacement and stress overload have the largest weights (0.1485 and 0.1145, respectively). This indicates that the hazard source and retaining structure factors are the key influencing factors of the operation risk of the Huangtupo landslide mitigation project.

(3) This study constructs a bivariate normal cloud model for the operational risk of landslide mitigation projects, measuring operational risk from the perspectives of accident probability and consequences. The results are presented visually in graphical form, providing a basis for quickly and accurately assessing the operational risk of landslide mitigation projects. Case study results show that this method can be used for evaluating the operational risk of landslide mitigation projects. Among the primary indicators (hazard source and retaining structures), the risk status of cumulative displacement and stress overload have a significant impact on the risk level of Huangtupo landslide mitigation project and should be given attention.

This study analyzes the Huangtupo landslide mitigation project in the TGRA as a case study, the results of the risk assessment are consistent with the actual conditions of the project. A comparison with other common

assessment methods shows that the results are generally consistent. The proposed operational risk evaluation model for landslide mitigation projects, which integrates BWM, the improved CRITIC method, and the bivariate normal cloud model, demonstrates both feasibility and applicability. However, the results demonstrate the feasibility of the proposed framework in the Huangtupo landslide, certain limitations persist. The current assessment relies on expert scoring for weight initialization and risk level definitions, which introduces a degree of subjectivity . Furthermore, the established indicator thresholds (Table 2) are optimized for the specific geological conditions of the Huangtupo landslide and may require recalibration when applied to different regional contexts or engineering scales. Future work should focus on integrating real-time automated monitoring data to further reduce model uncertainty and enhance the dynamic adaptability of the system to diverse landslide mitigation types.

Ethical Statement

All methods used in this study were carried out in accordance with relevant guidelines and regulations. The experimental protocols involving expert consultation for risk weighting and evaluation were approved by the Academic Committee of the Hubei Center of Geological Disaster Control. Informed consent was obtained from all participants prior to the study. Each expert participated on a voluntary basis and acknowledged that their professional judgments would be utilized for scholarly publication.

Data availability

The datasets used and/or analysed during the current study available from the corresponding author on reason able request.

References

1 Anonymous. Hubei Provincial Department of Land and Resources launches follow-up planning implementation work for geological disaster prevention and control in the Three Gorges Reservoir area. *Resources, Environment and Engineering*, 2012, 26(2):1, doi:CNKI:SUN:HBDK.0.2012-02-010.

2 Chen, H. *et al.* Inducing factors and deformation mechanism of the Zhangjiacitang landslide in the Three Gorges Reservoir Area. *Scientific Reports* **13**, doi:10.1038/s41598-023-40186-6 (2023).

3 Luo, S. *et al.* Insights into Reservoir-Triggered Landslides Development and Its Influence Factors in the Three Gorges Reservoir Area, China. *Journal of Earth Science* **35**, 1979-1997, doi:10.1007/s12583-024-0024-1 (2024).

4 Dong, J. *et al.* Evolution of landslide susceptibility in the Three Gorges Reservoir area over the three decades from 1991 to 2020. **16**, 2468323 (2025).

5 Chen, H. *et al.* Inducing factors and deformation mechanism of the Zhangjiacitang landslide in the Three Gorges Reservoir Area. **13** (2023).

6 Xue, Y., Miao, F., Wu, Y. & Dias, D. J. E. G. Dynamic stability assessment of reservoir colluvial landslide using a hypoplastic clay constitutive model considering the effects of drying-wetting cycles on the hydro-fluctuation belt. (2022).

7 Hamza, A. *et al.* Advanced structural interventions for slope stabilization and disaster resilience. **3**, 1-22 (2025).

8 Wang, G. J. L. Impact of global changes on landslide hazard and risk. **22** (2025).

9 Zhang, Y., Hu, X., Tannant, D. D., Zhang, G. & Tan, F. J. L. Field monitoring and deformation characteristics of a landslide with

piles in the Three Gorges Reservoir area. **15**, 581-592 (2018).

10 Liu, S. *et al.* Satellite InSAR as a New Tool for the Verification of Landslide Engineering Remedial Works at the Regional Scale: A Case Study in the Three Gorges Resevoir Area, China. *Applied Sciences* **10**, doi:10.3390/app10186435 (2020).

11 Jiang, S.-H., Li, D.-Q., Zhang, L.-M. & Zhou, C.-B. Time-dependent system reliability of anchored rock slopes considering rock bolt corrosion effect. *Engineering Geology* **175**, 1-8, doi:10.1016/j.enggeo.2014.03.011 (2014).

12 Huang, J., Ju N. Research on evaluation method of landslide control project effect. *Journal of Engineering Geology*, **2012**, 20(2):189-194, doi:10.3969/j.issn.1004-9665.2012.02.006.

13 Xia, P., Zeng, B., Liu, J. & Pan, Y. Study on the Stability Evaluation Index System for Rock Slope–Anchoring Systems. *Applied Sciences* **15**, doi:10.3390/app15169147 (2025).

14 Li, Y. *et al.* Comprehensive risk management of reservoir landslide-tsunami hazard chains: a case study of the Liangshuijing landslide in the Three Gorges Reservoir area. *Landslides* **22**, 671-691, doi:10.1007/s10346-024-02283-z (2024).

15 Liu J. *et al*. Research on ship navigation risk assessment method based on HHM-RFRM. *Chinese Management Science*, **2019, 27(5):10**.doi:CNKI:SUN:ZGGK.0.2019-05-018.

16 Tang, H., Wasowski, J. & Juang, C. H. J. E. G. Geohazards in the three Gorges Reservoir Area, China - Lessons learned from decades of research. **261**, 16 (2019).

17 Tian, Y., Qiao, H., Hua, L. J. A.-A. J. o. R. & Uncertainty in Engineering Systems, P. A. C. E. A MMEM-BN–Based Analyzing Framework for Causal Analysis of Ship Collisions. **10** (2024).

18 GB/T 38509-2020, Code for Design of Landslide Prevention [S].

19 20120664-T-334, Specification for Investigation of Landslide Prevention Engineering [S]..

20 Chongqing Design Institute. GB 50330-2013 Technical Specification for Building Slope Engineering [M]. China Building Industry Press, 2014..

21 Li, S. C. *et al.* Risk assessment of water inrush in karst

tunnels based on attribute synthetic evaluation system. **38**, 50-58 (2013).

22 Guo, S. & Zhao, H. J. K.-b. s. Fuzzy best-worst multi-criteria decision-making method and its applications. **121**, 23-31 (2017).

23 Wang, L., Jin, R., Zhou, J. & Li, Q. J. A. S. Construction risk assessment of yellow river bridges based on combined empowerment method and two-dimensional cloud model. **13**, 10942 (2023).

24 Corominas, J. *et al.* Recommendations for the quantitative analysis of landslide risk. *Bulletin of Engineering Geology and the Environment*, doi:10.1007/s10064-013-0538-8 (2013).

25 Wang, Z. & Zhao, C. Assessment of Landslide Susceptibility Based on ReliefF Feature Weight Fusion: A Case Study of Wenxian County, Longnan City. *Sustainability* **17**, doi:10.3390/su17083536 (2025).

26 Yao, P. *et al.* Safety level assessment of shield tunneling in water rich sandy pebble strata with large particle size. *Sci Rep* **13**, 3854, doi:10.1038/s41598-023-30718-5 (2023).

27 Xiao J., Li Y., Cai J. Experimental study on response characteristics of lotus pond landslide under water level fluctuations. Journal of Engineering Geology, 2020, 28(5):8. doi:10.13544/j.cnki.jeg.2020-326..

28 Zhang Yuming. *Study on Multi-Field Characteristics and Evolution Mechanism of Majiagou Landslide-Anti-slide Pile System under Reservoir Operation Conditions*. China University of Geosciences, (2018).

Acknowledgments

This research was supported by the Hydrogeology and Engineering Geology Institute of Hubei Geological Bureau, and China University of Geosciences (Wuhan).

Author contributions

J. C.: Methodology, Validation, Visualization, Writing-Original Draft. Z. C.: Conceptualization, Funding Acquisition, Methodology. Y. S.: Methodology, Validation data. X. Q.: Formal analysis, Resources. L. W.: Formal analysis, Resources. S. Z.: Formal analysis, Resources.

Funding

This work was funded by Hubei Provincial Natural Science Foundation Innovation and Development Joint Fund Project (No.:2025AFD435).

Declarations

Competing interests

The authors declare no competing interests.

Additional information

Correspondence and requests for materials should be addressed to J.C.