Research Article

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The critical role of *c* and *φ* in ensuring stability: A study on rockfill dams

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Abstract: Slope stability analysis is an important part of rockfill dam design, and the uncertainty of rock and soil physical and mechanical parameters has a significant impact on slope stability. In this article, based on physical and mechanical parameters c and φ, simplified Bishop's method and mean clustering method are adopted to study the influence of parameter cohesion c and internal friction Angle φ on slope safety factor k of composite geomembrane rockfill dam, and the key and non-critical areas of the dam are preliminarily differentiated according to the different influences of the changes in different sections of the dam body on slope safety factor c and φ. The research results show that whether c and φ change ±5 and ±10% simultaneously with single parameter or double parameter, it shows that cohesion force c has little influence on slope stability, while internal friction Angle φ is the most sensitive factor in slope stability calculation, and its numerical accuracy has a great influence on the calculation result of safety factor. In addition, the influence of c and φ in key areas on the stability of the dam body is more significant. Therefore, in the construction of a composite geofilm rockfill dam, a relatively accurate φ value is required when selecting parameters, especially in key areas. This study not only has a certain guiding significance for the property requirements of the selected soil, engineering safety, and engineering optimization design, but also puts forward some new methods and ideas for optimizing the design scheme and improving the safety of the dam.

Keywords: rockfill dam, slope stability, c and φ

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1 Introduction

Rockfill dams are frequently utilized in hydraulic engineering projects. Stability analysis is a crucial component of their design, involving the calculation of safety factors [1–3]. This analysis typically utilizes deterministic methods, with the safety factor method being a commonly employed approach due to its convenience and reliance on historical practical knowledge. This method effectively consolidates the various uncertainties present in the system into a coefficient that serves as the system's output. Nevertheless, a significant limitation of the current approach is the insufficient consideration of the uncertainty associated with geomechanical indicators, leading to inaccuracies in safety representation. In the practical application of composite geomembrane rockfill dams, the uncertainty surrounding mechanical parameters c and φ plays a crucial role in influencing the stability of rock-soil slopes. Additionally, the presence of multiple partitions in composite geomembrane rubble mound dams results in varying levels of stability within the dam body due to the fluctuations in c and φ across different regions. Hence, conventional deterministic approaches are insufficient in addressing these uncertainties. Presently, methods for evaluating slope stability primarily consist of limit equilibrium [4,5], numerical analysis [6,7], and uncertainty analysis [8–13].

The examination of slope stability safety with regard to statistical uncertainty holds substantial practical significance in the engineering construction of rockfill dams. In recent years, a multitude of researchers have delved into comprehensive research on slope reliability and statistical uncertainty. Liang et al. [14,15] incorporated reliability theory into the assessment of dam slope stability reliability, taking into account the uncertainty associated with soil parameters, which are characterized by normal and log-normal distributions. Samui et al. [16] performed a slope reliability analysis utilizing the First-Order Second-Moment method with a support vector machine, focusing on the implicit functional relationships of slope reliability. In a similar vein, Cho [17] introduced a First-Order Reliability Method that accounts for various failure modes in slope reliability analysis, particularly those resulting from alterations in soil layer sand properties. Johari et al. [18] examined the relationship between various parameters and established models for internal friction angle and cohesion through the utilization of truncated normal distribution functions. Additionally, they developed models for tensile crack depth and seismic rate using truncated exponential distribution functions. The authors characterized random variables through joint distribution functions to conduct a reliability analysis of rock slopes. Li et al. [19] introduced a stochastic response surface approach for handling correlated non-normal variables, which involves transforming these variables into independent standard normal variables through Nataf transformation. Wu [20] performed slope reliability analysis by generating numerous samples of soil strength parameters using a two-dimensional Copula joint probability distribution and subsequently compared the results with those obtained through the First-Order Reliability Method, thus confirming the efficacy of the proposed methodology. Zhenyu et al. [21] achieved enhanced accuracy in the assessment of stability reliability in rockfill dams by employing a nonlinear shear criterion. They also investigated the impact of shear strength parameter distribution on reliability indicators, opting for normal and lognormal distributions. Subsequently, Wu et al. [22] explored the interplay between variables by incorporating an optimization algorithm for coordinate systems in the analysis of high rockfill dam reliability.

Researchers have increasingly focused on the research of statistical uncertainty in geotechnical engineering. Phoon and Kulhawy [23] posited that statistical uncertainty arises due to the limited information gathered at geotechnical engineering sites. Honjo and Setiawan [24] investigated the statistical uncertainty of random field parameters at specific depths, integrating statistical uncertainty with other sources of uncertainty in their calculations. Wang et al. [25–28] utilized Bayesian theory-based methodologies to address the probability model of the friction angle of sandy soil, capturing the statistical uncertainty of parameters through the acquisition of posterior distribution samples. Similarly, Ching et al. [29] employed both frequentist and Bayesian approaches to examine the statistical uncertainty of random field parameters, assessing the comparative effectiveness of the two methodologies in characterizing statistical uncertainty. The field of fuzzy mathematics theory has experienced ongoing development since its inception and has found applications in diverse domains. The utilization of fuzzy mathematics in rockfill dam engineering primarily centers on three key areas: evaluating dam foundation stability, optimizing rock-soil strength parameters, and integrating fuzzy stochastic theory with reliability analysis. Edincliler et al. described the results of a series of triaxial cycle tests on waste tire mixtures and tested the application of neural networks and neural fuzzy (NF) in predicting the damping ratio and shear modulus of mixtures [30]. Firat Cabalar et al. used experimental data to develop a constitutive model of the mixture of Leighton meat sand component B and Leighton meat sand component E based on NF [31]. Pourghasemi et al. used a fuzzy logic and analytic hierarchy Process (AHP) model to draw the landslide sensitivity map of Iran's slippery area (Haraz) [32]. Xie et al. proposed an adaptive evaluation method for shield tunneling machine based on the fuzzy analytic Hierarchy Process (FAHP) and AHP [33]. Peng et al. proposed a set of risk assessment indicators based on FAHP based on the analysis of the risk assessment principle of land conflict index system [34]. Fuzzy mathematics avoids the complexity of the details of several problems and focuses on the influence of major factors. Fuzzy mathematics simplifies complex problem intricacies and emphasizes the impact of fundamental factors.

In summary, it can be found that uncertainty theory and fuzzy mathematics theory have been applied in many aspects, but there are few studies on the stability analysis of rockfill slope. This article mainly takes Kililong III Power Station in Cambodia as the research object. From the physical and mechanical properties of rock and soil mechanical parameters, the following two points are studied: the influence on the safety factor of dam slope of composite geomembrane rockfill dam; in addition, the mean value clustering method in fuzzy mathematics is used to distinguish the critical and non-critical areas which have different influence on the stability of dam slope. The study has certain guiding significance for the property requirements, engineering safety, and engineering optimization design of composite geomembrane rockfill dam.

2 Research method

2.1 Study area

The Kirirom III hydropower station is situated in the midstream section of the Deg River, a tributary of the Kombok River, within the Kampong Speu Province to the southwest of the Cambodian capital, Phnom Penh (Figure 1). The watershed area upstream of the dam site spans 104.6 km^2, while the length of the primary river channel preceding the dam site is approximately 19.8 km. The average flow rate at the dam site over the long term is 4.11 m^3/s, with a corresponding long-term average runoff of 129.6 million m^3. The standard reservoir level is 331.50 m, with a total storage capacity of 46.26 million m^3, and an installed power station capacity of 18 megawatts. The central project of the power station includes a slope rockfill dam with a geomembrane on the riverbed, a right bank dam shoulder with gravity blocks, an open spillway on the right bank, as well as a water conveyance system on the right bank, a power generation plant, and a left bank ecological flow conveyance structure.

This study provides a detailed description of an inclined rockfill dam equipped with a geomembrane lining. The dam has a crest elevation of 335.50 m, a width of 6 m, and a length of 506.28 m. The lowest elevation of the concrete connecting plate foundation is 284.00 m, and the maximum height of the dam is 51.50 m. The upstream dam slope ratio is 1:2.5, with terraces located at elevations of 305.00 m and 320.00 m, each having a width of 5 m. The downstream dam slope has a ratio of 1:2, with a terrace situated at an elevation of 315.00 m and a width of 2 m. The dam incorporates PE composite geomembrane inclined walls to mitigate seepage.

2.2 Outlines the calculation methodology for analyzing the stability safety factor of rockfill dam slopes

The analysis of stability in rockfill dam slopes is a critical technology for ensuring the safe operation of such structures [35]. In order to maintain stability, it is imperative to calculate the safety factor of rockfill dams, which serves as a measure of the margin of safety between the potential failure state of the slope and its current condition.

Various methods exist for calculating the safety factor of slope stability, including the Swedish Circular Arc Sliding Method [36], simplified Bishop Method [37,38], Swedish Strip Method [39], Spencer Method [40,41], and Morganstern–Price Method [42], among others. Among the many methods, the simplified Bishop method is widely used because of its relative simplicity, high computational efficiency, and wide application range. This method assumes that the sliding surface is a circular arc and simplifies the soil mechanical model, making the calculation process more intuitive and suitable for rapid evaluation of slope stability. In addition, the simplified Bishop method can provide more reasonable safety factor results when considering the soil shear strength and water pressure and is especially suitable for common slope conditions in engineering practice. Therefore, this study mainly adopts the simplified Bishop method to calculate the safety factor.

Simplified Bishop method is a common limit equilibrium method used to evaluate slope stability. This method was proposed by Alan W. Bishop in 1955 to calculate the safety factor of a slope in a relatively simple way, that is, the ratio of the anti-sliding force of the slope to the driving force. The basic principle is to divide the slope into a series of vertical slices, assuming that each slice is independent, and do not consider the balance of horizontal forces, but

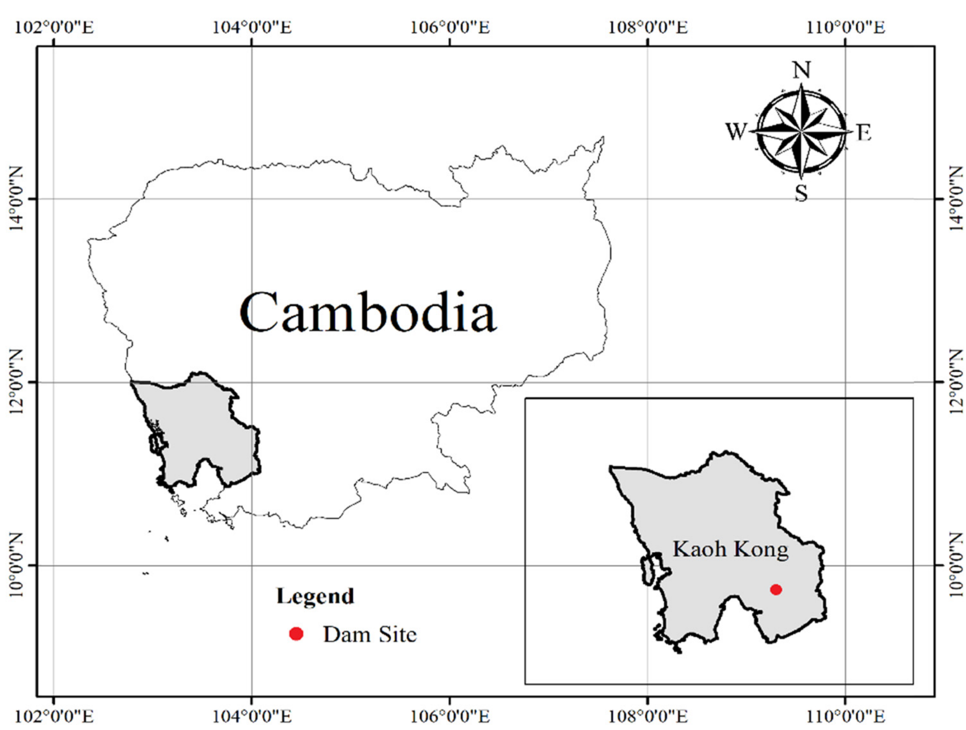

Figure 1: The geographical location of the research area.

only consider the balance of forces and moments in the vertical direction. This method ignores the shear force between the slices on the sliding surface, thus simplifying the calculation process.

2.3 The method for classification analysis and calculation of various regions in rockfill dams

Fuzzy mathematics [43], as conceptualized by Lotf Zadeh in 1965, serves as a mathematical framework designed to address the representation and manipulation of information characterized by imprecision or uncertainty. This branch of mathematics is primarily employed for the purpose of delineating and managing ambiguous, vague, or imprecise concepts that are commonly encountered in practical applications. Central to the discipline is the theory of fuzzy sets, which serves as an extension of conventional set theory. Within the realm of fuzzy sets, the membership of each element in a given set is quantified by a value that ranges between 0 and 1, as opposed to the binary nature of traditional set theory where elements are either fully included (1) or excluded (0).

This study primarily utilizes the fuzzy *c*-means clustering method [44,45] derived from fuzzy mathematics, which is intricately linked to the principles of fuzzy mathematics. Within the fuzzy *c*-means clustering method, the membership function in fuzzy mathematics is applied to determine the degree of membership of each data point to each cluster. This measurement signifies the extent to which each data point belongs to a specific cluster, thereby illustrating the fuzzy association between data points and clusters. The fuzzy *c*-means clustering method iteratively optimizes the membership degrees and cluster centers by minimizing an objective function that aligns with the fuzzy minimum distance criterion in fuzzy mathematics. This objective function is defined as the weighted sum of the membership degrees assigned to each data point and their respective distances to the cluster centers, serving as a metric for the fuzzy distance between data points and cluster centers.

The concept and method of fuzzy mathematics provide a mathematical tool for fuzzy mean clustering to deal with fuzziness and uncertainty. By introducing membership function, fuzzy mean clustering can better deal with those data sets with ambiguous or overlapping boundaries, and provide a more flexible clustering analysis method. The subsequent computational procedures are outlined as follows:

1. determine the number of clusters C, set $l = 0$, and initialize the fuzzy matrix $U^{(l)}$ with an initial grouping C;
2. compute the initial cluster centroid vectors $V_i^{(l)}$ using equation (1);
3. calculate the updated membership fuzzy matrix $U^{(l+1)}$ using equation (2);
4. define a convergence criterion value ε. If $\| U_{ik}^{(l+1)} - U_{ik}^{(l)} \| < \varepsilon$, then U and V are the desired solutions. Otherwise, set $l = 1 + i$, return to step 2, and repeat the iterative computation process.

$$V_i = \sum_{k=1}^{n} (u_{ik})^m \cdot \underline{x}_k / \sum_{k=1}^{n} (u_{ik})^m, \tag{1}$$

$$u_{ik} = 1 / \sum_{i=1}^{e} \left(\frac{\| \underline{x}_k - V_i \|}{\| \underline{x}_k - V_j \|} \right)^{\frac{2}{m-1}}, \tag{2}$$

where $\underline{x}_k$ represents the safety factor corresponding to the c, φ variation of each region; u_{ik} denotes the elements of the matrix U; m is any real number greater than or equal to 1; and n signifies the number of c, φ iterations for variation. ($i = 1,2,\ldots,C$; $k = 1,2,\ldots,n$).

2.4 Research design

This study focuses on the Kirirom III Hydroelectric Power Station composite geomembrane rockfill dam project as a case study (Figure 2 and Table 1) to examine the impact of

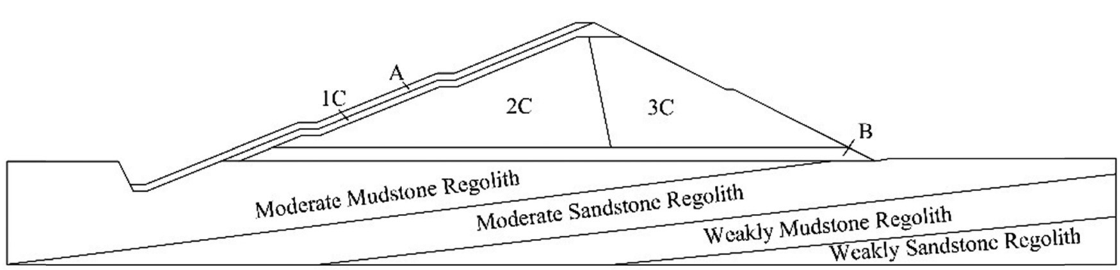

Figure 2: The sectional division of the composite geomembrane rockfill dam. Note: A represents fine sand and crushed stone materials; B denotes fresh and slightly weathered rock materials; 1C, 2C, and 3C refer to materials excavated from buildings or material yards, with 3C consisting of 50% soil materials.

physical-mechanical parameters c and φ on slope stability. The specific procedures are as follows:
(1) Under the least favorable circumstances (completion period), the slope stability coefficient is computed individually for changes in parameter c and parameter φ, followed by a comparative analysis.
(2) Determine the slope stability coefficient under conditions of simultaneous variation in parameters c and φ, and subsequently contrast these results with those obtained from individual parameter adjustments.
(3) Determine the slope stability coefficient for different regions of the dam body based on variations in parameters c and φ, and employ the fuzzy k-means clustering method to categorize the regions of the rockfill dam into critical and non-critical areas.

3 Result and discussion

The cohesion (c) and the angle of internal friction (φ) are essential parameters in geotechnical mechanics, significantly influencing slope stability analysis. These parameters collectively define the shear strength of soil, indicating its resistance to shear deformation or sliding. In slope safety analysis, shear strength dictates the stability of a slope and identifies the conditions under which slope failure may occur.

3.1 The impact of alterations in individual parameters on the slope stability factor

Cohesion (c) is commonly defined as the cohesive force between soil particles, contributing to the soil's shear strength independent of normal stress. Conversely, the angle of internal friction (φ) characterizes the interparticle interactions within the soil, indicative of its shear resistance. This parameter is subject to variations based on factors including particle morphology, size, arrangement, and surface texture. The impact of single-parameter variations on the slope safety factor primarily entails independently adjusting the values of c and φ, and subsequently determining the safety factors of the upstream and downstream dam slopes. This approach facilitates a sensitivity analysis of slope stability under single-parameter variations. Detailed calculation results are presented in Tables 2 and 3 and Figure 3.

According to the data presented in Figure 3, it is evident that the cohesion (c) and angle of internal friction (φ) curves for both upstream and downstream slopes demonstrate a predominantly linear upward trajectory within a specific range. Notably, the curve for parameter (φ) displays a steeper incline compared to that of parameter (c). It can be deduced that, given a proportional disturbance, the variability in parameter (φ) significantly influences the enhancement of safety factor (k). Consequently, the deliberate utilization of larger rock and soil materials in engineering applications is expected to yield substantial improvements in slope stability, resulting in greater efficacy with reduced exertion.

In the construction of composite geomembrane rockfill dams, it is imperative to prioritize the accuracy of geotechnical and physicomechanical parameters, particularly the internal friction angle (φ) value, from a material selection standpoint. A higher internal friction angle (φ) value in the rock and soil materials enhances the stability of the dam slopes. Consequently, in practical engineering scenarios, it is advisable to select rock and soil materials with higher internal friction angle values φ to guarantee the stability of the dam structure.

3.2 The influence of concurrent variation of two parameters on the slope safety factor

The joint variability of parameters c and φ exerts a complex yet significant influence on the slope safety factor. The

Table 1: Relevant geotechnical and physico-mechanical parameters of various zones in the dam body

Dam zoning	Density γ (KN/m^3)	Cohesive force c (KPa)	Internal friction angle φ (°)
A	19.75	2	38
B	21.5	0	37
1C	21.5	0	37
2C	21	0	37
3C	20.5	10	36
Moderate Sandstone Regolith	25.8	700	39
Weakly Sandstone Regolith	26.2	700	39
Moderate Mudstone Regolith	25	200	30
Weakly Mudstone Regolith	25.5	200	30

Table 2: The calculation results of the safety factors of the upstream and downstream slopes when the cohesion (*C*) varies independently

***c*-Value**	**−10%**	**−5%**	**0**	**±5%**	**±10%**
The safety factor *k* of the upstream slope	2.201	2.209	2.218	2.227	2.236
The safety factor *k* of the downstream slope	1.776	1.786	1.795	1.805	1.814

Table 3: The calculation results of the safety factors of the upstream and downstream slopes when the internal friction angle (*φ*) varies independently

***φ*-Value**	**−10%**	**−5%**	**0**	**+5%**	**+10%**
The safety factor *k* of the upstream slope	1.957	2.076	2.218	2.358	2.506
The safety factor *k* of the downstream slope	1.595	1.691	1.795	1.905	2.019

mechanical properties of soil, specifically cohesion (*c*) and internal friction angle (*φ*), are crucial parameters that collectively influence slope stability. The safety factor of a slope is typically determined by comparing the soil's shear strength to the applied stresses, with cohesion and internal friction angle values playing a primary role in affecting soil shear strength [46].

When the cohesion (*c*) and angle of internal friction (*φ*) values increase concurrently, the safety factor of the slope is likely to increase due to the corresponding increase in the soil's shear strength. This enhances the slope's resistance to shear forces, thereby reducing the likelihood of landslides or collapse. Conversely, a simultaneous decrease

Table 4: The calculation results of the safety factors *k* for the upstream and downstream slopes when both the *c* and *φ* vary simultaneously

The value of *c* and *φ*	**−10%**	**−5%**	**0**	**+5%**	**+5%**
Upstream security coefficient	1.939	2.076	2.218	2.367	2.524
Downstream security coefficient	1.572	1.681	1.795	1.915	2.039

in both *c* and *φ* values may lead to a decrease in the safety factor of the slope. The reduction in shear strength of the soil renders the slope more vulnerable to external forces, thereby heightening the likelihood of landslides or collapse and amplifying the potential for disasters. Consequently, it is imperative in engineering practice to meticulously assess the fluctuations of these factors and implement suitable strategies to uphold or improve slope stability, thereby safeguarding the integrity of the project.

This study primarily examines the simultaneous manipulation of cohesion (*c*) and angle of internal friction (*φ*) values for analysis and computation. Detailed calculation results are presented in Table 4, accompanied by corresponding relationship curves depicted in Figure 4.

Examination of the concurrent variation of cohesion (*c*) and angle of internal friction (*φ*) demonstrates a consistent increase in safety factors (*k*) for both upstream and downstream slopes, indicating a linearly increasing trend. This finding underscores the impact of alterations in physicomechanical parameters on slope stability.

In contrast to single-parameter variation scenarios, we have now established the safety factors (k_{upstream} = 2.218, $k_{\text{downstream}}$ = 1.795) associated with the absence of parameter changes as the reference point. We analyze the

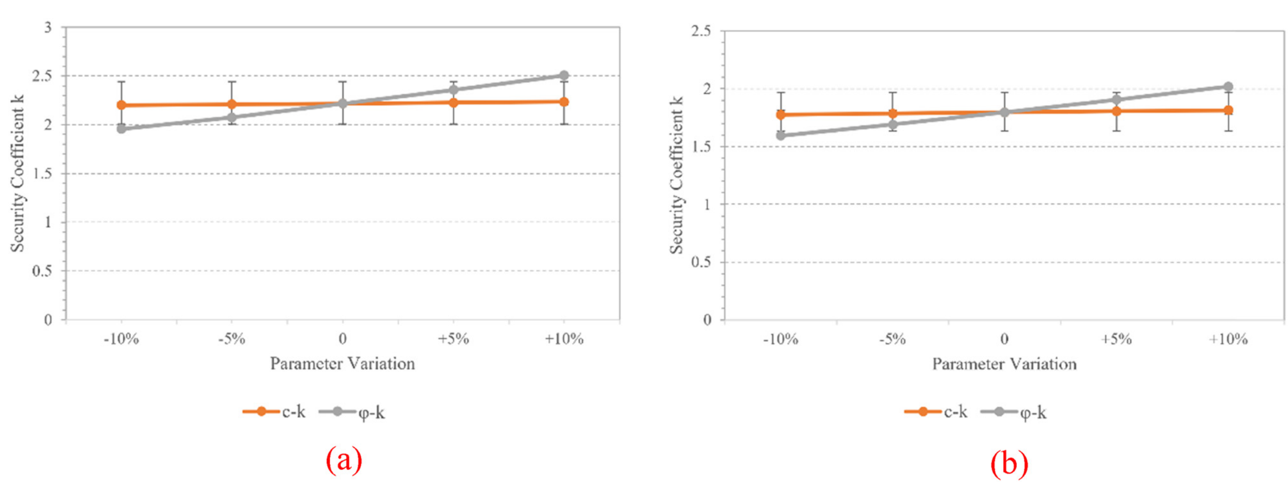

Figure 3: The relationship between the *c*, *φ* and the safety factor *k* for (a) the upstream slope and (b) the downstream slope under single-parameter variations.

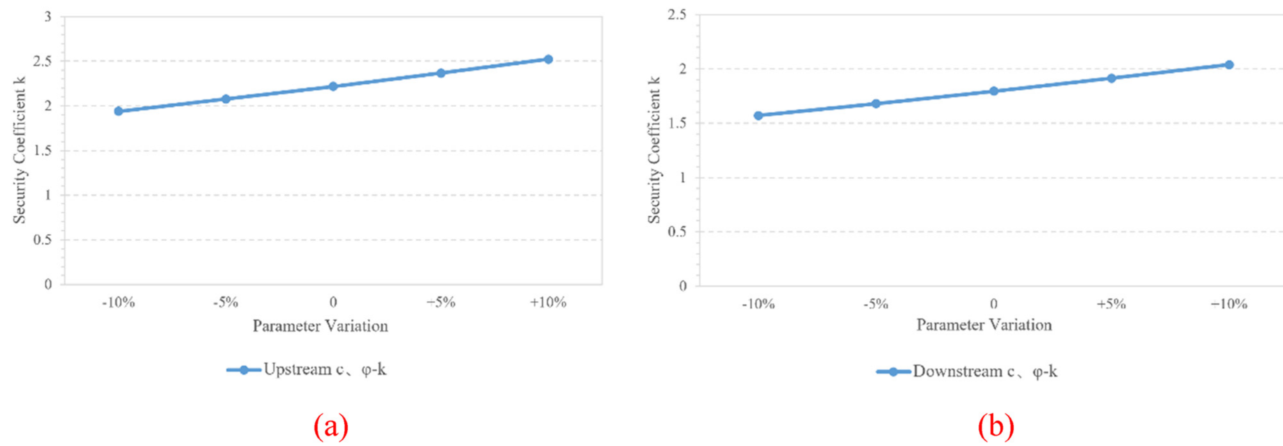

Figure 4: The relationship between the c, φ and the safety factor k for (a) the upstream slope and (b) the downstream slope when both parameters vary simultaneously.

Table 5: The comparison of the changes in safety factor (k) induced by single-parameter variations and simultaneous variations of both parameters

Parameter variation	−10%	−5%	+5%	+10%
Changes in k when upstream c and φ vary independently	−0.278	−0.133	+0.149	+0.306
Changes in k when upstream c and φ vary simultaneously	−0.279	−0.142	+0.149	+0.306
Changes in k when downstream c and φ vary independently	−0.219	−0.113	+0.120	+0.243
Changes in k when downstream c and φ vary simultaneously	−0.223	−0.114	+0.120	+0.244

alterations in slope safety factors resulting from single-parameter variations and concurrent variations of both parameters in relation to the cohesion (c) and angle of internal friction (φ) values. Detailed findings are presented in Table 5.

Based on the data presented in Table 5, it is evident that the change in safety factor (k) for both upstream and downstream slopes is relatively minor when both parameters are varied simultaneously, as opposed to when only one parameter is varied. This indicates a potential autocorrelation between the physicomechanical parameters c and φ of the soil, suggesting that the disparity between these parameters could serve as a safety buffer in engineering practices.

Table 6: The slope safety factors (k) corresponding to the variation of c and φ values in different zones of the upstream dam body

Zones	−30%	−20%	−10%	+10%	+20%	+30%
A	1.513	1.625	2.005	2.283	2.412	2.459
1C	1.579	1.777	1.977	2.275	2.411	2.432
2C	1.686	1.857	2.103	2.233	2.275	2.275
B	1.912	1.979	2.101	2.225	2.275	2.275

3.3 Identification of key and non-key areas in the dam body

A rockfill dam, a prevalent hydraulic engineering structure, can be categorized into key and non-key regions. Key areas are those sections of the dam body that have a substantial impact on its structural stability and safety, often referred to as areas sensitive to stability. In contrast, non-key areas are considered minor and do not have a direct impact on the overall stability of the dam body.

This study is centered on the zoning of the composite geomembrane rockfill dam. The downstream section of the dam body, as depicted in Figure 2, is relatively uncomplicated, with the main focus being on area 3C. Conversely, the

Table 7: The classification of various zones in the upstream area of the rockfill dam

Zones	Membership function value		Membership type
	u_{1i}	u_{2i}	
A	0.976	0.024	Key
1C	0.990	0.010	Key
2C	0.487	0.513	Non-key
B	0.020	0.980	Non-key

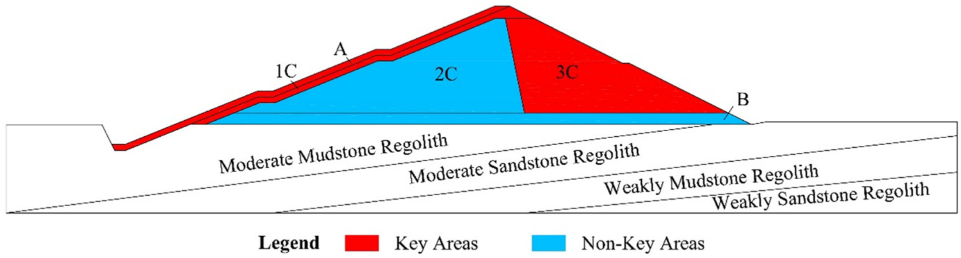

Figure 5: Distribution map of key and non-key areas of the dam body.

upstream section is characterized by greater complexity. Consequently, the fuzzy *k*-means clustering method is utilized to analyze the critical and non-critical regions of the dam body.

The simplified Bishop method is utilized to determine slope safety factors (k) based on variations in cohesion (c) and angle of internal friction (φ) values in different sections of the upstream rockfill dam, as outlined in Table 6. Additionally, the fuzzy *k*-means clustering method is employed to perform cluster analysis on distinct regions of the upstream section in order to differentiate between critical and non-critical areas of the dam body. In this study, the relevant parameters are categorized into two classes: key and non-key areas, so $C = 2$, $m = 2$, $\varepsilon = 0.01$. The initial matrix is established as $U^{(0)} = \begin{bmatrix} 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 \end{bmatrix}$, and iterative calculations are performed based on equations (1) and (2). Specific results are given in Table 7.

From Tables 6 and 7, it is evident that with $u = 0.9$, the distinction is made. Regions A and 1C are categorized as key areas, while regions 2C and B are classified as non-key areas. Key areas play a crucial role in maintaining the stability of the dam slope. Therefore, it is essential to accurately determine the physicomechanical parameters c and φ for regions A and 1C to ensure that the upstream slope of the composite geomembrane rockfill dam meets the necessary stability criteria. The distribution map of key and non-key areas of the dam body is shown in Figure 5.

4 Conclusion

This article mainly takes composite geomembrane rockfill dam as the research object, studies the influence of physical and mechanical parameters on the dam slope safety factor, and uses the fuzzy mathematical principle to distinguish the critical and non-critical areas that have different influences on the stability of the dam slope, and draws some useful conclusions:

(1) There is a linear relationship between physical and mechanical parameters c and φ and slope safety factor within a certain range. For rockfill dam slope, whether the single parameter or the double parameter c and φ changes ±5 and ±10% at the same time, the numerical change of cohesion force c has little influence on the stability of dam slope, while the numerical change of internal friction Angle φ plays a major role in the stability of dam slope. Therefore, φ is considered the most sensitive factor in the calculation of the safety factor of dam slope stability.

(2) The mutual correlation and autocorrelation of physical and mechanical parameters c and φ will also have an impact on slope safety factor k. Considering the autocorrelation of c and φ, the safety factor k obtained is larger than that without considering the autocorrelation. However, in engineering practice, the mutual correlation between c and φ is often treated as independent without considering their autocorrelation. Therefore, the calculated safety factor k is smaller than the true value and can be used as a safety reserve.

(3) The dam body of a composite geomembrane rockfill dam is more complex, more zones, and generally medium and small projects, so the c and φ parameters of each area are accurate and uneconomical. The *k*-mean clustering method of fuzzy mathematics is used to calculate and classify each area of the dam body, and $u = 0.9$ is taken as the basis for determining the partition, and the selection of physical and mechanical parameters in key areas can be further improved.

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Data availability statement: The data supporting the findings of this study are available within the article. Additional datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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