Stability analysis of slopes based on cloud model-Monte Carlo coupling

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Risk analysis of dam slopes is crucial for ensuring the safety and stability of hydraulic engineering. To improve the accuracy and reliability of risk analysis, we adopt the cloud theory approach and conduct a study on the distribution types of soil shear strength indicators based on indoor geotechnical tests. We propose a "cloud model-Monte Carlo" coupling model that uses the cloud model to describe the uncertainty of risk factors and determine the probability distribution types of shear strength parameters, while the Monte Carlo method is used to simulate random variables in the model. The effectiveness of the proposed model is validated through a risk analysis of a slope of an earth-rock dam, with results showing significantly greater accuracy and reliability compared to traditional methods. The calculation results show that the risk probability corresponding to the design flood level of the dam is 9.01×10^{-6}, exceeding its allowable risk standard of 0.5×10^{-6}, hence the need for reinforcement treatment. The proposed model can accurately evaluate the risk of dams and provide the scientific basis for decision-making in dam safety management.

1 Introduction

In recent years, with the continuous acceleration of urbanization and the development of engineering construction, geological disasters have posed a serious threat to people's life and property safety (Tu et al., 2023). Among them, the slope stability problem has been a hot issue of great concern in geological engineering (Wen et al., 2022). In slope control, the soil shear strength parameter is one of the most important parameters for evaluating the safety of slope engineering. To analyze the risk of dam landslides, Monte Carlo simulation is a widely used method for dam slope risk analysis (Lu et al., 2022), which involves generating random samples of uncertain variables and simulating the dam behavior under different scenarios. However, traditional Monte Carlo simulations assume that the uncertain variables follow a specific probability distribution (Chorol and Gupta, 2023). In contrast, cloud modeling is a novel uncertainty modeling approach (Cheng et al., 2022) that captures the stochasticity and ambiguity in uncertain variables. Therefore, we propose a new approach combining cloud models and Monte Carlo simulations to analyze dam landslide risk. Specifically, we use the cloud model for solving

uncertainty problems and Monte Carlo simulation for generating stochastic samples and simulating dam behavior.

In previous studies, conventional methods (Rouzéa and Dattaa, 2016; Wang-Wang et al., 2018; Zhang et al., 2022a) have faced uncertainty issues in parameter selection under limited data conditions, leading to the simultaneous fitting of multiple distribution functions. In contrast, cloud theory can address the uncertainty problem in distribution types. Cloud theory was proposed by Professor Li (Li et al., 2009), which can effectively convert quantitative and qualitative information and visualize it through cloud maps (Ma and Zhang, 2020). Among them, the normal cloud model is the most important type of cloud model and has been widely used in prediction, comprehensive evaluation, data mining, intelligent control, and other fields (Liu et al., 2021; Ruan et al., 2021). Cloud theory has also been extensively applied in the assessment field (Chen et al., 2023; Guojiao et al., 2023). Monte Carlo simulation, as a classic random number simulation method, has been extended to various fields such as medicine (Santos et al., 2022), water conservancy (Vihola et al., 2020), and science and technology materials (Wang et al., 2020). Considering the scalability and reliability of cloud models in fuzzy decision-making fields (Mao et al., 2018; Mao et al., 2022; Yang et al., 2023), we developed a "cloud model-Monte Carlo" coupling model to calculate slope failure probability and perform risk assessment.

Risk analysis originated in the United States (Xie and Sun, 2009) and was first applied in nuclear power plant risk assessment. Risk analysis includes identifying potential hazards (Ge et al., 2020a), assessing their likelihood and consequences, and formulating mitigation measures to reduce risks (Wu et al., 2021; Zhang et al., 2022b). In terms of dam safety, hazardous situations include natural disasters such as floods or earthquakes, as well as human errors or equipment malfunctions. The consequences of these hazards can range from property and economic losses to loss of life and environmental degradation (Ge et al., 2020b; Wu et al., 2020; Ge et al., 2022; Zhang et al., 2023). Various methods such as probabilistic risk assessment and quantitative risk analysis (Li et al., 2018; Wang et al., 2022) can be used for risk assessment. These methods involve collecting design, location, and operation data of the dam, as well as external factors such as weather patterns and geological conditions. Based on these data, mathematical models are established to simulate the performance of the dam under different hazardous situations and estimate associated risks (Li et al., 2021; Wang et al., 2023).

In the past few decades, many studies have focused on developing probabilistic methods to analyze slope stability (Cai et al., 2021; Chakraborty and Dey, 2022) and have demonstrated their superiority in risk assessment. However, many factors need to be considered when evaluating slope stability (Raghuvanshi, 2019; Yang et al., 2021), and simple deterministic methods may not satisfy complex practical situations. This article aims to introduce a probabilistic-based method, where we propose a new approach for slope stability analysis based on the "cloud model-Monte Carlo". We demonstrate the effectiveness of this method by applying it to a case study of earth-rockfill dams. The proposed method provides an assessment of dam landslide risk and can provide a reference for decision-makers to formulate effective risk management strategies.

2 Materials and methods

2.1 Indoor tests

The experimental parameters employed in this study were derived exclusively from indoor geotechnical tests utilizing remolded soil samples. Sampling was conducted within a rectangular area located in the northeast of Tianshuihu, Pingyu County, China, with dimensions of approximately 500 m in length and 150 m in width. According to the geological profile of the region, the geological structure of the Tianshuihu area is characterized by homogeneous cohesive soils, mainly composed of fourth-quaternary loamy soil and clay. To mitigate uncertainties arising from spatial and temporal factors, sampling depth was limited between half a meter to 1 m, with the obtained soil samples being plastic loamy soil. After the sifting of soil samples, direct shear testing was performed, following the specific steps outlined in Figure 1.

In this study, 26 sets of powdered clay test data obtained from indoor direct shear tests were selected for the study, including the shear strength index c and the internal friction angle index φ. The specific values are shown in Table 1.

2.2 Research overview

The earth-rockfill dam (Yong, 2004) is a rolled clay core wall dam with a maximum dam height of 70 m, a crest width of 12 m, and a base width of 465 m. The normal water level is 185 m, the dead water level is 167 m, the total storage capacity is 1.13 billion m³, and the effective storage capacity is 570 million m³. The upstream slope is from bottom to top at a ratio of 1:4.0, 1:3.5, 1:3.0, 1:2.0, and the downstream slope is from bottom to top at a ratio of 1:4.0, 1:3.0, 1:2.0. Approximately 144 m below the dam base is a thick clay core wall, and the slope is 1:4.0, 1:0.5. Above 144 m, the slope is 1:0.1–1:0.2. The river length above the hub dam site is 120 km, the controlled drainage area is 2,000 square kilometers, the annual average flow rate is 37.8 m³/s, and the annual average runoff volume is 1.2 billion m³. The design flood peak flow rate corresponding to a once-in-a-millennium event is 6,640 m³/s, and the corresponding flood level is 188.1 m. The verification flood peak flow rate corresponding to a once-in-a-ten-thousand-years event is 8,700 m³/s, and the corresponding flood level is 189.5 m.

The analysis object is the unreinforced earth-rockfill dam with an upstream water level of 188.1 m, a downstream water level of 132.0 m, and a dam base elevation of 120.0 m. The non-stochastic mechanical parameters of the dam body are shown in Table 2. In recent years, the reservoir has had many safety hazards: the core wall narrows above the elevation of 144 m, and the slope decreases from the original ratio of 1:0.5 to 1:0.1; starting from an elevation of 150 m, gravelly soil has been used in the core wall, resulting in severe seepage of the dam body, the infiltration line overflows the dam slope, and large-scale mortification occurs on the downstream slope, which affects the stability and safety of the dam body.
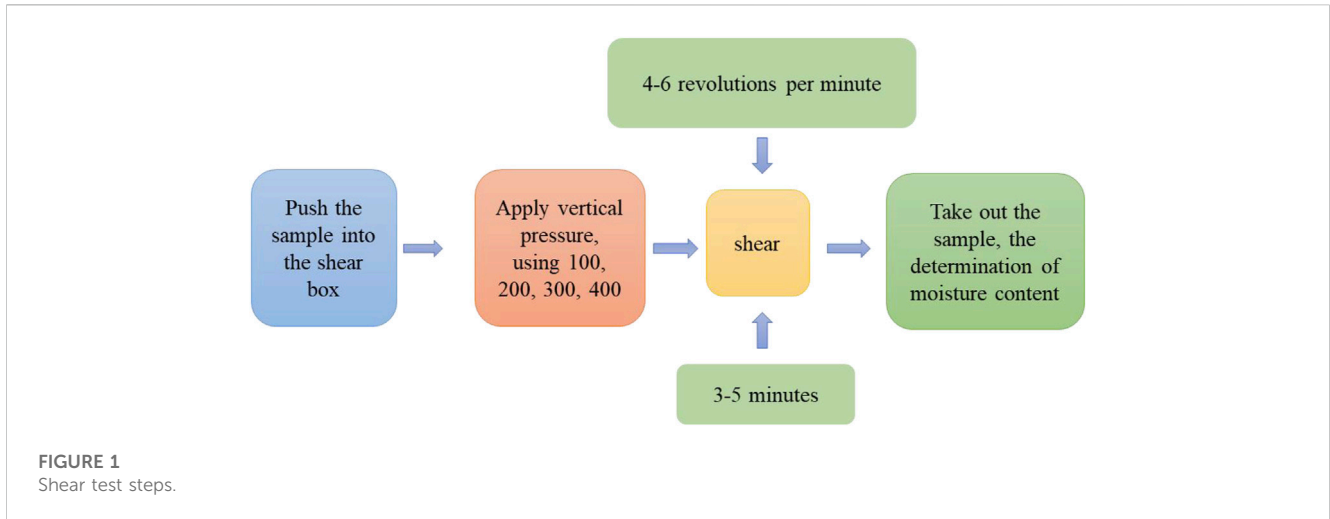
FIGURE 1
Shear test steps.

TABLE 1 Record sheet of direct shear test for soil samples (No. 1–26 soil).

Group	Cohesion (kPa)	Internal friction angle φ (°)	Group	Cohesion (kPa)	Internal friction angle φ (°)
1	12.2	10.4	14	18.9	15.8
2	15	11.6	15	16.3	16.8
3	15	12.2	16	16.4	17
4	15	12.4	17	17.2	17.2
5	19.7	13.5	18	17.3	17.2
6	15	14	19	17.3	18.8
7	15.5	14	20	21	18.8
8	21.8	14.6	21	17.7	19.5
9	15.8	15.1	22	17.7	19.5
10	15.8	15.4	23	18.3	20.9
11	15.8	15.6	24	18.3	21.5
12	18.8	15.6	25	18.3	24.6
13	16	15.7	26	18.4	25.9

TABLE 2 Non-random mechanical parameters of earth and rock dams.

Physical properties	Wet capacity	Dry capacity	Saturated capacity	Floating capacity
Unit	t/m^3	t/m^3	t/m^3	t/m^3
Quantity	1.995	1.730	2.090	1.090

2.3 Model construction

The "cloud theory-Monte Carlo" approach to analyzing the risk of earth and rock dams is shown in Figure 2.

The method proposed in this paper is a cloud model used to determine the type of probability distribution of shear strength parameters. Monte Carlo methods are used to simulate the random variables in the cloud model and to calculate the probability of dam slope failure based on the probability distribution of the random variables.

2.3.1 Basic principles of cloud model

The cloud model, based on fuzzy mathematics and statistical theory, is a powerful tool for describing the randomness and fuzziness between uncertain language and precise numerical values. It has been applied to several uncertain problems and

FIGURE 2
Flow chart of the "cloud theory—Monte Carlo" based dam slope instability calculation.
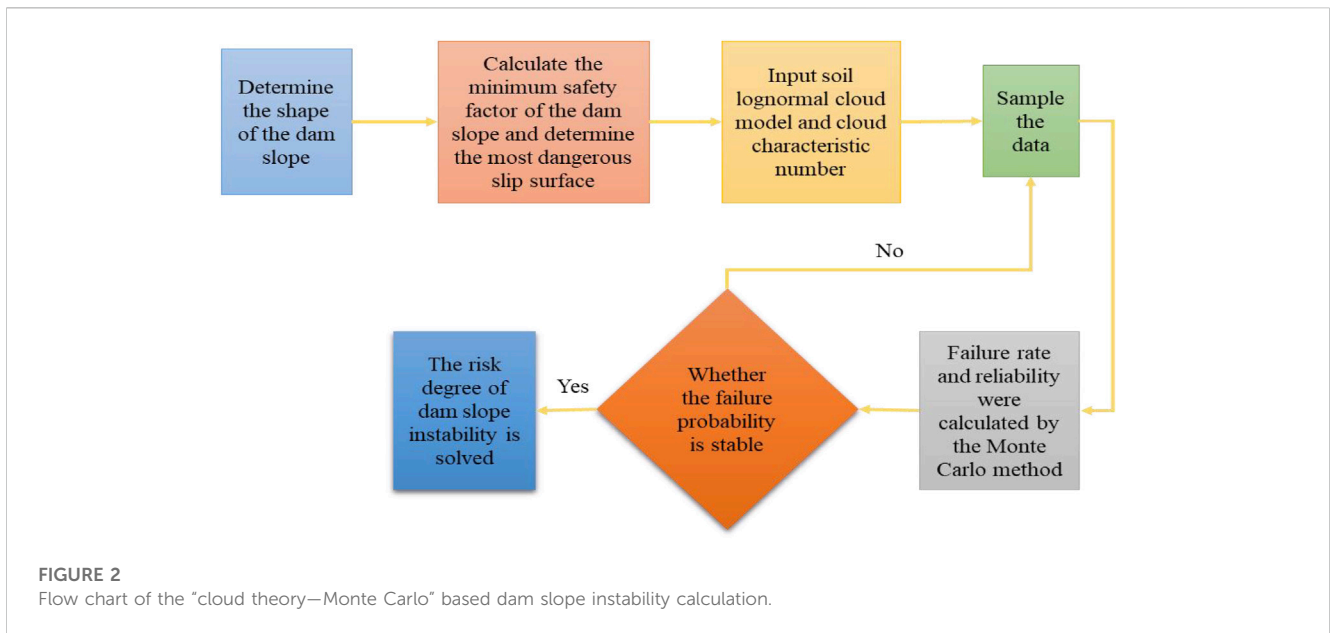
owing to its superiority in handling uncertainty issues, we have incorporated it into our study of inferred soil shear strength distribution indices.

Let U be a quantified domain represented by precise numerical values, and C be a qualitative concept defined on the domain U. If the quantitative value $x \in U$ is a random realization of the qualitative concept C, and satisfies $x \sim N(Ex, En'^2)$, where $En' \sim N(En, He^2)$, and the degree of certainty of x for C satisfies μ, then the distribution of x on the domain U is known as the normal cloud.

$$\mu = e^{-\frac{(x-Ex)^2}{2(En')^2}} \tag{1}$$

The cloud model no longer emphasizes precise function representation (Yangping et al., 2019), but instead employs three numerical features to represent the uncertainty of concepts: expectation "Ex", entropy "En", and hyper-entropy "He". "Ex" represents the central position of the concept in the domain and is the value that best represents this qualitative concept. "En" describes the level of discreteness of the qualitative concept, characterizing its randomness and fuzziness. The greater the entropy, the larger the range of acceptable numerical values for the concept, making the concept more macroscopic. "He" is a measure of uncertainty in entropy and is generally determined empirically. According to the 3"En" rule of statistics, the cloud droplets contributing to the concept are typically situated within the interval [Ex-3En, Ex+3En].

2.3.2 Inverse cloud algorithm optimization

The radiation fitting algorithm of the inverse cloud generator is based on the radiative digital characteristics of clouds and their corresponding radiative expectation functions. It expresses the probability distribution characteristics of cloud droplets' energy radiation over the entire numerical domain space. By following data radiation and improving the inverse cloud generator algorithm based on its fitting, the specific description of the algorithm is as follows:

Input: The coordinates li of each cloud droplet in the numerical domain space along with their respective degree of certainty $C_T(l)$ representing the concept.

Output: The values of Ex, En, and He for the concept, and the number of cloud droplets N.

The estimated value $\hat{Ex}(l)$ of Ex is obtained by fitting the known cloud droplets using the cloud expectation curve $C_T(l)$.

$$C_T(l) = \frac{1}{\hat{f}(l)} e^{-\frac{[\hat{f}(l)(l-\hat{Ex})]^2}{2[En(l)]^2}} \tag{2}$$

$$\hat{Ex}(l) = \frac{\sum_{i=1}^{n} \hat{f}(l_i) l_i}{\sum_{i=1}^{n} \hat{f}(l_i)} \tag{3}$$

The cloud droplets with $C_T(l) > 0.999$ are removed, leaving m droplets. We then calculate $\hat{En}(l_i)$; as well as $\hat{En}(l)$ and $\hat{He}(l)$, the estimated values of En and He respectively.

$$\hat{En}(l_i) = \frac{\left| f(l_i)(l_i - \hat{Ex}) \right|}{\sqrt{-2 \ln(f(l_i) C_T(l_i))}} \tag{4}$$

$$\hat{En}(l) = \sqrt{\frac{\sum_{i=1}^{m} [\hat{f}(En(l_i)) En(l_i)]}{\sum_{i=1}^{m} [\hat{f}(En(l_i))]}} \tag{5}$$

$$\hat{He}(l) = \sqrt{\frac{\sum_{i=1}^{n} [\hat{f}(En(l_i))(En(l_i) - \hat{En}(En(l_i)))]^2}{\sum_{i=1}^{n} \hat{f}(En(l_i))}} \tag{6}$$

2.3.3 Cloud model pervasiveness

The geometric shape of the normal cloud has distinct characteristics, with its expectation curve reflecting the shape of the normal cloud. It can be deduced that for any $0 < \mu \leq 1$, as determined by μ.

$$X = Ex \pm \sqrt{-2 \ln \mu} En' \tag{7}$$

As En' is a random variable, and x is a symmetrical random variable located on both sides of Ex. Therefore, it is sufficient to analyze only X_1, as the analysis of X_2 is entirely analogous.

$$X_1 = Ex + \sqrt{-2\ln\mu}En' \qquad (8)$$

$$X_2 = Ex - \sqrt{-2\ln\mu}En' \qquad (9)$$

From $En' \sim N(En, He^2)$, it can be deduced that X follows a normal distribution with an expectation of EX and a standard deviation of B. Therefore, according to this formula, the discreteness of cloud droplets is directly proportional to He and inversely proportional to y. This implies that as He increases, so does the discreteness of cloud droplets, while decreasing y (i.e., approaching the foot of the mountain) leads to more dispersed cloud droplets.

$$EX = Ex + \sqrt{-2\ln\mu}En' \qquad (10)$$

$$B = \sqrt{DX} = \sqrt{-2\ln\mu}He \qquad (11)$$

By solving for μ from EX, the expectation curve y of the normal cloud can be obtained.

$$\mu = e^{\frac{-(EX-Ex)^2}{2En^2}} \qquad (12)$$

$$y = e^{\frac{-(x-Ex)^2}{2En^2}} \qquad (13)$$

2.3.4 Calculation of the coefficient of safety for dam slope stability

Because most slope stability analysis problems are super-stationary, SL274-2001(SL274-2001, DAMS, 2002) (Chinese Standards) states that the equations of ultimate equilibrium must be established using the simplified Bishop bar method the Swedish bar method, and the Spencer method.

According to the simplified Bishop's bar method, the following limiting equation of state is established.

$$G(X) = \frac{1}{\cos\alpha_i + \tan\varphi_i\sin\alpha_i}\left[c_i l_i + (w_i - u_i b_i)\tan\varphi_i\right] - w_i\sin\alpha_i \qquad (14)$$

Where, α_i is the angle between the gravity line of the soil strip and the radius in the bottom surface passing through this line; c_i is the cohesive force at the bottom surface of the strip and φ_i is the angle of internal friction at the bottom surface of the strip; w_i is the self-weight of the strip; b_i is the width of the strip; and u_i is the pore water stress.

2.3.5 Calculation of the risk level of the dam slope
2.3.5.1 Calculation of $\Delta F_0(h_i)$

The number of levels upstream of an earth and rock dam is considered a random variable. Its calculation can be statistically analyzed on a long series of observations of the reservoir water level, which in turn leads to a probability plot of the probability distribution characteristics of the water level. Given a certain water as Z_m, the value of $\Delta F_0(h_i)$ is calculated from the corresponding frequency value. Alternatively, the value of $\Delta F_0(h_i)$ can be found by applying the probabilistic algorithm for reservoir regulation calculations concerning the literature (Yaowu and Dongwei, 1994).

2.3.5.2 Calculation of $\bar{F}_L(h_i)$

According to the previous description, $\bar{F}_L(h_i)$ represents the average probability that the sliding moment is greater than the anti-slip moment at a certain water level h_i. The expressions are.

$$\bar{F}_L(h_i) = \int_r^\infty f(l/h)dl \qquad (15)$$

The specific condition probability density function for the sliding moment L of a dam under a certain water level H, denoted as (l/h) in the formula, is extremely complex, and its solution is very difficult to obtain. Nevertheless, using the Monte Carlo method can yield high results. The solution process for $\bar{F}_L(h_i)$ is related to the form of the slip surface, and different slip surfaces will produce different values. Therefore, it is necessary to determine the maximum value of $\bar{F}_L(h_i)$. However, directly seeking the maximum value is not practical. Hence, we first calculate the minimum safety factor K_{min} (Zhang et al., 2006) for the landside dam slope and then use the corresponding most dangerous slip arc to obtain the maximum value of $\bar{F}_L(h_i)$.

2.3.6 Coupled "cloud model-Monte Carlo" model for dam slope instability risk analysis

The relationship between the sliding moment S and the anti-slip moment R is a key factor affecting the stability of the dam slope. When $S>R$, the dam slope becomes unstable, according to which, the following mathematical model of the risk of instability of the slope of an earth and rock dam can be established, setting the functional function as

$$g(\cdot) = g(L, R) = R - L \qquad (16)$$

$$P_f = P(L > R) = \iint_{g(\cdot)<0} f_{R,L}(r, l)drdl \qquad (17)$$

Where, $f_{R,L}(r, l)$ is the joint probability density distribution function of the sliding moment L and the anti-slip moment R of the earth and rock dam.

Due to the great difficulties in the practical application of the above equation, it is transformed into

$$P_f = \int_{-\infty}^\infty \int_0^l f_R(r)dr f_L(l)dl = \int_{-\infty}^\infty F_R(l)f_L dl \qquad (18)$$

The problem of using probabilistic combinations to estimate P_f indirectly exists and can be solved perfectly. Thus, let the joint probability density function of the sliding moment L and the water level upstream of the dam H be

$$f_{HL}(h, l) = f(l/h)f_o(h) \qquad (19)$$

Where, (l/h) is the conditional probability density function of the water level H for the sliding moment L under the given conditions and the probability density function $f_o(h)$ is for the water level upstream of the dam.

The probability density function for the sliding moment L of an earth and rock dam slope can be calculated by the full probability density formula, expressed as follows:

$$f(l) = \int_{-\infty}^{\infty} f(l/h) f_0(h) dh \qquad (20)$$

Combining Eq. 18 with Eq. 19 yields

$$P_f = P(L > R) = \int_r^{\infty} \left[\int_{-\infty}^{\infty} f(l/h) f_0(h) dh \right] dl$$
$$= \int_0^{\infty} \left[\int_{-\infty}^{\infty} f(l/h) dl \right] f_0(h) dh \qquad (21)$$

If

$$F_l(h) = \int_r^{\infty} f(l/h) dl \qquad (22)$$

What about there

$$P_f = P(L > R) = \int_{h_1}^{h_2} F_l(h) f_0(h) dh \qquad (23)$$

where, h_1 is the minimum water level specified in the risk of instability calculation for the earth and rock dam slopes and h_2 is the maximum water level specified in the risk of instability calculation for the earth and rock dam slopes.

Eq. 23 is the formula for calculating the risk of instability in the slope of an earth and rock dam, but it is very difficult to solve the formula directly by integration. Therefore, in the actual calculation, it is necessary to apply the method of discrete numerical integration to solve it. After dividing the part of the load probability density distribution curve on $L \le h2$ into N segments, the solution is given by the following equation.

$$P_f = P(L > R) = \int_{h_1}^{h_2} F_l(h) f_0(h) dh = \sum_{i=1}^{N} \Delta F_0(h_i) \bar{F}_L(h_i) \qquad (24)$$

Where, $F_l(h)$ is the probability that the sliding moment corresponding to a certain water level h is greater than the anti-slip moment; N is the calculated number of segments of the water level frequency curve upstream of the earth and rock dam; $\Delta F_0(h_i)$ is the probability of the ith segment of the water level frequency curve upstream of the earth and rock dam; $\bar{F}_L(h_i)$ is the i-th segment of the sliding moment L is the mean value of the probability that L is greater than the anti-slip moment R.

In the process of slope risk analysis, the shear strength parameter cohesion and the internal friction coefficient $f = \tan \varphi$ of the landslide material are analyzed as random variables and it is assumed that c and φ are statistically independent of each other and obey lognormal cloud distributions of $D(\mu_c = Ex_c, \sigma_c = En_c), D(\mu_f = Ex_f, \sigma_f = En_f)$ respectively. N cloud drops are generated for c and f to obtain a cloud distribution plot of the two.

When using the Monte Carlo method of calculation, the cloud distribution of the shear strength parameter is allowed to replace the distribution histogram, and the standard deviation of the factor of safety and the mean of the distribution are obtained from the cloud distribution as in Eqs. 25–(26).

$$En = \sigma_Y = \left[\ln \left(1 + V_X^2 \right) \right]^{\frac{1}{2}} \qquad (25)$$

$$Ex = \mu_Y = \ln \mu_X - \frac{1}{2} \sigma_{\ln x}^2 = \ln \left(\frac{\mu_X}{\sqrt{1 + V_X^2}} \right) \qquad (26)$$

$$x_i = e^{y_i} \qquad (27)$$

Where, X is the lognormal cloud distribution (its mean is the expectation of the cloud Ex, the standard deviation is the entropy of the cloud En; and the coefficient of variation is Vx; $Y = lnx$ is the normal distribution (mean μ_Y and standard deviation σ_Y); x_i is the random number of variables X.

2.3.7 Steps for calculating the "cloud model—Monte Carlo" model

The "cloud model-Monte Carlo" model used in the calculation process of the failure probability P_f of the earth-rock dam slope can be summarized into several steps.

1) Input each random statistical characteristic and distribution model.
2) The uncertainty cloud model is used to generate cloud drops and sample uncertain quantities such as cohesion c and internal friction angle φ.
3) The random set of uniformly distributed random numbers is generated and the corresponding parameters are generated according to the distribution law of each variable.
4) Generated random numbers and parameters are substituted into the function of the Swedish strip division method for multiple calculations, the number of failures is recorded, and the failure probability P_f is calculated.
5) Solve for the risk of dam slope instability based on the failure probability P_f.

3 Results

## 3.1 Cloud distribution model for shear strength index

Based on the small sample data, the three numerical features of the shear strength parameter c were derived by the inverse cloud generator, and then the cloud distribution map was obtained by the forward cloud generator (φ values, c values log cloud distribution map of the same analysis path), and the basic parameters of the cloud model are shown in Table 3.

Through multiple cycles of the forward and reverse cloud generators, 1000 cloud drops were simulated, generating the cloud distribution shown in Figure 3.

According to Figure 3, it can be seen that the generalized normal distribution of clouds can effectively model the discrete nature of finite sample data. The cloud droplets generated based on the three characteristic figures are mainly distributed in the intervals [12,22] [0.75,1.75] [12.5,20], and [1.1,1.3], by the '3 days' rule in cloud theory. This indicates that the cohesion and internal friction angles obey both normal and lognormal cloud distributions. In order to determine the optimal probability distribution model for the shear strength index of the soil, a comparison was made. The results show that the tail cloud drops of the lognormal cloud distribution for cohesion and internal friction angle are 'lighter' than the normal cloud distribution and that the drops fluctuate less around the desired curve. This indicates that the variability between the sample data is reduced and the data is more concentrated after the logarithmic transformation. The log-transformed coefficient of variation for the soil parameters is calculated to be 0.043, which is

TABLE 3 Basic parameters of the Cloud model.

Mechanical index	Possibility type	Ex	En	He	A first-order sample center distance	Variance	Coefficient of variation
cohesion	normal	17.116	2.075	0.317	1.656	4.404	0.121
	lognormal	1.230	0.053	0.008	0.042	0.029	0.043
internal friction angle φ	normal	16.677	3.623	1.037	2.89	14.201	0.226
	lognormal	1.209	0.090	0.016	0.071	0.024	0.128

FIGURE 3
Sample parameter cloud distribution.
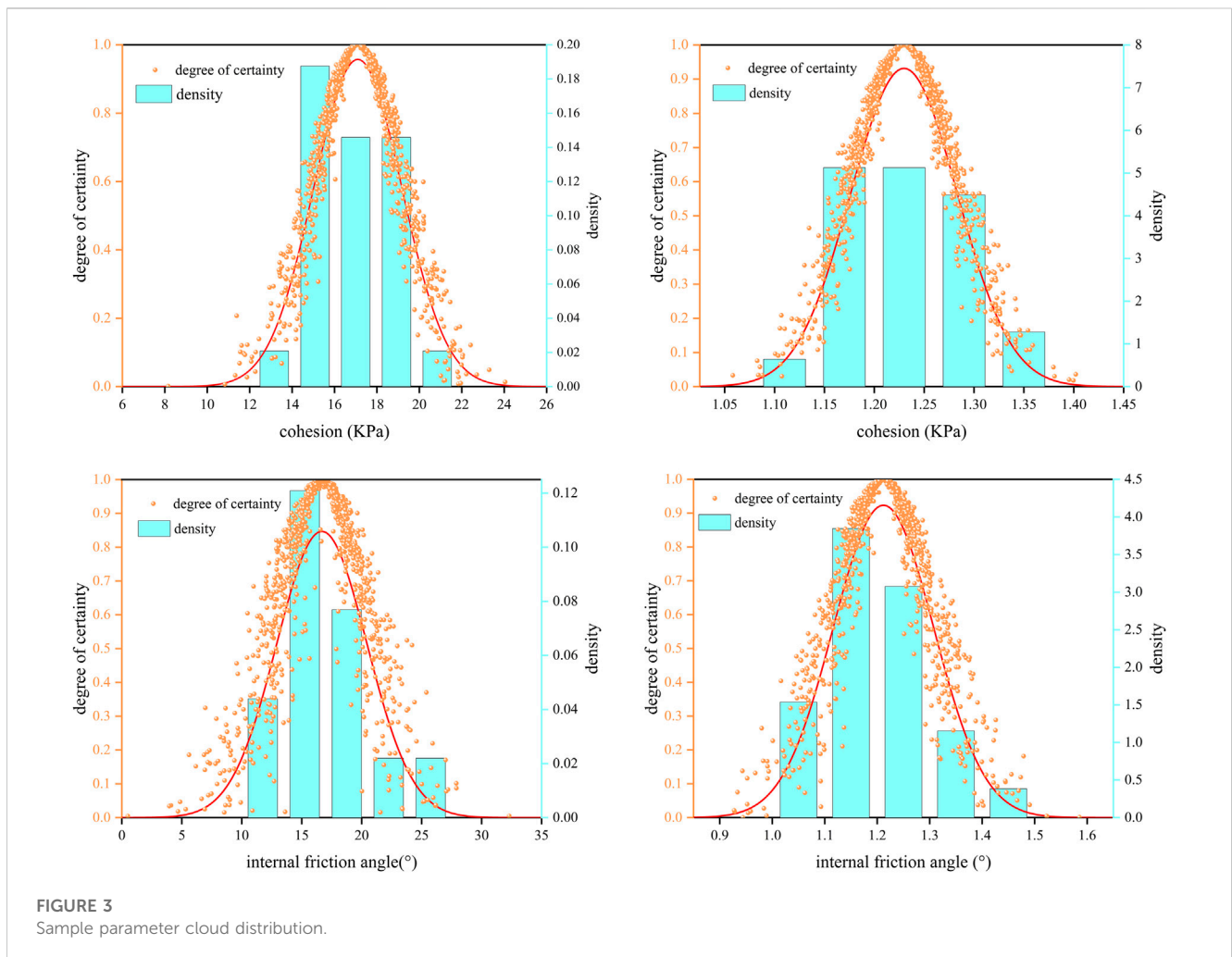
much smaller than the untransformed coefficient of 0.121 and is consistent with the inferred results for the cloud distribution. Therefore, the log-normal cloud distribution is considered to be the optimal probability distribution model for cohesion and internal friction angle.

In order to make full use of the sample information without over-relying on the sample data, this study adopts a cloud theory-based method for studying the distribution types of soil shear strength indicators. As can be seen from Figure 3,

the thickness of the clouds is not strictly normally distributed but is a generalized normal cloud distribution. In contrast to the distribution histogram and its fitted curve, the pan-normal distribution of clouds describes the uncertainty of finite data by introducing the super entropy He. As shown in Figure 3C, the cloud thickness is large and the cloud droplet distribution is discrete appearing fogged in the internal friction angle cloud distribution plot, indicating a large uncertainty in the sample data for the internal friction angle, a property that is not

FIGURE 4
Cloud distribution of mean slope calculation results.
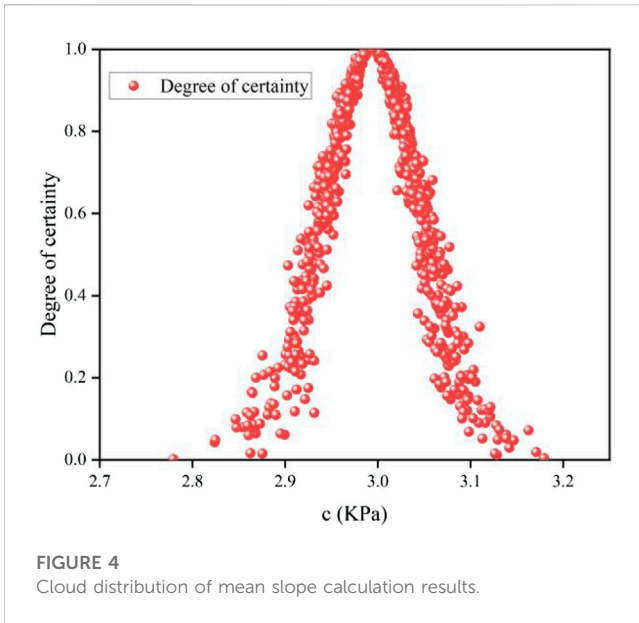
represented in the histogram of the internal friction angle distribution.

3.2 "Cloud Model-Monte Carlo" based slope stability risk analysis

3.2.1 Cloud simulation of shear strength parameters

The cohesive force c and the coefficient of internal friction $f=\tan\varphi$ of the landslide soil are considered random variables and are assumed to follow a log-normal cloud distribution. After 1000 simulations, the cloud distribution of the coefficient of safety is shown in Figure 4. The expected value Ex and variance En of the safety factor are shown in Table 4.

3.2.2 Determination of the minimum safety factor
3.2.2.1 Calculation assumptions

This calculation assumes a starting elevation of 160 m. The infiltration line of the earth and rock dam body is determined using the finite element method, which is not limited by irregular geometry and inhomogeneous materials, and the calculation results are highly reliable.

3.2.2.2 Calculation method

During the period of steady seepage, the Swedish strip division method was used to carry out the downstream slope stability analysis of the earth and rock dam, and the minimum safety factor and the

location of the most dangerous slip surface were obtained through the calculation.

3.2.2.3 Calculation results

The minimum safety factors obtained using the Swedish arc method at each water level, together with the values specified in the code, are shown in Table 5 below.

3.2.3 Calculation of slope failure probability
3.2.3.1 Probability of failure $\bar{F}_L$ (h_i) calculation

After obtaining the minimum safety coefficient from the slope stability analysis, the calculation was carried out using the Monte Carlo method and the relevant electro-computing procedures. In general, the probability of failure was under 0.1% according to the number of solutions $N > \frac{100}{P_f}$, and to meet the requirements of calculation accuracy, the number of solutions was set to 200,000 times to calculate the probability of failure of the downstream dam slope, and the calculation results are shown in Table 6.

3.2.3.2 Calculation of the interval frequency $\Delta F_0 (h_i)$

Based on the upstream flood level frequency curve of the earth and rock dam Figure 5, the interval frequency value $\Delta F_0 (h_i)$ can be found as shown in Table 7.

3.2.4 Coupled "cloud Model-Monte Carlo" model for dam slope risk calculation

The degree of risk $\bar{R}$ can be calculated by the following equation.

$$\bar{R} = P_f = P(L > R) = \int_{h_1}^{h_2} F_L(h) f_0(h) dh = \sum_{i=1}^{N} \Delta F_0(h_i) \overline{F_L}(h_i)$$

(28)

The results of the calculation are shown in Table 8.

For a parameter F that fits the lognormal cloud distribution, let y fit the normal cloud distribution and have

$$y = lnF \quad (29)$$

or

$$F = e^y \quad (30)$$

Then F can be transformed into a normal cloud distribution.

The following transformation relationship exists between the expectation and entropy of F and y, i.e.,

$$En_y = \left[\ln\left(1 + V_F^2\right)\right]^{\frac{1}{2}} \quad (31)$$

$$Ex_y = \ln\left(\frac{Ex_x}{\sqrt{1 + V_F^2}}\right) \quad (32)$$

In the above equation: μ_Y and σ_Y are the standard deviation and mean of y respectively.

The coefficient of variation is obtained from Eqs. 31–(32) as

TABLE 4 Characteristic values of random mechanical parameters of earth and rock dams.

Variable name	Symbol	Distribution type	Mean	Variance	Coefficient of variation
Cohesion	c	log-normal cloud	3	0.29	0.5
Internal friction angle coefficient	f	log-normal cloud	0.5095	0.,24	0.2

TABLE 5 Calculation of the slope stability factor of safety for the earth and rock dams.

Dam slope	Upstream water level/m	Coefficient of safety K_{min}	Range of specified values
Downstream	188.1	1.29	1.24
	186.0	1.32	
	185.0	1.34	
	184.0	1.36	
	182.0	1.40	
	180.0	1.49	
	178.0	1.54	
	176.0	1.60	
	174.0	1.67	
	172.0	1.68	
	170.0	1.70	
	168.0	1.76	
	166.0	1.76	
	164.0	1.85	
	162.0	1.89	
	160.0	1.92	

TABLE 6 Calculation of slope failure probability $\bar{F}_L$ (h_i) for earth and rock dams.

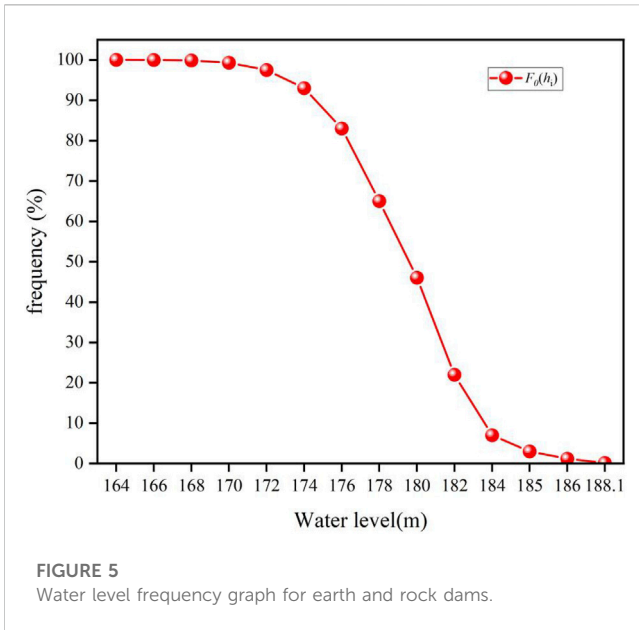| Dam slope	Safety factor K_{min}	Probability of failure $\bar{F}_L$ (h_i)/%
Downstream	1.29	0.15101
	1.32	0.13526
	1.34	0.19311
	1.36	0.11174
	1.40	0.11876
	1.49	0.08711
	1.54	0.08701
	1.60	0.07515
	1.67	0.05250
	1.68	0.03825
	1.70	0.03450
	1.76	0.02525
	1.76	0.03350
	1.85	0.01920
	1.89	0.01635
	1.92	0.01715

FIGURE 5
Water level frequency graph for earth and rock dams.

TABLE 7 Flood level frequency relationships upstream of earth and rock dams.

Water level/m	Frequency $F_0(h_i)$%	$\Delta F_0(h_i)$/%
164.0	99.999	
166.0	99.98	0.019
168.0	99.85	0.13
170.0	99.3	0.55
172.0	97.5	1.8
174.0	93	4.5
176.0	83	10
178.0	65	15
180.0	46	22
182.0	22	24
184.0	7	15
185.0	3	4
186.0	1.2	1.8
188.1	0.15	1.05

$$V_F = \frac{\sigma_F}{\mu_F} = \frac{En_F}{Ex_F} \tag{33}$$

Since y less than 0 is equivalent to F less than 0, the reliability index $\beta = Ex_y/En_y$ not only reflects the probability that $Y < 0$, but also represents the probability that probability of $F < 1$. For a normal cloud distribution, the variables y and β alike can be expressed in terms of Ex_F, En_F.

$$\beta = \frac{\mu_y}{\sigma_y} = \frac{Ex_y}{En_y} = \frac{\ln\left(\frac{Ex_x}{\sqrt{1+V_F^2}}\right)}{\left[\ln\left(1+V_F^2\right)\right]^{\frac{1}{2}}} \tag{34}$$

According to the above equation, for $\mu_F = Ex_y = 3$, $V_F = 9.7\%$, a review of the data shows that the probability of $F > 1$ is 99% and can be obtained by the following equation.

$$En_y = \left[\ln\left(1 + 0.097^2\right)\right]^{\frac{1}{2}} = 0.109 \tag{35}$$

$$Ex_y = \ln\left(\frac{3}{\sqrt{1 + 0.097^2}}\right) = 0.252 \tag{36}$$

$$\beta = \frac{0.251}{0.109} = 2.204 \tag{37}$$

The improved risk analysis method based on cloud theory yields a risk level of 879.01×10^{-6}, which is smaller and more accurate than the traditional method of 929.25×10^{-6}, proving that this method is more reliable.

3.2.5 Risk evaluation

In recent years, the main method of risk analysis has been based on parameters following a normal distribution. However, this may lead to negative values for certain parameters, particularly when analyzing slope engineering parameters such as cohesion. This can result in lower reliability as cohesion may have negative values. To address this issue, this paper analyzes parameters following a logarithmic normal cloud distribution, aligning the stability measurement standard of slope instability with the traditional analysis method of functional functions less than zero.

Traditional slope stability analysis uses deterministic models to obtain the safety factor F. However, risk analysis based on cloud theory uses two indicators, the expectation Ep and entropy En, to determine the failure probability of the slope by analyzing the variability characteristics of influencing factors, which is more reasonable. Studies have shown that the probability of dam collapse due to landslides in earth-rock dams is on the order of 10^{-5} per dam per year, therefore, we set the landslide probability of earth-rock dams at 10^{-5} per dam per year. Taking into account the safety factors, the statistical probability of landslides for each dam per year is set at $1 \times 10^{-5.}$ Therefore, the safety reliability of earth-rock dams against landslides is above 99.999%.

However, determining the value of landslide risk for earth-rock dams is influenced by many factors. The process of determining risk standards requires repeated weighing between economic benefits, political risks, environmental assessments, and dam safety. Referring to relevant risk standards, this paper sets the allowable landslide risk standard at 0.5×10^{-6}, resulting in a safety reliability indicator of over 99.9995.

The calculation results show that the risk probability corresponding to the design flood level of the dam is 9.01×10^{-6}, exceeding the allowable risk standard of 0.5×10^{-6}, thus reinforcement treatment is necessary.

4 Discussion

This study proposes a "cloud model-Monte Carlo" coupling model and applies it to evaluate the risk of specific earth-rock dam landslides. The results show that the proposed model is effective in analyzing the risk of dam slope failure and provides a comprehensive assessment of potential risks related to the dam. The cloud model is used to determine the probability distribution

TABLE 8 Calculation of the risk of dam slope instability for earth and rock dams.

Water level/m	The factor of safety K_{min}	$F_L(h)$/%	$\overline{F_L}(h_i)$/%	$F_0(h_i)$/%	$\Delta F_0(h_i)$/%	Degree of risk R
164.0	1.85	0.151	99.999			
166.0	1.76	0.13525	0.0265	99.98	0.019	0.05
168.0	1.76	0.1931	0.0294	99.85	0.13	0.38
170.0	1.70	0.11175	0.0294	99.3	0.55	1.62
172.0	1.68	0.11875	0.0359	97.5	1.8	6.646
174.0	1.67	0.0871	0.0454	93	4.5	20.43
176.0	1.60	0.087	0.0634	83	10	62.4
178.0	1.54	0.07525	0.0807	65	15	121.05
180.0	1.49	0.0525	0.087	46	22	191.4
182.0	1.40	0.03825	0.1029	22	24	246.96
184.0	1.36	0.0345	0.1148	7	15	172.2
185.0	1.34	0.02525	0.1519	3	4	60.76
186.0	1.32	0.0335	0.1642	1.2	1.8	25.56
188.1	1.29	0.0192	0.1427	0.15	1.05	14.98
Σ						879.11

type of uncertain shear strength parameters. Then, the Monte Carlo method is used to generate a large number of random samples based on the cloud model for simulating the probability of dam slope failure. In addition, the results of the risk assessment indicate that under normal conditions, the risk of dam slope failure is relatively low, but it significantly increases under extreme weather conditions (such as heavy rain). This suggests the need to take appropriate measures to reduce the risk of dam slope failure under extreme weather conditions, such as strengthening the dam structure or implementing emergency response plans.

Overall, the cloud model-Monte Carlo coupling model provides an effective approach for evaluating the risk of dam slope failure. The results of this study can provide valuable information to dam managers and decision-makers to make informed decisions under different weather conditions and ensure dam safety.

5 Conclusion

Firstly, this paper employs a research method based on cloud theory to study the distribution types of soil shear strength indicators. The optimal probability distribution model for cohesion and internal friction angle is found to be the logarithmic normal cloud distribution. Moreover, we propose a "cloud model-Monte Carlo" coupling model, which can effectively evaluate the risk of dam landslides. The cloud model can handle the uncertainty of shear strength parameters and determine their probability distribution models. The Monte Carlo method can simulate the random behavior of input variables and calculate the probability of output variables. The combination of these two methods can provide more accurate risk assessment

results. In slope risk analysis, the "cloud theory-Monte Carlo" model can calculate failure probability and risk degree more accurately and reliably compared to traditional methods.

Secondly, referring to relevant risk standards, this paper sets the allowable landslide risk standard for earth-rock dams at 0.5×10^{-6}, with a safety reliability indicator of over 99.9995%. The calculation results show that the risk probability corresponding to the design flood level of the dam is 9.01×10^{-6}, exceeding the allowable risk standard. Therefore, it is necessary to reinforce the earth-rock dam to reduce the risk of failure.

Finally, the proposed cloud model-Monte Carlo coupling model has broad application prospects in the field of dam risk assessment. It can be used to analyze the risks of various types of dams and provide accurate risk assessment results. In future research, the model can be further improved to enhance its accuracy and applicability, while being more widely applied and validated.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

Method: MC; Experiment: MC, JS, LM, and WJ; Data analysis: MC and ZS; Prepare the original manuscript: MC; Writing, reviewing and editing: MC and LH; Fund buy-out, LH; Guidance: LH and HZ

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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