

Article

Runout Assessment of Rainfall-Induced Landslides by Coupling BO-XGBoost and Continuum–Discontinuum Simulation

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Highlights

What are the main findings?

- BO-XGBoost predicted landslide runout with $R^2 = 0.858$ and MAE = 113.94 m.
- A two-stage particle strength softening model was incorporated into CDEM.
- The coupled BO-XGBoost–CDEM workflow reproduced the Wangjiawan runout.

What are the implications of the main findings?

- The framework enables rapid and reliable rainfall-induced landslide assessment.
- The method links runout prediction with the numerical simulation of failure evolution.
- The approach supports hazard zoning and mechanism analysis in landslide risk studies.

Abstract

Reliable prediction of landslide runout distance and influencing areas is critical for landslide hazard zoning and risk assessment. This paper proposed a rainfall-induced landslide prediction and simulation platform based on the developed interpretable Bayesian optimization-extreme gradient Boosting (BO-XGBoost) model and the continuum–discontinuum element method (CDEM) incorporated with a particle strength softening model. First, based on kinematic prediction theory, several key influencing features were selected from rainfall-induced landslide cases to train the BO-XGBoost model. The nonlinear relationship between runout distance and influencing features was effectively captured by the model, with an R^2 of 0.858. According to Shapley Additive Explanations (SHAP) analysis, the elevation difference between the rear and front edges was identified as the dominant controlling feature. Then, the particle flow method was introduced into CDEM and a particle strength softening model was proposed to simulate the landslide process. The applicability of the proposed softening model was validated through the case of the Yigong landslide. Additionally, a collaborative application of the BO-XGBoost model and CDEM simulation was implemented for the Wangjiawan landslide. The runout distances predicted by the BO-XGBoost model and CDEM simulation were 256.8 m and 320 m, respectively, corresponding to relative errors of 14.40% and 6.67% compared with the observed value of 300 m. The methodological innovation and application results demonstrate that

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this paper provides a reliable reference for the assessment and mechanism analysis of landslides.

Keywords: landslide runout prediction; Bayesian optimization; XGBoost; SHAP interpretability; continuum–discontinuum element method

MSC: 86A60; 37M05; 68T05; 74S05

1. Introduction

Rainfall-induced landslides are characterized by rapid movement and extensive impact, making them one of the major hazards that threaten the safety of life and property in mountainous regions [1,2]. Within the disaster prevention and mitigation system for landslides, accurately predicting the landslide process is a prerequisite for hazard zoning and risk assessment. However, the post failure evolution of a landslide is essentially a nonlinear dynamic problem governed by the coupled effects of topography, mechanical properties of geomaterials, and kinematic parameters [3,4]. Achieving rapid and high accuracy assessment of landslides remains a challenge in the field of disaster prevention and mitigation.

Researchers have conducted extensive studies on the prediction of landslide runout distance, including empirical statistical analysis [5–10], physical model tests [11,12], and numerical simulations [13,14]. However, traditional empirical and statistical methods are generally insufficient to capture the nonlinear relationships among the controlling features. Machine learning algorithms have strong learning capability and nonlinear mapping ability, enabling more accurate predictions [15,16]. Xu et al. [17] compared several data-driven models for estimating the runout distance of loess landslides and established prediction models using landslide geometric parameters and other features, verifying the feasibility of machine learning for landslide runout prediction. Giarola et al. [18] developed a data-driven method for estimating shallow landslide runout and found that the random forest model performed best among the tested algorithms. Ju et al. [19] proposed a terrain-matching-oriented machine learning method to predict the runout paths of natural terrain landslides in Hong Kong. Zhang et al. [20] established a maximum horizontal runout distance prediction equation for catastrophic landslides based on gene expression programming, and analyzed the effects of maximum vertical height difference, landslide volume, and landslide posture on the maximum horizontal runout distance. Compared with individual machine learning methods and other hybrid algorithms, ensemble learning algorithms generally exhibit better predictive performance. The risk of overfitting can be effectively reduced by using boosting or bagging strategies, which show great potential for predicting landslide runout distance [21,22]. For example, Qiu et al. [23] employed a genetic algorithm-optimized extreme gradient boosting (GA-XGBoost) model to estimate the travel distance of earthquake-induced landslide debris flows in the Nepal Himalaya, demonstrating the potential of boosting-based ensemble models for long-runout prediction under complex terrain conditions. Li et al. [24] further developed an autoencoder-optimized light gradient boosting machine (AE-LightGBM) model for predicting the runout distance of rainfall-induced landslides. However, traditional machine learning models commonly suffer from the “black-box” effect. Owing to the absence of the physical simulation of landslide dynamic evolution, the interpretability and mechanistic support of the corresponding prediction results are maintained at a relatively limited level. Combining the efficient prediction capability of machine learning with the physical process

representation ability of numerical simulation can fully exploit the complementary advantages of data-driven rapid prediction and whole-process numerical modeling [25].

Numerical simulation methods can describe the post-failure process of landslides in detail by establishing terrain, stratigraphic, and material models. For the analysis of large-deformation processes after slope failure, discontinuum-based methods, such as smoothed particle hydrodynamics (SPH) [26], the material point method (MPM) [27], computational fluid dynamics (CFD) [28], the discrete element method (DEM) [29,30], and discontinuous deformation analysis (DDA) [31] mainly focus on the interaction forces among discrete blocks and particles, and therefore have significant advantages in dealing with the large displacement and large deformation of slopes. To overcome the limitations of purely continuum or discontinuum models, the continuum–discontinuum element method (CDEM), which combines the advantages of the finite element method and the discrete element method, has been gradually introduced into the simulation of landslides. Feng et al. [32] proposed a semi-spring and semi-edge combined contact model and applied it to the analysis of the Jiweishan landslide, investigating its failure mode, sliding distance, and critical friction angle. Xu et al. [33] further used CDEM to simulate the process of the Jiweishan landslide, revealing the mechanisms of basal shear sliding, rear-edge tensile cracking, lateral cutting of key blocks at the front edge, and the formation of debris flow. Wang et al. [34] utilized CDEM to analyze the dynamic response and failure modes of rock slopes containing weak interlayers, demonstrating that this method can capture the failure process of rock masses from continuous deformation to interface cracking and sliding. Dai et al. [35] applied CDEM to investigate the evolution of damage zones and potential influence areas of unstable slopes, extending its application in landslide disaster simulation. Nevertheless, existing CDEM-based landslide simulation studies still have certain limitations. For rainfall-induced landslides, the strength of the sliding mass is jointly affected by rainfall infiltration, saturation softening, particle collision, frictional sliding, and shear failure, showing obvious stage-dependent degradation characteristics [36,37]. In existing simulations, constant parameters or simple reduction methods are often adopted to handle strength variation, which makes it difficult to describe the softening behavior of the sliding mass before and after initiation and during high-speed runout. Moreover, CDEM is sensitive to terrain modeling, contact parameters, strength parameters, and softening parameters. It usually requires extensive trial calculations and parameter calibration, making it difficult to meet the demand for the rapid prediction of landslide runout distance.

In response to the limitations and existing issues of current studies, this paper proposes an analysis procedure that integrates BO-XGBoost and CDEM to investigate the runout distance and dynamic process of landslides. Based on rainfall-induced landslide samples, an indicator system for runout distance prediction was constructed. The hyperparameters of XGBoost were adaptively tuned using Bayesian optimization, and the Shapley Additive Explanations (SHAP) analysis was introduced to quantify the contribution of each feature to the prediction results. Meanwhile, a particle strength softening model was incorporated into CDEM to describe strength degradation, and the applicability was validated using the Yigong landslide case in Tibet. On this basis, the Wangjiawan landslide was taken as an example to compare the BO-XGBoost prediction results with the CDEM simulation results, thereby analyzing the feasibility of integrating machine-learning-based rapid assessment with whole-process numerical representation for landslide runout distance evaluation.

2. Research Methods

Theory of BO-XGBoost

XGBoost is an efficient ensemble learning algorithm based on gradient boosting decision trees, and it is well suited for nonlinear regression problems with limited samples and complex feature interactions [38]. By integrating a series of weak regression trees in an additive manner, the algorithm can capture the nonlinear mapping between input variables and the target response while maintaining strong generalization ability. In addition, the incorporation of second-order gradient information and regularization terms improves both computational efficiency and resistance to overfitting. The tree construction strategy of XGBoost is illustrated in Figure 1.

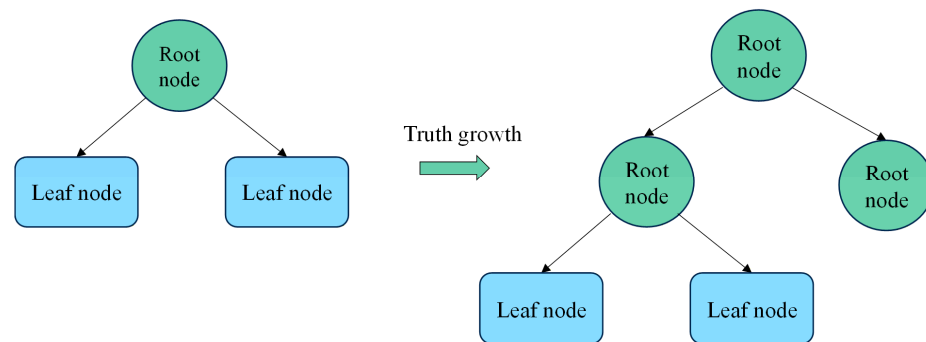


Figure 1. Level-wise tree construction of XGBoost.

The objective function of the XGBoost can be expressed as:

$$L^{(t)} = \sum_{i=1}^n l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \quad (1)$$

where t represents the number of iterations; $L^{(t)}$ denotes the loss function; y_i and $\hat{y}_i$ respectively represent the actual and predicted values of the sample i ; $l(y_i, \hat{y}_i^t)$ stands for the training error of the sample; $\Omega(f_t)$ refers to the regularization term.

The XGBoost algorithm also utilizes the Taylor formula to perform quadratic expansion of the objective function for achieving gradient boosting. The approximate form of the objective function is as follows:

$$L^{(t)} \approx \sum_{i=1}^n [l(y_i, \hat{y}_i^{(t-1)}) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega(f_t) \quad (2)$$

where g_i is the first-order statistic of the loss function, $g_i = \partial_{\hat{y}_i^{(t-1)}} l(y_i, \hat{y}_i^{(t-1)})$; h_i is the second-order statistic of the loss function, $h_i = \partial_{\hat{y}_i^{(t-1)}}^2 l(y_i, \hat{y}_i^{(t-1)})$.

The objective function can be redefined from the perspective of leaf nodes. In a given tree structure, each leaf node collects a set of samples j . Therefore, the objective function can be represented as a statistic of the sample set on these leaf nodes. Specifically, it can be approximated as:

$$L^{(t)} \approx \sum_{j=1}^T \left[\left(\sum_{i \in I_j} g_i \right) \omega_j + \frac{1}{2} \left(\sum_{i \in I_j} h_i + \lambda \right) \omega_j^2 \right] + \gamma T \quad (3)$$

The optimal weight and objective function corresponding to the leaf node can be obtained by taking the partial derivative of $L^{(t)}$ on ω_j :

$$\omega_j^* = - \frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda} \quad (4)$$

$$L^{(t)} = - \frac{1}{2} \sum_{j=1}^T \frac{\left(\sum_{i \in I_j} g_i \right)^2}{\sum_{i \in I_j} h_i + \lambda} + \gamma T \quad (5)$$

Although XGBoost has strong predictive capability, its performance is highly dependent on hyperparameters such as the number of trees, learning rate, tree depth, minimum child weight, and sampling ratios. To avoid inefficient manual tuning, Bayesian optimization (BO) is introduced to automatically search for the optimal hyperparameter combination [39]. BO is a sequential global optimization method for black-box functions. It constructs a probabilistic surrogate model for the true objective function and then determines the next sampling point through an acquisition function, thereby balancing global exploration and local exploitation. Bayesian optimization has also been applied to ensemble learning models for landslide susceptibility assessment and has shown improved predictive performance [40]. In this study, the objective of BO is to minimize the prediction error of the XGBoost model on the training set.

The BO procedure can be summarized as follows. First, an initial set of hyperparameter samples is generated and evaluated. Second, a surrogate model is established to approximate the relationship between hyperparameters and model performance. Third, the acquisition function is maximized to identify the most promising hyperparameter combination for the next evaluation. Finally, the newly obtained result is added to the sample set, and the surrogate model is updated iteratively until the stopping criterion is satisfied. Through this process, the global optimum can be approached with relatively few evaluations. By combining the nonlinear learning capability of XGBoost with the adaptive search strategy of BO, the proposed BO-XGBoost model achieves improved prediction accuracy, robustness, and parameter-selection efficiency for landslide runout distance prediction. The overall flowchart of the BO-XGBoost model is shown in Figure 2.

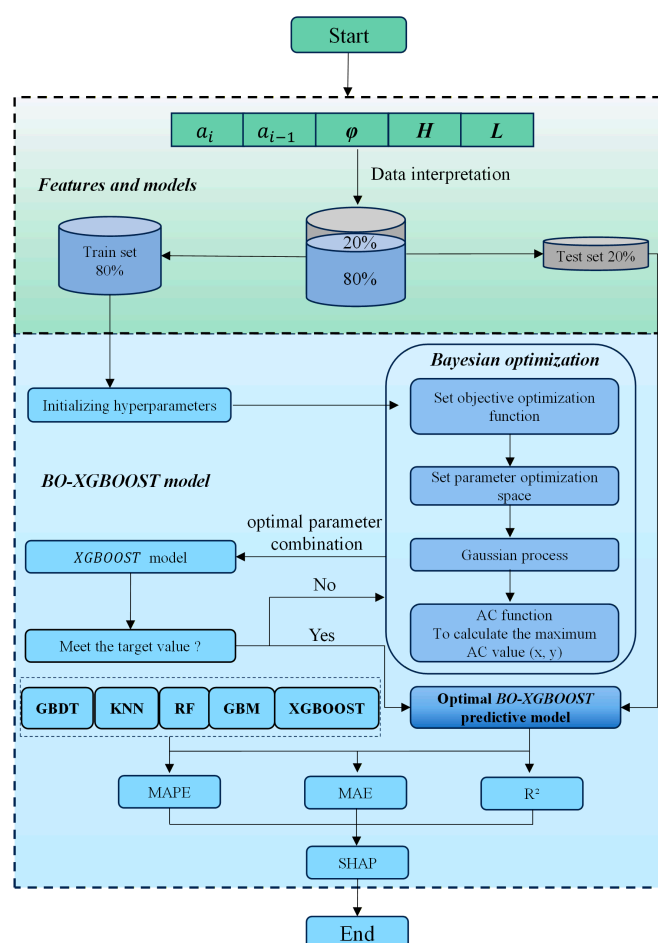


Figure 2. Flowchart of the BO-XGBoost model.2.2. Conception of CDEM.

The continuum–discontinuum element method is particularly suitable for simulating the progressive failure of geomaterials because it can describe not only the continuous deformation of a soil mass before instability, but also the discontinuous motion after cracking and collapse. Therefore, CDEM provides an effective framework for analyzing landslide initiation, failure evolution, and post-failure movement. The motion of each element can be described using Lagrange's equation, which can be expressed as:

$$\frac{d}{dt} \left(\frac{\partial L_f}{\partial \dot{u}_i} \right) - \frac{\partial L_f}{\partial u_i} = Q_i \quad (6)$$

where u_i and v_i represent generalized coordinates, Q_i denotes the work conducted by non-conservative forces, and L_f is the Lagrange function, described as:

$$L_f = T - U + W, \quad (7)$$

where T , U , and W represent the kinetic energy, elastic potential energy, and the work conducted by conservative forces, respectively.

After spatial discretization, the dynamic equilibrium equation of the CDEM system can be written in matrix form as:

$$M\ddot{u}(t) + C\dot{u}(t) + Ku(t) = F(t), \quad (8)$$

where $\ddot{u}$, $\dot{u}$, and u represent the acceleration, velocity, and displacement arrays of all nodes within the element, and M , C , K , and F denote the element's mass matrix, damping matrix, stiffness matrix, and external load array.

A key feature of CDEM is that materials are treated as a continuum before failure and transformed into a discontinuous system once cracking occurs [41,42]. During large deformation, contact relations among particles and blocks are identified through global and local contact search algorithms, enabling the detection of particle–point, particle–edge, and particle–surface interactions, as seen in Figure 3. On this basis, the contact constitutive model is introduced to calculate the interaction forces between contacting bodies. The normal and tangential contact forces are calculated incrementally as:

$$\Delta F_n = k_n A \Delta u_n, \quad \Delta F_s = k_s A \Delta u_s \quad (9)$$

where F_n and F_s are the normal and shear contact forces, k_n and k_s are the normal and tangential contact stiffnesses, A is the cross-sectional area of the contact key, and Δu_n and Δu_s are the increments of normal and tangential displacement, respectively. When the tensile or shear stress exceeds the corresponding strength limit, the contact state is updated according to the failure criterion, thereby allowing the simulation of crack development, block detachment, and sliding movement. In the CDEM simulations, the interaction between particles and blocks was governed by the particle–block contact model. The main contact strength parameters include cohesion and internal friction angle, which control the shear resistance of the contact interface. For a contact key formed by two different materials, the contact parameters were determined according to the weaker contact rule. Specifically, the lower cohesion and lower internal friction angle of the contact key were adopted as the contact cohesion and contact friction angle.

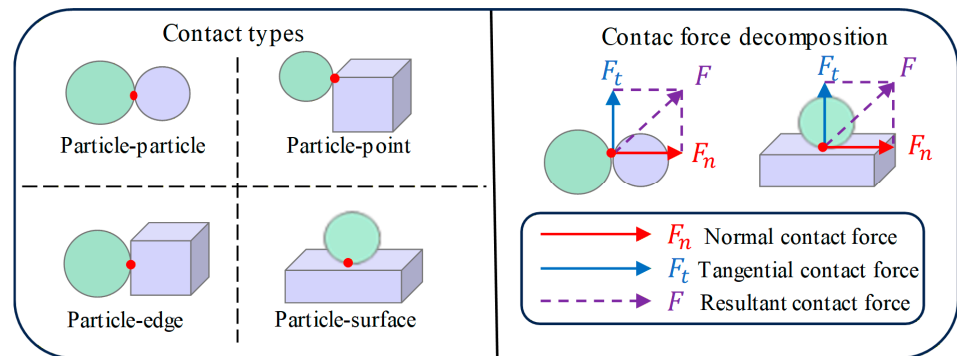


Figure 3. Contact types and force decomposition.

3. Development of BO-XGBoost Model

3.1. Selection of Influencing Features

Landslide is jointly influenced by multiple factors throughout the runout process, including topographic conditions, the mechanical properties of geomaterials and dynamic parameters. Based on previous research within the theoretical framework of Wu's kinematic prediction formula [43], this section employs a machine-learning approach to achieve feature extraction. The kinematic equations are given as follows:

$$V_{T_i}^2 = 2gH - 2gH \cot a_i \tan \varphi$$

$$V_{i_0} = V_{T_i} \cos(a_{i-1} - a_i)$$

$$a = g \sin a_{i-1} - \cos a_{i-1} \tan \varphi$$

$$L = \frac{V_{T_i}^2 \cdot \cos^2(a_{i-1} - a_i)}{2g \cdot (\cos a_{i-1} \cdot \tan \varphi - \sin a_{i-1})}$$

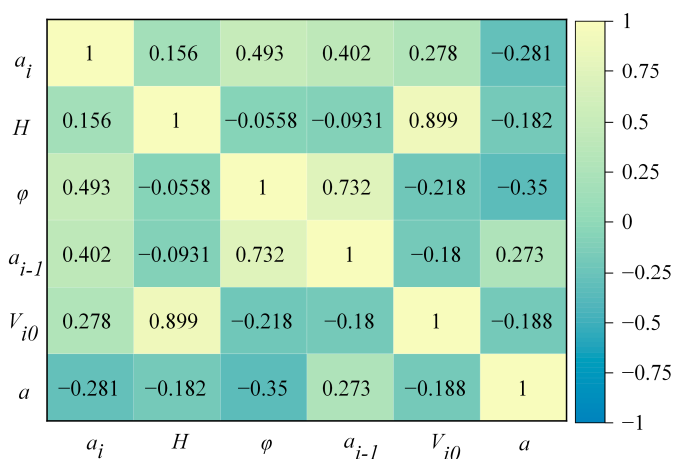
(10)

where L is the runout distance, $V_{T_i}^2$ is the velocity of the sliding mass at the shear outlet, V_{i_0} is the horizontal initial velocity component in the runout zone, a is the acceleration in the runout zone, a_i is the ground slope angle after the sliding mass exits the shear outlet, a_{i-1} is the slope angle of the sliding mass, φ is the internal friction angle of the sliding mass, and g is the gravitational acceleration.

The features affecting landslide runout distance are classified into three categories: slope morphology and geometric characteristics, physical properties of geomaterials, and kinematic parameters. Among them, the slope morphology and geometric characteristics include the slope angle of the sliding mass, the elevation difference between the rear and front edges H , and the slope angle below the shear outlet a_{i-1} . The physical properties of geomaterials are represented by the internal friction angle φ , which reflects the shear strength characteristics of the soil. The kinematic parameters include the horizontal initial velocity in the runout zone V_{i_0} and the acceleration in the runout zone a . To assess the correlations among the selected indicators, a Pearson correlation coefficient matrix heatmap was constructed, as shown in Figure 4. Most feature pairs exhibited weak to moderate linear correlations. However, the elevation difference H showed a relatively strong correlation with the horizontal initial velocity v_{i_0} in the runout zone. The kinematic parameters were derived from the kinematic runout formulation and are therefore naturally related to slope conditions. To reduce feature redundancy and potential multicollinearity, these two kinematic parameters were therefore excluded from the final input feature set. The retained indicators, including the elevation difference H , the ground slope angle α_i , the slope angle of the sliding mass α_{i-1} , and the internal friction angle φ , represent the principal terrain and material resistance conditions controlling landslide runout. Based on the above indicator system, a dataset containing 44 rainfall-induced landslide cases was established [43], as presented in Table 1.

Table 1. Slope factor dataset.

No.	a_i	H	φ	a_{i-1}	L
1	17	200	12.8	10	1000
2	25	283	19	16	1350
3	30	150	18	10	400
4	24	300	10	2	1600
5	39	700	23	8	880
6	35	270	23.2	16	1000
7	35	263	14.5	8	1500
...					
41	42	250	14.9	0	360
42	35	340	14.9	0	525
43	25	213	14.9	0	387
44	27	213	14.9	0	366

**Figure 4.** Pearson correlation coefficient matrix of the six candidate indicators before feature screening.

3.2. Performance Analysis of Model Prediction

In this study, root mean square error was selected as the objective function for hyperparameter optimization. The rainfall-induced landslide cases were randomly divided into a training set and an independent test set at a ratio of 80:20. This split was adopted because it is a commonly used strategy in machine-learning tasks, providing data for model training and hyperparameter optimization while retaining an independent subset for evaluating generalization performance. To reduce the potential overfitting risk caused by the sample size, Bayesian optimization was performed on the training set, and the independent test set was not involved in hyperparameter tuning. During Bayesian optimization, 5-fold cross-validation was adopted within the training set. Specifically, the training set was divided into five folds. In each round, four folds were used to train the XGBoost model, and the remaining fold was used for validation. This process was repeated five times so that each fold served once as the validation subset. The parameter optimization range and corresponding results are presented in Table 2.

Table 2. Search range and optimal value of hyperparameter of the XGBoost model.

Hyperparameters	Search Ranges	Optimal Values
N_estimators	(50, 1000)	579
Learning_rate	(0.01, 0.3)	0.1
Max_depth	(3, 15)	6
Min_child_weight	(1, 10)	2.62
Subsample	(0.1, 1)	0.49
Colsample_bytree	(0.5, 1)	1

Three regression evaluation metrics were selected to quantitatively assess the model's predictive performance: the coefficient of determination (R^2), mean absolute error (MAE), and mean absolute percentage error (MAPE). To elaborate, R^2 quantifies the extent to which the regression model aligns with the observed data. The closer the value of R^2 approaches 1, the stronger the fit of the model to the data, indicating a higher degree of precision in capturing and interpreting variations within the dataset. Furthermore, the MAE reflects the average absolute error between the predicted and actual values, while the MAPE represents the percentage of the average relative error between the predicted and actual values. In nonlinear fitting, smaller MAE and MAPE values indicate a higher degree of fitting and prediction accuracy. The formulae for calculating the three regression evaluation metrics are provided as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (11)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\%$$

where n signifies the number of samples, y_i represents the actual value, $\hat{y}_i$ denotes the predicted value, and $\bar{y}$ refers to the mean of the actual values of the samples.

The predicted and observed values of the KNN, RF, AE-LightGBM, GBDT, GA-XGBoost, and BO-XGBoost models are presented in Figure 5a–f. Three performance evaluation indicators were used to evaluate the predictive performance of each model on the test set. The results show that the conventional machine learning models provide relatively limited prediction accuracy. The models were ranked according to their predictive performance on the test set in ascending order as follows: KNN $\approx$ RF < AE-LightGBM < GBDT < GA-XGBoost < BO-XGBoost. KNN and RF showed comparable performance, while AE-LightGBM and GBDT improved the prediction results to some extent. Although AE-LightGBM is an advanced hybrid model, its predictive advantage was not fully reflected in the present dataset. LightGBM was originally developed as a highly efficient gradient boosting framework for large scale data learning [44]. The present database may limit the feature representation ability of the autoencoder and the performance advantage of AE-LightGBM. GA-XGBoost performed better than AE-LightGBM and GBDT, indicating that genetic algorithm can improve the predictive performance. Compared with all tested models, BO-XGBoost achieved the best predictive performance on the test set. Its R^2 increased to 0.858, while the MAE decreased to 113.94 m. The scatter distribution of the predicted and observed values was closer to the $y = x$ reference line. Under the present small sample condition, Bayesian optimization can identify a more suitable hyperparameter combination, which helps improve the generalization performance of XGBoost.

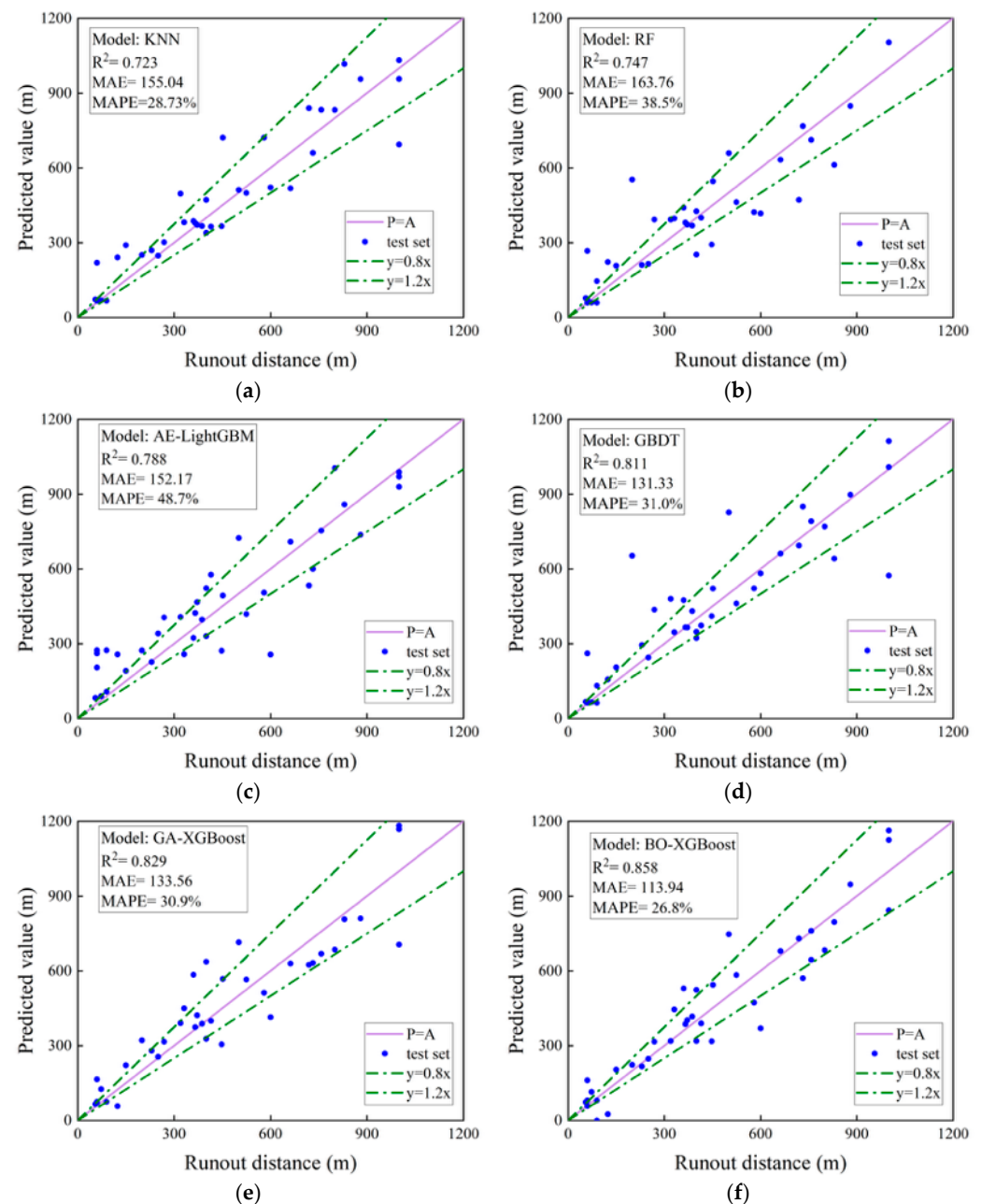


Figure 5. Prediction results of different model test sets. (a) KNN model; (b) RF model; (c) AE-LightGBM; (d) GBDT model; (e) GA-XGBoost; (f) BO-XGBoost model.

3.3. SHAP Interpretability Analysis

In machine learning, most algorithms are treated as black-box models, and their reliability and interpretability often need to be improved by explainable methods. Based on the concept of Shapley values in game theory, the SHAP algorithm can intuitively reflect the weight and influence of each feature in the prediction process by accurately quantifying the contribution of each feature to the model output [45,46]. A prominent advantage of SHAP analysis lies in its capacity to provide both global and local interpretation. Global interpretation reveals the overall importance distribution of features across the dataset, whereas local interpretation explains the contribution of each feature to an individual prediction. Zhou et al. [47] also demonstrated that the combination of XGBoost and SHAP could effectively improve the interpretability of rainfall-induced landslide susceptibility assessment. Based on SHAP analysis, this study investigated the mechanism of the BO-XGBoost model and quantitatively characterized the prediction pattern of landslide

runout distance. For feature i in the feature set S , the Shapley value is calculated as follows:

$$\varphi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [v(S \cup \{i\}) - v(S)] \quad (12)$$

where N is the set of all features; S denotes all subsets of features that do not include feature i ; $|S|$ represents the number of features in subset S ; $|N|$ is the total number of all features; $v(S)$ denotes the contribution of feature subset S to the model prediction output; and $v(S \cup \{i\})$ denotes the contribution of the feature subset $S \cup \{i\}$, which includes feature i , to the model prediction output.

Feature importance is positively correlated with the mean absolute Shapley value, with larger values indicating greater importance in model prediction. As shown in Figure 6, the elevation difference between the rear and front edges was the dominant feature, accounting for 49.25% of the total model decision weight. This suggests that landslide is strongly controlled by gravitational potential energy release and its conversion into kinetic energy during downslope movement, which is consistent with energy-based interpretations of landslide [48,49].

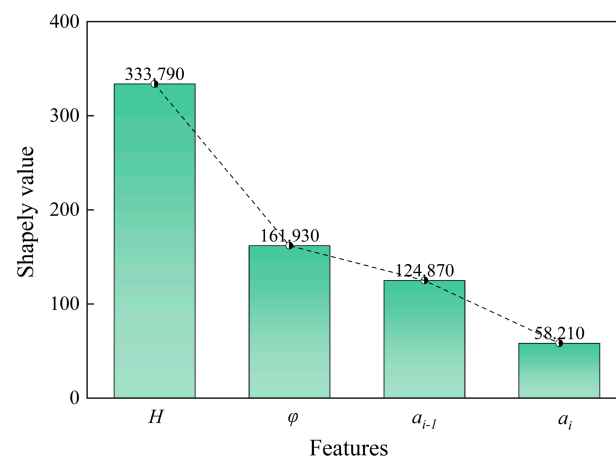


Figure 6. Mean absolute SHAP values of the influencing features.

As shown in Figure 7a–d, the SHAP dependence plots further clarify how the four retained indicators influence the predicted landslide runout distance. The slope angle of the sliding mass α_i generally contributed positively when it was below approximately 25° . Within this range, an increase in slope angle strengthened the downslope component of gravity and promoted the conversion of gravitational potential energy into kinetic energy. However, when the slope angle exceeded 25° , some SHAP values became negative. This indicates that a steeper slope does not necessarily produce a longer runout distance. Under steep slope, stronger internal deformation, fragmentation, particle collision, and interaction with irregular ground may increase energy dissipation and reduce the ability of the sliding mass to maintain sustained forward motion [50].

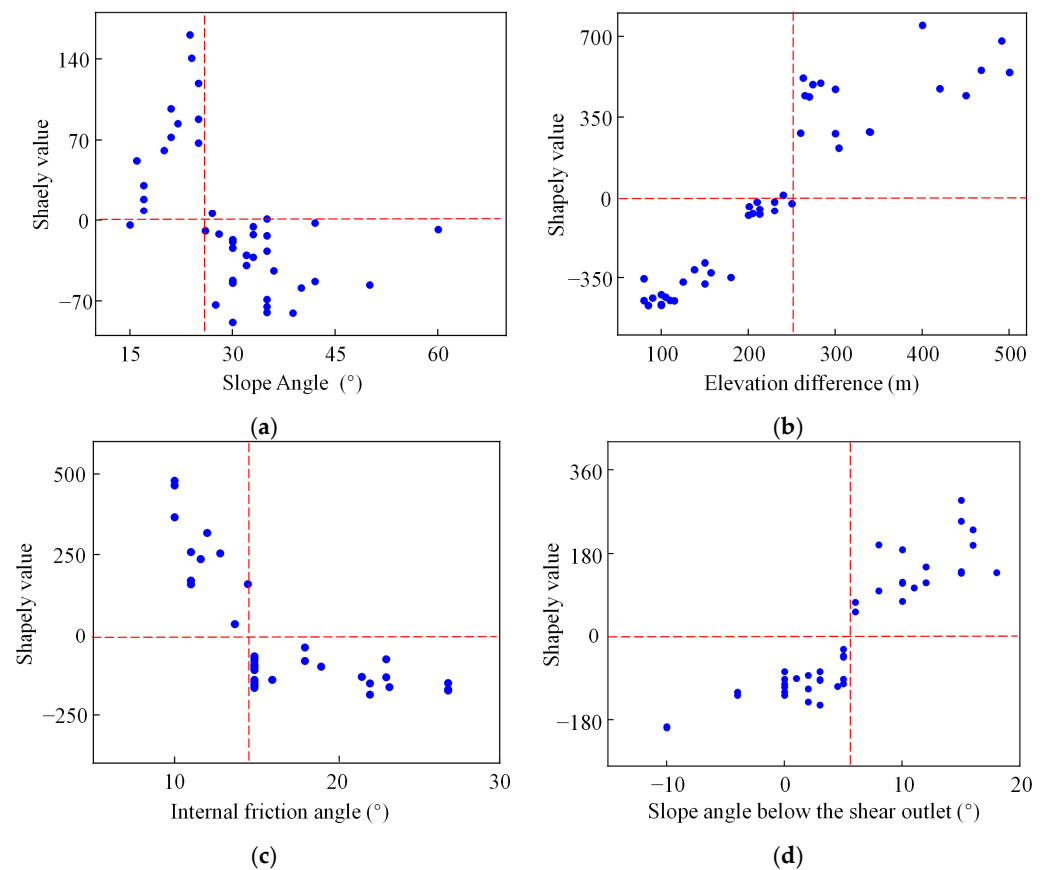


Figure 7. Scatter plots of SHAP values for the influencing features. (a) Slope angle; (b) elevation difference; (c) internal friction angle; (d) slope angle below the shear outlet.

The elevation difference between the rear and front edges H exhibited a clear positive relationship with the SHAP value. A larger elevation difference provides greater gravitational potential energy, which enhances landslide mobility and generally increases the predicted runout distance. Nevertheless, the dispersion of SHAP values at similar values of H suggests that the available potential energy is also affected by material resistance and downstream terrain conditions. In contrast, the internal friction angle φ showed an overall negative effect. Larger friction angles increase the resistance to movement and accelerate mechanical energy dissipation, causing the sliding mass to stop earlier. The model was particularly sensitive to this parameter when φ was below approximately 15° , where small variations could lead to noticeable changes in the predicted runout distance. The ground slope angle below the shear outlet α_{i-1} also presented a generally positive contribution, especially when it exceeded approximately 5° . A steeper runout zone helps maintain downslope motion, whereas a gentle slope favors earlier deposition. Overall, the SHAP results indicate that H controls the available energy, φ governs frictional resistance, and the two slope angles influence the initiation and continuation of landslide movement.

4. Validation and Case Study

4.1. Development of the Particle Strength Softening Model

To describe the strength softening behavior of landslide, a strength softening model was developed within the CDEM. The model includes an equivalent wetting-induced weakening condition and a continuous softening stage during runout. In actual rainfall-induced landslides, rainfall may reduce matric suction, increase pore-water pressure, disturb the soil structure, and promote local shear deformation before complete saturation is

achieved. Since coupled rainfall infiltration and seepage analysis was not explicitly performed in the present CDEM model, the evolution of saturation degree was not directly simulated. Therefore, the initial softening stage is interpreted as an equivalent wetting-induced weakening condition. Similar strength softening concepts have been used in rainfall-induced landslide simulations [51]. Accordingly, the first stage of the proposed model represents the initial reduction in material strength caused by rainfall wetting. Thereafter, the strength progressively degrades from the initiation strength to the residual strength under the combined effects of collision, friction, shear failure, and structural disintegration.

Before landslide initiation, the sliding mass is characterized by its initial strength parameters, namely the initial tensile strength σ_{t0} , the initial cohesion c_0 and the initial internal friction angle φ_0 . Parameter reduction method is adopted here to describe this initial softening, expressed as follows:

$$\begin{aligned}\sigma_t^{(s)} &= \lambda_t \sigma_{t0} \\ c^{(s)} &= \lambda_t c_0 \\ \tan \varphi^{(s)} &= \lambda_t \tan \varphi_0\end{aligned}\quad (13)$$

where $\sigma_t^{(s)}$, $c^{(s)}$, and $\varphi^{(s)}$ represent the tensile strength, cohesion, and internal friction angle after the equivalent initial weakening stage, respectively; λ_t is the softening reduction coefficient for saturation.

After initiation, the movement of the sliding mass in CDEM is mainly governed by the interaction forces at particle–particle and particle–block contacts [32]. During this process, frictional collision, sliding, and intense shearing can induce progressive strength degradation and strongly affect the final runout distance and deposition range. Therefore, the accumulated tangential contact displacement was introduced in this study as a state variable to characterize the cumulative frictional, shear, and sliding history at contact interfaces. This treatment is consistent with the contact-force formulation in CDEM, in which the normal and tangential contact forces are calculated from the corresponding displacement increments. In addition, ring-shear tests on landslide materials have shown that under large shear displacement, the shear strength commonly evolves from peak strength to residual strength. The residual strength is therefore widely used to describe the large-deformation shear state of long-runout landslides and debris flows [52,53]. Accordingly, a continuous softening function based on accumulated tangential contact displacement was introduced in this study. The expressions are written as:

$$\begin{aligned}\kappa_s &= \sum \sqrt{(\Delta u_{s1})^2 + (\Delta u_{s2})^2} \\ \sigma_t(\kappa_s) &= \sigma_{t,r} + (\sigma_t^{(s)} - \sigma_{t,r}) e^{-\beta_t \kappa_s} \\ c(\kappa_s) &= c_r + (c^{(s)} - c_r) e^{-\beta_t \kappa_s} \\ \tan \varphi(\kappa_s) &= \tan \varphi_r + (\tan \varphi^{(s)} - \tan \varphi_r) e^{-\beta_t \kappa_s}\end{aligned}\quad (14)$$

where Δu_{s1} and Δu_{s2} are the displacement increments in the two tangential directions of the contact local coordinate system, respectively; κ_s is the accumulated tangential contact displacement, which is used to characterize the effect of friction, shearing, and sliding at the particle contact interface; $\sigma_{t,r}$, c_r and φ_r are the residual tensile strength, residual cohesion, and residual internal friction angle, respectively; and β_t is the softening coefficient based on the accumulated tangential contact displacement, which controls the rate of strength degradation. For previously occurred landslide cases with available field observations, β_t can be calibrated under the constraints of observed runout distance and

deposition morphology. For prediction applications, the softening coefficient can be further constrained by the runout distance predicted by the BO-XGBoost model and the kinematic quantities calculated from the landslide runout formulation.

On 9 April 2000, a catastrophic landslide occurred in the source area of Zhamunong Gully, Yigong Township, Bomi County, Tibet Autonomous Region, China [54]. Within a few minutes, approximately $3 \times 10^7 \text{ m}^3$ of rock mass detached from a mountaintop at an elevation of 5500 m and impacted the loose colluvial deposit. Following the impact, the rock mass disintegrated and entrained the loose deposit, causing it to slide away from the gully bed and propagate outward collectively, thereby forming a high-speed and long-runout landslide. The triggering factor was the melting of ice and snow caused by high temperatures, which gradually saturated the collapsed rock mass and led to a reduction in its strength. Although the Yigong landslide was not directly rainfall induced, the softening model is not limited to rainfall triggered landslides. It describes both the initial strength reduction before movement and the continuous strength degradation during runout and can therefore be applied to landslides involving progressive material weakening. Accordingly, the hydraulic weakening effect induced by saturation of the sliding mass was considered in the numerical simulation. Meanwhile, the progressive degradation of material strength parameters with the movement of the sliding mass was further incorporated, using the aforementioned model as the strength decay law. For terrain modeling, the surface terrain was reconstructed from SRTM DEM data with a spatial resolution of 30 m. The SRTM data were acquired during February 2000, and therefore were used to represent the pre-failure terrain condition of the landslide area. The reconstructed surface was then imported into GiD, where geometric extrusion, cutting, and zoning operations were performed to generate the complete 3D CDEM model. The collapsed rock mass is located at an elevation of approximately 2900–4400 m, with a long and narrow morphology and slopes of about 16–27°. The loose deposit layer was cut along the gully floor and lateral accumulation zones in GiD, and the maximum depth was constrained by the reported value of approximately 130 m [55]. In this way, the model distinguishes the collapsed rock mass, the loose colluvial deposit, and the bedrock terrain. The main material parameters adopted for the bedrock, collapsed rock mass, and loose colluvial deposit in the Yigong landslide simulation are summarized in Table 3. These parameters were assigned based on reported data and numerical calibration, and their recommended laboratory testing standards are specified as follows. The density, cohesion and internal friction angle can be determined according to the Standard for Geotechnical Testing Method (GB/T 50123-2019) [56]. The elastic modulus and Poisson's ratio of strongly weathered rock or rock-like materials should be obtained or verified according to the Standard for Test Methods of Engineering Rock Mass (GB/T 50266-2013) [57].

Table 3. Material mechanical parameters of Yigong landslide.

	$\rho/\text{kg}\cdot\text{m}^{-3}$	E/GPa	C_0/MPa	$\varphi_0/(\text{°})$	$\sigma_{t,r}$	C_r	$\varphi^{(s)}$	λ_t	β_t
Bedrock	2790	25	25	50	25	25	50	1	1
Collapsed rock mass	2500	22	20	48	0	0	20	0.7	0.004
Loose colluvial deposit	2500	20	20	45	0	0	18	1	0.004

4.2. Validation and Parameter Sensitivity Analysis

As can be seen from Figure 8, the model can reproduce the landslide process. After landslide initiation, the collapsed rock mass first slides down the slope surface under gravity and undergoes disintegration upon impacting the loose colluvial deposit. During 100–200 s, the sliding mass gradually transitions from a relatively intact block movement to a flow type movement pattern. At 250 s, the front part of the sliding mass reaches the

frontal area, where deceleration and initial deposition occur. During 300–400 s, the deposit continues to expand as the remaining material is transported from the upper gully and accumulates in the frontal area. By 400 s, the sliding mass has mostly stopped, forming a broad deposit at the gully outlet and the frontal zone. The final deposit exhibits a tongue-shaped expansion, with material spreading along the gully and accumulating in the gentle frontal area. This depositional pattern is broadly consistent with field observations of the Yigong landslide. The landslide traveled approximately 9000 m with an elevation difference of about 3110 m, and formed a deposit approximately 3000 m long and 2500 m wide. The deposit had an average thickness of 60 m, and reached a maximum thickness of 100 m. Overall, the simulated results are consistent with the field investigation descriptions in terms of the movement path, transport mode, and final depositional pattern [55].

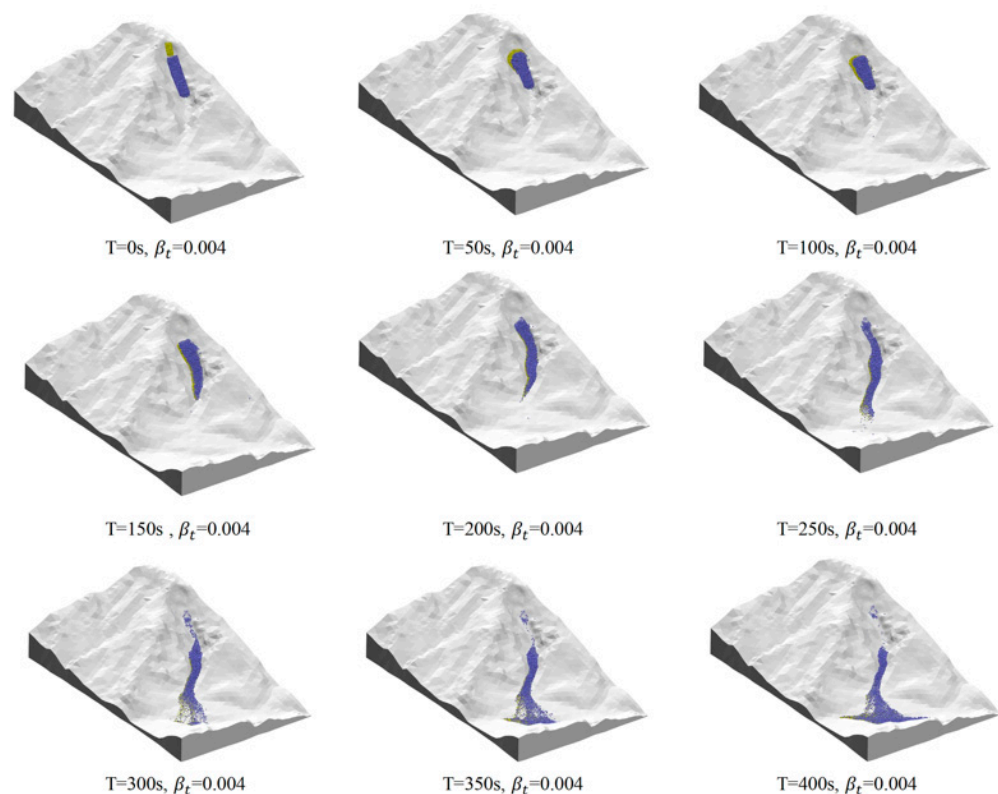


Figure 8. Simulated snapshots of the Yigong landslide at different times.

To further investigate the influence of the softening model on the landslide, a sensitivity analysis of the initial strength reduction coefficient was conducted using values of 0.5, 0.7, and 0.9. The total particle volume and the parameters controlling continuous softening during runout were kept unchanged. As shown in Figure 9, decreasing λ_t enhances the initial weakening of the sliding mass and consequently increases its early mobility. When $\lambda_t = 0.9$, the sliding mass retains relatively high strength and greater integrity during the early motion, resulting in a comparatively compact deposition pattern. At $\lambda_t = 0.7$, the balance between initial weakening and structural integrity produces the best agreement with the observed deposition morphology. When λ_t is reduced to 0.5, stronger initial weakening promotes greater internal rearrangement and lateral spreading, producing a moderately broader and more dispersed deposit. Although the runout distance and deposition extent varied systematically with λ_t , the overall flow path and the principal deposition zone remained similar among the three cases. The differences among the three simulations indicate that the initial strength reduction coefficient mainly controls the initiation and early acceleration of the sliding mass. Based on the comparison

with the observed runout and deposition pattern, $\lambda_t = 0.7$ was adopted in the subsequent simulations.

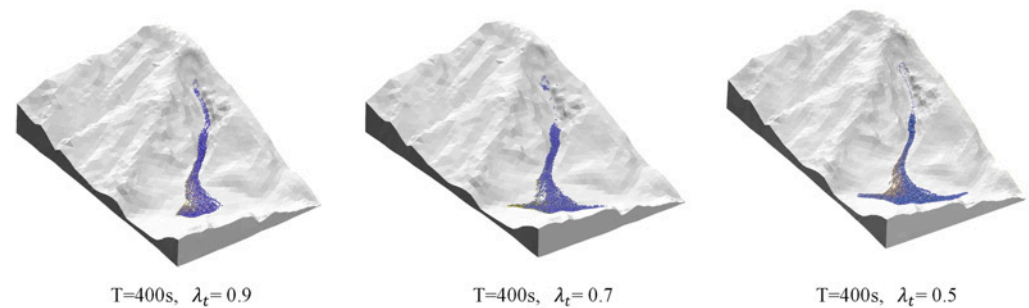


Figure 9. Sensitivity analysis of the initial strength reduction coefficient.

Moreover, the softening coefficient β_t was selected for sensitivity analysis. This parameter governs the decay rate of strength parameters with the accumulated tangential contact displacement κ_s . Under the same accumulated tangential contact displacement, a larger β_t results in a faster decay of $e^{-\beta_t \kappa_s}$. When β_t is small, strength degradation is slow, and the sliding mass retains relatively high strength. As shown in Figure 10, six groups of conditions were set for comparative analysis: $0.125\beta_0$, $0.25\beta_0$, $0.5\beta_0$, β_0 , $5\beta_0$, and $25\beta_0$, where β_0 is the softening coefficient under the baseline condition. With an increase in β_t , the degree of the sliding mass disintegration and the dispersion of particles increase markedly, and the frontal deposition area gradually expands. Under weak softening conditions, the sliding mass maintains strong integrity, and deposits mainly concentrate near the gully outlet; under strong softening conditions, the sliding mass is more susceptible to fragmentation and disintegration, transforming into a debris flow movement pattern, and the final deposit exhibits a wider tongue-shaped distribution.

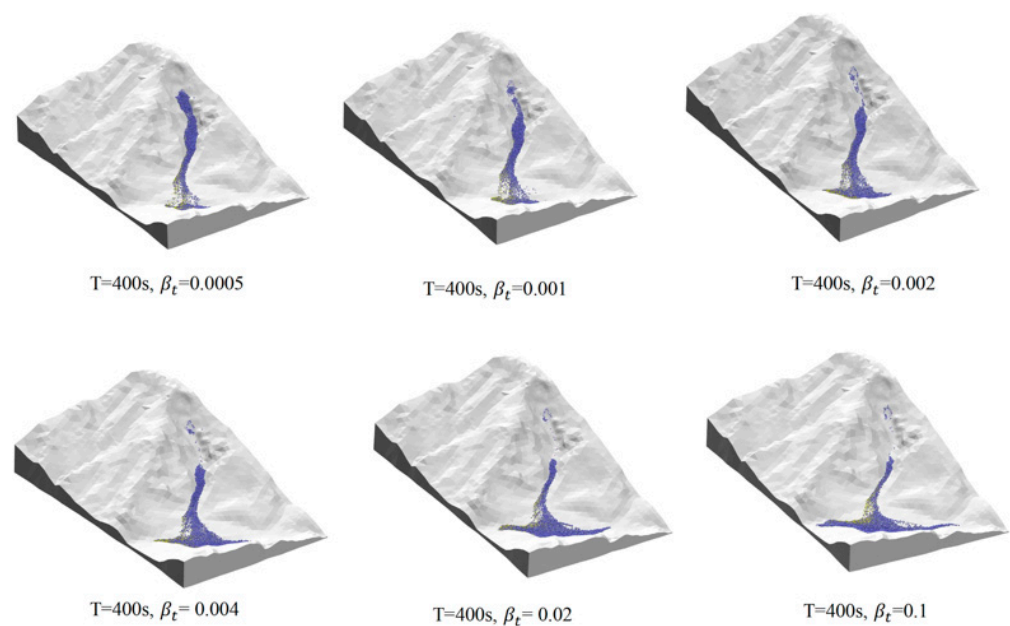


Figure 10. Sensitivity analysis of the continuous softening coefficient.

As shown in Figure 11a,b, for the loose colluvial deposit, both the internal friction angle and cohesion decreased gradually with time. When $\beta_t = 0.0005$ and $\beta_t = 0.001$, the strength parameters decayed relatively slowly and had not fully reached the residual

values at 400 s, indicating that the material still retained a certain shear strength during movement. As β_t increased, the strength decay rate accelerated significantly. When $\beta_t = 0.02$ and $\beta_t = 0.1$, the internal friction angle and cohesion of the loose colluvial deposit decreased within a short time and approached the residual state. The strength parameters of the collapsed rock mass were more sensitive to variations in β_t , see Figure 11c,d. When $\beta_t = 0.1$, the strength parameters of the collapsed rock mass dropped rapidly to the residual level within a short time; when $\beta_t = 0.02$, they also decayed quickly at an early stage. In contrast, under smaller β_t , the strength degradation process was more gradual, and the sliding mass maintained a certain degree of integrity and shear resistance over a longer period. The collapsed rock mass tended to disintegrate rapidly under strong softening conditions, thereby providing higher mobility for the subsequent sliding.

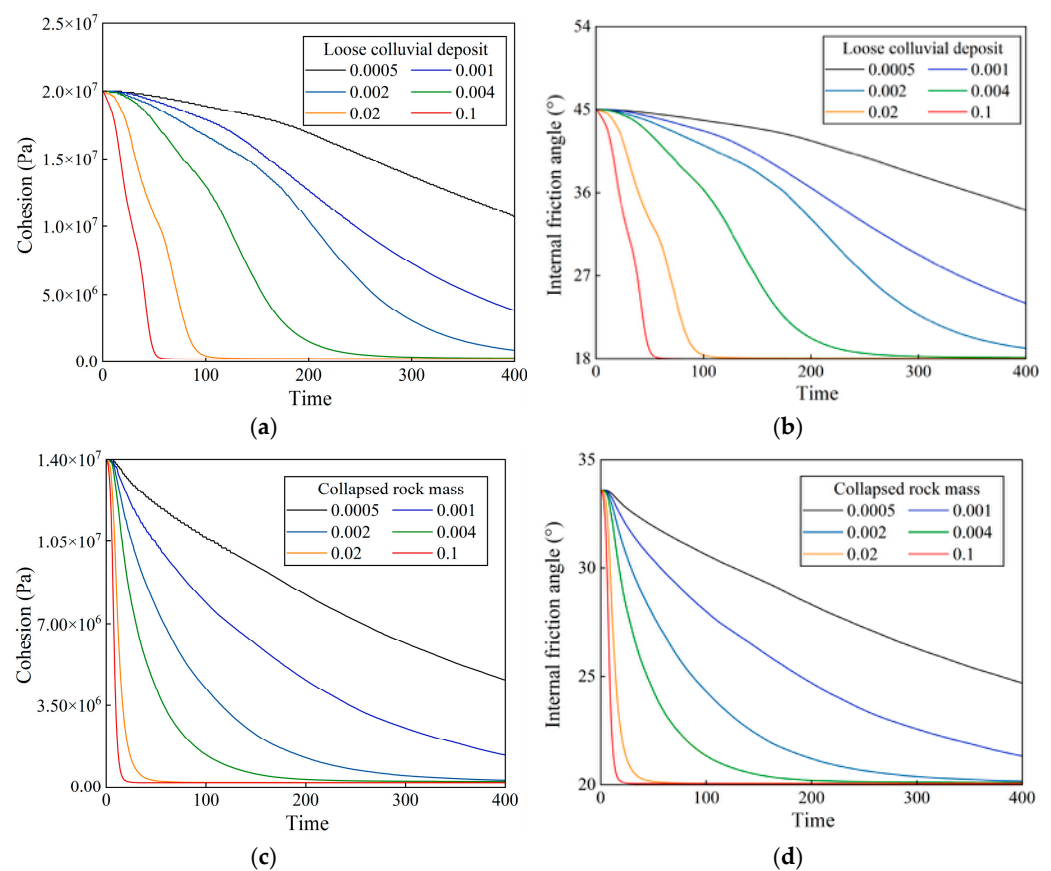


Figure 11. Strength parameters under different softening coefficients: (a) cohesion of the loose colluvial deposit; (b) internal friction angle of the loose colluvial deposit; (c) cohesion of the collapsed rock mass; (d) internal friction angle of the collapsed rock mass.

4.3. Collaborative Method Combining CDEM and BO-XGBoost

Based on the above analysis, CDEM is capable of simulating the landslide process. Its accuracy, nevertheless, is dependent on terrain reconstruction, soil parameters, contact parameters, and softening parameters. Extensive trial calculations and parameter calibration are required to obtain reasonably accurate simulation results. In contrast, the BO-XGBoost enables the rapid estimation of runout distance. Therefore, this section adopts a combined BO-XGBoost and CDEM analysis workflow. In the first stage, the trained BO-XGBoost model is used to generate an initial estimate of the landslide runout distance, denoted as L_{pred} . To quantify the prediction uncertainty of the BO-XGBoost model more explicitly, predictive uncertainty was evaluated using out of sample residuals from repeated holdout validation. The dataset was randomly partitioned 100 times into 80% training subsets and 20% holdout subsets. The optimized BO-XGBoost hyperparameters

were fixed during this procedure. For each landslide sample, the median holdout prediction was used as the representative predicted value, and the residual was calculated as:

$$e_i = L_i - \tilde{L}_i \quad (15)$$

where L_i is the observed runout distance of the i th sample, and $\tilde{L}_i$ is the median holdout prediction of the same sample. This procedure produced one representative validation residual for each of the 44 landslide cases. Figure 12 presents the distribution of the out of sample residuals obtained from repeated holdout validation. The residuals were mainly concentrated around zero, indicating that the BO-XGBoost model has no obvious systematic bias. To describe this residual behavior, the normal distribution and Student t distribution were fitted for comparison. The normal distribution assumes that residuals are concentrated around the mean and that large prediction errors occur with low probability. Therefore, it is suitable when the residuals have relatively thin tails. In contrast, the student t distribution introduces a degree of freedom parameter to control the tail thickness. A smaller degree of freedom produces heavier tails and allows for a higher probability of large prediction errors. The student t distribution better captures the sharp central peak and heavy tail of the residuals than the normal distribution.

For the Wangjiawan landslide, the BO-XGBoost model predicted an initial runout distance of $L_{\text{pred}} = 256.8$ m. The predictive interval for a new landslide case was then expressed as $[L_{\text{pred}} + e_{\text{low}}, L_{\text{pred}} + e_{\text{up}}]$, and e_{low} and e_{up} are the lower and upper residual quantiles obtained from the fitted residual distribution. In this study, the error band was calculated using the 10th and 90th residual quantiles. As shown in Figure 12, the predictive interval for the Wangjiawan landslide was 99.9–396.6 m. This interval was used as the empirical prediction uncertainty range for comparison with the subsequent CDEM simulation results.

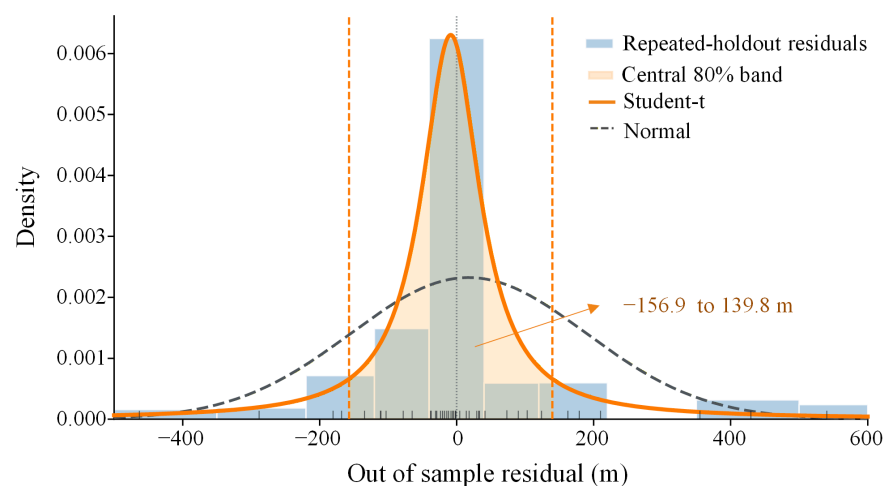


Figure 12. Residual distribution of the BO-XGBoost model based on repeated holdout validation.

Meanwhile, the horizontal initial velocity in the runout zone V_{i0} was introduced as an additional kinematic constraint. The uncertainty interval of V_{i0} is defined as $[V_{i0}(1 - \delta_v), V_{i0}(1 + \delta_v)]$, where δ_v is the allowable relative velocity error. The horizontal initial velocity in the runout zone was calculated from the kinematic runout formulation rather than obtained from direct field measurement. Therefore, this velocity represents an indirect kinematic estimate. Previous studies have shown that debris flow and landslide velocities are commonly estimated by back calculation, empirical equations, or flow motion equations, and the estimated values are affected by terrain interpretation, material property inputs, and measurement conditions. Prochaska et al. [58] reported that debris flow velocities are commonly back calculated from superelevation events or predicted using

flow equations, both of which involve subjective estimates and model parameter selection. Cao et al. [59] reported that relative errors of several percent to about 10% can be obtained for well-calibrated debris flow velocity prediction methods, while larger errors may occur for less accurate models. Schimmel et al. [60] also showed that different velocity estimation methods may produce differences of about 5% to 10%. Considering that V_{i0} in this study was derived from a simplified kinematic formulation, a conservative tolerance of 20% was adopted as an auxiliary velocity window. As can be seen from Figure 13, the material strength parameters, contact parameters, and softening parameters in CDEM were adjusted so that both the simulated runout distance and the horizontal initial velocity were consistent with the above constraints. If a large discrepancy exists between the numerical simulation and the machine-learning prediction, the possible sources of error should be further examined. When the numerical simulation result falls within the machine-learning prediction interval, the prediction result can be considered reasonable.

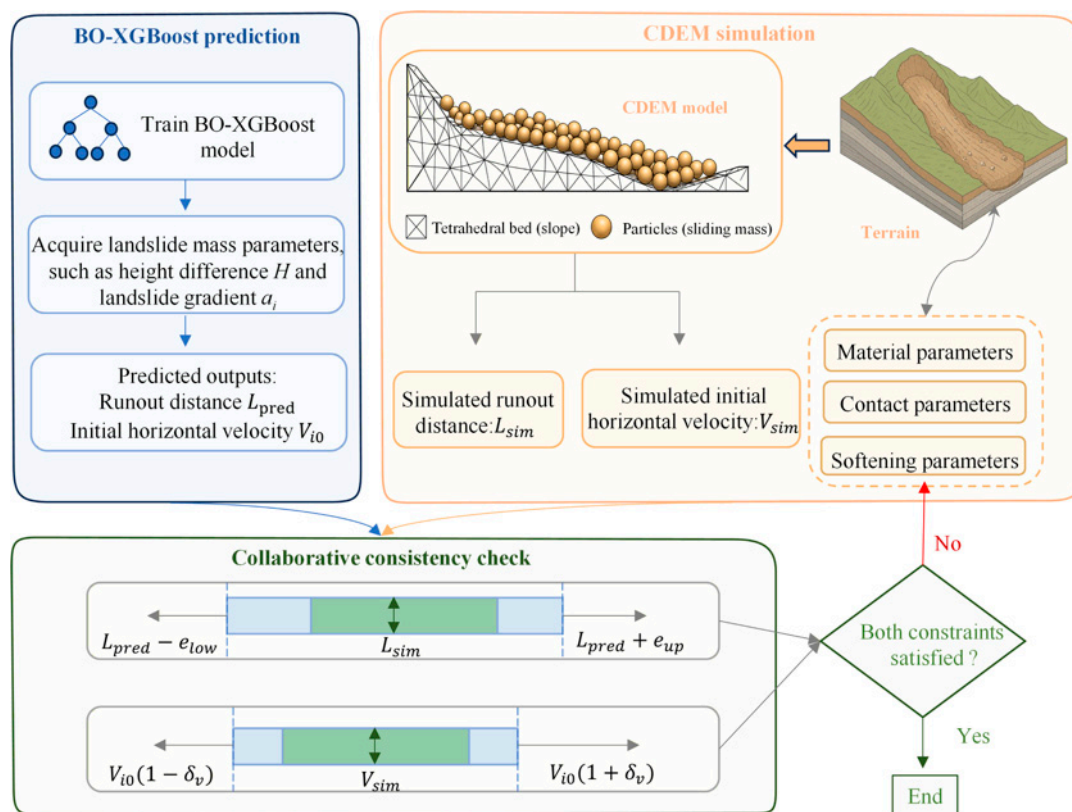


Figure 13. Flowchart of the collaborative method.

4.4. Case Validation with Wangjiawan Landslide

The Wangjiawan landslide was selected to validate the applicability of the collaborative method. This rainfall-induced soil landslide occurred on 1 July 2017 in Ningxiang County, Hunan Province, China. As shown in Figure 14a,b [61], the sliding volume was about $7.8 \times 10^4 \text{ m}^3$. The sliding mass rapidly disintegrated along the slope and moved at a high speed, ultimately reaching a runout distance of approximately 300 m and causing 9 fatalities. As presented in the geological profile of Figure 15, this landslide is classified as a small-scale bedding soil landslide with a U-shaped planform. The slope angle in the source area is 40° , and the elevations of the rear and front edges are 404 m and 329 m, respectively, yielding a relative height difference of 75 m. Geological investigations indicate that the soil is primarily composed of silty clay, the sliding zone is a weak interlayer rich in mud, and the slip surface consists of slate. For terrain modeling, the Sentinel-derived DEM data from 2015 were used to reconstruct the original surface. The source area

was extracted by combining the DEM-based terrain reconstruction with the landslide zoning, geological profile, and deformation-mechanism analysis reported by Wu et al. [62]. The source area was U-shaped, with an area of approximately 18,400 m², a slope length of 155 m, a maximum width of 155 m, and a main sliding direction of 135°. Based on these constraints, the source area was separated from the reconstructed terrain and assigned as the sliding mass in the simulation.

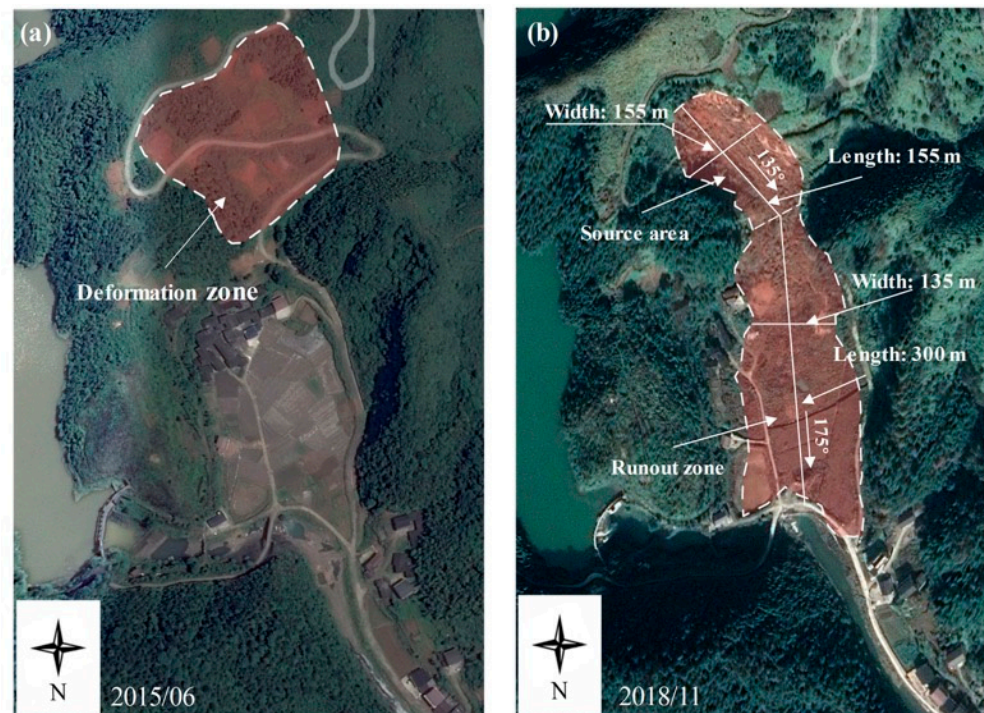


Figure 14. Remote sensing interpretation map of the Wangjiawan landslide: (a) pre-landslide satellite image in 2015; (b) post-landslide satellite image in 2018.

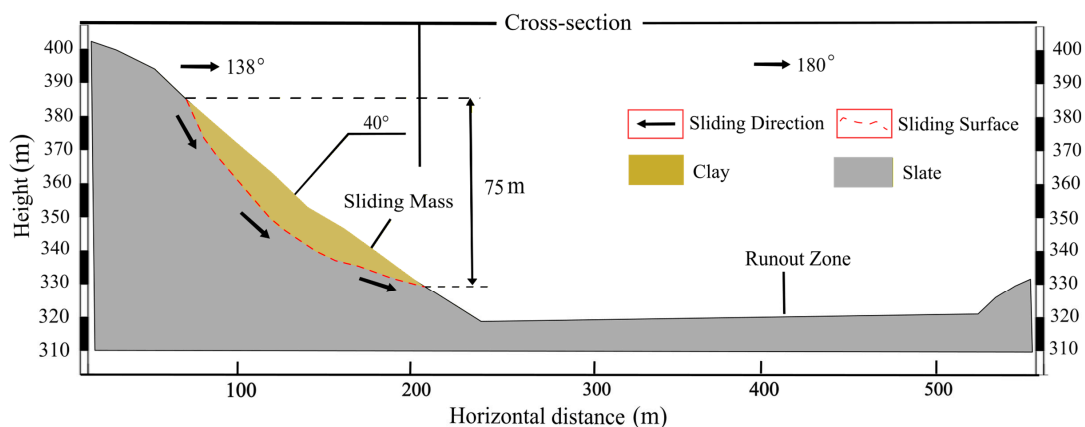


Figure 15. Geological profile of the Wangjiawan landslide.

For the BO-XGBoost prediction, the input parameters were assigned as follows: slope angle 40°, elevation difference between the rear and front edges 75 m, internal friction angle 12°, and slope angle below the shear outlet −1°. The horizontal initial velocity $v_{i0} = 24.996$ m/s was calculated from the kinematic runout formulation. Based on these inputs, the trained BO-XGBoost model yielded a predicted runout distance of 256.8 m. The corresponding plausible runout interval was calculated as 99.9–396.6 m. The observed runout distance of about 300 m falls within this interval, indicating that the BO-XGBoost model can provide a reasonable estimate for rapid assessment. Meanwhile, according to the

velocity constraint defined in Section 4.3, the uncertainty interval of the horizontal initial velocity in the runout zone was calculated as 20.00–30.00 m/s. Within the CDEM framework, the underlying block was meshed using tetrahedral elements with a size of 15 m, while the sliding mass was discretized into 5955 particles with particle diameters ranging from 1 to 3 m. The simulation parameters were calibrated based on literature data and field investigations, primarily including a density of 1860 kg/m³, an elastic modulus of 9.45 MPa, a Poisson's ratio of 0.3, a cohesion of 30 kPa, a residual cohesion of 10 kPa, an internal friction angle of 12°, a residual internal friction angle of 6°, and a softening coefficient β_t of 0.004.

As shown in Figure 16, the landslide process lasts approximately 40 s. Within the first 5 s, the sliding mass begins to move slowly downslope under gravity; its overall morphology remains relatively intact. The velocity curves in Figure 17a indicate that the velocities at the front, middle, and rear monitoring points are all in an early rising phase. Meanwhile, the potential energy loss starts to increase, and part of the gravitational potential energy is gradually converted into the translational kinetic energy of the sliding mass, see Figure 17b. During the 5–15 s, the velocity of the sliding mass increases and disintegration occurs. This stage represents the period of the most intense response of the sliding mass. The front monitoring point is the first to reach its peak velocity, at approximately 23.7 m/s; the middle monitoring point subsequently peaks at 20.6 m/s; and the rear monitoring point peaks at 18.6 m/s. In the energy curves, the translational kinetic energy reaches its maximum of approximately 1.4×10^{10} J at around 10 s, indicating that a large amount of gravitational potential energy is converted into the kinetic energy of the sliding mass during this stage. In the 15–25 s, the sliding mass enters the flat area and slides continuously southward along the flat ground. During this period, sustained collision, friction, and shearing occur among the sliding mass. At approximately 30 s, the frontal sliding mass crosses the flat ground, and subsequently begins to accumulate preferentially at the northwest corner of the flat area. After about 30 s, the potential energy loss and the equivalent dissipated energy gradually stabilize and ultimately approach approximately 6.8×10^{10} J. When the sliding mass stops moving, the soil has descended to the frontal gully and the frontal flat ground, forming a distinct deposit.

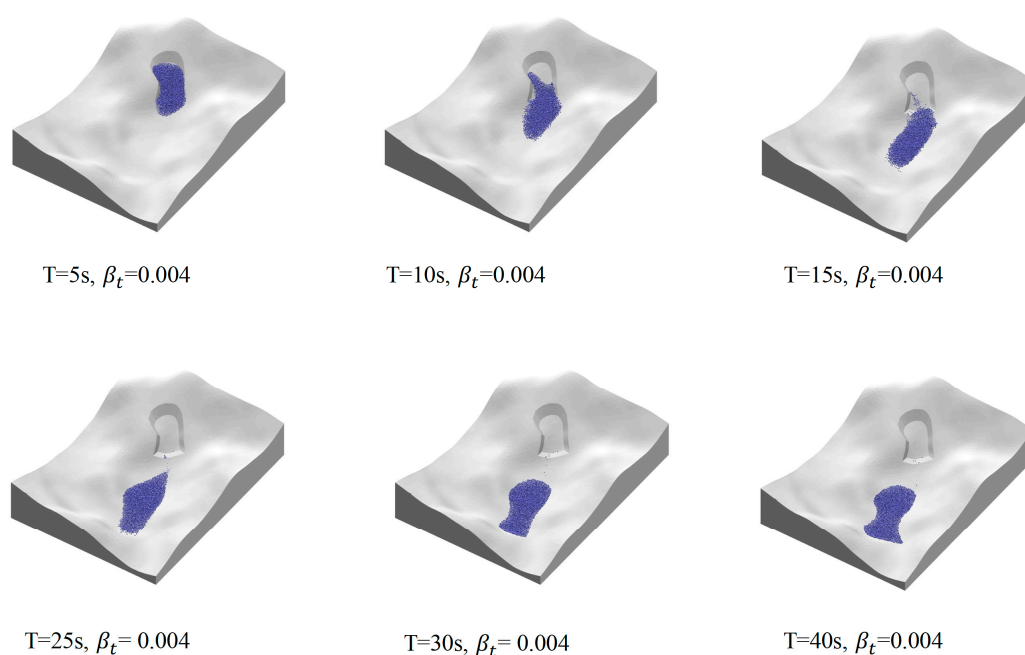


Figure 16. Simulated snapshots of the Wangjiawan landslide at different times.

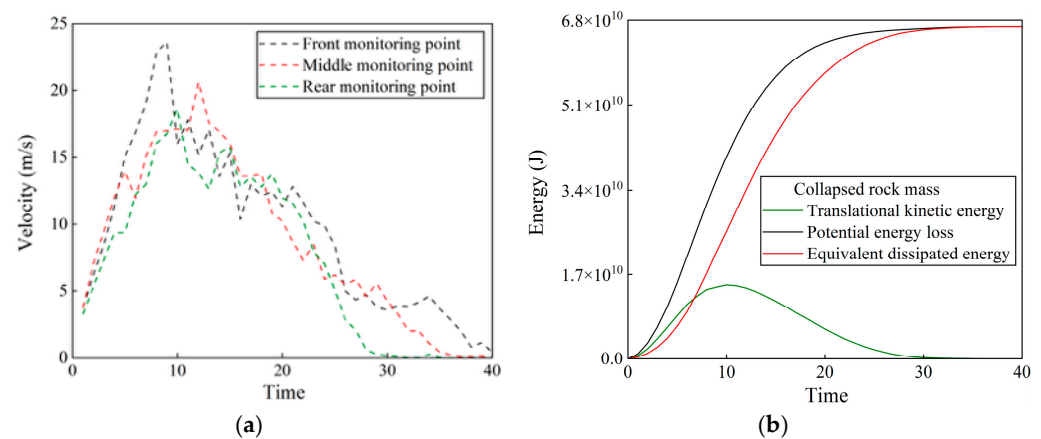


Figure 17. Velocity and energy evolution during the landslide movement: (a) velocity variation of monitoring points; (b) energy evolution of the sliding mass.

To further evaluate the spatial performance of the CDEM simulation, a comparison between the observed affected area and the simulated affected area was conducted following the evaluation concept of Heiser et al. [63]. The observed footprint was interpreted from the remote-sensing image in Figure 14b, while the simulated footprint was extracted from the final CDEM result after the sliding mass reached a stable state. The comparison considered three components: the overlapping area, the missed observed area, and the extra simulated area. These components represent correct spatial prediction, underestimation, and overestimation, respectively. The estimated results are summarized in Table 4. The observed affected area was approximately $4.92 \times 10^4 \text{ m}^2$, and the simulated affected area was approximately $5.05 \times 10^4 \text{ m}^2$. The overlapping area was approximately $4.75 \times 10^4 \text{ m}^2$, accounting for 0.91 of the total union area. The missed-area ratio and extra-area ratio were 0.03 and 0.06, respectively. Accordingly, the spatial fit index was calculated as 0.82. This value indicates that the simulated affected area has a reasonable spatial agreement with the observed landslide scar and deposition pattern. The extra simulated area was slightly larger than the missed area, suggesting a limited overestimation near the distal front. This result is consistent with the runout comparison, in which the simulated runout distance of approximately 320 m was slightly larger than the observed value of approximately 300 m. In addition, the simulated runout distance fell within the predictive interval. The relative velocity error δ_v was 5.18%, which was lower than the allowable error of 20%. All calculations were performed on a workstation equipped with an Intel Core i7-13700 CPU, 32 GB RAM, and a 64-bit Windows 11 operating system. The BO-XGBoost model was implemented in Python 3.10, and the CDEM simulation was conducted using the CDEM Suite V2.0.1.152 on the same workstation without GPU acceleration. For the BO-XGBoost model, the training and Bayesian optimization required approximately 5 min, and the single prediction time was less than 10 s. In the traditional CDEM workflow without BO-XGBoost assistance, repeated trial simulations were required to calibrate the contact parameters, strength parameters, and softening coefficient, resulting in a total time cost of approximately 12 h. In contrast, the proposed BO-XGBoost-assisted CDEM workflow used the predicted runout distance as a reference to narrow the parameter calibration range, reducing the total time to approximately 8 h. Overall, the validation between the machine learning prediction and the numerical simulation results demonstrates that this collaborative method can improve the reliability of landslide runout distance prediction.

Table 4. Spatial evaluation of the Wangjiawan landslide simulation.

Evaluation Component	Description	Value
Total union area	Overlap + missed + extra area	$5.22 \times 10^4 \text{ m}^2$

Overlap ratio	Normalized overlapping area	0.91
Missed area ratio	Normalized underestimated area	0.03
Extra simulated area ratio	Normalized overestimated area	0.06
Spatial fit index	Overall area-based performance index	0.82

5. Conclusions

Accurate prediction of landslide runout distance and its influencing areas is a prerequisite for hazard zoning and risk assessment. Although numerical simulations can reproduce the landslide evolution process, their parameter calibration is cumbersome, and even slight variations in parameters can significantly alter the movement characteristics of the sliding mass. In contrast, machine learning models enable rapid prediction but lack a mechanistic interpretation of the landslide process. Therefore, when seeking an efficient and interpretable method for landslide runout assessment, integrating machine learning with numerical simulation can preserve the predictive capability of the former while exploiting the whole-process characterization advantage of the latter.

This study developed a BO-XGBoost model and a particle strength softening model within the CDEM to achieve an accurate assessment of landslides. Several key influencing features were selected, and Bayesian optimization was employed to adaptively tune the hyperparameters of XGBoost, establishing the BO-XGBoost model. The results showed that the BO-XGBoost model achieved the best overall predictive performance with an R^2 of 0.858, outperforming conventional models such as KNN, RF, and GBDT. SHAP-based interpretability analysis further identified the elevation difference between the rear and front edges as the dominant controlling feature, accounting for 49.25% of the total model decision weight. This reveals that the conversion of gravitational potential energy into kinetic energy constitutes the core mechanism governing runout distance. In contrast to conventional approaches that treat the strength parameters as constant, a particle strength softening model was proposed within the CDEM framework, as sliding masses often exhibit strength weakening under collision, disintegration, and water-induced softening. Validation using the Yigong landslide in Tibet demonstrated that the simulated movement path, disintegration process, and final deposition pattern were consistent with field observations. Parameter sensitivity analysis further indicates that the softening coefficient β_t is a key parameter governing the degradation rate of the sliding mass strength. In the proposed softening model, β_t controls the transition rate from the initially weakened strength state to the residual strength state. A larger β_t leads to a faster reduction in cohesion, internal friction angle, and tensile strength, which promotes rapid disintegration of the sliding mass, enhances its mobility, and results in a wider tongue-shaped deposit. In contrast, a smaller β_t corresponds to a slower degradation process, allowing the sliding mass to retain greater integrity and shear resistance during movement. In terms of prediction accuracy, MAE represents the mean absolute deviation between the predicted and observed runout distances, while MAPE represents the corresponding mean relative error in percentage form. The BO-XGBoost model achieved an MAE of 113.94 m and a MAPE of 26.8%, demonstrating its ability to provide reliable rapid assessment of rainfall-induced landslide runout distance.

Nevertheless, the proposed particle strength softening model can also be transferred to the mechanism analysis of similar disasters, such as rock avalanches and debris flows, helping to understand the strength degradation patterns of different soil masses. The feature importance ranking obtained from SHAP analysis is not only applicable to the present case, but also provides a basis for landslide susceptibility analysis and key indicator screening in other regions. In future work, more well-documented rainfall-induced landslide cases with complete geometric, mechanical, and kinematic information will be collected to further improve the robustness and generalization ability of the BO-XGBoost

model. Meanwhile, BO-XGBoost can be further used to predict additional landslide characteristics, such as deposition area, maximum velocity, movement duration, impact range, maximum deposit thickness, and energy indicators. These predicted physical quantities can serve as multi-objective constraints for numerical simulation. By constraining CDEM simulations with multiple predicted targets, the calibration process can be reduced, and more accurate numerical results can be obtained.

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Abbreviations

The following abbreviations are used in this manuscript:

BO	Bayesian Optimization
XGBoost	Extreme Gradient Boosting
BO-XGBoost	Bayesian Optimization-Extreme Gradient Boosting
CDEM	Continuum–Discontinuum Element Method
SHAP	Shapley Additive Explanations
KNN	K-Nearest Neighbors
RF	Random Forest
DT	Decision Tree
GBDT	Gradient Boosting Decision Tree
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Square Error
R ²	Coefficient of Determination
SPH	Smoothed Particle Hydrodynamics
MPM	Material Point Method
CFD	Computational Fluid Dynamics
DEM	Discrete Element Method
DDA	Discontinuous Deformation Analysis
GA-XGBoost	Genetic Algorithm-Optimized Extreme Gradient Boosting
AE-LightGBM	Autoencoder-Optimized Light Gradient Boosting Machine

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