International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-13

https://doi.org/10.70917/ijcisim-2026-0398
Article

Analysis of prediction and prevention countermeasures of shallow loess landslides in the construction of residential areas

Yuming Zhang [1] and Shiyang Lin [1,*]

[1] School of Architecture and Engineering, Weifang University of Science and Technology, Weifang, Shandong, 262700, China

* Correspondence author: nckuvictory@126.com

Abstract: In loess plateau areas affected by perennial heavy flooding, landslide disasters occur frequently, posing serious challenges to residential construction. In this paper, the prediction and prevention countermeasures of landslides are proposed by analyzing and predicting the monitoring data of loess landslides in a residential area under construction. The study used an intelligent variable frequency landslide displacement meter for displacement monitoring, combined with the moving average method and slope model for early warning of landslide occurrence. The results show that using this method, four sudden landslides were warned with high accuracy and the maximum advance warning time was 33 hours. The slope model performs well in the prediction of landslide destabilization time, and the confusion matrix analysis of the model shows that the prediction accuracy of 3m resolution data is the highest, with a true rate of 0.68, a false-positive rate of 0.40, and a precision of 0.65. The analysis of the success curve shows that the accuracy of the model prediction is improved significantly with the improvement of the resolution of data in the digital elevation model, which is especially suitable for the prediction of point landslides. In this paper, the reliability of the slope model is verified, and a method of landslide deformation stage division based on the tangent angle model is proposed, which provides a scientific basis for the prediction and prevention of landslide disasters in residential areas under construction.

Keywords: Loess landslide, prediction model, slope model, early warning mechanism, accelerated deformation, success curve

1. Introduction

China is one of the countries in the world where loess is widely distributed. According to relevant information, loess is a kind of sediment of special nature. Loess in China covers an area of 640,000 square kilometers, accounting for about 6.6% of China's total land area, mainly distributed in the western region, and roughly accounts for 4.9% of the world's loess coverage, with thicknesses ranging from a few meters to more than 300 meters [1-2]. Loess is a special kind of soil with unique physico-mechanical properties, such as large pores, vertical joints, and loess wetting. Therefore, loess areas are prone to avalanches, slides, and flow geohazards [3-4]. Due to the special physical properties of loess, it is prone to geologic disasters such as avalanches and landslides when encountering abnormal climate such as rainfall, especially in the Northwest Loess Plateau region, which belongs to the high susceptibility area of geologic disasters in China, and whose loess avalanches, landslides, and debris flow geologic hazards have made a very high academic contribution and academic status in the international arena [5-7].

The combing of related literature shows that in the past decades, the research of most scholars still focuses mainly on the causes, mechanisms, monitoring and early warning, and prevention and control technologies of loess landslides and loess avalanches. According to statistics, in the Loess Plateau region, loess landslides occur very frequently every year, seriously threatening the life and property safety of residents and road transportation and other infrastructures, and becoming a typical geological disaster phenomenon in the loess region that still cannot be effectively eradicated [8-9]. Taking the thickness of landslides as a criterion for classification, landslides can be divided into four types: shallow landslides, medium landslides, thick landslides, and giant thick landslides [10]. According to the field investigation of previous studies, it was found that shallow landslides induced by heavy rainfall are characterized by unpredictability, suddenness of outbreaks, and concealment [11-12]. Therefore, shallow loess landslides are very typical and academic research value, how to study the mechanism of shallow landslide occurrence, as well as the law of motion for disaster mitigation and prevention is of profound significance.

With the advancement of urbanization, residential buildings increase, and residential construction changes the original slope, and shallow landslides are a high incidence type of geological disasters in residential areas [13-14]. Although the probability of large-scale outbreaks of loess landslides is very low, however, most of the shallow loess landslide slide thicknesses induced by heavy rainfall storms are within two meters, and this type of landslides is characterized by a high outbreak frequency and a high density of distribution, and even cause sudden regional geohazard events [15-17]. Therefore, it is necessary to carry out research on the prediction and prevention techniques of shallow loess landslides, which can provide a scientific basis for disaster prevention and mitigation under extreme climatic conditions in the residential areas of the Loess Plateau of China.

Loess landslide disasters, as a common geological hazard, frequently threaten people's lives and properties, especially in residential areas in loess areas. With the acceleration of urbanization, the occurrence of loess landslide disasters not only affects the construction and safety of residential areas, but also poses a great challenge to the local economy and social stability. The complexity of loess landslide disasters lies in their suddenness and unpredictability, especially in slip avalanche-type and static liquefaction-type landslides, where the occurrence of the disaster is often strongly sudden and uncontrollable. Therefore, how to accurately predict and timely warn loess landslides has become an important topic in disaster prevention and mitigation research. Although some progress has been made in the existing loess landslide prediction methods, most of them rely on complex numerical simulations and high technical costs, and the prediction accuracy and application range are relatively limited.

In order to solve this problem, this paper combines the actual situation of a residential area under construction with the on-site monitoring by an intelligent inverter landslide displacements meter, and combines with slope modeling and other methods to discuss the landslide prediction and early warning mechanism in depth. Firstly, by collecting the landslide monitoring data in the area, the data are filtered and processed using the moving average method to ensure the accuracy and reliability of the data. Subsequently, the destabilization time of the landslide is analyzed through the prediction method of slope model to assess the accuracy and feasibility of the prediction. The study also verifies the predictive performance of the model through methods such as confusion matrix and success rate curve, thus providing theoretical support and technical guarantee for the early warning mechanism of loess landslides.

2. Study design

2.1. Overview of the study area

The geomorphology of a residential area under construction is dominated by loess plateaus and river valleys. The entire loess plateau consists of the Black Plateau and the Square Plateau, with a length of 7.8km and a width of 3.0km, and the terrain is high in the west and low in the east. Under the influence of perennial flooding, the groundwater level of the plateau rises at a rate of about 0.3 m/a, and landslides are frequent along the edge of the plateau. According to the survey statistics, there are more than 80 landslides in this area, and the landslides in this area can be divided into six sections, namely, 1#, 2#, 3#, 4#, 5# and 6#, according to the different locations of occurrence. From the viewpoint of landslide disaster mode, the landslides occurring in a residential area under construction can be classified into four categories: loess bedrock type, loess mudflow type, slip avalanche type and static liquefaction type landslides, among which the slip avalanche type and the static liquefaction type landslides have obvious sudden characteristics.2024, four sudden-type landslides were successfully warned, which were mainly distributed in the north side and the south side, among which, the slip avalanche-type landslides were 6# and 5#, and the static liquefaction-type landslides were 4# and 4#, which were mainly distributed in the north side and the south side. Liquefaction-type landslides are 4#, the specific landslide warning information is shown in Table 1.

Table 1. Basic characteristics of landslides predicted in 2024

Numbering	Landslide	Time of occurrence	Landslide type	Early warning time
1	6#	2024-3-12	Slide collapse	2.5h
2	6#	2024-3-26	Slide collapse	45min
3	4#	2024-4-25	Static liquefaction type	20min
4	5#	2024-10-27	Slide collapse	33h

2.2. Research methodology

2.2.1. Acquisition and processing of monitoring data

This paper adopts the landslide displacement meter with intelligent frequency conversion function for displacement monitoring, which can obtain the complete deformation data of sudden loess landslide. Combined with the development pattern and characteristics of a sudden loess landslide in a residential area under construction, the monitoring instrument is deployed: for the static liquefaction-type landslide, the monitoring instrument is deployed in the vicinity of the trailing edge of the landslide where the groundwater seepage is strong; for the slip-collapse-type landslide, the monitoring instrument is mainly concentrated in the vicinity of the trailing edge of the landslide where the multilevel cracks are developed. Many successful warning cases have also verified the feasibility of the above deployment principles. When the landslide enters the accelerated deformation stage, the landslide area will slide in the form of a sliding block, and the direction of the displacement vectors at each monitoring point will tend to be the same, so there is little difference in the monitoring data of different monitoring points in the accelerated deformation stage for early warning and prediction. The slope model is based on the accelerated deformation stage of the monitoring data for prediction and calculation, so the monitoring data selected in this paper can reflect the trend of landslide deformation, to achieve the purpose of effective early warning and prediction [18].

The moving average method is used to filter the monitoring data to reduce the influence of instrument noise and the surrounding environment on the monitoring data and reflect the landslide deformation trend [19]. The calculation formula is as follows:

$$\overline{S}_i = \frac{1}{N}\left[S_i + S_{i-1} + \cdots + S_{i-(N-1)}\right] \tag{1}$$

Where: S_i - cumulative displacement of landslide at i moment/mm.

N -number of moving average terms.

$\overline{S}_i$ -displacement/mm after moving average processing.

The size of the standard error of prediction of the processed data is positively and linearly correlated with the value of N, the smaller the value of N, the smaller the error, where N is taken as 28.

2.2.2. Landslide deformation stage determination

The improved tangent angle model obtained by dimensionless processing of coordinate changes enables landslide deformation curves to be compared under the same tangent angle characteristics, therefore, the model is used to determine the stage of landslide deformation [20], which is calculated as follows:

$$T_i = \frac{S_i}{\overline{v}} \tag{2}$$

$$\alpha_i = \arctan\frac{T_i - T_{i-1}}{t_i - t_{i-1}} \tag{3}$$

Where: S_i - cumulative displacement of landslide at i moment/mm.

T_i, T_{i-1} - the transformed vertical coordinate value with the same magnitude as time, the difference between the two is one monitoring period, such as 1 day, 1 week and so on.

$\overline{v}$ -rate/(mm-d-¹) of the isokinetic deformation phase of the landslide.

α_i -improvement tangent angle/(°).

t_i, t_{i-1} -monitoring moments, which differ by one monitoring cycle.

When the tangent angle is greater than 45°, it can be considered that the landslide enters the initial acceleration deformation stage; when the tangent angle is greater than 80°, the landslide enters the middle acceleration stage; when the tangent angle is greater than 85°, the landslide enters the acceleration stage; the closer the tangent angle is to 90°, the closer the landslide is to occur. Sudden type loess landslide deformation is slow and unstable in the early stage, the tangent angle has a large fluctuation, through the calculation found that when the tangent angle reaches 60 °, the fluctuation decreases and the trend of change is more obvious. Therefore, this paper takes the 60° tangent angle as the starting point, and divides the late accelerated stage of landslide into six deformation stages of 60°~65°, 65°~70°, 70°~75°, 75°~80°, 80°~85°, and 85°~90° with an interval of 5°.

2.2.3. Slope model

The SLO instability time prediction model is derived from the "accelerated creep theory" which summarizes the relationship between strain and time during the accelerated creep phase of rock [21], see equation (4):

$$\varepsilon = -A\log(t_f - t) + B \tag{4}$$

Where: ε -strain.

t -time/d.

t_f -destabilization time/d.

A , B -constants.

Based on Eq. (4), the cumulative landslide displacement s is made to replace the strain ε , and at the same time, both sides of Eq. (4) are differentiated with respect to the time t to obtain Eq. (5), and Eq. (6) is obtained after rearranging:

$$v = \frac{ds}{dt} = \frac{A}{t_f - t} \tag{5}$$

$$vt = vt_f - A \tag{6}$$

Where: v -landslide displacement rate/(mm-d-¹).

Considering $v \cdot t$ as y , v as x , and t_f as slope in Eq. (6), Eq. (6) is transformed into a linear equation with t_f as the slope, and finding the destabilization time t_f is also transformed into finding the slope k of the equation, i.e., finding the slope of the linear equation (SLOPE), which is the SLO prediction model. This model is essentially a deformation of the velocity inverse model under linear conditions, with the premise assumption that the change in velocity inverse during the acceleration phase of a landslide follows a linear trend. Compared with other prediction models, this model transforms the predicted instability time into the slope for solving, which does not require complex fitting and parameter solving, and has certain advantages in performing the prediction of the instability time of sudden-onset loess landslides.

2.2.4. Selection of data for prediction calculations

The slope model is proposed based on the accelerated creep phase of the landslide, and the calculation data should be selected from the accelerated deformation phase in order to ensure the model adaptability and the reliability of the prediction results. The selection of the calculation cutoff point is significant for timely judgment of landslide danger, and the calculation cutoff point too early may lead to too large a deviation of time forecast, and too late may lead to insufficient time for emergency treatment. A large number of successful warning cases of landslides show that when the tangent angle reaches 85°, the landslide enters the critical slip stage, and the probability of destabilization is extremely high, and at this time, the release of early warning and forecasting information can effectively guide the emergency response to the disaster and reduce the economic losses and casualties caused by landslides. Therefore, in order to better assess the prediction results, in this paper, when carrying out the prediction calculation of landslide destabilization time, the first set of data of each accelerated deformation stage is the starting point of calculation, and the tangent angle reaches 85° as the cut-off point of calculation, and the prediction calculation is carried out in a cumulative way as shown in Fig. 1.

However, it is found that the landslide deformation curve obtained by monitoring instruments is not stable due to the influence of many factors such as measurement errors, environmental changes, local sliding of landslides and limitations of data processing means, and the addition of new data will have a greater impact on the prediction results, so this paper extracts the data of key deformation stages for simplified calculation on the basis of cumulative calculation, and selects only the data of landslide tangent angles at 60°, 65° This ensures that the calculated data can reflect the trend of landslide deformation, and also reduces the influence of deformation fluctuation on the prediction results.

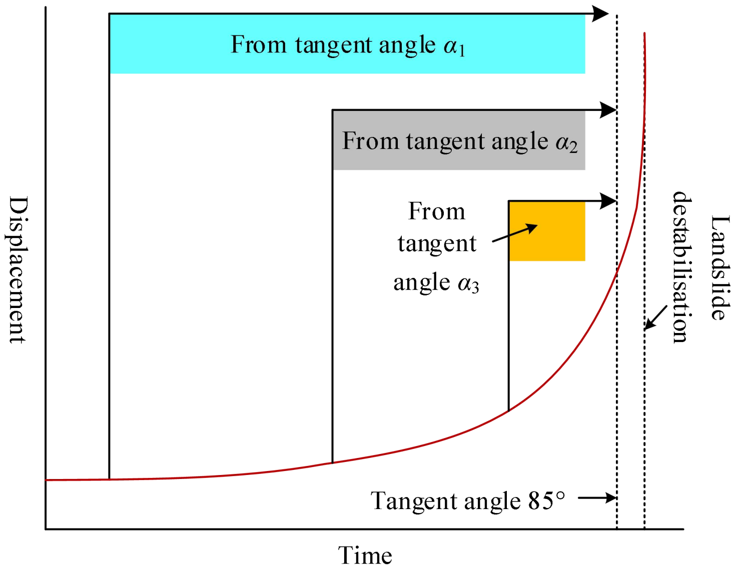


Figure 1. Cumulative calculation

2.3. Characteristics of the spatial distribution of landslide hazards

2.3.1. Dispersal and aggregation of landslides

Kernel density analysis methods can be used to analyze the density of point elements within a neighborhood. In kernel density mapping, points falling into the search area have different weights, and points close to the center of the grid search area will be given a larger weight, and the weight decreases with the increase of their distance from the center of the grid. In order to obtain the spatial dispersion and aggregation characteristics of landslide points, the ArcGIS kernel density analysis tool is applied to calculate the density of landslide point elements in their surrounding neighborhoods, using a circle as the search window and defining a radius of 3km.

Multi-distance spatial clustering analysis (Ripley's K function) can quantitatively portray the degree of aggregation of landslide points at different spatial scales, Ripley's K function can reflect the degree of spatial aggregation of points on the scale of the degree of dependence of the tool “multi-distance spatial clustering analysis” in Arcgis using Ripley's K function is a commonly used mathematical form, and the expression of the transformation formula $L(d)$ is:

$$L(d)=\sqrt{\frac{A\sum_{i=1}^{n}\sum_{j=1,j\neq i}^{n}k(i,j)}{\pi n(n-1)}} \tag{7}$$

Where: n is the number of landslide hazard sites; A is the area of the study area; d is the distance; and $k(i,j)$ denotes the actual distance between the landslide site i and the landslide site j within d; The distance d is the k expected value and $L(d)$ is the k observed value, when the k observed value is greater than the k expected value, the landslides are clustered and distributed; When k observed values are smaller than k expected values, landslides are discretely distributed. The k observations are within the upper and lower confidence intervals, indicating that the distribution of landslides is random; If k observations are below the upper and lower confidence intervals, it means that the distribution of landslide points is uniform.

Based on the ArcGIS multi-distance spatial clustering analysis tool to analyze the loess landslide disaster points, in the range of step length 1-10km k observation value is greater than the expected observation value and the high and low confidence intervals, and the k observation value shows an upward trend, which indicates that the landslide points are clustered distribution in the spatial distribution [22].

2.3.2. Fractal characteristics of landslides

Fractal theory mainly studies the self-similarity and law of things, with the in-depth study and development of fractal theory, it has been widely used in the field of geography. Fractal refers to the geometric object with self-similarity, and its most basic property is the scalar invariance in the process of contraction and expansion, the local enlargement is similar to the whole, and the overall shrinkage is not different from the local. Fractal dimension is an important parameter in fractal theory for the quantitative characterization of broken, non-smooth, irregular and extremely complex fractal objects. There are various methods to determine the fractal dimension in fractal research, such as circle covering method, box dimension number method, yardstick method, etc. In the study, the landslide will be abstracted as a point to study the spatial distribution characteristics of the landslide, so the commonly used box dimension number method is used to study the fractal distribution characteristics of the landslide.

The box dimension method is to divide the region into a number of n lattices with side length r, count the number of lattices with landslides falling into them $N(r)$, and then keep changing the side lengths of the grid, count the number of lattices with landslides falling into them after each change of the side lengths $N(r)$ if r and the number of lattices $N(r)$ satisfy the following relation equation:

$$N(r) = Cr^{-D} \tag{8}$$

where C is the coefficient to be determined and D is the fractal dimension value. Then the spatial distribution of the studied object is characterized by fractal structure within the variation range of scale r. The fractal dimension value D can reflect the complexity and susceptibility of landslides, the larger the value of D indicates that the landslides are more active and the distribution structure is more complex.

In order to obtain the grids with different side lengths r and count the number of grids $N(r)$ that landslide points fall into, we use the Create Fishing Grid tool in the ArcGIS10.2 software to create grids with side lengths of $1km \times 1km, 2km \times 2km, \cdots, 10km \times 10km$ to cover the study area range, and then we count the following the number of grids $N(r)$ containing landslide points. Take the logarithm of the side length r of the grid and the number of grids containing landslides $N(r)$, and then make a scatter plot of $\ln(r)$ versus $\ln N(r)$, and fit a straight line using Eq. (9):

$$\ln N(r) = -a\ln(r) + b \tag{9}$$

where a is the subdimensional value and b is a constant.

The relational equation of the one-dimensional linear equation fitted by the double logarithmic relationship curve yields the fractional dimension value of the spatial distribution of landslides to be 0.6784 and the correlation coefficient to be 0.9418, which is illustrated by the correlation coefficient significance test with the significance level of α of 0.01, which shows that the spatial distribution of landslides has an obvious fractal characteristic.

3. Prediction and test analysis of loess landslides in the study area

3.1. Data sources and parameter selection

The slope model predicts the stability of shallow loess landslides based on digital elevation model data and soil physical and mechanical parameters of the study area. In this paper, digital elevation model data with resolutions of 3, 5 and 10 m were generated by scanning and digitizing contour lines using 1:5000 topographic maps. The mechanical parameters of the soil input to the model mainly include cohesion, friction angle and density, according to the experimental results of 120 sets of in-situ samples obtained in the field, the average natural water content of the soil in the study area is obtained to be 10%, and the mechanical parameters in the corresponding state are shown in Table 2, in general, the stability of the natural dry loess slopes is better, therefore, this paper selects the mechanical parameters of the soil in the natural state and the 5 m resolution of the digital elevation model data for preliminary verification. Rainfall will lead to an increase in the water content of the soil body and thus reduce the strength of the soil body, and the stability of the slope will be reduced, and concentrated and sustained heavy rainfall usually leads to a significant increase in the water content of the soil body, which causes landslides to occur, so this paper is based on the results of the experiments, and selects the mechanical parameters of the soil body under the wet state with a water content mass fraction of 22% as the input parameters of the model.

Table 2. Input data of the mode

Soil state	Moisture content/%	Acceleration ($m \cdot s^{-2}$)	Cohesion /kpa	Friction Angle/ (°)	Density ($kg \cdot m^{-3}$)	Floor limit/m^3	Slide limit /m^3
Natural state	10	9.95	32	30	1482	12	1200
Humid state	22	9.95	8	25	1763	12	1200

3.2. Relationship between strength parameters of loess and water content

According to the partial stress-strain curve and Mohr-Coulomb damage theory of the slip zone soil obtained from the test, the stress Moore's circle is drawn under the coordinate system of τ-σ(shear stress-normal stress), the slope and intercept of the tangent line of the stress circle are obtained under the water content rate, and the change rule of φ and c with the water content rate of the slip zone soil samples are summarized, and the corresponding curves are shown in Fig. 2. It can be seen that c increases and then decreases with the increase of water content, and the maximum value of 133.61kPa occurs at 15.21%. φ shows an overall decreasing trend with the increase of water content, and φ decreases steeply before reaching the water content of 15.21%, and then it basically stays the same, but there is still a tendency to decrease, and then it starts to decrease significantly at about 25%. In contrast, c is more sensitive to water content, indicating that the change of water content mainly affects the cohesion between soil particles, especially near the plastic limit, where the values of the two parameters decrease more significantly.

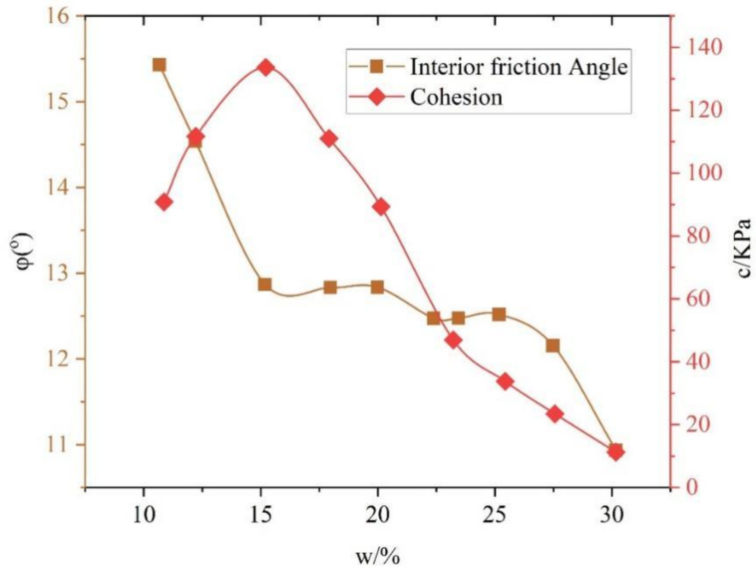


Figure 2. Variation of moisture content

3.3. Prediction of the stress state at the time of near-slip

The stress state of the soil body mainly refers to the average principal stress p and shear stress q of the soil body, which are both related to the overburden pressure σ1 and surrounding pressure σ3 of the soil body. Therefore, the overburden pressure and surrounding pressure of the slip zone soil are calculated according to the soil properties and thickness of the overburden soil body to characterize the stress state of the slip zone soil particles at the time of near-slip. In order to ensure the accuracy and representativeness of the calculation results, the profile of the restored original terrain was used as the calculation profile, and a certain number of soil particles were taken at 5 m horizontal spacing on the slip belt to determine the soil properties and thickness of the overlying soil. This time, the main profile 3-3′ was selected for calculation, with a total of 25 soil research points.

The formulas for calculating the overlying soil pressure and surrounding pressure are as follows:

$$\begin{aligned} \sigma_1 &= \gamma H \\ \sigma_3 &= \xi \gamma H \end{aligned} \tag{10}$$

According to the test results of the soil samples from the survey exploratory wells, the natural capacity of the landslide body is 19.8 kN/m3. According to the empirical data of the soil, the lateral pressure coefficient of the powdery clay in the hard state is taken as 0.40, and the thickness of the overburden soil can be measured on the profile. The magnitude of stress on each soil particle is then calculated using Equation $p = (\sigma_1 + \sigma_2 + \sigma_3)/3, q = \sigma_1 - \sigma_3$.

3.4. Prediction accuracy test

Prediction accuracy test is an important step in evaluating the prediction performance of the model, and this paper uses two methods, the confusion matrix and the success curve, which are currently more common internationally, for validation. The confusion matrix describes the relationship between the identification type of the sample data and the real attributes, focusing on the accuracy of the model classification. The success rate curve reflects the degree of matching between the various classification stages of the predicted data and the actual data, which reflects the accuracy of the predicted data itself, and is widely used in different fields for the advantage of being able to visually describe the quality and conciseness of the distribution of the predicted data.

Therefore, this paper evaluates the prediction accuracy of the slope model from two perspectives: the reasonableness of the classification of the prediction data and the reliability of the data. Confusion matrix method to test the prediction accuracy, firstly, the predicted data and actual measurements of the landslide model are classified, and the true rate, false positive rate and accuracy are calculated as shown in Fig. 3.

Model Classification	Ground Truth Classification: Landslide occurred	Ground Truth Classification: No landslide occurred
Instability	True Positive (TP) The model predicts instability, and a landslide actually occurs.	False Positive (FP) The model predicts instability, but the actual condition is stable.
Stability	False Negative (FN) The model predicts stability, but a landslide actually occurs.	True Negative (TN) The model predicts stability, and the actual condition is stable.

$$\begin{matrix} TruePositive \\ Rate(TPR) \end{matrix} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$\begin{matrix} FalsePositive \\ Rate(FPR) \end{matrix} = \frac{False\ Positive}{False\ Positive + True\ Negative}$$

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + False\ Negative + True\ Negative}$$

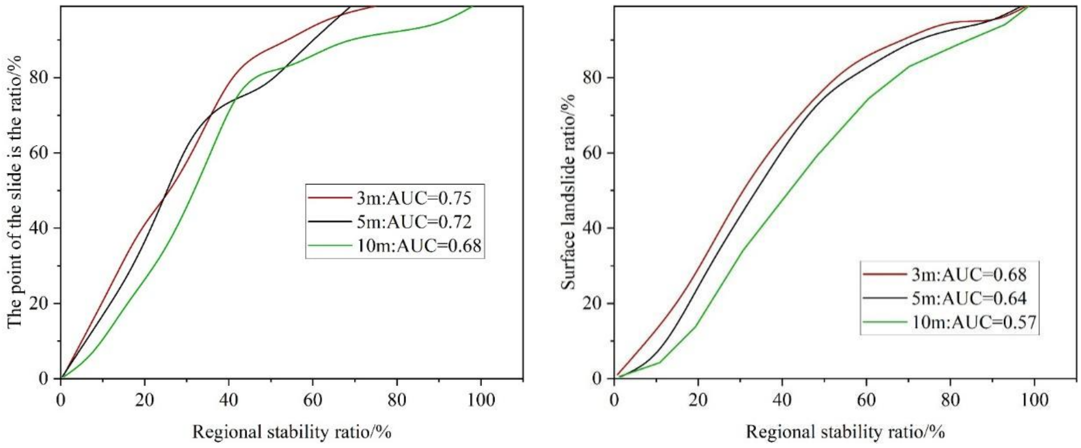
Figure 3. Confusion matrix diagram

The model prediction performance is then evaluated. Usually, an ideal model should satisfy the conditions that the true rate reaches the maximum value and the false positive rate reaches the minimum value at the same time, and when the true rate/false positive rate is >1, the model prediction results are considered acceptable. The evaluation results of the confusion matrix are shown in Table 3, and the accuracy and "true rate/false positive rate ≥ 1" of the digital elevation model data with 3, 5 and 10 m resolution satisfy the prediction requirements, and the data with 3 m resolution has the highest true rate (0.68). Therefore, the validation results of the confusion matrix method indicate that the prediction results and classification methods of the slope model are reliable.

Table 3. Evaluation of the confusion matrix for the calculative result

Resolution	True rate	False positive rate	Accuracy	True rate/false positive rate
3	0.68	0.40	0.65	1.7
5	0.63	0.36	0.69	1.75
10	0.58	0.30	0.68	1.933333

When evaluating the prediction accuracy of the slope model, the success curve uses ArcGIS to count the stability classes from low to high, calculate the proportion of landslide points or areas to the total landslide points or areas in the study area, plot the cumulative proportional change rule of the stability classes in the study area, and then calculate the area under the curve (AUC) to judge the prediction performance of the model. Usually, the larger the value of the area under the curve, the higher the prediction accuracy of the model. In the prediction results of point and surface landslides, as shown in Fig. 4, the proportion of landslides located in areas with low stability class increases significantly with the increase of resolution, which indicates that the resolution of the digital elevation model data significantly affects the prediction accuracy, and the value of the area under the curve meets the requirements of prediction accuracy. The area values under each curve are higher than those of the surface landslides in the prediction results of the digital elevation model data with the same resolution, indicating that the distribution map of point landslides may be more suitable for the test of the model adaptability. Therefore, both tests prove that the slope model prediction results are reliable, and also show that the digital elevation model data resolution has an important effect on the prediction results, the confusion matrix method is suitable for evaluating the accuracy of the model classification, and the success curve is more suitable for evaluating the attributes of the prediction data itself.



(a)Point landslide (b)Facial shape landslide

Figure 4. Success rate curve of the model prediction result

3.5. Sensitivity analysis

When the physical deterministic model evaluates the stability of landslides, the detail and reliability of the input parameters directly affects the accuracy of the evaluation results, and thus the detailed information of the input parameters in the study area is needed. However, in practice, it is difficult to obtain the detailed information of each input parameter completely due to the constraints of terrain, budget, working time and other conditions. Therefore, the sensitivity analysis of input parameters is carried out in advance so as to identify and obtain the key input parameters, which can effectively reduce the cost and time. In the model sensitivity analysis, a set of standard values is first selected for all parameters, the variation range of each parameter is set, and then the degree of change of the safety coefficient is calculated with a certain rate of change, so as to derive the degree of sensitivity of the prediction model to each parameter. The standard values and the range of change of each parameter selected for the sensitivity analysis of the slope model, and the analysis results are shown in Table 4.

Table 4. Standard parameters and their variation ranges

Parameter	Standard value	Range of variation
Spherical radius	11	6~18
Cohesion	26	0~54
Slide area	32	20~45
Block gravity	210	110~420
Interior friction Angle	22	12~34
Potential sliding surface inclination	34	26~38
Slide Angle	28	22~32
Horizontal acceleration coefficient	0.2	0~0.4
Vertical component of radius	5	3~8

The parameter sensitivity analysis is shown in Fig. 5, which shows that the safety coefficient calculated by the model will be increased by increasing the sphere radius, cohesive force, sliding surface area, internal friction angle and potential sliding surface inclination, and decreased by increasing the unit gravity, apparent inclination of sliding direction, horizontal acceleration coefficient, and vertical component of sphere radius. Meanwhile, the safety coefficients calculated by the model are more sensitive to cohesion, sliding direction and raster unit gravity, while the sensitivity to the angle of internal friction, sphere radius and potential sliding surface inclination is relatively low. Based on the sensitivity analysis of the model parameters, the model prediction accuracy can be effectively improved by strengthening the acquisition of geotechnical engineering parameters and slope structure data from indoor and field tests when using the model to predict landslide stability in the study area.

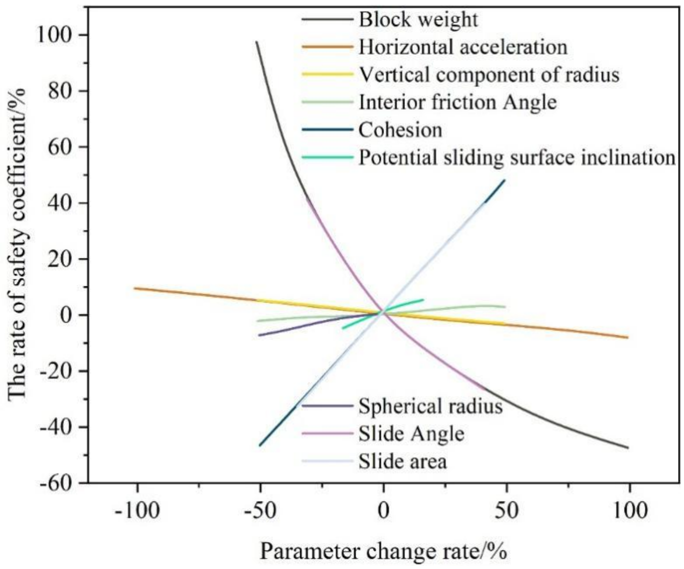


Figure 5. Diagram of the parameter sensitivity analysis

4. Conclusion

In this paper, in the study on the prediction and prevention of loess landslides in a residential area under construction, the combination of landslide displacement monitoring data and the prediction method of slope modeling has achieved a better early warning effect. Through the early warning analysis of four landslide events, it is found that the slope model shows high accuracy and reliability in the prediction of instability time, especially in the prediction of slip avalanche-type landslides and static liquefaction-type landslides, the true rate reaches up to 0.68, and the false-positive rate is 0.40. The analysis of the success rate curve further verifies the high efficiency of the model, especially in the prediction of point landslides, with the digital resolution of the elevation model is increased, the prediction accuracy of the model is significantly improved. This study provides effective technical support for the early warning and prevention of loess landslides in residential areas under construction, and provides a data base for future landslide disaster management. In the future, with the further development of the technology, the accuracy and applicable range of the prediction model will be improved, so as to better serve the prevention and control of loess landslides.

Funding
[Fund Project] This paper is a university-level scientific research project of Weifang University of Science and Technology: Study on the mechanism of dynamic water pressure landslide and its prevention and control technology (number: KJRC2019007).

About the Author
Yuming Zhang (1990.01-), male, Han, from Linyi, Shandong province, associate professor of Weifang University of Science and Technology, his research interests include analysis of rock and soil geological disasters.
Shiyang Lin (1979.05-), male, Taiwan, China, associate professor of Weifang University of Science and Technology, his research interests include intelligent information technology.

References

1. Zhu, Y., Jia, X., & Shao, M. (2018). Loess thickness variations across the Loess Plateau of China. Surveys in Geophysics, 39, 715-727.
2. Zhang, Y., & Chen, Y. (2020). Research trends and areas of focus on the Chinese Loess Plateau: A bibliometric analysis during 1991–2018. Catena, 194, 104798.
3. Peng, J., Sun, P., & Igwe, O. (2018). Loess caves, a special kind of geo-hazard on loess plateau, northwestern China. Engineering Geology, 236, 79-88.
4. Xue, Y., Zhang, X., Li, S., Qiu, D., Su, M., Xu, Z., ... & Xia, T. (2019). Sensitivity analysis of loess stability to physical and mechanical properties: Assessment model. International Journal of Geomechanics, 19(7), 06019012.
5. Huo, A., Yang, L., Peng, J., Cheng, Y., & Jiang, C. (2020). Spatial characteristics of the rainfall induced landslides in the Chinese Loess Plateau. Human and Ecological Risk Assessment: An International Journal, 26(9), 2462-2477.
6. Xie, W. L., Li, P., Zhang, M. S., Cheng, T. E., & Wang, Y. (2018). Collapse behavior and microstructural evolution of loess soils from the Loess Plateau of China. Journal of Mountain Science, 15(8), 1642-1657.
7. Zhuang, J., Peng, J., Wang, G., Javed, I., Wang, Y., & Li, W. (2018). Distribution and characteristics of landslide in Loess Plateau: A case study in Shaanxi province. Engineering Geology, 236, 89-96.
8. Qiu, H., Hu, S., Wang, X., Yang, D., Pei, Y., & Ma, S. (2020). Size and spatial distribution of loess slides on the Chinese Loess Plateau. Physical Geography, 41(2), 126-144.
9. Luo, L., Guo, W. Z., Tian, P., Liu, Y. L., Wang, S. K., & Luo, J. W. (2023). Unique landslides (loess slide-flows) induced by an extreme rainstorm in 2018 on the Loess Plateau: A new geological hazard and erosion process. International Journal of Sediment Research, 38(2), 228-239.
10. Peng, J., Wang, S., Wang, Q., Zhuang, J., Huang, W., Zhu, X., ... & Ma, P. (2019). Distribution and genetic types of loess landslides in China. Journal of Asian Earth Sciences, 170, 329-350.
11. Zhuang, J., Peng, J., Wang, G., Iqbal, J., Wang, Y., Li, W., ... & Zhu, X. (2017). Prediction of rainfall-induced shallow landslides in the Loess Plateau, Yan'an, China, using the TRIGRS model. Earth Surface Processes and Landforms, 42(6), 915-927.
12. Sun, P., Wang, H., Wang, G., Li, R., Zhang, Z., & Huo, X. (2021). Field model experiments and numerical analysis of rainfall-induced shallow loess landslides. Engineering Geology, 295, 106411.
13. Liu, Y., Shao, C., Wu, Y., Lan, H., Yang, Y., Yan, Z., ... & Yang, L. (2024). Analysis of house damage and prevention strategies for cut slope house-building landslides in tectonically weak and humid hilly areas: a case study of Jiangxi Province. Landslides, 21(7), 1567-1580.
14. Peng, J., Fan, Z., Wu, D., Huang, Q., Wang, Q., Zhuang, J., & Che, W. (2019). Landslides triggered by excavation in the loess plateau of China: A case study of Middle Pleistocene loess slopes. Journal of Asian Earth Sciences, 171, 246-258.
15. Qiu, H., Hu, S., Cui, P., Yang, D., Xu, B., Zhu, X., & He, Y. (2017). Pattern analysis of loess landslides and their scale dependency. Quaternary Sciences, 37(2), 307-318.

16. Sun, P., Wang, G., Wu, L. Z., Igwe, O., & Zhu, E. (2019). Physical model experiments for shallow failure in rainfall-triggered loess slope, Northwest China. Bulletin of Engineering Geology and the Environment, 78, 4363-4382.
17. Deng, J., Ma, C., & Zhang, Y. (2022). Shallow landslide characteristics and its response to vegetation by example of July 2013, extreme rainstorm, Central Loess Plateau, China. Bulletin of Engineering Geology and the Environment, 81(3), 100.
18. Yabo Li,Xinli Hu,Haiyan Zhang,Hongchao Zheng & Ningjie Li. (2025). Displacement prediction and failure mechanism analysis of rainfall-induced colluvial landslides. Journal of Hydrology,660(PA),133361-133361.
19. Xiao Ping Zhou,Xu Kai Yuan & Da Yang. (2024). Prediction of landslide failure time based on moving average convergence and divergence coupling with Bayesian updating method. Engineering Geology, 343, 107781-107781.
20. Muin Muslim & Muslim Arung Bahari. (2024). Anak Krakatau Landslide Tsunami and Sediment Transport Simulation Using Non-Orthogonal Boundary Fitted Technique in Spherical Coordinate Model. Journal of Coastal Research,116(sp1),146-150.
21. Wu ChunYi & Chou PoKai. (2021). Prediction of total landslide volume in watershed scale under rainfall events using a probability model. Open Geosciences,13(1),944-962.
22. Jiang, Hua & Xi, Jian-Qing. (2012). Research and Application of Multiple Distance Spatial Clustering Algorithm Based on Neighborhood Searching. Journal of Computational and Theoretical Nanoscience, 9(10), 1628-1632(5).