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ORIGINAL PAPER

Landslide susceptibility prediction considering rock integrity and stress state: a case study

He Wang[1] · Tianhong Yang[1] · Penghai Zhang[1] · Feiyue Liu[2] · Honglei Liu[1] · Peng Niu[1]

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Abstract

Landslide is a major disaster threatening the safety and orderly production of an open-pit mine, so slope stability evaluation is of great significance to the support and monitoring arrangement. Landslide susceptibility mapping (LSM) was widely used in landslide prediction. The former research focused on the algorisms to improve its accuracy, which is relatively complete and left little room for further improvement. In this paper, new factors, including RQD and numerical simulation (NS), are selected to solve the limitation of traditional LSM on the integrity and stress state of the slope. The RQD value was obtained by machine learning and converted into rasters by the ordinary Kriging interpolation method. The slope stress was calculated by the finite difference method and converted into raster data using a program written by Fish language. Based on the information value (INV) method, gradient boosting decision tree (GDBT) was used as the main algorism to generate the LSM-NS. Finally, because LSM-NS contains landslides that have already occurred and those in high susceptibility due to its stress state, commonly used validation methods such as AUROC could no longer be used. Multiple validation methods were applied, such as stress monitoring and UAV tilt photography. The result indicates that the stress increases with crack generating in the high susceptibility area of LSM-NS, where traditional LSM could not predict. Therefore, the addition of RQD and NS could further improve the accuracy using existing algorism. LSM-NS is recommended as the more suitable model for landslide susceptibility assessment in a small area due to its excellent accuracy and efficiency.

Keywords Landslide susceptibility map · Information value · Gradient boosting decision tree · Mechanics analysis · Anchor cable stress gauge

Introduction

Landslide is one of the major disasters threatening the safety of personnel and property in open-pit mine. The prevention methods, such as support and monitoring, are usually deployed in the position where historical landslides occurred. However, subjectivity and lack of standard in area selection may lead to excessive support, resulting in a waste of resources and economic benefits reduced. Landslide susceptibility map (LSM) is a favorable way to evaluate landslide risk, which could combine sufficient factors into account and have a relatively thorough guideline (Fell et al. 2008).

Landslide susceptibility modeling can be classified into statistics and machine learning methods. Statistical methods, such as Analytic Hierarchy Process (AHP), Certain Factor (CF), Dempster-Shafer model, and Information Value (INV), were used to preliminarily determine the weight relationship among evaluation factors (Chen et al. 2017a; Chen et al. 2017b; He et al. 2019; Mondal and Maiti 2013; Zhang et al. 2021). To improve the evaluation accuracy, machine learning methods such as decision tree and random forest achieved good results (Chen et al. 2020; Chen et al. 2021). The data of landslide susceptibility is strongly non-linear data, and deep learning methods can extract the critical factors from the non-linear data; CNN is more mature in deep learning and can solve the problem of pattern recognition (Anwer et al. 2018) and also been applied to LSMs (Azarafza et al. 2021; Lin et al. 2023). The GBDT model

✉ Tianhong Yang
yangtianhong@mail.neu.edu.cn

1 School of Resources & Civil Engineering, Northeastern University, Shenyang, Liaoning 110000, People's Republic of China

2 State Key Laboratory of Mining Response and Disaster Prevention and Control in Deep Coal Mines, Anhui University of Science & Technology, Huainan, Anhui 232001, People's Republic of China

is more interpretable than CNN and more suitable for landslide susceptibility assessment (Chen et al. 2020; Huan et al. 2022). As more and more algorithms have been applied to LSM, there is little room for accuracy improvement. Fortunately, specific factor selection could further improve the accuracy of LSM.

The slope is a fuzzy system controlled by many factors, in which the stress and the integrity of rock mass are essential indexes to reflect the state of the slope (Tao et al. 2020; Zhang et al. 2019). Some research tried to combine 2D mechanical calculation with LSM (Xie et al. 2006; Zou et al. 2021). However, LSM is often used in large-scale areas, and the complexity of modeling and calculation makes the 3D qualitative methods rarely considered (Akgun and Erkan 2016). For the slope with complex deep geological structure and stress release caused by excavation, the 2D mechanical calculation cannot accurately reflect the state of the slope (Zhang et al. 2019), so it is of great significance to introduce 3D mechanical analysis into the LSM.

This paper proposes a new LSM method considering rock integrity and mechanical analysis, which can solve the limitations on mechanical relations and deep geological structure. Firstly, based on the INV method, the LSM is divided into five regions with different landslide risk levels, providing a training dataset for GDBT. Then, based on ordinary Kriging interpolation, the continuous RQD grids were obtained and used as one of the factors. Furthermore, a program was developed with the FISH language embedded in FLAC software to export and convert the calculated stress field into raster data. At last, taking the factors above, the landslide susceptibility map combined with numerical simulation (LSMNS) is redrawn by GBDT. LSMNS can predict landslide susceptibility based on the historical landslide location and potential landslide based on the stress state of the slope. The accuracy of LSM was evaluated by UAV photography, slope radar, and anchor cable stress meter monitoring data. Compared with the traditional LSM, LSMNS has a stronger prediction ability. Thus, it provides a theoretical basis and support for the early prevention and control of mine slope.

Study area

Wushan Copper and Molybdenum Mine is located in the north boundary of Inner Mongolia, within longitude 117°15′~117°20′ E and latitude 49°24′00″~49°26′30″ N (Fig. 1). The mining area covers about 9.84 km^2. The area is a low hilly area with a north-east trend and an average elevation of about 750m. The highest elevation in the northern section is Daliitu Mountain, at 889.5m, while the southern section of the mine, Unugatu Mountain, is 862.8m and the lowest elevation is 650.7m. The natural slope of the hillside is mostly between 9.2 and 18.4°. The mining area is located in the mid-latitude region and has a temperate semi-arid continental climate. The spring season is characterized by significant temperature changes, rapid transitions, windy, and relatively dry, with an average precipitation of 32mm; the summer is short and warm, with long sunshine hours and concentrated and heavy rainfall, with an average

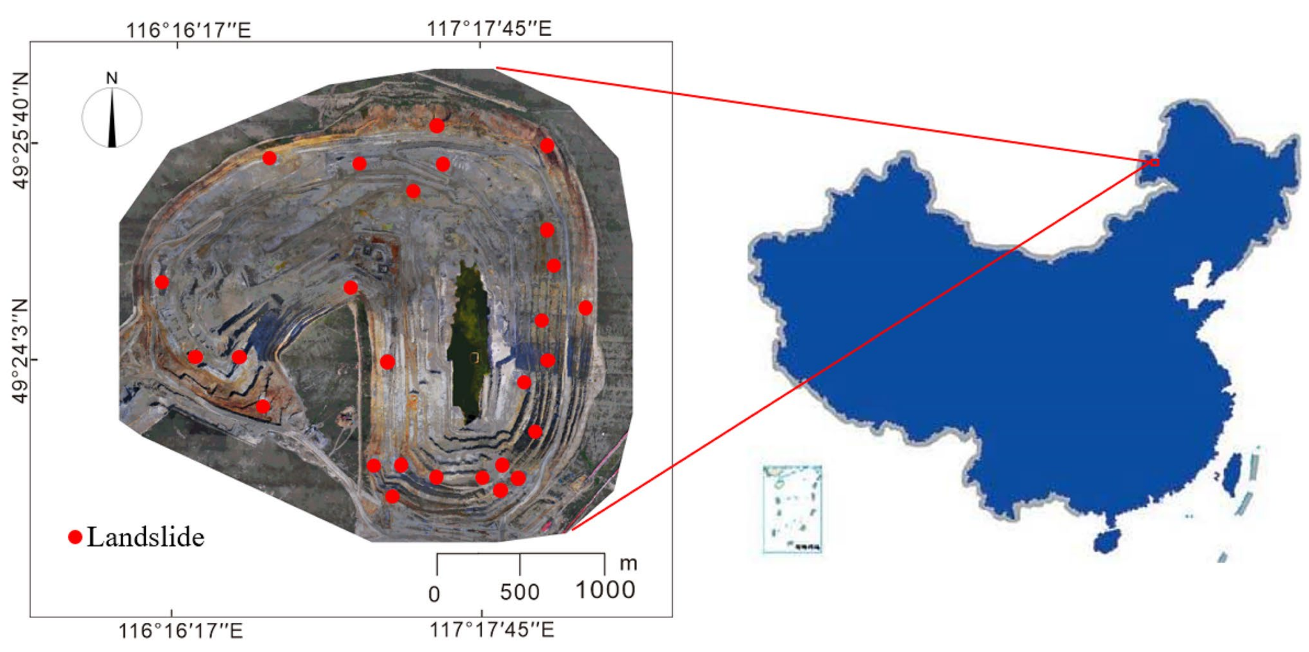


Fig. 1 Study area and landslide inventory map

precipitation of 212.7mm. There are few water systems in the area and no rivers formed.

The maximum height of the final slope is about 510m with slope angle of 43–45°. At present, the lowest mining is 605m. The highest point of the pit is 855m at the top of the east slope, and the height difference is 250m, which belongs to the high steep slope. Black mica granite is widely exposed within the mine area, covering over 60% of the area. Other lithology is shown in Fig. 6d.

With the continuous expansion of rock mass exposed by mining, the stability of rock mass becomes worse and worse under the action of faults, joints, and weathering, resulting in 27 landslides of different scales.

Methods

Methods used in this study mainly include the following steps (Fig. 2): (1) UAV tilt photogrammetry and data set establishment; (2) RQD value obtaining and its grid generated by the ordinary Kriging interpolation method; (3) preliminarily evaluation of the landslide susceptibility using the information value method; (4) selection of stable slope samples in the area with very low landslide risk; (5) landslide susceptibility using gradient boosting decision tree; (6) 3D model construction and calculation of the stress; (7) landslide susceptibility mapping using the LSM-NS method; and (8) comparison and verification of results.

Information value

Information value is a statistical analysis method developed from information theory (Yin 1988), which was modified and first applied in the field of mineral resources (Westen and Bonilla 1994). It has been gradually used for landslide susceptibility in recent years.

The INV measures the contribution rate of a particular factor to landslide based on grids in geological information system (GIS). The evaluation factors were segmented and the landslide grids in each section were counted. The more landslide grids contained in a grade of a factor, the more landslide susceptibility of this grade is. The information value I of each causative factor X_i can be expressed as:

$$I(X_i, S) = \ln\frac{N_i/N}{T_i/T}$$

where T is the total number of grids in the study area, N is the total number of grids in which landslides occurred, T_i is the grids number of fa X_i, and N_i is the grids number of factor X_i in which landslides occurred.

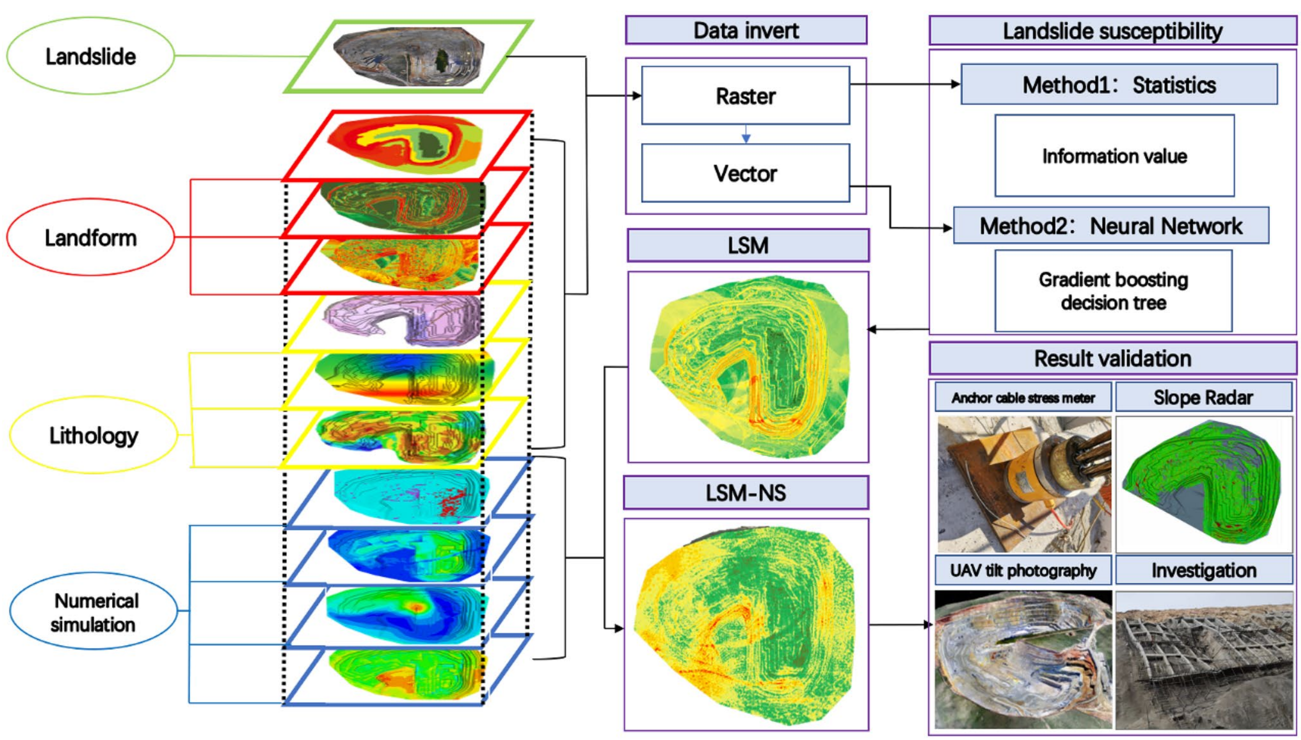


Fig. 2 Flowchart of the study

After calculating all the information values, the susceptibility in a single grid is the sum of the information values of each factor:

$$I = \sum_{i}^{n} I(X_i, S) = \sum_{i}^{n} \ln \frac{P(X_i, S)}{P(X_i)}$$

Gradient boosting decision tree

The gradient boosting algorithm is a machine learning method for regression and classification problems and generally forms prediction models by the combination of weak prediction models (Friedman 2002). Gradient boosting decision tree is a representative boosting algorithm combined with decision tree (Elith et al. 2008; Schapire et al. 2005), which can flexibly process continuous and discrete data, and has extreme robustness to outliers. This model can identify complex nonlinear relationships while calculating the relative importance of variables. The GBDT algorithm can learn the combination of data features that are beneficial to the judgment of prediction results and enrich the data features, which is very suitable for optimizing landslide susceptibility. The GBDT algorithm was developed in Python using the GBDT class library of scikit-learn.

Factor selection

The selection of landslide susceptibility factors is the basis and critical problem of LSM. There are 13 evaluation factors commonly used in landslide susceptibility mapping (Fell et al. 2008); some factors such as rainfall and vegetation coverage rate have little change in the mining area, while RQD and clay mineral content have a significant influence on the slope stability and can be obtained due to the reduction of the evaluation range. Therefore, elevation, slope, aspect, lithology and fault, expansive mineral content, and RQD are selected to predict landslide susceptibility.

(1) Elevation

The elevation is relevant to the exposure time of the slope, along with the degree of weathering and erosion (Liu et al. 2020a). The increase in height also provides a more effective surface and slide force for landslides, which is closely related to the occurrence of landslides (Fig. 6a).

(2) Slope

The slope is an essential factor in evaluating slope stability. Many scholars have studied the relationship between slope and landslide (Bandara and Ohtsuka 2017; Xie et al. 2019). Unlike the natural slope, the slope angle of open pit mine was always selected as large as possible (Liu et al. 2020c), which leads to less viscous force and more sliding force of the potential sliding surface and brings larger risks for landslide (Fig. 6b).

(3) Aspect

Aspect is a controversial factor for LSM in open-pit mines. Some considered aspect could hardly affect stability in a relatively small area. However, support has been found in an open-pit mine in Inner Mongolia, whose north slope has a better stability compared to its south slope with little difference in geological condition. Different solar radiation intensity affects water evaporation, groundwater distribution, and rock mass' mechanical characteristics (Fig. 6c).

(4) Lithology and fault

Many investigations show that the regional distribution of landslides is remarkably concentrated in slope with weak lithology. The fault fracture zone makes the rock mass lose its continuity and integrity, which further decreases the strength of the rock mass and increases the risk of landslide (Fig. 6d).

(5) Expansive minerals

Rapid snowmelt in spring and rainfall in summer lead to a large amount of water infiltration into the slope, and volume of expansive minerals can increase about 30% (Matsukura and Mizuno 1986; Zhang et al. 2016), which causes the expansion of the rock mass' primary fractures, and produces secondary fractures. According to the geological survey, abundant expansive minerals such as illite and montmorillonite exist in the internal structure and joints of the slope of Wushan open-pit mine (Fig. 6e).

(6) RQD

RQD is a quantitative index to measure rock quality, which is a specific parameter to reflect the degree of rock integrity (Zhang 2010; Zhang et al. 2012). Therefore, RQD has become essential to engineering rock mass evaluation (Madani et al. 2018). From the perspective of rock mass integrity alone, the higher RQD value is, the lower landslide susceptibility value should be. There are 9605 core images from 160 boreholes collected from Wushan open-pit mine. The drilling was carried out from 2007 to 2010. The exploration line distance was 100 m, and the core recovery rate was recorded in each core image (Fig. 3).

To obtain the RQD of the whole evaluation range, the current RQD value is converted into a data set, and the

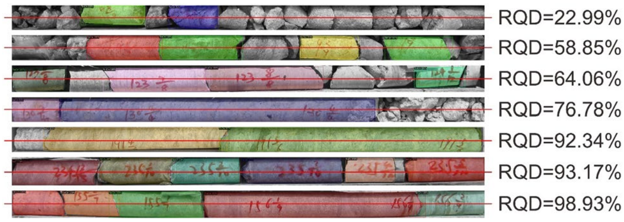


Fig. 3 RQD based on machine learning (Liu et al. 2020b)

ordinary Kriging interpolation method is used to generate raster data (Fig. 7f).

(7) Mechanical analysis

The distance from slope to fault is often used as an evaluation factor in LSM (Abedini and Tulabi 2018; Lin et al. 2017). However, the distance division is too subjective, and faults with different mechanical properties are usually treated equally, which is unreasonable considering mechanics. Numerical simulation is a common stability analysis method in open-pit mine. The calculation model contains the structure and mechanical properties of rock mass and faults (Fig. 4).

This paper uses the finite difference method to calculate the slope's stress and displacement. Considering the Mohr-Coulomb criterion for geotechnical mechanics (Fig. 5):

$$\sigma_3 \geq \sigma_t$$

where σ_3 and σ_t are tensile stress and uniaxial tensile strength of rock mass. When $\sigma_3 \geq \sigma_t$, tensile failure occurs. (Fig. 6).

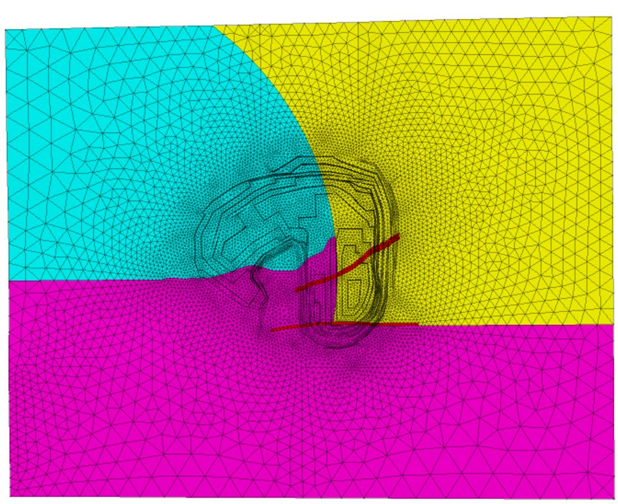


Fig. 4 Calculation model

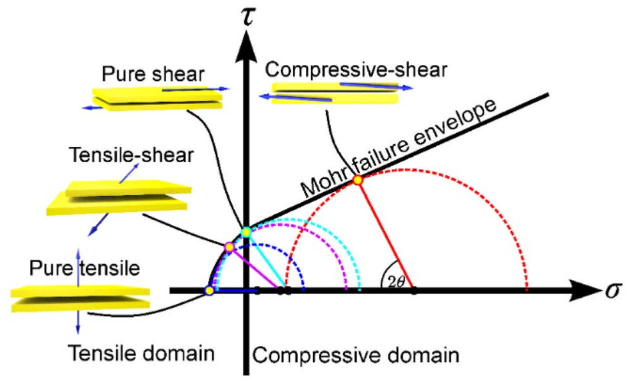


Fig. 5 Mohr-Coulomb criterion

$$f_s = \sigma_1 - \sigma_3 \frac{1+\sin\varphi}{1-\sin\varphi} - 2c\sqrt{\frac{1+\sin\varphi}{1-\sin\varphi}}$$

where $\sigma_1$and σ_3 are the maximum and minimum principal stresses, and c and φ are the cohesion and internal friction angles. Shear failure will occur when f_s>0.

As the number of selected factors increases, some factors with strong correlation will influence the model's prediction accuracy. The correlation coefficients among the selected factors are calculated (Table 1). Pearson correlation coefficient is calculated by the following formula:

$$\rho(X,Y) = \frac{COV(X,Y)}{\sigma_X\sigma_Y} = \frac{E\left[\left(X-\mu_X\right)\left(Y-\mu_Y\right)\right]}{\sigma_X\sigma_Y}$$

where σ_X、 σ_Y is the standard deviation of X and Y, and $COV(X, Y)$ is the covariance of X and Y.

The result shows that there is no apparent correlation among the factors. The factors are converted into raster and re-graded. The study area is composed of 43221392 grids of 0.5 × 0.5m.

Results

Information value

According to the information value (Table 2), the slope located in 690–780m has a positive susceptibility, which is reasonable due to longer exposure time and more merged stages. The slope angle between 30 and 70° has a similar value because the average angle is 60°, and nearly all landslides occurred only conclude single stage in Wushan open-pit mine. For the aspect factor, slopes facing north (315–90) have a relatively high risk, which confirms that the aspect does affect slope stability. Fault, due to its low integrity and

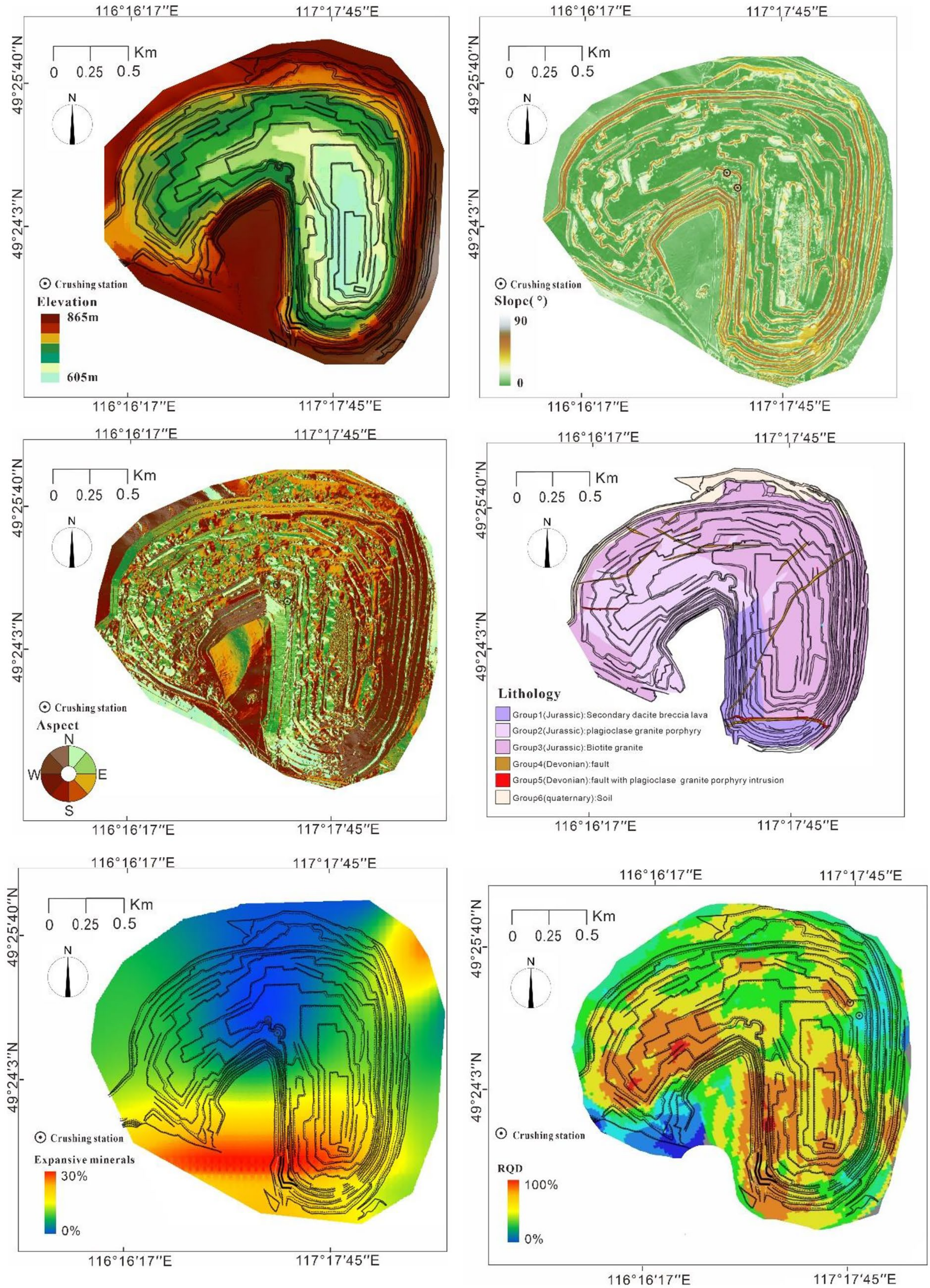


Fig. 6 Landslide influencing factors maps: a elevation; b slope; c aspect; d lithology; e clay minerals; f RQD

Table 1 Pearson correlation of each factor

	Elevation	Slope	Aspect	Lithology and faults	Expansive minerals	RQD
Elevation	1					
Slope	−0.05018	1				
Aspect	−0.00733	−0.02868	1			
Lithology and faults	−0.03461	0.02545	−0.04744	1		
Expansive minerals	−0.00533	0.01924	−0.02286	−0.05535	1	
RQD	−0.13286	−0.09872	0.09598	−0.00433	−0.06584	1

Table 2 Segmentation and information values of evaluation factors

Influencing factors	Classes	Landslide grids	Class grid	Information volume
Elevation(m)	608–630	298	2172076	−4.14875
	630–660	6922	3189310	−1.38751
	660–690	34875	5449129	−0.30609
	690–720	104540	6969137	0.545671
	720–750	91094	7112776	0.387592
	750–780	113598	9407414	0.32876
	780–810	24355	6905772	−0.90203
	810–846	0	2015778	0
Slope(°)	0–10	14669	30010893	−2.87823
	10–20	9787	4492890	−1.38385
	20–30	29296	2326902	0.370506
	30–40	87399	1813408	1.712869
	40–50	99520	1773053	1.865248
	50–60	80460	1608797	1.749866
	60–70	48510	965726	1.754238
	70–80	5941	203454	1.211785
	80–90	100	26273	−0.82578
Aspect(°)	0–45	47467	5791327	−0.05873
	45–90	62499	4010550	0.583815
	90–135	43096	3698345	0.293137
	135–180	2837	4309777	−2.58055
	180–225	1432	5270876	−3.46553
	225–270	26338	6273487	−0.72773
	270–315	78794	7358331	0.208596
	315–360	113219	6508703	0.693776
Lithology	Group3	255556	31500513	−0.06897
	Group1	61608	3478720	0.71172
	Group2	30651	4573687	−0.26006
	Fault	45261	885545	1.77159
RQD	< 20%	217073	11496110	0.775818
	20–40%	143276	11273309	0.379928
	40–60%	13353	7110647	−1.53226
	60–80%	301	8009639	−5.4437
	80–100%	1679	7454112	−3.65297
Expansive minerals	≤ 15%	47748	25583026	−1.49046
	15%–30%	125849	15374258	−0.01208
	≥ 30%	202085	4386533	1.71568

cohesion, is significantly large (1.77) compared with other lithology, which is the main controlling factor in Wushan open-pit mine. The expansive mineral content is proportional to landslide susceptibility, while RQD is the opposite. The information value of each factor is shown in Table 2.

Gradient boosting decision tree

Based on the landslide susceptibility map generated by the INV, stable samples are randomly selected in very low landslide susceptibility areas. Data sets contain 9214 grids which were divided into verification sets and training sets in a 3:7 ratio. To improve the model's prediction ability, parameters such as learning rate in GBDT are adjusted and optimized according to the prediction results (Table 3). The Huber method is selected as the loss function, and a smaller quantile alpha is chosen to enhance the model's adaptability to the data set.

Mechanics analysis

Unlike the natural slope, stress unloading caused by excavation changes the distribution of stress and displacement of the slope. Flac3D software is used to calculate the maximum principal stress and maximum shear stress of Wushan open-pit mine after excavation from 2018 to 2020 (Fig. 7). Rock mechanical parameters are shown in Table 4. According to the calculation results, lithology, faults, and different mechanical parameters of slope lead to uneven stress distribution under the effect of excavation. Slopes in high stress areas tend to landslide even if there is no landslide that happened before. Therefore, the prediction ability of LSM can be improved considering slope stress status. A program was developed by Fish language to export the calculation result into vector data sets and then converted into raster data in SuperMap software.

Table 3 Parameters of gradient boosting decision tree

Parameter	Value
n estimators	80
Learning rate	0.1
Subsample	0.8
Loss	Huber
Alpha	0.7

Landslide susceptibility mapping

Landslide susceptibility using INV is similar to that generated by GBDT, but LSM generated by GBDT decreases the landslide susceptibility of the non-mining area and shows a

Table 4 Rock mechanical parameter

Lithology	Cohesion (KPa)	Friction angle (°)	Young modulus/Gpa	Poisson's ratio
Dacitic breccia	330	35	15.37	0.18
Fault	125	29	13.32	0.17
Biotite granite	400	37	17.78	0.31
Granite porphyry	310	34	9.98	0.29

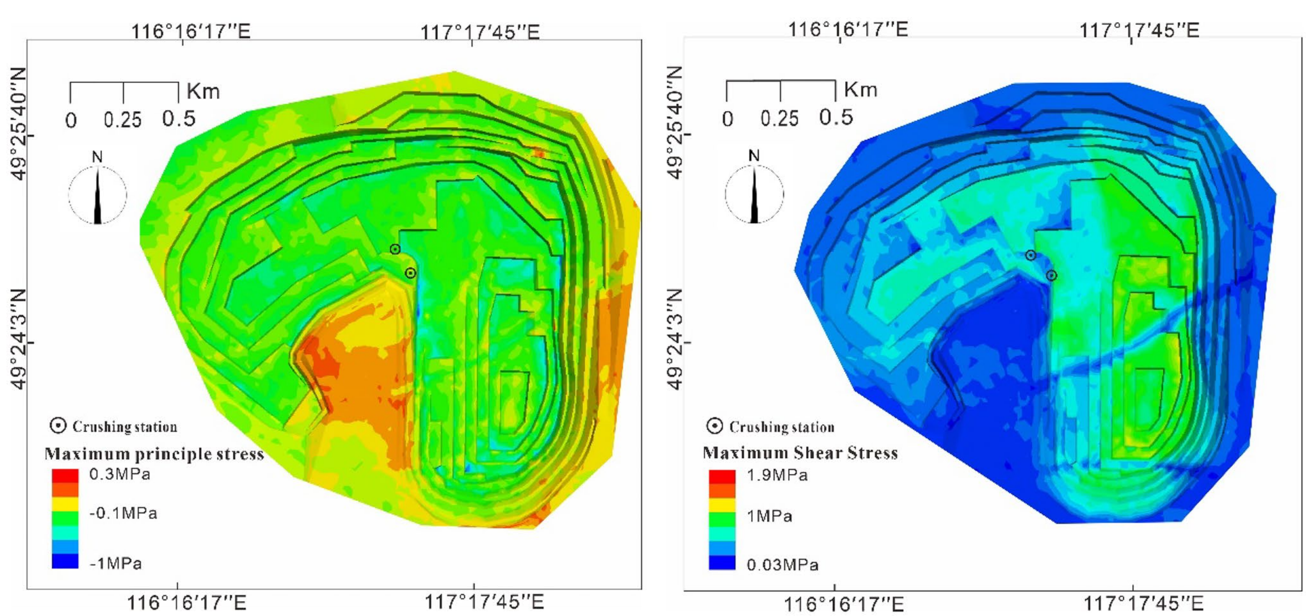


Fig. 7 Simulation result: a maximum principle stress; b maximum shear stress

better ability in landslide prediction, so GBDT was selected as the main algorism of LSM. By comparing the LSM with and without RQD factor and numerical simulation, three major differences are found (Fig. 8). In LSM-NS, the landslide susceptibility of area 1 and area 3 was heightened; according to the record, there are landslides that occurred in these areas during the mining process, but little landslide happened in area 2. Zone 3 is the location of fault F5, where small-scale landslides often occur, posing a threat to the ore transport corridor. During the support, a landslide occurred in this area, resulting in equipment loss. There has been no landslide in area 1 so far; due to the excavation of rock mass on three sides, its stability will continue to weaken. According to the situations above, LSM-NS shows a better ability in landslide susceptibility mapping. Then, based on the Natural breakpoint method, the LSM-NS map was divided into five levels. The distribution of LSM-NS risk levels is shown in Table 5.

Susceptibility assessment and validation

Landslide data sets are often divided into training sets and test sets, and the test sets are used to evaluate the prediction accuracy. AUC is mainly used to measure the accuracy of the landslide susceptibility map (Bui et al. 2016; Pham et al. 2018; Tien Bui et al. 2017). However, it is still a verification of the existing data, which could not fully represent the prediction ability of the algorism. To verify the landslide susceptibility, anchor cable stress gauges were deployed in areas mentioned in 5.4 (Fig. 9).

This study selects the monitoring data until November 2, 2021. The mean value of each group is shown in Fig. 10.

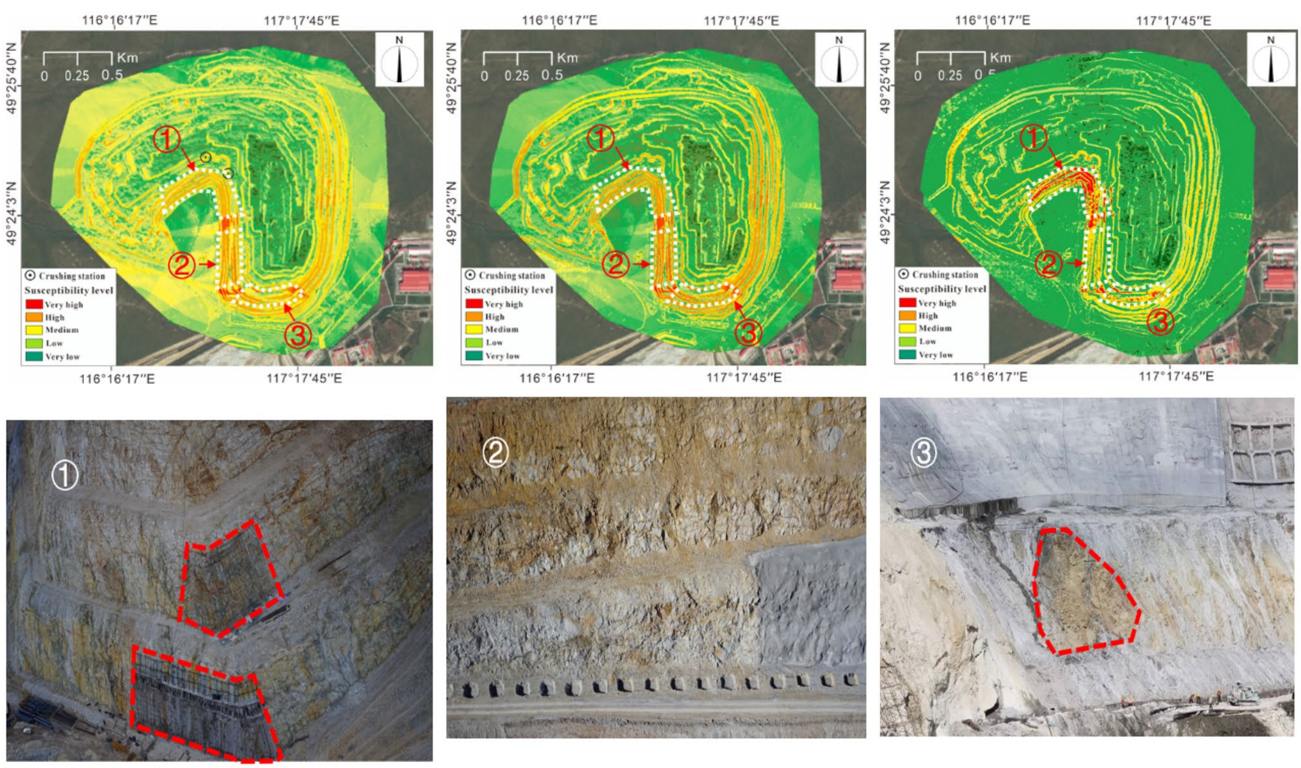


Fig. 8 Landslide susceptibility map using: a INV; b GBDT; c LSMNS

Table 5 Landslide susceptibility zoning raster statistics

Landslide susceptibility	Landslide grids	Proportion of landslide	Total grids	Grid Proportion	Landslide ratio(%)
Very low	0	0	5614095	0.129892	0
Low	12397	3.299865	18133872	0.419558	0.068364
Moderate	26299	7.000335	14734840	0.340915	0.178482
High	278472	74.12439	4429189	0.102477	6.287201
Very high	65514	17.43868	309396	0.007158	21.17481

There will be two stages after the installation of anchor cable stress meter (Yang et al. 2020). The first is the stress relaxation stage caused by the creep of anchoring rock mass. Significant stress fluctuation always occurs during this period, so the monitoring value is unavailable for slope stability assessment. In the second stage, the stress curves become smooth. According to the data, the southeast slope is stable after cutting slope treatment, while the stress of southwest 750m platform keeps fluctuating between −2kN and 5kN. The increase mainly shows in the southwest 765m platform and the crush station with 7kN and 10kN in 10 days, which is consistent with the LSMNS.

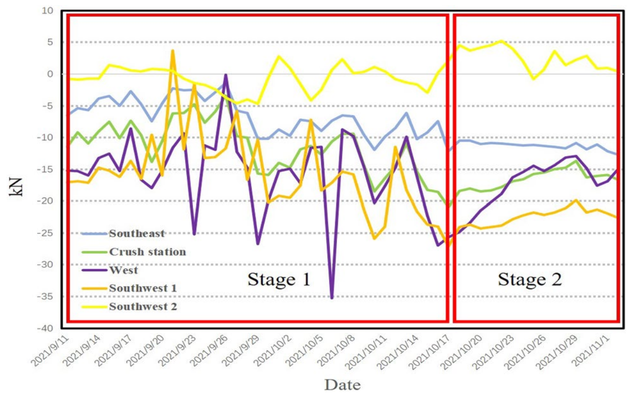


Fig. 10 Tendon anchorage dynamometer curve

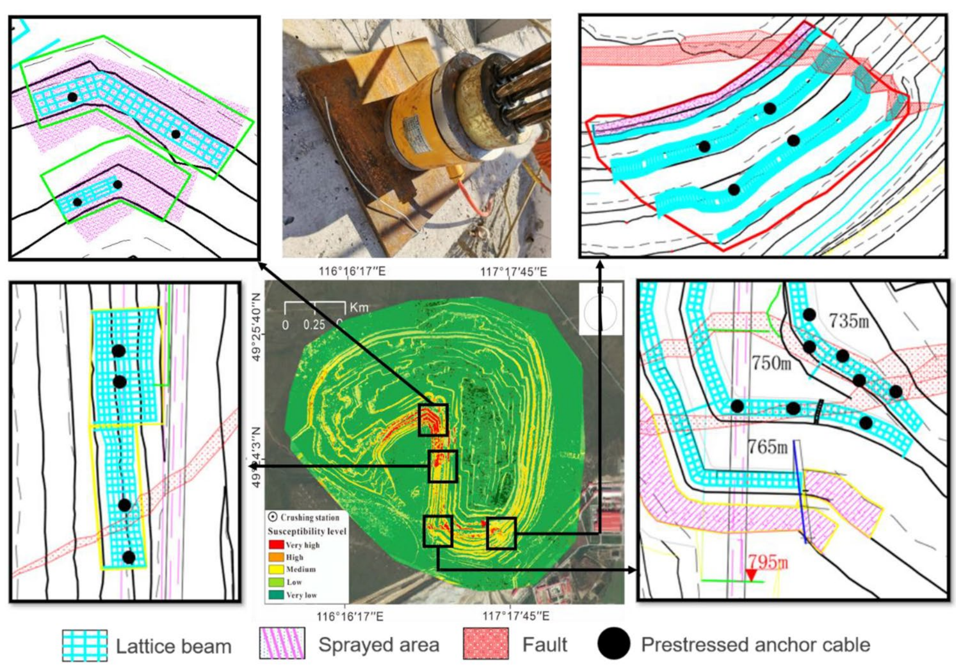
Discussions

The monitoring result shows that LSMNS can effectively improve the limitation in mechanical mechanisms and deep geological structure, thereby improve the prediction accuracy and prediction ability of landslide susceptibility. In the past decades, scholars have used statistical methods or combined with machine learning methods to evaluate landslide susceptibility. These studies have contributed greatly to the advance of methods; however, little research has taken RQD as a factor or combined with mechanical analysis.

LSM is based on the theory that landslides in an area always have similar characteristics and regular distribution. But some slopes, especially artificial slopes, tend to landslide in non-regular areas, which is usually influenced by deep geological structures and excavation. LSM has few predictions ability in this kind of landslide. Based on Mohr-Coulomb theory, the calculation of stress, displacement, and safety factor has been widely used in slope stability analysis and is a recognized effective method (Kumar et al. 2017; Liu et al. 2020a; Umrao et al. 2017). However, some factors such as slope direction, clay mineral content, and angle between the structural plane and slope surface are often difficult to be reflected in mechanical analysis modelling. GIS technology has advantages in reflecting these factors. Therefore, LSM combined with mechanical analysis can improve their limitations and comprehensively evaluate slope stability.

AUC is often used in LSM accuracy measurement. This method requires landslides to be randomly divided into training and validation sets. However, these methods take historical landslides as the validation set, which can only

Fig. 9 Monitoring design based on landslide susceptibility map



prove the prediction accuracy for existing landslides, but not the prediction ability for potential landslides. Stress value is an important index reflecting the stability of geotechnical engineering. Monitoring data has higher rationality and scientific connotation to measure the results of landslide susceptibility.

The LSM based on mechanical analysis proposed in this paper is applied to open-pit mines to assist with early support schemes. With the mining process, the slope conditions are constantly changing. Therefore, a static landslide susceptibility map still cannot fully meet the needs of slope stability evaluation.

Conclusions

Open-pit mine landslide susceptibility analysis improves the visualization and precision of landslide prediction and may satisfy the need of early protection and treatment of mine slopes. In this study, five factors suitable for open-pit mine were selected from 13 commonly used landslide susceptibility factors. Considering the determinants of mine slope stability, new factors relevant to open-pit mine landslide susceptibility mapping were proposed.

This method considers the influence of rock integrity and mechanical relationship on slope stability. Rock integrity is measured by the RQD index. Based on the core data of 160 boreholes, the rock integrity grid is obtained by the ordinary Kriging interpolation method. Based on Fish language, the stress is calculated by Flac3D software and converted into raster data. Using this method, the landslide source area is determined through the combination of UAV, slope radar, and other monitoring means, which can provide a sufficient basis for formulating an early slope protection plan.

Moreover, this study suggests that the LSMNS method has certain advantages and prospects in improving the reasonability and applicability of landslide susceptibility evaluation in the mining area. The innovation of this method lies in the reasonable adjustment of evaluation factors according to the evaluation scope and the addition of more detailed factors. Based on the traditional landslide susceptibility map theory, it believes that landslides are spatially aggregated and affected by the slope failure mechanism.

Finally, the proposed method is applied to a case study of Wushan open-pit mine, and various monitoring methods are arranged to verify the prediction results. The LSMNS results are in accordance with the actual disaster situation and the monitoring results, which strongly suggest that LSMNS can provide specific guidance for evaluating open-pit landslide susceptibility.

In addition, an accurate landslide susceptibility map can better guide the formulation of slope support treatment plan to reduce the cost of slope treatment under the premise of ensuring mine safety. Therefore, the landslide susceptibility map prepared in this study will help mine decision-makers better plan the mining sequence and construction location of critical facilities, which is applicable to Wushan open-pit mine and other landslide-prone areas with similar conditions in the world.

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Declarations

Conflict of interest The authors declare no competing interests.

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