Influence of DEM resolution on landslide simulation performance based on the Scoops3D model

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ABSTRACT
Using the physical deterministic model to analyze landslide stability has become a hotspot of landslide disasters research all over the world. The Digital Elevation Model (DEM) resolution has a great influence on the simulation effect of 3D physical models. However, few researchers have studied the prediction performance of the 3D models under different DEM resolutions. Therefore, based on the 3D model Scoops3D, the spatial distribution of landslides was simulated and predicted under five different DEMs resolutions (2.5 m, 5 m, 10 m, 20 m, and 30 m). The optimal parameters of the model were obtained through field investigations and laboratory experiments, and then, the simulation results were compared with the actual landslides distribution. Receiver operating characteristic (ROC) analysis and \%LR_{class} index were used to quantitatively evaluate the prediction performance of the 3D model under five different DEMs resolutions. The results show that Scoops3D has good performance in landslide spatial distribution prediction. In addition, we also found that the simulation results of high-resolution DEM were not ideal, while the prediction results of medium resolution DEMs (i.e., 5 m and 10 m) were more accurate. Therefore, this study provide a reference to select the most suitable DEM resolution for landslide stability analysis.

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1. Introduction
Landslide is one of the most common geological disasters worldwide, posing a serious threat to human life and infrastructure (Ma et al. 2021; Zhou et al. 2022). Especially in recent decades, destructive landslide events have increased significantly due to global warming and extreme weather events (Qiu et al. 2018; Zhu et al. 2021). Therefore, it is particularly important to conduct landslide stability analysis, which
will help reduce losses and provide theoretical and basic data support for landslide disaster risk prevention and control.

In the relevant research of landslide stability analysis, the qualitative analysis, quantitative analysis, and physical deterministic simulation methods have most commonly been used to study the spatial distribution of landslide stability (Abedini and Tulabi 2018). Among them, physical deterministic models take geotechnical parameters into account when analyzing landslide sensitivity, which improves the accuracy of the model simulation (Guo et al. 2022). Terhorst and Kreja (2009) used SINMAP to conduct a sensitivity analysis of the slope of the study area and compared it with the actual situation. It was found that the model did not consider the influence of the hydrological parameters, which was a major factor and caused the simulation results to be problematic. Liao et al. (2011) used TRIGRS to simulate the landslide induced phenomenon after a typhoon. By adjusting the influence radius of the different typhoons, it was found that the early warning abilities of both scenarios were quite high, and it was also proposed that the results would be better if other elements of the landslides were perfected. Although these models can obtain relatively ideal simulation results, they are all one-dimensional models based on the infinite slope model, ignoring the influence of the sliding surface and the sliding direction (Park et al. 2013; He et al. 2021), while the Scoops3D model proposed by Reid et al. (2015) overcomes the above limitations. As a physical deterministic model, the Scoops3D model has been widely used in recent years because it takes into account the actual topography, geomorphology, hydrology, lithology, and other conditions during the simulation process. The simulation results obtained using the geotechnical parameters are highly accurate and are in line with the actual situation (Finn et al. 2018; Traglia et al. 2018; Weidner et al. 2019; Chen et al. 2020). Nevertheless, regardless of the method used, it is necessary to use Digital Elevation Model (DEM) as the basic data for analysis. The DEM not only records the spatial elevation information but also serves as the source of geomorphic parameters such as the slope (Sarma et al. 2020). The accuracy of the DEM has a direct effect on the accuracy of the results of the stability analysis of geological hazards (Vaze et al. 2010). Therefore, many scholars have carried out studies on the influence of DEMs with different resolutions on landslide stability. Some scholars believe that the higher the resolution, the better the landslide stability analysis results and model results. A high resolution can reflect the actual topography, and its simulation results can distinguish the unstable area from the stable area, which leads to a better estimate of the size of the landslide and more realistic and effective simulation results (Sy et al. 2013; Viet et al. 2017; Wang et al. 2017). Conversely, some researchers have found that a high-resolution DEM does not produce the best simulation results by comparing different resolutions. It often leads to over-prediction and increases the calculation time of the model (Schlögel et al. 2018; Sarma et al. 2020). In the current study, there is still no clear conclusion regarding the influence of DEM resolution on the prediction performance of slope stability analysis (Keijzers et al. 2011; Mahalingam and Olsen, 2016). However, in slope stability analysis, selecting the most suitable DEM resolution can not only obtain more accurate and realistic results, but also save time and cost, which is an extremely important basic measure in disaster prevention and mitigation.
Therefore, in this study, we took Jiajiagou as the study area and devoted ourselves to studying the influence of different DEM resolutions on the simulation results of Scoops3D. The validity of the results was comprehensively evaluated by the receiver operating curve (ROC) and $LR_{class}$ index. The influence of DEM resolution on landslide stability prediction is presented quantitatively, which can provide a certain reference for landslide disaster research.

2. Study area

The study area, Jiajiagou, is located in Qinghai Province, northwestern region of China ($35°51’18.78''$–$35°54’24.28''$ N, $102°08’58.87''$–$102°10’45.50''$ E) (Figure 1). In terms of topography, it is located in the transition zone between the Loess Plateau and the Tibetan Plateau (Jia et al. 2019), and geomorphology is dominated by mountains and hills. The geological structure is the Qilian fold system. It is a Mesozoic-Cenozoic intermittent mountain valley, with frequent earthquakes, typical landslides,
and diverse spatial forms (Guo et al. 2018; Yin et al., 2021). The exposed strata in this area are mainly Tertiary semi-consolidated red clay and Quaternary loess (Xiao 2018). The area of the study area is about 15 km², and the maximum relative height difference is about 900 m. The study area has a plateau continental semi-arid climate. Affected by the climate, the temperature in this area is low, the daily variation is large, the annual variation is small, and the rainfall is little and uneven in seasonal distribution, mainly concentrated in the summer. There is a valley between the mountains that converges.
into a seasonal river during the summer, which flows from north to south into the Yellow River. The vegetation in this area is well developed, and the landscape is dominated by alpine meadow and meadow grasslands (Zhang et al. 2018), with sparse population and little impact on landslide disasters. The residents mainly gather in the mountainous plateaus along the banks of the river, only a few kilometers away from the study area, which is convenient for our field investigation.

3. Materials and methodology

3.1. Scoops3D model theory

The Scoops3D model was developed by the United States Geological Survey (USGS) in 2015. The limit equilibrium method is used to calculate each three-dimensional block to obtain the safety factor of each block.

Scoops3D is a three-dimensional slope stability analysis tool based on a DEM. First, the model takes the rotation center of each ellipsoidal potential sliding surface as a node, searches and analyzes the safety factor corresponding to each cell, and obtains the position and volume of the unstable block (Figure 2) (Reid et al. 2015).

Scoops3D calculates the shear strength of each sliding surface using the linear Coulomb-Terzaghi instability criterion, which is defined as follows:

$$s = c + (\sigma_n - u) \tan \varphi$$  \hspace{1cm} (1)

In Equation (1), $s$ is the shear strength; $c$ is the cohesive force of the soil; $\varphi$ is the internal friction angle of the soil; $\sigma_n$ is the normal stress applied to the sliding body; and $u$ is the pore water pressure acting on the shear plane. The safety factor $F$ can be expressed as follows:

$$F = \frac{s}{\tau}$$  \hspace{1cm} (2)

where $s$ is the ratio of shear strength; and $\tau$ is the shear stress.

Theoretically, when $F < 1$, the slope is unstable and a landslide occurs. In the equilibrium state, the shear stress $\tau$ is equal to the shear strength $s$ multiplied by the proportionality constant $1/F$. In this study, the simplified Bishop method, which is an option in the Scoops3D model, was used to calculate the safety factor $F$ as follows:

$$F = \frac{\sum R_{i,j} [c_{i,j}A_{i,j} + (W_{i,j} - u_{i,j}A_{i,j}) \tan \phi_{i,j}]}{\sum W_{i,j}(R_{i,j} \sin \alpha_{i,j} + k_{i,j}e_{i,j})Fs(\cos \beta_{i,j}Fs + \sin \alpha_{i,j} \tan \phi_{i,j})}$$  \hspace{1cm} (3)

where $A_{i,j}$ is the area of the trial surface at the base of each of $i, j$ column; $\alpha_{i,j}$ is the apparent dip of the column base in the direction of rotation; $\beta_{i,j}$ is the inclination angle of the potential sliding surface of the three-dimensional cylinder; $W_{i,j}$ is the weight of the three-dimensional cylinder; $U_{i,j}$ is the pore water pressure acting on the sliding surface of the three-dimensional cylinder; $k_{i,j}$ is the horizontal vibration load acting on the center of the three-dimensional cylinder; and $c_{i,j}$ and $\phi_{i,j}$ are for the trial surface at the $i, j$ column (Reid et al. 2015).
Scoops3D divides the hydrological conditions into two states: water and no water. When there is water, it is divided into several conditions. Since the study area selected in this paper is located in the northeastern part of the Tibetan Plateau, it is characterized by semi-arid climate conditions. Due to the paleogeographic environment, the red rock has a high salt content and poor groundwater flow, so the water can be ignored. Therefore, the safety factor $F$ can be obtained as follows:

$$F = \frac{\sum R_{i,j}[\varepsilon_{i,j}A_{i,j} + W_{i,j}\tan\phi_{i,j}]}{\sum W_{i,j}[R_{i,j}\sin\alpha_{i,j} + k_{i,j}\varepsilon_{i,j}]Fs(\cos\beta_{i,j}Fs + \sin\alpha_{i,j}\tan\phi_{i,j})}$$

(4)

3.2. Parameterization

3.2.1. Digital elevation model (DEM)

To verify the influence of DEM with different resolutions on the prediction performance of the 3D model, a 2.5 m resolution DEM obtained by Japan Remote Sensing Technology Center was adopted in this study. Then, based on ArcGIS10.5 software, the 2.5 m resolution DEM was resampled into four DEMs with different resolutions (5 m, 10 m, 20 m, and 30 m). There are three resampling methods in the software: the nearest neighbor method, the bilinear interpolation method and the cubic convolution method. The resampling method mainly considers the impact of the actual terrain and slope of the study area on the model results. Wang et al. (2016) compared the influence of the different sampling methods on the quality of the DEM data obtained and found that the nearest neighbor method had the largest error. Chen et al. (2011) studied the influences of the different sampling methods on the DEM accuracy, and combined with the influencing factors of slope and bilinear interpolation, they concluded that the results of the cubic convolution and the bilinear interpolation were better. Liang et al. (2018) discussed the influence of the resampling method on the gullies, and combined with different verification methods, they concluded that the bilinear interpolation method produced the best result after the gully was developed and mature. According to the previous research results and combined with the actual situation of large relief and steep slopes in the study area, the bilinear interpolation method was used for the resampling in this study.

3.2.2. Geotechnical parameters

Rock and soil parameters (internal friction Angle, cohesion, soil bulk density) and landslide search parameters (maximum landslide area, minimum landslide area, search radius, search multiplier) are the key parameters for slope stability analysis by the Scoops3D model. For the geotechnical parameters required in the model, first, we evenly divided the study area into 20 grids, and we used the computer to conduct random sampling. Then, appropriate adjustments were made according to the topography during the actual sampling process. Field investigation shows that the thickness of the landslide soil layer is less than 2 m. During the sampling process, we removed the disturbed soil on the surface and sampled the soil at a depth of about 2 m (Figure 3). The samples obtained in the field were sealed in plastic and the parameters such
as the cohesion and internal friction angle were obtained through indoor direct shear tests. The results of the geotechnical parameters obtained from the experiment are shown in Figure 4. When determining the input parameters of the model, we obtained the average value of each parameter after removing the extreme values. Finally, the soil parameters selected for use in this study were as follows: an internal friction angle of 9.4°, a cohesion of 14.3 kPa, and a soil bulk density of 15 kN/m³. When conducting box search on the model, different settings will affect the final results of the model (Palazzolo et al. 2021), thus, we selected the most realistic landslide search area parameter according to field investigation results and landslide
inventory. It was found that the number of landslides with an area of $1 \times 10^3 \sim 4 \times 10^4$ m$^2$ accounted for the majority, up to 81.82% (Figure 5). Therefore, the search area of $1 \times 10^3 \sim 4 \times 10^4$ m$^2$ was selected to test the model comprehensively. For the vertical increment, we took its general value for the different resolutions: 1.25, 2.5, 5, 10, and 15. For the other parameters that do not affect the simulation results, we used the system’s default values. Since the landslides in the study area are shallow landslides and the soil layer properties are uniform, the soil properties do not change obviously with depth, so the single-layer properties were adopted for the simulations in this study, and other properties were not studied.

Figure 4. The distribution of the experimental data.

Figure 5. Distribution map of landslide area in the study area.
3.3. Landslide inventory

A landslide inventory can be used as a database to record the attributes of each landslide, such as the time, location, size, spatial form, and inducement (Godt et al. 2008; Yang et al. 2022; Liu et al. 2022). The landslide inventory is the first step of the preparation before the simulation calculations, and also the reference standard for judging the performance of the model. Thus, establishing a landslide inventory is the most important step in landslide stability research. First, we performed visual interpretation of the landslides in this area based on Google Earth Pro and combined with relevant literature and field investigation, through comparison and verification, a total of 66 landslides were identified in the study area. The landslide inventory and typical landslides in the study area are shown in Figure 3. According to the statistics, there are 24 landslides with areas of less than 10,000 m², accounting for 36% of the landslides in the whole study area, and a total of 29 landslides with areas of 10,000 m² to 30,000 m², accounting for 44% (Figure 5). The landslide boundaries were determined by Google images and processed in ArcGIS. To evaluate the predictive performance of the model based on different DEM data, the non-landslide group was selected as the control group. In order to ensure the scientific and rationality of the data, there are three principles for selecting non-landslide points: firstly, select the region (the actual stable region) after masking the actual landslide occurrence boundary in the whole research region; Secondly, non-landslide points are randomly generated based on ArcGIS software; Thirdly, the number of non-landslide points is determined by a ratio of 1:2 to landslide points (Arnone et al. 2016; Liu et al. 2021). Therefore, according to these principles, 132 non-landslide points were selected in the study area as controls.

3.4. The evaluation indexes of model accuracy

In order to quantitatively evaluate the validity of the simulation results, the True Positive Rate (TPR) and the False Positive Rate (FPR) of the Receiver Operating Characteristics (ROC) curve were used to evaluate the model’s performance and the simulation results (Sarma et al. 2020). In simple terms, the ROC curve compares the actual landslide and non-landslide points with the predicted spatial distribution of the landslide stability obtained using the model. The calculation principles of the TPR and FPR are shown in Table 1. However, it is not sufficient to evaluate the prediction performances of the different DEM resolutions using only the TPR and FPR values. If both the TPR and FPR values are high, over-prediction may occur. Therefore, the True Skill Statistic (TSS = TPR - FPR), a supplementary statistic index, was used to enhance the analysis of results. According to the TSS statistic, TSS = 1 is the ideal performance, that is, TPR = 1 and FPR = 0, corresponding to all observed landslide cells equal to all stability cells predicted by the model, that is to say, the model predictions are completely correct (Sarma et al. 2020; Palazzolo et al. 2021).

In addition, to better evaluate the performance of the landslide model investigated in this study, an index called \( LR_{\text{class}} \) was used in the analysis. The calculation of \( LR_{\text{class}} \) is based on the proportion of the landslide points in each Fs grade, the conditions of all of the landslide points (66 landslides), and the predicted landslide area of
LR_{\text{class}} = \frac{S}{A} \tag{5}

A is the percentage of the landslide locations contained in each $F_s$ class; and $S$ is the percentage of the predicted areas in each $F_s$ class.

The advantage of $\%LR_{\text{class}}$ is that both the stable and unstable regions predicted by the model are taken into account, which effectively decreases the amount of over-prediction (Tran et al. 2018). In addition, the $\%LR_{\text{class}}$ index at different stability classes $i$ is the proportion of the total value of the $LR_{\text{class}}$ of all of the classes $i$ (Equation (6)).

$$\%LR_{\text{class}}^i = \frac{LR_{\text{class}}^i}{\sum_{i=1}^{n} LR_{\text{class}}^i} \tag{6}$$

In the classification of $F_s$, in order to facilitate an intuitive comparison, we divide it into two categories: $F_s < 1$ indicates an unstable slope; and $F_s \geq 1$ indicates a stable slope (Tran et al. 2018). This classification method is becoming increasingly popular (Tran et al. 2018; He et al. 2021; Palazzolo et al. 2021).

### 4. Results and discussion

#### 4.1. Landslide stability analysis using different resolution DEMs

In this study, DEMs with five different resolutions were selected to simulate the landslide stability using the Scoops3D model, and the different simulation results are shown in Figure 6. Simultaneously, we covered the landslide points in the simulation results, and the specific identification accuracy will be explained in detail in the following paragraphs. According to the calculation results of the 3D model, the slope stability was classified into five levels: stable ($F_s \geq 1.5$); potentially stable ($1.25 \leq F_s < 1.5$); potentially unstable ($1 \leq F_s < 1.25$); unstable ($0.75 \leq F_s < 1$); and extremely unstable ($F_s < 0.75$) (Vandromme et al. 2020; He et al. 2021). As can be seen from Figure 6, the $F_s$ value calculated using the model is generally low on both sides of the valley and in the area through which the Yellow River flows. In the
northwestern part of the study area, the $Fs$ value is higher and the slope is stable, which is consistent with the field investigations.

As can be seen from Figure 6, in the section where $Fs < 0.75$, the extremely unstable region suddenly decreased by 25.03% when the resolution decreased from 2.5 m to 5 m. Based on the overall trend, the proportion of the predicted extremely unstable regions became smaller as the resolution became coarser. Among the five resolutions, the prediction results based on the 30 m resolution DEM had the lowest proportion of unstable regions (only 6.71%). In terms of the proportion of unstable regions predicted by the model for the DEMs with different resolutions, the proportion of unstable regions for the 2.5 m resolution DEM was the lowest, while the

Figure 6. The spatial distribution of the landslide stability and the proportion of each $Fs$ level for the five different resolutions. The histograms to the right of the model results diagrams show the proportions of the study area in the different $Fs$ classes.

- **Landslide**
- **Non-landslide**

Factor of safety
- $Fs<0.75$
- $0.75\leq F_s<1$
- $1\leq F_s<1.25$
- $1.25\leq F_s<1.5$
- $F_s\geq1.5$
proportion of unstable regions for the other four resolutions was the highest among all of the Fs classes. The simulation results for the five resolutions were close in the potentially unstable region and the potentially stable region. When $Fs \geq 1.5$, as the resolution decreased, the proportion of the identified stable regions gradually increased. The simulation results were stable in terms of the area, and the ratio for the 30 m resolution was 16.62% higher than that for the 2.5 m resolution. This demonstrates that at different resolutions, the higher the resolution, the more unstable regions will be identified; while the lower the resolution, the more stable regions will be identified.

### 4.2. Accuracy assessment of simulation results at different resolutions

The ROC curves were used to verify the validity for the results of Scoops3D simulation. The results explain that the results of the Scoops3D simulation are satisfactory. That is, true positive rate is greater than false positive rate (TPR $>$ FPR). However, the results of different DEMs are almost the same, and the area under the ROC curve (AUC) varies slightly, with the maximum difference being only 0.016 (Figure 7).

In the meantime, to quantitatively analyze the influence of the DEM resolution on the simulation results of the Scoops3D model, the TPR and FPR values of the simulation results under five different resolutions were calculated. From the perspective of the TPR value alone, the simulation results of five resolutions are good, all above 80%. Among them, DEM simulation results with 2.5 m resolution are the best (96.97%), followed by DEM simulation results with 5 m and 10 m resolution (93.94% and 95.45%, respectively). In terms of the prediction of non-landslide points, the FPR value increases with increasing resolution. The FPR value of the 2.5 m resolution

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**Figure 7.** ROC analysis for the Scoops3D simulation results under five different resolutions.
(55%) is the highest (62.88%), which indicates that when landslide stability analysis is performed with 2.5 m DEM resolution, more than half of the results simulated by the Scoops3D model will mistake stable slope for landslide. However, regardless of which resolution is used for the landslide stability analysis, the TPR value is always greater than the FPR value, which indicates that the prediction accuracy of the Scoops3D model is higher than the error rate. Especially when the TPR value is higher and the FPR value is lower, the prediction ability of this model is better (Sarma et al. 2020).

More accurate conclusions cannot be drawn by the TPR and FPR values alone, so the TSS is used as a supplementary statistic index to further evaluate the prediction performance of the model. From the TSS statistic value (Table 2), it can be seen that the TSS values of 5 m and 10 m resolutions are higher, which are 47.73% and 45.45% respectively, achieving random prediction of correct and incorrect landslides identification. However, the TSS value of 2.5 m resolution is the lowest, and its actual prediction ability is greatly reduced. This suggests that it is not that the higher the DEM resolution, the better the simulation result will be.

Understandably, the ROC report alone does not prove to be a sufficient indicator (Sarma et al. 2020). Thus, to better evaluate the accuracy of the model simulation results for different resolutions, we also calculated the $\%LR_{class}$ of the simulation results for the five resolutions, and the specific results are shown in Table 3. As can be seen from Table 3, under the 2.5 m resolution, the Scoops3D model has the highest prediction rate of landslide (96.97%), but it also has the highest prediction of unstable areas (62.64%). However, the prediction of the lowest resolution (30 m) shows an opposite result to that of 2.5 m resolution. For the prediction of landslide points, the overall accuracy of prediction decreases with the decrease of resolution. From the accuracy evaluation based on $\%LR_{class}$, the Scoops3D model has produced relatively ideal results in landslide stability simulation with five DEMs with different resolutions, and the accuracy is above 85%. Among them, the simulation results at 10 m resolution have the highest accuracy, and the $\%LR_{class}$ reaches 95.48%, which is 0.39% higher than the simulation results at 2.5 m resolution. This indicates that it is not that the higher the resolution, the better the simulation result, which is consistent with the research of Viet et al. (2017). The simulation results are very similar (~95%) for DEM with 2.5 m, 5 m and 10 m resolution, while the accuracy of 30 m DEM is the lowest (86.08%), 9.4% lower than the highest accuracy. Hence, from the perspective of $LR_{class}$ evaluation method, the result of 10 m resolution is relatively optimal, followed by the result of 5 m resolution.

Based on the ROC plot and $LR_{class}$, it can be seen that the selection of DEM with different resolutions has an impact on the prediction effect of the Scoops3D model. Therefore, DEM with appropriate resolution should be selected as the basic input.
Table 3. Compound exponential $\%LR_{class}$ comparison of the predicted results at different resolutions.

|          | % of observed landslide sites (a) | % of predicted area (b) | $LR_{class}=(c)/(d)$ | $\%LR_{class}=(e)/(d)$ |
|----------|----------------------------------|-------------------------|-------------------|------------------------|
|          | 2.5 m  | 5 m  | 10 m | 20 m | 30 m | 2.5 m  | 5 m  | 10 m | 20 m | 30 m | 2.5 m  | 5 m  | 10 m | 20 m | 30 m | 2.5 m  | 5 m  | 10 m | 20 m | 30 m |
| $Fs < 1$ | 96.97   | 93.94 | 95.45 | 89.39 | 80.30 | 62.64  | 49.59 | 50.15 | 47.78 | 39.36 | 1.55   | 1.89  | 1.90  | 1.87  | 2.04 | 95.09   | 94.03 | 95.48 | 90.34 | 86.08 |
| $Fs \geq 1$ | 3.03 | 6.06 | 4.55 | 10.61 | 19.70 | 37.36  | 50.41 | 49.85 | 52.22 | 60.04 | 0.08  | 0.12  | 0.09  | 0.20  | 0.33 | 4.91    | 5.97  | 4.52  | 9.66  | 13.92 |
| Sum      | 100     | 100     | 100     | 100     | 100     | 100     | 100     | 100     | 100     | 100     | 1.63   | 2.01   | 1.99   | 2.07   | 2.37 | 100     | 100     | 100     | 100     | 100   |
parameter when using the Scoops3D model for landslide stability analysis. From the research results of this study, the results with 5 m and 10 m resolutions are relatively optimal, which is consistent with the conclusion reached by Arnone et al. (2016) and Schlögel et al. (2018) by comparing the influences of different resolutions on models. This provides a reference for other researchers to select the best DEM resolution for landslide stability analysis and prediction using the Scoops3D model.

4.3. Difference analysis of the model simulation results

Some geomorphic parameters such as the slope, slope aspect, curvature, and roughness, are often taken as important factors in the evaluation of landslide induction. The actual situation of Jiajiagou is considered, and the slope is regarded as the key factor affecting the slope stability (Wang et al. 2014). Therefore, we only discuss the influence of the slope factors in this paper. We used ArcGIS10.5 to extract the slopes from the different resolution DEMs for the analysis, and the slopes were divided into four grades ($<15^\circ$, $15^\circ$–$30^\circ$, $30^\circ$–$45^\circ$, $>45^\circ$). Based on the field investigations, we statistically analyzed the average slope ratio of the landslides in the study area (Figure 8). As can be seen from Figure 8a, no landslide occurs in areas with slopes of less than $15^\circ$, while 84.21% of the landslides occur in areas with slopes of $30^\circ$–$45^\circ$. Therefore, we mainly focused on the area with a slope of $30^\circ$–$45^\circ$ when analyzing the influence of the resolution of the DEM on the simulation results. Then, we counted the proportion of unstable areas ($F_s < 1$) in the simulation results obtained using different resolution DEMs for this slope grade (Figure 8b). As can be seen from Figure 8b, for the resolution of 2.5 m, the unstable areas are the largest within the $30^\circ$–$45^\circ$ region, and 93.59% of the area is identified as unstable slopes, which are also the reason why it has the highest FPR value. Regarding the larger proportion of steep slopes when a high-resolution DEM is used, based on field investigations, it was found that this may be caused by the presence of many erosion gullies in the study area (Figure 9).
When a high resolution DEM is used, the field topography can be characterized in detail. The changes in the slope caused by erosion gullies cause the slope to become steeper, which is close to the slope of the sliding surface of a landslide, and thus, leads to incorrect identification during the model identification. A high resolution may wrongly identify these erosion gullies as unstable bodies, and the safety factor obtained from the calculations of the three-dimensional model will be lower. Resampling to coarser resolutions filters out high slope gradients and smooths the landscape (Sy et al. 2013). By comparing the slopes generated using different resolutions, we found that the high resolution could reflect the actual topography, but it led
to mistaken identification of some erosion gullies as landslides, which eventually resulted in over-prediction of the model. However, when the micro-topography was smoothed at a coarse resolution, the false positive rate of the model results was low.

Based on this study, we conclude that there are still many shortcomings in our work, mainly reflected in the model itself and the incomplete data. As we know, there are many types of landslides induced by different factors, which cannot be reflected in the model, resulting in inaccurate simulation results, such as rainfall-induced landslides. In addition, the complex topographic and hydrological parameters in the field cannot be treated simply by stratification. The accuracy of the input data greatly affects the predictability of the model.

5. Conclusions

This study evaluates the effect of DEMS with different resolutions on the performance of the Scoops3D model in landslide stability and prediction. The results show that the Scoops3D has a good prediction ability. The study also demonstrates that an increase in resolution does not always mean an improvement in simulation results, with the best predictive capabilities attributable to the medium resolutions (i.e., 5 m and 10 m). Thus, this paper successfully highlights that researchers can obtain satisfactory landslide stability and prediction based on the Scoops3D model using the medium resolutions (i.e., 5 m and 10 m). However, since the size and characteristics of landslides may influence the value of the optimal resolution, in the following study, landslide characteristics (e.g., area, perimeter, shape) should be combined to analyze the influence of DEMs with different resolutions on the prediction ability of Scoops3D model.

Disclosure statement

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