P. Thambidurai
T. N. Singh *Editors*

Landslides: Detection, Prediction and Monitoring

Technological Developments

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ISBN 978-3-031-23858-1 ISBN 978-3-031-23859-8 (eBook)
https://doi.org/10.1007/978-3-031-23859-8

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Dedicated to
Dr. Kalavathi Thambidurai
IIT Bombay

Contents

Chapter 13
Application of Scoops3D and GIS for Assessing Landslide Hazard in Trung Chai Commune, Sapa, Vietnam

Binh Van Duong, I. K. Fomenko, Kien Trung Nguyen, Dang Hong Vu, O. N. Sirotkina, and Ha Ngoc Thi Pham

Abstract Landslides are one of the natural disasters that have frequently occurred in the northern region of Vietnam. Located in Laocai province, the Sapa district is known as a landslide hotspot in the mountainous region of Vietnam. The rapid economic development and construction in this area have significantly increased the likelihood of landslides. Therefore, landslide hazard assessment is critical for developing a strategy for reducing landslide risk and long-term territorial planning. This study presents the results of a landslide hazard assessment due to rainfall using a physically-based Scoops3D model in the Trung Chai commune, Sapa district. The initial data for the analysis model in Scoops3D consists of topographic data (DEM, distribution of soil thickness), soil properties, hydrogeological conditions, and earthquake loading. As a result, the factor-of-safety maps (FS maps) have been established, and the study area was divided into four hazard zones: unstable, quasi-stable, moderately stable, and stable. The study results indicate that the unstable zone covers 18.12% of the study area under the influence of rainfall in 16 h, and 61.11% of total landslides were accurately predicted, including the largest landslide in the study area (the Mong Sen landslide). The percentage of landslide ratio for each predicted factor-of-safety class (%LRclass index) of 64.19% demonstrated the acceptable performance of the Scoops3D model in this study. The study results identified the advantages and limits of this model for evaluating landslide hazards

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P. Thambidurai and T. N. Singh (eds.), *Landslides: Detection, Prediction and Monitoring*,
https://doi.org/10.1007/978-3-031-23859-8_13

on a large scale, allowing for the development of solutions to enhance the prediction quality of future studies.

Keywords Landslide · Landslide hazard · Scoops3D · GIS · Limit equilibrium method · Trung Chai · Sapa · Vietnam

13.1 Introduction

Landslide is a natural disaster that occurs because of geodynamic processes, causing the instability of a slope, the displacement of rocks on the slopes, and the destruction of everything in its area of influence (Cruden and Varnes 1996). Landslides may be triggered by different causes, including rainfall, earthquakes, and human activities. Among these causes, rainfall is the most common trigger of landslides (79% of fatal non-seismic landslides from 2004 to 2016) (Froude and Petley 2018). Rainfall-induced landslides have occurred frequently in Vietnam, particularly in the mountainous northern provinces of Hagiang (Hung et al. 2016), Backan (Le and Kawagoe 2018), Hoabinh (Tien Bui et al. 2013), and Laocai (Tien Bui et al. 2017). A study by Nguyen and Dao (2007) indicated eight primary causes of landslides in Northwest Vietnam: the slope of relief; the weathering process of rocks; modern present tectonic movement; hydro-system (surface streams and groundwater); vegetation density; striking and dipping of original rock; physical property and structure of original rock; and human activity. Landslide hazard assessment (LHA) plays a critical role in landslide study and risk management. Over the past three decades, the efficacy of landslide hazard assessments has improved because of the development of GIS-based approaches, such as direct (the landslide inventory method) and indirect (multi-criteria decision-making analysis, probabilistic, deterministic, statistical, and artificial intelligence methods). Deterministic methods based on physical and mechanical processes have been successfully employed in various landslide hazard and susceptibility assessments. These studies have been frequently conducted on a local scale using the B-GeoSVC model (Yang et al. 2019), SLIP and TRIGRS model (Saadatkhah et al. 2015; Marin et al. 2021), Scoops3D model (Zhang and Wang 2019; Rashid et al. 2020), r.slope.stability model (Palacio Cordoba et al. 2020) and on a site-specific scale using PCRaster model (Van Beek and Van Asch 2004), TRIGRS and TiVaSS models (Tran et al. 2017a, b), TRIGRS model (Tran et al. 2017a, b; Fusco et al. 2021). However, deterministic methods have only been employed in a limited number of studies conducted on a regional scale (e.g. Wang et al. 2020). These methods do not require long-term landslide inventory data and are thus more helpful in areas with no landslide inventory data (Luo and Liu, 2018). However, physically-based methods need detailed geotechnical parameters and considerable time and effort for simulations, experiments, and field studies (Yang et al. 2019). Therefore, these methods are only applicable over vast regions with very homogenous geological and geomorphological conditions and simple landslide types.

Because of the difficulties associated with gathering data to build an assessment model, the deterministic method has only been applied to several landslide studies in Vietnam (Loi et al. 2017; Le and Kawagoe 2018; Tran et al. 2021, 2022). In this study, to enhance the efficacy of landslide risk management, a Scoops3D model was developed to assess the landslide hazard caused by rainfall in the Trung Chai commune, Sapa district, Vietnam. Two simulation scenarios were performed to establish Factor of Safety (FS) maps, and the study area was categorised into four hazard zones. Finally, the model's performance was determined by comparing the FS map to the locations of 18 observed landslides.

13.2 Materials and Method

13.2.1 Study Area

In comparison to other northern Vietnamese areas, Sapa, a mountainous district in the northwest of Lao Cai Province, has experienced more landslides and soil erosion (Dang et al. 2018; Tran et al. 2021). Land-use changes associated with the expansion of agricultural and community tourism have accelerated the frequency of natural catastrophes, affecting the sustainability of the Sapa district (Dang et al. 2018). Landslides in Lao Cai, especially in the Sapa district, have garnered significant attention over the past decade because of the high number of fatalities, property loss, and ecological destruction they have caused (Tien Bui et al. 2017). Mountain commune Trung Chai (Fig. 13.1) is located in the northeastern part of the Sapa district, with an area of about 38.4 km^2 and an elevation ranging from 581 to 2176 m. Annual rainfall ranges from 2000 to 3600 mm.

Rainfall is concentrated from June to August, accounting for around 80–85% of total annual rainfall in the study area (Tien Bui et al. 2017). Trung Chai is one of the communes in Sapa that is at the highest risk of landslides. The most well-known landslide in the study area is the Mong Sen event (Fig. 13.2a), which occurred in 1998, 2000, 2002, and 2009. This landslide is located on the 4D national road connecting Laocai city with the Sapa district. The geological composition of the study area is formed of granodiorite, granite, and granite-migmatite rocks of the Posen complex, all of which have reasonably high strength. The weathering process of bedrock led to the formation of a thick cover layer with high permeability, increasing the landslide hazard in the study area. Previous studies have shown that rainfall is the primary cause of landslides in the study area (Tien Bui et al. 2017; Tran et al. 2021). A landslide that occurred in 2020 at Km12 + 600 − Km12 to 900 on provincial road 152 (Fig. 13.2b) was determined to be the result of heavy rainfall and slope excavation.

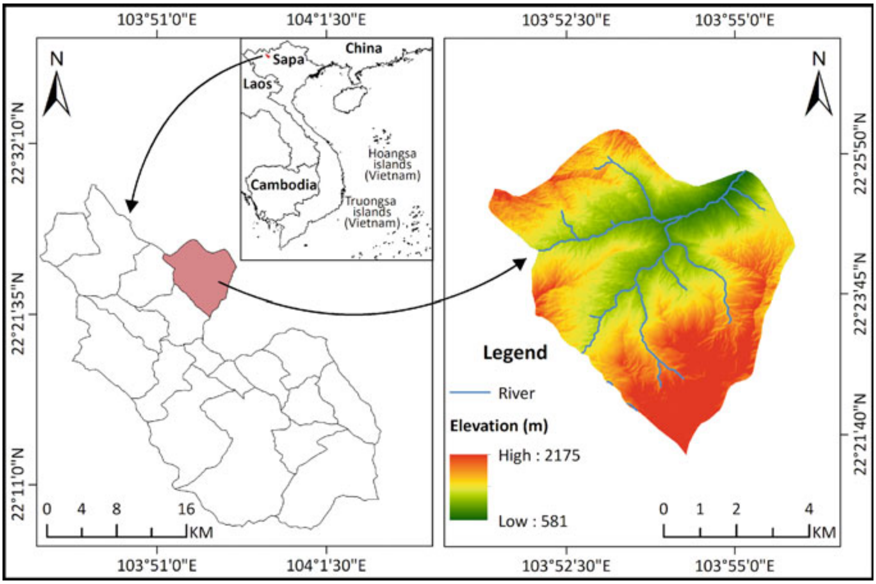

Fig. 13.1 Location of the study area

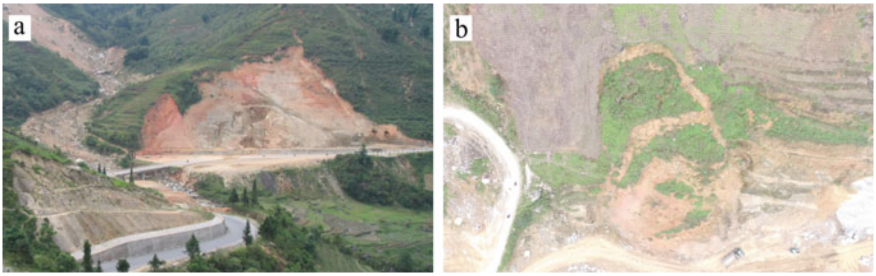

Fig. 13.2 **a** Mong Sen landslide and **b** a landslide on DT152 road

13.2.2 Landslide Hazard Assessment using Scoops3D Model

Scoops3D (Reid et al. 2015) is a computer program developed by the United States Geological Survey (USGS) for assessing landslide stability over a digital terrain expressed by a digital elevation model (DEM). Scoops3D has been effectively used in various landslide stability studies worldwide, including in Vietnam (Zhang and Wang 2019; Rashid et al. 2020; Tran et al. 2021). Using the 3D "method of columns" limit-equilibrium analysis, Scoops3D computes the slope stability with a spherical potential sliding surface (Fig. 13.3).

Scoops3D investigates and evaluates slope stability by determining the FS of millions of potential three-dimensional slope failures at various depths on the DEM

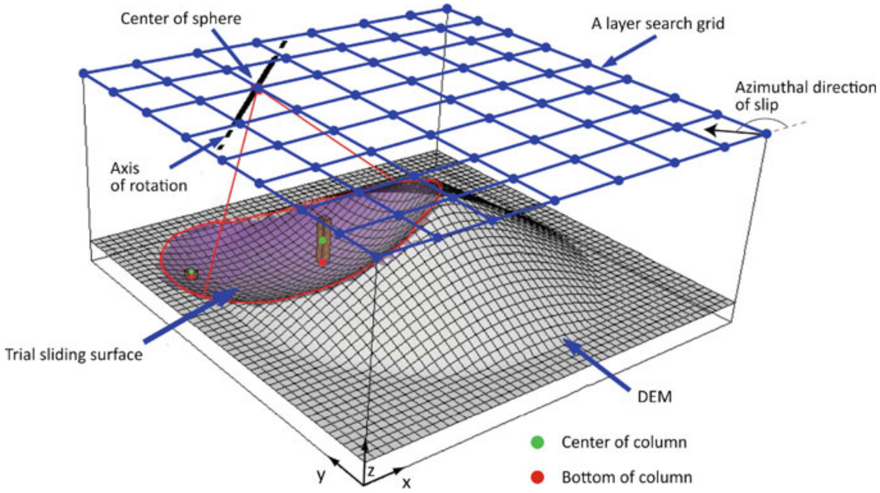

Fig. 13.3 Schematic drawing of Scoops3D model including a DEM with potential trial sliding surface and search grid. Each point on the search grid corresponds to denotes the center of multiple spherical trial surfaces (modified from Reid et al. 2015)

grid (Reid et al. 2000). In Scoops3D, numerous trial surfaces are required in three-dimensional analysis to assess slope stability because of the spatial variations in input data such as local topography, material parameters, and hydrogeological conditions. Compared to other physically based methods, the technique for searching for failure surfaces used by Scoops3D is a significant improvement. For modeling, users may select a suitable range for the 3D grid of sphere centers, which can be any point above the DEM, depending on the time and capability of their computer (Tran et al. 2021).

Generally, in analyzing slope stability by using the limit equilibrium method (LEM), the FS is defined as a ratio of the average shear strength (s), to the shear stress (τ) that controls the limit equilibrium state along a specified trial sliding surface (Tran et al. 2021):

$$FS = \frac{s}{\tau} \tag{13.1}$$

In this equation, the FS is less than one when the shear stress (τ) exceeds the shear strength (s) of material on the examined slope. The shear strength of soil on the trial surface is determined by using the following equation:

$$s = c' + (\sigma_n - u)\tan\varphi' \tag{13.2}$$

where c denotes effective cohesion, φ denotes effective internal friction angle, σ_n denotes normal stress, and u denotes pore-water pressure.

When evaluating the stability of spherical potential sliding surfaces in Scoops3D, Bishop's simplified method (Bishop, 1955) is frequently utilized since it provides more accurate results on the FS. The factor of safety is determined as follows using three-dimensional extensions of Bishop's simplified method:

$$FS_{3D} = \frac{\sum R_{i,j}\left[c_{i,j}A_{h_{i,j}} + \left(W_{i,j} - u_{i,j}A_{h_{i,j}}\right)tan\varphi_{i,j}\right]/m_{\alpha_{i,j}}}{\sum W_{i,j}\left(R_{i,j}sin\alpha_{i,j} + k_{eq}e_{i,j}\right)} \quad (13.3)$$

where:

$R_{i,j}$ denotes the distance from the axis of rotation to the center of the base of a column;

$A_{h_{i,j}}$ denotes the area of the trial surface at the base of each *i, j* column;

$W_{i,j}$ denotes the weight of the column *(i, j)* above the slip surface;

$\alpha_{i,j}$ denotes the apparent dip of the column base in the direction of rotation;

$e_{i,j}$ denotes the horizontal driving force moment arm for a column (equal to the vertical distance from the center of the column to the elevation of the axis of rotation) and

$$m_{\alpha_{i,j}} = cos\varepsilon_{i,j} + (sin\alpha_{i,j}tan\varphi_{i,j})/FS_{3D} \quad (13.4)$$

with $\varepsilon_{i,j}$ denotes the true dip of the trial surface at the column base; and

k_{eq} denotes the horizontal pseudo-acceleration coefficient (Fig. 13.4).

The scheme for assessing landslides using Scoops3D is shown in Fig. 13.5. Generally, Scoops3D, like other physically-based models, needs a variety of input variables related to the spatial distribution and strength parameters of soil layers, soil thickness, pore-water pressure (PWP), earthquake loading, and topographic conditions.

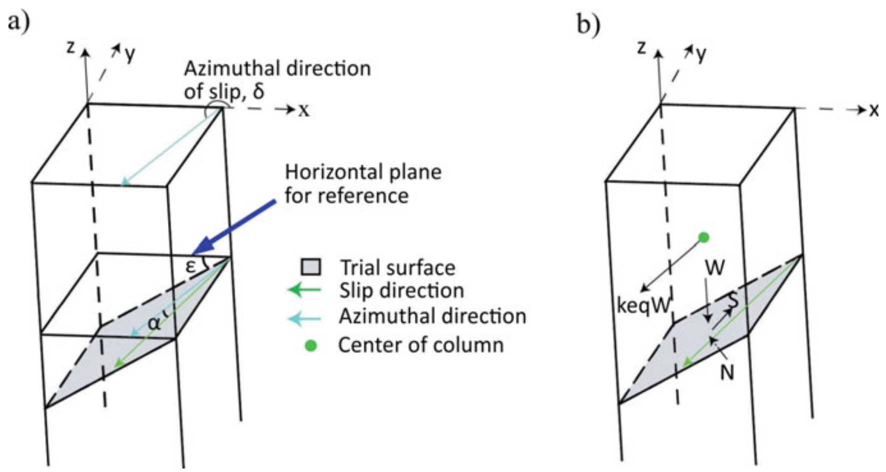

Fig. 13.4 Schematic diagrams illustrating **a** slip direction and **b** forces acting on a 3D column (Reid et al. 2015)

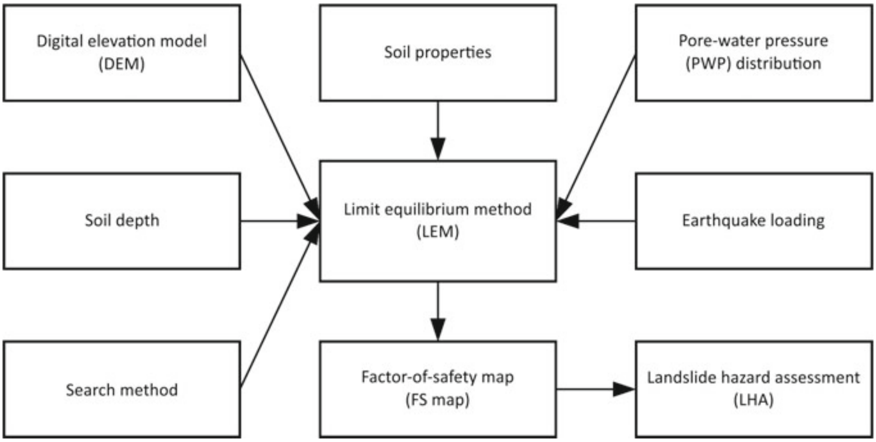

Fig. 13.5 Scheme for assessing landslide hazards using Scoops3D

The quality of the initial data has a significant influence on the prediction performance of the Scoops3D model (Reid et al. 2015).

13.2.3 Data Preparation

The survey results were employed to generate a DEM and determine the distribution of soil depth, PWP, soil properties, and earthquake loading for assessing landslide hazards in the study area. Terrain parameters may be the most critical input data when developing an analysis model for assessing landslide hazards (Tran et al. 2017a, b). Reid et al. (2015) indicated that Scoops3D examines the stability of all parts of a DEM using a systematic slope stability analysis for trial sliding surfaces formed at each node in the search grid. For accounting for all potential sliding surfaces, the vertical extent of the search grid is analyzed in the range of the lowest elevation and the elevation at which the stability map has no change (Tran et al. 2021). A DEM may be produced using various techniques, including Terrestrial Surveying, Aerial Photogrammetry, Light Detection and Ranging (LiDAR), and Interferometric Synthetic Aperture Radar (InSAR). Selecting the appropriate DEM resolution should be based on the purpose of the modeling, the features of the study area, and the availability of relevant data (Tran et al. 2016; Chang et al. 2019). In this study, the 5 m DEM was used for analysing landslide hazards (Fig. 13.6). When conducting a slope-instability study, it is critical to consider the soil thickness on a slope, which relates to the failure depth. Furthermore, soil thickness plays a significant role in the hydrological impact, as shown by the ratio of the saturated depth to the soil thickness (Ho et al. 2012). The prediction of soil thickness is challenging due to its dependency on complex interactions of numerous elements (topography, parent material, climate, biological, chemical, and physical processes) (Tesfa et al. 2009).

Soil thickness may be determined by examining its connection to other variables such as slope (Patton et al. 2018), relative relief (Pradhan and Kim, 2021), slope gradient (Brosens et al. 2020), elevation (Saadatkhah et al. 2015), or a combination of variables (Li et al. 2020). Many authors have developed various models for predicting the spatial distribution of soil thickness (Salciarini et al. 2006; Tesfa et al. 2009; Catani et al. 2010; Park et al. 2013; Tran et al. 2017a, b). However, determining the physico-mechanical properties and soil thickness over a large area is challenging in all simulation cases. The soil layer thickness in this study was determined using the correlation between measured soil thickness in the study area and topographic slope (Salciarini et al. 2006; Tran et al., 2017a, b, 2018). the distribution of soil thickness in the study area is presented Fig. 13.7, which shows values ranging from 2.0 to 20 m.

Pore-water pressure is the most frequently employed hydrological variable in physically-based models for identifying triggering conditions and predicting shallow landslides (Bordoni et al. 2018). Determining the distribution of PWP is critical for assessing slope stability under the influence of rainfall. There are several options for simulating PWP in Scoops3D: the impact of groundwater pressure is not considered; a pore-water pressure ratio (r_u) is used; simulation using a piezometric surface; simulation using a 3D distribution of saturated pore-pressure heads; simulation using

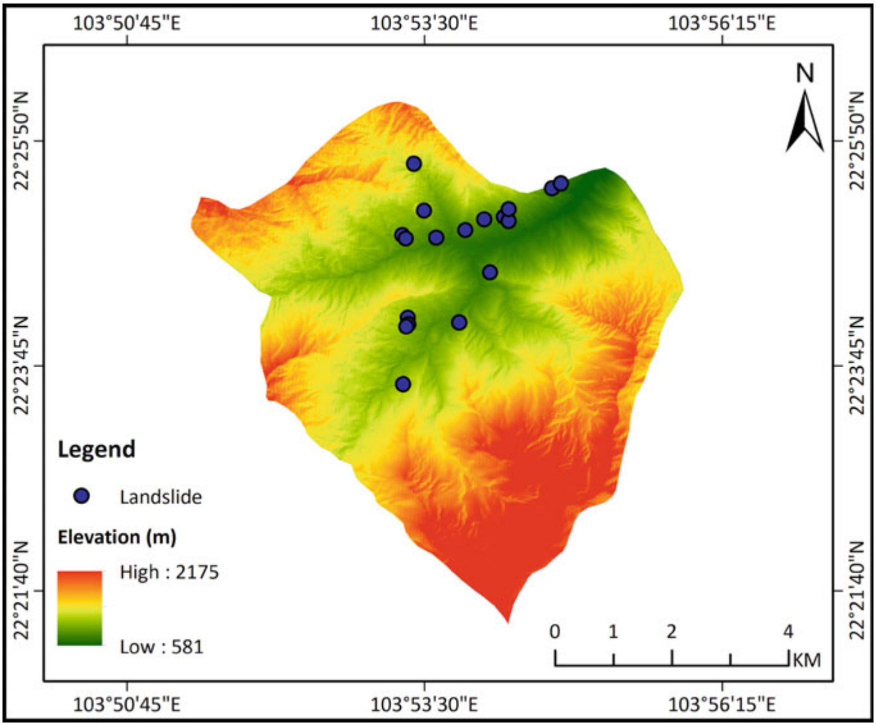

Fig. 13.6 Elevation map of the study area

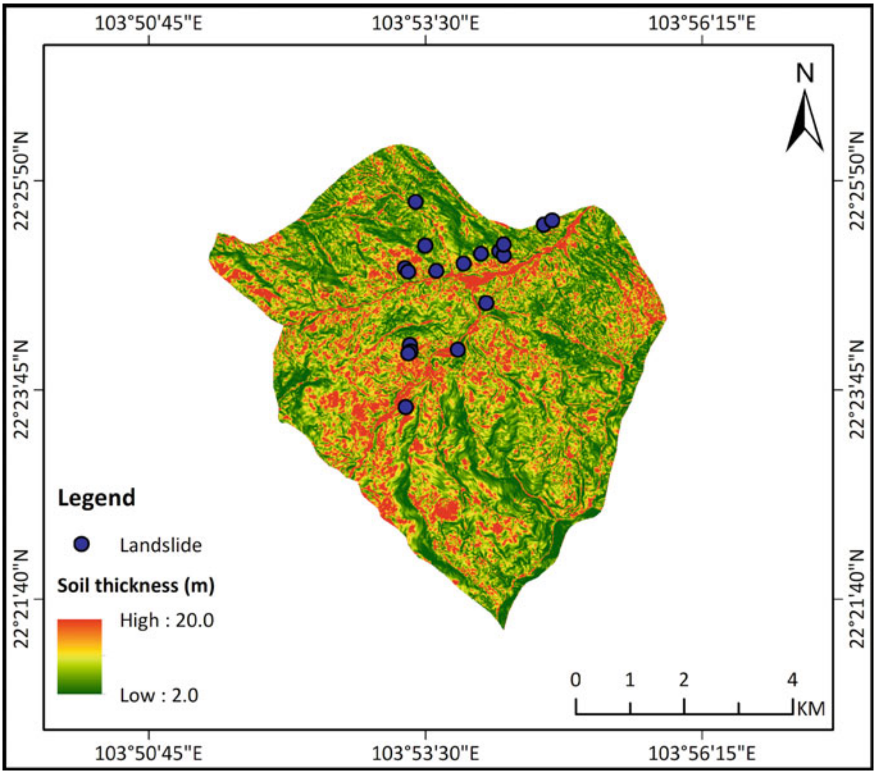

Fig. 13.7 Soil thickness distribution map of the study area

a 3D distribution of variably saturated pore-water heads pressure. Because of the absence of PWP data, the pore-water pressure ratio (r_u) was employed to simulate PWP in this study. The SLIDE model was used to determine the relationship between pore-water pressure ratio and rainwater infiltration in the study area (Liao et al. 2010). The heavy rainfall recorded on May 31, 2020 (Fig. 13.8) represents an "extreme case" for the study area and may be considered as the factor triggering widespread shallow landslides. As a result, the rainfall data, with a cumulative rainfall of 139.1 mm in 16 h and a maximum of 155.9 mm, was used to model landslides' stability.

In Scoops3D, to analyze slope stability, it is necessary to define the properties of all slope materials underlying the DEM. Three methods can be used to determine the distribution of these properties: input uniform, homogeneous properties; input layered material properties; and input 3D spatially varying properties. Because of the data availability, the layered material properties were used to analyze slope stability. Regarding the input data for the Scoops3D model, field studies and laboratory testing have been conducted to determine the shear strength, unit weight, and hydraulic conductivity parameters. The physico-mechanical properties of the soil

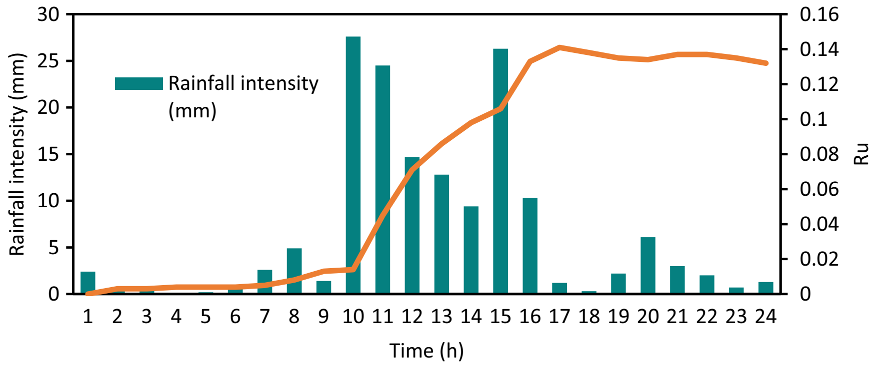

Fig. 13.8 Relationship between rainfall intensity and pore-water pressure ratio

Table 13.1 Soil parameters for landslide hazard assessment

Parameter	Symbol	Unit	Natural state	Saturated state
Unit weight	γ	kN/m^3	18.2	19.3
Friction angle	φ	(°)	16.3	12.2
Cohesion	c	kN/m^2	20.2	15.2

layer, including unit weight (γ), internal friction angle (φ), and cohesion (c), are shown in Table 13.1.

In the mountainous region, an earthquake triggers a landslide due to the mechanism of seismic wave–ground motion. In Scoops3D, the seismic loading is modeled as a uniform horizontal force ($k_{eq}W$), in which k_{eq} is the pseudo-horizontal acceleration coefficient. Previous studies have shown that landslides occurred in Lao Cai province and Sapa district due to rainfall (Tien Bui et al. 2017; Tran et al. 2021; Le et al. 2021). Terzaghi (1950) suggested that a horizontal seismic coefficient of 0.5 is an appropriate value for assessing seismic stability in catastrophic earthquakes. Marcuson and Franklin (1983) proposed that a horizontal seismic coefficient between 1/2 and 1/3 of Peak Horizontal Ground Acceleration (PHGA) might be used. Other reference summarizes values of extensively employed horizontal seismic coefficients in Table 13.2. In addition, no earthquakes have been recorded in the study area when landslides occur. Thus, in this study, we selected $k_{eq} = 0$ when analyzing landslide hazards.

13.2.4 Model Validation

A successful landslide hazard assessment (LHA) model should provide maximum consistency between actual and predicted landslides and reduce the predicted unstable zone to give valuable information for prediction (Park et al. 2013). It is

Table 13.2 Some reference values of k_{eq}

Horizontal pseudo-acceleration coefficient, k_{eq}	Remark	
0.5	Catastrophic earthquakes	Terzaghi (1950)
0.2	Violent, destructive earthquakes	
0.1	Severe earthquakes	
1/2 of PHGA – 1/3 of PHGA	Marcuson and Franklin (1983)	
0.1–0.25	In the United States	Kavazanjian et al. (1997)
0.15–0.25	In Japan	
0.1–0.2	$F_S \geq 1{,}15$ (Seed 1979)	
0.025	Minor Earthquake, $F_S > 1{,}0$	United States Army Corps of Engineers (1970)
0.05	Moderate Earthquake, $F_S > 1{,}0$	
0.1	Major Earthquake, $F_S > 1{,}0$	
0.15	Great Earthquake, $F_S > 1{,}0$	
1/2 of PHGA	$F_S > 1{,}0$ (Hynes-Griffin and Franklin 1984)	

required to compare landslide hazard maps and a landslide inventory map with the appropriate index to evaluate the model performance (Huang and Kao 2006). Various indicators have been proposed for determining the efficacy of landslide hazard assessments. In this study, the $\%LR_{class}$ index proposed by Park et al. (2013) was used to evaluate the performance of the Scoops3D model. Tran et al. (2018) modified the LR_{class} equation developed by Park et al. (2013), resulting in Eq. (13.5). LR_{class} (landslide ratio for each predicted factor-of-safety class) is an intermediate index defined as the ratio of the percentage of landslide locations in each FS class to the area percentage of each FS class. The $\%LR_{class}$ index for FS class *i* ($\%LR^{i}_{class}$) is the ratio of the LR_{class} value of FS class *i* to the total value of LR_{class} for all FS classes (Eq. 13.6) (Tran et al. 2018; Marin et al. 2021).

$$LR_{class} = \frac{\%landslidesineachFSclass}{\%areaofeachFSclass} \tag{13.5}$$

$$\%LR^{i}_{class} = \frac{LR^{i}_{class}}{\sum_{i=1}^{n} LR^{i}_{class}} \tag{13.6}$$

13.3 Results

Based on the input data, Scoops3D computes the factor of safety for all DEM cells. It is accepted that predicted zones with FS less than 1.0 are classified as unstable, whereas predicted zones with FS greater than 1.0 are classified as stable. In this study, the Scoops3D model was used to analyze two different scenarios: the stability of slopes in natural state and the stability of slopes under the influence of 16-h rainfall in the study area. As a result, two factor-of-safety maps were established for the study area and classified into hazard zones depicting the distribution of slope conditions based on the change in factor of safety (FS). The FS value has been categorized in these maps using the Mandal and Maiti classification (Mandal and Maiti 2015), which divides the stability state of the slope into four different classes: stable, moderately stable, quasi-stable, and unstable. A detailed description of the classification is represented in Table 13.3.

The analysis results of the distribution of 18 historical landslides indicated that most landslides occurred in zones between 581 and 900 m in elevation (11 landslides) (Fig. 13.9) and with weathering crust thickness ranging from 4 to 12 m (12 landslides) (Fig. 13.10).

The FS map in Fig. 13.11 shows that the study area is not at risk of landslides under natural conditions, such as when there is no rainfall. This result demonstrated that, despite the existence of a weathering crust ranging in thickness from 2 to 20 m, the slopes in the study area are generally stable in the absence of triggering variables like rainfall. According to the statistics, 91.2% of the study area has slopes that exist in a stable condition, with the remaining 8.8% having slopes that exist in a moderately stable condition.

When modeling in the natural conditions, the FS map of the study area was classified into two hazard zones: moderately stable (8.8%) and stable (91.2%). However, under the influence of rainfall, the FS map was classified into four hazard zones: unstable (18.12%), quasi-stable (15.04%), moderately stable (11.92%), and stable zone (54.92%) (Fig. 13.12). The unstable zone demonstrated the effect of rainfall on slope stability in the study area, including the location of 18 historical landslides. Heavy precipitation decreases the shear strength and increases the weight of the soil mass on the slope, increasing the likelihood of landslides occurring.

The model performance evaluation and the landslide location assessment results are presented in Table 13.4 and Fig. 13.13. A relatively good correlation between

Table 13.3 Classification of factor of safety (Mandal and Maiti 2015)

Factor of safety (F_S)	Slope state	Remark
<1.0	Unstable	Stabilizing factors are needed for stability
1.0–1.25	Quasi-stable	Minor destabilizing factor lead to instability
1.25–1.5	Moderately stable	Moderate destabilizing factor lead to instability
>1.5	Stable	Only major destabilizing factors lead to instability

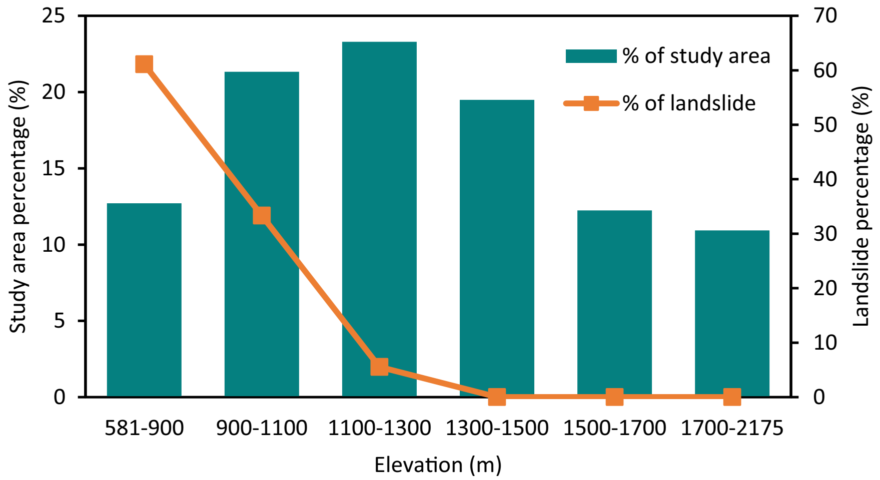

Fig. 13.9 Relationship between the distribution of landslides and elevation

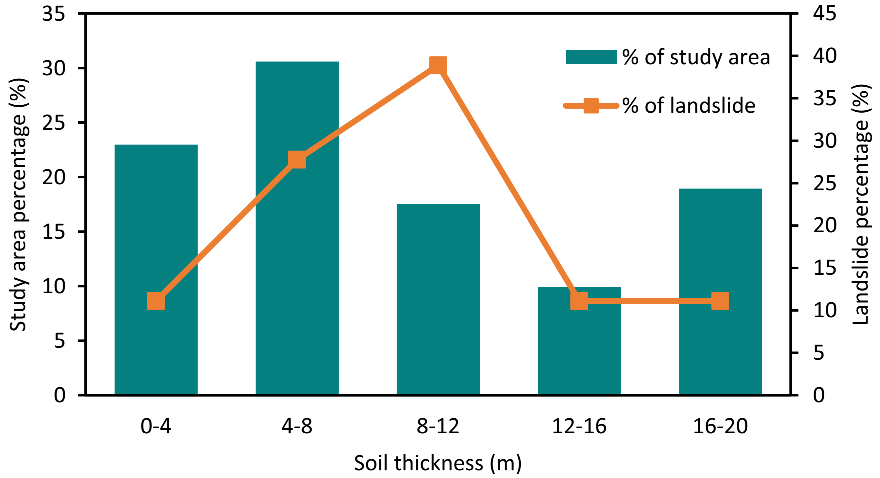

Fig. 13.10 Relationship between the distribution of landslides and soil thickness

the simulated scenario and the observed landslide sites, with an accuracy of around 61% for assessing the landslide location, is illustrated in Fig. 13.13. The results of the $\%LR_{class}$ assessment in Table 13.4 show a significantly acceptable performance of the Scoops3D model in predicting landslides since it accurately predicted the probability of including these landslides by more than 64%.

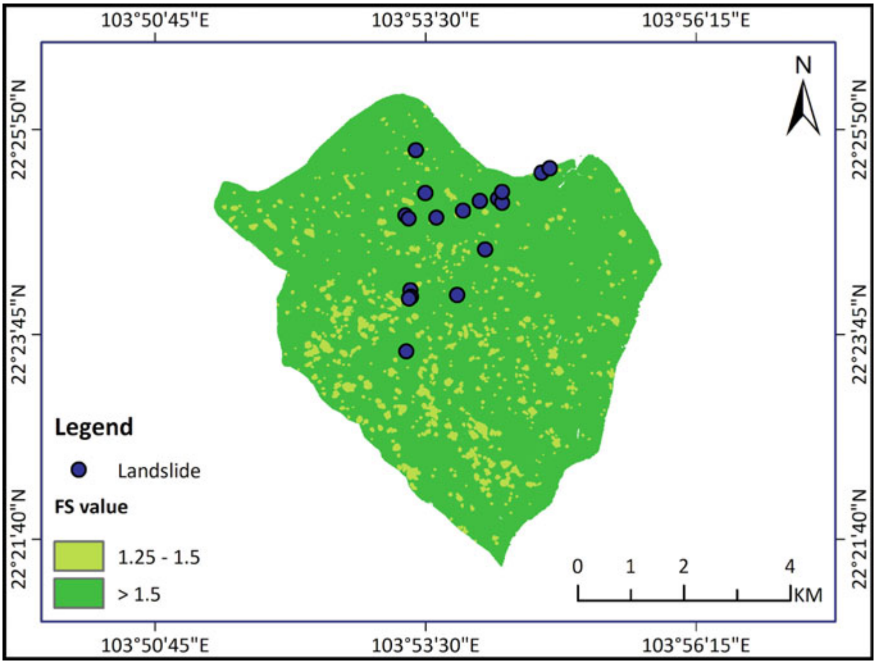

Fig. 13.11 Factor-of-safety map (natural condition)

13.4 Discussion

The preparation of landslide hazard maps is a significant step in landslide risk assessment and management. Even though physically-based models have considerable uncertainty, they have been extensively employed to produce landslide susceptibility and hazard maps (Melchiorre and Frattini 2012; Wang et al. 2019; Park et al. 2022). This uncertainty is caused by the spatial distribution of rock layers with varied thicknesses, the variety of hydrogeological conditions, and the heterogeneity in the physical and mechanical properties of the soil and rock at different locations. The use of physical models provides a better understanding of the process interactions that cause slope instability and may aid in the design of suitable mitigation strategies (Van Beek and Van Asch 2004). For the first time in Vietnam, the Scoops3D physically-based model has been utilized to assess the landslide hazard on a local scale. Due to the rough mountainous terrain of the study area, collecting topographic data, physical and mechanical parameters of soil and rock, and detailed information on the locations of slope failure is challenging. This model has been successfully established using collected data for assessing landslide hazards in the study area with reasonably good results. In physically-based models, including Scoops3D, topographic conditions play a significant role in the spatial and temporal distribution of landslides (Montgomery and Dietrich 1994). Analysis of historical landslides indicated that 61% of

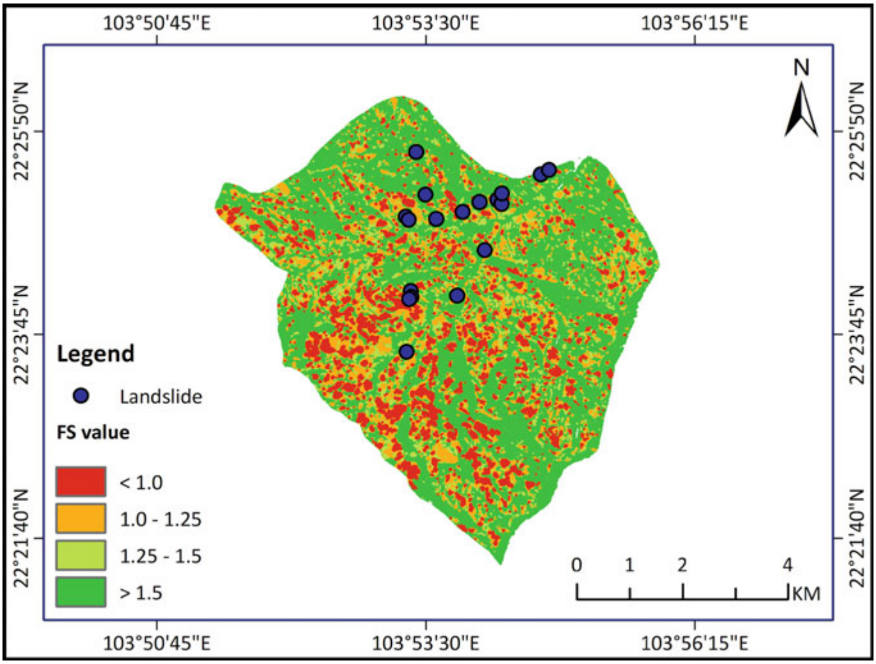

Fig. 13.12 Factor-of-safety map ($t = 16$ h)

Table 13.4 Performance evaluation of Scoops3D model

FS class	% Class area	Number of landslides	% Landslides	LR_{class}	% LR_{class}
<1.0	18.12	11	61.11	3.37	64.19
1.0–1.25	15.04	3	16.67	1.11	21.15
1.25–1.5	11.92	1	5.55	0.47	8.95
>1.5	54.92	3	16.67	0.3	5.71

landslides occurred along roads in an area with an elevation between 581 and 900 m. This area is characterized by high population density, infrastructure construction, and terraced rice fields, thus increasing the likelihood of landslides, particularly during the rainy season (Dang et al. 2018). The combination of water and human activities such as road construction and slope excavation increases the shear stress, reduces the shear strength of slope materials, and plays a significant role in the landslide process (Bozzano et al. 2011; Froude and Petley 2018; Wubalem 2021). As a result, it is possible to conclude that the landslide process in the study area involves a complex interaction of numerous factors, with rainfall acting as a trigger. The study area is located in the Northwest region of Vietnam, where various small and medium earthquakes occur (Nguyen et al. 2011). According to an earthquake catalog published by the Vietnam Institute of Geophysics, 332 earthquakes with local magnitudes ranging

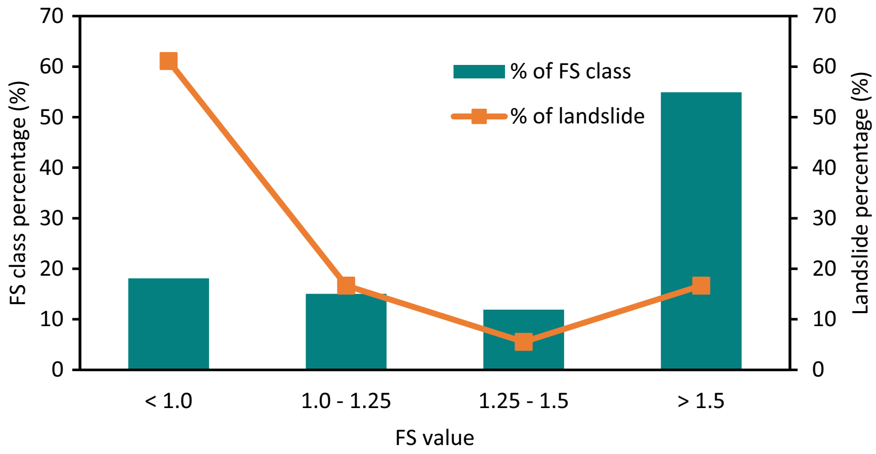

Fig. 13.13 Distribution of landslide locations in each FS class

from 3.0 to 6.8 were recorded in Northwest Vietnam between 1903 and April 2012 (Nguyen 2014). However, neither the Sapa district nor the Trung Chai commune has recorded any earthquake-induced landslides. Consequently, studies for landslide inventory and susceptibility/hazard mapping for the study area and other regions provide promising future research directions.

When data on landslide inventories are insufficient or incomplete, the $\%LR_{class}$ approach is the most recommended (Park et al. 2013; Tran et al. 2018). Along with the AUC value, the $\%LR_{class}$ index has been used in numerous landslide susceptibility/hazard assessment studies to evaluate the efficacy of the Scoops3D prediction model. Tran et al. (2018) determined that $\%LR_{class} = 87.44\%$ for the TRIGRS-Scoops3D coupled model used to assess landslide stability in a 0.4 km^2 area in the southern part of Seoul. Palazzolo et al. (2021) used the Scoops3D model to evaluate the landslide stability of a 2 km^2 river basin in northern Italy with a $\%LR_{class} = 82\%$. A coupled TRIGRS-Scoops3D model has also been utilized to assess landslide stability in the Niangniangba basin, China, with a $\%LR_{class}$ value of 80.16% (He et al. 2021). The comparison of our results ($\%LR_{class} = 64.19\%$) with those mentioned above indicated worse performance. It can be explained that by Tran et al. (2018) and Palazzolo et al. (2021) conducted their studies on a site-specific scale (<10 km^2), thereby reducing the uncertainty of the input data and thus improving model performance. Although He et al. (2021) conducted a study over a larger area (53.81 km^2), the high quality of input data and landslide inventory map and the combination of Scoops3D and TRIGRS models has enhanced prediction efficiency. Because of the lack of high-quality input data and insufficient information on historical landslides in the study area, the effectiveness of the prediction model is decreased. However, the results are considered promising since they provide a reasonable basis for predicting landslide hazards in the study area.

13.5 Conclusion

Enhancing public awareness of landslide hazards and developing effective prediction methods are efforts to manage and mitigate landslide risk in Vietnam's mountainous regions. Based on this idea, a Scoops3D model was used in this study for landslide hazard assessment. For preparing the FS maps, the input data in Scoops3D were selected and analyzed, such as the elevation map, the map of the distribution of soil thickness, rainfall data, soil parameters, and earthquake loading. As a result, the study area was divided into four landslide hazard zones: unstable, quasi-stable, moderately stable, and stable. The results showed that under the effect of heavy rainfall of 139.1 mm within 16 h, the unstable zone increased from 0 (natural conditions) to 18.12% of the study area. The analysis revealed that 61.11% of total landslides were accurately predicted, including the largest landslide of Mong Sen. Most landslides are distributed in areas with an elevation of 581 to 900 m (11 landslides) and a weathering crust thickness of 4–12 m (12 landslides). The performance of the Scoops3D is determined by comparing the FS map to the recorded landslides in the study area using the $\%LR_{class}$ index. Due to the limits and uncertainty of the input data, the Scoops3D model used in this study has worse performance when compared to other landslide stability studies. However, because accurate input data for modeling the initial conditions are not fully available, these outcomes are acceptable for this model. Therefore, the following recommendations may be made to improve the accuracy of the prediction results, including enhancing the quality of input data, establishing a pore-water pressure monitoring system, and combining the Scoops3D model with other prediction models. When the input data quality is improved, the Scoops3D model may be an effective predictor for assessing landslide hazards in the study area. The landslide hazard map can be used for land use management, long-term spatial planning, infrastructure and residential development, disaster management, and early warning in the study area.

Acknowledgements We sincerely thank to the Institute of Geological Sciences—Vietnam Academy of Science and Technology as part of the national science and technology for financial support for this research by project under grant number ĐTĐL.CN-81/21.

Declaration The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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