Paper:

Developing a Landslide Susceptibility Map Using the Analytic Hierarchical Process in Ta Van and Hau Thao Communes, Sapa, Vietnam

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Landslides are considered one of the most serious problems in the mountainous regions of the northern part of Vietnam due to the special topographic and geological conditions associated with the occurrence of tropical storms, steep slopes on hillsides, and human activities. This study initially identified areas susceptible to landslides in Ta Van Commune, Sapa District, Lao Cai Region using Analytical Hierarchy Analysis. Ten triggering and conditioning parameters were analyzed: elevation, slope, aspect, lithology, valley depth, relief amplitude, distance to roads, distance to faults, land use, and precipitation. The consistency index (*CI*) was 0.0995, indicating that no inconsistency in the decision-making process was detected during computation. The consistency ratio (*CR*) was computed for all factors and their classes were less than 0.1. The landslide susceptibility index (LSI) was computed and reclassified into five categories: very low, low, moderate, high, and very high. Approximately 9.9% of the whole area would be prone to landslide occurrence when the LSI value indicated at very high and high landslide susceptibility. The area under curve (AUC) of 0.75 illustrated that the used model provided good results for landslide susceptibility mapping in the study area. The results revealed that the predicted susceptibility levels were in good agreement with past landslides. The output also illustrated a gradual decrease in the density of landslide from the very high to the very low susceptible regions, which showed a considerable separation in the density values. Among the five classes, the highest landslide density of 0.01274 belonged to the very high susceptibility zone, followed by 0.00272 for the high susceptibility zone. The landslide susceptibility map presented in this paper would help local authorities adequately plan their landslide management process, especially in the very high and high susceptible zones.

Keywords: landslide susceptibility, AHP, GIS, Sapa

1. Introduction

Landslides are among the most significant natural disasters worldwide, occurring throughout all types of terrains and climatic conditions [1–4]. The northern mountainous regions have long been considered one of the most landslide-prone regions in Vietnam [5, 6]. Requirements of economic development and population pressure have also significantly burdened the slope stability in hilly areas with the replacement of arteries and residential regions on natural slopes. In addition, other activities, including deforestation, mining, land cover change, slope cut, and tree cutting on slope sides, would result in increased slope failures, especially during triggering events, such as prolonged rainstorms due to heavy tropical cyclones and depressions of greater frequency and higher intensity [7].

With regards to Al-Umar [8], Chalkias et al. [9], Witten et al. [10], Bui et al. [11], and Metternicht et al. [12], three major techniques for landslide susceptibility are quantitative, qualitative, and semi-quantitative methods. Statistical and physically based methods are two main approaches to the quantitative method. The statistical method generally assumes the same combination of instability parameters across the target region. The physically based method would apply different mechanisms, but it requires detailed input data and is often associated with high uncertainty [4]. The qualitative method, including inventory and heuristic approaches, is an expert-based approach drawing on landslide inventory and historical information to determine and evaluate major parameters. This approach also identifies sites with similar conditions of geomorphology and geology to estimate the susceptibility of failures. The inventory map requires satellite images, in addition to ground surveys and a historical database of landslide occurrence, to highlight the scale and location of past landslides. This approach is seen as one of the most fruitful susceptibility mapping techniques, providing the spatial distribution of historical landslides. It would be used to evaluate risks of slope failure on a regional scale. The heuristic approach depends mainly on the knowledge and experiences of scientists, and involves the type and degree of landslide risks, requiring long-term data of landslide and causative factors to evaluate potential failures. The semi-quantitative approach refers to a qualitative method incorporated with ranking and weighing to evaluate landslide susceptibility [13, 14]. The Analytical Hierarchy Process (AHP), introduced by Saaty in 1980 [15–17], is an example of the semi-quantitative approach.

In Vietnam, most studies have applied the statistical method to evaluate the landslide hazard for medium-scale prediction using a statistical index and logistic regression model [11, 18], support vector machines [14, 19], decision tree, and Naïve Bayes [19] neuro-fuzzy model, fuzzy logic and evidential belief function model [13], Bayesian regularized neural network (BRNN) [20], and artificial neural network [21]. The AHP method was also applied in some studies to evaluate landslide risks in Vietnam, such as the Son La reservoir basin (Son La), Deo Gio (Bac Kan), and Mai Chau (Hoa Binh) [22–24]. For example, in research on landslide susceptibility and zoning in the Son La hydropower basin, eight criteria, including elevation, aspect, slope angle, rainfall, lithology, weather crust, linear, and vegetation cover, were used to determine the landslide susceptibility index (LSI) [22]. Seven other parameters (slope aspect, slope angle, lithology, land use, soil type, the density of deep dissection, and density of horizontal dissections) were used to calculate LSI in Ha Giang [25]. Hien [26] computed the LSI in Quang Nam Province considering nine conditioning factors, namely slope, fault density, lithological, weathering crust, autumn rainfall, deep disruption density, land use, river density, and distance to roads.

The primary advantage of AHP is that all parameters of landslide would be included in the computation and perform a certain role in the decision-making process. Based on heuristic and inventory analysis, the semi-quantitative method would identify the risk region in small-scale areas [27]. The AHP also allows opinions to be quantified and transformed into a coherent decision model [15]. Althuwaynee et al. [28] found that AHP is a more reliable method for criteria rating than the Bayesian method. According to Kayastha et al. [29], for the Tinau watershed in Nepal, the AHP was considered a reasonable approach for landslide susceptibility when it produced a reliable outcome. Similarly, AHP provided output with about 53% overlap with the observed landslide layer in the research of landslide susceptibility in the Izeh Basin, southwestern Iran [30].

In this paper, the AHP model combined with GIS techniques was used to establish a landslide susceptibility map for a region in Ta Van and Hau Thao Communes, Sapa District, Lao Cai Province, Vietnam. This approach is used to evaluate the weights, normalize factors, and identify landslide occurrences into five categories, very low, low, medium, high, and very high. To evaluate landslide susceptibility, 10 parameters were considered – geomorphology (elevation, slope, aspect, relief amplitude, and valley depth), geology (lithology), distance to faults, distance to roads, rainfall, and land use. The receiver operating characteristic technique (ROC) is used to evaluate the accuracy of the final map based on the landslide inventory map, in addition to field surveys.

2. Study Area

Sapa, a district of northwestern Lao Cai Province, has experienced more slope failure events than other regions in North Vietnam [3, 31]. Special characteristics in topography and geology, including complicated terrain surface, steep slopes, and narrow valleys have led to widespread landslides in this district; most of the landslides (51/53) documented in 2014 occurred on artificial slopes [32]. Since 2010, Provincial Road No. 152, cutting through the steep mountain slope at Ta Van and Hau Thao Communes, has been displaced several times from km7 + 550 to km7 + 600, with the largest displacement of around 1 m and 2 m toward the vertical and transverse directions, respectively [33]. This sliding block is located close to a special cultural heritage area of Ta Van Village, the "Sapa Antique Engraved Rocks Area." Recently, a serious landslide occurred along Road 152 at km9 + 100 on August 5, 2019, leading to about 300 m^3 of loose soil and rock and causing one death (**Fig. 1(d)**). Therefore, identifying the landslide vulnerability is necessary to set up adequate measurements to protect the preservation region and reduce losses caused by slope failures.

The research area is located in the mountainous terrain between longitudes 103.88°E to 103.93°E, and latitudes 22.28°N and 22.33°N in Ta Van and Hau Thao Communes, Sapa District, Lao Cai Province. It belongs to the high rainfall region of the Hoang Lien Son mountain range, with an average annual rainfall of about 2755 mm (from 1943 to 3679 mm) [34]. Herb cultivation is the main crop in Sapa, while rice has been cultivated in the terraced rice ecosystem [31]. The rainy season from May to September often accounts for approximately 80–85% of the annual precipitation. The topography in this region tends to be dissected in both vertical and horizontal directions, leading to strong relief amplitudes [14]. The elevation ranges from 747 to 2372 m with slope angles varying from 0° to 85°. This region has a complicated geological structure with different formation ages and is covered by granite rock, sub-alkaline granosyenite in Ye Yen Sun complex, thick-bedded marble, dolomite and tremolite marble in Da Dinh formation, conglomerate, gritstone, clay shale, and calcareous siltstone in Cam Duong formation, and diorite, granite, and granodiorite in Po Sen complex [35]. The study area consists of debris deposits of granites with large and small tectonic faults in the northwest-to-southeast direction [28, 33]. The distribution of geological formations with different ages and origins in addition to large cleavages are two major contributions to the tectonic faults in this area. The cover soil layer is highly weathered with a thickness from 10 to 20 m [28, 33]. There are two soil types in this region:

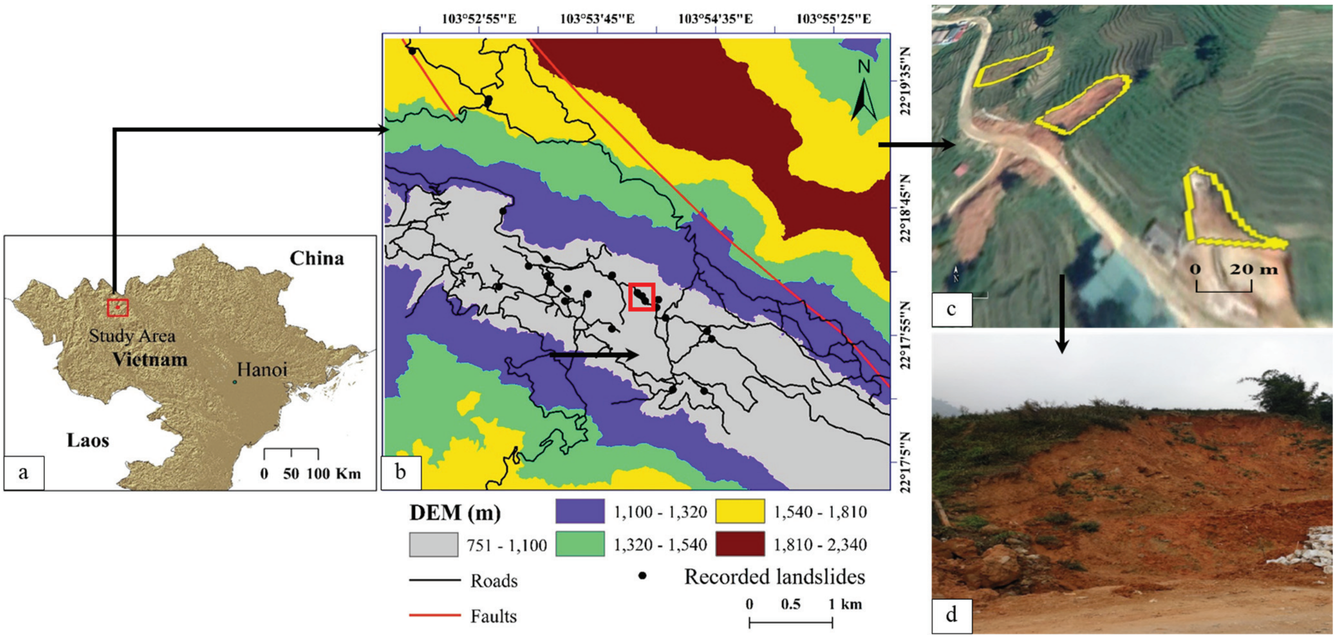

Fig. 1. a) Location of study area; b) Digital elevation model (DEM) of the study area [3]; c) Aerial photo of some landslide scars (solid lines) along Road 152; d) Landslide in the field.

Lithosols and Ferric Acrisols, fine-textured, steeply dissected to the mountainous (I-Af-3c) and Orthic Acrisols within 90 cm, medium and fine-textured, steeply dissected to mountainous (Ao90-2/3c) [36].

3. Methodology and Dataset

3.1. Methodology

The flow chart of landslide susceptibility mapping is showed in **Fig. 2**.

3.1.1. Analytic Hierarchical Process

Based on Satty's proposal [15–17], the AHP method was applied to assign preferences among variables, wherein a sequence of pair-wise comparisons would reduce the complexity of the decision. While it involves subjective preference in the ranking of factors, the AHP method has several advantages by considering all information related to landslide in the decision-making process; additionally, decision rules are based on the experience and knowledge of experts. This widely used method includes five consecutive steps for the implementation process: i) identify component factors for a decision-making problem, ii) arrange factors in a hierarchical order, iii) assign a numerical value for each factor associated with the subjective relevance, iv) set up a matrix for comparison, and v) compute the normalized eigenvector [29].

The AHP method involves the construction of decision criteria to identify the importance of each criterion using a numerical relational scale, including equally (1), moderately (3), strongly (5), very strongly (7), extremely (9),

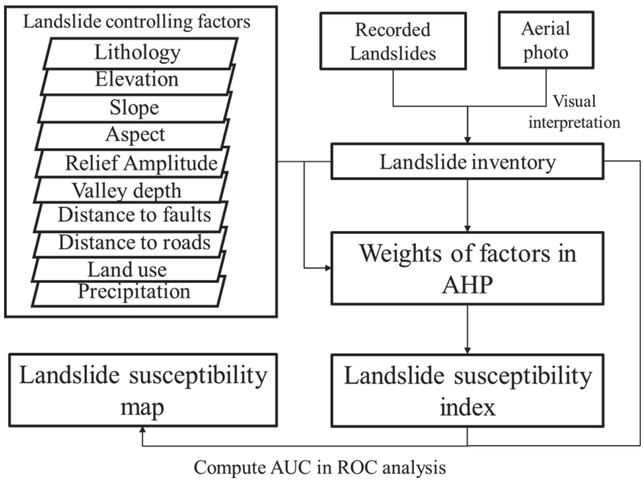

Fig. 2. Flow chart of landslide susceptibility.

and the intermediate values (2, 4, 6, 8). The AHP also enables the determination of the rating inconsistencies using the consistency index (*CI*), computed as a function of the largest eigenvalue λ_{max} and the number of comparison n:

$$CI = \frac{\lambda_{max} - n}{n - 1}. \qquad (1)$$

An average random consistency index (*RI*) was generated randomly from the reciprocal matrixes using scales of 1/9, 1/7, 1/5, 1/3, 1, 3, 5, 7, and 9 [15]. A consistency ratio (*CR*) between the consistency index (*CI*) and the random consistency index (*RI*) is used to check the consistency of the comparison performance [16]. The inconsistency is acceptable in case the value of CR is smaller than or equal to 0.1; subjective judgment will be required if CR is greater than 0.1.

3.1.2. Landslide Susceptibility Mapping

All the weighted parameters will be combined using the weight linear combination (WLC) method. The sum of the products of the weight value of causative factor (W_j) and that of the class in the causative factor j (w_{ij}) yields the landslide susceptibility index (LSI) for n causative factors:

$$LSI = \sum_{j=1}^{n} W_j w_{ij}. \qquad (2)$$

3.1.3. Landslide Validation

One of the most important tasks in the landslide prediction modelling is validation from the landslide inventory map using the receiver operating characteristic technique. A ROC curve consists of a two-dimension graph illustrating the true-positive rate on the vertical axis and the false-positive rate on the horizontal axis [37]. The area under the ROC curve (AUC), varying from 0.5 to 1.0, tests the pixel classification with and without landslides. The value of AUC, which is closer to 1, refers to a higher accuracy of the model.

3.2. Dataset

According to Varnes [38], landslide hazard is defined as the probability of landslide occurrence based on a set of geo-environmental parameters. In this study, a database of landslide conditional and causative factors was collected from the field survey, in addition to other inventory maps, such as those of geology, topography, land use, and soil types. Landslide triggering parameters can be mapped directly from in situ data, field surveys, and sampling data, or indirectly using interpolation processes. Some examples of the direct map group are lithology, land use, precipitation, and landslide inventory maps. Elevation, slope, aspect, valley depth, relief amplitude, distance to roads, and distance to faults belong to the indirect map group.

Regarding the direct map group, information on geology and faults was obtained from geological and mineral resources map (Sheet Kim Binh) at the scale of $1:200{,}000$ [35]. The lithology map was established based on the geology map with the same scale. The high-resolution land use and land cover map for 2016 with a resolution of 10 m was obtained from Japan Aerospace Exploration Agency (JAXA) [39]. In addition, the road system was collected from the open-street map, while precipitation data were collected from the meteorological authorities [34]. The digital elevation map was used to generate slope, aspect, relief amplitude, and valley depth maps. While those maps were created with different scales, the overlay task was implemented with ArcGIS software.

The landslide inventory map was established using 25 historical landslide locations, in addition to air photograph interpretations, which were verified and mapped during the field surveys [32, 40].

3.2.1. Lithology

Lithology is considered one of the major triggering parameters because the variation of lithology structures would affect the permeability and strength of slope material [14, 41]. The lithological map of the study area was classified into three groups: Metamorphic rock with rich carbonate component (MRC) in Da Dinh formation (NP_3-$\varepsilon_1 \text{đđ}$), Metamorphic rock with rich quartz component (MRQ) in Cam Duong formation ($\varepsilon_1 c\text{đđ}_1$), and acid-neutral magmatic rocks (AMR) in Po Sen complex ($\delta\gamma PZ_1 ps$) and Ye Yen Sun complex (γEys) [32, 35] (**Fig. 3(a)**).

3.2.2. Topography Condition

Elevation is often utilized as a topographic factor in landslide susceptibility assessment; it does not directly influence the occurrence of landslides, but it exerts a significant influence on other parameters, including tectonics and rainfall [8, 11]. In addition, slope failure is often associated with topographic conditions generated from the DEM map. In this study, we utilized the ALOS World 3D (AW3D) 1 m DEM, which was computed through an image matching process taken with the Digital Globe satellite constellation [3]. This data source is the most important for generating many causative factors, such as slope, aspect, valley depth, and relief amplitude. The elevation map was reclassified into five groups: i) 751–1100 m, ii) 1100–1320 m, iii) 1320–1540 m, iv) 1540–1810 m, and v) 1810–2340 m (**Fig. 1(b)**). Slope performs a significant role in bearing shear stresses on the displacement, especially at higher slope angles [41]. We applied the natural break to separate the slope condition in this region into five categories: i) flat to gentle slope ($<13°$), ii) moderate slope (13°–25°), iii) moderately steep slope (25°–37°), iv) steep slope (37°–51°), and v) very steep slope (51°–86°) (**Fig. 3(b)**). Aspect – the steepest downslope direction of each grid-cell – is often applied to evaluate the landslide susceptibility because it can influence wind, precipitation, and solar radiation. In this study, the slope aspect was divided into nine classes: i) North (N), ii) Northeast (NE), iii) East (E), iv) Southeast (SE), v) South (S), vi) Southwest (SW), vii) West (W), viii) Northwest (NW), and ix) Flat (**Fig. 3(c)**).

The valley depth is defined as the elevation difference between the given pixel and the upstream ridge. It serves to identify the distribution of the upslope area, which is the result of material loading on the slope [42]. The valley depth map was established using SAGA GIS software and included five categories: i) <5.6 m, ii) 5.6–14 m, iii) 14–24 m, iv) 24–37 m, and v) >37 m (**Fig. 3(d)**). The relief amplitude, an important factor for landslide occurrences, refers to the difference between the highest and

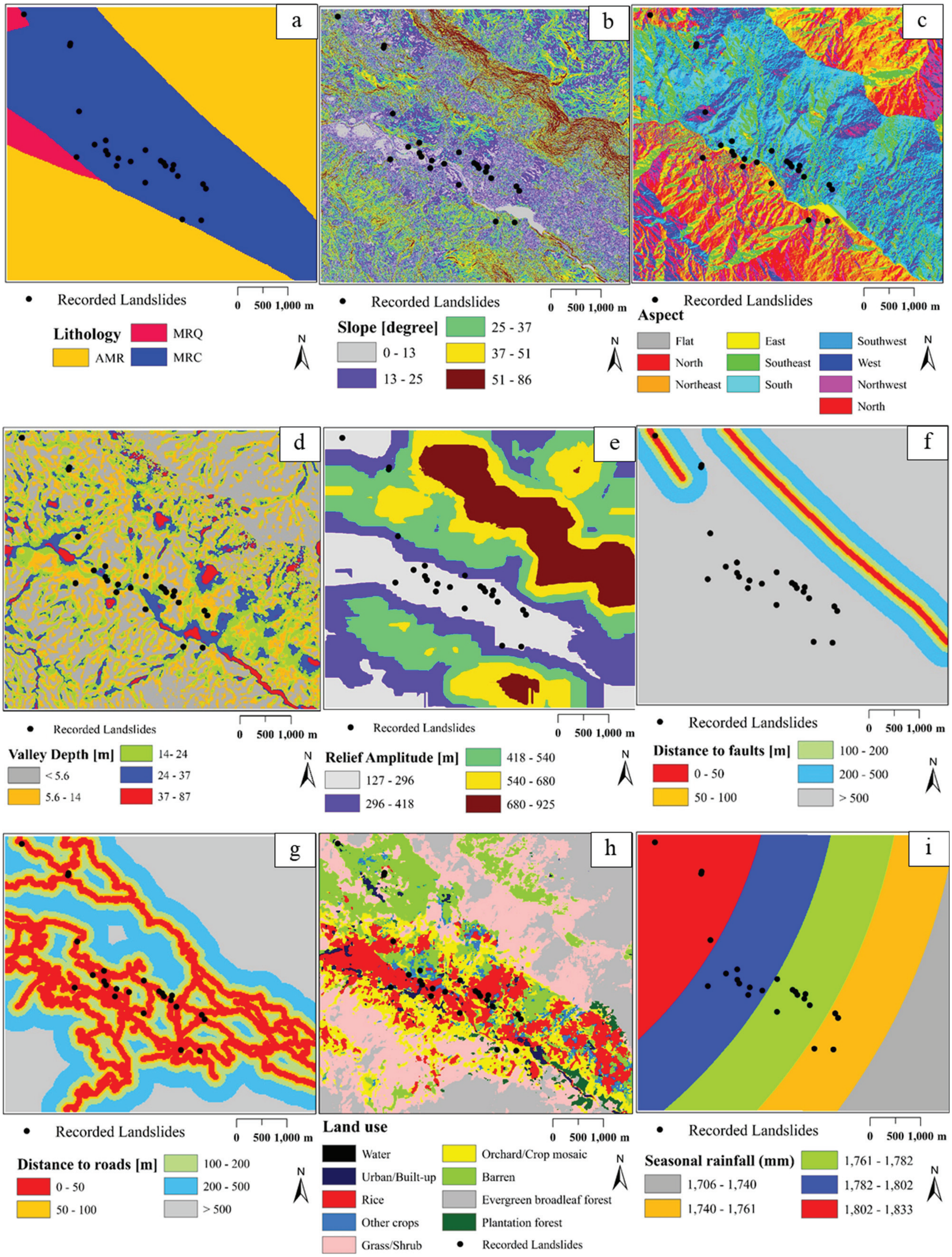

Fig. 3. a) Lithology [35]; b) Slope; c) Aspect; d) Valley depth; e) Relief amplitude; f) Distance to faults; g) Distance to roads (© OpenStreetMap contributors); h) Land use [39]; i) May–September precipitation [34].

lowest points within a terrain unit. This map was constructed using the focal statistic tool in ArcGIS 10.2 and was classified into five categories: i) <296 m, ii) 296–418 m, iii) 418–540 m, iv) 541–680 m, and v) >680 m (**Fig. 3(e)**).

3.2.3. Distance to Faults

The geological fault often relates to the high landslide susceptibility due to the decrease of rock strength caused by tectonic break [43]. Distance to the fault, extracted from the geological map, significantly contributed to slope instability due to the strength of the rock mass. This was constructed based on Euclidean Distance in ArcGIS 10.2 software and reclassified into five categories: i) <50 m, ii) 50–100 m, iii) 100–200 m, iv) 200–500 m, and v) >500 m (**Fig. 3(f)**).

3.2.4. Distance to Road

The distance to road is major anthropogenic parameter affecting landslide occurrence. Road constructions in mountainous terrain often leads to the appearance of steep slope-cut and affects the natural equilibrium condition of rock and soil. Additionally, the nearer the distance to the road system, the higher the risk of landslide hazards. The distance to road map was generated using Euclidean Distance in ArcGIS 10.6 and was classified into five groups: i) <50 m, ii) 50–100 m, iii) 100–200 m, iv) 200–500 m, and v) >500 m (**Fig. 3(g)**).

3.2.5. Land Use

Changes in land use or land cover, especially the intrusion of residential areas and other activities in the forest, would trigger slope instability. Moreover, landslide may occur in un-vegetated land as well as in vegetation ground cover with strong and large root systems [14]. The land use map in this dataset includes 12 categories: i) Water, ii) Urban/Built-up, iii) Rice, iv) Other crops, v) Grass/Shrub, vi) Orchard/Crop mosaic, vii) Barren land, viii) Evergreen broadleaf forest, ix) Coniferous forest, x) Deciduous forest, xi) Plantation forest, and xii) Mangrove [39]. In this study, the land use was reclassified into seven major groups: i) natural forest, ii) plantation forest, iii) other croplands, iv) rice, v) urban/built-up, vi) barren, and vii) others (**Fig. 3(h)**).

3.2.6. Rainfall

Spatial distribution of rainfall would trigger landslide occurrences through pore pressure on the unstable slope [44]. Additionally, landslides often occur in the rainy season. In this study, average seasonal precipitation in the rainy season (May–September) in the study area was interpolated from observed data at local rain-gauge stations and grouped into five categories: i) 1706–1740 mm, ii) 1740–1761 mm, iii) 1761–1782 mm, iv) 1782–1802 mm, and v) 1802–1833 mm (**Fig. 3(i)**) [45].

4. Results and Discussion

In this study, a multi-criteria evaluation approach was used to identify the potential occurrences of the landslides in Ta Van–Hau Thao through the application of a GIS-based AHP. Ten variables were employed for susceptibility analysis: slope, elevation, aspect, lithology group, valley depth, relief amplitude, precipitation, distance to roads, distance to faults, and land use (**Table 1**).

The AHP model considers the weighting of variables and their classes and is based on ratings provided by expert opinion. Such opinions might vary according to each individual expert; in other words, AHP could be subject to certain limitations of uncertainty and subjectivity. The spatial relationship between landslide conditioning factors and locations of landslides is therefore necessary for expert judgment. In this study, 70% of the recorded data were used to analyze typical characteristics of past landslide scars to establish the pair-wise comparison matrix for factors and class regarding their weight based on Saaty methodology [15–17, 44, 46].

Regarding the performed weighting process, the most important variable is the slope (0.2811), followed by the lithology group (0.2043) and relief amplitude (0.1464). While elevation is often treated as an indirect contribution to the slope failure [27], the least important parameters in this study are elevation (0.0160) and slope aspect (0.0219). Gentle slopes typically demonstrate a low probability of landslides due to their lower shear stress. In addition, most of landslides in this study area were recorded along the main road during the transect walk investigation. The rise in slope angle from 13°–25° combined with road excavation and inadequate construction on slope sides would activate the occurrence of landslide. Very steep slopes are subject to landslides due to the lack of adequate land-use plan, such as deforestation and constructions; consequently, a decrease of landslide occurrence was observed in this category. The region with a relief amplitude of below 296 m has the greatest proportion of landslide points (49% of landslides were recorded in the study site), making up approximately 38% of the whole region, followed by that with relief amplitude from 296 m to 400 m. Additionally, the region of moderate value of valley depth (5.6–14 m) has the largest proportion of landslide points, followed by the region with valley depth of 14–24 m. In this study site, the area with large and extremely large values of relief amplitude and valley depth is not associated with historical landslides.

The consistency index (*CI*) of 0.0995 illustrated that there was no inconsistency in the decision-making process during the computation. The consistency ratio (*CR*) was computed for all factors and their classes; the values of less than 0.1 indicated suitable and reliable results.

The LSI value of the study area ranged between 0.09 and 0.46 and was reclassified into five landslide susceptibility classes: very low (0.09–0.16), low (0.67–0.26), moderate (0.26–0.36), high (0.36–0.41), and very high (0.41–0.46) (**Fig. 4**).

The landslide susceptibility zonation map was verified

Table 1. Weights of factors and classes using AHP pairwise matrix.

Factor	Class	Class weight	Factor weight
Lithology $CR = 0.075$	ARM	0.231	0.204
	MRC	0.665	
	MRQ	0.104	
Aspect $CR = 0.025$	N	0.050	0.022
	NE	0.076	
	E	0.087	
	SE	0.137	
	S	1.161	
	SW	0.184	
	W	0.148	
	NW	0.143	
	F	0.014	
Relief Amplitude [m] $CR = 0.006$	<296	0.444	0.146
	296–418	0.262	
	418–540	0.153	
	540–680	0.089	
	>680	0.053	
Distance to fault [m] $CR = 0.006$	<50	0.444	0.061
	50–100	0.262	
	100–200	0.153	
	200–500	0.089	
	>500	0.053	
Seasonal rainfall [mm] $CR = 0.018$	1706–1740	0.051	0.028
	1740–1761	0.086	
	1761–1782	0.139	
	1782–1802	0.233	
	>1802	0.490	

Factor	Class	Class weight	Factor weight
DEM [m] $CR = 0.054$	751–1100	0.503	0.016
	1100–1320	0.260	
	1320–1540	0.134	
	1540–1810	0.068	
	1810–2343	0.035	
Slope [°] $CR = 0.031$	<13	0.168	0.281
	13–25	0.413	
	25–37	0.267	
	37–51	0.091	
	51–86	0.060	
Valley depth [m] $CR = 0.006$	<5.6	0.153	0.114
	5.6–14	0.444	
	14–24	0.262	
	24–37	0.089	
	>37	0.053	
Land use $CR = 0.025$	Natural forest	0.032	0.041
	Plant forest	0.046	
	Other crop lands	0.159	
	Rice	0.350	
	Urban/built up	0.070	
	Others	0.237	
	Barren	0.106	
Distance to road [m] $CR = 0.006$	<50	0.444	0.086
	50–100	0.262	
	100–200	0.153	
	200–500	0.089	
	>500	0.053	

using field information based on past landslides, most of which were documented during the transect walk along the main roads. In this study, the ROC curve analysis was conducted based on the true-positive rate and false-positive rate of identified landslides. All inventory landslide data (25 locations) were used in the computation. The area under the curve value of the accuracy curve was computed using the pROC package in R [47]. The AUC value of 0.75 indicates 75% prediction accuracy of the model. The large-scale geological map, in addition to the limit of landslide data, especially for small landslides (**Table 2**), constituted the major constraints on better simulation. According to recent studies, almost all of the surveyed landslides were found in accessible areas along main arteries and near residential regions and were typically associated with road-cut slopes [3, 39, 48–50]. In addition, rapid changes to exposed land after sliding events, as well as residential and other infrastructure facilities, also led to difficulties in documenting past landslides. The very high susceptibility areas in remote regions were difficult to reach; therefore, some landslides could not be recorded.

The results given in **Table 2** showed that the landslide density for the very high susceptibility zones was 0.01274, which is the largest value in the five zones. This value persisted with other research, showing that an ideal susceptibility map of landslide occurrence typically illustrated a small extent area of very high susceptibility [27]. The output also illustrated a gradual decrease in the density of landslides from the very high to the very low susceptible regions, which showed a considerable separation in the density values. This revealed a good agreement between the calculation and classification of susceptibility associated with the occurrences of past landslides.

5. Conclusion

A landslide susceptibility map in Ta Van and Hau Thao Communes has been established using the AHP model. The results showed that 1.24% and 8.66% of the whole study area belonged to very high and high susceptible classes, respectively, and were prone to landslide occur-

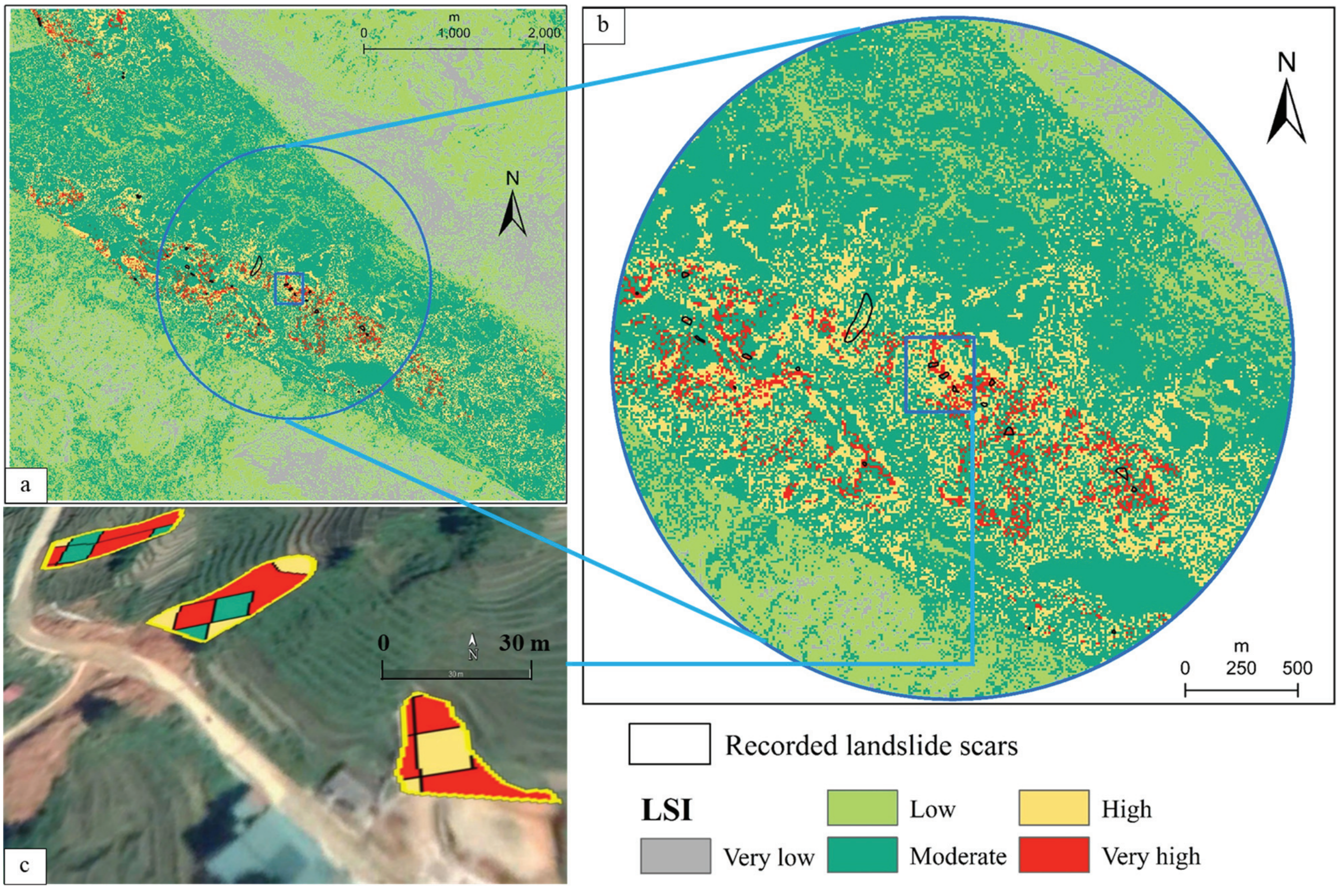

Fig. 4. a) Landslide Susceptibility Index computation in the study area; b) Zoom in LSI at center region of the study area; c) LSI overlaid on aerial photo of some landslide scars along road 152.

Table 2. Observed landslide density in the landslide susceptibility zonation map.

Susceptibility zones	Area of susceptibility zone within the study site		Area of susceptibility zone within recorded landslide scars		Landslide density
	[m^2]	[%]	[m^2]	[%]	
Very low	4,613,674	13.77	0	0.00	0
Low	13,760,040	41.06	140	0.65	0.00001
Moderate	11,821,279	35.27	8,302	38.40	0.00070
High	2,902,286	8.66	7,888	36.49	0.00272
Very high	414,958	1.24	5,288	24.46	0.01274

rence. The output showed agreement with related studies in indicating the significance of the slope (13°–37°) and lithology group (MRC). Very low, low, and moderate susceptibility would occur at 13.77%, 41.06%, and 35.27% of the total study area, respectively (**Fig. 4**). The AUC value of 75% showed the accuracy of the AHP model in landslide susceptibility assessment in the study area. The landslide susceptibility map presented in this paper would be a good source for local authorities to focus on the very high and high susceptible zones for the adequate management of landslides.

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