



An Integration of the Fractal Method and the Statistical Index Method for Mapping Landslide Susceptibility

Binh Van Duong, Igor K. Fomenko, Denis N. Gorobtsov, Kien Trung Nguyen, Dang Hong Vu, Daria D. Shubina, and Ha Ngoc Thi Pham

Abstract

Appropriate land use planning and the sustainable development of residential communities play a crucial role in the development of mountainous provinces in Vietnam. Because these regions are especially prone to natural disasters, including landslides, landslide studies can provide valuable data for determining the evolution of the landslide process and assessing landslide risk. This study was conducted to assess landslide susceptibility in Muong Khoa commune, Son La province, Vietnam, using the Statistical Index method (SI) and the integration of the Fractal method and Statistical Index method (FSI). To produce landslide susceptibility zonation (LSZ) maps, eight causative factors, including elevation, slope aspect, slope, distance to roads, distance to drainage, distance to faults, distance to geological boundaries, and land use, were considered. Using SI and FSI models, two landslide susceptibility zonation maps (LSZ) were produced in ArcGIS, and the study territory was categorized into five susceptibility zones: very low, low, moderate, high, and very high. The area percentage of susceptibility zones predicted by the SI model is 10.11, 18.49, 29.71, 28.59, and 13.10%, respectively. Meanwhile, the susceptibility

map generated by the FSI model divided the study area into zones with corresponding area proportions of 18.92, 18.71, 20.01, 22.94, and 19.42%. Using the ROC method, the prediction performance of the two models was determined to be $AUC = 71.18\%$ (SI model) and $AUC = 75.18\%$ (FSI model). The $AUC > 70\%$ indicated that the models established a good relationship between the spatial distribution of past landslides and causative factors. In addition, the two models accurately predicted the occurrence of landslides in the study area. The FSI model has improved prediction performance by identifying the role of each factor in the landslide occurrences in the study area and, therefore, may be effectively utilized in other regions and contribute to Vietnam's landslide prevention strategy.

Keywords

Landslide susceptibility · Fractal method · Statistical index method · ROC method · Muong Khoa · Son La · Vietnam

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1 Introduction

As a result of the rapid urbanization occurring in the northern mountainous regions of Vietnam, long-term territorial planning and sustainable development of residential areas are essential tasks. The expansion of urban areas and agricultural land coincides with the decrease in natural forest areas, resulting in an increase in the probability of natural disasters (Nguyen et al. 2019). Sediment-related disasters, such as landslides, have attracted a great deal of attention from researchers in Vietnam and worldwide due to their diversity in magnitude, morphological characteristics, and severity of damage (Biswas et al. 2022; Sim et al. 2022).

Numerous qualitative (Dahl et al. 2010; Wang et al. 2013), quantitative (Ma et al. 2020; Ou et al. 2021), and

semi-quantitative (Guillen et al. 2022) landslide susceptibility assessments have been conducted at various spatial scales. The main goal of landslide susceptibility assessments is to identify areas with the highest landslide potential based on an inventory of past landslide events and associated factors. When identifying landslide susceptibility zones, statistical models have demonstrated their simplicity and prediction efficiency, and consequently, they have been extensively utilized worldwide (Juliev et al. 2019; Ram et al. 2020).

Using the Statistical Index (SI) and Fractal-Statistical Index (FSI) models, landslide susceptibility assessments were conducted in Muong Khoa commune, Bac Yen district, Son La province, Vietnam. The analysis results demonstrated that the FSI model provided greater prediction efficacy, and this model is prospective for use in landslide studies in other regions of Vietnam.

2 Study Area

Similar to other “hot spots” for landslides in the Northwest area of Vietnam (Thanh Thi Pham et al. 2020), the mountainous terrain, tropical climate, geological conditions, and human activity in Son La province have all contributed to the significant number of landslides (1689 events) (Bui et al. 2022). Bac Yen district, located in the eastern portion of Son La province, is distinguished by highly complicated

topographical characteristics. In the Bac Yen district, a high frequency of landslide and debris flow occurrences has been documented, accompanied by severe consequences. The results of a field survey and statistical analysis in the Bac Yen district have identified seven areas with a high density of landslides, including Muong Khoa commune (VIGMR 2014). Muong Khoa (84.16 km²) is a mountainous commune in the western portion of the Bac Yen district with elevations between 115 and 1563 m (Fig. 1). The landslide process that was documented in this area mostly developed in the weathering crust formed from the rocks of the Ban Cai Formation (D_{3bc}), the Da Nieng Formation (C_{1dn}), and the Vien Nam Formation (T_{1vn}). Rainfall is the main trigger of landslide events, while human activity, weathering crust, vegetation cover, etc. are considered conditioning factors.

The landslide event (Fig. 2) occurred on Highway 37 near the Muong Khoa market in the Muong Khoa commune of the Bac Yen district. There were no fatalities caused by the landslide, but three houses were completely devastated. The sliding mass has an estimated size of 80 by 160 m and occurred in a 10- to 15-meter-thick weathering crust. The landslide was first triggered in early 2020 and reactivated in September 2022 due to a prolonged rain event. The field survey results determined that the landslide was triggered by heavy accumulated rainfall and formed in a thick weathering crust on terrain with a high slope gradient caused by human construction activities.

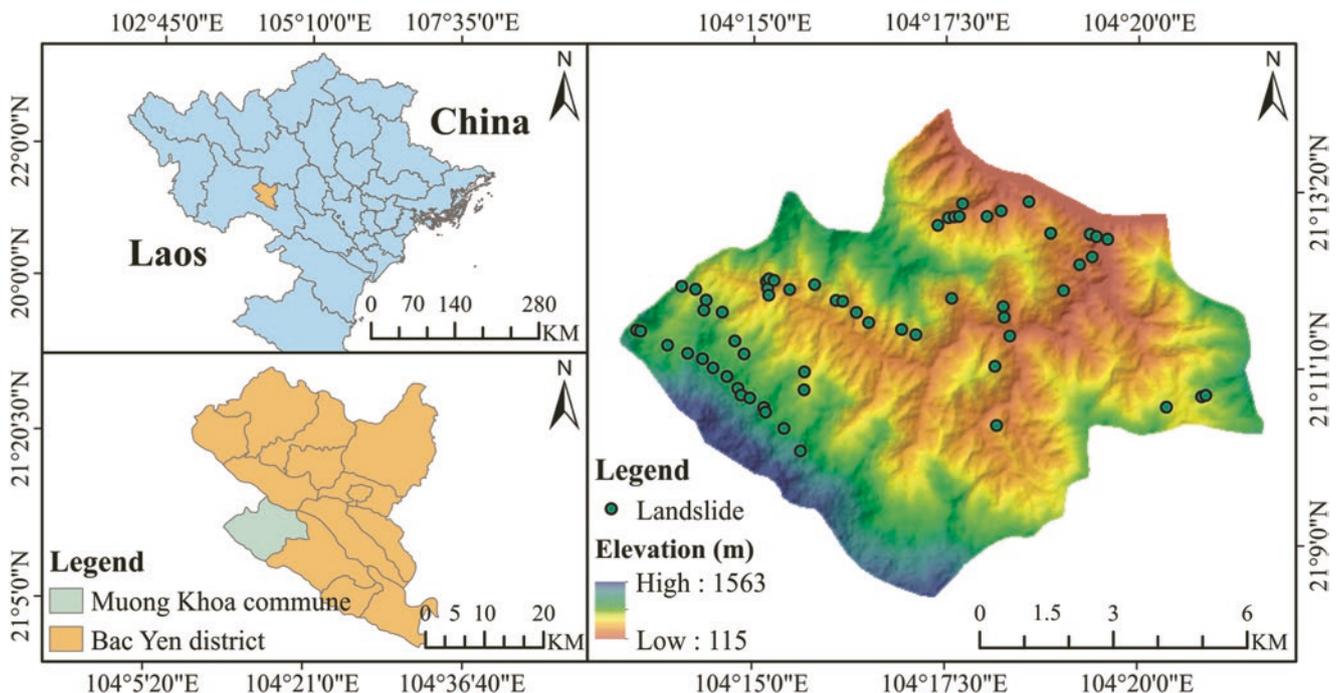


Fig. 1 Location of study area



Fig. 2 Photos of landslide event in the study area. Photo by T. K. Nguyen

3 Landslide Susceptibility Assessment Using the Statistical Index and Fractal-Statistical Index Methods

3.1 Methods

Developed by Van Westen (1997), the statistical index model has proven effective for quantitatively assessing the potential for landslides in various regions around the globe (Rai et al. 2022; Wang et al. 2016). The class weight (W_{SI}) values of causative factors are determined using the following formula based on the distribution of landslides within the factor classes:

$$W_{SI} = Ln\left(\frac{D_{LSi}}{D_{LS}}\right) \quad (1)$$

where: D_{LSi} is the landslide density in the i_{th} factor class and D_{LS} is the landslide density in the study area. Positive W_{SI} values represent areas with significant landslide potential, while negative W_{SI} values represent areas with low landslide density. The value $W_{SI} = -1$ is assigned to the factor class due to the lack of landslide distribution (Zhang et al. 2016).

Because the statistical index method only provides information on the class weight values of the causative factors, fractal analysis was utilized to quantify the contribution of each causative factor in the development of the landslide process in the study area. Since being introduced by Mandelbrot (1967), the fractal theory has been successfully used in studies to determine the geometrical features of landslides (Pourghasemi et al. 2014) and predict the spatial distribution of landslides (Liu et al. 2019; Zhao et al. 2021). The fractal theory expresses the variation in fractal dimension D as a function of the linear scale (r) (Liu et al. 2019):

$$D = f(r) \quad (2)$$

Rouai and Jaaidi (2003), based on their analysis, concluded that the distribution of landslides is characterized by a heterogeneous fractal structure. Therefore, the variable dimension fractal method (VDFM) was utilized to determine the D value for the causative factors based on the relative density of landslides (Hu et al. 2020). The factor weight (W_i) value of each causative factor is calculated using the following formula:

$$W_i = \frac{D_i}{\sum_{i=1}^n D_i} \quad (3)$$

Finally, the formula [4] is used to determine the landslide susceptibility index (LSI) value:

$$LSI = \sum W_{SI} \times W_i \quad (4)$$

3.2 Spatial Relationship Between Conditioning Factors and Landslide Distribution

The landslide inventory map in this study was established using aerial photography and field survey data. A total of sixty landslide sites were identified, with estimated volumes ranging from 8.75 m³ to 21,000 m³ (Fig. 3). According to statistical analysis results, 34 landslides have a mass volume of less than 200 m³, 22 sliding masses have a mass volume between 200 and 1000 m³, and the remaining four landslides range in mass volume from 1000 to 21,000 m³. The volume of small sliding masses accounts for only 7.74% of the total landslide volume in the study area, while the remaining 22 and four landslides account for 20.74 and 71.52%, respectively. All sixty landslides were used to build landslide susceptibility models for the study area.

For mapping landslide susceptibility in the study area, eight causative factors, including elevation, distance to roads, slope, distance to geological boundaries, distance to faults,

Fig. 3 Landslide volume statistics in the study area

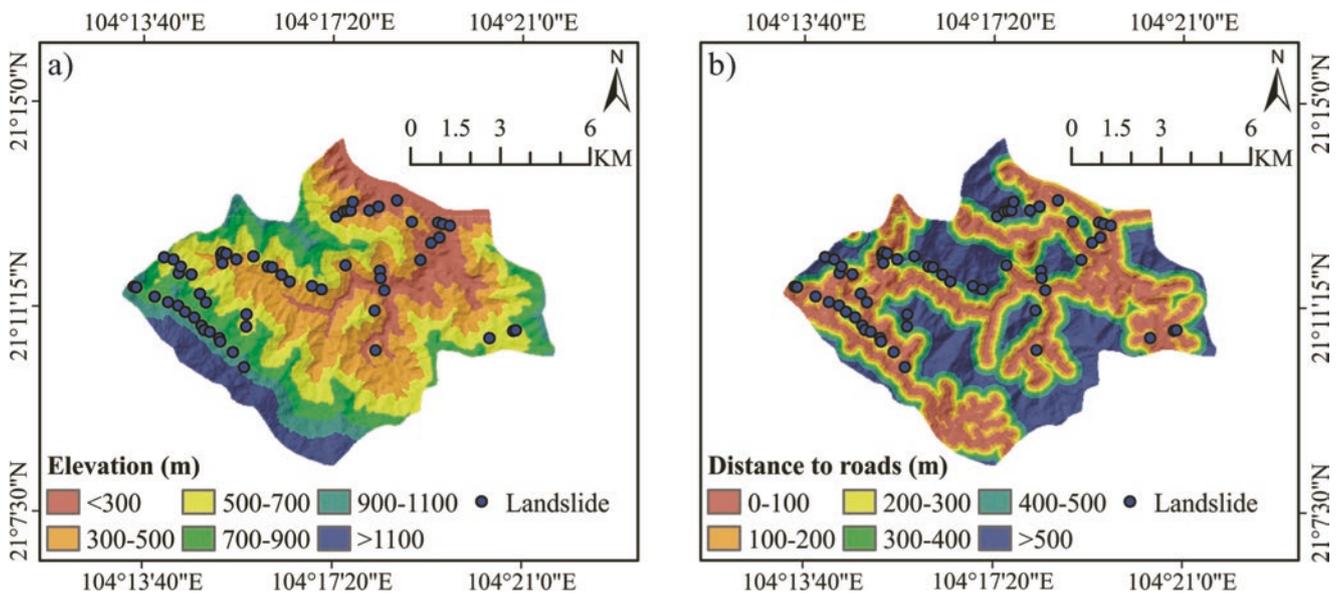
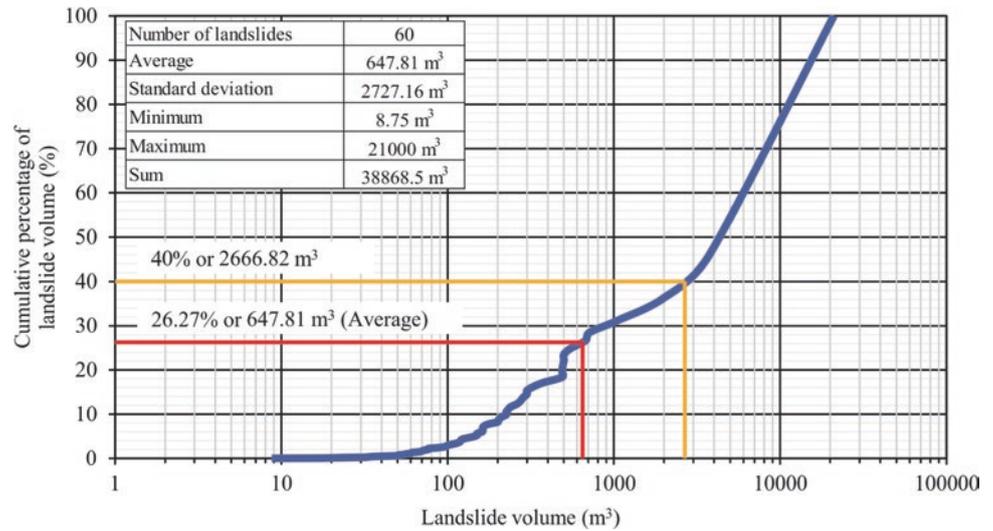


Fig. 4 (a) Elevation map and (b) map of distance to roads

land use, slope aspect, and distance to drainage, were selected in this study. The EarthData database (<https://www.earthdata.nasa.gov>) was first accessed to download the open-access global ASTER DEM (30-meter resolution). Afterward, DEM-derived factor maps, including elevation (Fig. 4a), slope (Fig. 5a), slope aspect (Fig. 7a), and distance to drainage (Fig. 7b), were prepared in ArcGIS 10.5. The relationship between these factor maps and past landslides was then analyzed by subdividing them into subclasses. The map of distance to roads (Fig. 4b) was produced in ArcGIS using OpenStreetMap data downloaded from the Geofabrik database (<https://download.geofabrik.de>) and then divided into six subclasses. The Vietnam Institute of Geosciences and Mineral Resources (VIGMR) provided the data employed to prepare maps displaying the distance to geological boundaries (Fig. 5b) and faults (Fig. 6a). In this study, land use clas-

sification was performed in ERDAS 2015 using Landsat 8 Operational Land Imager (OLI) (Date Acquired: 10/15/2022, Path 128, Row 45), and the study territory was divided into water, urban area, forest, shrubland, agricultural land, bare land, and river bed (Fig. 6b). The results of the analysis of the relationship between landslide distribution and causative factors using the SI method are shown in Table 1.

3.3 Results of Landslide Susceptibility Assessment Using Statistical Index and Fractal-Statistical Index Methods

The analysis of the relationship between past landslides and causal factors (Table 1) revealed that 47% of landslides occurred in areas below 500 m in elevation. Less

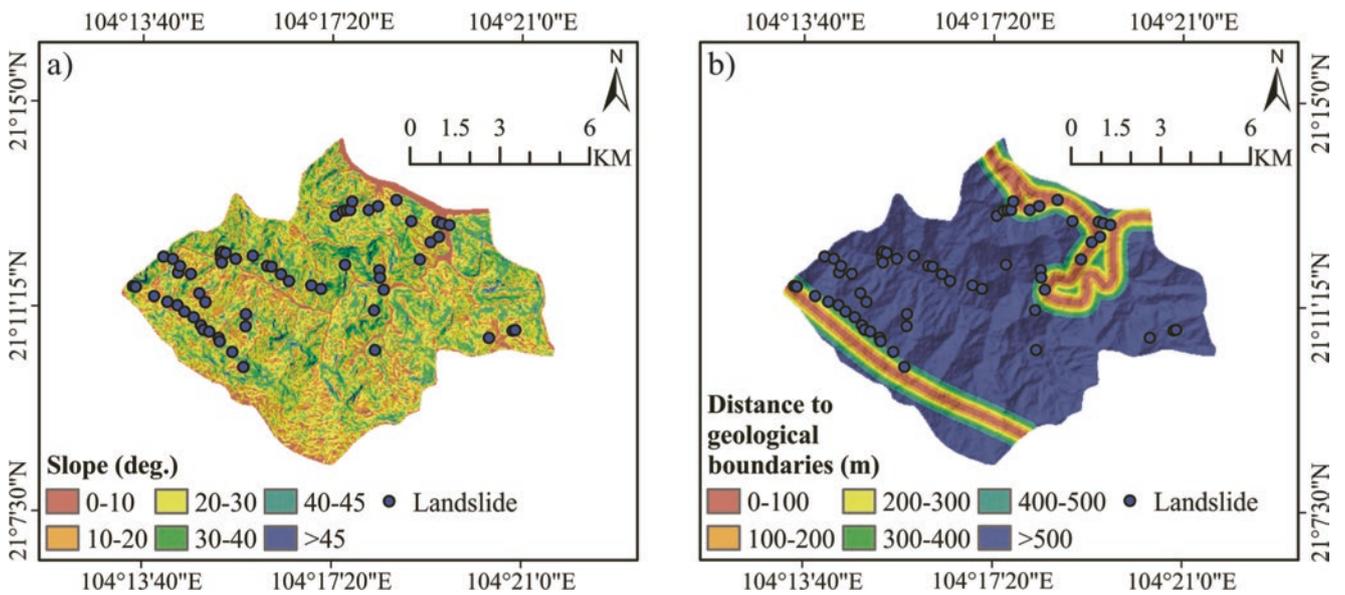


Fig. 5 (a) Slope map and (b) map of distance to geological boundaries

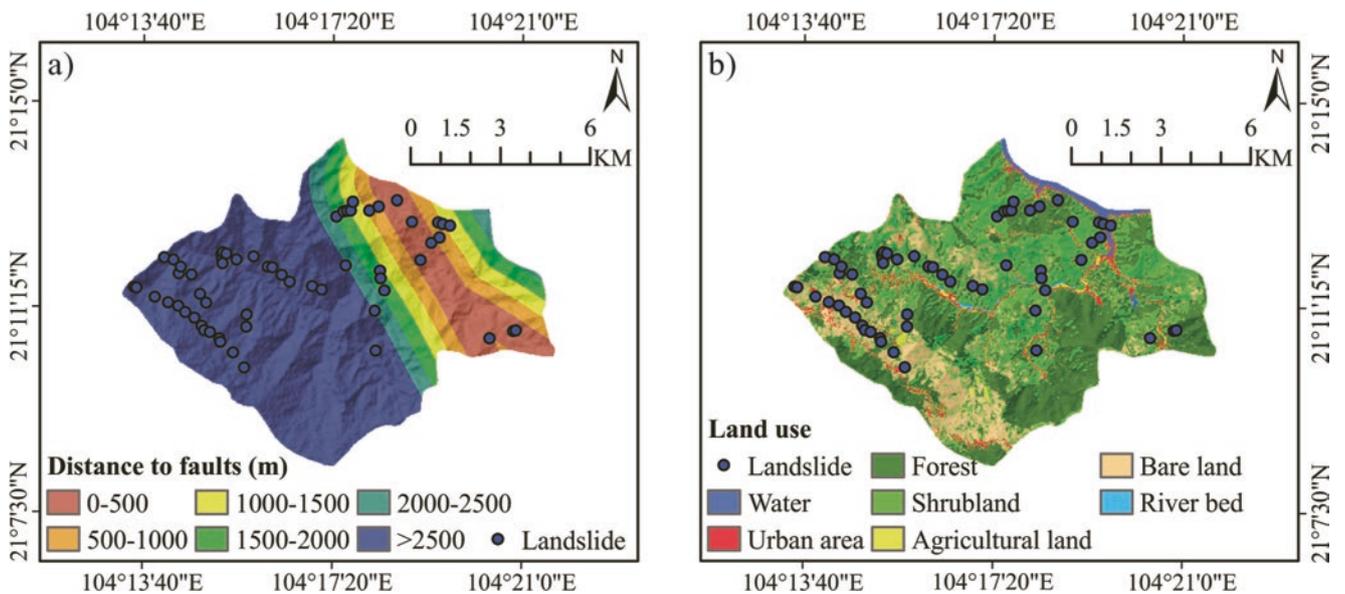


Fig. 6 (a) Map of distance to faults and (b) land use map

than 100 m from roads is associated with a significant frequency of landslides. This result indicates that construction activities in the study area have increased the likelihood of landslides. Therefore, landslides occurred frequently in areas with slopes between 10 and 30°. The highest W_{SI} values were determined for urban areas, agricultural land, and bare land. This distribution highlights the significance of vegetation cover and the influence of human activities on the development of landslides in the study area. The highest frequency of landslides was recorded on the east, south, and southwest slope aspects.

Due to the correlation between the drainage system and the degree of saturation of the slope material, landslides occurred frequently within 300 m of the drainage system. The landslide process in the study area is also related to the geological boundaries and fault system. According to Table 2, fractal analysis results showed that the distance to drainage is the most significant factor in the landslide process in the study area (Fig. 7).

Figures 8 and 9 show the LSZ maps and the distribution of susceptibility zones in the Muong Khoa commune. As depicted in Fig. 9a, 18.92% of the study area was predicted

Table 1 Analysis of the relationship between landslide distribution and causative factor using SI method

Factor	Class	Class pixel	% Class pixel	Landslide	% Landslide	W _{SI}
Elevation (m)	<300	14,085	15.064	10	16.667	0.101
	300–500	25,032	26.772	18	30	0.114
	500–700	23,144	24.753	14	23.333	−0.059
	700–900	16,693	17.854	7	11.667	−0.425
	900–1100	7477	7.997	11	18.333	0.830
	>1100	7068	7.559	0	0	−1
Distance to road (m)	0–100	25,279	27.037	20	33.333	0.209
	100–200	14,995	16.038	8	13.333	−0.185
	200–300	12,648	13.527	7	11.667	−0.148
	300–400	8973	9.597	6	10	0.041
	400–500	8054	8.614	4	6.667	−0.256
	>500	23,550	25.187	15	25	−0.007
Slope (deg.)	0–10	7000	7.487	2	3.333	−0.809
	10–20	22,125	23.663	21	35	0.391
	20–30	38,050	40.696	23	38.333	−0.060
	30–40	22,992	24.591	12	20	−0.207
	40–45	2671	2.857	1	1.667	−0.539
	>45	661	0.707	1	1.667	0.858
Distance to geological boundaries (m)	0–100	6471	6.921	6	10	0.368
	100–200	5351	5.723	5	8.333	0.376
	200–300	5520	5.904	1	1.667	−1.265
	300–400	4072	4.355	5	8.333	0.649
	400–500	4126	4.413	3	5	0.125
	>500	67,959	72.684	40	66.667	−0.086
Distance to faults (m)	0–500	10,622	11.361	7	11.667	0.027
	500–1000	7499	8.02	5	8.333	0.038
	1000–1500	6848	7.324	3	5	−0.382
	1500–2000	7195	7.695	6	10	0.262
	2000–2500	5584	5.972	1	1.667	−1.276
	>2500	55,751	59.627	38	63.333	0.060
Land use	Water	1609	1.722	0	0	−
	Urban area	3378	3.615	5	8.333	0.835
	Forest	33,193	35.522	13	21.667	−0.494
	Shrubland	39,711	42.497	25	41.667	−0.020
	Agri. land	751	0.804	1	1.667	0.729
	Bare land	14,596	15.62	16	26.667	0.535
	River bed	206	0.22	0	0	−1
Slope aspect	Flat	924	0.988	0	0	−1
	North	16,531	17.68	7	11.667	−0.416
	Northeast	19,443	20.795	12	20	−0.039
	East	13,970	14.941	12	20	0.292
	Southeast	8284	8.86	6	10	0.121
	South	6509	6.962	8	13.333	0.65
	Southwest	8588	9.185	7	11.667	0.239
	West	8995	9.62	3	5	−0.654
Distance to drainage (m)	Northwest	10,255	10.968	5	8.333	−0.275
	0–100	27,232	29.125	21	35	0.184
	100–200	21,430	22.92	18	30	0.269
	200–300	18,356	19.632	15	25	0.242
	300–400	11,976	12.809	5	8.333	−0.43
	400–500	8667	9.27	1	1.667	−1.716
>500	5838	6.244	0	0	−1	

Table 2 Calculated factor weights based on fractal analysis

Factor	Linear regression formulation	Correlation coefficient (R ²)	D _i	W _i
Elevation	$y = 1.4008x + 0.8049$	0.9991	1.4008	0.122
Distance to road	$y = 0.86x + 0.2206$	0.9995	0.86	0.075
Slope	$y = 1.4093x + 0.8526$	1	1.4093	0.123
Distance to geological boundaries	$y = 1.5477x + 0.6255$	0.9996	1.5477	0.135
Distance to fault	$y = 1.5897x + 0.2328$	0.9994	1.5897	0.138
Land use	$y = 1.5472x + 0.8353$	0.9999	1.5472	0.135
Slope aspect	$y = 1.5399x + 0.61$	0.9995	1.5399	0.134
Distance to drainage	$y = 1.5949x + 0.2683$	0.9997	1.5949	0.139

to be a very low (VL) susceptibility zone using the FSI model. Compared to the outcome predicted by the SI model (10.11%), this result is highly significant for land use planning and residential area development. The SI model predicted a higher percentage of low (L), moderate (M) and high (H) susceptibility zones, whereas the FSI model indicated that 19.42% of the study area was classified as a very high (VH) susceptibility zone, which is 6.32% larger than the SI model. The model efficiency is evaluated based on the number (area) of predicted landslides, especially in the VH zone. Figure 9b reveals that 58.33% of landslides were predicted in the VH zone, compared to 48.33% predicted by the SI model. This outcome proved the effectiveness of the FSI model in this study when compared to the SI model.

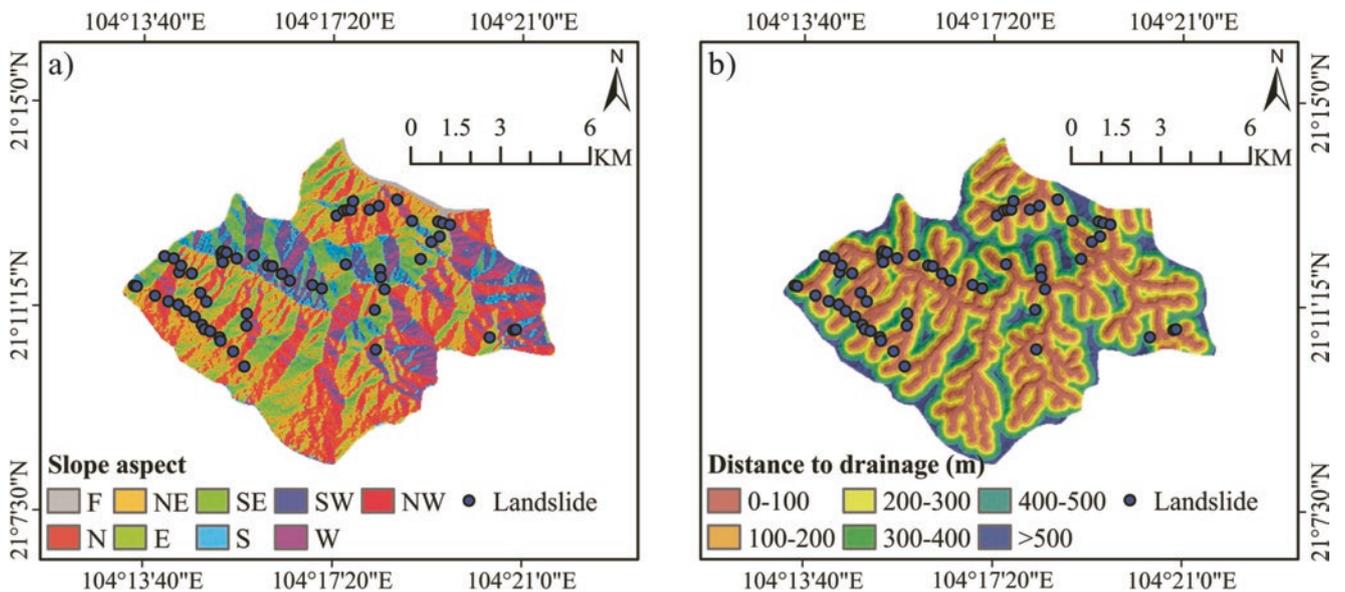


Fig. 7 (a) Slope aspect map and (b) map of distance to drainage

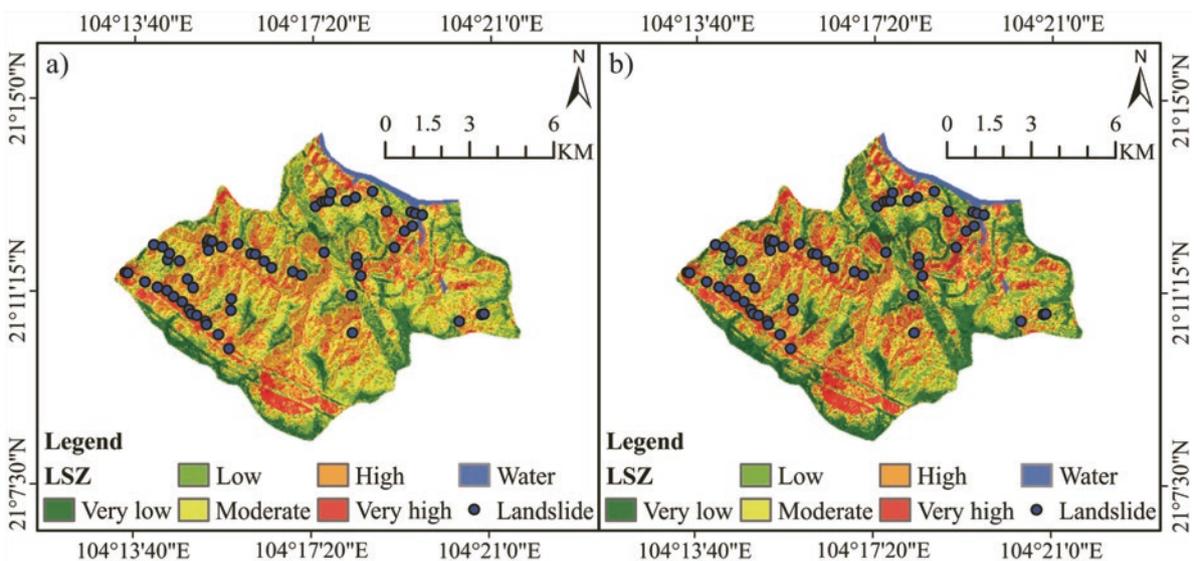


Fig. 8 LSZ map using (a) SI and (b) FSI models

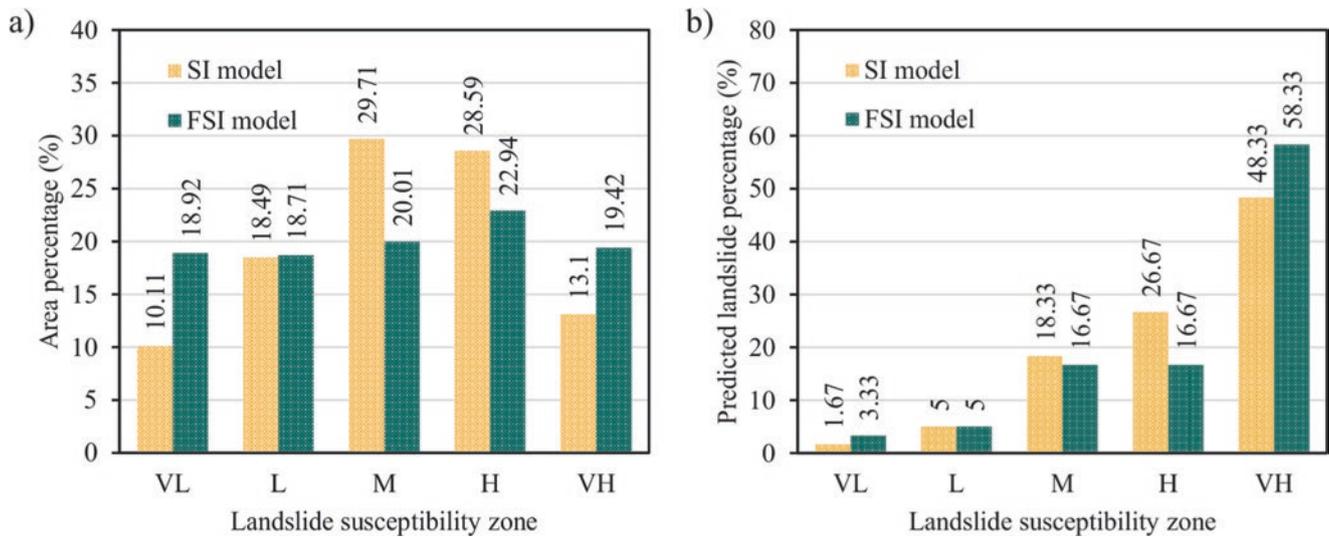
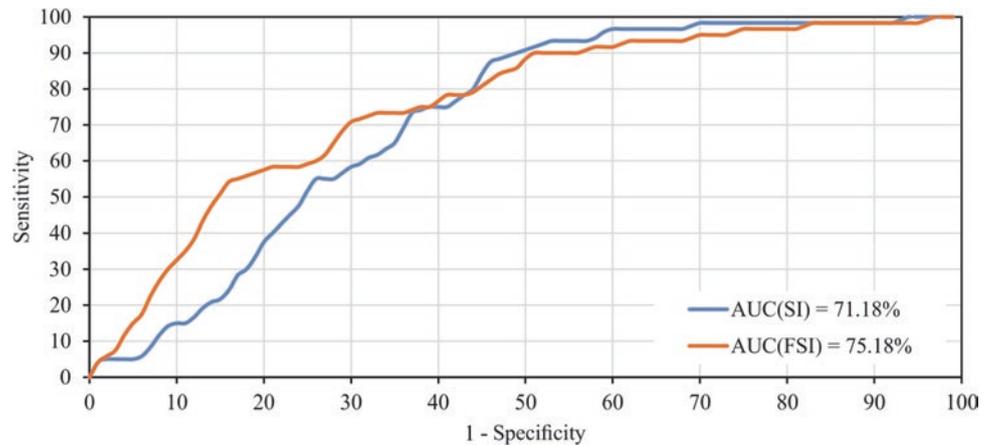


Fig. 9 (a) Area percentage of landslide susceptibility zones and (b) predicted landslide percentage using SI and FSI models

Fig. 10 ROC curves of landslide susceptibility models



The prediction model's performance was evaluated using the ROC method (Swets 1986), and the ROC curves are displayed in Fig. 10. All the AUC values for the models are greater than 70%, indicating that the models have good performance and are suitable for assessing the spatial distribution of landslides in the study area. Because fractal analysis evaluated the role of each factor in the landslide process, the FSI model provided better performance. Future studies can improve the performance of the FSI model with improved input data quality and an up-to-date landslide inventory map.

4 Conclusions

Bivariate statistical methods have been extensively utilized in landslide studies because of their efficiency and simplicity. This study employed an integration (FSI) of the Fractal method and the Statistical Index method to enhance the efficacy of assessing the potential for landslide development in Muong

Khoa commune, Bac Yen district, Son La province. Statistical analyses were conducted to determine the class weight of each causal factor, whereas the factor weight values were calculated using the fractal method. A higher AUC value indicates that the FSI model improved the accuracy of the landslide susceptibility zonation maps, as demonstrated by the conducted analyses. Simultaneously, the FSI model predicted a larger area with very low landslide susceptibility, providing a significant base for territorial planning and land use management. Consequently, the fractal method can be combined with other statistical methods to produce highly accurate prediction models. In addition, the methodologies and results of this study can be employed in landslide studies in other areas of Vietnam.

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