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Assessment of landslide susceptibility using geoinformatics and a frequency ratio model: a case study of Mae Tha River Watershed in Northern Thailand

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Abstract

A landslide is one form of geological hazard that causes socioeconomic impacts, geo-environmental changes, and damage to human lives and properties globally. The Mae Tha River watershed, located in a complex faulted- and high-slope terrain, is considered to be especially susceptible to occurrences of landslides. This study aimed to evaluate landslide susceptibility across this unique watershed using the integration of geoinformatics and a statistical frequency ratio model. Across the watershed, 67 landslide scars in the mountainous region were observed and examined for use as landslide inventory data. The landslide inventory data were combined with causative factors to produce a landslide susceptibility index as well as zones. The analysis revealed that approximately 36% of the entire watershed was highly susceptible to landslides, particularly the high terrain in the watershed's east and west. The accuracy, reliability, and predictability of the landslide susceptibility data were validated using the values of the area under the receiver operating characteristic (ROC) curve analysis (AUC). AUC values between 0.6 and 0.8 indicated that the model's performance in identifying and predicting landslide susceptibility classes was reasonably satisfactory to good. The results suggested that the frequency ratio model was an efficient statistical tool for landslide susceptibility assessment. Effective landslide susceptibility classes can be produced for community planning and mitigation purposes in this watershed as well as other areas with similar conditions.

Keywords: Frequency ratio model, Landslide inventory, Landslide susceptibility, Mae Tha fault, Mae Tha River

1. Introduction

A landslide is a significant and potentially devastating geohazard that poses damaging risks to human life and property. It can destroy structures and infrastructure, and reduce the quality of the environment and natural resources. It is a rapid downslope mass movement in which the driving force from overburdened loads has exceeded the resistance force of the material strength and soil density of earth [1]. Landslides commonly occur in the tropics where intense rainfall and rainstorms increase pore pressure and cause a reduction of the shear strength of soil, resulting materials slide on sloped terrain. Therefore, knowledge of areas susceptible to landslides is essential so at-risk countries can prepare appropriate landslide prevention and mitigation strategies. One efficient method for identifying potential risk areas is the creation of a reliable and accurate map of landslide-prone locations. Landslide hazard evolution models can be divided into qualitative and quantitative approaches. The qualitative approach assesses the potential landslide areas by combining the weighted averages of several parameters based on the decisions of experts, i.e., weighted linear combination (WLC) and the analytical hierarchy process (AHP) [2]. However, the main problems concerning the qualitative approach are a need for more understanding of the area of interest and the subjectivity and non-quantitative nature, leading to unacceptable generalization. On the other hand, the quantitative approach evaluates the potential landslide area based on the relationship between landslide inventory and landslide conditioning factors. Popular quantitative approaches include the weight of evidence model (WEM) [3], logistic regression (LR) [4], artificial neural network (ANN) [4], and frequency ratio (FR) [4]. Notably, the FR model has been employed for landslide susceptibility and has been proven to effectively predict landslide occurrences worldwide [5] including in northern Thailand [6]. The model provides more realistic landslide susceptibility data and future landslides that potentially occur under the same conditions as past landslides using a means geographic information system (GIS) [7]. However, the disadvantages and limitations of the FR model include the high degree of oversimplification when data are inadequate and the applicability of the model on a regional scale over small areas [8].

Northern Thailand is a region that remains susceptible to landslides. Previously, landslide hazard zones were evaluated and revealed to include 6,500 villages in 1,100 sub-districts that were highly susceptible to landslides [9]. Despite the severity of landslide problems in northern Thailand, the assessment of landslide occurrence and slope instability is largely insufficient. The Mae Tha River watershed is located in the east of the Chiang Mai Basin where the Mae Tha River flows through it. It covers approximately 350 km^2 in Ta Nuea and Mae Tha Sub-districts, Mae On District, Chiang Mai Province, and Tha Pla Duk Sub-district, Mae Tha District, Lamphun Province. The total population is approximately 13,000 people. Most of the area in the watershed is covered by rainforest and deciduous forests in high mountains. The foothills are shrubland, and the central valley comprises communities, buildings, and agricultural areas. Geologically, the watershed comprises a compilation of various rock types underneath the high topography (low-to-medium grade metamorphic rocks with a granitic intrusion in the east and a massive sandstone interbedded with finer clastic rocks in the west) and small portions of terraces and alluvial deposits in the middle of the watershed. The watershed is also bounded by the Mae Tha Fault Zone (MTFZ), considered in Thailand to have a moderate-to-high degree of fault activity [10] (Figure 1). Although the watershed is relatively small and in a remote mountainous area, the central valley flat, villages, and farming have experienced landslides and debris flow delivered from the surrounding high topography.

To evaluate landslide susceptibility across the Mae Tha River watershed, identifying the scars caused by previous landslides is necessary. The assumption has been made in the study that landslides occur in the same place or under the same conditions as before. Repeated tectonic and seismic events can cause terrain instability and the potential for landslides. Therefore, this study identifies landslide susceptibility across the Mae Tha River watershed using the FR model. The model combines the presence of landslide inventory and causative factors. The accuracy and reliability of the model are validated using the area under the receiver operating characteristic (ROC) curve [11]. This study aims to provide accurate and reliable landslide susceptibility data concerning the Mae Tha River watershed so city planners, governors, and decision-makers can recognize landslide susceptible classes and reduce the impact of landslides on the population.

2. Materials and methods

2.1 Landslide scars and inventory data

Landslide inventory data are essential for analyzing landslide susceptibility because the spatial extent of landslide scars on the surface is more prone to cause present or future landslides. Historical landslide events and scars that had been recorded in Landsat 5 and 8 satellite images taken since 1985 were identified. The boundaries of the landslide scars were delineated at the source area and the prominent scarp of the landslide, excluding the depositional zone of the landslides [12] (Figure 2). This sampling scheme proceeded to the extraction of landslide scars throughout the watershed.

2.2 Landslide causative factors

Landslides typically occur by interaction among various causative factors. In this study, ten causative factors were chosen for the analysis based on data availability and a literature review. These factors were divided into four categories comprising climate, geomorphology, geology, and land cover (Table 1, Figure 3).

Table 1 Information and data sources used for landslide susceptibility assessment in the Mae Tha River watershed.

Data categories	Classification scheme	Data sources (year of data used)	Scale/ resolution
-	Landslide inventory	Landsat 5 and 8 satellites (1985-2021)	-
Climate	Accumulated rainfall	Early Warning System, Department of Water Resources (DWR) (2016-2021)	1:50,000
Geomorphology	Altitude	Topographic Map, Department of Mineral Resources (DMR) (2000) DEM from ALOS PALSAR (2009)	1:50,000 12.5 × 12.5 m
	Terrain slope	DEM from ALOS PALSAR (2009)	12.5 × 12.5 m
Geology	Lithology	Thailand geologic map, DMR (1995)	1:250,000
	Soil texture	Soil series, LDD (2021)	1:25,000

Table 1 (continued) Information and data sources used for landslide susceptibility assessment in the Mae Tha River watershed.

Data categories	Classification scheme	Data sources (year of data used)	Scale/ resolution
Geology	Distance to rivers	DEM from ALOS PALSAR (2009)	12.5 × 12.5 m
	Distance to fault lines	Thailand geologic map, DMR (1995) DEM from ALOS PALSAR (2009)	1:250,000 12.5 × 12.5 m
	Fracture density	Thailand geologic map, DMR (1995) DEM from ALOS PALSAR (2009)	1:250,000 12.5 × 12.5 m
Land Cover	Land use and land cover	Land use series, Land Development Department (LDD) (2020) Sentinel-2 imagery (2021)	1:50,000 10 × 10m
	NDVI	Sentinel-2B imagery (2021)	10 × 10m

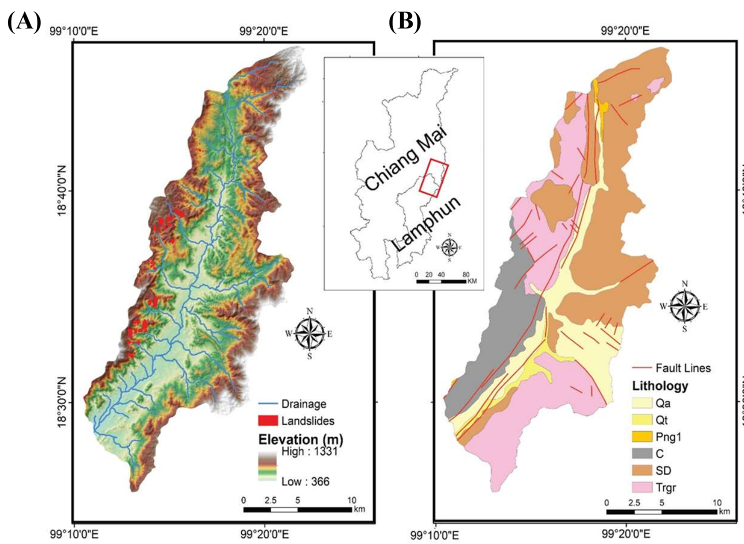

Figure 1 Location map of the Mae Tha River watershed showing (A) topographic features of the watershed (the red rectangle in the inset) with the location of 67 landslides, and (B) lithology of the watershed and its abbreviations, including Qa: alluvial sediment, Qt: terrace sediment, Png1: tuffaceous sandstone, C: clastic sedimentary rocks, SD: medium-grade metamorphic rocks, Trgr: granitic rock.

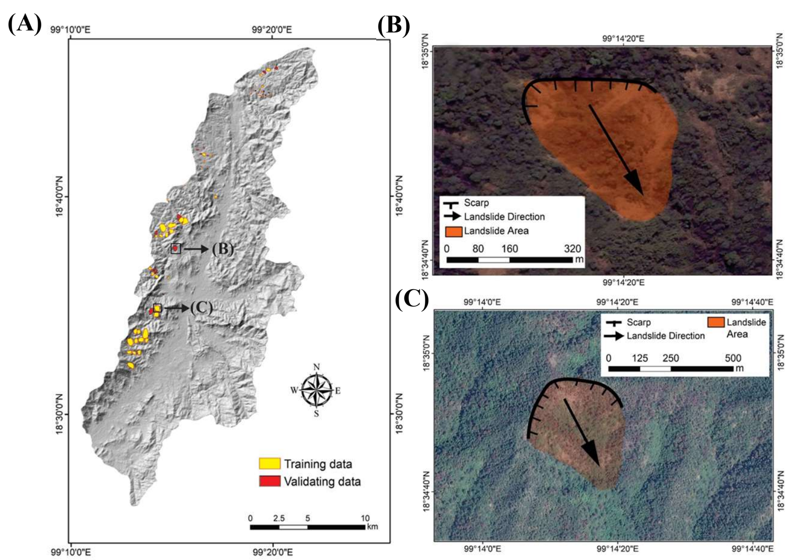

Figure 2 (A) The landslide inventory in the watershed shows the training data (yellow polygon) and validating data (red polygon). (B) and (C) Examples of landslide scars on aerial photographs recorded in 2010 and 2014.

2.2.1 Climatic-related factor

The climate-related factor is the amount of precipitation that can reduce material strength as well as trigger soil and fragmented rocks to slide on sloped surfaces. Across the Mae Tha River watershed, the spatial variation in accumulated rainfall during the last five years obtained from 9 rain gauge stations fluctuates significantly [13].

The accumulated rainfall over the watershed was interpolated using the Kriging geostatistical process. Because the interpolated rainfall values were not evenly distributed and had significant variance, the Jenks natural breaks optimization method was used to divide the spatial variation in accumulated rainfall into five classes (Figure 3A). This method is relatively suitable for grouping similar values from high variance, compared to quantile, geometrical, interval, equal interval, and standard deviation classification methods [3]. This classification method was applied to other numerical landslide causative factors (i.e., altitude, slope, fracture density, and NDVI).

2.2.2 Geomorphic-related factors

The geomorphic-related factors are altitude and terrain slope. Altitude determines the levels of geomorphic and geological processes, mass movement on the slope, vegetation covers, and runoff direction. The spatial variation in altitude across the watershed ranged from 366 to 1331 m and was divided into five classes (Figure 3B). Likewise, terrain slope is one of the most critical parameters for controlling landslide occurrence. With increasing slope, shear stress is accumulated to slide materials on sloped terrain [14]. The slope gradient of the terrain was calculated using a topography toolset in ArcGIS that proceeded with a three-by-three-cell moving window. The spatial variation in the terrain slope was also divided into five classes (Figure 3C).

2.2.3 Geologic-related factors

The geologic-related factors include lithology, soil texture, distance to rivers, distance to faults, and fracture density. Lithology provides the material that supports landslide occurrence and forms landslide development. The variation in lithology across the watershed was separated into five classes based on the mechanical properties of rocks to landslides: alluvial deposits, terrain deposits, clastic sedimentary rocks, low-to-medium grade metamorphic rocks, and granite and granodiorite (Figure 3D).

Soil is a product of rock disintegration, including different volumes of gravel, sand, silt, and clay particles. Soil texture data collected by the Land Development Department, Thailand was classified into five classes based on soil drainage and drainage properties [15] (Figure 3E). The proximity of unstable slopes to rivers can trigger channels to erode streambanks and undercut the slope toe. Thus, a closer distance to a river impacts stronger erosion and a higher degree of landslide occurrence [16]. In this work, stream networks were extracted from a built-in script of the hydrology toolset in ArcGIS. The channel networks were buffered with equal intervals of 100 m and then the spatial variation was divided into five classes (Figure 3F).

Rock exposure to active major and minor faults developed broken and joint fractures [16]. Fractured materials on the terrain slope are less stable and more prone to landslide occurrence. The main Mae Tha fault lines and minor faults were extracted from a 1:250,000 scaled geologic map and DEM analysis. These lineaments were equally buffered into intervals of 250 m in width and divided into five classes (Figure 3G). Fracture density is a particular landslide causative factor in the fault zone because rocks are highly fractured and weakened by seismic ruptures as well as fault activities. Lineament expression on a surface was delineated from remotely sensed images and the implication from rectangular drainage patterns [17]. Fracture density was calculated using a fracture density calculation provided by [18]. The spatial variation in fracture density was divided into five classes (Figure 3H).

2.2.4 Land cover-related factors

The land cover-related factors involve land use and land cover (LULC), and normalized difference vegetation index (NDVI). The spatial variation in LULC defines surface coverage and land use practice that affects the sensitivity of areas to landslides. Land cover data were obtained from Land Cover Surveys by the Land Development Department, Thailand [15], while land use practices were classified from the multi-temporal Sentinel-2 imagery collected during 2021 [19]. LULC were combined into a single class and divided the spatial variation into five classes (Figure 3I). Moreover, NDVI can determine the health and vitality of vegetation across the watershed. NDVI values were calculated based on the difference between the near-infrared (NIR) wavelength obtained from Landsat 8-band 5 and the red (RED) wavelength derived from Landsat 8-band 4 [20]. The spatial variation of NDVI values was divided into five classes (Figure 3J).

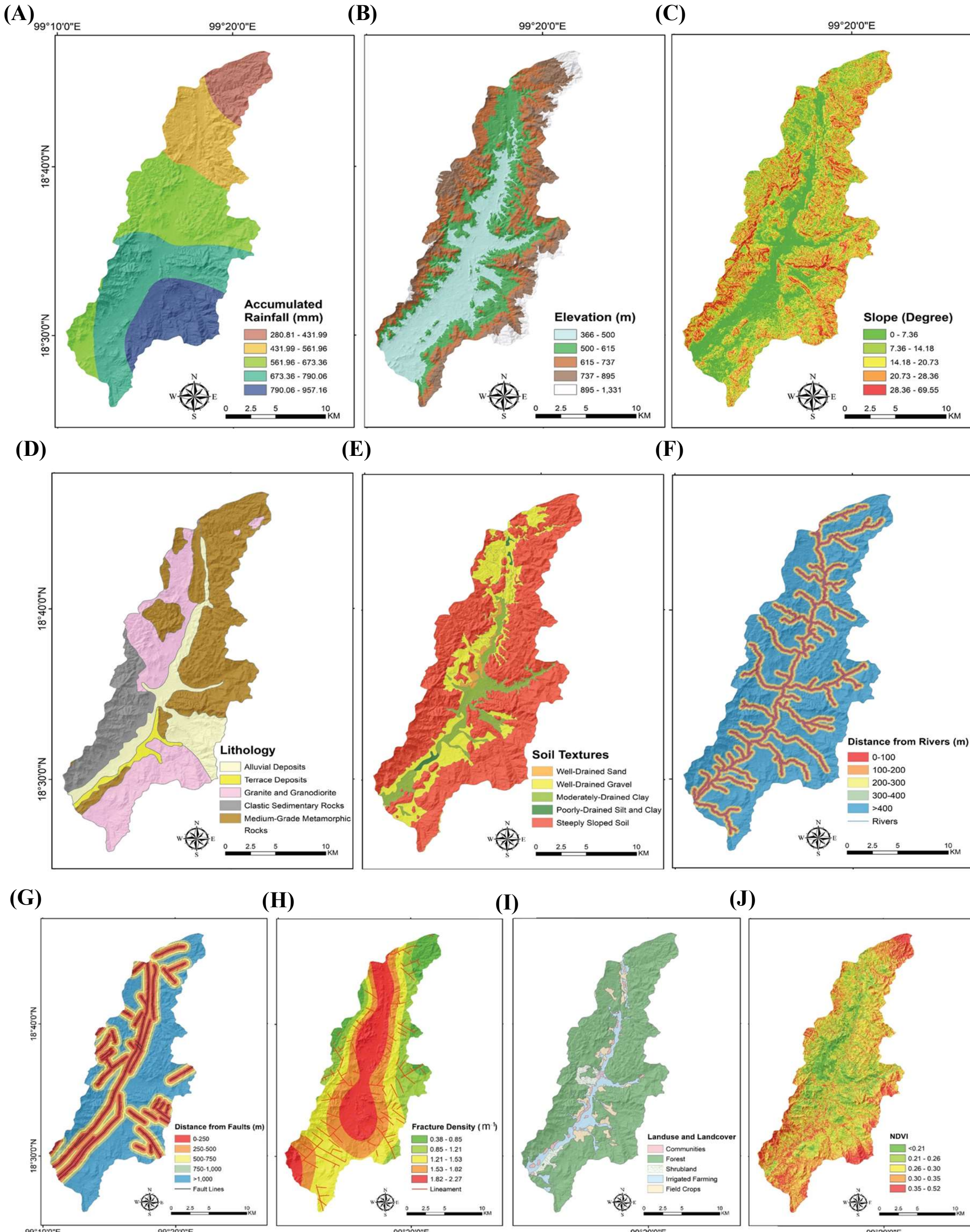

Figure 3 Landslide causative factors: (A) Accumulated rainfall, (B) Elevation, (C) Terrain slope, (D) Lithology, (E) Soil textures, (F) Distance from rivers, (G) Distance from fault lines, (H) Fracture density, (I) Land use and land cover (LULC), and (J) Normalized difference vegetation index (NDVI).

2.3 Model description and validation

The FR model is a statistical representation to assess landslide susceptibility based on the relative ratio of the area of landslide occurrence (area of landslide scars or inventory) to the total study area**.** The landslide inventory was separated into two datasets**:** a training dataset (random 70% of total landslide inventory) and a validating dataset (the remaining 30% of total landslide inventory) [21]. The Subset Feature in Geospatial Analyst in ArcGIS was utilized to randomly select landslide scars for the training dataset**.** Then, the training dataset was combined with landslide causative factors as follows:

$$FR=\frac{A}{B}=\frac{N_{pix}(1)/N_{pix}(2)}{\sum N_{pix}(1)/\sum N_{pix}(2)} \qquad (1)$$

where A is the landslide area in every unit, B is the total area of landslide in the entire units, $N_{pix}(1)$ is the number of pixels for landslide in each class of causative factor, and $N_{pix}(2)$ is the total number of pixels in the same class [7]. Subsequently, all FR values are added to obtain the landslide susceptibility index (LSI) as:

$$LSI = FR_1 + FR_2 + FR_3 + \ldots + FR_n \qquad (2)$$

where FR is the frequency ratio values, 1, 2, 3, and n is the number of causative factors. It should be noted that each FR was multiplied by 100 to make an integer number before adding up in equation (2). Once LSI values were calculated, they were classified into five landslide-susceptible classes based on the Jenks natural breaks classification method.

Model validation is necessary to evaluate the accuracy and reliability of landslide susceptibility. This study relies on the area under the receiver operating characteristic (ROC) curve (AUC) analysis [11]. ROC is a graph between a success rate curve, indicating how well the model can classify the regions into landslide-susceptible classes using a training dataset and a prediction rate curve, suggesting how well the model can predict future landslide occurrences using the validating dataset [21]. The ROC graph was plotted using the "Calculate ROC curves and AUC values" tool from the ArcSDM5toolbox [22].

The accuracy and predictability of the model were evaluated based on 1) the proximity of the ROC curve to the top left of the graph and 2) the range of the AUC values. If the AUC value is lower than 0.50, the indication is poor performance in landslide identification and prediction. AUC ranges from 0.50-0.60, 0.60-0.70, 0.70-0.80, 0.80-0.90, and >0.90 imply that the performance of the model to identify and predict landslide susceptibility are unsatisfactory, satisfactory, good, very good, and excellent, respectively [23].

3. Results and discussion

3.1 Landslide inventory data

The high western mountain embodies 67 landslide scars that cover 4.08 km^2. These scars were preliminarily predicted as either translational landslides or debris flows because of the bare surface left by the earth's material removals on crystalline and clastic sedimentary rocks. Debris flow may occur with landslides due to heavy and intense rainfall in the past. However, identifying the type of landslides is challenging due to the low image resolution of thick vegetation covering landslide boundaries.

3.2 Roles of landslide causative factors

Each landslide causative factor is discussed as an individual influential factor for landslide occurrence. The different classes of accumulated rainfall reveal that accumulated rainfall greater than 562 mm has a high FR value greater than 1, indicating a strong influence on landslide probability (Table 2). This high value corresponds to the fact that prolonged and heavy rainfall on mountain slopes reduces the material strength and causes materials on sloped terrain to slide.

In terms of terrain slope, the results revealed that a slope that is steeper than 30^{o} has the highest FR value of 2.23, while the lower classes of slope provide consecutively lower FR values. Steepening terrain slopes cause material instability on a slope to slide. Regarding terrain elevation, the altitude ranged between 600 and 900 m dominates landslide occurrence in the watershed with the FR value greater than 1 (Table 2).

Clastic sedimentary rocks underlying the high terrains are highly prone to landslides with an FR value of 3.07. The oxidation process in conglomerate and sandstone interbedded with fine-grained siltstone and shale and soluble limestone causes high susceptibility to landslides. In contrast, terrain underneath coarse-grained granite and medium-grade metamorphic rocks presents relatively lower FR values of 0.92 and 0.39, respectively. Fractured granitic and metamorphic rocks containing unstable mineral assemblages of feldspars within thin soil are less competent to landslides (Table 2).

Undifferentiated soil texture on steeply sloped terrain has the highest FR value at 1.32 (Table 2). The combination of steep slopes, soil mix, and runoff provides higher energy, velocity, and erosive power for transportation, erosion, and slope instability. Although landslides are likely to occur on moderately to poorly drained silt and clay, the drainage ability of soil depends strongly on the variation in the terrain gradient.

Some landslide causative factors play minor roles in controlling landslide susceptibility. Fluvial networks enhance slope instability and induce the collapse of bank materials from undercutting and scouring at the slope toe. Similarly, active faults with small earthquake events can develop fractures in rocks that induce rockslide and overburden mass to slide. However, the results from the analysis reveal that these factors largely depend on the terrain slope on which landslides occur, at the farthest distance from fluvial networks and fault lines.

Table 2 Spatial relationships between each landslide causative factor and landslide using the FR model.

Factors	Classes	Number of pixels in class	Number of pixels in class (%): a	Number of pixels in landslide class	Number of pixels in landslide class (%): b	Frequency ratio (b/a)
Accumulated rainfall (mm)	280-432	200243	8.82	1229	5.74	0.65
	432-562	372851	16.43	550	2.57	0.16
	562-673	676248	29.80	8169	38.17	1.28
	673-790	656462*	28.93*	11453*	53.52*	1.85*
	790-957	363458	16.02	0	0.00	0.00
Altitude (m)	366-500	611457	26.96	164	0.77	0.03
	500-615	595557	26.26	4414	20.63	0.79
	615-737	538622*	23.75*	11573*	54.09*	2.28*
	737-895	380696	16.79	5245	24.51	1.46
	895-1331	141492	6.24	0	0.00	0.00
Terrain slope (º)	0-7.36	508872	22.52	1183	5.53	0.25
	7.36-14.18	545679	24.15	3903	18.26	0.76
	14.18-20.73	562110	24.88	6041	28.26	1.14
	20.73-28.37	455084	20.14	6298	29.46	1.46
	28.37-69.55	187609*	8.30*	3955*	18.50*	2.23*
Lithology	Alluvial deposit	365312	16.11	0	0.00	0.00
	Terrace deposit	59776	2.64	0	0.00	0.00
	Clastic sedimentary rocks	322240*	14.21*	12466*	58.1^{5}*	3.07*
	Medium-grade metamorphic rock	886208	39.08	1597	7.45	0.39
	Coarse-grained granite and granodiorite	634368	27.97	7374	34.40	0.92
Soil textures	Well-drained sand	28416	1.25	0	0.00	0.00
	Well-drained gravel	434304	19.15	1523	7.11	0.37
	Moderately drained clay	190080	8.38	0	0.00	0.00
	Poorly drained silt and clay	13248	0.58	0	0.00	0.00
	Steeply sloped soil	1601856*	70.63*	19883*	92.89*	1.32*
Distance from river system (m)	0-100	263110	11.60	1348	6.30	0.54
	100-200	237196	10.46	1099	5.14	0.49
	200-300	223268	9.85	1059	4.95	0.50
	300-400	213248	9.40	1706	7.97	0.85
	>400	1330964*	58.69*	16184*	75.64*	1.29*
Distance from fault lines (m)	0-250	432331	19.06	3239	15.14	0.79
	250-500	367876	16.22	3259	15.23	0.94
	500-750	295217	13.02	1530	7.15	0.55
	750-1000	233767	10.31	1469	6.87	0.67
	>1000*	938610*	41.39*	11899*	55.61*	1.34*
Fracture density (m^{-1})	0.38-0.85	176000	7.76	758	3.54	0.46
	0.85-1.2	344064*	15.17*	5415*	25.30*	1.67*
	1.21-1.53	651840	28.74	10155	47.45	1.65
	1.53-1.83	551168	24.30	5074	23.71	0.98
	1.83-2.27	544704	24.02	0	0.00	0.00
Land use and land cover	Community and water body	38264	1.69	0	0.00	0.00
	Forest	1866741*	82.31*	20991*	98.06*	1.19*
	Shrubland	64259	2.83	100	0.47	0.16
	Irrigated farming	194388	8.57	315	1.47	0.17
	Field crops	104210	4.60	0	0.00	0.00
NDVI	(-0.05)-0.21	184576	8.14	795	3.72	0.30
	0.21-0.26	440960	19.44	3290	15.38	0.52
	0.26-0.30	692992	30.56	5791	27.07	0.88
	0.30-0.35	661120	29.15	7829	36.59	1.89
	0.35-0.52	288128*	12.71*	3691*	17.25*	2.15*

*Represents the highest value for each landslide causative factor.

Fracture density is relatively high, where major active faults, minor faults, and fractures accumulate. However, the relatively high FR values of the fracture density are in the low-to-moderate classes (0.85-1.53 m^{-1}), where wet climate, steep terrain slope, high altitude, and underlying clastic sedimentary rock dominate (Table 2). Similar to the land cover-related factors, the high FR value corresponds to a healthy and higher density of trees and green vegetation. The relatively lower FR values fall in cultivated lands, semi-bare shrubland and grasslands (Table 2). This study implies that the land cover-related factor is subordinate to other climatic-, geomorphometric-, and geologic-related factors in controlling landslide susceptibility.

3.3 Landslide susceptibility and model validation

Although landslide causative factors have a hierarchical relationship, this study combines a training dataset from the landslide inventory data with all factors to calculate the landslide susceptibility index (Figure 4A). The index is converted to landslide susceptibility classes (Figure 4B). Totals of 41.32% and 27.86% of the area are in moderate and high landslide susceptibility classes, respectively. These levels of susceptibility are along the foothills and mountainous zones in the east and west. The central basin is considered to have very low to low susceptible classes with a percentage of 13.32% and 9.79% of the entire area, respectively. The very high susceptibility class, defined as 7.71%, is in the high mountain in the west (Table 3).

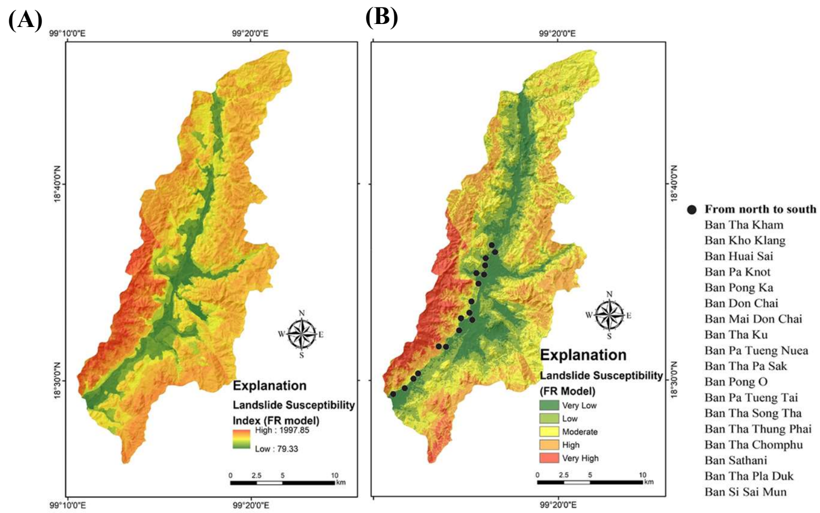

Figure 4 (A) Landslide susceptibility index of the watershed. (B) Landslide susceptibility classes of the watershed with the villages' names that are highly susceptible to landslides. The data are derived by combining a training dataset of landslide inventory and ten landslide causative factors via Equations 1 and 2 using the FR model.

Table 3 Assessment of landslide susceptibility classes in the Mae Tha River watershed using the FR model.

Susceptible classes	Number of landslide pixels	Number of total pixels	The area of the hazard zones (km^2)	The percentage of the area of the hazard zones (%)
Very low	0	300581	46.97	13.32
Low	354	220742	34.49	9.79
Moderate	3549	932033	145.63	41.32
High	10222	628386	98.19	27.86
Very high	11924	173993	27.19	7.71

The high to very high susceptible zones for a landslide are distributed along the high mountain in the west because the terrain ranges in the high elevation, is covered by soil on a slope steeper than 30° and is underlain by fractured clastic sedimentary rocks. The very high landslide susceptibility zone, where the dense distribution of historical landslide events and scars are observed, is close to seven villages in the Mae Tha sub-districts and eleven villages in the Tha Pla Duk sub-districts (Figure 4B). Compared to the general moderate level of landslide susceptibility across the watershed derived from the landslide susceptibility map of Chiang Mai and Lamphun provinces from the Department of Mineral Resources, Thailand 2021 [24], the landslide susceptibility map in this research provides more details on high to very high susceptible zones for landslide in the high mountain in the west. Hence, this map provides in-depth and local-scale landslide information for local government and city planners to conduct mitigation risk and management planning for the area.

The area under the ROC curve (success rate and prediction curve) analysis can be used to evaluate model reliability and predictability. The results reveal that the ROC of the success rate curve gets closer to the top-left of the diagram, with an AUC value of 0.812 (Figure 5). The results for AUC and ROC curves on the success rate curves represent the very good performances of the model to identify landslide susceptibility. The predictability of approaching landslide occurrence from the prediction rate curve presents the AUC value of 0.673, indicating a fair prediction for forthcoming landslide events in the watershed (Figure 5). Based on the model evaluation on AUC and ROC curves, the finding suggests that landslide-prone areas correspond with the landslide susceptibility map generated by the FR model. This study has shown that the FR model is sufficient for the spatial analysis of landslide susceptibility across the watershed. However, further research on landslide susceptibility and occurrence in the Mae Tha River watershed is necessary to refine and improve the methodology used in this study.

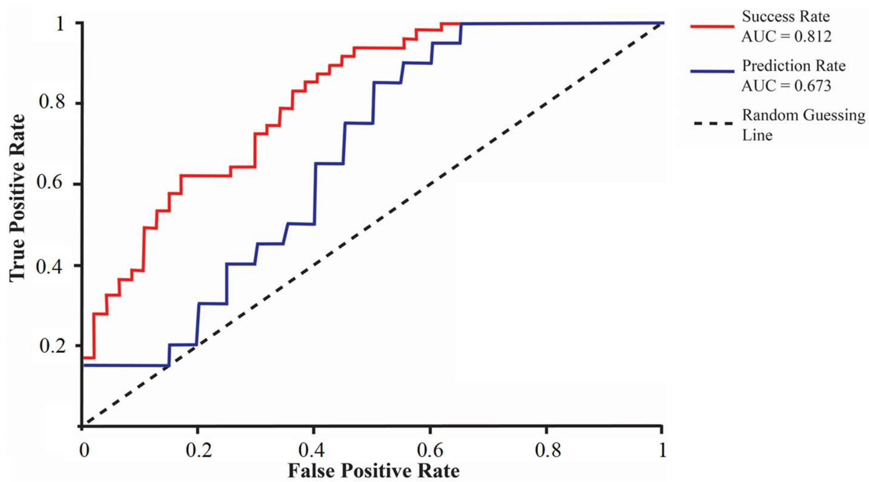

Figure 5 The ROC curve for validation testing. The AUC for landslide susceptibility data using the FR model.

4. Conclusion

This study highlights the use of geoinformatics and statistical FR models to evaluate landslide susceptibility data across the Mae Tha River watershed. The accuracy and reliability of landslide susceptibility classes obtained from the FR model reveal that areas of terrain with undifferentiated soil on the steep slope, high altitudes, wet climates, and underlying clastic sedimentary rocks mainly control the distribution of landslides across the watershed. Approximately 36% of the entire watershed is considered an area with high-to-very-high landslide susceptibility, mainly located above the base of the mountains or hills in the west. This model performs a suitable identification of landslide-susceptible zones and a moderate prediction of future landslides in the watershed. Hence, in-depth and local-scale landslide information across the Mae Tha River watershed would be beneficial for local governments and agencies aiming to implement suitable plans to reduce property damage and economic losses.

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