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Landslide Susceptibility Mapping of Mamit District in Mizoram, India: An Analytical Hierarchy Process Approach

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Abstract

Objectives: To locate areas most susceptible to landslides within the Mamit district of Mizoram, India, by combining Geographic Information System workflows with the Analytic Hierarchy Process. **Methods:** Twelve predictors were assembled and processed in ArcGIS 10.8, then weighted via Saaty's pairwise comparisons. Factor sensitivity was tested by using map removal method. **Findings:** Integrating the weights produced a susceptibility map in which approximately 33 percent of the district was classed into 'high' or 'very-high' susceptibility classes. To validate this, we compared the map with 315 past landslides using ROC analysis, which provides an AUC of 0.903, which is generally considered excellent. Despite the AHP expert-based model having identified natural variables such as rainfall as the main influential factor; a map removal sensitivity study revealed that the anthropogenic factor of distance to roads was the most influential predictor of landslide locations. The landslide inventory was highly supportive of this data-driven finding, as 68 percent of the past landslides happened within 200m of the road. **Novelty:** This study is the first validated AHP-based susceptibility map for the Mamit District, with accuracy suitable for district-scale planning.

Keywords: Analytical Hierarchy Process; Geographic Information Systems; Landslide Susceptibility; Mamit District; Mizoram

1 Introduction

Recently, some studies in the Eastern Himalaya region applying the Analytical Hierarchy Process (AHP), a multi-criteria decision-making method, to the generation of the landslide susceptibility map have come up with different levels of accuracy. Research in the Darjeeling areas experienced high prediction ability (AUC=0.968)⁽¹⁾, where the Area Under the Curve (AUC), a measure of the model performance, indicates that higher values mean better predictive ability. Similarly, an AHP study carried out in the state of Meghalaya obtained an AUC score of 0.913⁽²⁾, which is described as good predictive performance. Along with such findings, however, significant methodological deficiencies still remain in the AHP-based landslide susceptibility zonation applications. Validation of the AHP methods is usually not consistent across applications. Various studies implementing this AHP procedure have shown a consistency ratio (CR) that

exceeds the accepted value of 0.08, indicating potential reliability issues. CR is a measure of the consistency of the pairwise comparisons of the factors, which signifies the reliability of expert judgements. Also, in most cases, AHP often cannot integrate multi-temporal environmental data that are also crucial in making flexible predictions, since it is not designed to deal with dynamic temporal and spatial transformations of the triggering factors^(1,3-5).

However, the widespread use of AHP models in broader cases is hindered by the inconsistent expert judgment as well as the limited transferability of the model across other regions. Significant validation limitations are also revealed in recent studies on moisture-based triggers of landslides in the Northeast Himalayas. While some machine learning models, like the Random Forest (RF) and Artificial Neural Networks (ANN) may attain high accuracy levels at approximately 0.871 and 0.881 AUC, respectively^(6,7). The AHP models, when tuned with care (such as Darjeeling (AUC 0.968) and Meghalaya (AUC 0.913)^(1,2), demonstrate an equally strong performance as the more advanced ML models and can achieve comparable performance.

This study highlights the compelling necessity of regional comprehensive studies in the improvement of Landslide Early Warning Systems (LEWS) and observes that a case of a minimal network of monitoring makes it difficult to understand the complex interaction⁽⁸⁾. AHP-based landslide susceptibility research conducted in Mizoram also tends to be limited to hazard mapping (at a basic level)⁽⁹⁾. The use of the multi-criteria analysis in this study also indicates that, when used with a strict methodological approach, the Analytic Hierarchy Process (AHP) has the ability to produce high predictive accuracy and a relatively high consistency ratio of almost 0.1^(3-5,10).

Based on these observations, the current study is the first statistical AHP-based landslide susceptibility map in the Mamit District. The process involves a combination of twelve distinct landslide conditioning factors, a comprehensive consistency test, detailed area under the curve (ROC-AUC) validation, and ground truth validation through local fieldwork. The final susceptibility map generated was also compared with the currently existing AHP-based models in the Eastern Himalayas. The results provide district-level data that can be used as a guide in disaster management, without having to incorporate machine-learning approaches.

1.1 Study Area:

Located between 23.94°N longitude and 92.48°E latitude, the Mamit district is situated in the northeast region of India. The district has an area of approximately 3,050 square kilometres. It is characterized by complex terrain with a variety of landforms, such as hills, valleys, and plains, making it an ideal location for studying landslide susceptibility. It is surrounded by three other districts: Kolasib to the east, Aizawl to the south, and Tripura in the north. The study area lies under the Survey of India toposheet nos. 84A/5 and 84A/9. Geologically, the Mamit district forms part of the Surma Basin and is characterised by tertiary-age rocks. The most common rocks of the area include sandstone, siltstone, and shale, which may be interbedded and have distinct levels of weathering and fracturing⁽⁹⁾. Over the past decades, the Mizoram state, including the Mamit district, has undergone massive deforestation due to the shifting cultivation system and infrastructure development, which has significant consequences for slope stability and landslide manifestation^(3,9,11). Figure 1 shows the map of the Mamit district.

2 Methodology

2.1 Data Acquisition and Preprocessing

A Digital Elevation Model (DEM) from ALOS PALSAR, having a resolution of 12.5 m (GeoTIFF format) for the area under study, was acquired from the Alaska Satellite Facility. Topographic features such as curvature, slope degrees, elevation, and aspect were generated from this DEM using ArcGIS 10.8 software. Geological data, such as lithology, geomorphology, and faults, were attained through the Geological Survey of India Bhukosh portal. The Indian Meteorological Department (IMD) annual rainfall data (2012-2022) at 0.25° × 0.25° resolution was downloaded and converted to grids and later into raster format using the Inverse Distance Weighted (IDW) interpolation tool to create continuous rainfall surfaces within the study region. The Land Use and Land Cover (LULC) was determined using the Landsat 8 OLI images (30m resolution) by using the maximum likelihood supervised classification technique, which is a widely used supervised classification method for LULC mapping^(1,2,12). The Normalised Difference Vegetation Index (NDVI) was computed using the respective bands of the Landsat image: NIR (Band 5) and Red (Band 4). Raster layers were resampled in a uniform spatial resolution (12.5 m) for higher accuracy and resolution. Sources of data and their description are summarised in [Table 1], and the workflow process is shown in [Figure 2].

2.2 Preparing Thematic Layers of Landslide Inducing Factors

Twelve conditioning factors were chosen according to physical relevance to landslide processes in mountain areas and based on previous studies of the Himalayan terrains^(3,9). These include:

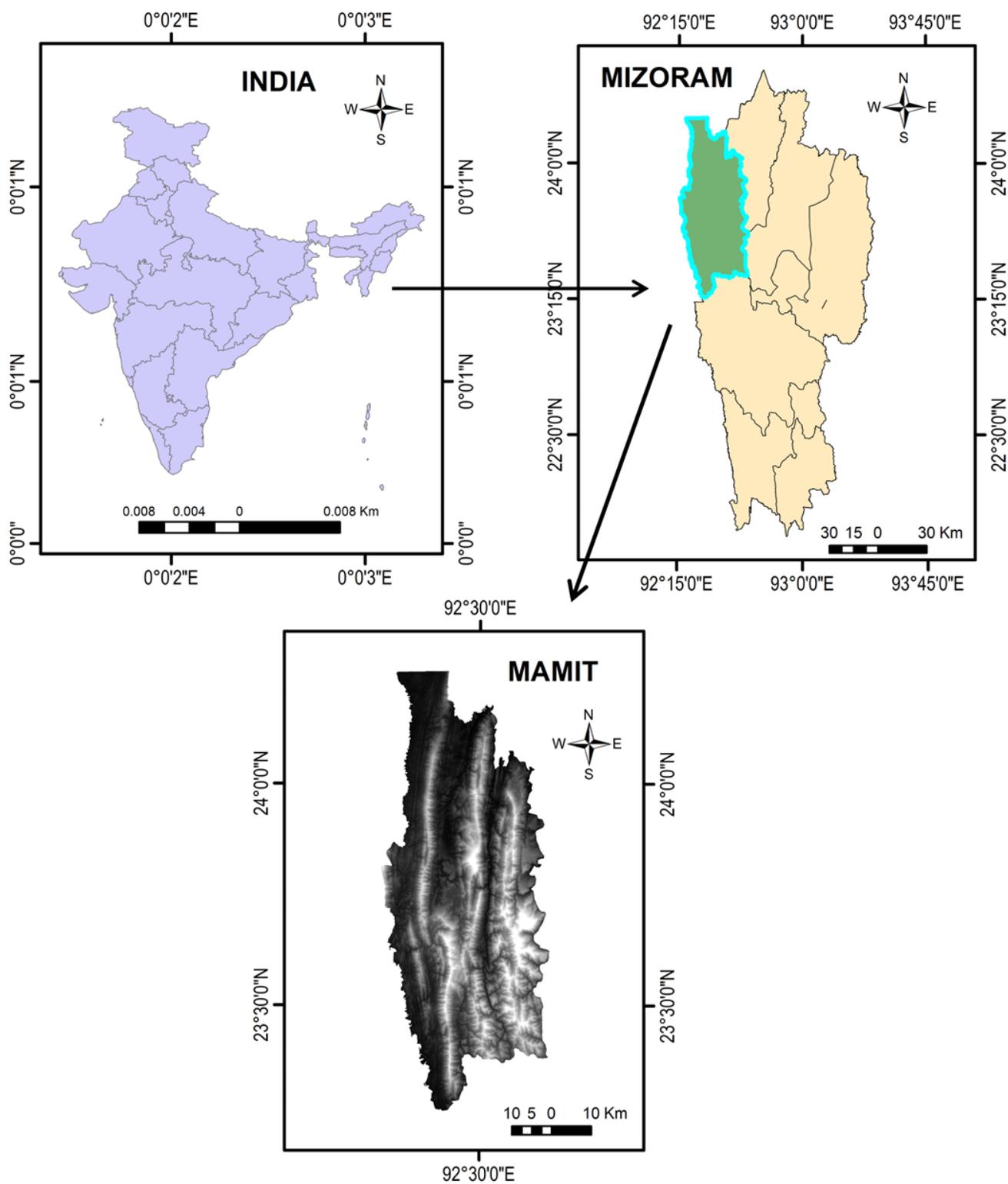


Fig 1. Map of the study area

Table 1. The data utilized along with the sources for the present study

Data	Description	Source
Landsat 8 OLI	To prepare NDVI and LULC	https://earthexplorer.usgs.gov
ALOS PALSAR DEM (12.5 m resolution)	To derive slope, aspect, curvature, elevation, and drainage	https://search.asf.alaska.edu
Net CDF gridded (0.25x0.25 degree)	To derive annual rainfall	https://www.imdpune.gov.in
Geological shapefiles	Extract lithology, geomorphology, faults	https://bhukosh.gsi.gov.in
Landslide locations	Validation of landslide points in the study area	Fieldwork and GSI data

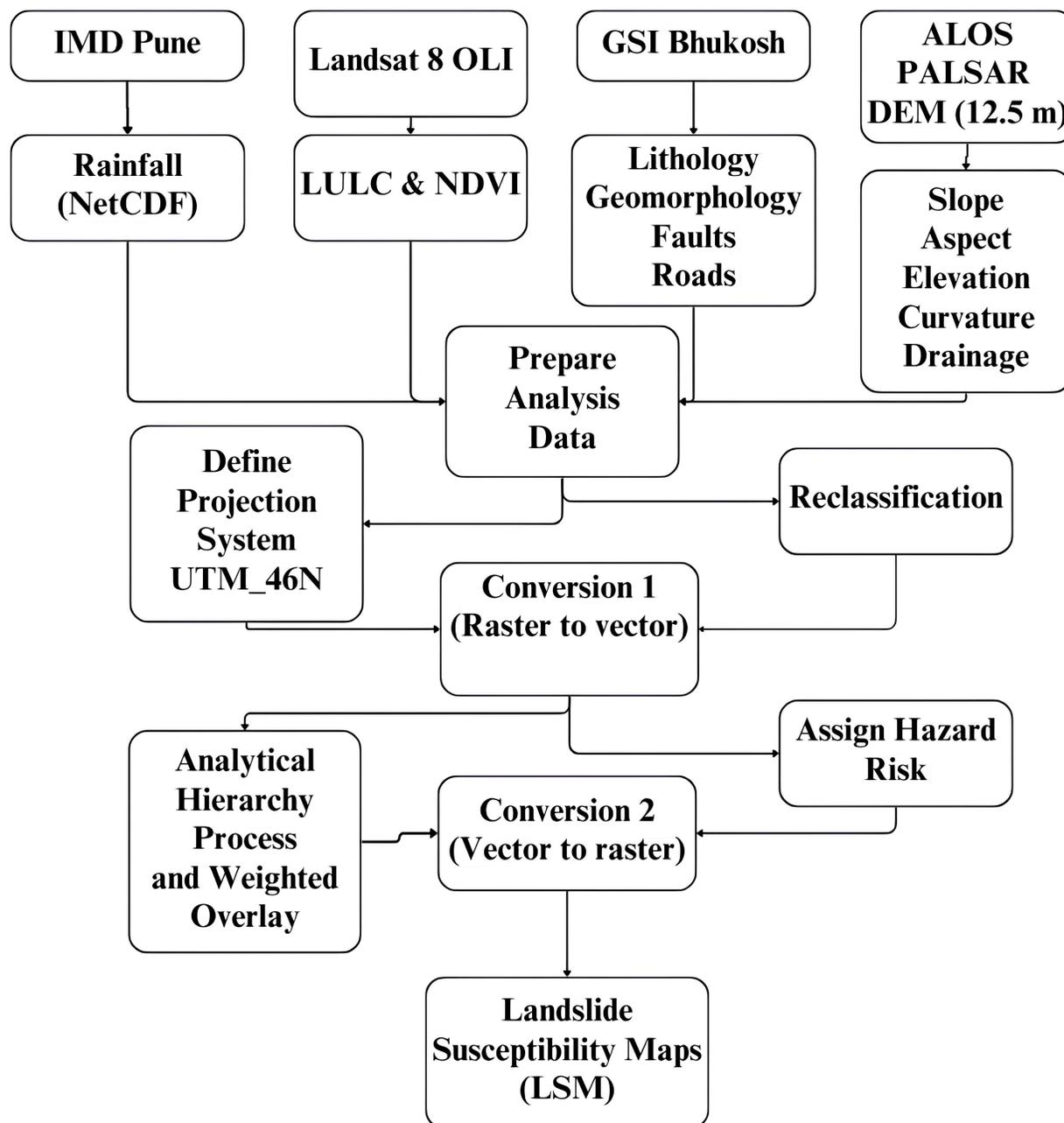


Fig 2. Flowchart of the work performed in this study

1. **Topographic:** slope, elevation, curvature, aspect
2. **Geological:** lithology, geomorphology, distance to faults
3. **Hydrological:** annual rainfall, distance to drainage
4. **Environmental:** NDVI, LULC
5. **Anthropogenic:** distance to roads

Each factor raster was reclassified into distinct classes and values by Jenks natural breaks method. The different thematic maps of the selected landslide-inducing factors generated using ArcGIS 10.8 software are shown in Figure 3.

2.3 Analytical Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP) is a commonly used technique in environmental planning and natural hazard evaluation, including landslides^(13,14). It has become a vital instrument for landslide hazard or susceptibility mapping by solving complex decision-making problems with multiple criteria^(13,15). In landslide susceptibility mapping (LSM), AHP is used to assess and rank a range of factors that influence landslide susceptibility, such as aspect, slope angle, elevation, and soil type, etc., by assigning weights based on their relative importance^(3,4,16).

2.3.1. Pairwise comparison

The comparative importance of each landslide factor was assessed using the Analytic Hierarchy Process, which was implemented by Saaty^(1,2,5). Three domain experts ranked factors using the standard 1–9 pairwise scale. The judgements were averaged and used to construct a 12 × 12 comparison matrix. Factor weights were computed by extracting the eigenvector:

$$W_i = \frac{\text{Eigenvalue}_i}{\sum_{j=1}^n \text{Eigenvalue}_j} \tag{1}$$

This method converts expert knowledge into normalised, scalable weights⁽⁷⁾. The pairwise comparison matrices of each landslide-inducing factor are given in Table 2.

Table 2. Pairwise comparison matrices for different factors

Factors	Slope	Elevation	Aspect	Curvature	Rainfall	LULC	NDVI	Lithology	Geomorphology	Dist. to fault	Dist. to roads	Dist. to drainage
Slope	1	1	3	2	1/3	3	3	2	2	3	3	3
Elevation	1	1	3	3	1/3	2	2	1/2	1/2	1	1	1
Aspect	1/3	1/3	1	1	1/3	1/3	1/3	1/3	1/3	1	1	1
Curvature	1/2	1/3	1	1	1/3	1/3	1	1/3	1/3	1/3	1/3	1/3
Rainfall	3	3	3	3	1	3	3	1	3	3	3	3
LULC	1/3	1/2	3	3	1/3	1	2	1/3	1	2	2	2
NDVI	1/3	1/2	3	1	1/3	1/2	1	1/3	1/3	1/3	1/3	1/3
Lithology	1/2	2	3	3	1	3	3	1	2	3	3	3
Geomorphology	1/2	2	3	3	1/3	1	3	1/2	1	2	2	2
Dist. to faults	1/3	1	1	3	1/3	1/2	3	1/3	1/2	1	1	1
Dist. to roads	1/3	1	1	3	1/3	1/2	3	1/3	1/2	1	1	1
Dist. to drainage	1/3	1	1	3	1/3	1/2	3	1/3	1/2	1	1	1
Sum	8.50	13.67	26.00	29.00	5.33	15.67	27.33	7.33	12.00	18.67	18.67	18.67

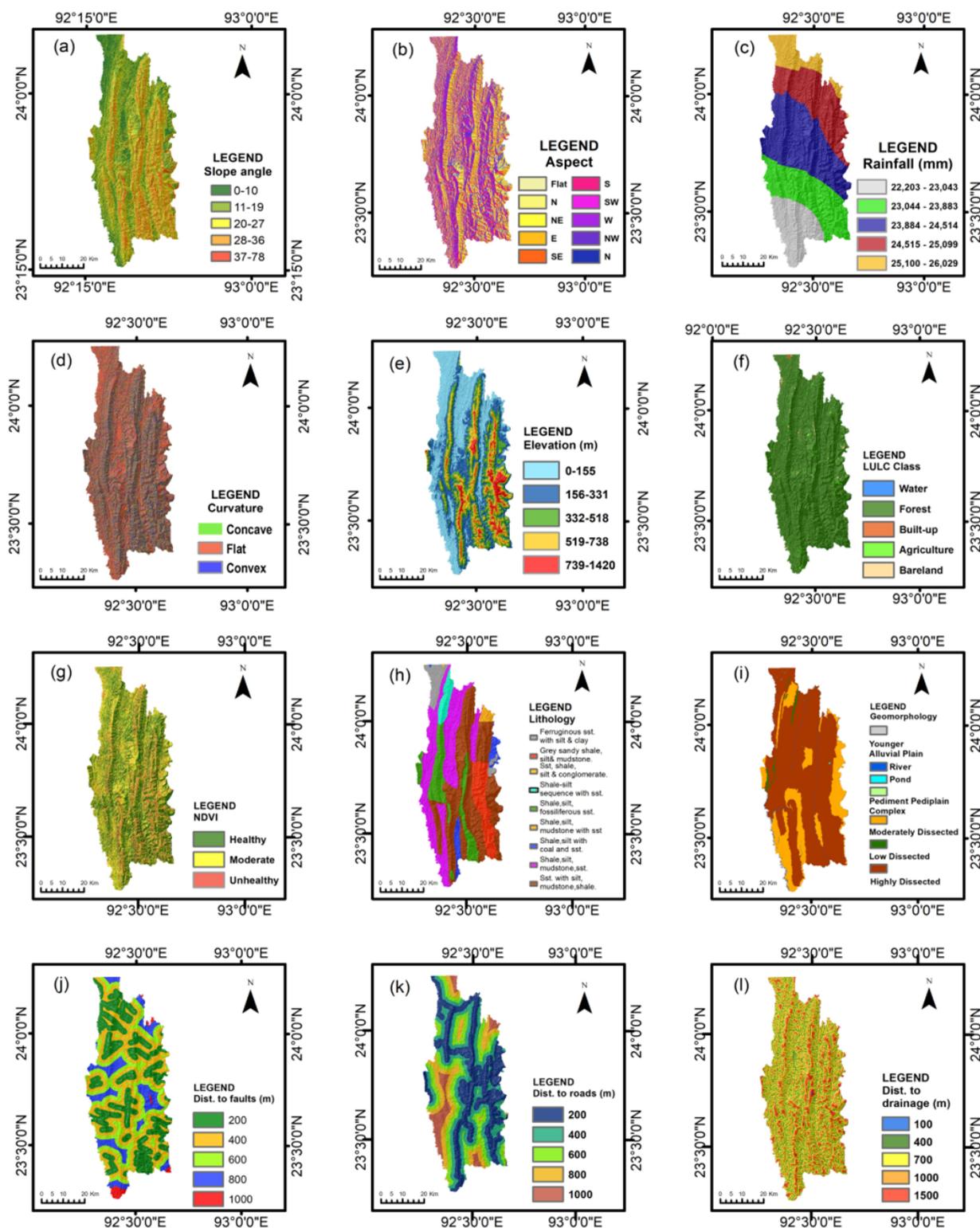


Fig 3. Thematic maps of landslide inducing factors, (a) slope, (b) aspect, (c) rainfall, (d) curvature, (e) elevation, (f) LULC, (g) NDVI, (h) lithology, (i) geomorphology, (j) distance to fault, (k) distance to roads and (l) distance to drainage

2.3.2. Calculation of Factor Criteria Weights (CW)

Using a pairwise comparison matrix, the AHP method calculates the relative weights of each factor^(4,5,7). The CW for each factor was calculated using the equation:

$$CW = \frac{\text{Sum of factors}}{\text{Total number of factors}} \tag{2}$$

This calculation, as shown in Table 3, provides normalised weights that reflect the relative importance of each conditioning factor^(2,5). Modern-day research has shown that proper weight determination is crucial for accurate landslide susceptibility mapping, as it directly influences the final susceptibility classification^(2,4,16). The pairwise comparison and weights of each sub-factor class are also given in Table 4.

Table 3. Normalised pairwise comparison with Criteria Weights (CW)

Factors	Slope	Elevation	Aspect	Curvature	Rainfall	LULC	NDVI	Lithology	Geomorphology	Dist. to Fault	Dist. to Roads	Dist. to drainage	Sum	Criteria Weights	Criteria weight %
Slope	0.11	0.07	0.11	0.08	0.06	0.17	0.12	0.37	0.21	0.15	0.15	0.15	1.75	0.15	15
Elevation	0.11	0.07	0.11	0.11	0.06	0.11	0.08	0.06	0.04	0.05	0.05	0.05	0.91	0.08	8
Aspect	0.04	0.02	0.04	0.04	0.06	0.02	0.01	0.04	0.02	0.05	0.05	0.05	0.45	0.04	4
Curvature	0.06	0.02	0.04	0.04	0.06	0.02	0.04	0.04	0.02	0.02	0.02	0.02	0.39	0.03	3
Rainfall	0.34	0.22	0.11	0.11	0.18	0.17	0.12	0.12	0.21	0.15	0.15	0.15	2.04	0.17	17
LULC	0.04	0.04	0.11	0.11	0.06	0.06	0.08	0.04	0.07	0.1	0.1	0.1	0.91	0.08	8
NDVI	0.04	0.04	0.11	0.04	0.06	0.03	0.04	0.04	0.02	0.02	0.02	0.02	0.46	0.04	4
Lithology	0.04	0.15	0.11	0.11	0.18	0.17	0.12	0.12	0.21	0.15	0.15	0.15	1.67	0.14	14
Geomorphology	0.04	0.15	0.11	0.11	0.06	0.06	0.12	0.04	0.07	0.15	0.15	0.15	1.21	0.1	10
Dist. to Faults	0.04	0.07	0.04	0.11	0.06	0.03	0.12	0.04	0.02	0.05	0.05	0.05	0.69	0.06	6
Dist. to Roads	0.11	0.07	0.11	0.01	0.09	0.17	0.01	0.04	0.07	0.05	0.05	0.05	0.84	0.07	7
Dist. to drainage	0.04	0.07	0.04	0.11	0.06	0.03	0.12	0.04	0.02	0.05	0.05	0.05	0.69	0.06	6
													12	1	100

Table 4. Pairwise Comparison and Weights of Sub-Factor Classes

Sub-Factors	1	2	3	4	5	6	7	8	9	10	Wi
Slope (Degree)											
0° - 10°	1	1/4	1/6	1/7	1/8						0.03
11° - 19°	4	1	1/3	1/4	1/5						0.07
20° - 27°	6	3	1	1/2	1/3						0.16
28° - 36°	7	4	2	1	1/2						0.28
37° - 78°	8	5	3	2	1						0.46
	CI	0.03	RI	1.12	CR	0.03					
Elevation (m)											
0 - 155	1	1/2	1/3	1/4	1/5						0.09
156 - 331	2	1	1/2	1/3	1/4						0.12

Continued on next page

Table 4 continued

332 - 518	3	2	1	1/2	1/3							0.2
519 - 738	4	3	2	1	1/2							0.29
739 - 1420	5	4	3	2	1							0.3
	CI	0.04	RI	1.12	CR	0.04						
Aspect												
Flat (-1)	1	2	3	2	1	1	1	2	3	2		0.15
North (0-22.5)	1/2	1	2	1	1/2	1/2	1/2	1	2	1		0.08
Northeast	1/3	1/2	1	1/2	1/3	1/3	1/3	1/2	1	1/2		0.04
East	1/2	1	2	1	1/2	1/2	1/2	1	2	1		0.08
Southeast	1	2	3	2	1	1	1	2	3	2		0.15
South	1	2	3	2	1	1	1	2	3	2		0.15
Southwest	1	2	3	2	1	1	1	2	3	2		0.15
West	1/2	1	2	1	1/2	1/2	1/2	1	2	1		0.08
Northwest	1/3	1/2	1	1/2	1/3	1/3	1/3	1/2	1	1/2		0.04
North (337.5-360)	1/2	1	2	1	1/2	1/2	1/2	1	2	1		0.08
	CI	0.11	RI	1.49	CR	0.07						
Curvature												
Concave	1	3	2									0.54
Flat	1/3	1	1/2									0.16
Convex	1/2	2	1									0.3
	CI	0.01	RI	0.58	CR	0.01						
Lithology												
Ferruginous Sandstone...	1	1/2	3	1/2	2	1/3	1/2	1/4	1	2		0.08
Grey Sandy Splintery...	2	1	4	1	3	1/2	1	1/3	2	3		0.12
Sandstone, Clay, Grit	1/3	1/4	1	1/5	1/2	1/7	1/4	1/8	1/3	1/2		0.02
Sandstone, Shale...	2	1	5	1	3	1/2	1	1/3	2	3		0.12
Shale, Siltstone...	1/2	1/3	2	1/3	1	1/5	1/3	1/6	1/2	1		0.04
Shale, Siltstone & Mud...	3	2	7	2	5	1	2	1/2	3	4		0.21
Shale, Siltstone with...	2	1	4	1	3	1/2	1	1/3	2	3		0.12
Shale, Siltstone, Mud...	4	3	8	3	6	2	3	1	4	5		0.29
Shale-Siltstone Seq...	1	1/2	3	1/2	2	1/3	1/2	1/4	1	2		0.08
SST with Subordinate...	1/2	1/3	2	1/3	1	1/4	1/3	1/5	1/2	1		0.04
	CI	0.01	RI	1.49	CR	0.01						
Geomorphology												
River	1	1	1/8	1/7	1/6	1/5	1/4					0.02
Pond	1	1	1/8	1/7	1/6	1/5	1/4					0.02
Highly Dissected...	8	8	1	2	3	4	5					0.35
Moderately Dissected...	7	7	1/2	1	2	3	4					0.23
Low Dissected...	6	6	1/3	1/2	1	2	3					0.15
Younger Alluvial Plain	5	5	1/4	1/3	1/2	1	2					0.1
Pediment Pediplain	4	4	1/5	1/4	1/3	1/2	1					0.07
	CI	0.01	RI	1.32	CR	0.01						
Distance to Faults (m)												
200	1	2	4	6	8							0.51
400	1/2	1	3	5	7							0.27
600	1/4	1/3	1	2	4							0.12
800	1/6	1/5	1/2	1	2							0.06
1000	1/8	1/7	1/4	1/2	1							0.04
	CI	0.03	RI	1.12	CR	0.03						
Rainfall (mm)												
22,203 - 23,043	1	1/3	1/4	1/5	1/7							0.05
23,044 - 23,883	3	1	1/2	1/3	1/5							0.1
23,884 - 24,514	4	2	1	1/2	1/3							0.18
24,515 - 25,099	5	3	2	1	1/2							0.28
25,100 - 26,029	7	5	3	2	1							0.4
	CI	0.02	RI	1.12	CR	0.02						

Continued on next page

Table 4 continued

NDVI							
Unhealthy Vegetation	1	3	5				0.64
Moderate Healthy	1/3	1	3				0.26
Healthy Vegetation	1/5	1/3	1				0.1
	CI	0.01	RI	0.58	CR	0.01	
LULC							
Water	1	1/8	1/9	1/6	1/7	0.02	1/7
Forest	8	1	1/5	3	1/3	0.15	1/3
Built-up	9	5	1	7	2	0.45	2
Agriculture	6	1/3	1/7	1	1/4	0.09	1/4
Bare land	7	3	1/2	4	1	0.29	1
	CI	0.09	RI	1.12	CR	0.08	
Distance to Roads (m)							
200	1	3	5	7	9		0.54
400	1/3	1	3	5	7		0.26
600	1/5	1/3	1	2	4		0.11
800	1/7	1/5	1/2	1	2		0.06
1000	1/9	1/7	1/4	1/2	1		0.03
	CI	0.04	RI	1.12	CR	0.04	
Distance to Drainage (m)							
100	1	3	5	7	8		0.52
400	1/3	1	3	5	6		0.25
700	1/5	1/3	1	2	3		0.11
1000	1/7	1/5	1/2	1	2		0.06
1500	1/8	1/6	1/3	1/2	1		0.05
	CI	0.03	RI	1.12	CR	0.02	

2.3.3. Consistency Ratio calculation

AHP includes a consistency index (CI) calculation to confirm the reliability of pairwise comparisons^(1,4,5). This is determined by using the following equation:

$$\begin{aligned}
 CI &= \frac{\lambda_{max} - n}{n - 1} \\
 &= \frac{12.93 - 12}{12 - 1} = 0.08
 \end{aligned}
 \tag{3}$$

Where λ_{max} is the principal eigenvalue of the pairwise comparison matrix and ‘n’ is the number of factors being compared. The consistency ratio (CR) was calculated to spot any variations in the evaluation of the weight of each pair of conditions, using the following equation:

$$\begin{aligned}
 CR &= \frac{CI}{\frac{RI}{CR}} \\
 &= \frac{0.08}{1.54}, CR = 0.05
 \end{aligned}
 \tag{4}$$

Where the consistency index is CI and RI (with a value of 1.54, when n = 12) is the random consistency index. The results of the consistency calculation are shown in Table 5. The calculated consistency ratio serves as a quality control mechanism for the analysis. Studies have consistently shown that maintaining CR < 0.1 is essential for producing credible landslide susceptibility maps^(2,5,17). In this calculation, a consistency ratio of 0.05 was obtained, which is below the acceptable limit of 0.1, showing that the analysis was consistent.

Table 5. Consistency calculations for each factor

Factors	Slope	Elevation	Aspect	Curvature	Rain-fall	LULC	NDVI	Lithology	Geomorphology	Dist. to fault	Dist. to roads	Dist. to drainage	Weighted sum value (WSV)	Criteria Weight (CW)	WSV/CW
Slope	0.14	0.08	0.12	0.07	0.06	0.24	0.12	0.28	0.19	0.18	0.18	0.18	1.82	0.14	13.15
Elevation	0.14	0.08	0.12	0.10	0.06	0.16	0.08	0.07	0.05	0.06	0.06	0.06	1.03	0.08	13.06
Aspect	0.05	0.03	0.04	0.03	0.06	0.03	0.01	0.05	0.03	0.06	0.06	0.06	0.50	0.04	12.85
Curvature	0.07	0.03	0.04	0.03	0.06	0.03	0.04	0.05	0.03	0.02	0.02	0.02	0.43	0.03	12.84
Rain-fall	0.42	0.24	0.12	0.10	0.18	0.24	0.12	0.14	0.28	0.18	0.18	0.18	2.36	0.18	13.18
LULC	0.05	0.04	0.12	0.10	0.06	0.08	0.08	0.05	0.09	0.12	0.12	0.12	1.02	0.08	12.92
NDVI	0.05	0.04	0.12	0.03	0.06	0.04	0.04	0.05	0.03	0.02	0.02	0.02	0.51	0.04	12.72
Lithology	0.07	0.16	0.12	0.10	0.18	0.24	0.12	0.14	0.19	0.18	0.18	0.18	1.84	0.14	13.00
Geomorphology	0.07	0.16	0.12	0.10	0.06	0.08	0.12	0.07	0.09	0.12	0.12	0.12	1.22	0.09	12.94
Dist. to faults	0.05	0.08	0.04	0.10	0.06	0.04	0.12	0.05	0.05	0.06	0.06	0.06	0.76	0.06	12.83
Dist. to roads	0.05	0.08	0.04	0.10	0.06	0.04	0.12	0.05	0.05	0.06	0.06	0.06	0.76	0.06	12.83
Dist. to drainage	0.05	0.08	0.04	0.10	0.06	0.04	0.12	0.05	0.05	0.06	0.06	0.06	0.76	0.06	12.83
SUM															155.15
													$\lambda_{max} =$	$\sum WSV/CW \div n$	12.93

2.4 Landslide Inventory and Validation Dataset

A landslide inventory of 315 geo-referenced historical events was compiled from past landslide spots collected using a handheld GPS device through extensive fieldwork. These locations were used to validate the model outputs. The susceptibility map was validated using ROC curve analysis and AUC metrics, a standard approach in susceptibility mapping studies^(1,6,12).

2.5 Landslide Susceptibility Map Generation

After obtaining the main factor weights, the process of AHP was applied on a second level to weight each of the classes in each factor. Table 4 contains the pairwise comparison matrices, weights of the sub-factor classes, and consistency tests of all the sub-factor classes. Each conditioning factor raster was multiplied by its corresponding AHP-derived weight using a raster calculator in ArcGIS 10.8. The study area Landslide Susceptibility Map was derived from the equation:

$$LSM = \sum_{i=1}^{12} W_i \times F_i \tag{5}$$

Where W_i is the weight of the i^{th} landslide conditioning factor, and F_i denotes the value of the same.

The susceptibility map of Mamit District was then reclassified into five susceptibility zones: ‘Very Low’, ‘Low’, ‘Moderate’, ‘High’, and ‘Very High’. Validation using ROC curves yielded an AUC value of 0.903, demonstrating the outstanding prediction quality of the model.

2.6 Sensitivity Analysis of Factors

The method of a map removal was used to specifically determine the effect of each factor on model prediction performance. So, factor sensitivity analysis was conducted to determine the importance of each factor by using the map removal process^(12,18,19). This was done by removing factors one by one and re-adjusting their weights. This approach allowed us to thoroughly evaluate how much each criterion mattered in the overall results, and showed the most significant factors and quantified the effect of adjusting their weights⁽¹²⁾. This approach is a well-established method to determine factor importance in geospatial modelling and has been effectively utilised in similar environmental studies within the state⁽¹⁹⁾. The resulting LSM thematic maps generated after the removal of one factor at a time are illustrated in Figure 4.

3 Results and Discussion

Twelve thematic map layers responsible for inducing landslides were generated using ArcGIS 10.8 and integrated using the Analytic Hierarchy Process to produce a composite Landslide Susceptibility Map for the Mamit District.

The AHP pairwise analysis delivered normalised weights of each factor, and the process attained a Consistency Ratio = 0.05, which is less than the accepted ratio of 0.10, which signifies that there is strong logical consistency of expert judgement input^{(3)–(5)}. Final weights ranking of the factors are as follows: rainfall (17%), slope (15%), lithology (14%), geomorphology (10%), elevation (8%), LULC (8%), distance to roads (7%), distance to faults (6%), distance to drainage (6%), aspect (4%), NDVI (4%), and curvature (3%), as shown in Table 3.

3.1 Interpretation of Factor Rankings

Rainfall emerged as the strongest factor, and this is in line with the fact that the annual average rainfall level in Mizoram is over 2,500 mm⁽⁸⁾. The importance of slope is in accordance with the regional AHP results in Kalimpong and Darjeeling^(1,3). Lithology was given a high level of importance because the region is known to possess weathered sedimentary formations, which are also recognised to correlate with slope instability in North Sikkim and surrounding regions^(3,8).

3.2 Landslide Susceptibility Zonation Map

The final LSM was reclassified by Jenks Natural Breaks into five susceptible classes, such as ‘Very Low’, ‘Low’, ‘Moderate’, ‘High’, and ‘Very High’ susceptibility areas^(3,12). This outcome reveals the good spatial match that exists between plotted high-susceptibility areas and previous landslide destinations⁽¹⁾.

The LSM was validated using a landslide inventory of 315 events determined by field observations. Out of which 70.16 percent were found in ‘High’ and ‘Very High’ zones, 22.5 percent were in ‘Moderate’, and only 7.34% were in ‘Low’ and ‘Very Low’ zones. This outcome map reveals a good spatial match that exists between plotted high-susceptibility areas and previous landslide destinations. The LSM generated using AHP model for Mamit district is shown in Figure 5, and the distribution of past landslides within each susceptibility class is shown in Table 6.

Table 6. Distribution of landslides within each susceptibility class

Susceptibility Class	Area (Sq. Km)	Area %	No. of landslide points	Landslide % in class
Very Low	80.95	2.69	0	0 %
Low	818.05	27.19	6	1.9 %
Moderate	1673.36	55.62	68	21.59 %
High	428.59	14.25	221	70.16 %
Very High	7.47	0.25	20	6.35 %

3.3 Model Validation and Comparative Performance

The AHP-derived LSM model was validated using the Receiver Operating Characteristic curve with field-derived landslide points [Figure 6]. The Area Under the Curve reached 0.903 (90.3%), classifying the model as “outstanding” in predictive performance^(1,6).

The performance of the current AHP model is superior when compared with previously published studies⁽²⁾. The AUC of this study is comparable to hybrid models such as fuzzy-AHP-ANN in the Darjeeling Himalayas, which reached about 0.91, and North Sikkim about 0.88⁽⁷⁾. Compared to the recent and peer-reviewed AHP, statistical, and machine learning models of

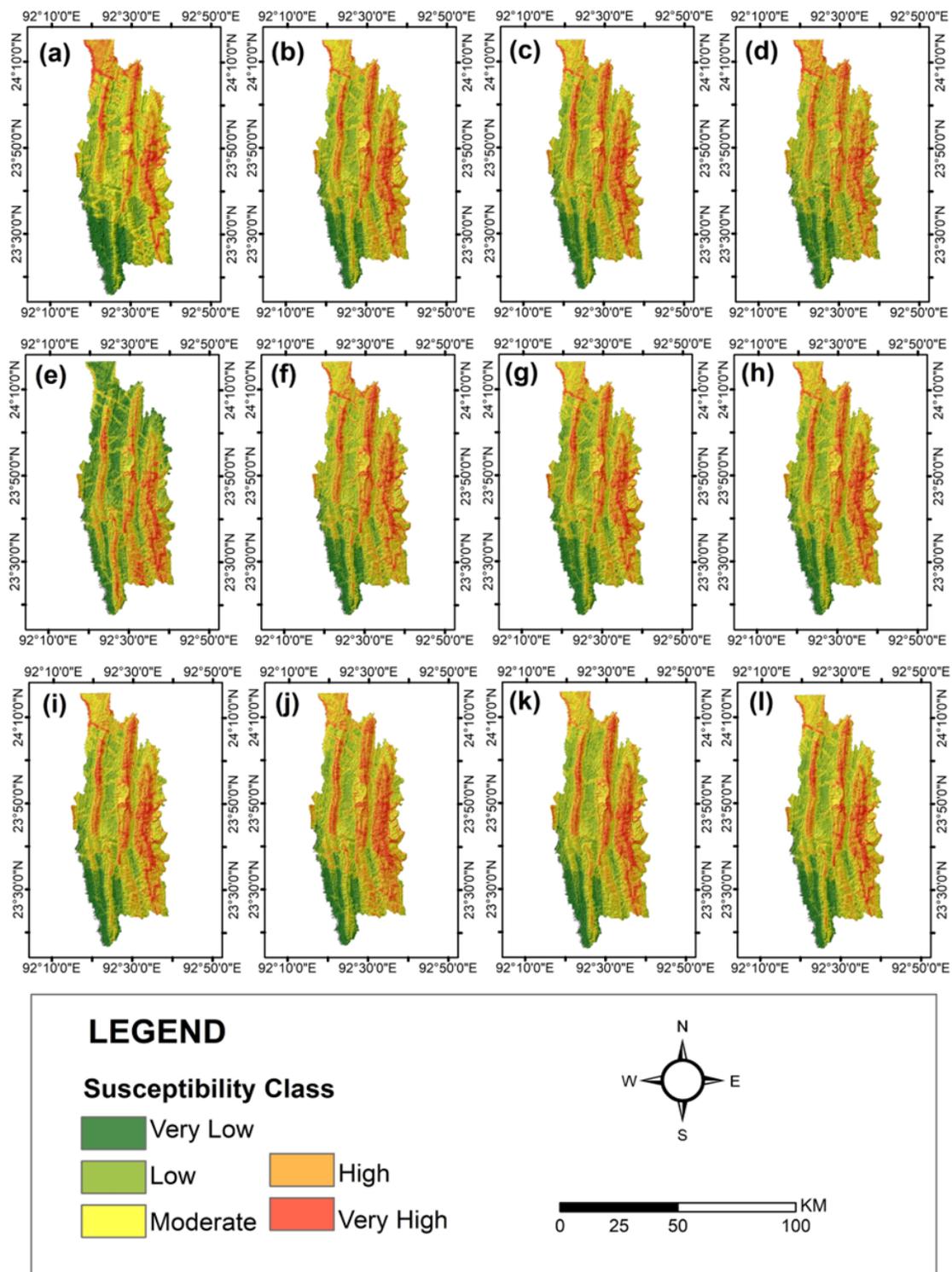


Fig 4. LSM with factors removed: (a) Slope, (b) Aspect, (c) Curvature, (d) Elevation, (e) Rainfall, (f) Lithology, (g) Geomorphology, (h) LULC, (i) NDVI, (j) Distance to roads, (k) Distance to faults and (l) Distance to drainage

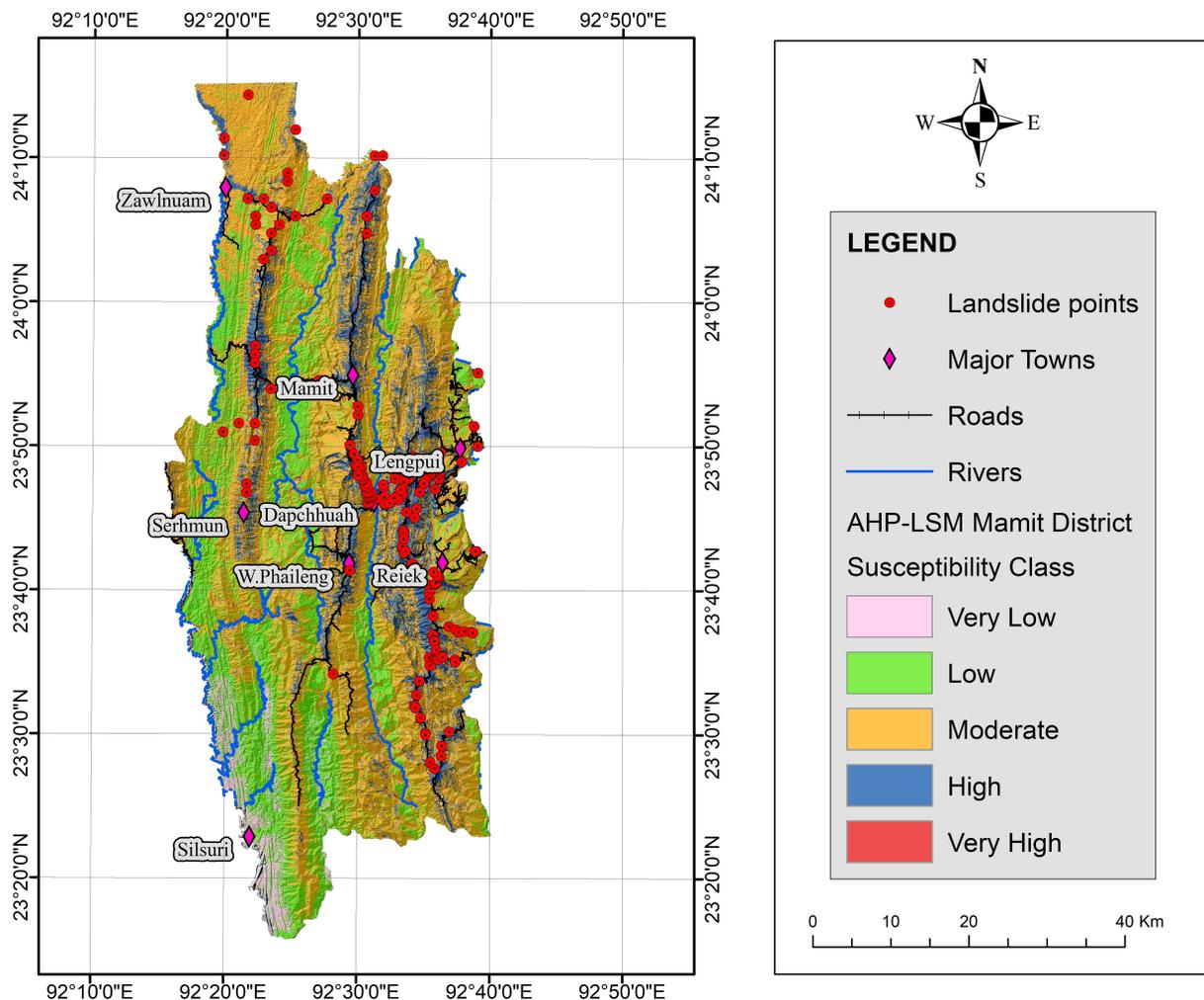


Fig 5. AHP Landslide Susceptibility Map of Mamit District

similar high-relief areas, the result was as excellent as or achieved better-ranked comparative measures, subject to the condition that model weights are strictly determined^(2,16).

3.4 Factors Sensitivity Analysis

To measure the relative significance of each landslide conditioning factor using a quantitative approach, and going beyond the expert-generated AHP weights, an extensive map removal sensitivity analysis was applied according to the well-established geospatial methods and procedures^(18,19). The outcomes of this analysis proved to be vital information over the first AHP weighting⁽¹⁹⁾. The proximity to the roads was identified as the strongest factor, pointing to its underestimated role in the occurrence of landslides^(3,18). Such unprecedented significance is the familiar reasoning behind cut-slope failures along highways of the study region, where 68 percent of landslides are found within 200m from the roads. Precipitation retained large significance, as confirmed by its large AHP value and revealing its extra-high precipitation routine to be a dominant natural trigger⁽⁸⁾ for landslides in Mizoram. Important changes in sensitivity were identified: lithology was less sensitive than would have been expected, and fault proximity was the least sensitive parameter. Anthropogenic factors were found to be more sensitive by 37 percent compared to geological factors.

Figure 7 shows the sensitivity analysis comparison chart of the removed factor and their AUC score, along with the total AHP-AUC without removing any factor. Lower AUC values mean that the removed factor has greater importance. Distance to roads is found to have the least AUC score in this map removal sensitivity analysis.

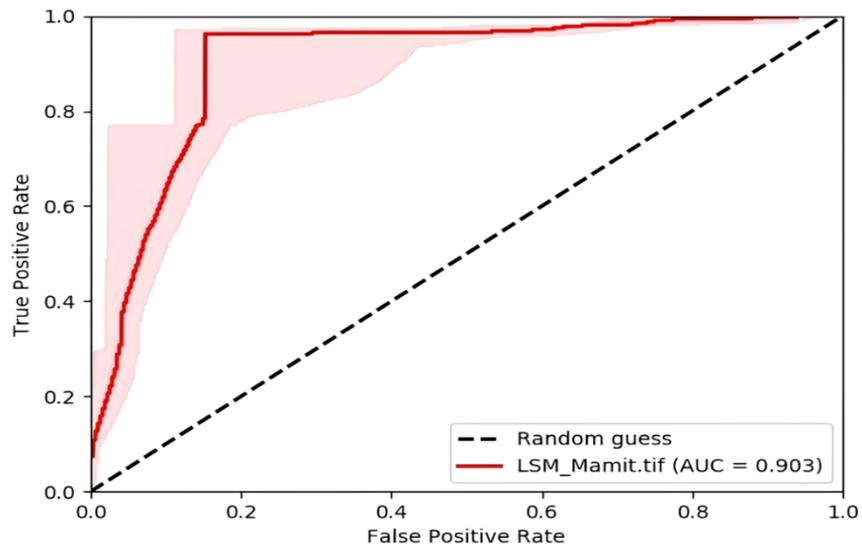


Fig 6. AHP-based ROC-AUC Curve for validation of the Landslide Susceptibility Map (LSM)

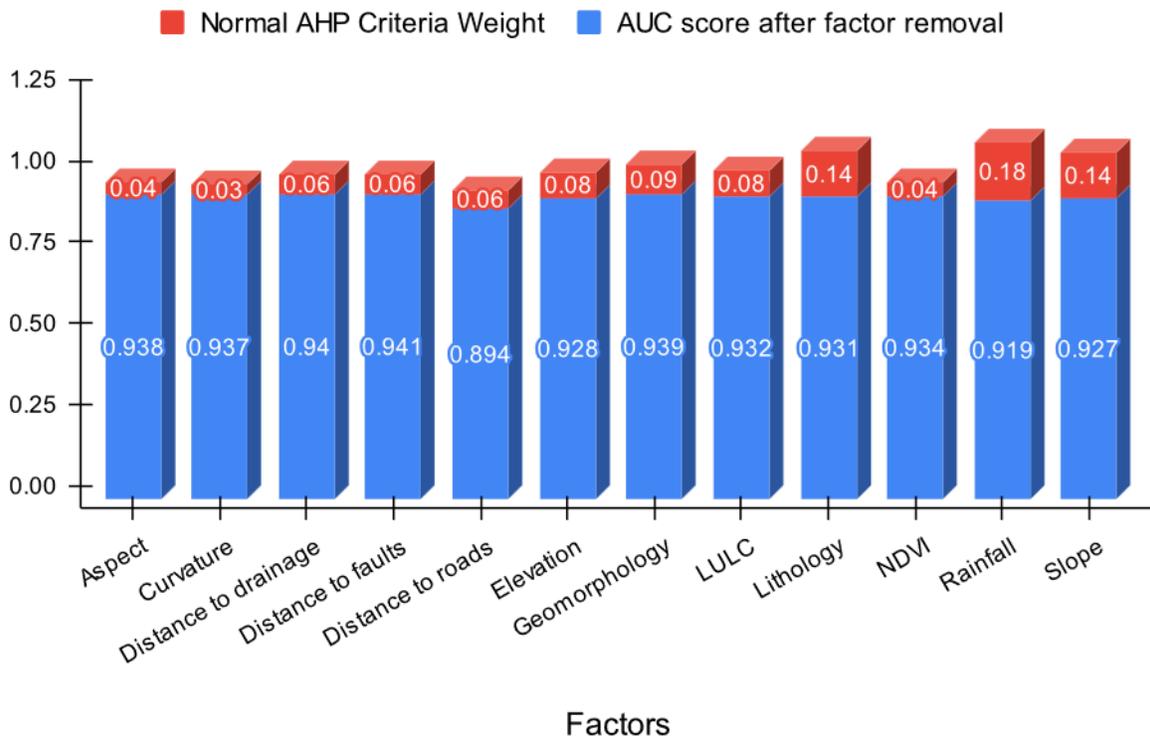


Fig 7. Map Removal Sensitivity Analysis of factors with their AUC score

4 Conclusion

By producing a calibrated AHP-GIS-based high-resolution susceptibility map for the Mamit District, this research serves to fill a gap in the limited available data on landslides in the study region and the pressing need for robust predictability analysis. The model was highly internally consistent and had good predictive performance, as compared to the performance of recent AHP, statistical, and ML-based studies in similar high-relief areas. This study achieved three major findings. Firstly, rainfall, slope, and lithology are found to be the three most important natural factors that trigger landslides, owing to the heavy monsoon regime in the state of Mizoram. Second, the model was highly applicable since approximately 70 percent of the observed landslides in the past were represented in areas of high susceptibility zones within the generated map, which was verified through geological fieldwork. Thirdly, the factor sensitivity analysis showed that proximity to the road is a major landslide-inducing factor within the study area. This is because construction of roads often destabilises slopes, which increases the likelihood of landslides, and it is highly recommended that improved road engineering and proper drainage should be prioritised in disaster management budgets.

The study also confirms that with limited resources and expert-driven AHP frameworks, one can create an accurate and effective susceptibility map comparable to machine learning models. Despite potential issues like inconsistent data for influencing factors, this study provides upfront methods for including sensitivity checks in susceptibility modelling and creating affordable risk maps, particularly for developing mountainous areas. Future research should concentrate on combining high-frequency remote sensing data for better precipitation adjustment and exploring machine learning-AHP hybrid approaches for predicting dynamic risks. This integration would lead to a better understanding of how landslide susceptibility changes over time, shifting from static susceptibility maps to those that incorporate real-time environmental changes.

4.1 Novelty and Strengths:

This study introduces several distinct advantages. An AHP framework was applied using 12 conditioning factors, while most earlier studies used seven to nine factors. Also, 315 field-verified landslide points were used for validation, a larger sample than other comparable studies. The study also incorporated a ten-year time series of spatial rainfall raster interpolation rather than static averages. No machine learning methods were used, yet the results were comparable to ML-based outputs.

These results validate the strength of a well-calibrated AHP model in complex, high-rainfall terrain, especially when consistency checks and robust validation data are used. Field-to-model agreement, ROC scores, and relative weight trends all suggest this model is highly generalizable to similar hilly terrain districts with insufficient data for observations.

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