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INTEGRATING AHP-BASED MULTI-CRITERION DECISION ANALYSIS FOR LANDSLIDE SUSCEPTIBILITY ASSESSMENT: A CASE STUDY OF BANDARBAN DISTRICT, BANGLADESH

SM Rifdu Rafee*[1], Sishir Das[2], Susmay Saha[3], Rudra Samonto Das[4], Ibrahim Hossain[5] and Hussain Muhammad Abdullah[6]

[1] *Student, Department of Civil Engineering, Mymensingh Engineering College, Bangladesh,*
e-mail: rifduabd@gmail.com
[2] *Student, Department of Civil Engineering, Mymensingh Engineering College, Bangladesh,*
e-mail: sishir05.ce@gmail.com
[3] *Student, Department of Civil Engineering, Mymensingh Engineering College, Bangladesh,*
e-mail: susmay2776@gmail.com
[4] *Student, Department of Civil Engineering, Mymensingh Engineering College, Bangladesh,*
e-mail: rudrasamonto@gmail.com
[5] *Student, Department of Civil Engineering, Mymensingh Engineering College, Bangladesh,*
e-mail: hossainibrahim357@gmail.com
[6] *Student, Department of Civil Engineering, Mymensingh Engineering College, Bangladesh,*
e-mail: hmabdullah6670@gmail.com

***Corresponding Author**

ABSTRACT

Landslides are a major geoenvironmental threat in the hilly areas of southern Bangladesh, especially in Bandarban District. Deforestation, frequent hill cutting for urbanization, and heavy monsoon rainfall are some of the factors that increase ground instability in this region. As the landslide risk in Bandarban is complex, this study used a holistic approach. It combined the Analytic Hierarchy Process (AHP) with Geographic Information Systems (GIS) to assess and map landslide susceptibility in Bandarban. Nine landslide triggering factors, including slope, elevation, rainfall, land use/land cover, vegetation, lithology, and proximity to drainage, faultlines, and roads, were identified based on expert opinions and previous research. AHP was used to assign weights through pairwise comparison, and consistency ratio (CR) was checked to ensure the assigned weights were reliable. Then the weighted thematic layers were integrated using the GIS overlay method to generate a Landslide Susceptibility Map (LSM). Each parameter was mapped as a spatially distributed map from remote sensing data (ASTER GDEM, Sentinel 2), secondary sources, and field information using ArcGIS PRO software. The susceptibility map was classified into five categories: Very Low, Low, Moderate, High, and Very High. The results showed that most of the districts fall under very low (14.03%), low (26.67%), and moderate (27.73%) susceptibility zones, while high (22.43%) and very high (9.13%) zones are concentrated along steep slopes, faulted lithological units, and densely drained areas, indicating the critical risk areas. The model was validated using the Area Under the Curve (AUC) technique with landslide inventory data and achieved 89% accuracy, which shows the robustness of the AHP-based approach in delineating hazard-prone areas. This study presents a comprehensive susceptibility assessment that can be used as a scientific basis for regional planning, slope management, and catastrophe risk reduction in Bandarban, Bangladesh. Policymakers, engineers, and local authorities can use the results of mapping and identifying landslide-prone areas to prioritize infrastructure development, community awareness programs, and mitigation measures to reduce landslide risk and improve resilience in one of Bangladesh's most hazard-prone hill districts.

Keywords: *Bandarban district, Landslide Susceptibility, Remote sensing, AHP, ARCGIS Pro*

1. INTRODUCTION

Landslides refer to the downslope movement of rock, soil, or debris, which is caused by gravitational forces. Such movements can be flowing, sliding, toppling, falling, or spreading, and many of them exhibit compound behavior simultaneously or sequentially (Gariano & Guzzetti, 2016). This phenomenon may lead to serious loss of life and large-scale destruction of infrastructure and ecosystems, especially in mountainous locations. Landslides are one of the most harmful natural hazards in Bangladesh, particularly in the southeastern uplands, where communities living in the hilly terrain are constantly affected (Alam & Ray-Bennett, 2021). The Chattogram Hill Tracts (CHT) primarily consist of three southeastern districts: Rangamati, Khagrachhari, and Bandarban. Within the CHT, Bandarban District is widely regarded as a highly landslide-prone district (LPD) owing to its monsoon-dominated hydro-geomorphic setting and slope-destabilizing anthropogenic activities (e.g., hill cutting, construction, and road excavation) (Khatun et al., 2022). Physiographically, Bandarban lies within the fold-and-thrust belt of the outer Indo–Burman ranges near the Myanmar border (Hossain et al., 2024); the terrain is steep and deeply dissected, with local relief exceeding 900 m. Major rivers, including the Sangu and Matamuhuri, drain the hill country toward the Bay of Bengal. Bedrock comprises predominantly sandstones and shales that are variably indurated and strongly folded. Bandarban's climate is humid tropical, with heavy monsoon rainfall and a mild dry season; mean annual rainfall commonly ranges from 3,000 to 3,500 mm. Seasonal downpours frequently trigger landslides and floods and shape agricultural practices. A substantial share of the population resides on steep hillslopes, and hillside settlements, swidden (jhum) cultivation, and informal earthworks for housing and access roads locally alter slope stability (Rasul et al., 2004). Over the past two decades, Bandarban and its upazilas have experienced landslides, resulting in numerous fatalities and injuries. During this period, the district was the most affected among landslide-prone areas, with a total of 91 fatalities; it was reported that 53 fatalities occurred in 2010 alone (Sultana, 2020). Beyond the human toll, roads, telecommunications, electricity infrastructure, and environmental resources have been repeatedly damaged, underscoring the urgent need for preventive measures.

Landslide susceptibility mapping (LSM) supports risk reduction by estimating the relative likelihood of landslide occurrence from conditioning factors such as slope, lithology, land cover/vegetation, rainfall, and proximity to anthropogenic disturbance. In Bangladesh and the CHT, LSM has been developed using bivariate statistics (e.g., Frequency Ratio, Weight of Evidence), multivariable statistical models (e.g., logistic regression), knowledge-driven multi-criteria decision-making approaches (e.g., AHP and fuzzy logic), machine-learning algorithms (e.g., Random Forest, SVM, ANN, boosting), and hybrid ensembles; among these, the Frequency Ratio method is widely used and often shows strong performance in case studies (Chowdhury, 2023). However, in Bandarban, district-scale susceptibility evidence remains limited and several applications rely on older or inconsistent input datasets, while advanced machine-learning approaches often require extensive inventories and ancillary data that may not be consistently available across the district (Sultana et al., 2025; Ullah, 2024). Therefore, this study develops a district-scale landslide susceptibility zonation for Bandarban using an AHP–GIS framework in ArcGIS Pro and validates the resulting map using an independent landslide inventory, alongside upazila-level susceptibility summaries to inform planning and mitigation. Compared with prior Bandarban studies, this work emphasizes updated and harmonized inputs and a focused set of nine key conditioning factors with an internally consistent weighting scheme (CR = 0.027); to the best of our knowledge, published Bandarban LSM studies have not integrated Sentinel-2 (2025)–derived vegetation/land-cover information, updated 2025 road information and a CHIRPS rainfall record through 2024 within a single AHP-based district-wide workflow. The study further evaluates model performance using ROC–AUC and provides upazila-wise susceptibility statistics to support land-use planning, corridor management, and slope-risk prioritization.

2. STUDY AREA

The study area, Bandarban District, lies in the southeastern Chittagong Hill Tracts of Bangladesh (21°11′–22°22′ N, 92°04′–92°41′ E), covering about 4,479 km² (Nahar et al., 2020). It features rugged hills with elevations ranging from below 10 m to over 1,000 m, including Tazing Dong, the country's highest peak. The region experiences a humid tropical monsoon climate with over 3,000 mm of annual rainfall, making it highly prone to landslides. The geology comprises sandstone, shale, and siltstone, while land use includes hill forests, agriculture, and settlements. The Sangu River and the Matamuhuri River flow through this district. The majority of the tribal people of Bangladesh live in this region. The district's seven upazila**s** collectively form the spatial boundary for the susceptibility analysis.

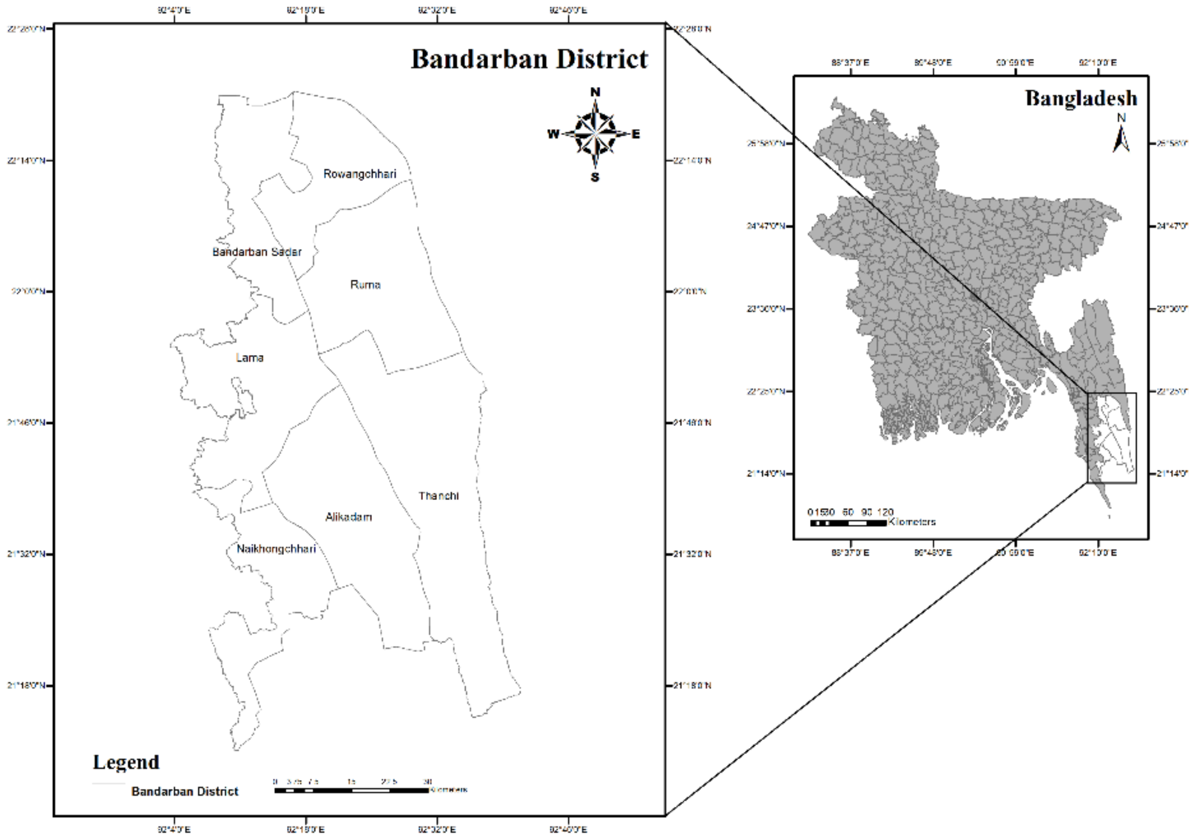

Figure 1: Study Area Map for Bandarban District

3. MATERIALS AND METHODS

3.1 Data Acquisition and Preparation Techniques

The datasets used in this study were obtained from freely available global and national sources (Table 1) and prepared to create a consistent spatial database for the AHP-based landslide susceptibility assessment of Bandarban District. The selection of conditioning factors was guided by a comprehensive review of landslide susceptibility studies conducted in Bangladesh and comparable monsoon-dominated hill regions. Factors such as slope, rainfall, lithology, and LULC are consistently identified as primary controls on landslide occurrence in the Chattogram Hill Tracts. Additional proximity-based factors (distance to roads, streams, and faults) were included to capture anthropogenic disturbance and structural controls. NDVI was incorporated as a proxy for vegetation cover and slope protection. Factors such as soil depth and seismicity were excluded due to the absence of reliable spatial datasets at the district scale. Pairwise comparisons were conducted based on expert judgment from civil engineering and geomorphology backgrounds, supported by relative importance reported in previous peer-reviewed landslide susceptibility studies conducted in Bangladesh and South Asia. Based on this process, nine conditioning factors (elevation, slope, lithology, distance to streams, distance to faults, distance to roads, LULC, rainfall, and NDVI) were selected for the final model, as shown in Fig. 3. All layers were reprojected to WGS-84 and WGS-84 Web Mercator as required, resampled to a common 30 m grid, vector features were converted to Euclidean distance rasters, continuous variables were normalized, and categorical layers reclassified into ordered susceptibility classes following literature thresholds and local geomorphic judgement. These processed, harmonized layers were then used as inputs to the AHP weighting and subsequent susceptibility mapping.

Table 1: Datasets used in the study

Data Type	Description	Time	Resolution	Source
Elevation	ASTER GDEM V003	2013	30m	https://search.earthdata.nasa.gov/
Slope	ASTER GDEM V003	2013	30m	https://search.earthdata.nasa.gov/
Distance to Streams	ASTER GDEM V003	2013	30m	https://search.earthdata.nasa.gov/
Rainfall	Annual Rainfall from CHIRPS	2014 - 2024	0.05˚	https://data.chc.ucsb.edu/products/CHIRPS/v3.0/
Lithology	Polygon shape file format		1:1,000,000	https://certmapper.cr.usgs.gov/data/apps/world-maps/
Distance to Faults	Polyline shape file format		1:5,000,000	https://certmapper.cr.usgs.gov/data/apps/world-maps/
LULC	Sentinel-2A Imagery	2025	10 m	https://browser.dataspace.copernicus.eu/
NDVI	Sentinel-2A Imagery	2025	10 m	https://browser.dataspace.copernicus.eu/
Distance to Roads	Line shape file format	2025		https://www.openstreetmap.org/

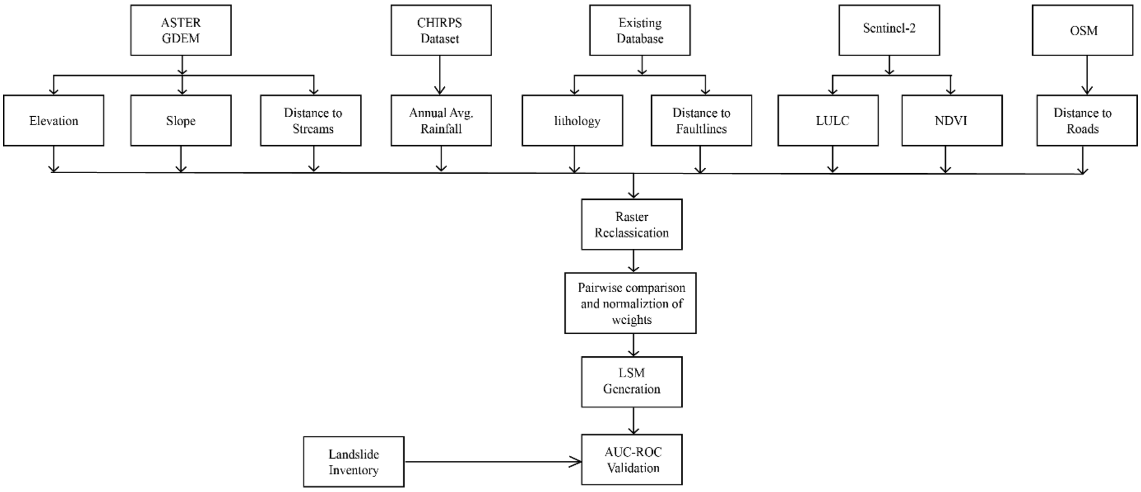

Figure 2: Methodological Workflow

3.2 Analytic Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP) is a decision-making method used to rank various variables based on their relative importance within a specific phenomenon (Şener et al., 2010). This method involves assigning relative importance to each factor through pairwise comparisons in a hierarchical structure, relying on expert knowledge and judgment. It serves as an effective tool for determining the level of significance each factor contributes to landslide susceptibility and for ranking them accordingly. In this study, nine factors were selected as contributing variables, leading to the creation of a 9x9 comparison matrix. Each factor was compared using Saaty's (Saaty, 1990) scale (1-9), as outlined in Table 2, to construct this matrix. Once the pairwise comparison matrix was established, the weights of each factor were determined by normalizing the matrix (Muralitharan & Palanivel, 2015; Roy et al., 2021). This normalization process involves dividing each element by the sum of its respective column, resulting in a normalized matrix. The relative weights were then calculated by averaging the values across each row of the normalized matrix. To validate the consistency of the weights, the eigenvector, consistency ratio (CR), and consistency index (CI) were calculated. The maximum eigenvalue (λ_{max}) was computed as the average of the eigenvalues. The consistency index (CI) and consistency ratio (CR) were calculated using the formulas presented in equations (1) and (2).

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{1}$$

$$CR = \frac{CI}{RI} \tag{2}$$

Here, n is the number of factors and RI is the Random Index value which is obtained from the following table.

Table 2: Saaty's Importance Scale and Random Consistency Index

Importance of Intensity (1-9)	1	2	3	4	5	6	7	8	9
Definition	Equal	Weak	Moderate	Moderate Plus	Strong	Strong Plus	Very Strong	Very Very Strong	Extreme
Selected Parameter Number (n)	1	2	3	4	5	6	7	8	9
R.I. value	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

If the CR is less than 0.1, the pairwise comparisons are considered logical and acceptable. If it exceeds 0.1, the matrix is deemed inconsistent and must be adjusted. In this study, the CR values were all below 0.1, ensuring the reliability of the factor prioritization and the resulting landslide susceptibility map.

3.3 Modelling of Landslide Susceptibility Map

The landslide susceptibility model for the Bandarban District was developed as a raster-based, multi-criteria workflow integrating thematic factors with Analytic Hierarchy Process (AHP) weighting. First, heterogeneous datasets were assembled: ASTER GDEM for terrain; CHIRPS gridded rainfall for long-term precipitation; Sentinel-2 optical imagery for land surface characteristics; lithology and fault traces from national geologic compilations; road networks from OpenStreetMap; and a georeferenced landslide inventory for independent validation. DEM tiles were mosaicked and hydrologically conditioned to derive flow direction and flow accumulation, from which the drainage network was vectorized and converted to a continuous Euclidean-distance surface (distance to streams). Standard terrain derivatives—elevation and slope—were computed from the DEM. Sentinel-2 images were composited to minimize cloud contamination; two products were then generated: (i) a supervised land-use/land-cover (LULC) map (trained with representative samples and assessed for basic accuracy), and (ii) the Normalized Difference Vegetation Index (NDVI) from bands 8 and 4. Geologic layers were clipped to the study extent to yield lithology classes and a Euclidean-distance raster to mapped fault lines, and the OSM network was similarly processed to obtain distance to roads. CHIRPS yearly records from 2014 to 2024 were aggregated to multi-year annual means to represent average precipitation. Each factor was harmonized to a common spatial resolution and projection, and then reclassified to ordinal susceptibility ranks (1–5 from very low to very high) using natural break or data-driven breakpoints suited to local distributions. Factor importance was elicited with AHP: a pairwise comparison matrix (Saaty 1–9 scale) was constructed across all criteria; the principal eigenvector provided normalized weights and the consistency ratio (CR) was checked to be acceptable ($CR < 0.10$) before proceeding. The Landslide Susceptibility Map (LSM) was produced via weighted overlay of the standardized rasters, followed by rescaling and cartographic classification into susceptibility zones (very low to very high). Model performance was evaluated using threshold-independent AUC-ROC analysis, using landslide inventory points as positive and randomly sampled non-landslide points as negative; AUC gave an overall measure of performance and guided sensitivity checks on factor weights or class thresholds. The resulting Landslide Susceptibility Map (LSM) shows the spatial distribution of hazard and helps to prioritize risk reduction in Bandarban.

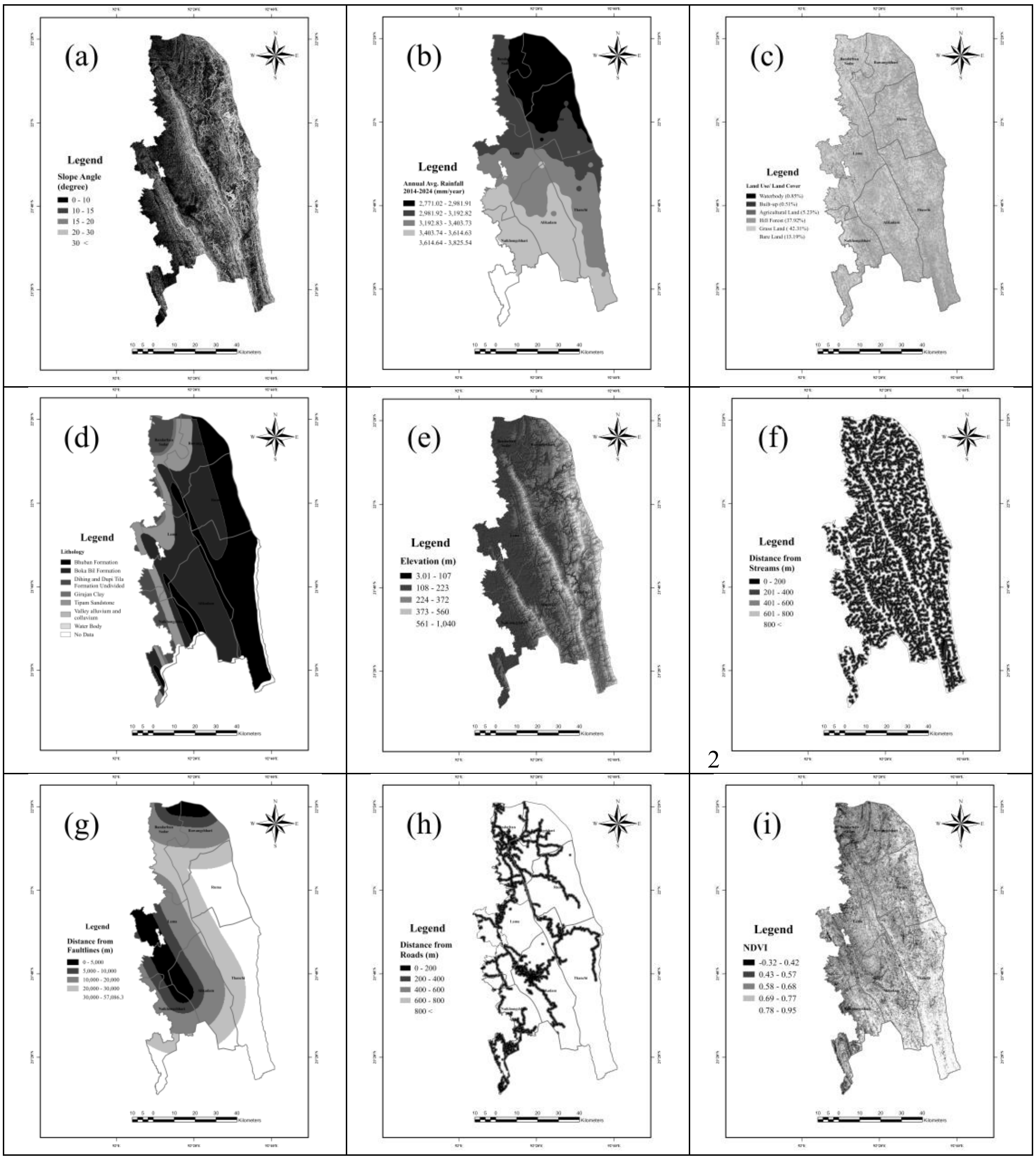

Figure 3: Landslide Conditioning Factors - (a) Slope, (b) Rainfall, (c) LULC, (d) Lithology, (e) Elevation, (f) Distance from Streams, (g) Distance from Faultlines, (h) Distance from Roads, (i) NDVI

4. RESULTS AND DISCUSSIONS

4.1 Factor Weighting

The decision-making process has been consistent, with a Consistency Ratio (CR) value of less than 0.1 (CR = 0.027). The most dominant factor identified was slope, accounting for 26.91%. This suggests that landslides predominantly occur in steep, rugged areas where shear stress is high and colluvial stability is low. During the monsoon season, Bandarban experiences frequent, prolonged rainfall, leading to massive floods accompanied by landslides. Rainfall, contributing 18.70%, is the second most significant trigger, highlighting the practical implications of this climatic phenomenon. The geology of Bandarban comprises weakly cemented, interbedded sandstones and siltstones, which further contribute to the region's susceptibility to landslides. Human activities, such as hill cutting, road construction, and building development, compromise natural slope stability, making these areas more vulnerable to landslides. The high weight assigned to lithology (12.33%) and Land Use/Land Cover (LULC) (14.02%) underscores the role of these factors in exacerbating the situation. Landslide-prone areas are typically characterized by high elevation and steep slopes. However, many failures are concentrated at lower to mid-elevations along valley flanks and road corridors, while some high-elevation areas remain relatively stable, particularly those covered by dense forest and experiencing minimal disturbance. This is why elevation (10.79%) holds medium importance, despite its association with slope angle. Other factors, while still significant, are secondary in comparison to these primary elements according to the analysis.

Table 3: Weightage of Landslide Susceptibility Factors

	SL	**RF**	**LULC**	**LG**	**ELV**	**DS**	**DF**	**DR**	**NDVI**	**Weight (%)**
SL	1	2	3	3	2	4	5	6	9	26.91
RF	1/2	1	2	2	1	3	5	6	8	18.70
LULC	1/3	1/2	1	2	1	2	4	5	7	14.02
LG	1/3	1/2	1/2	1	2	2	3	4	6	12.33
ELV	1/2	1	1	1/2	1	1	2	3	5	10.79
DS	1/4	1/3	1/2	1/2	1	1	1	2	4	6.92
DF	1/5	1/5	1/4	1/3	1/2	1	1	1	3	4.74
DR	1/6	1/6	1/5	1/4	1/3	1/2	1	1	2	3.57
NDVI	1/9	1/8	1/7	1/6	1/5	1/4	1/3	1/2	1	2.02
Maximum eigenvalue (λmax) = 9.31, CI = 0.039, n = 9, RI = 1.45, CR = 0.027										

Here, SL= Slope, RF= Rainfall, LULC= Land Use Land Cover, LG= lithology, ELV= Elevation, DS= Distance from Streams, DF= Distance from Faultlines, DR= Distance from Roads, NDVI= Normalized Difference Vegetation Index, CI= Consistency Index, RI= Random Index, CR= Consistency Ratio.

4.2 District-wide Spatial Distribution

Bandarban District is divided into five susceptibility classes: very low, low, medium, high, and very high. Very low susceptibility covers 14.04% of the district (750.13 km²), which are stable, flat areas or well-managed slopes and are the least prone to landslides. Low susceptibility, which is 26.67% (1425 km²), includes areas with relatively stable terrain, gentle slopes, and less rainfall impact, and is less vulnerable to landslides. A big portion, 27.73% (1481.77 km²), falls under medium susceptibility, where moderate slopes and rainfall contribute to a moderate risk of landslide. These areas are in balance between stability and vulnerability, and a landslide can occur under heavy rainfall. High susceptibility class, which covers 22.43% of the district (1198.77 km²), includes areas with steeper slopes and higher rainfall and are more prone to landslides, especially during the monsoon. And a very high susceptibility class, which is only 9.13% (487.91 km²) of the district, includes the most vulnerable areas, typically found in steep gradients and poor soil stability, where landslides can occur. The analysis shows that Bandarban's mountainous terrain and seasonal rainfall drive the susceptibility to landslides, and a large portion of the district is of moderate to high susceptibility.

Table 4: District-wide Susceptibility Distribution

Landslide Susceptibility Category	**Area (km^2)**	**Percentage (%)**
Very Low	750.13	14.04
Low	1425.00	26.67
Medium	1481.77	27.73
High	1198.77	22.43
Very High	487.91	9.13

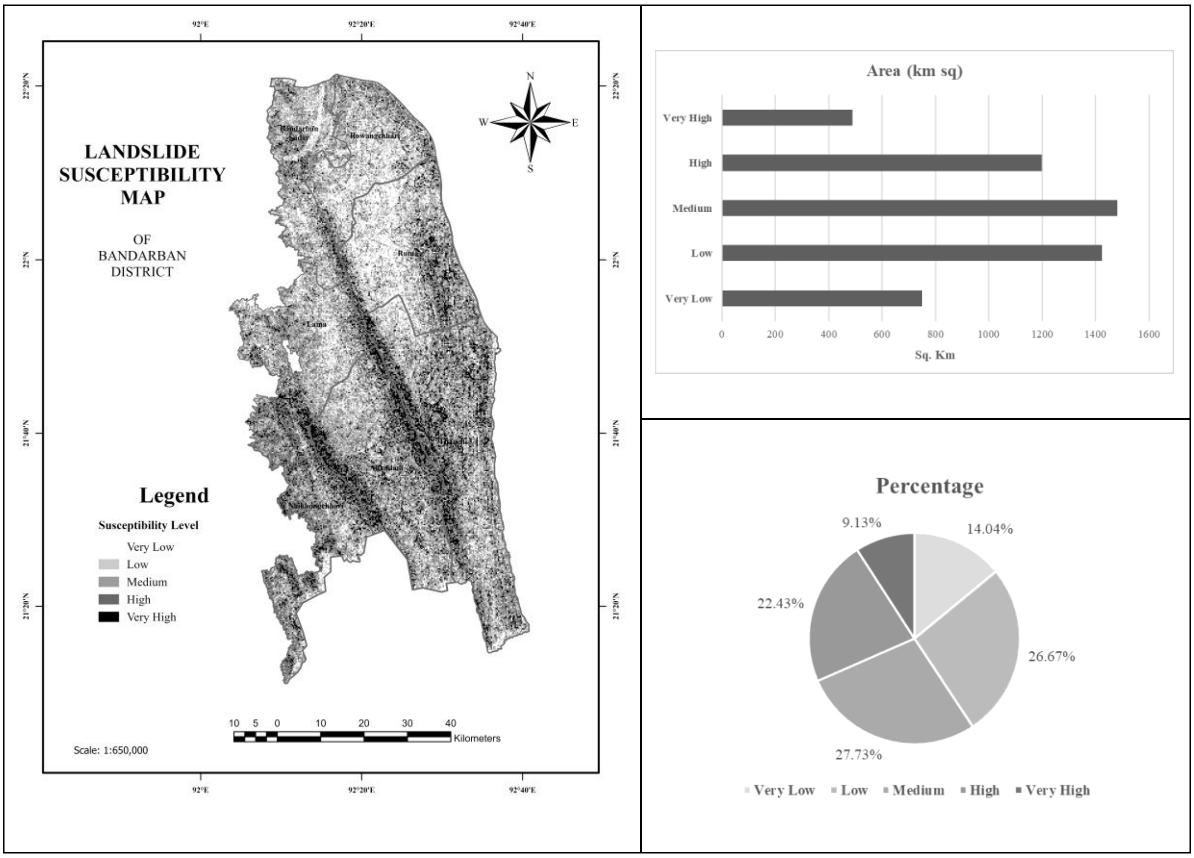

Figure 4: Landslide Susceptibility Map of Bandarban District with Area and Percentage

4.3 Upazila-Scale Susceptibility Patterns

Upazila-scale analysis reveals marked spatial heterogeneity across Bandarban. The southwestern pair Naikhongchhari and Lama emerge as the principal hotspots: in Naikhongchhari, high and very high classes together occupy 75% of the upazila (193.8 and 216.5 km², respectively), with negligible very low–low coverage (5.3%). Lama shows a similar skew, with 279.9 km² classified as high and 212.9 km² as very high, totalling 65.6% of its area. Bandarban Sadar also concentrates risk, with 39.8% high and 15.4% very high (206.8 and 80.3 km²), yielding a combined 55.2%. Ruma is more balanced: medium and high dominate (34.7% and 30.4%), very high reaches 10.7%, and the combined high–very high extent is 374.0 km² (41.2%). Thanchi represents a transitional zone where medium susceptibility is most prevalent (35.3%; 199.0 km²), and only 5.5% falls in very high. In contrast, the eastern highland upazilas, Rowangchhari and Alikadam, are largely low to very low: Rowangchhari records 53.4% in the two lowest classes and only 1.9% very high (23.7 km²), while Alikadam has 68.8% low to very low and an almost negligible very high share (0.32%; 2.6 km²). The prevalence of medium to very high susceptibility along the south–southwestern corridor (Lama–Naikhongchhari–Bandarban Sadar) likely reflects steeper dissected slopes, road cuts and settlements along transport corridors, and extensive land-use modification, whereas the lower susceptibility in Rowangchhari - Alikadam is consistent with larger tracts of intact forest and lower anthropogenic disturbance. Overall, these patterns delineate priority upazilas for mitigation, with Naikhongchhari and Lama warranting immediate attention, Sadar and Ruma requiring targeted slope management, and Thanchi functioning as an important buffer where prevention can still avert escalation. Across the district, the “medium” class forms a continuous belt, accounting for roughly 24–35% in most upazilas (199–371 km²), typically coinciding with mid-slope agricultural mosaics, plantation, and secondary forest edges where site-specific triggers can tip slopes to failure.

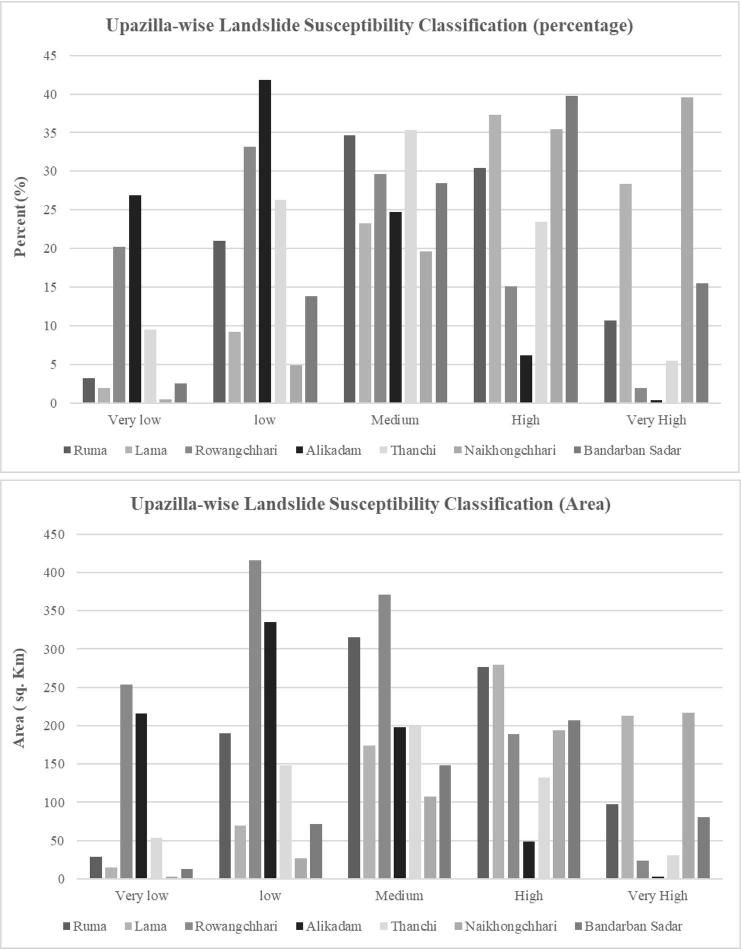

Figure 5: Upazila-wise Landslide Variability Distribution (Area and percentage)

4.4 Model Validation

For model validation, 118 landslide inventory points were used as positive samples, and an equal number of randomly generated non-landslide points were selected from areas outside the mapped landslide locations. The Receiver Operating Characteristic (ROC) – Area Under the Curve (AUC) method was applied to evaluate the model’s discriminative performance independently of classification thresholds. The AHP-based landslide susceptibility map was statistically validated using the ArcSDM tool in ArcGIS Pro, which compares landslide-prone and non-landslide-prone locations against the susceptibility output. Figure 6 shows the ROC curve and AUC for the AHP result. AUC can evaluate the accuracy of the model's output (Darabi et al., 2022). The higher the AUC value, the more accurate the model and vice versa. An AUC value less than or equal to 0.5 means the model is not suitable for the study, while an AUC value close to 1 means the ideal model with maximum accuracy (Youssef et al., 2015). The AHP method achieved an accuracy of 0.89 (89%), indicating that the model effectively generated the LSM and can be considered successful.

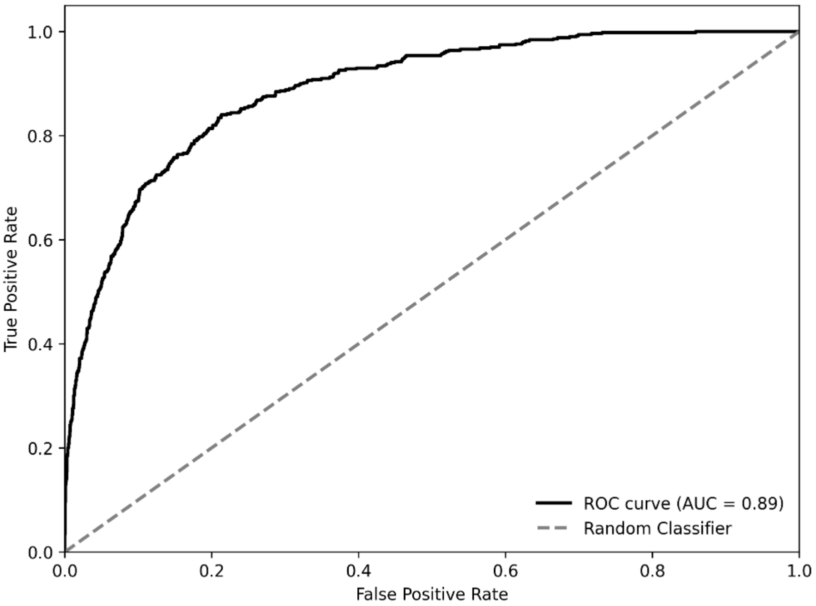

Figure 6: ROC-AUC Validation

5. CONCLUSIONS

This study demonstrates that an AHP–GIS framework can generate a district-scale landslide susceptibility map for Bandarban with strong discrimination against the landslide inventory (ROC–AUC~ 0.89). Consistent with previous landslide studies in the CHT and similar monsoon-mountain settings, the results identify slope and rainfall as the most influential controls, and the final zonation indicates low–moderate susceptibility across much of the district while high–very high hotspots cluster on steep terrain and in specific upazilas (notably toward the southwest). However, the outputs are subject to important limitations and uncertainties: the 30 m ASTER GDEM may smooth micro-topography that governs local failures; CHIRPS rainfall may not capture localized extreme events; AHP weighting involves some subjectivity despite consistency checks; and the validation inventory may be incomplete in remote areas. In addition, the analysis relies on secondary datasets and lacks real-time or long-term monitoring, so the susceptibility model is static and cannot represent temporal changes or short-term triggers. Accordingly, the map should be interpreted as a relative susceptibility product for screening and prioritization rather than deterministic prediction. Practically, the identified hotspot zones can support land-use zoning (e.g., limiting new hillside construction in high-susceptibility belts), prioritize slope stabilization and drainage management along road cuts and expanding settlements, and guide targeted monitoring and preparedness during peak monsoon periods. To further improve landslide risk assessment in this area, future work should include temporal data (e.g., rainfall time-series and land-use changes) to enable dynamic modeling, integrate advanced machine learning with AHP to improve the performance, expand ground-truth validation, and incorporate an informed decision framework to refine the model and make it practical for disaster risk management. Furthermore, the application of deep learning and many hybrid ensemble models can improve the performance drastically.

DECLARATION OF USE OF AI

In the preparation of this manuscript, we employed the use of "SciSpace" to aid in the identification of relevant literature, summarizing technical articles, and clarifying complex research findings. Furthermore, we utilized "Grammarly" to enhance the language quality, ensure grammatical correctness, and uphold a consistent academic tone throughout the document. Additionally, artificial intelligence (AI) tools were incorporated to assist with various aspects of the writing and research process, ensuring precision and efficiency in the development of the manuscript.

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