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Landslide Susceptibility Assessment in the Nilgiris District, Western Ghats: A Comparative Approach Using Frequency Ratio and AHP Models

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Abstract

The Nilgiris district in Tamil Nadu, India, ranks as one of the most susceptible to landslides in the Western Ghats Mountain ranges due to the rugged terrain, fragile geology and high monsoonal rainfall. The terrain in the study area presents considerable elevation ranges between 91 m and 2634 m above mean sea level. The slope gradients attain as high as 89.8°. This study attempts to evaluate the susceptibility to landslides through the combined approach of the Analytical Hierarchy Process (AHP) and Frequency Ratio techniques. Various factors influencing landslides were integrated into the model. These include elevation, slope, aspect, curvature, Hill shade, geology, geomorphology, lithology, lineament density and their distances from roads, rivers and lineaments. Land use/land cover information derived from Landsat-8 satellite images and annual rainfall between 2370 mm and 2850 mm were also used as parameters. According to the AHP model results, the most influencing factor was slope with a weight of approximately 0.36, followed by geology with a weight of approximately 0.28. Rainfall and lineament density also showed considerable influence. Five susceptibility zones were identified as very low, low, moderate, high and very high. Approximately 27-29% of the district area falls within the high to very high susceptibility zones, particularly around Udhagamandalam and Coonoor. Gudalur shows relatively low susceptibility. The model results were validated through the Receiver Operating Characteristic (ROC) curve. The Area under the curve (AUC) values for the AHP model were found to be 0.81, while the FR model results showed a high accuracy with a value of 0.87.

Keywords: Analytical Hierarchy Process, Geospatial analysis, Hazard mapping, Landslides Susceptibility, Nilgiris district, ROC-AUC validation

Introduction

Landslide is among the most destructive types of natural hazards prevalent in hilly areas throughout the world. Landslides cause significant human mortality, infrastructural damages, and environmental problems. In India, the Himalayas and Western Ghats are prone to landslides due to their mountainous topography, fragile geology, and intense rainfall during monsoons. The Nilgiris district in Western Ghats is particularly notorious for landslide susceptibility. The susceptibility to landslides in the Nilgiris district can be attributed to its steep topography, geological instability, and increasing anthropogenic interference (1). The Nilgiris district is characterized by varied elevations ranging from 91 m to 2634 m above mean sea level with slopes up to 90º. The geological composition mainly comprises Charnockite, gneiss, schist, and quartzite (2). The high topography combined with intense monsoonal rainfall increases the susceptibility of the district to landslides. In addition to the natural conditions, anthropogenic activities have substantially contributed to increased slope instabilities. Such activities include deforestation, road construction, quarrying, development of tourism-related infrastructure, and increasing urbanization. Landslides are frequently observed when there is increasing anthropogenic

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disturbance in hilly terrain since such practices alter the natural drainage pattern and destabilize hill slopes. The Nilgiris district has had many cases of landslides leading to devastating consequences over the past few decades. For instance, severe landslides in 1978 disrupted transport links, while those of 2009 claimed more than 60 lives in the district. Recent monsoon-induced landslides have led to the destruction of tea plantations, residential areas, and transport infrastructure in different parts of the Nilgiris district (3, 4). Hence, assessing the landslide susceptibility within the district has become necessary for effective disaster management planning. Remote sensing (RS) and Geographic Information Systems (GIS) have increasingly been used for landslide susceptibility mapping (LSM) in the recent decades (5). The RS techniques provide access to digital images, digital elevation models (DEM), and spatial analysis techniques required for landslide hazard studies. Literature revels that several LSM methodologies such as statistics, machine learning, and multi-criteria decision-making have been developed. The Analytical Hierarchy Process (AHP) and Frequency Ratio (FR) models are popular because of their effectiveness and straightforward implementation (6). AHP is based on subjective analysis of landslide factors, while FR model establishes statistically significant relationships between the factor classes and landslide distribution (7). Past studies indicated logical consistency of weightings generated by AHP and high prediction accuracy of FR models (8). Therefore, combining both AHP and FR models would improve the accuracy of the LSM results. Past studies have suggested that factors like slope gradient, elevation, lithology, rainfall intensity, land use and cover, and anthropogenic disturbance play important roles in landsliding processes (9, 10). Steep slopes, intense rainfall, and large-scale anthropogenic interference are important contributors to landslides in locations such as Udagamandalam and Coonoor in the Nilgiris district (11, 12). Although numerous LSM studies have been conducted in the region, comprehensive comparison of these models remains limited (13). This indicates the need to undertake further work in LSM using an integrative approach based on GIS and RS technologies (14).

The current study is conducted in the Nilgiris district, located in the southern parts of Western Ghats, as shown in Figure 1. The district lies between latitudes 10º58′N and 11º48′N and longitudes 76º21′E to 77º05′E with an area of about 2,549 km². It constitutes a significant highland landscape and biosphere reserve of peninsular India (15).

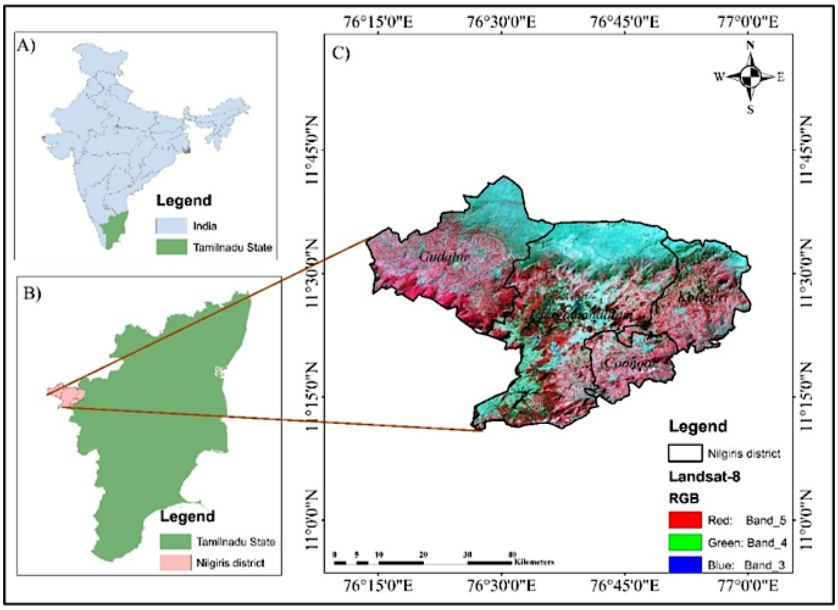

Figure 1: Geographical Location of the Study Area. A) India, B) Tamilnadu State, C) Nilgiris District Boundary (Study Region)

The region acts as the watershed for rivers like Bhavani, Moyar, and Kabini, which have tributaries in Nilgiris. Nilgiris district is located within Tamil Nadu and shares boundaries with Kerala and Karnataka states. The terrain of Nilgiris district is highly dissected, rugged, and includes steep slopes, rolling uplands, and deep valleys. Its elevation varies from 91 m in valleys to 2,634 m at Doddabetta, the highest peak in Tamil Nadu state. Figure 2 presents the map of elevation and slope of the district. Areas with high elevations and steep slopes are considered highly susceptible to landslides due to gravity-induced erosion processes. Nilgiris district has a tropical montane climate characterized by rains during both the southwest and northeast monsoons. Owing to the orographic effect, there is relatively higher rainfall in areas like Udagamandalam and Coonoor. High-intensity rainfalls are known as major triggers for landslides. Figure 3 presents the map of rainfall and geological formation of the study area. The district is predominantly formed by ancient Charnockite, gneiss, schist, and quartzite rocks intersected by joints, faults, and lineaments that increase instability of slopes (16, 17). Anthropogenic activities like quarrying, slope cutting, and plantations exacerbate hazard risks. Thematic layers, including slope, aspect, elevation, curvature, lithology, geomorphology, lineament density, distance to faults, distance to rivers, distance to roads, land use/cover, and rainfall, are used in this study to conduct landslide susceptibility mapping using GIS and RS along with AHP and FR models (18).

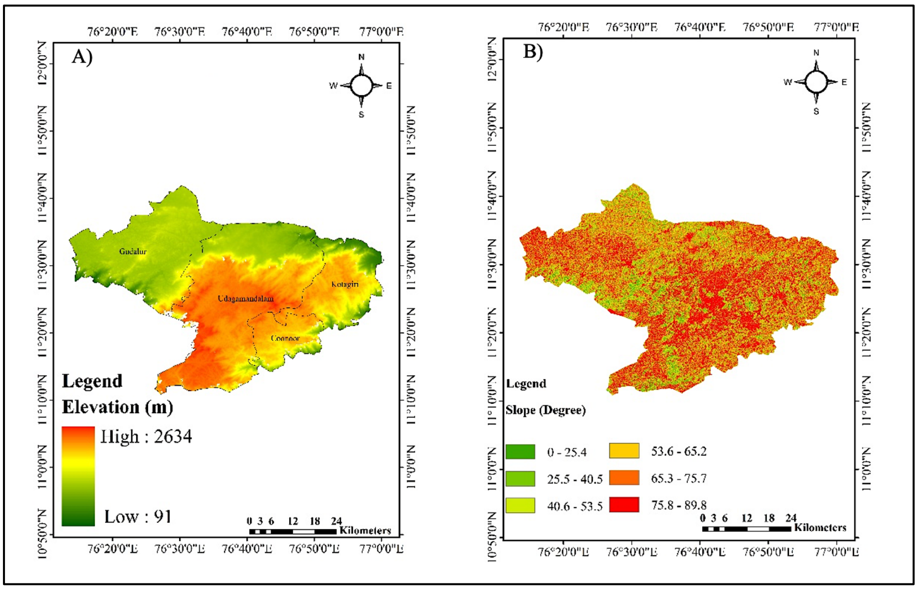

Figure 2: Spatial Distribution. A) Elevation, B) Slope Maps Showing Elevation Zones and Major Physiographic Features

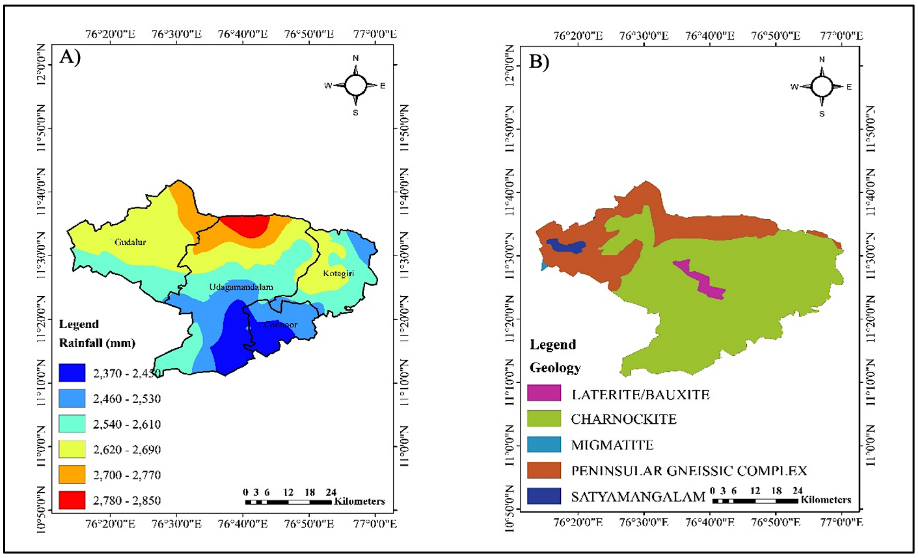

Figure 3: Study Area. A) Spatial Distribution of Rainfall Map Derived from IMD Data, B) Geological Map of the Study Area

Methodology

The present investigation employs a structured geospatial and multi-criteria decision-making framework to develop a LSM for the Nilgiris district. The methodology involves five major steps:

a) compilation of relevant spatial datasets,
b) preparation of thematic layers,
c) application of the AHP to derive relative weights of conditioning factors,
d) integration of weighted factors in a GIS environment and
e) validation.

The overall methodological workflow shown in Figure 4 and has been carefully formulated by considering the distinctive physiographic characteristics and geological setting of the study region (19). Each analytical step is designed to ensure logical progression from data preparation to model implementation and validation (20). The detailed procedures adopted in this study are described in the following sub-sections. The AHP and FR methods were selected due to their simplicity, transparency and proven effectiveness in landslide susceptibility studies (21-23). These approaches allow the integration of expert knowledge with statistical relationships between landslide occurrences and conditioning factors, making them suitable for regional-scale susceptibility assessment in mountainous terrains such as the Nilgiris district.

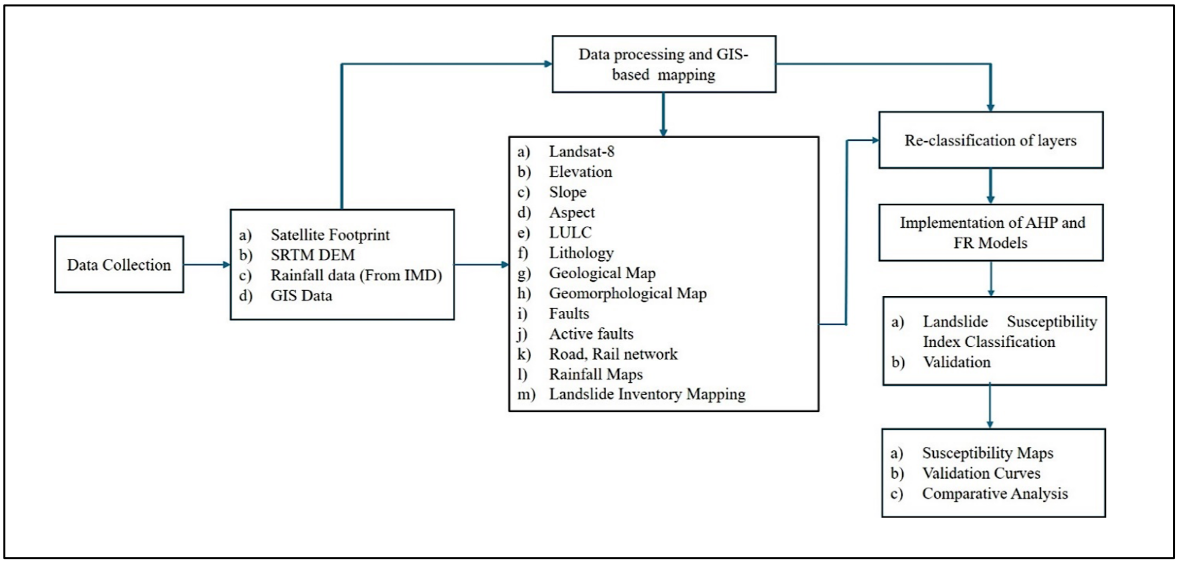

Figure 4: Step-by-step Methodology Adopted in the Current Study to Develop the LSM of the Nilgiris District of Tamilnadu State

Source Data

Multiple datasets obtained from diverse sources, scales and spatial resolutions were assembled to support the landslide susceptibility analysis, with emphasis on terrain, geological, hydrological, climatic and anthropogenic factors (24). A Digital Elevation Model derived from the Shuttle Radar Topography Mission at 30 m spatial resolution was employed to generate elevation, slope, aspect and curvature layers. Geological, geomorphological and fault-related information was sourced from the Geological Survey of India at a scale of 1:500,000 and subsequently digitized for geospatial analysis (25). Drainage networks and lineament density layers were delineated using digital elevation model -based techniques in combination with existing thematic maps. Rainfall data were obtained from the IMD at a spatial resolution of 0.25º, providing essential climatic input for the study (26). The land use and land cover information were extracted through the processing of Landsat-8 OLI/TIRS imagery at 30 m resolution. Additionally, field-verified GPS locations representing both landslide and non-landslide sites were incorporated to enhance model robustness and validation reliability (27). A detailed summary of all datasets utilized in the study is presented in Table 1.

Table 1: Summary of Datasets Used in the Study, Including Sources, Spatial Scales and Applications

Data Type	Source	Scale/Resolution	Purpose
DEM	USGS (SRTM 30 m)	30 m	Derivation of slope, aspect, elevation, curvature
Geological Map	GSI	1:500,000	Geological Composition and Structural Controls
Geomorphology	Bhukosh	1:50,000	Terrain classification
Fault and Lineament Data	GSI and Bhukosh	1:500,000	Structural instability factors
Drainage Network	DEM	30 m	Drainage density and river proximity
Rainfall Data	IMD	0.25° grid (25 km)	Rainfall distribution and intensity analysis
Landsat-8 OLI/TIRS Imagery	USGS	30 m	LULC classification
Landslide Inventory	Bhukosh and NRSC	Point data	Validation and susceptibility modelling

Note: DEM = Digital Elevation Model, USGS = United States Geological Survey, SRTM = Shuttle Radar Topography Mission, GSI = Geological Survey of India, IMD = India Meteorological Department; LULC = Land Use/Land Cover, OLI/TIRS = Operational Land Imager/Thermal Infrared Sensor, NRSC = National Remote Sensing Centre.

Results and Discussion

Development of Thematic Layers

All compiled datasets were processed and transformed into standardized thematic layers within a GIS environment. digital elevation model-derived parameters included slope, classified into five categories (0-10º, 10-30º, 30-50º, 50-70º and >70º) and elevation, grouped into six ranges (91-500 m, 500-1000 m, 1000-1500 m, 1500-2000 m, 2000-2500 m and >2500 m). Slope aspect was categorized into nine directional classes, namely north, south, east, west, northeast, northwest, southeast, southwest and flat, while curvature was classified into concave, convex and flat surfaces. Major lithological units, including Charnockite, gneiss, quartzite, schist and granite, were digitized from the geological maps of the Nilgiris obtained from the geological survey of India. Hydrological factors such as distance from rivers and drainage density were derived using digital elevation model-based hydrological analysis, whereas structural parameters, including lineament density and distance from faults, were extracted from available geological survey of India datasets (28). Rainfall distribution was generated through spatial interpolation of station-based data obtained from the IMD and subsequently classified into six rainfall zones ranging from <1200 mm to >2800 mm. Land use and land cover information was categorized into forest, plantation, agricultural land, built-up areas, barren land and water bodies. To ensure spatial consistency, all thematic layers were resampled to a common spatial resolution of 30 m prior to integration and the spatial distribution of the prepared layers is illustrated in Figures 5-9.

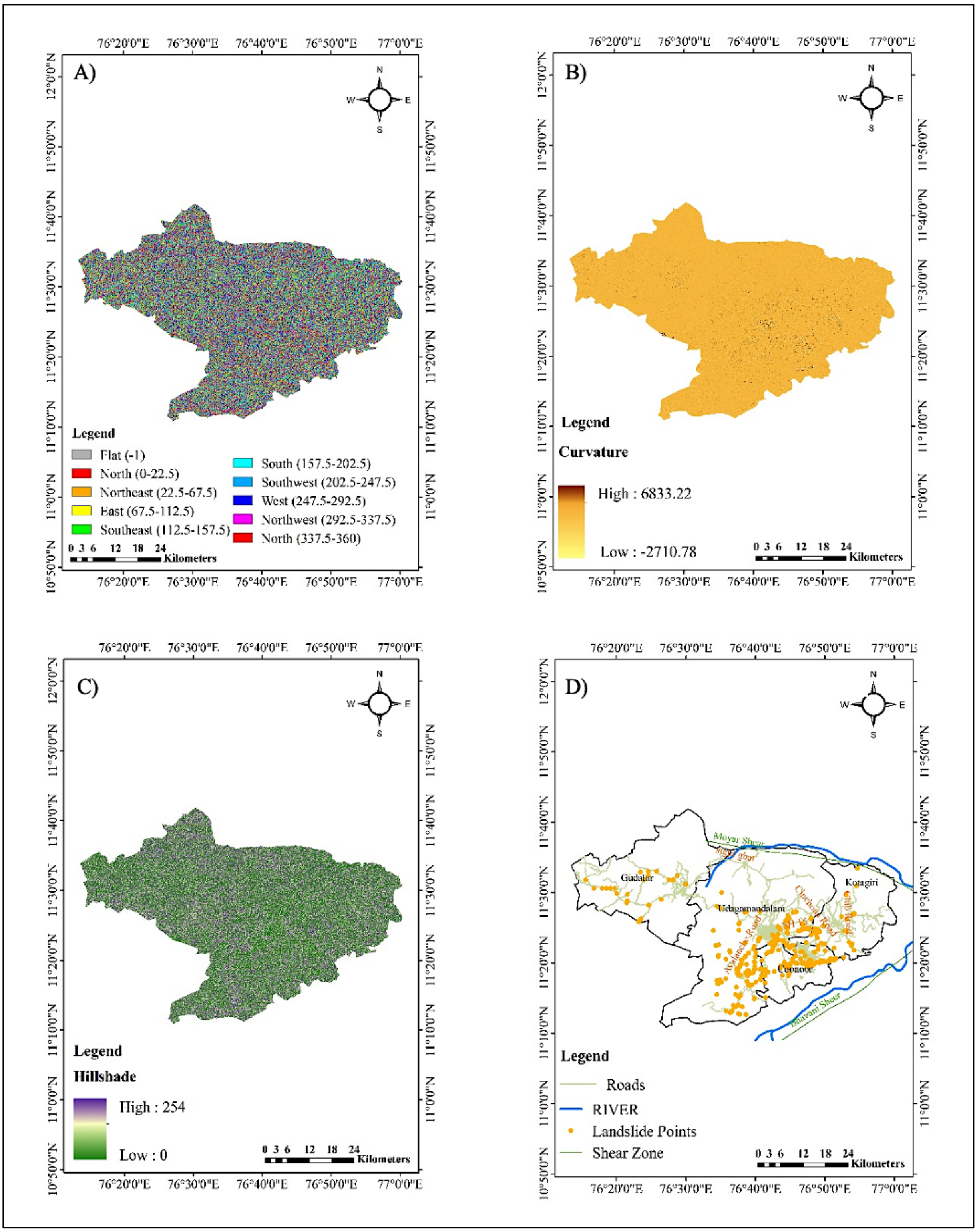

Figure 5: Spatial Distribution. A) Aspect, B) Curvature, C) Hillshade
D) Road Network with Shear Zones Orientation

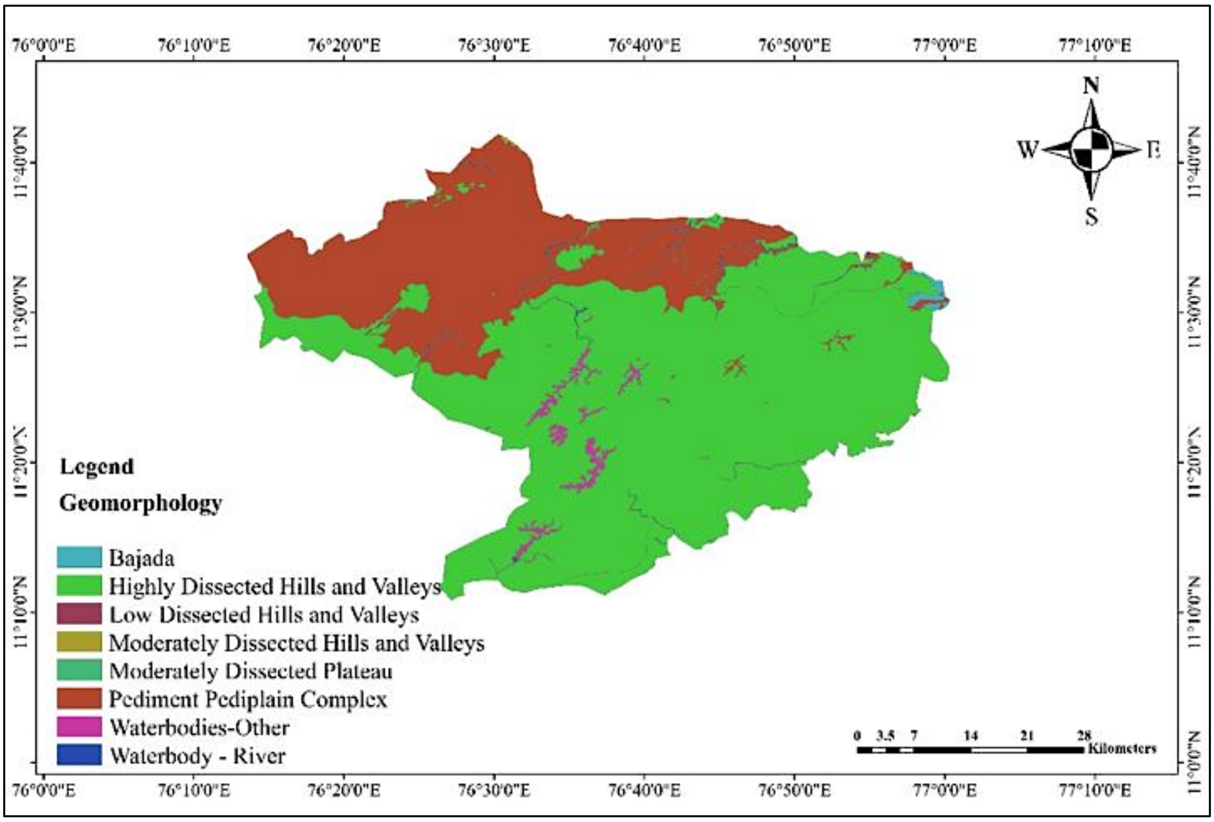

Figure 6: Representation of Major Geomorphological Features within the Study Region

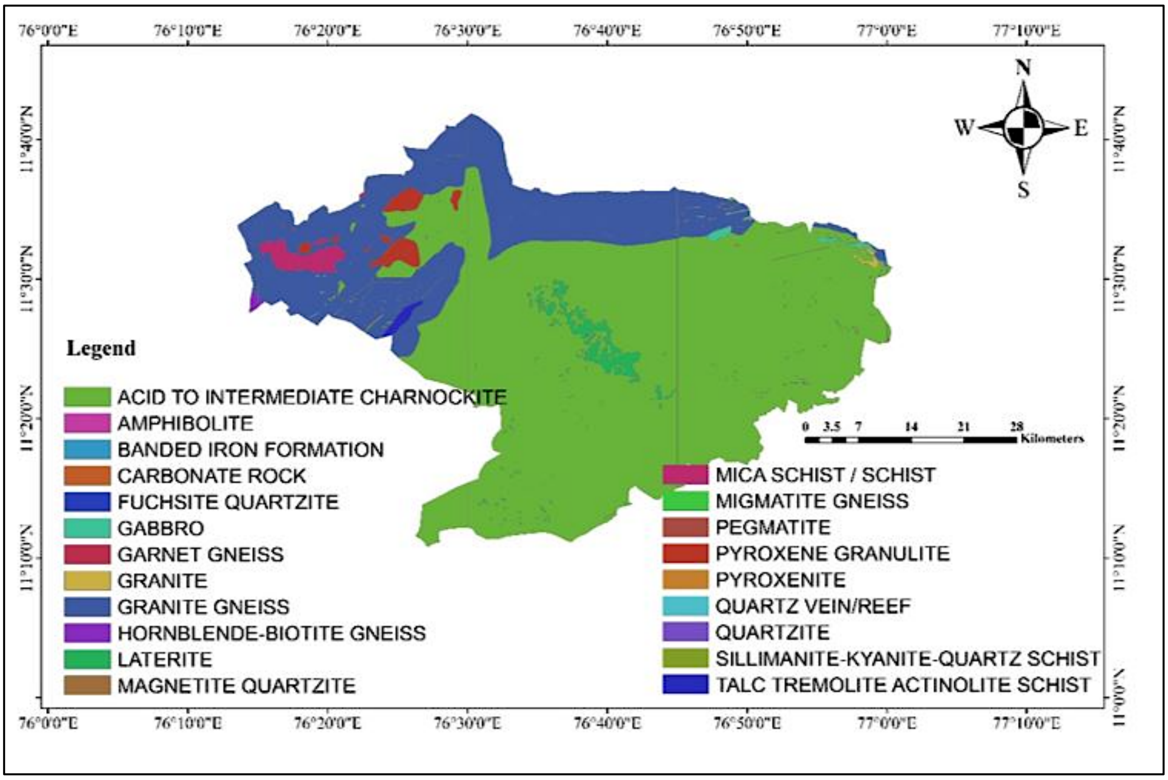

Figure 7: Spatial Representation of Lithological Formations in the Study Region

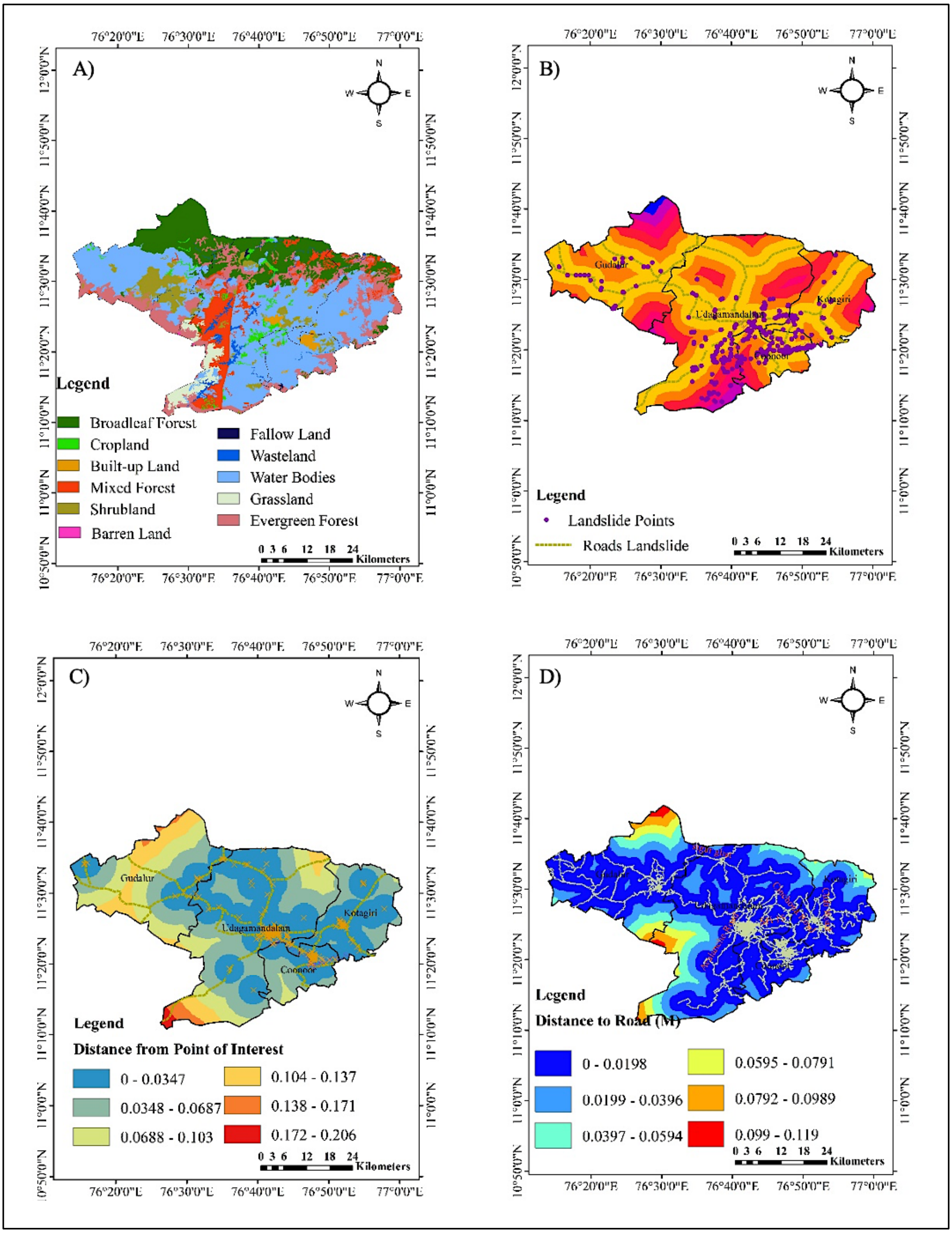

Figure 8: Spatial Distribution. A) Land Use and Land Cover Map, B) Proximity to Roadside Landslides, C) Point of Interest (Important Places), D) Road Network

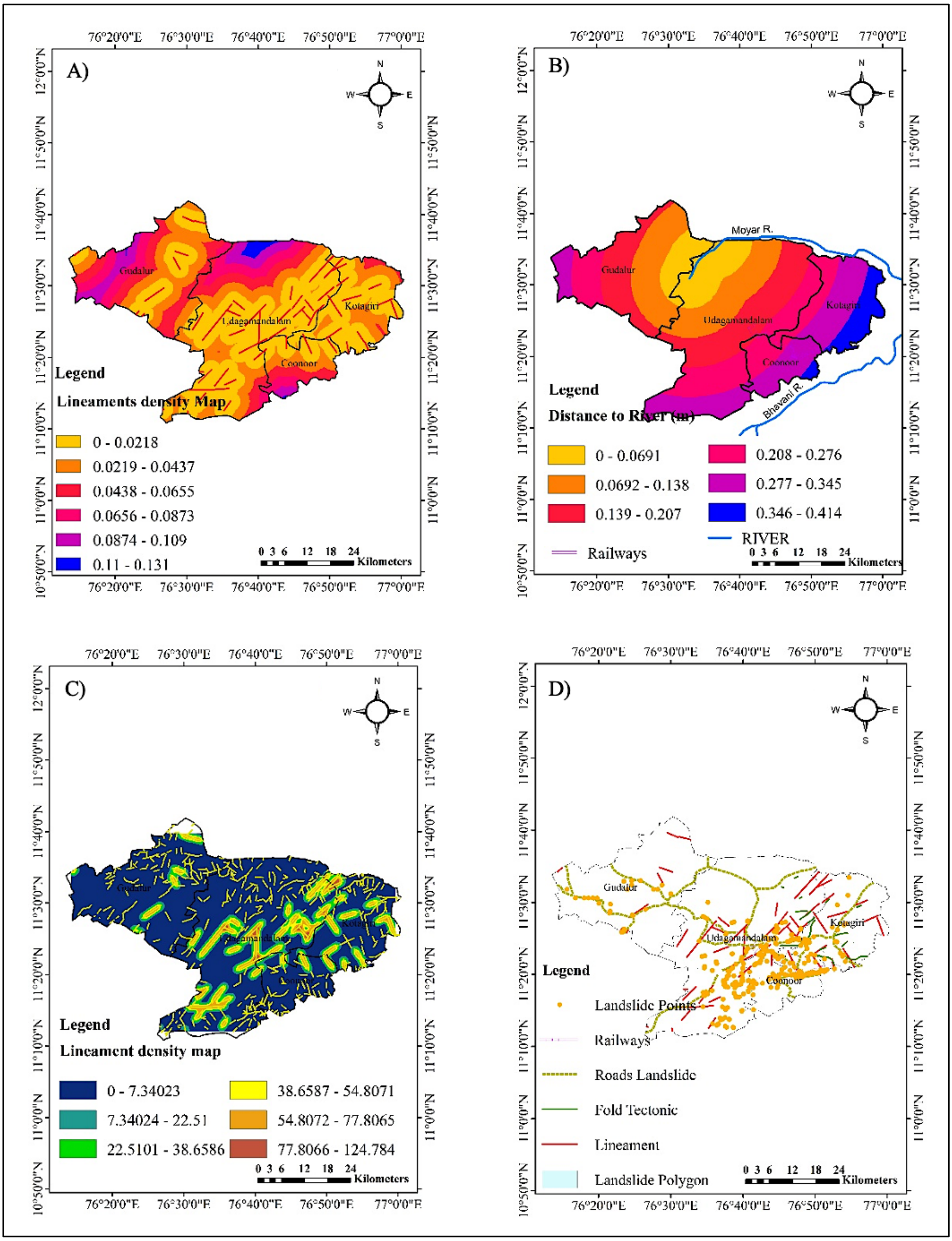

Figure 9: Proximity. A) Lineaments, B) River, C) Lineament Density, D) Landslide Inventory Map

All thematic layers were generated using ArcGIS spatial analysis tools. Slope, aspect and curvature layers were derived from the digital elevation model using standard terrain analysis functions. Lineament density was calculated using the line density tool, while the drainage network was extracted using the hydrology toolbox with an appropriate flow accumulation threshold. These procedures ensure consistency and reproducibility in the generation of conditioning factor layers. Different lithological units exhibit varying susceptibility to weathering and slope failure (29).

For instance, schist formations tend to undergo relatively rapid weathering, producing thicker soil profiles and reduced shear strength that increase the likelihood of shallow landslides. In contrast, charnockites are generally more resistant to weathering; however, structural discontinuities such as joints and fractures may still facilitate slope instability under intense rainfall conditions.

Landslide Conditioning Parameter Identification

The identification of landslide conditioning parameters was guided by the physiographic setting of the Nilgiris district and their demonstrated significance in previous landslide susceptibility investigations. Based on a comprehensive review of earlier studies and data availability, a total of eleven key parameters were selected for analysis (30). These include slope, elevation, aspect, curvature, lithology, geomorphology, lineament density, distance from faults, distance from rivers, land use and land cover and rainfall. Each parameter contributes either directly or indirectly to slope instability by influencing terrain morphology, material strength, hydrological conditions, or anthropogenic stress, thereby playing a critical role in landslide initiation and propagation, instance, steep slopes and fragile lithologies like Charnockite and gneiss are highly prone to mass movements, whereas rainfall plays a triggering role (31). Anthropogenic activities such as expansion of settlements, tea plantations and road construction were captured under land use and land cover (32). Thus, both natural and human-induced factors were systematically incorporated in the model.

AHP Techniques

The AHP method was adopted for assessing the relative importance of the landslide conditioning factors affecting the slope instability in the study area. AHP is based on the principle of pair-wise comparisons, where each factor is compared with other factors to establish the relative importance of each factor for the occurrence of landslides. A series of pair-wise comparisons are conducted, where the relative importance of each factor is determined using fundamental scale of relative importance of AHP approach, as depicted in Table 2. This results in the formation of a reciprocal decision matrix, where the diagonal elements are equal to one and the reciprocal property is maintained for the corresponding non-diagonal elements (33). Expert knowledge, literature and observations were adopted for establishing the appropriate pair-wise comparison scores for the conditioning factors (34).

Table 2: Fundamental Scale for Pairwise Comparison

Numeric Value	Verbal Description	Meaning
1	Equal importance	Both factors contribute equally
2	Between equal and weak	Slight preference of one over the other
3	Moderate importance	Moderate dominance of one factor
4	Between moderate and strong	Intermediate preference
5	Strong importance	Strong dominance of one factor
6	Between strong and very strong	Intermediate preference
7	Very strong importance	Demonstrated importance
8	Between very strong and extreme	Intermediate preference
9	Extreme importance	Absolute dominance

Reciprocal values (1/2 -1/9) are applied in cases where the significance of one conditionality factor is deemed less significant than the other. In this case, aij refers to the relative value obtained from comparing factor i to factor j, whereas k refers to the relative value assigned numerically from the pairwise comparison of the two factors. For instance, if the relative value of i over j is aij=k, then the reciprocal is aji=1/k. To address the scale-related differences, the decision matrix was normalized, where the relative weights for each conditioning factor was determined using the eigenvector method. The weights were determined from the eigenvector corresponding to the maximum eigenvalue of the pair-wise comparison matrix (35). This eigenvector was then normalized to ensure that the sum of the weights is equal to one. To establish the logical consistency of the pair-wise comparisons conducted by the experts, the Consistency Index (CI) and Consistency Ratio (CR) were adopted as standard measures for the AHP method, where the mathematical expressions for the calculation of the CI and CR are depicted in Equations [1, 2]. A CR less than 0.10 was considered acceptable, which would imply an appropriate level of logical consistency in the pairwise comparison results.

$$n_{ij} = \frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}}, \qquad w_i = \frac{1}{n}\sum_{j=1}^{n} n_{ij}, \qquad \sum_{i=1}^{n} w_i = 1 \qquad [1]$$

$$\lambda_{max} \approx \frac{1}{n}\sum_{i=1}^{n}\frac{(A\mathbf{w})_i}{w_i}, \qquad CI = \frac{\lambda_{max} - n}{n-1}, \qquad CR = \frac{CI}{RI} \qquad [2]$$

Random Index values used for the assessment of the consistency results. Moreover, the complete pairwise comparison matrix, along with the normalized matrix and the weights assigned to each conditioning factor, along with the corresponding ranking, is presented in Tables 3 and 4. The pairwise comparison matrix was tested for consistency using the CR within the AHP. The value of the CR was calculated based on the values of the Random Index (27), where Random Index values depended on the size of the comparison matrix. The assessment of consistency is crucial for ensuring that the expert assessments and the weights assigned to each theme in the process are reliable. As a rule, a CR less than 0.10 denotes acceptable consistency in the procedure of pairwise comparison. In this study, the obtained CR value satisfied the threshold for acceptable consistency.

Weighted Overlay Analysis of Conditioning Parameters

After determining the weights of the conditioning parameters, all the thematic layers were transformed to a raster format and reclassified into five susceptibility levels: very low, low, moderate, high and very high. Each class within an individual thematic layer was assigned an appropriate rating value, which was subsequently multiplied by the corresponding weight obtained through the AHP procedure (27). The integration of weighted thematic layers was carried out using the weighted linear combination technique within a GIS framework to compute the Landslide Susceptibility Index (LSI) for each raster cell across the study area. The mathematical expression used for LSI computation is presented in Equation [3].

$$LSI(x,y) = \sum_{i=1}^{n} w_i \cdot r_i(x,y) \qquad [3]$$

Where, w_i represents the normalized weight of the i^{th} factor, r_i (x, y) denotes the reclassified score of the same factor at location (x, y).

The computed LSI values were subsequently normalized and grouped into five susceptibility classes, namely very low, low, moderate, high and very high. This classification facilitated the generation of the LSM, which spatially delineates areas with varying levels of landslide potential across the Nilgiris district.

FR-based susceptibility analysis

Apart from the use of the AHP method, the FR model was used to statistically examine the relationship between landslide events and conditioning parameters that were chosen. The Failure Ratio method is one of the commonly used statistical techniques to examine the relationship between landslide events and the different classes of conditioning parameters. The main principle of the method is that landslide events tend to concentrate in areas where the percentage of landslide events is higher than the percentage of the specific class of any of the conditioning parameters. Thus, the value of the Failure Ratio for the thematic parameters was calculated according to the following formulation of Equation [4].

$$FR_{ij} = \frac{\left(\frac{N_{ij}}{N_t}\right)}{\left(\frac{A_{ij}}{A_t}\right)} \qquad [4]$$

Where, N_{ij} denotes the number of landslide pixels occurring within class j of the i^{th} conditioning factor, N_t represents the total number of landslide pixels across the entire study region, A_{ij} refers to the total number of pixels corresponding to class j and A_t indicates the overall number of pixels within the study area.

The LSI for each grid cell was subsequently computed by summing the natural logarithms of the FR values of all conditioning parameters, as defined by Equation [5].

$$\mathrm{LSI}(x, y) = \sum_{i=1}^{n} \ln\left(\mathrm{FR}_{ij}\right) \quad [5]$$

Computed LSI values were normalized and classified into five susceptibility classes ranging from very low to very high susceptibility. LSI values ranging from 0.47 to 0.496 were classified as very low susceptibility, 0.49 to 0.51 as low susceptibility, 0.51 to 0.53 as moderate susceptibility, 0.53 to 0.55 as high susceptibility and 0.55 to 0.57 as very high susceptibility zones. Figure 10 presents the spatial distribution of landslide susceptibility zones derived through the application of the AHP and FR approaches. It has been derived that the distribution of landslide susceptibility zones is not random and tends to cluster more than the others. It has also been derived those areas like Udhagamandalam, Coonoor, the southwestern part of Gudalur and some areas of Kotagiri are mostly classified as high to very high susceptibility zones. It could, therefore, be derived that the inherent factors along with high rainfall and anthropogenic factors like road development are responsible for the generation of landslides in the Nilgiris district. Finally, the derived values of the LSI were classified into five classes: very low, low, moderate, high and very high susceptibility zones, using the natural breaks (Jenks) classification method, which optimally classifies the data into the desired number of classes by maximizing the variance between classes and minimizing the variance within classes (36).

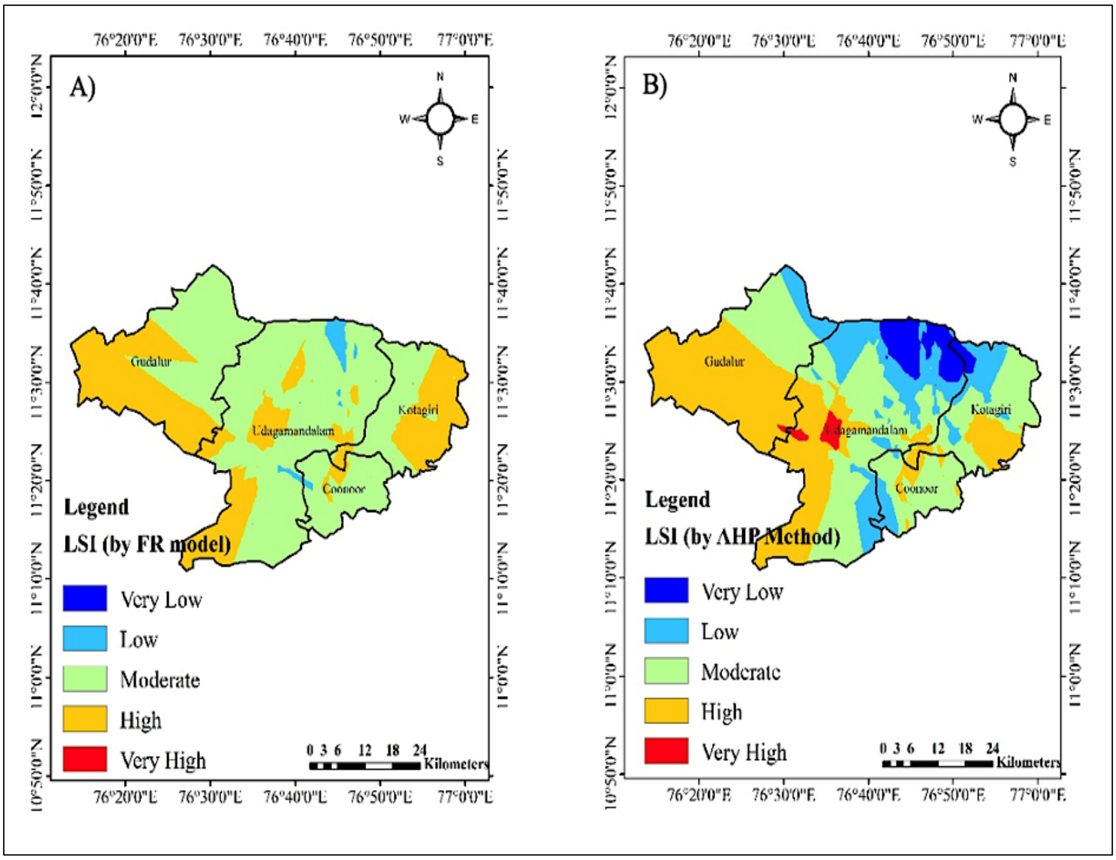

Figure 10: Landslide Susceptibility Patterns Across the Nilgiris District Generated. A) FR Techniques, B) AHP Method

Model Validation

The predictive capability of the LSZ was assessed through Receiver Operating Characteristic (ROC) curve analysis. Landslide inventory points obtained from the literature surveys and secondary sources were overlaid on the susceptibility map to compare observed occurrences with predicted susceptibility classes. The Area Under the Curve (AUC) was subsequently computed as a quantitative indicator of model performance, reflecting the trade-off between the true positive rate and the false positive rate over a range of decision thresholds. The mathematical formulations used to derive the ROC curve and AUC values are provided in Equations [6, 7].

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}, \qquad \mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP}+\mathrm{TN}} \qquad [6]$$

$$\mathrm{AUC} = \int_0^1 \mathrm{TPR}\left(\mathrm{FPR}^{-1}(u)\right) du \qquad [7]$$

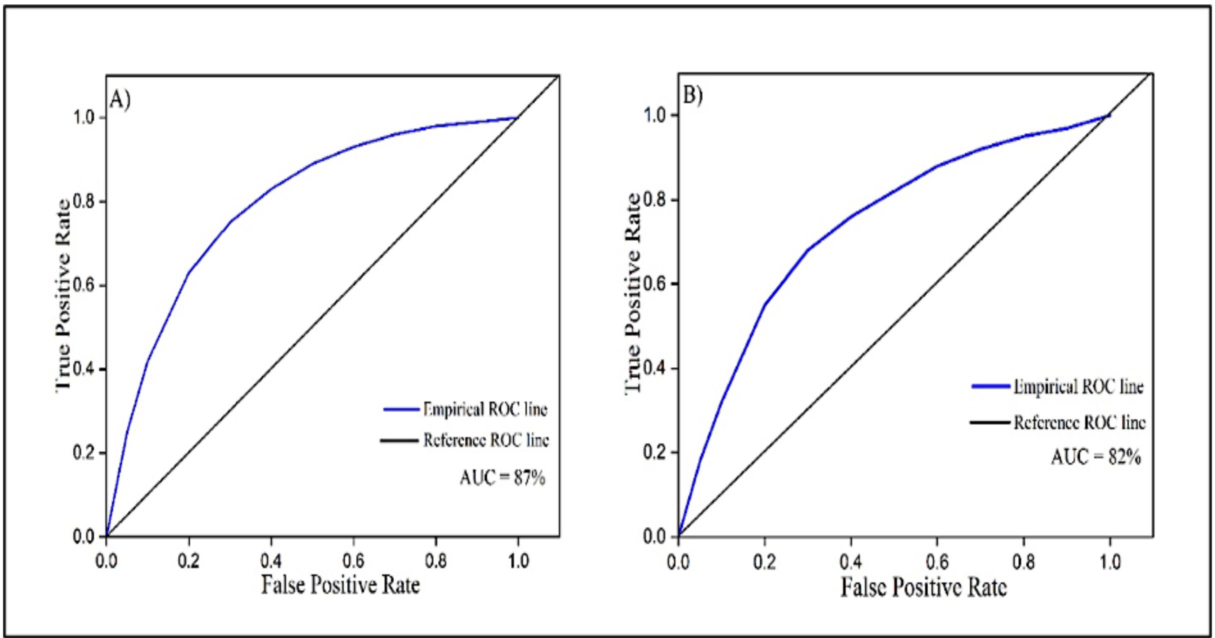

Figure 11: Validation of the LSM. A) FR, B) AHP Model (AOC 87% and 82%) Using an Empirical ROC Line

In order to improve the robustness of the model and to avoid the possibility of over-fitting, the landslide inventory dataset was split into training and validation sets. The training set was used to build the susceptibility models, while the validation set was used to test the performance of the models through ROC analysis. A value of AUC greater than 0.8 was taken to indicate an excellent prediction ability, thereby validating the effectiveness of the AHP-GIS method for carrying out LSM studies. The ROC curve for the research presented in this paper is given in Figure 11. The ROC curves also demonstrate the robustness of the proposed susceptibility modelling for carrying out landslide risk assessment in the Nilgiris district. The pairwise comparison values were computed based on the fundamental AHP scale (37). These values were also based on expert judgment with respect to the geomorphological characteristics of the Nilgiris terrain, as well as the findings from various studies carried out on landslide susceptibility modelling. Parameters like slope and geology were given high values of dominance since these were the most dominant factors for landslides in the Western Ghats region.

A comparative assessment of LSZ obtained from the FR model and the AHP model shows that the FR model has delineated a larger area under high landslide susceptibility compared to the LSZ obtained from the AHP model, which may be due to the high sensitivity of the FR model to landslide conditions. The comparative assessment is given in Table 5.

Table 3: Pairwise Comparison Matrix

Factors	SL	EL	AS	CU	LI	GE	LD	FP	DP	RA	LULC
Slope (SL)	1	2	3	3	4	4	5	5	5	6	6
Elevation (EL)	0.5	1	2	2	3	3	4	4	4	5	5
Aspect (AS)	0.33	0.5	1	1	2	2	3	3	3	4	4
Curvature (CU)	0.33	0.5	1	1	2	2	3	3	3	4	4
Lithology (LI)	0.25	0.3	0.5	0.5	1	2	3	3	3	4	4
Geomorphology (GE)	0.25	0.3	0.5	0.5	0.5	1	2	2	2	3	3
Lineament Density (LD)	0.2	0.3	0.3	0.3	0.3	0.5	1	2	2	3	3
Fault Proximity (FP)	0.2	0.3	0.3	0.3	0.3	0.5	0.5	1	2	3	3
Drainage Proximity (DP)	0.2	0.3	0.3	0.3	0.3	0.5	0.5	0.5	1	2	2
Rainfall (RA)	0.17	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.5	1	2
Land Use Land Cover (LULC)	0.17	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.5	0.5	1

Table 4: AHP-based Normalized Comparison Matrix and Priority Weights of Conditioning Parameters

Factor	Normalized Value	Weight (%)	Priority Rank
Slope	0.210	21.0	1
Elevation	0.150	15.0	2
Aspect	0.070	11.0	3
Curvature	0.060	8.0	4
Lithology	0.110	7.0	5
Geomorphology	0.080	7.0	6
Lineament Density	0.070	7.0	7
Fault Proximity	0.070	7.0	8
Drainage Proximity	0.060	6.0	9
Rainfall	0.070	6.0	10
Land Use Land Cover	0.050	5.0	11

Table 5: Percentage Area Distribution of Landslide Susceptibility Categories for AHP And FR Models

Susceptibility Category	Area Coverage (AHP, %)	Area Coverage (FR, %)
Very Low	16.0	13.2
Low	22.0	20.0
Moderate	28.9	29.4
High	20.5	23.1
Very High	12.6	14.3

Note: AHP = Analytical Hierarchy Process, FR = Frequency Ratio.

Conclusion

The integration of landslide conditioning parameters using FR and AHP models has produced two distinct landslide susceptibility maps for the Nilgiris district. In both cases, the calculated values of LSI were reclassified into five zones of very low, low, moderate, high and very high landslide susceptibility using the natural breaks method Jenks. The spatial patterns obtained from both FR and AHP models show that landslide susceptibility is heterogeneously distributed over the terrain and is strongly associated with conditioning factors like slope gradient, elevation, lithology, drainage density and rainfall intensity. According to the landslide susceptibility map obtained from the AHP model, approximately 12.6% of the total area falls under the very high landslide susceptibility category, mainly including steep escarpments, structurally disturbed areas and high drainage density areas.

The high landslide susceptibility category comprises 20.5% of the total area, mainly including areas with moderately steep slopes and high rainfall intensity. The moderate landslide susceptibility category comprises 28.9%, while the low and very low landslide susceptibility categories comprise 22.0% and 16.0%, respectively. If we compare the LSM obtained from the FR model with the LSM obtained from the AHP model, we can see that the FR model has delineated a different spatial pattern of landslide susceptibility over the Nilgiris terrain. In the FR model, the very high landslide susceptibility category comprises 14.3% of the total area, while the high landslide susceptibility category comprises 23.1%. The moderate landslide susceptibility category comprises the maximum area of approximately 29.4%. The low and very low landslide susceptibility categories comprise 20.0% and 13.2%, respectively.

The comparison between LSZ obtained from the FR model and the AHP model indicates that both models are consistent in highlighting the most vulnerable regions, although the FR approach assigns relatively higher weights to local triggering factors such as slope and drainage density, resulting in a broader extent of high-susceptibility zones. The moderate susceptibility zones identified in both AHP and FR models occupy a significant portion of the study area and may represent transitional geomorphic environments where slope stability conditions are moderately balanced. Such zones are observed in parts of Kotagiri, Kunda and peripheral areas of Udagamandalam, where moderate slope gradients and mixed land-use patterns occur. These areas may become more vulnerable under changing rainfall intensity, land-use modifications, or anthropogenic disturbances. Therefore, continuous monitoring and sustainable land management practices are necessary to prevent potential slope instability in these regions.

Validation of Susceptibility Maps

The predictive potential of the generated landslide susceptibility maps was evaluated through ROC curve analysis using landslide inventory locations. AUC values were calculated for both AHP and FR models as a quantitative measure of model reliability, where values close to unity indicate high predictive potential. For the AHP model, a calculated AUC of 0.82 indicates a high potential to differentiate landslide-prone regions from stable regions. Similarly, the FR model calculated a slightly higher AUC of 0.87, indicating a high potential to simulate landslide occurrences in these regions. The predictive potential of landslide susceptibility models was evaluated using ROC curve analysis. It is a quantitative measure of model effectiveness in differentiating landslide and non-landslide regions correctly. ROC-AUC is commonly applied in landslide susceptibility studies to test statistical and multi-criteria decision-making models. ROC-AUC values were compared to conclude that although both models are highly efficient in LSZ, the FR model indicates a high sensitivity to spatial changes in landslide occurrences. This is in conformity with earlier studies carried out in terrain analogues of Western Ghats and Himalayan regions, where it was established that statistically driven landslide susceptibility models were slightly more efficient in simulating landslide occurrences in these regions because of their data-driven nature. Nevertheless, it is worth noting that the AHP approach is advantageous in incorporating expert judgment, especially in regions where landslide inventory data are not available in their entirety.

An integrated evaluation of topographic, geomorphological, hydrological and climatic variables further reveals that slope angles exceeding 25º, elevation ranges between 1000 m and 1800 m and zones receiving annual rainfall greater than 2700 mm are especially susceptible to slope failure. These results emphasize the combined influence of terrain configuration and hydro-climatic forcing in controlling landslide activity within the study region. It is further recommended to conduct a future study that should incorporate high-resolution datasets, such as LiDAR-based digital elevation models, finer-scale rainfall records and field-verified landslide inventories, to improve accuracy. Advanced data-driven approaches, including machine learning and ensemble models, can be applied to capture non-linear relationships among factors. Integrating soil moisture dynamics, land-use change and time-series remote sensing will further enhance predictive capability. Development of near-real-time monitoring systems and rainfall-threshold-based early warning frameworks will provide actionable insights for disaster preparedness in the Nilgiris.

Abbreviations

AHP: Analytical Hierarchy Process, AUC: Area Under the Curve, CI: Consistency Index, CR: Consistency Ratio, GIS: Geographic Information Systems, IMD: Indian Meteorological Department, LSI: Landslide Susceptibility Index, LSM: Landslide Susceptibility Mapping, ROC: Receiver Operating Characteristic.

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Author Contributions

Krishna Reddy Maddikera: study conceptualization, landslide inventory preparation, supervision, model validation, manuscript preparation, addressing reviewer comments, Ravi Kumar Gudupudi: geospatial data acquisition and preprocessing, Mahesh Babu Kota: AHP analysis, thematic map preparation, FR modelling, comparative analysis, Padma Priya KT: manuscript revision, addressing reviewer comments, Manjusha Chinta: AHP analysis, thematic map preparation, Madhusudhan Reddy M: AHP analysis, thematic map preparation, Jyothi Peta: manuscript revision, addressing reviewer comments, Salla Arun Tejadhar Reddy: literature review, result interpretation, final manuscript editing. All authors reviewed and approved the final manuscript.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declaration of Artificial Intelligence (AI) Assistance Process

Artificial Intelligence (AI) tools, including GPT-based language models, were used only for language editing and paraphrasing. All scientific ideas, methodology design, data analysis and interpretations were developed by the authors based on existing literature. The authors retain full responsibility for the content.

Ethics Approval

Not applicable.

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