

Landslide Susceptibility Mapping of Chikkamagaluru District, Karnataka Using Ensemble of Frequency Ratio and Evidential Belief Function Models with Geospatial Techniques

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Abstract - Landslide susceptibility mapping (LSM) is a critical tool for disaster risk reduction in geologically active terrain. Chikkamagaluru district in the Western Ghats of Karnataka, India, experiences recurring landslide events during monsoon seasons due to its steep slopes, high rainfall, and complex lithological composition. This study applies an ensemble approach integrating the Frequency Ratio (FR) and Evidential Belief Function (EBF) statistical models using Geographic Information System (GIS) to produce landslide susceptibility zone maps for the district. Eighteen conditioning factors, including elevation, slope, slope aspect, curvature, NDVI, rainfall, lithology, land use/land cover (LULC), geomorphology, and hydrological indices such as TWI and SPI, were derived from multi-source spatial datasets and analysed in ArcGIS. Eight ensemble scenarios were evaluated using Receiver Operating Characteristics (ROC) curves and Area Under Curve (AUC) values. The best-performing model (Scenario 4: EBF + FR) achieved an AUC of 0.919 for the success rate and 0.899 for the predictive rate. Results indicate that areas near major roads and regions of highly dissected hills and valleys exhibit the highest susceptibility. The findings provide a spatially explicit baseline for land-use planners, disaster managers, and policymakers to prioritise mitigation and early warning interventions in the district.

Key Words: Landslide susceptibility mapping, Frequency Ratio, Evidential Belief Function, GIS, Chikkamagaluru, Western Ghats.

1. INTRODUCTION

Landslides are among the most destructive geomorphic hazards globally, causing significant loss of life, property damage, and long-term environmental degradation. According to the World Bank, approximately 3.7 million km² of the Earth's land surface is susceptible to landslide occurrence. India records one of the highest rates of human-triggered fatal landslides worldwide; the Geological Survey of India estimates that about 0.42 million km² — nearly 12.6% of the country's land area — is landslide-prone. The Western Ghats region of Karnataka is particularly vulnerable due to its rugged topography, intense monsoon rainfall, rapid land-use change, and fragile lithological formations.

Chikkamagaluru district in Karnataka lies in the heart of the Western Ghats and has recorded seven significant landslide

events between 2009 and 2022. As of May 2023, 77 villages across 47 gram panchayats in the district have been officially designated as “danger zones” by meteorological authorities. The district's diverse terrain — ranging from 184 m to 1,888 m above mean sea level — combined with annual rainfall varying from 529 mm to 2,329 mm, creates highly variable conditions for slope instability.

Geographic Information Systems (GIS) offer a powerful platform for integrating multi-source spatial data to model and map landslide susceptibility. Statistical bivariate methods such as the Frequency Ratio (FR) and Evidential Belief Function (EBF) have been widely validated in landslide research globally. The FR model quantifies the probabilistic relationship between historical landslide locations and each conditioning factor class, while EBF applies Dempster-Shafer theory to estimate four mass functions — Belief, Disbelief, Uncertainty, and Plausibility — providing a more nuanced characterisation of spatial evidence. This study develops and validates eight ensemble combinations of these two models for the Chikkamagaluru district, aiming to identify the most accurate configuration for district-level landslide susceptibility zonation.

The objectives of this study are: (i) to prepare thematic maps of eighteen landslide conditioning factors using multi-source remote sensing and GIS data; (ii) to apply FR and EBF models and derive eight ensemble susceptibility scenarios; (iii) to validate all scenarios using ROC-AUC analysis; and (iv) to produce a final landslide susceptibility zone (LSZ) map suitable for practical planning and disaster mitigation applications in Chikkamagaluru district.

2. STUDY AREA

Chikkamagaluru district is located in the south-western part of Karnataka, India (approximately Latitude 13.3161°N, Longitude 75.7720°E; MSL +1090 m). The district is bounded by the Western Ghats and encompasses diverse terrain including high mountain ranges, valleys, coffee plantations, and significant forest cover. The Western Ghats, a UNESCO World Heritage Site, dominate the northern and western portions of the district, giving rise to steep slopes susceptible to mass movement.

The district receives seasonal rainfall predominantly during the south-west monsoon (June–September), with annual totals ranging from 529 mm in the eastern lowlands to 2,329 mm in the western ghat areas. The highly dissected hills and valleys, combined with varied lithological units including Peninsular

gneisses, granites, amphibolites, and quartz-muscovite schist, create complex slope stability conditions. The area has experienced multiple landslide events triggered by intense rainfall, road construction activities, and deforestation, making it an important study area for systematic susceptibility assessment.

3. LITERATURE REVIEW

Batar and Watanabe (2021) applied the Weights of Evidence (WoE) method for landslide susceptibility mapping in the Rudraprayag district of the Indian Himalayan Region, achieving a prediction accuracy of 85.7%. Their study highlighted the importance of landslide inventory quality and the need for region-specific validation frameworks. Regmi et al. (2013) compared FR, Statistical Index (SI), and WoE models in Central Nepal using ArcGIS, finding that all three models achieved comparable performance with the FR model marginally superior (success rate: 76.8%; prediction rate: 75.4%). Sarkar and Kanungo (2004) demonstrated the utility of an integrated GIS and remote sensing approach for LSM and emphasised the need for periodic map updates to account for changing land conditions.

Reichenbach et al. (2018), in a comprehensive global review, observed a distinct geographical bias in LSM studies and noted that susceptibility maps have yet to achieve widespread adoption in land-use planning. Tengtrairat et al. (2021) applied machine learning methods integrated with web GIS for automated landslide-risk prediction in Chiang Rai, Thailand, demonstrating the emerging role of automated spatial pipelines. Meena et al. (2022) used U-Net deep learning models for landslide detection in the Himalayas, achieving a Matthews Correlation Coefficient (MCC) of 76.59%, illustrating the potential of pixel-level semantic segmentation. Mondal and Mandal (2020) applied the EBF model for the Darjeeling Himalaya, achieving a prediction accuracy of 80.20%, validating its reliability for Indian geological settings. Dang et al. (2019) employed the GIS-based FR method for Da Lat city in Vietnam, finding that 27.41% of the study area fell in the high susceptibility category, with very high susceptibility covering 18.21%.

The present study builds on this established body of knowledge by applying an ensemble framework that combines FR and EBF across eight mathematically distinct scenarios, an approach that has not been previously applied to the Chikkamagaluru district, and which allows systematic comparison of model performance under the same spatial data conditions.

4. DATA AND METHODOLOGY

4.1 Data Sources

Six primary datasets were used to derive the eighteen conditioning factors employed in this study (Table 1). Topographic derivatives (slope, aspect, curvature, TWI, SPI, TRI, roughness, TPI, STI, RDLS, slope classes) were computed from ASTER DEM data. NDVI was derived from Landsat 8 imagery. Lithological and geomorphological layers were sourced from the Geological Survey of India. Road network distance layers were derived from OpenStreetMap, and LULC was obtained from Sentinel-2 based classification.

Table -1: Spatial datasets used in the study

Data / Layer	Source
ASTER DEM (30 m resolution)	NASA EarthData
Landsat 8 NDVI	USGS EarthExplorer
Lithology, Geomorphology, Lineament	Geological Survey of India
Open Street Map (Roads)	OpenStreetMap
Rainfall (0.04×0.04°)	CHRS Data Portal
LULC (10 m resolution)	ArcGIS Sentinel-2 Land Cover

4.2 Landslide Inventory

A total of 96,270 landslide pixels (training and validation inventory) were mapped from historical records, field surveys, and remote sensing interpretation for the Chikkamagaluru district. The dataset was divided in a 70:30 ratio, with 70% used for model training and 30% retained for independent validation, following standard practice in landslide susceptibility studies.

4.3 Frequency Ratio (FR) Method

The Frequency Ratio is a bivariate statistical method that expresses the spatial correlation between a conditioning factor class and observed landslide occurrences. For each sub-class j of conditioning factor i , the FR value is calculated as the ratio of the proportion of landslide pixels in that sub-class to the proportion of the total pixels the sub-class occupies within the study area. An FR value greater than 1 indicates a positive correlation with landslide occurrence; values less than 1 indicate lower susceptibility. The Landslide Susceptibility Index (LSI) for each pixel is computed as the sum of FR values across all conditioning factors.

4.4 Evidential Belief Function (EBF) Method

The EBF model is grounded in the Dempster-Shafer theory of evidence, which provides a formal framework for reasoning under uncertainty. Four mass functions are computed for each conditioning factor class: Belief (Bel), Disbelief (Dis), Uncertainty (Unc), and Plausibility (Pls), derived from a weight function that quantifies the proportion of landslide pixels falling within each factor class relative to the proportion outside it, enabling differentiated weighting of spatial evidence across classes.

4.5 Ensemble Scenarios

Eight ensemble combinations of the FR and EBF Belief layers were evaluated to identify the most accurate LSM configuration (Table 2). These scenarios ranged from arithmetic combinations (addition, multiplication, weighted averages) to individual model outputs as benchmarks. Final susceptibility maps were classified into five zones: Very Low, Low, Medium, High, and Very High.

4.6 Validation

Model performance was evaluated using the Receiver Operating Characteristics (ROC) curve and the Area Under the Curve (AUC). AUC values for both the success rate (training data) and predictive rate (validation data) were computed for all eight scenarios. AUC values approaching 1.0 indicate excellent discriminatory ability.

5. RESULTS AND DISCUSSION

5.1 Thematic Maps of Conditioning Factors

Eighteen thematic maps were prepared covering topographic, hydrological, geological, and anthropogenic conditioning

factors. Elevation in the study area ranges from 184 m to 1,888 m, reflecting significant altitudinal variation across the district. Slope values range from 0° to 74°, with steeper gradients concentrated along the central Western Ghats ridgeline. The Topographic Wetness Index (TWI) varied from -3.63 to 34.85, indicating a wide range of moisture retention conditions. The Stream Power Index (SPI) ranged from 0 to 498.26, highlighting concentrated erosive energy in valley channels. LULC analysis identified six major classes: water bodies, tree cover, flooded vegetation, crops, built-up areas, and bare ground; tree-covered areas accounted for the majority of the landscape and were identified as a stabilising factor in EBF analysis.

Distance to road (DTR) emerged as a highly influential factor, with the EBF Belief value for the 0–300 m road buffer class reaching 0.906, and the FR value being 2.22 — both indicating a strong positive correlation between proximity to roads and landslide occurrence. This is consistent with the role of road construction activities in destabilising natural slopes through excavation and vegetation clearance.

5.2 EBF and FR Model Results

EBF analysis was performed across all eighteen conditioning factors, yielding Belief, Disbelief, Uncertainty, and Plausibility maps. For slope, the highest Belief value (0.615) was recorded in the 27°–74° class, confirming that steep slopes carry the highest landslide susceptibility. In the geomorphology factor, highly dissected hills and valleys returned a Belief of 0.234 — the highest among all geomorphic units — indicating their dominant role in conditioning landslide events. For LULC, tree-covered areas produced a higher Belief value (0.448) than other classes, reflecting the concentration of historical landslide events in naturally forested but high-relief terrain.

FR analysis similarly highlighted slope as a key discriminator, with the FR value for the 27°–74° class reaching 6.84 — the highest among all slope sub-classes. In the rainfall factor, the 1,250–1,609 mm class yielded an FR of 3.34, while the 1,610–1,969 mm class yielded 2.53, indicating that moderate-to-high rainfall zones are particularly susceptible. Distance to road within 300 m recorded an FR of 2.22, reinforcing the anthropogenic contribution to slope instability.

5.3 Ensemble Model Validation

Table 2 presents the AUC values for the success rate and predictive rate across all eight ensemble scenarios.

Table -2: AUC values for success rate and predictive rate across all eight ensemble scenarios

Scenario	Ensemble Model	Success Rate (AUC)	Predictive Rate (AUC)
1	(EBF × FR)/2	0.894	0.887
2	(2×FR) + EBF	0.907	0.890
3	(2×EBF) + FR	0.911	0.889
4	(EBF + FR)	0.919	0.899
5	(EBF × FR)	0.911	0.889
6	(EBF + FR)/3	0.915	0.894
7	Individual EBF	0.907	0.885
8	Individual FR	0.919	0.899

Scenarios 4 and 8 yielded the highest predictive rate AUC of 0.899, with Scenario 4 (EBF + FR) and Scenario 8 (Individual FR model) performing identically on this metric. Scenario 4 also achieved the highest success rate AUC (0.919), tied with

Scenario 1. The convergence of high AUC values across multiple scenarios indicates that both FR and EBF are robust models for this study area, and that their combination does not diminish predictive power relative to individual models. Scenario 7 (Individual EBF) recorded the lowest predictive AUC (0.885), suggesting that EBF alone is marginally less predictive than FR for this dataset, likely due to its stricter treatment of factor classes with no observed landslide occurrences.

The susceptibility zone area analysis for Scenario 7 — the scenario with the most even spatial distribution — indicates that 7.43% of the district falls in the Very Low susceptibility class, 18.05% in Low, 35.74% in Medium, 18.04% in High, and 20.74% in Very High. For most other scenarios, the Very Low class dominates (>90% of area), reflecting the spatial concentration of historical landslides in specific high-risk zones rather than a diffuse distribution across the district.

5.4 Key Susceptibility Drivers

Based on the predictor rate analysis across both models, the most influential conditioning factors in this study area were: Relief/Elevation (PR ≈ 8.09), Distance to Road (PR ≈ 7.31), TRI (PR ≈ 6.27), Profile Curvature (PR ≈ 6.27), and NDVI (PR ≈ 8.09). These results highlight the combined role of topographic energy (elevation and TRI), human infrastructure (road proximity), and vegetation cover in determining landslide susceptibility in the Chikkamagaluru district.

6. CONCLUSIONS

This study developed and validated an ensemble GIS-based landslide susceptibility mapping framework for Chikkamagaluru district, Karnataka, using Frequency Ratio and Evidential Belief Function models across eight combination scenarios. The key conclusions are as follows:

- The best-performing ensemble (Scenario 4: EBF + FR) achieved an AUC of 0.919 (success rate) and 0.899 (predictive rate), demonstrating excellent spatial predictive accuracy.
- Distance to road, slope gradient, and terrain ruggedness index (TRI) are the dominant conditioning factors for landslide occurrence in the district, highlighting the critical role of anthropogenic activity alongside natural slope conditions.
- Highly dissected hills and valleys, predominantly in the central and southern Western Ghats portions of the district, carry the highest geomorphic susceptibility.
- The susceptibility zone maps produced can directly support land-use planning, road development guidelines, and early warning system placement in Chikkamagaluru district.
- Future research should explore machine learning integration (Random Forest, CNN) and field-verified 3D slope stability models to further improve predictive precision and capture non-linear factor interactions.

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