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Evidential Belief Function (EBF) Model for Landslide Susceptibility Analysis in Idukki District, Kerala, India

Ch. N Vara Laxmi [a++*] and K. Padma Kumari [a#]

[a] *School of Spatial Information Technology, IST, JNTUK, Kakinada, Andhra Pradesh-533003, India.*

Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

A Geo-statistical Dempster-Shafer Theory Evidential Belief Function (DST-EBF) model is selected for Landslide susceptibility evaluation. The aim of the study is to delineate zones prone to landslides within the Idukki district, Kerala using the EBF model and Geographical Information System (GIS) Technique. The objective is to integrate diverse datasets to assess and predict the landslide-prone areas, providing valuable insights for risk management and mitigation startgies. Topographical, Anthropogenic, and Geological factors are considered Landslide Conditioning Factors (LCFs), and Landslide Inventory data are used to establish and validate the Suscebtlity zones. Landslide inventory data is randomly divided into Training(70%) and Testing (30%) data. The resultant Landslide Susceptibility map is categorized into five zones using natural breaking classification method: Very low (20.96%), Low (29.71%), Medium (24.50%), High (18.63%), and Very high (6.20%), respectively, within the study area. The success rate and prediction rate were calculated

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++ *Research Scholar;*
\# *Professor and HOD;*
**Corresponding author: E-mail: lakshmichitikela@gmail.com;*

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using the AUC_ROC method and the EBF Model achieved the highest precision with a success rate of 0.935, and a prediction rate of 0.943 in the current study.

Keywords: Dempster- Shafer theory; landslide susceptibility; evidence belief function; AUC-ROC; GIS.

1. INTRODUCTION

Landslides are the most happening natural geographical hazard in the western Ghat region, Kerala. Thus, as landslides can result in fatalities and significant damage to Human settlements, their systematic prediction and avoidance are crucial components of land use planning (Park, 2011). According to the Kerala State Disaster Management Plan 2016(Kerala State Emergency Operations Centre, 2016) (Solanki et al., 2019), Kerala is prone to recurring landslides, with debris flows being the most common occurrence. The Idukki district is located in the heart of the westernghats, is highly susceptible to landlsides, making it imperative to identify and map landslide prone zones for effective risk management and mitigation strategies.

Geospatial techniques, particulary when integrated with advanced bivariate statistical models , have emerged as a powerful tools for landlside susceptibility analysis. The bivariate statistical models include the frequency ratio (Biswas et al., 2023) (Pham et al., 2020) (Binh Thai Pham et al., 2015), EBF model (Mondal & Mandal, 2020) (Habiballah et al., 2023) (Lee et al., 2013) (Park, 2011), weight of evidence (Kayastha et al., 2012) (Barman & Das, 2024b), index of entropy (Constantin et al., 2011) (Pourghasemi et al., 2012) (Barman & Das, 2024a). Among these models DST-EBF model is particulary noteworthy for its ability to integrate various datasets and handle uncertainties in spatial data and it provides robust framework for predicting susceptable zones by combining multiple condition factors. beyond landslide susceptibility analysis, EBF model can be used is various applicatons in various fields, including environmental management, hazard assessment, and risk analysis.

2. MATERIALS AND METHODS

Study Area: The study area is Idukki district (Fig. 1) in the Western Ghats region (Akshaya et al., 2021) (Vineetha et al., 2019), Kerala, located between Longitude 76°.62′, and 77°.41′, Latitude 9°.27′, 10°.35′ covers a geographical area 5004.55 sqkm. The district shares boundaries with the districts of Pathanamthitta to the south, Thrissur to the north, Kottayam district to the west, and Tamil Nadu to the east (Directorate of Census Operations, Kerala, 2011).

The flowchart depicted in Fig. 2 illustrates the methodology utilized in the study and is briefly explained in the mentioned below sections.

Landslide Inventory Data: It was prepared by 1,850 historical landslide points that were identified from Bhukosh portal (https://bhukosh.gsi.gov.in/Bhukosh/Public)(Barman et al., 2023), historical records (NASA-Co-operative Open Online Landslide Repository (COOLR) (NASA) (https://gpm.nasa.gov/landslides/index.html) and Google Earth dataset (Ali et al., 2021).

Landslide conditioning factors: The magnitude of the landslide depends on Topographical (Slope, Elevation, profile Curvature, Aspect, Relief amplitude, slope classes, Topographic Wetness Index (TWI), Topographic Position Index (TPI), Topographic Ruggedness Index (TRI), Sediment Transport Index (STI), Stream Power Index (SPI)) (Poddar & Roy, 2024), Hydrological (Rainfall, Distance to Drainage(DTD)), geological (lithology, distance to lineament, and geomorphology), Environmental (Normalized Difference Vegetation Index (NDVI), Land use/Land cover (LU/LC)), and Anthropogenic factors (Distance to Road (DTR)).

Application of the EBF model for Landslide susceptibility mapping (LSM): In the present work, Landslide Inventory data and 19 landslide conditioning factors were used to generate LSM utilizing GIS-based EBF model. The EBF model is based on the “Dempster- Shafer theory” (Nampak et al., 2014), to use it, first all the thematic layers (landslide conditioning factors) (Althuwaynee et al., 2012) should be converted into layers of evidential data. In EBF model, four basic functions: Bel (degree of belief), Dis (degree of disbelief), Unc (degree of uncertainty), and Pls (degree of plausibility) (Lee et al., 2013) with a range of [0, 1].

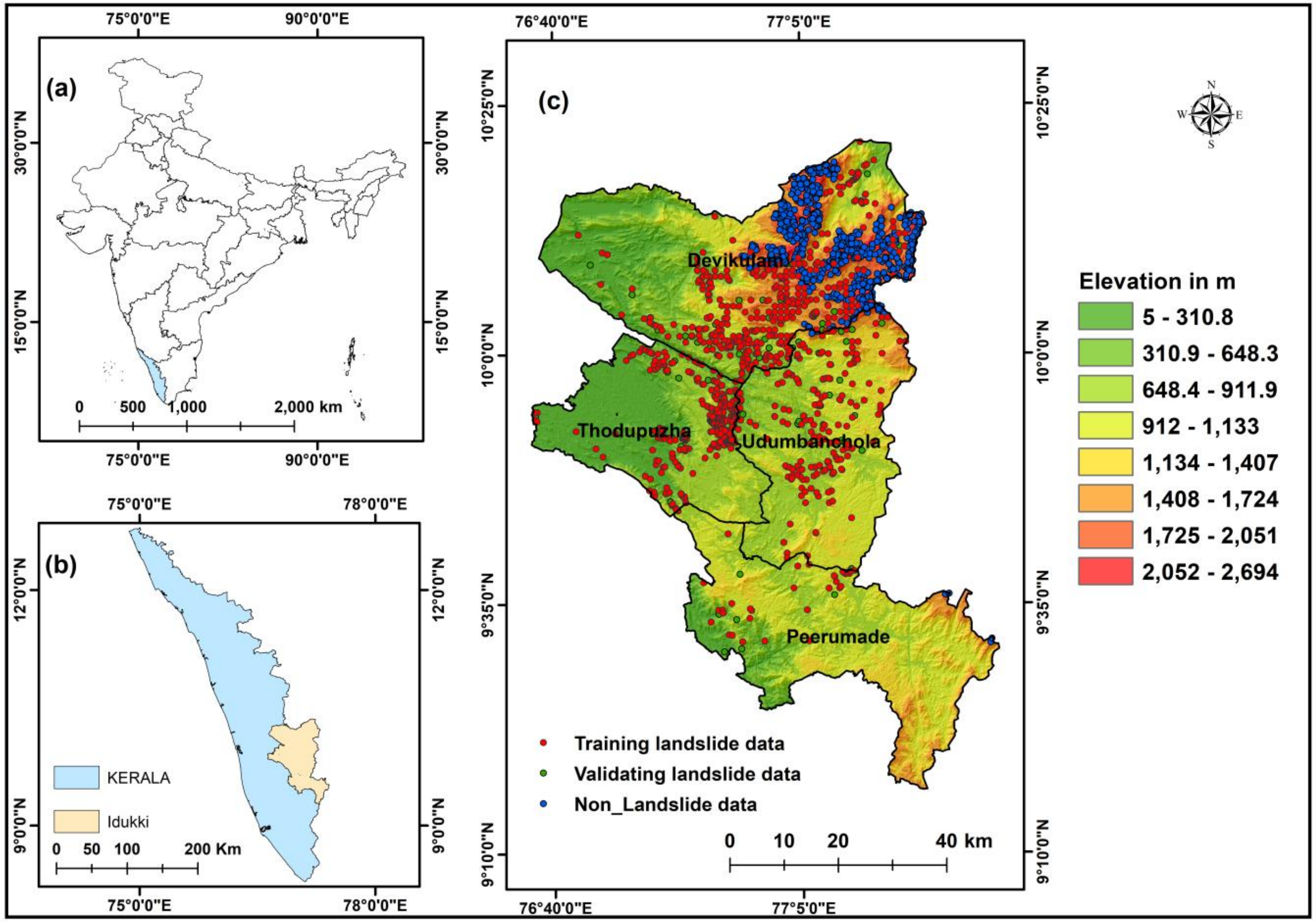

Fig. 1. Location Map of the Study Area

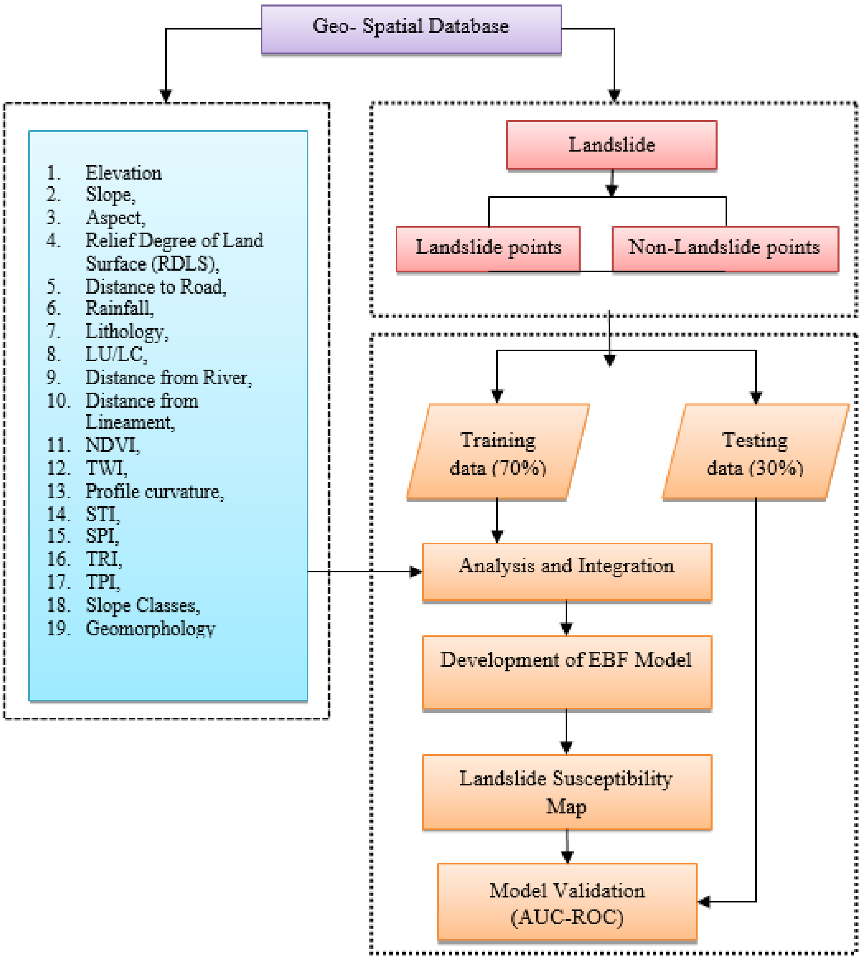

Fig. 2. Workflow of the methodology

The Dempster-Shafer theory of evidence is described by Equation (1) (Althuwaynee et al., 2012).

$$\begin{aligned} &m: P(H) = \{0,1\} \\ &m(\emptyset) = 0\ m(B) = 1 \\ &m(B) = 1: \sum_{H\subset P(H)} m(H) = 1 \end{aligned} \tag{1}$$

Where m is Mass function, P(H) is power set of H , representing all Subsets of a hypothesis set H, m(B) is the Belief mass assigned to subset 'B' of 'H'.

Based on mass function (m), belief functions can be expressed in equation (2)

$$Bel(B) = \sum_{H\subset B} m(H) \tag{2}$$

The integrated EBF values of the LCFs will be implemented sequentially by using Equations (3) & (4). The Bel function (Fig. 3) can be calculated by Equation (4)(Nampak et al., 2014), L is spatial layers of landslide conditioning factors, E_{ij} is evidence, Where 'i' is the amount of layers, 'j' is domain attribute individually to obtain certain accurate results(Park, 2011).

$$\begin{aligned} \lambda &= (T_p)E_{ij} \\ &= [N(L\cap E_{ij})/N(L)]/[N(E_{ij}) - N(L\cap E_{ij})/(N(A) - N(L))] \\ &= N/D \end{aligned} \tag{3}$$

$$Bel = \frac{(T_p)E_{ij}}{\sum(T_p)E_{ij}} \tag{4}$$

Where T_p is the class pixel involved by landslide occurrence, $N(L \cap E_{ij})$ is the number of landslide occurrence pixels in a domain, N(L) is the total number of landslide occurrences, $N(Eij)$ is the number of pixels in a domain (Althuwaynee et al., 2012), and N(A) is the total number of pixels in a domain.

3. RESULTS AND DISCUSSION

Prediction Rate(PR) of Conditioning Factors: The PR of every landslide conditioning factor is calculated using formula (5) (Meena et al., 2022), and the EBF model uses the Bel function as input data (Table 1).

$$PR = \frac{SA_{Max} - SA_{Min}}{Min\,[SA_{Max} - SA_{Min}]} \quad (5)$$

Where SA serves as Spatial Association indicator between conditioning factor and landslides.

The maximum, minimum values, and prediction rate values for the EBF model are in Table 1. The LSM is produced utilizing 'Raster calculator' tool in the Spatial analyst toolbox in the ArcGIS Platform, the map is demonstrated in Fig. 4. The percentage of area of the EBF model for landslide prediction is represented in Table 2.

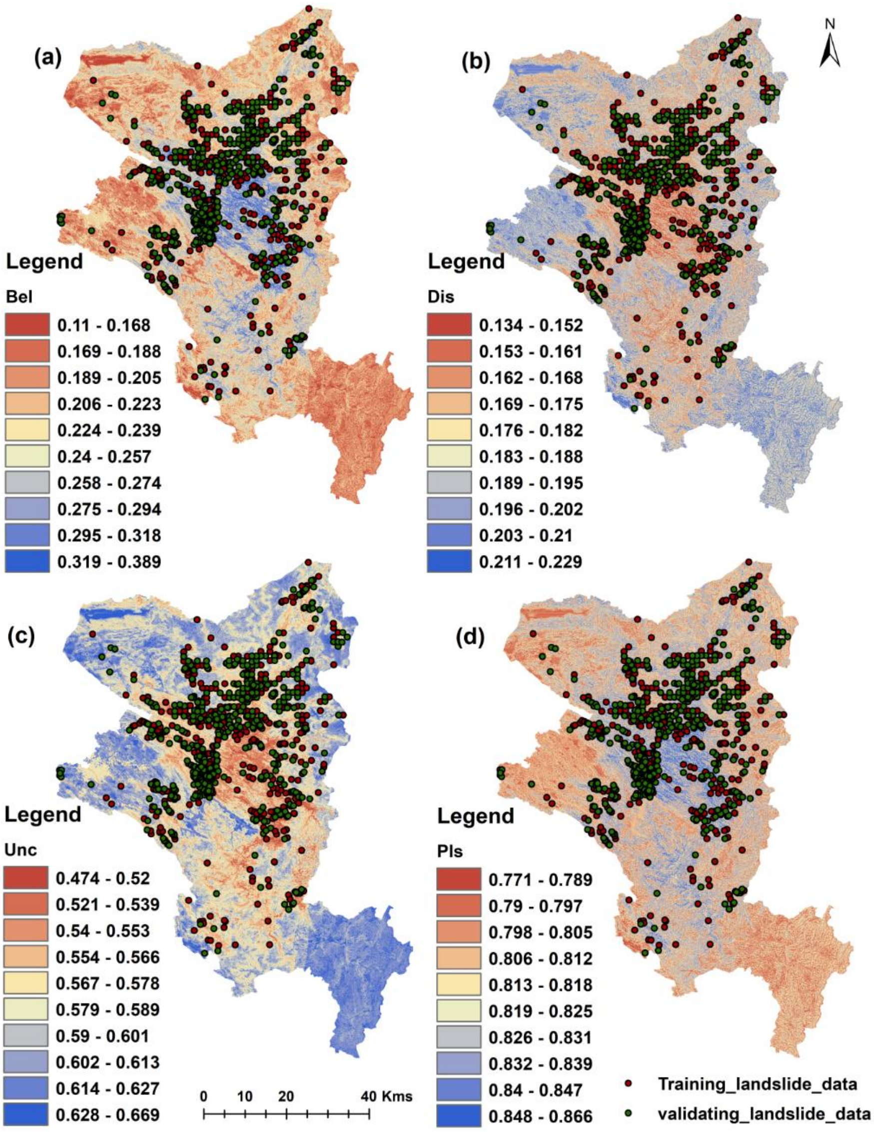

Fig. 3. Integrated results of Evidence Belief Function (EBF) (a) Belief (bel), (b) Disbelief (Dis), (c) Uncertainty (Unc), and (d) Plausibility (Pls)

Table 1. Predictor Rate (PR) of EBF

Factors	EBF			
	SA_Max	SA_Min	I SA_Max -SA_Min I	PR_EBF
Elevation	0.528	0.069	0.458	7.289
Slope	0.339	0.074	0.266	4.228
Slope_Aspect	0.154	0.006	0.148	2.354
Profile_curvature	0.418	0.271	0.148	2.346
Relief Amplitude	0.339	0.100	0.239	3.799
NDVI	0.343	0.089	0.255	4.051
SPI	0.332	0.041	0.291	4.630
TWI	0.275	0.121	0.153	2.439
TRI	0.390	0.056	0.334	5.305
DTD	0.409	0.017	0.391	6.224
STI	0.482	0.065	0.417	6.627
TPI	0.476	0.238	0.238	3.777
Slope classes	0.291	0.050	0.241	3.836
DTR	0.709	0.004	0.706	11.224
DTL	0.236	0.173	0.063	1.000
LULC	0.793	0.000	0.793	12.608
RAINFALL	0.436	0.005	0.431	6.852
Lithology	0.237	0.000	0.237	3.777
Geomorphology	0.413	0.000	0.413	6.570

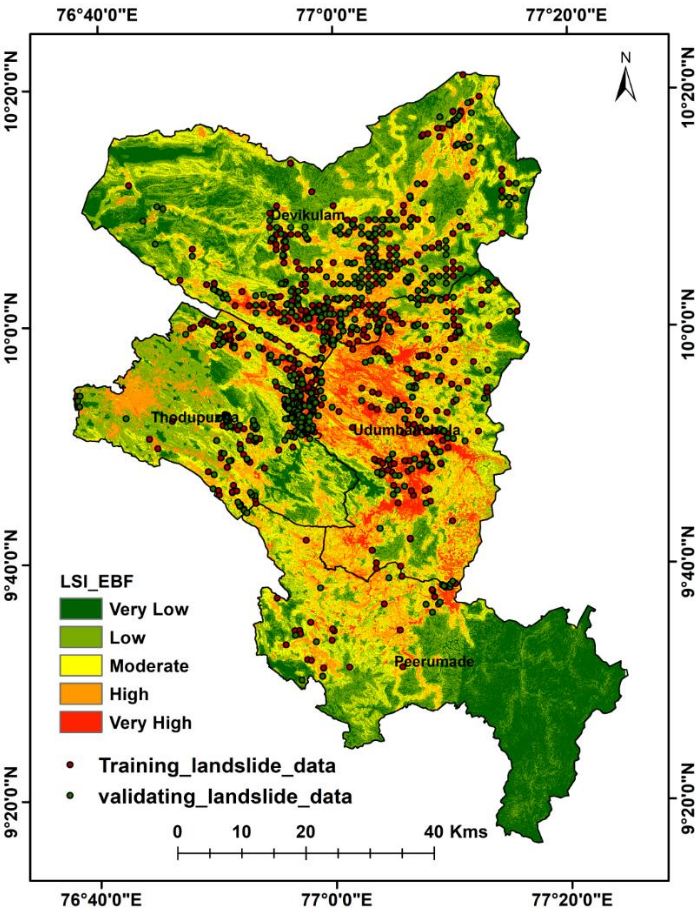

Fig. 4. Landslide prediction map for EBF model

Table 2. Percentage of area of EBF model for landslide prediction

Susceptibility class	Area(Sqkm)	Area in %
Very low	1047.00	20.96
Low	1483.79	29.71
Medium	1223.51	24.50
High	930.47	18.63
Very high	309.79	6.20

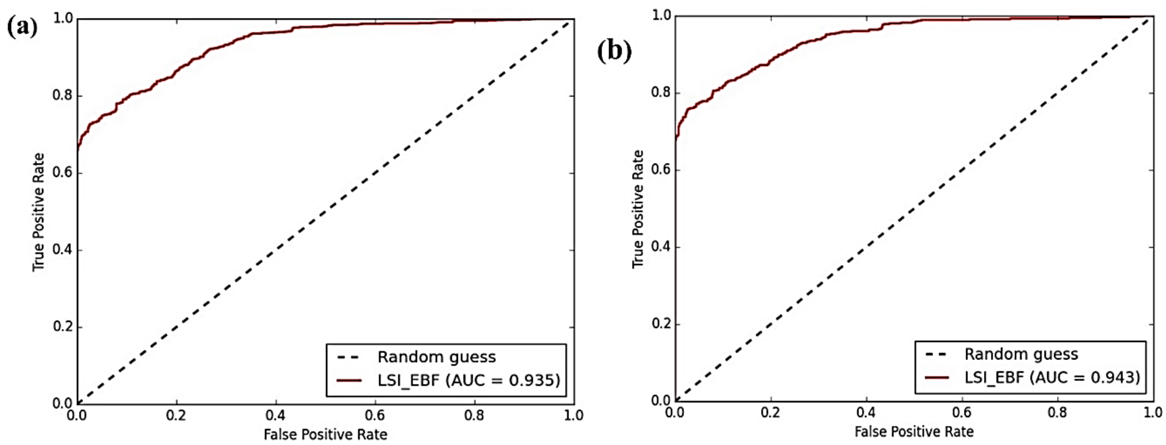

Fig. 5. The success and prediction rate for Landslide susceptibility map; (a) Success rate (b) Prediction rate

Validation: The process's most important stage is confirming the locations that are prone to landslides. The susceptibility map in the current study is created using the EBF model and it is verified by contrasting it with the training data(70%) and tesing data(30%). The success rate and Prediction rate are assessed using AUC-ROC Apporoach (Fig. 5).

4. CONCLUSION

The landslide-prone areas in the Idukki are predicted by using the GIS-based EBF model. To produce susceptible zones, 19 conditioning factors and Landslide Inventory data (1850 points) are considered and prepared from various sources, 70% as training data to create the models and 30% as testing data to verify the model. The Landslide Susceptibility Models of EBF model are cross-validated by using the AUC-ROC method. EBF model exhibits higher accuracy in both the success rate and prediction rate in the study area. In the present study Land use/ land cover played highest role in landslide susceptbility zonation using EBF model. Distance to Road is the second dominant causative factor of landsclides. However, Aspect, Relief Amplitude, Profile curvature, TWI, TPI, and DTL were not found significant weight in Landsldie suseptability zonation. The LS maps of the study area are classified into five classes: Very low, Low, Moderate, High, and Very High through the natural break classification method each %area is 20.96%, 29.71%, 24.50%, 18.63%, and 6.20%. Based on the results, the high and very high-risk zones are been found in the middle of the Idukki district, and implement mitigation actions to lessen the landslide event's effects in the study location.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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