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Assessment of landslide susceptibility using statistical and random forest methods in selected catchments in Kerala, India

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Landslide mapping in Kerala is often conducted on spatially aggregated areas, limiting understanding of how landslide vary across different terrain types. This study addresses this gap by performing a comparative analysis of landslide susceptibility across five physiographically distinct catchments in Kerala, namely, Muthirapuzha, Pooyamkutty, Meenachil, Kuttiyadi, and Chaliyar using two different modeling approaches namely Random Forest (RF), representing machine learning techniques, and the Frequency Ratio (FR) method, representing conventional statistical approaches. Landslide susceptibility maps were developed by categorizing catchment areas into five classes, from *Very Low* to *Very High*. The conventional statistical approach, indicates that high and very high susceptibility zones together occupy 38.19% of Muthirapuzha, 20.21% of Meenachil, 22.12% of Kuttiyadi, 28.43% of Pooyamkutty, and 23.54% of Chaliyar. In contrast, the RF model produces a more differentiated spatial pattern, with high and very high susceptibility classes covering 31.49%, 25.42%, 38.58%, 32.99%, and 33.61% of the respective catchments. Model performance evaluation demonstrates the robustness of the RF approach, with AUC–ROC values of 0.87 (Chaliyar), 0.83 (Pooyamkutty), 0.93 (Muthirapuzha), 0.95 (Meenachil), and 0.96 (Kuttiyadi), and corresponding classification accuracies of 0.82, 0.76, 0.87, 0.90, and 0.88. Comparison with observed landslide inventories shows that actual landslide occurrences are comparable with the results obtained from RF method. These findings emphasise the influence of geomorphological, geological, and land-use characteristics on landslide occurrence in Kerala's monsoon-dominated environment. The study highlights the capability of machine learning to capture complex, non-linear interactions among conditioning factors, offering improved tools for landslide hazard mapping and regional disaster risk management.

KEYWORDS
frequency ratio, GIS, Kerala, landslide susceptibility, random forest, Western Ghats

1 Introduction

Landslides are sudden movements of soil, rock, or debris down a slope that cause extensive property damage, infrastructure disruption, and loss of human lives. These mass movements vary widely in scale, ranging from minor soil slips to catastrophic slope failures (Cruden, 1991). Landslide susceptibility refers to the likelihood that a landslide may occur in a particular region (Reichenbach et al., 2018; Shano et al., 2021).

Early research on landslide susceptibility primarily focused on young and tectonically active slopes, as these were believed to be the most prone to slope failures (Densmore et al., 1998; Rodríguez et al., 1999; Sharifi et al., 2013). However, more recent studies have revealed that landslides also occur in tectonically inactive and geologically old mountain systems. This shift led researchers to investigate non-tectonic drivers of mass movements such as land-use change, rainfall, and geomorphology, prompting increased attention to non-tectonic drivers such as geomorphology, land-use change, and hydroclimatic forcing (Gill and Malamud, 2017; Ramasamy et al., 2021; Skilodimou et al., 2018).

In India, about 13% of the land area has reported landslide occurrences (Kaur et al., 2017). Initial research concentrated on the active Himalayan ranges and later expanded to the Eastern and Western Ghats, particularly regions with heavy monsoon rainfall (Venkata Rao et al., 2024; Ramasamy et al., 2021). Kerala, one of India's 28 administrative states, is bounded by the Arabian Sea to the west and the mountainous Western Ghats to the east (Jones et al., 2021). Of its 14 administrative districts, 13 are prone to landslides, with Idukki recording the highest frequency, while only the coastal district of Alappuzha remains relatively unaffected (Jones et al., 2021; Kuriakose et al., 2009).

Landslides are classified into several types based on the movement mechanism and material involved, including falling (free descent of rock or debris), sliding (downslope movement along a failure plane), flowing (fluid-like movement of saturated debris or soil), creeping (slow, gradual downhill motion), and spreading (lateral extension of unconsolidated material) (Hungr et al., 2014). In Kerala, the predominant type is the debris flow (locally termed Urul Pottal) characterised by the sudden downslope movement of saturated debris (Kuriakose et al., 2009).

Landslide susceptibility arises from the interaction of intrinsic and extrinsic factors. Intrinsic factors include elevation, slope, aspect, curvature, drainage density, and land use, while extrinsic factors involve rainfall, earthquakes, and volcanic activity (Akshaya et al., 2021; Sujatha and Sridhar, 2017; Dahal et al., 2012). In Kerala, with an average annual rainfall of about 3,000 mm, intense monsoon precipitation serves as the primary triggering factor for landslides (Achu et al., 2020; Jones et al., 2021; Kuriakose et al., 2009). The recent increase in the frequency and intensity of extreme events around the world underscores the need for comprehensive susceptibility assessments (Sridhar et al., 2019; Ashhar et al., 2025) and the resulting sediment and mass wasting (Nagireddy et al., 2023; Nagireddy et al., 2022).

Landslide susceptibility, can be evaluated using both quantitative and qualitative approaches (Leon et al., 2014; Nourani et al., 2014; Shano et al., 2021). Qualitative methods are knowledge-driven, while quantitative methods may be physically based or data-driven (Jones et al., 2021; Whitehurst et al., 2021). Statistical methods are broadly classified into bivariate and multivariate methods. Frequency ratio method which is a widely used bivariate method, assess the relationship between landslide occurrence and causative factors by comparing the likelihood of landslides in specific factor classes to their overall occurrence (Kebeba et al., 2024; Shano et al., 2021; Sujatha and Sridhar, 2021). These methods especially the frequency ratio method have been successfully applied in India, including, Uttarakhand, Sikkim and Kerala (Pradeep et al., 2023; Singh et al., 2023; Sonker and Tripathi, 2022; Pal and Chowdhuri, 2019). The use of Geographic Information Systems (GIS) and Remote Sensing (RS) has further enhanced statistical modeling by providing high-resolution, georeferenced spatial data and robust analytical capabilities (Raghuvanshi et al., 2015; Sonker and Tripathi, 2022; Badapalli et al., 2025; Moghimi et al., 2024; Lokesh et al., 2025).

In recent years, machine learning algorithms, including Random Forest, have significantly been used in various applications and susceptibility mapping due to their ability to process complex, multidimensional datasets (Reddy et al., 2022; Sithara et al., 2025; Kang et al., 2024; Liu et al., 2023; Mondini et al., 2023; Khouzani et al., 2025).

This study evaluates the landslide susceptibility of five catchments in Kerala using both a GIS-based statistical approach and the Random Forest (RF) machine learning algorithm. Given that rainfall is the dominant external triggering factor, this study emphasizes the internal catchment characteristics that control susceptibility to landslides across these catchments. Although Random Forest (RF) based landslide susceptibility mapping and the frequency ratio, a bivariate statistical method, have been widely applied, most existing studies either focus on a single basin or assume geomorphic homogeneity across the study region. In contrast, the present study addresses this gap by conducting a study across five catchments with different terrain characteristics under comparable climatic conditions in Kerala, enabling terrain dependent landslide susceptibility study.

2 Materials and methods

2.1 Study area

Five watersheds with most of their extent within Kerala were selected for this study. Selecting different hydrologically independent catchments enables a better assessment of landslide susceptibility, rather than a site-specific or spatially aggregated assessment. Kerala, located on the southwestern coast of India, is a narrow strip of land bordered by the Arabian Sea to the west and the Western Ghats mountain range to the east (Renu et al., 2025; Sivan and Pramada, 2024; Akhila et al., 2025). The state is known for its lush greenery, high rainfall, and complex terrain of hills, valleys, and river systems. However, deforestation, quarrying, and unplanned construction on hill slopes have weakened the stability of its terrain (Reddy et al., 2022).

The five selected catchments are Meenachil, Pooyamkutty, Muthirapuzha, Chaliyar, and Kuttiyadi (Figure 1). The key physiographic and hydrological characteristics of the five selected catchments are summarized in Table 1. Meenachil, Pooyamkutty, and Muthirapuzha are located in southern Kerala, while Chaliyar

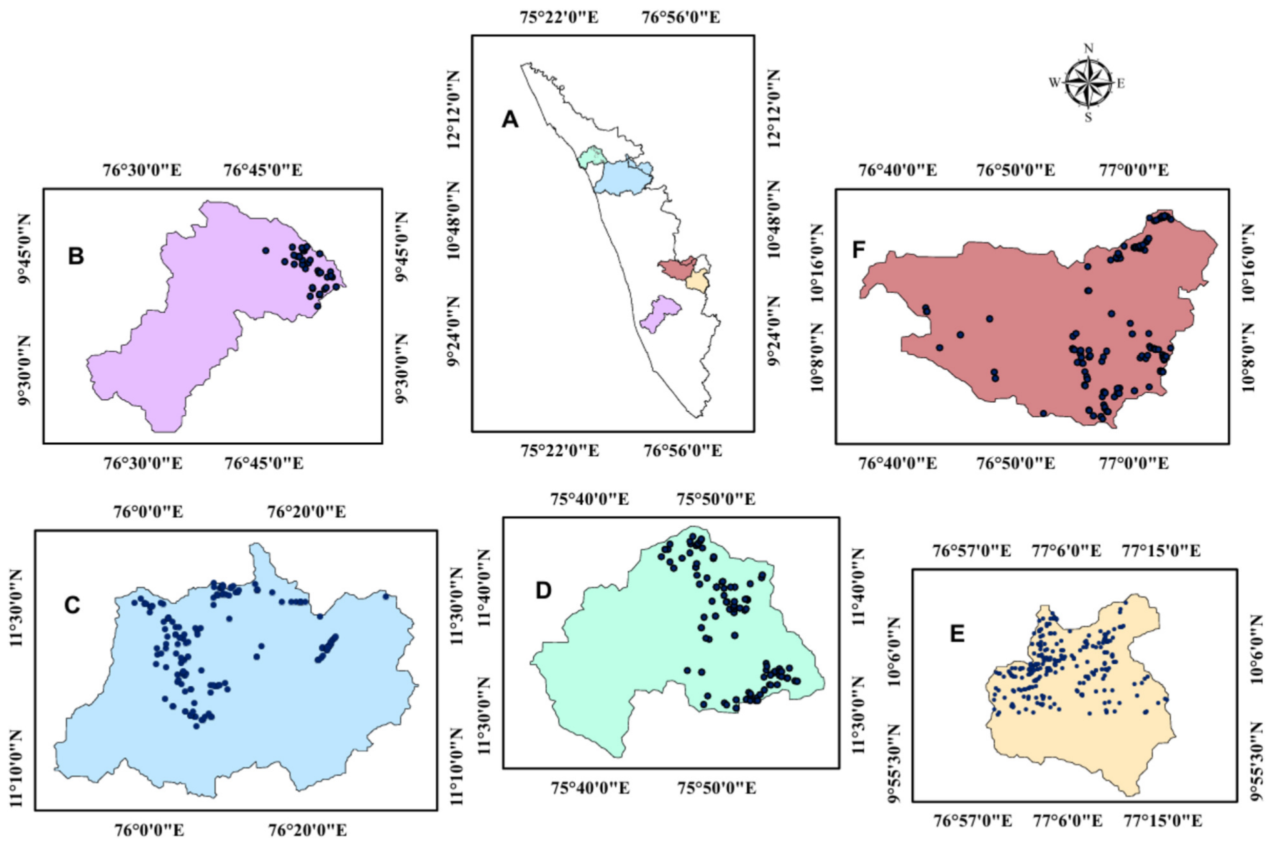

FIGURE 1
The selected catchments within Kerala showing mapped landslide locations, along with their geographical position in the state. **(A)** Kerala. **(B)** Meenachil. **(C)** Chaliyar. **(D)** Kuttiyadi. **(E)** Muthirapuzha. **(F)** Pooyamkutty.

TABLE 1 **Key physiographic and hydrological characteristics of the Catchments.**

Catchments	Area in Sq.km	Maximum Elevation (m)	Minimum Elevation (m)	Average Elevation (m)	Average annual rainfall (mm)
Chaliyar	2,369	2,589	0	338	2,600
Kuttiyadi	735	2053	0	240	5,170
Meenachil	1,313	1,195	1	97	2,778
Muthirapuzha (In Periyar river basin)	704	2,705	255	1,331	5,000
Pooyamkutty (In Periyar river basin)	1,057	2,640	38	868	3,000

and Kuttiyadi are in the northern part of Kerala Pooyamkutty and Muthirapuzha lie predominantly within the highlands of the Western Ghats and a part of Periyar River Basin; Kuttiyadi and Meenachil and Chaliyar spans all three physiographic zones, highland, midland, and lowland.

2.1.1 Meenachil Catchment

The Meenachil Catchment lies entirely within Kottayam district. The Meenachil River is about 78 km long, originating in the Western Ghats near Erattupetta at an elevation of approximately 1,195 m a.s.l. The Catchment covers an area of roughly 1,313 km^2, between latitudes 9°25′–9°55′ N and longitudes 76°30′–77° E. The eastern portion is hilly and underlain by Precambrian metamorphic rocks such as charnockite, while the midlands and lowlands have gentler slopes and elevations below 2 m near Vembanad Lake. The river and its tributaries drain rainfall from the highlands through agricultural and urban landscapes. The Catchment experiences a humid tropical climate influenced by both the southwest and northeast monsoons, yielding abundant rainfall throughout the year.

2.1.2 Chaliyar Catchment

The Chaliyar River, Kerala's fourth-longest, originates in the Elambalari Hills of the Western Ghats and flows westward into the Lakshadweep Sea. Its drainage network includes major tributaries such as Chaliyarpuzha, Punnapuzha, Kanjirapuzha, Karimpuzha, Iruvahnipuzha, and Thottumukkam Puzha (Cherupuzha), as well as smaller tributaries including Kurumanpuzha, Pandipuzha, Maradipuzha, Kuthirapuzha, and Karakkodupuzha. The Catchment lies around 11.16° N, 75.80° E, spanning parts of Wayanad, Malappuram, and Kozhikode districts. It covers 2,969 km^2, with elevations ranging from 2,589 m a.s.l in the upper reaches to below 5 m in the coastal plains (average 338 m). The Catchment has a monsoon-dominated tropical climate, receives about 2,600 mm of annual rainfall, and consists mainly of agricultural land interspersed with rocky and wasteland patches. The dominant soils are gravelly clay, clay, gravelly loam, and loam.

2.1.3 Kuttiyadi Catchment

Situated in northern Kerala at approximately 11°30′ N, 75°51′ E, the Kuttiyadi Catchment lies within Kozhikode district and forms part of the ecologically fragile Western Ghats. It covers about 735 km^2, extending from the foothills to elevations of 2,053 m a.s.l. The rugged terrain features steep hill slopes, narrow valleys, and a dense drainage network. Major tributaries, Onipuzha, Thottilpalampuzha, Kadiyangadupuzha, Mannathilpuzha, and Madappalipuzha, originate in the highlands and converge to form the Kuttiyadi River, which discharges into the Arabian Sea near Moorad. The Catchment receives an average annual precipitation of 5,170 mm, of which about 60% occurs during the southwest monsoon and 30% during the northeast monsoon.

2.1.4 Muthirapuzha Catchment

The Muthirapuzha Catchment, located in Idukki district in the southern Western Ghats, encompasses the hill station of Munnar and its surrounding areas. The terrain is rugged, with steep slopes and elevations ranging from <500 m to >2,500 m near Anamudi peak, the highest point in South India. The geology is dominated by Precambrian crystalline formations including charnockite, granite gneiss, hornblende–biotite gneiss, and khondalite rocks, which are structurally weak and prone to slope failure.

2.1.5 Pooyamkutty Catchment

The Pooyamkutty River, a major tributary of the Periyar, the longest river in Kerala, originates in the high-altitude Eravikulam–Anaimudi Reserved Forest region of the Western Ghats. Flowing mainly through Ernakulam district, it traverses ecologically sensitive zones with dense tropical forests and rugged mountains before joining the Periyar near Kuttampuzha. Elevations range from >2,000 m in the upper catchment to <100 m at the confluence. The Catchment has a tropical monsoon climate, receiving around 3,000 mm of rainfall annually. Land cover is dominated by evergreen and semi-evergreen forests, with limited plantation and agricultural areas in the lower reaches. The region forms part of the Western Ghats biodiversity hotspot, home to numerous endemic plant and animal species.

2.2 Data used

The primary input for any landslide susceptibility study is a landslide inventory or a record of historical landslide occurrences. In this study, the landslide location data were obtained as a shapefile from the *Bhukosh* data distribution portal of the Geological Survey of India (GSI), last updated in 2023. There were 170, 82, 268, 34 and 100 landslide points in Chaliyar, Pooyamkutty, Muthirapuzha, Meenachil and Kuttiyadi, respectively. Apart from this, random non-landslide points were generated equal to the number of landslide points in each catchment. The Python code used for this study has the provision to generate non-landslide points that are randomly distributed with each basin.

Additional datasets required for the analysis included Digital Elevation Models (DEMs), land use/land cover (LULC) maps, lithological maps, lineament maps, and rainfall data. The ALOS PALSAR 3D Digital Elevation Model, with a spatial resolution of 30 m, was used to derive topographic parameters such as elevation, slope, aspect, and curvature. Lineament maps representing major fault structures and the lithological map were also sourced from the Geological Survey of India.

Land use/land cover information was obtained from Sentinel-2 imagery at 10 m resolution, provided by the Environmental Systems Research Institute (ESRI). Watershed boundaries were delineated using data downloaded from the *HydroSHEDS* portal (www.hydrosheds.org). A summary of all datasets and their respective sources is presented in Table 2.

2.3 Methodology

Following an extensive literature review, ten landslide conditioning factors were identified for this study: elevation, slope, aspect, curvature, lithology, land use/land cover (LULC), drainage density, distance to stream, distance to faults, and Topographic Wetness Index (TWI).

Raster layers corresponding to these factors were generated for each watershed. All layers were resampled to a spatial resolution of 30 m and unified into a common raster format using the GIS platform. Table 3 presents the list of conditioning factors, their derivation methods, and data sources. Landslide susceptibility maps were then produced for each watershed using both a bivariate statistical approach based on frequency ratio in GIS environment and a Random Forest (RF) machine learning model using python codes in google colab. The susceptibility values were classified into five classes: Very low, Low, Moderate, High and Very high based on natural breaks so that the classes have maximum variance between them.

2.3.1 Landslide conditioning factors

Elevation indirectly influences slope stability by affecting local climate, vegetation, and rainfall distribution, particularly in the highlands where orographic precipitation is dominant. Slope is among the most critical factors, as steeper slopes

TABLE 2 Data sources and specifications used for landslide susceptibility analysis.

Data	Resolution	Source
Landslide inventory	-	Geological survey of India bhukosh.gsi.gov.in
DEM	30 m	ALOS world 3D www.eorc.jaxa.jp
Lithology	-	Geological survey of India bhukosh.gsi.gov.in
Lineament	-	Geological survey of India bhukosh.gsi.gov.in
LULC	10 m	Sentinel-2 https://livingatlas.arcgis.com/
Rainfall (30 years average annual rainfall from 1991–2020)	0.25° x 0.25°	Indian meteorological department
Watershed boundaries		www.hydrosheds.org

TABLE 3 Selected landslide conditioning parameters with descriptions and data sources.

Factor	Description	Derivation
Elevation	Height above sea level. Influences climate, vegetation, and erosion	Derived directly from DEM (e.g., using GIS software like QGIS or ArcGIS)
Slope	Steepness or gradient of the terrain. Influences runoff and landslide risk	Calculated from DEM using slope tools in GIS (e.g., Slope tool in ArcGIS or QGIS)
Aspect	The compass direction that a slope faces. Affects sunlight exposure and moisture	Calculated from DEM using the aspect tool in GIS.
Curvature	Measures the convexity or concavity of the slope—influences water flow and erosion	Derived from DEM using curvature functions
Lithology	Type and physical properties of the underlying rock. Influences soil formation and stability	Obtained from the geological survey of India in vector format
Land use/Land cover (LULC)	Classification of land surface (forest, urban, agriculture, etc.). Influences infiltration and erosion	Downloaded directly from the source mentioned in Table 2
Drainage density	Total length of streams per unit area. Indicates how dissected the landscape is	Extract streams from DEM (using flow accumulation), and calculate the total length of streams per area
Distance to Stream	Proximity of a location to the nearest stream. Influences erosion and moisture	Use the stream network derived from the DEM and apply the Euclidean distance function in GIS.
Distance to faults	Proximity to tectonic faults. Important in seismic hazard and slope stability	Use geological maps with fault lines, and apply Euclidean distance in GIS.
Topographic wetness index (TWI)	Indicates the spatial distribution of wetness. Higher TWI = more likely to accumulate water	$TWI = \ln(A_s/\tan(\beta))$, where A_s is the specific catchment area and β is the slope angle; calculated using GIS.

increase the likelihood of failure due to greater gravitational stress. Aspect influences the amount of solar radiation and surface moisture, affecting vegetation growth and soil cohesion.

Curvature indicates whether a slope is concave or convex: concave slopes tend to accumulate water, increasing pore pressure and failure probability, while convex slopes are prone to erosion. Lithology determines the strength, structure, and permeability of the underlying rock; weak, fractured, or weathered rocks are more vulnerable to slope instability. Land use/land cover directly impacts surface stability, vegetation provides root reinforcement and reduces runoff, while deforestation and construction increase erosion and instability.

Hydrological factors such as drainage density and distance to streams play key roles in erosion and saturation dynamics. Regions close to streams or with high drainage density are more likely to experience undercutting and water accumulation. Similarly, faults represent structural weakness; areas near fault zones are often characterized by fractured and weathered materials. Finally, the Topographic Wetness Index (TWI) quantifies potential soil moisture accumulation—higher values correspond to wetter areas with greater susceptibility to landslides.

2.3.2 Statistical susceptibility mapping

The study area was divided into grid cells (pixels), each classified according to the defined factor classes (e.g., slope intervals of 0°–5°, 5°–15°, etc. All continuous variables are classified into 5 classes based on the Natural Breaks method to get the maximum variance between the classes in line with recent literature that used statistical methods (Bhagya et al., 2023; Mersha and Meten, 2020; Beeram et al., 2024; Senan et al., 2023). The classes resulting from natural breaks were then confirmed once again against the classifications in the literature, such as flat slopes usually being below 10°, which are usually less susceptible. For each factor class, a weight was computed to represent the relative likelihood of landslide occurrence, calculated as in Equation 1 and the Landslide susceptibility index is calculated as Equation 2

$$W = \frac{N_{pix}(S_i)/N_{pix}(N_i)}{\Sigma N_{pix}(S_i)/\Sigma N_{pix}(N_i)} \tag{1}$$

$$LSI_k = \sum_{i=1}^{n} W_{i,k} \tag{2}$$

where:

- $N_{pix}(S_i)$ = number of pixels containing landslides within a specific parameter class,
- $N_{pix}(N_i)$ = total number of pixels within that parameter class,
- $\Sigma N_{pix}(S_i)$ = total number of pixels containing landslides in the entire catchment, and
- $\Sigma N_{pix}(N_i)$ = total number of pixels in the catchment.
- n is the number of factors
- LSI is the landslide susceptibility index of the kth pixel

A weight value greater than 1 indicates that the factor class contributes positively to landslide occurrence (high susceptibility), while a value less than 1 suggests lower susceptibility. The computed weights for all factor classes were combined through weighted summation to generate a landslide susceptibility index (LSI) for each pixel. The resulting LSI values were categorized into five susceptibility classes: *Very Low, Low, Moderate, High,* and *Very High* using natural breaks.

2.3.3 Random forest algorithm

The Random Forest (RF) algorithm, introduced by Breiman (2001), is a powerful ensemble learning method that constructs multiple decision trees using bootstrap aggregation (bagging). Each tree is trained on a randomly drawn subset of the original dataset (with replacement), creating *B* independent base learners. Approximately one-third of the data not used in each bootstrap sample, known as Out-of-Bag (OOB) samples, provide unbiased internal error estimates.

At each node of a tree, a random subset of predictor variables, determined by the max_features hyperparameter is selected, and the split that yields the greatest reduction in impurity (e.g., Gini index or entropy) is chosen. This randomization decorrelates the individual trees, improving generalization performance.

The final prediction is an ensemble output derived through majority voting (for classification) or averaging (for regression). Here, the training and testing data split is in the ratio 70:30. Key hyperparameters include n_estimators (number of trees), max_depth (maximum depth of each tree), and min_samples_split (minimum number of samples required at a leaf node). The best combination of hyperparameters is found by using the Grid search Method. The hyperparameter values tested are as follows.

- ‘n_estimators’: 100, 300, 500
- ‘max_depth’: 10, 20, None
- ‘min_samples_split’: 2, 5, 10
- ‘max_features’: ‘sqrt (total factors)’, ‘log2 (total factors)’

5-fold cross-validation is used for hyperparameter optimisation. The Random Forest algorithm is particularly suited for landslide susceptibility mapping due to its ability to handle nonlinear relationships, noisy data, and complex interactions among geomorphic variables (Belgiu and Drăguţ, 2016; Rabby et al., 2022). For the Random Forest (RF) model, categorical variables such as aspect, lithology, and land use were encoded using label encoding. The random forest algorithm was executed using the Sklearn package in Google Colab. The susceptibility values were categorized into five susceptibility classes: *Very Low, Low, Moderate, High,* and *Very High* using natural breaks.

3 Results and discussion

3.1 Statistical landslide susceptibility

Landslide conditioning factors were estimated and derived in a GIS environment. Figures 2–6 illustrate the spatial distribution of these conditioning factors for the five selected catchments namely; Muthirapuzha, Meenachil, Kuttiyadi, Pooyamkutty, and Chaliyar. This method directly quantifies the relationship between landslide occurrence and conditioning factors based on observed frequencies, without assuming linearity or independence among variables, which is a key limitation in other statistical methods like Regression and Weight of Evidence (WoE). Unlike AHP, which relies heavily on expert judgment and subjective weighting, this method is entirely data-driven, ensuring objectivity and reproducibility. Each factor was classified into distinct ranges before calculating the weights for landslide susceptibility using the bivariate statistical method. The continuous variables are classified based on natural breaks into 5 classes. The landslide susceptibility maps derived from the statistical method for all watersheds are shown in Figure 7. The percentage of the catchment area falling under each landslide susceptibility category, as derived using the statistical approach, is presented in Table 4. A comparative assessment reveals distinct spatial patterns of susceptibility across the five catchments, reflecting their geomorphological diversity and physiographic context.

3.1.1 Muthirapuzha

Among all Catchments, Muthirapuzha exhibits the highest susceptibility, with approximately **54%** of its area classified under *Moderate* to *High* susceptibility zones. The *Very High* susceptibility class alone accounts for **13.7%**, primarily located in the northern

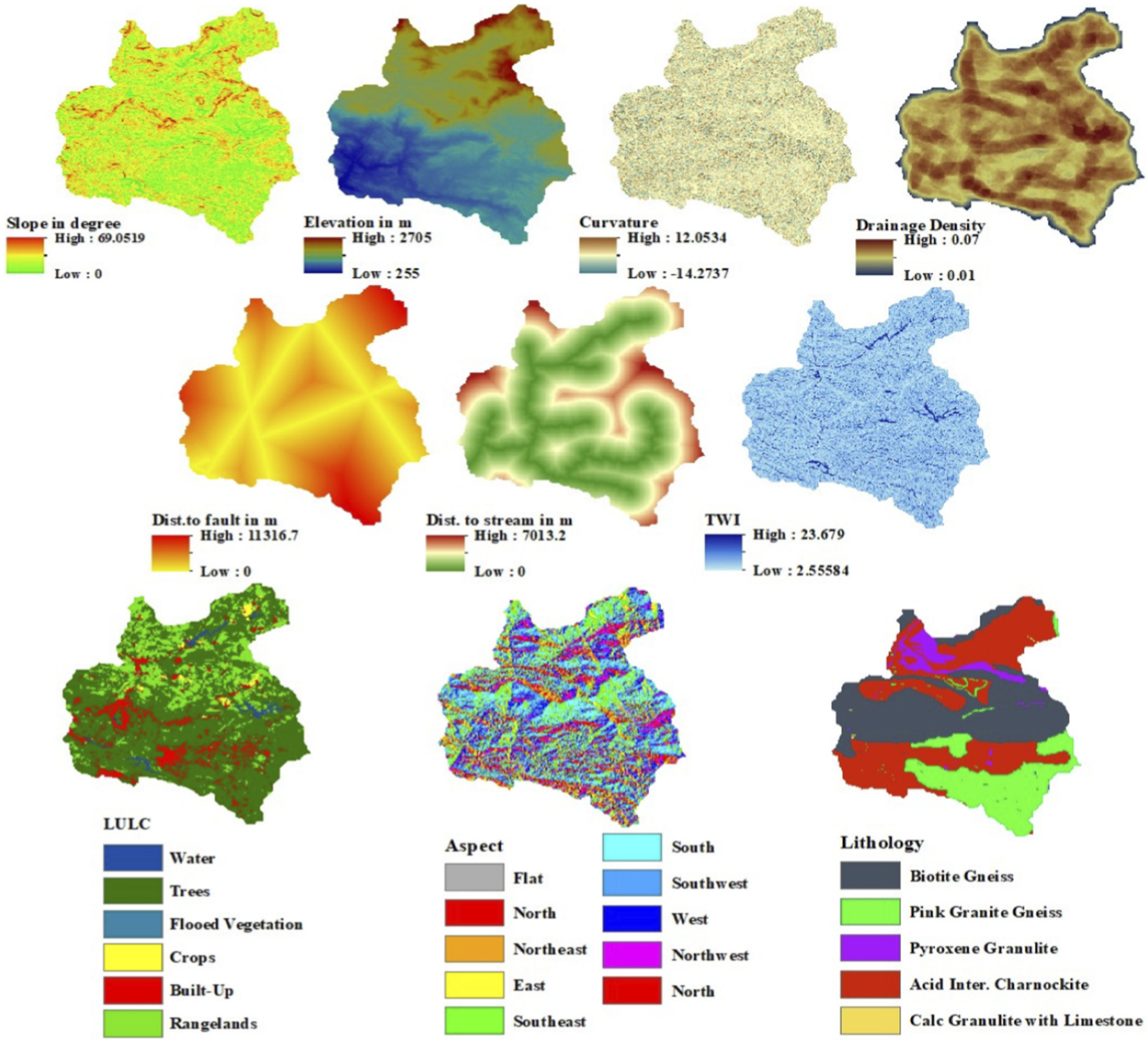

FIGURE 2
Spatial distribution of key landslide conditioning factors in the Muthirapuzha Catchment, including topographic, geological, hydrological, and land cover characteristics.

and central hilly regions, reflecting its generally unstable terrain. In contrast, the *Very Low* class covers only **10.41%** of the catchment. Landslide inventory data indicate clustering of events in steep, forested slopes, emphasizing that topographic steepness is the dominant control on slope instability in this watershed.

3.1.2 Meenachil

In contrast, the Meenachil catchment is the least susceptible, with **60.49%** of its area categorized under *Very Low* to *Low* susceptibility and only **7.78%** under *Very High*. These higher-risk zones are concentrated in the northeastern uplands. The Catchment's gentle slopes and moderate relief contribute to its overall stability, corroborated by the sparse and spatially localized distribution of landslide events.

3.1.3 Kuttiyadi

The Kuttiyadi Catchment demonstrates a balanced susceptibility profile. Approximately **61.19%** of its area falls within the *Very Low* to *Low* classes, while **22.12%** lies in the *High* and *Very High* categories. Elevated susceptibility occurs mainly in the Western Ghats region, characterized by steep slopes and rugged topography. This pattern corresponds closely with dense clusters of recorded landslides in the upper catchments, highlighting the role of elevation and slope steepness as key conditioning factors.

3.1.4 Pooyamkutty

The Pooyamkutty Catchment shows substantial landslide risk, with **28.43%** of its area classified as *High* and *Very High* susceptibility,

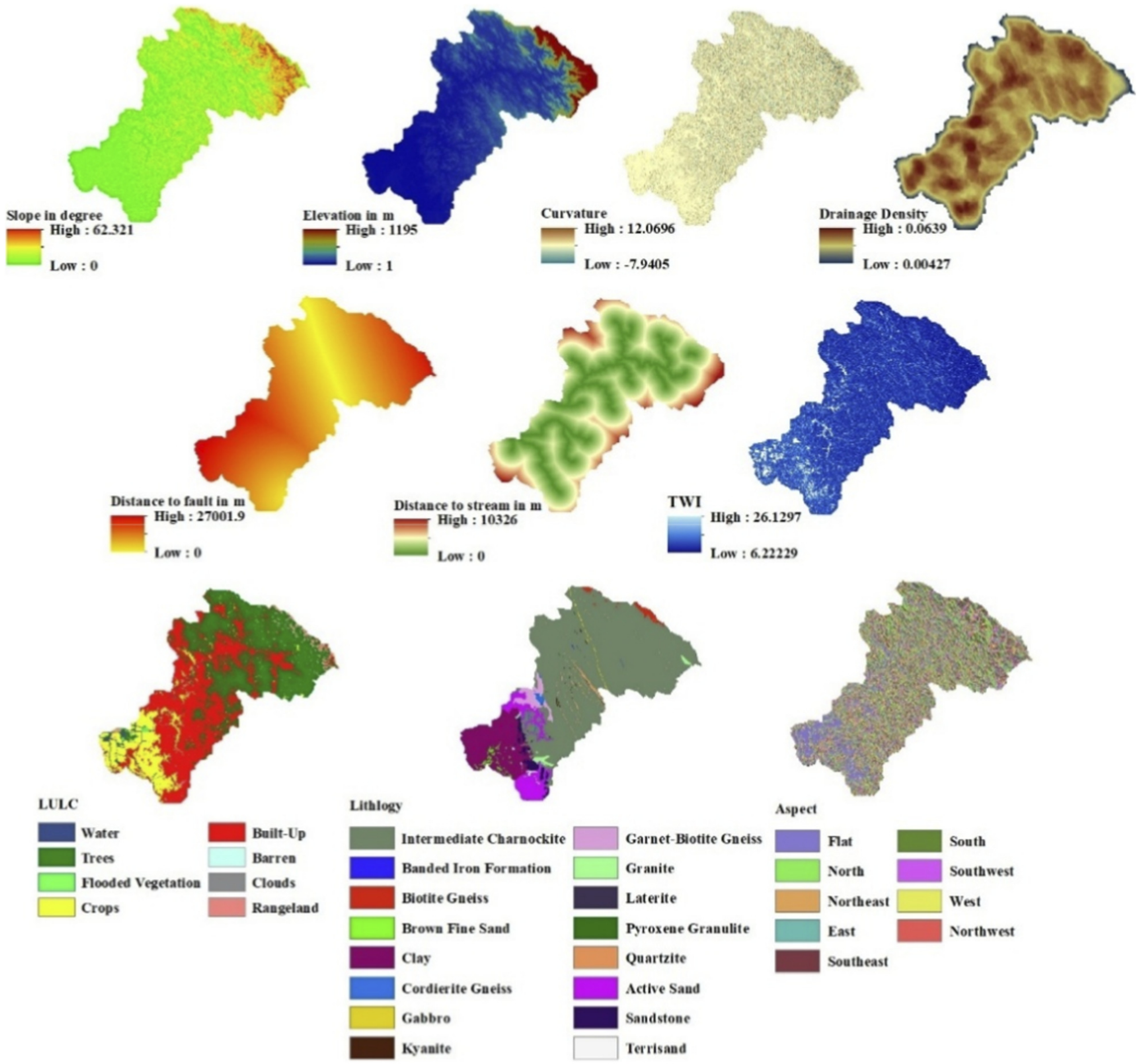

FIGURE 3
Spatial distribution of key landslide conditioning factors in the Meenachil Catchment, including topographic, geological, hydrological, and land cover characteristics.

indicating that a large portion of the catchment remains inherently vulnerable to slope failure. The *Moderate* class dominates (**30.81%**), suggesting widespread transitional terrain stability. Higher landslide densities are concentrated along the eastern and southeastern slopes, areas affected by deforestation, slope modification, and road development. The *Very Low* class accounts for only **17.22%**.

3.1.5 Chaliyar

The Chaliyar catchment exhibits a susceptibility pattern similar to that of Meenachil, with **57.33%** of its area categorized as *Very Low* or *Low*. However, several central upland regions display localized *High* (**16.18%**) and *Very High* (**7.36%**) susceptibility zones, consistent with the spatial distribution of recorded landslide events. These zones correspond to deeply dissected terrain characterized by high drainage density and weak lithological formations, where instability persists despite the catchment's generally stable setting.

Overall, the statistical method highlights strong physiographic control on landslide susceptibility across the catchments. The Muthirapuzha and Pooyamkutty catchments—both situated entirely within the Western Ghats highlands—exhibit the greatest susceptibility, while Meenachil and Chaliyar show comparatively lower risks due to gentler slopes and broader midland–lowland transitions. These patterns reaffirm the importance of topographic steepness, drainage density, and lithology as dominant controls on slope stability in Kerala's humid tropical environment.

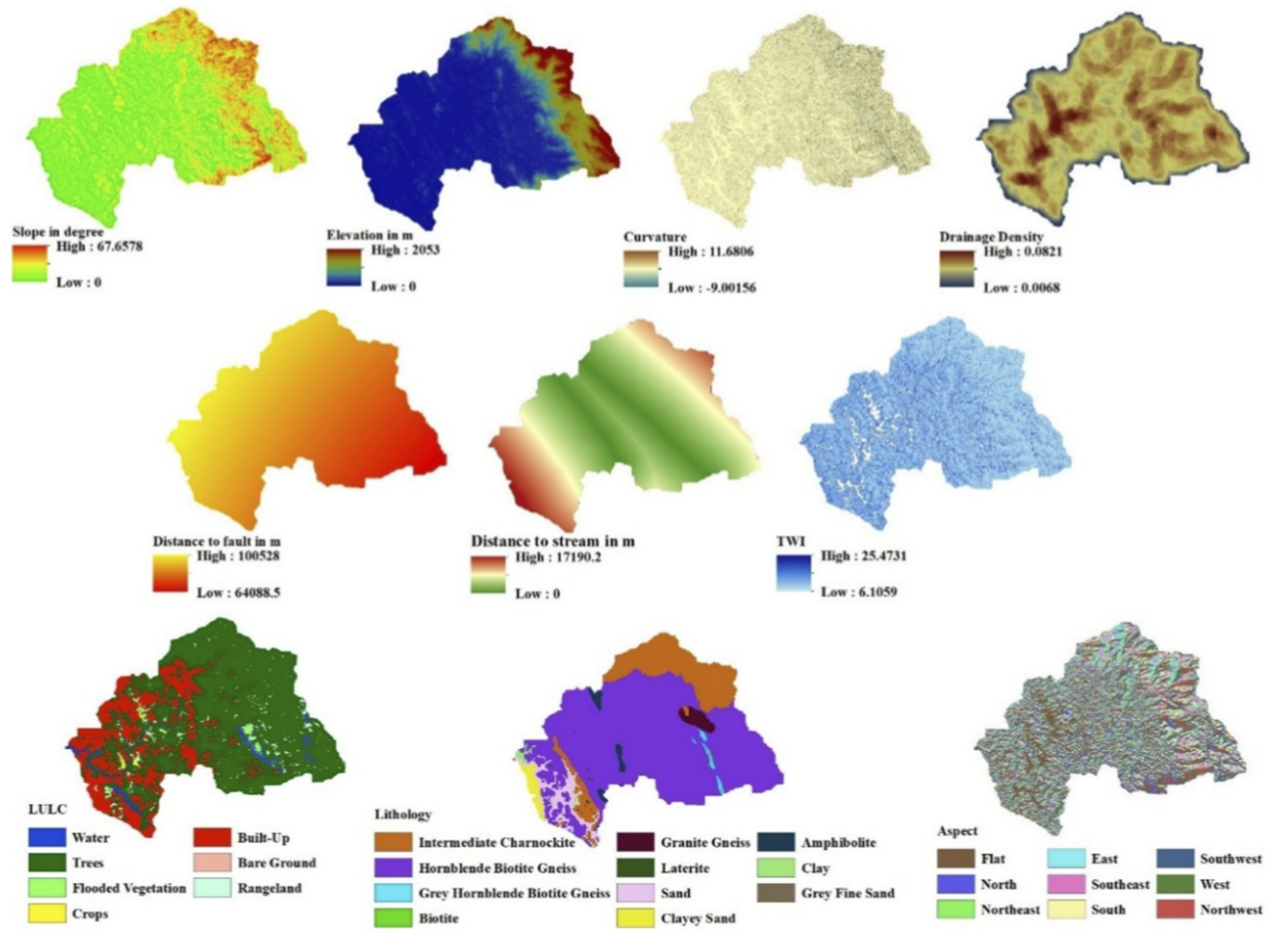

FIGURE 4
Spatial distribution of key landslide conditioning factors in the Kuttiyadi Catchment, including topographic, geological, hydrological, and land cover characteristics.

3.2 Landslide susceptibility using random forest

Figure 8 gives the ROC curves of each catchment. The RF model demonstrated superior predictive capability and robustness compared to the statistical approach across all catchments. High AUC values, ranging from 0.83 for Pooyamkutty to an outstanding 0.96 for Kuttiyadi, confirms its ability to capture complex, nonlinear relationships among conditioning factors. These strong performance metrics confirm that the RF model effectively integrates geomorphological, hydrological, and land-use characteristics to delineate landslide-prone areas with greater precision. The details of the random forest model for each catchment are given in Tables 5–7 summarises the percentage of area within each susceptibility class.

A uniform maximum tree depth of 10 across all catchments indicates a balanced model that effectively captures nonlinear relationships without overfitting, while variations in maximum features (log2 or sqrt of the total number of features) and minimum samples split reflect differences in predictor dominance and data heterogeneity among catchments. The number of trees is generally 100, except for Muthirapuzha, where a larger ensemble (500 trees) was required to stabilize predictions, suggesting higher internal variability. Model performance is consistently strong, with AUC-ROC values ranging from 0.83 to 0.96 and accuracies between 0.76 and 0.90, demonstrating good to excellent discrimination between landslide and non-landslide classes. Kuttiyadi and Meenachil exhibit the highest reliability, characterised by excellent AUC and balanced confusion matrices with minimal misclassification, whereas Pooyamkutty shows comparatively lower performance.

Table 6 gives the details of the most influential factors in each catchment with relative importance (Gini importance), inside parenthesis. In Chaliyar and Muthirapuzha, elevation and slope emerge as the most influential factors, indicating the strong role of relief, gravitational stress, and terrain energy in landslide initiation, while LULC and drainage density play secondary roles by modulating surface runoff and slope stability. Pooyamkutty stands out with aspect as the most important factor, followed closely by elevation and slope, suggesting that slope orientation has a pronounced influence on landslide occurrence in this catchment. In Meenachil and Kuttiyadi, slope is the dominant factor with elevation and drainage density further contributing by

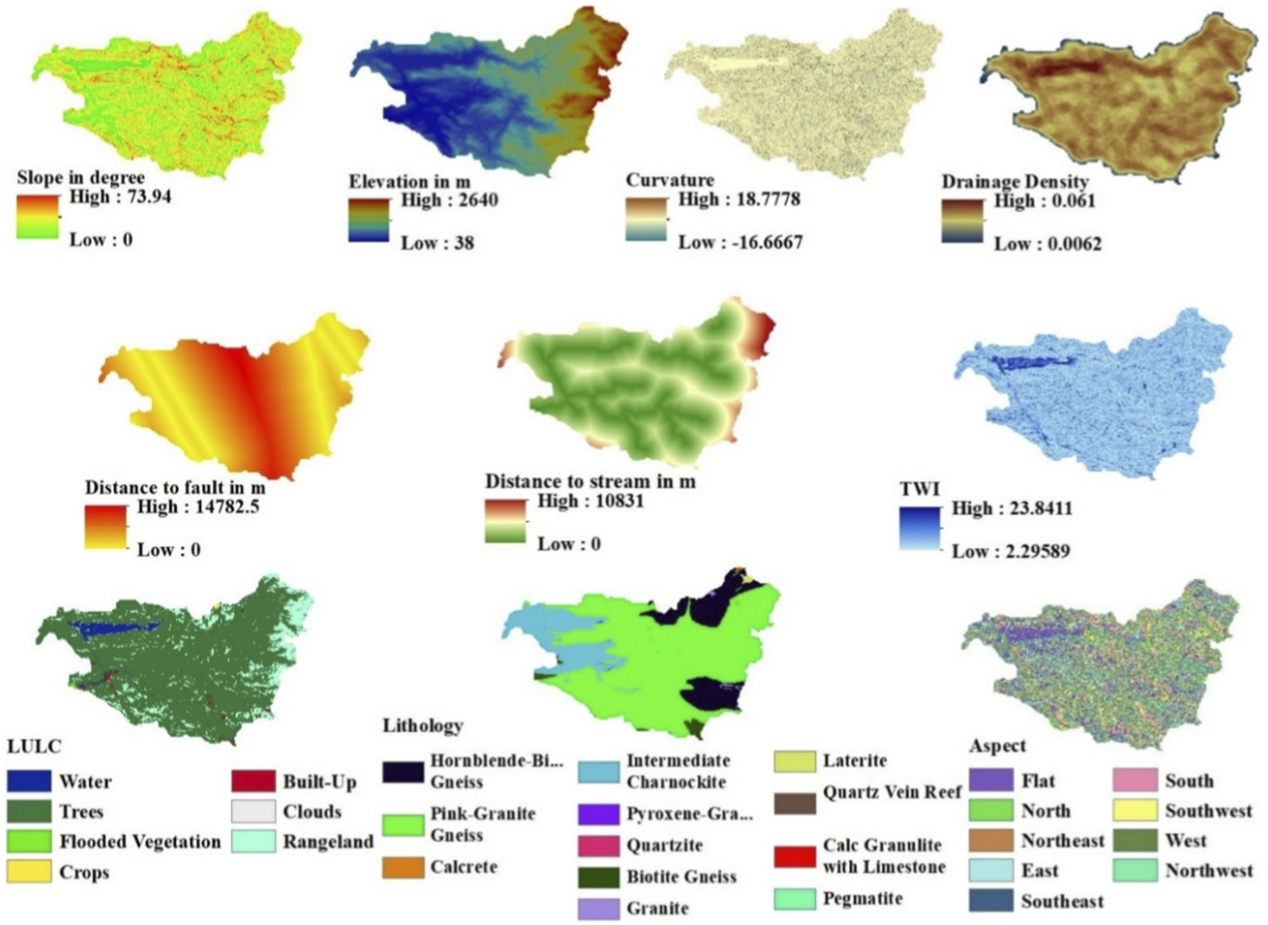

FIGURE 5
Spatial distribution of key landslide conditioning factors in the Pooyamkutty Catchment, including topographic, geological, hydrological, and land cover characteristics.

influencing runoff concentration and subsurface flow. Lithology and curvature generally rank lower across catchments, indicating comparatively lesser control through material strength and slope geometry. LULC shows variable importance, reflecting differences in human intervention and vegetation cover among basins. Overall, the importance ranking demonstrates that while topographic factors consistently govern landslide susceptibility, the relative importance of hydrological and surface characteristics varies with local physiographic and environmental conditions in each catchment.

Figure 9 presents the landslide susceptibility maps for the five Catchments derived using the Random Forest (RF) algorithm. The classification of susceptibility zones was performed using a data-driven scheme applied individually to each basin. Consequently, the thresholds defining the five susceptibility classes (Very Low, Low, Moderate, High, and Very High) correspond to the internal distribution of model outputs within each basin. The produced maps represent relative susceptibility patterns specific to each watershed. Direct numerical comparison of class intervals between basins may not be appropriate.

In spatial terms, the RF-generated susceptibility maps exhibit sharper and more distinct delineation of high-risk zones relative to the statistical model. The model produces well-defined susceptibility gradients and minimizes ambiguous transitional zones, enhancing interpretability for hazard management.

Quantitatively, the RF model revealed more decisive risk distributions across the catchments. The Kuttiyadi catchment emerged as the most vulnerable, with 38.58% of its area classified as *High* or *Very High* susceptibility, corresponding to its steep slopes and complex drainage network. The Chaliyar catchment followed closely, with 33.61% under the *High* and *Very High* classes, primarily concentrated in its dissected uplands. In Muthirapuzha, approximately 31.49% of the catchment area was mapped as *High* or *Very High* susceptibility, particularly concentrated in the northern portion where steep topography and weathered lithology coincide.

Interestingly, the Meenachil catchment, despite having relatively gentle slopes, achieved an AUC of 0.95. Although the proportion of *High*/*Very High* area (25.42%) was comparable to that obtained from the statistical method, the RF output delineated a much clearer and spatially coherent central risk corridor, demonstrating the model's enhanced discriminative power. Conversely, the Pooyamkutty catchment, with the lowest AUC (0.83), still exhibited notable improvement over the statistical model. About 32.99% of its area fell within the *High* and *Very High* susceptibility classes, corresponding

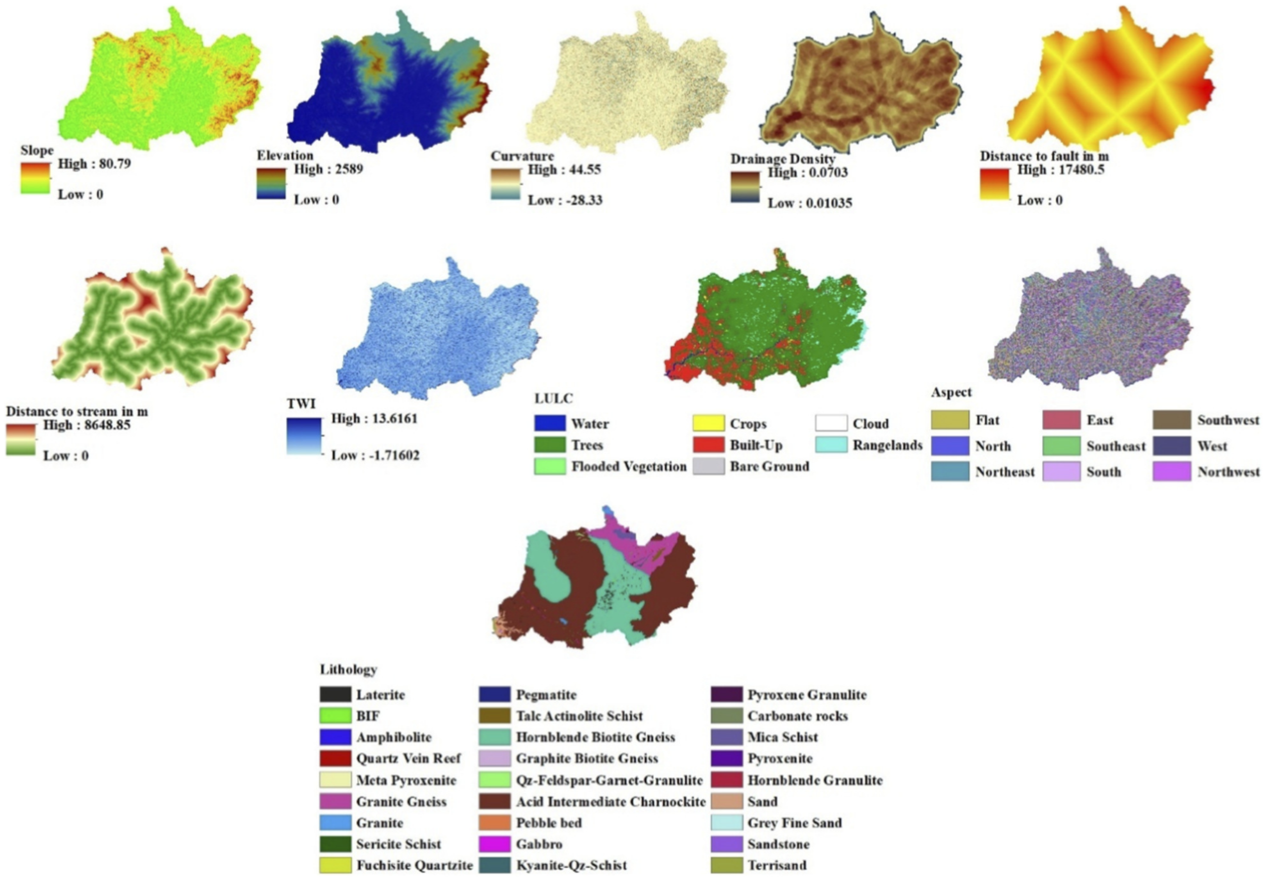

FIGURE 6
Spatial distribution of key landslide conditioning factors in the Chaliyar catchment, including topographic, geological, hydrological, and land cover characteristics.

well with observed landslide clusters along steep, deforested slopes and road-cut areas.

Overall, the RF model consistently produced more reliable susceptibility maps, effectively capturing the nonlinear interactions among terrain, lithology, and land-use factors. This improved predictive accuracy not only strengthens the scientific understanding of landslide mechanisms in Kerala's diverse physiographic settings but also provides a more robust foundation for regional land-use planning and disaster risk reduction.

3.3 Discussion

The results of this study were compared with other reported studies in the Western Ghats region. Suraj et al. (2024) estimated the landslide susceptibility of the two adjacent Iruvizhinji and Kuruman sub-watersheds of the Chaliyar basin using Shannon Entropy and the Frequency Ratio method. The study on these two sub-watersheds concluded a concentrated central portion of high susceptibility, which represents areas with the ghat road section in Kozhikode. The same areas have been flagged as having higher susceptibility in this study as well. Bhagya et al. (2023) studied the susceptibility of 20 local self-governing bodies of Kerala using the Analytic Hierarchy Process (AHP) and Fuzzy–AHP (F-AHP), out of which some are within the Meenachil Basin. For example, Poonjar-Thekkekkara, Thalanad, and Moonnilavu, which are located in the head reaches of Meenachil, are noted by Bhagya et al. (2023) is also shown to have high susceptibility in this study by both statistical and the random forest model. Swetha and Gopinath, (2020) studied the susceptibility of the highland areas of the Kuttiyadi River Basin using the analytic network process, and stated that the Kakkayam dam area, which witnessed a recent landslide, generally had very high susceptibility. This area comes under the higher reaches of Kuttiyadi, which was found to have higher susceptibility using both statistical and machine learning methods in this study. Jones et al. (2021) investigated landslide susceptibility in the Idukki district of Kerala using regression analysis and machine learning, and Munnar, a city located in the northern part of the Muthirapuzha, was identified to be susceptible in the susceptibility map resulting from the investigation. The northern part of Muthirapuzha and the eastern part of Pooyamkutty, adjacent to the Muthirapuzha basin is found to be dominantly susceptible in this study by both statistical method and random forest.

The comparison of Landslide Susceptibility Maps (LSMs) indicates that the Random Forest (RF) model consistently provides a

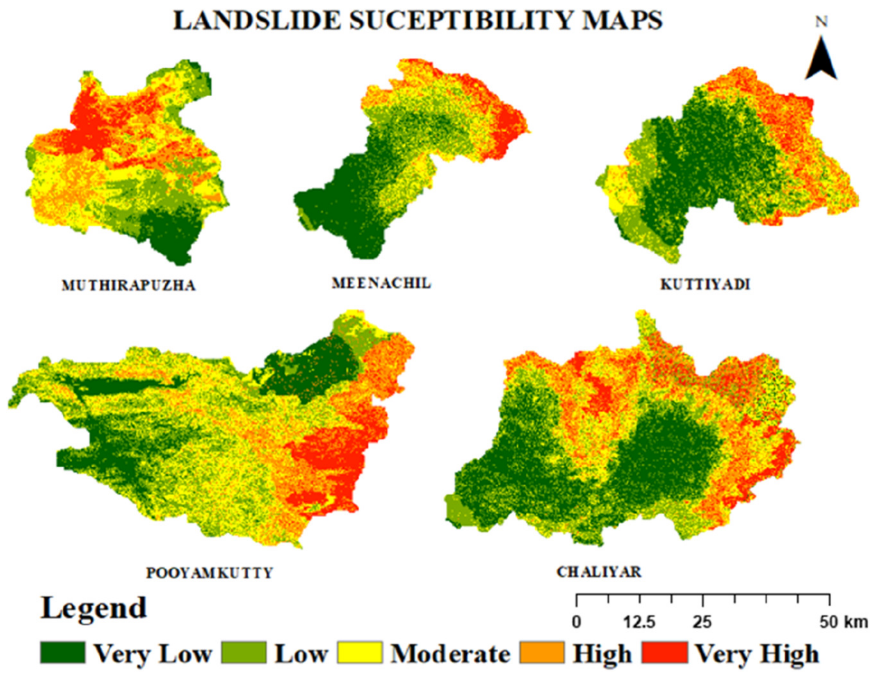

FIGURE 7
Landslide susceptibility maps for the selected Catchments in Kerala, derived from integrated analysis of topographic, geological, hydrological, and land cover conditioning factors.

TABLE 4 **Percentage area of each susceptibility class from the statistical method for the catchments.**

Catchment name	Muthirapuzha	Meenachil	Kuttiyadi	Pooyamkutty	Chaliyar
Very low	10.41	34.21	34.08	17.22	33.13
Low	22.15	26.28	27.11	23.54	24.20
Moderate	29.38	19.30	16.64	30.81	19.06
High	24.49	12.43	15.52	17.85	16.18
Very high	13.7	7.78	6.6	10.58	7.36

more decisive and spatially explicit assessment of risk across all five catchments than the simpler statistical method. In the Muthirapuzha catchment, the RF model delineates a continuous *High* to *Very High* susceptibility zone across the northern half, replacing the fragmented, scattered pattern produced by the statistical approach. Similarly, in Kuttiyadi, the RF output presents a clear segregation of the eastern headwaters as predominantly *High* to *Very High* susceptibility, whereas the statistical method yields a mixed mosaic of classes.

In the Meenachil catchment, the statistical model portrays a largely stable region with isolated high-risk patches. In contrast, the RF model identifies a distinct, continuous *Moderate-to-High* risk corridor, indicating its ability to detect spatially coherent hazard structures that linear statistical techniques tend to average out. The Pooyamkutty Catchment shows a more pessimistic but realistic distribution under the RF model, with extensive *Moderate* to *High* susceptibility zones reflecting the cumulative influence of steep slopes, deforestation, and anthropogenic modification. In Chaliyar, the RF map captures a far more intricate internal pattern of multiple interconnected high-risk patches, whereas the statistical approach restricts susceptibility mainly to the catchment periphery.

Overall, the RF model consistently produces maps with sharper risk boundaries and more concentrated high-risk zones, underscoring its superior capacity to model complex, non-linear interactions among conditioning factors. Landslide occurrence is inherently non-linear—the effect of one variable (e.g., slope) depends on others (e.g., lithology and rainfall). The ensemble nature of the RF algorithm allows it to represent such interactions naturally: for example, steep slopes may be hazardous only when composed of weak shale and subjected to intense rainfall.

The comparative evaluation of the five catchments further demonstrates how regional physiography and local conditioning factors jointly shape susceptibility patterns. Kerala's macro-scale structure—defined by steep relief, deeply weathered crystalline rocks, and intense monsoon rainfall—predisposes catchments within the Western Ghats to

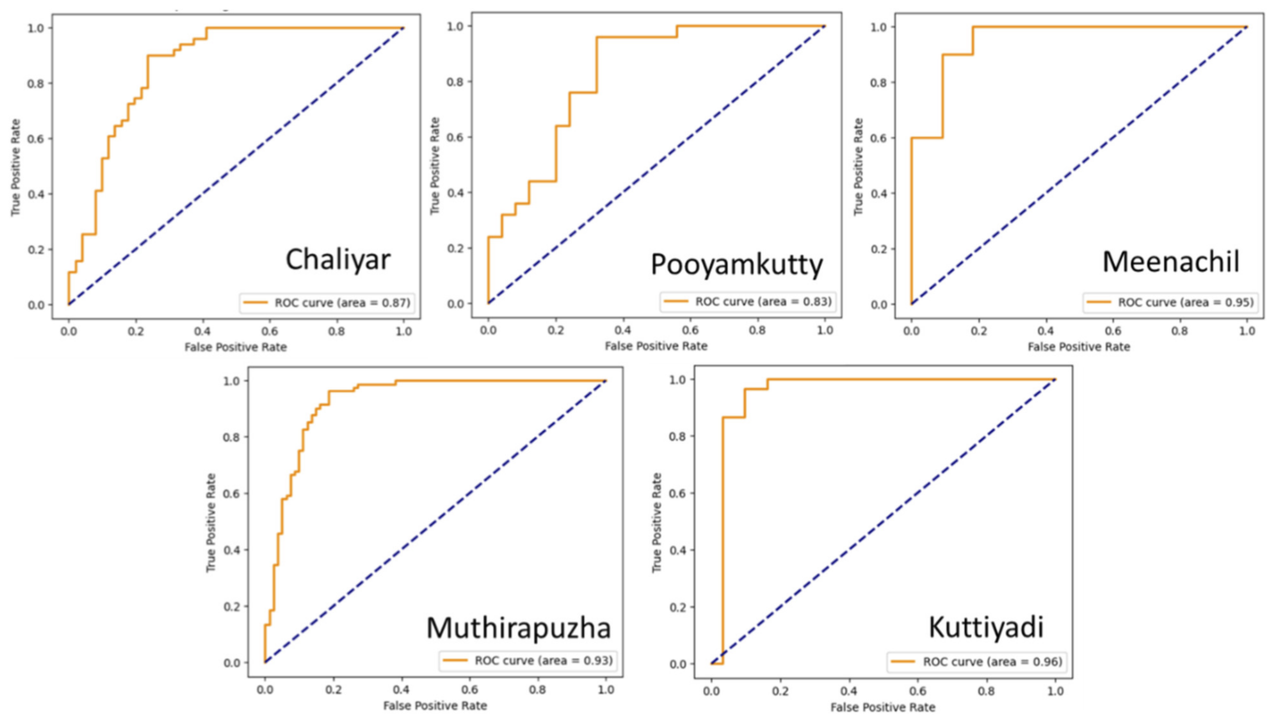

FIGURE 8
ROC Curves for each catchment.

TABLE 5 Details of RF models for each catchment.

Catchments	Best hyperparameters				AUC-ROC	Accuracy	Confusion matrix
	Max_ depth	Max_ features	Min_ samples _split	n_ estimators			
Chaliyar	10	log2	10	100	0.87	0.82	39 12 6 45
Pooyamkutty	10	log2	10	100	0.83	0.76	17 8 4 21
Muthirapuzha	10	Sqrt	2	500	0.93	0.87	66 15 5 76
Meenachil	10	log2	5	100	0.95	0.9	66 15 5 76
Kuttiyadi	10	Sqrt	5	100	0.96	0.88	24 7 0 30

high landslide risk (Ramasamy et al., 2021). The RF results affirm this trend. Muthirapuzha, located almost entirely in the high ranges, shows the highest susceptibility (31.49% *High/Very High* area), precisely outlining its rugged northern terrain. Similarly, Pooyamkutty, situated predominantly within the Highlands, displays pervasive risk (32.99% *High/Very High* area). Despite its slightly lower AUC (0.83), the model successfully captures the dominant influence of steep slopes and weathered lithology.

Catchments extending into the Midlands and Lowlands exhibit lower overall susceptibility owing to gentler gradients and reduced relief; however, the RF model refines this pattern by detecting localized, intense risk zones. In Kuttiyadi (AUC = 0.96), the model delineates pronounced risk in the eastern highlands, balanced by stable western lowlands—an accurate reflection of its physiographic transition. Meenachil (AUC = 0.95) similarly benefits from RF's precision, with a continuous *Moderate-to-High* corridor revealing subtle structural or anthropogenic vulnerabilities in the midlands that the statistical method overlooks. Chaliyar (AUC = 0.87) effectively captures the high-risk eastern Nilgiri slopes contrasting with the more stable Nilambur Valley lowlands. Chooralmala

TABLE 6 Most influential factors in each catchment.

Rank	Chaliyar	Pooyamkutty	Muthirapuzha	Meenachil	Kuttiyadi
1	Elevation (0.28)	Aspect (0.216)	Elevation (0.23)	Slope (0.28)	Slope (0.21)
2	Slope (0.22)	Elevation (0.213)	Dist. to stream (0.16)	Elevation (0.19)	Elevation (0.18)
3	LULC (0.14)	Slope (0.209)	Drainage density (0.14)	Dist. to stream (0.14)	Drainage density (0.17)
4	Aspect (0.1)	Curvature (0.142)	Slope (0.11)	Lithology (0.14)	Aspect (0.11)
5	Drainage density (0.09)	Dist. to stream (0.14)	Curvature (0.106)	Drainage density (0.12)	Dist. to stream (0.109)
6	Dist. to stream (0.07)	Drainage density (0.065)	Aspect (0.105)	Aspect (0.08)	Lithology (0.1)
7	Lithology (0.06)	LULC (0.01)	LULC (0.08)	Curvature (0.04)	Curvature (0.07)
8	Curvature (0.03)	Lithology (0.01)	Lithology (0.07)	LULC (0.01)	LULC (0.08)

TABLE 7 Percentage area of each susceptibility class from the Random Forest (RF) model for the Catchments.

Catchment name	Muthirapuzha	Meenachil	Kuttiyadi	Pooyamkutty	Chaliyar
Very low	22.87	25.26	26.37	15.12	27.2
Low	22.92	24.45	20.8	26.45	14.82
Moderate	22.69	24.84	14.23	25.42	24.36
High	20.07	12.96	20.36	21.05	16.25
Very high	11.42	12.46	18.22	11.94	17.36

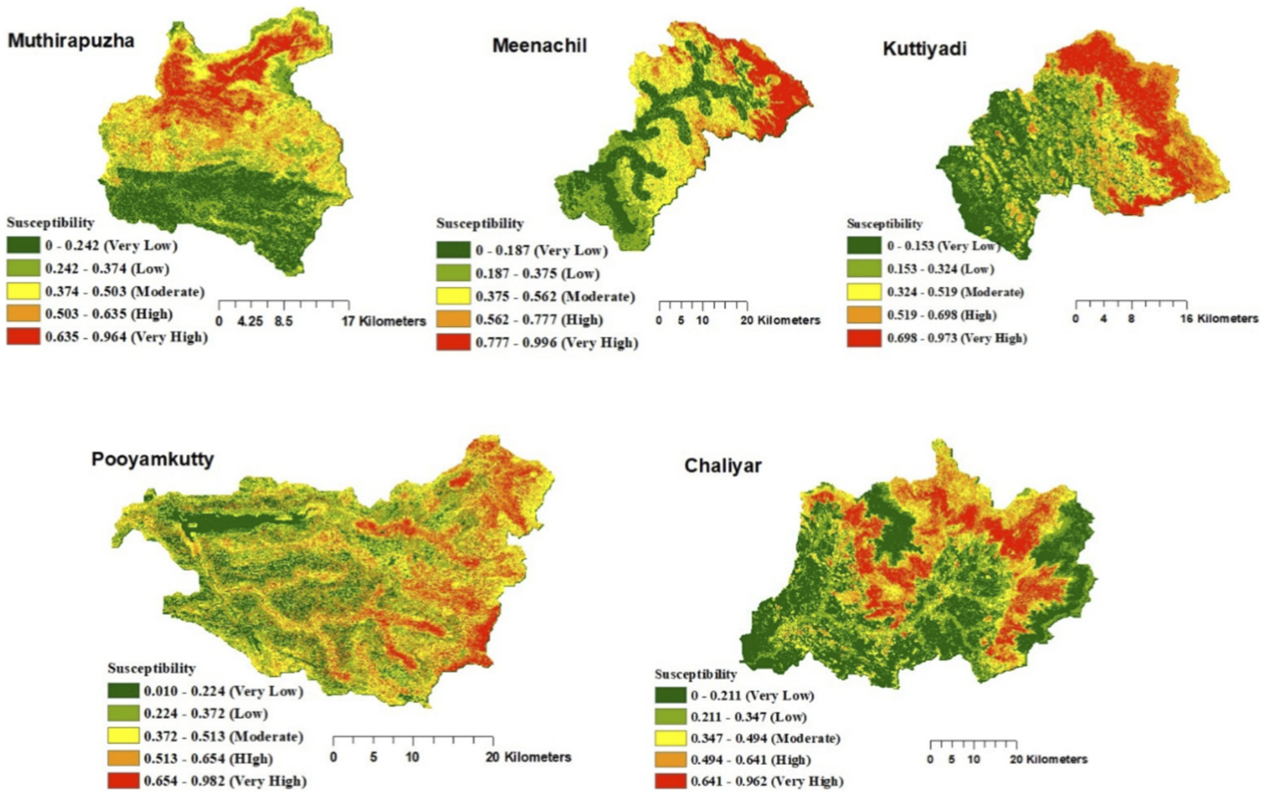

FIGURE 9
Landslide susceptibility maps of the five Catchments in Kerala, India, derived using the Random Forest (RF) model.

landslide, a severe event that significantly affected several people and hectares of land, that occurred in July 2024 (11.462345° N latitude and 76.132871° E longitude), also falls in the high susceptibility areas identified from this study (Achu et al., 2025).

A particularly noteworthy observation is the discrepancy in the eastern Chaliyar Catchment, where the statistical model classifies rugged terrain as uniformly *High* susceptibility, whereas the RF model identifies portions of Low susceptibility. This difference arises from RF's ability to handle compensatory and stabilizing factors. The statistical method, relying on additive factor weights, tends to overestimate risk by summing independent influences such as slope, rainfall, and relief. Conversely, the RF algorithm recognizes that stabilizing features—such as dense, mature forest cover or cohesive lithological units—can offset high-stress conditions locally. Thus, the RF model's apparently counterintuitive outputs are in fact more realistic, identifying true stability pockets within otherwise rugged terrain.

Across all catchments, the Random Forest model consistently exhibits stronger agreement with observed landslide inventories than the conventional statistical approach. The statistical approach produces diffuse susceptibility patterns that extend beyond actual landslide clusters. In contrast, RF yields more spatially coherent high-risk zones, supported by high AUC–ROC (0.83–0.96) and accuracy (0.76–0.90) values. The improvement is particularly pronounced in geomorphically heterogeneous and transition-zone catchments such as Kuttiyadi, Chaliyar and Meenachil, demonstrating the ability of RF to capture non-linear interactions among conditioning factors. The relatively weaker performance of the statistical approach observed in this study is primarily related to its limitations, which become pronounced in geomorphically heterogeneous, rainfall-triggered landslide environments such as the Western Ghats of Kerala (Reichenbach et al., 2018). The statistical approach evaluates each conditioning factor independently, assuming that landslide-controlling variables act in isolation (Chung and Fabbri, 2005). However, landslides in monsoon-dominated tropical terrains are governed by non-linear interactions among multiple factors such as slope steepness, lithology, land use, curvature, drainage density etc (Reichenbach et al., 2018). For example, debris flows in the Kuttiyadi and Muthirapuzha catchments predominantly occur where steep slopes (>20°), concave plan curvature, highly weathered gneissic or lateritic materials, and proximity to first-order streams coincide under intense rainfall. Statistical approach assigns separate weights to each factor class but fails to capture these compound effects, leading to simplified susceptibility patterns. Statistical approach is highly sensitive to the classification of continuous variables, such as slope, elevation, and topographic indices. These parameters must be discretized into predefined classes, and the selection of class thresholds strongly influences susceptibility (Reichenbach et al., 2018).

In summary, the Random Forest model provides a nuanced, physically consistent interpretation of landslide susceptibility across Kerala's diverse physiographic settings. By effectively integrating multiple, interacting variables, it mitigates the over-generalization inherent in traditional statistical methods and delivers spatially coherent, decision-ready hazard maps that can directly inform land-use planning and disaster risk reduction strategies in landslide-prone tropical mountain regions.

4 Conclusion

The spatially integrated analysis confirms that landslide susceptibility in the selected Catchments of Kerala is governed by terrain type and is a complex interplay of geomorphic, geological, and hydrological factors. The comparison between the Statistical and Random Forest (RF) models reveals that while both the methods successfully identified the landslide susceptibility, their predictive capability differ substantially. The RF model yields more spatially coherent high-risk zones that closely matches with observed landslide occurrences, particularly along highland–midland transition zones. The superior performance of the RF model is evidenced by higher AUC–ROC values (0.83–0.96) and classification accuracies (0.76–0.90) across all catchments. These findings highlight the importance of accounting for non-linear interactions among conditioning factors in monsoon-dominated, structurally complex terrains. Although intense monsoon rainfall remains the principal triggering factor for slope failures throughout Kerala, this study highlights that the spatial configuration of intrinsic factors, including topography, lithology, drainage density, and land use ultimately dictates where rainfall-induced triggers manifest as actual landslide events. Thus, effective landslide risk management requires not only quantitative mapping but also a process-based understanding of how these geographical factors interact within each watershed.

Overall, this catchment scale, terrain-based comparison provides new insight into how landslide controls and model performance vary across different terrain settings, moving beyond spatially aggregated regional assessments. The findings underscore the potential of the Random Forest model as a robust predictive tool for landslide susceptibility mapping in tropical mountain environments. It is also important to note that the accuracy of the inventory and the input datasets can affect the resulting susceptibility maps. The influence of data quality on the landslide susceptibility mapping process is a broad path to explore. Future work should emphasize high-resolution characterization of micro-geomorphological features and dynamic modelling of rainfall-induced pore-water pressure to improve localized hazard prediction, sensitivity analysis of the landslide conditioning factors, guide sustainable land-use planning, and support the development of early warning and mitigation systems in Kerala's landslide-prone terrain.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

RA: Conceptualization, Methodology, Writing – original draft. KA: Formal Analysis, Writing – original draft, Methodology, Conceptualization. HD: Conceptualization, Writing – original draft, Formal Analysis, Methodology. GA: Writing – original draft, Formal Analysis, Methodology, Conceptualization. FS: Writing – original draft, Methodology, Formal Analysis, Conceptualization. DD: Conceptualization, Writing – original draft, Methodology, Formal Analysis. SP: Resources, Methodology, Writing – review and editing, Conceptualization, Supervision. VS: Supervision, Conceptualization, Writing – review and editing, Resources.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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