



Machine learning modelling of flood susceptibility in a tropical river basin of South India

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Abstract

Flooding is a major recurring hazard in tropical monsoon climates, causing extensive damage to lives, infrastructure, and economic activities. The Achankovil River Basin in southern India is highly susceptible to recurrent monsoon-induced flooding, particularly in its low-lying downstream reaches. This study assesses flood susceptibility in the Achankovil River Basin using a machine-learning Maximum Entropy (MaxEnt) model and identifies the key environmental factors controlling flood occurrence. Ten geo-environmental variables, such as geomorphology, soil texture, Vertical Distance to Channel Network (VDCN), slope angle, rainfall, land use/land cover (LU/LC), distance from streams, Topographic Wetness Index (TWI), upslope curvature, and downslope curvature, were used together with a detailed flood inventory comprising 677 flood-affected locations. The model is validated using the Receiver Operating Characteristic (ROC) curve and area under the curve (AUC) value (ROC–AUC). The predicted flood susceptibility map is further grouped into low, moderate, high, and very high susceptibility regions. The results show that high and very high flood susceptibility zones are mainly concentrated in the downstream and central lowland regions along major river channels, characterised by low elevation, gentle slopes, and proximity to drainage networks, which favours inundation. In contrast, the eastern highland sector of the study area exhibits predominantly low flood susceptibility zones. The model validation returns an AUC value of 0.89, indicating good model accuracy and reliability. Besides, the model identified Vertical Distance to the Channel Network (VDCN) as the most important factor, followed by rainfall and slope angle. The findings confirm the robustness of the maximum entropy model and provide valuable insights for flood early warning and land-use development in the study area.

Keywords: Flood Susceptibility modelling, Achankovil, Kerala, India

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1 Introduction

Flooding is a global hazard that accounts for a substantial proportion of disaster-related economic losses and human casualties each year. Its impacts are particularly severe in tropical and monsoon-dominated regions, where intense and prolonged rainfall events frequently exceed the natural drainage capacity of river systems (De Risi et al., 2020). In recent decades, accelerating population growth, uncontrolled urbanization, shifting land-use patterns, and climate-induced increases in extreme rainfall have significantly heightened flood hazards, highlighting the critical need for robust flood-susceptibility mapping and sustainable flood-risk management (Murali and Srinivasan, 2025).

Owing to its monsoon-dominated climate, varied terrain, and high population density, India is highly prone

to flooding, with Kerala standing out for the marked increase in both the occurrence and intensity of flash floods, especially during the southwest monsoon. Extreme rainfall episodes in recent years, including the catastrophic floods of 2018 (Mishra et al., 2018; Saravanan et al., 2023) and subsequent events in 2019, have highlighted the sensitivity of Kerala's river basins to hydro-climatic extremes. The Achankovil river basin (ARB), a tropical west-flowing river originating from the Western Ghats, is prone to recurrent flooding in its low-lying downstream regions due to intense monsoonal rainfall, low relief, high groundwater levels, and backwater effects in coastal reaches. A recent study by Ajin et al. (2019) reported that large parts of the downstream ARB are recurrently affected by severe flooding during the Indian summer monsoon. Flooding in ARB is primarily

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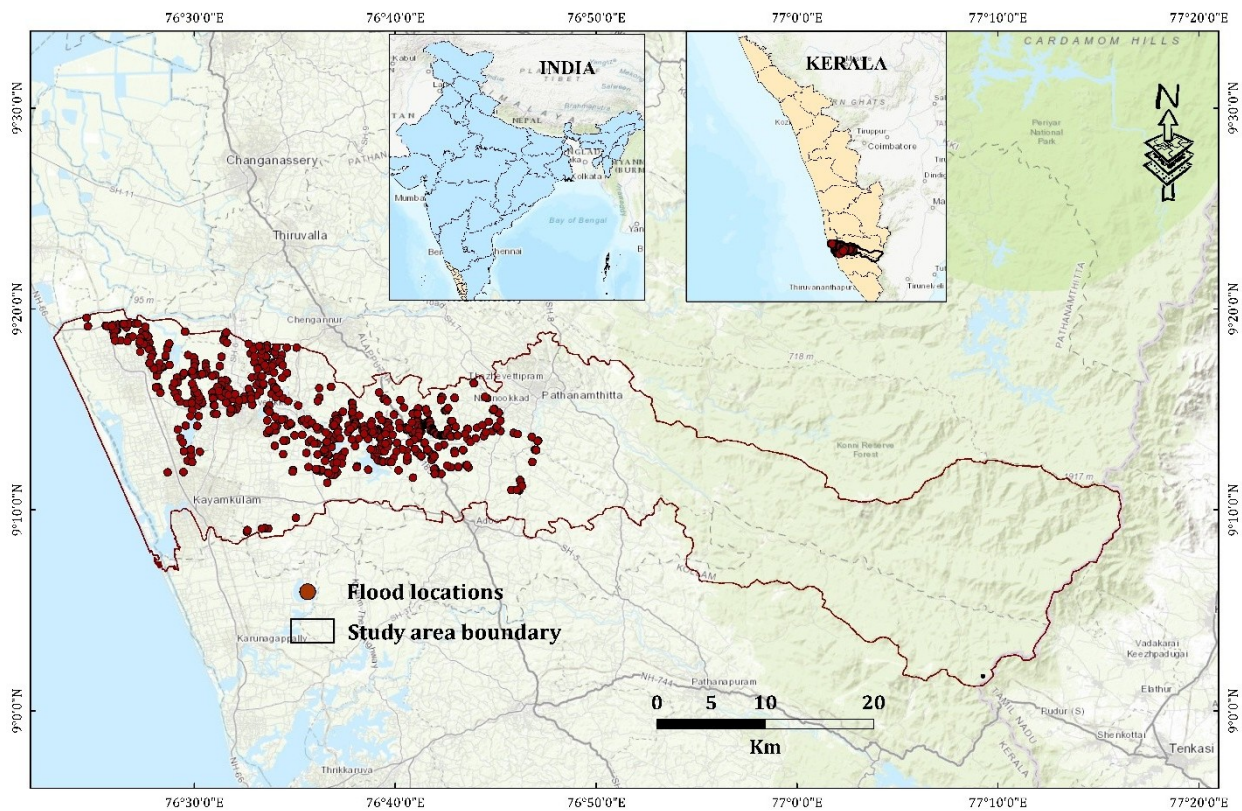


Fig. 1. Flood inventory and location map of the Achankovil River Basin.

driven by intense monsoonal rainfall, which generates excessive surface runoff that exceeds the river system's conveyance capacity (Petty, 2002). Consequently, several sectors of the basin, most notably the downstream stretches in Alappuzha district, experience frequent and severe flooding.

Flood susceptibility mapping provides a practical framework for identifying areas prone to flooding by integrating historical flood occurrences with relevant environmental and topographic factors. Recently, artificial intelligence and machine-learning techniques have become widely adopted methodologies in flood susceptibility modelling because they can effectively capture the complex, non-linear relationships between flood occurrence and its governing factors (Allocca et al., 2022). Among machine-learning models, the Maximum Entropy (MaxEnt), a presence-only model, has been widely utilised owing to its robustness, ability to work with presence-only data, and strong predictive performance in data-scarce regions (Phillips et al., 2006). Although numerous flood-susceptibility studies have been carried out in Kerala, the Achankovil river basin has received limited attention in comprehensive flood-susceptibility assessment. Most previous studies in the ARB have focused on flood events and their impacts, and on susceptibility mapping using outdated multi-criteria-based methodologies (Ajin et al., 2019), rather than on systematic susceptibility mapping using integrated geo-environmental factors and machine learning. In this context, this study develops a flood susceptibility map using the MaxEnt approach in the Achankovil River Basin. It identifies the key contributing variables influencing flooding and provides useful guidance for mitigation

planning, land-use regulation, and climate-resilient disaster mitigation.

2 Materials and Methods

2.1 Study area

The ARB, which covers about 1,340 km² and is drained by a prominent west-flowing river originating from the southern part of the Western Ghats. It originates in the high-elevation Western Ghats, at altitudes exceeding 1,859 m above MSL, and flows westward toward the coastal plains. Along its course, the river traverses the Achankovil Shear Zone (AKSZ), a prominent NW–SE-trending transcrustal structural zone that extends for more than 120 km with an average width of 10–20 km. This shear zone represents a major tectonic boundary separating the Trivandrum Block from the massif charnockites and exerts strong structural control on basin morphology and drainage organization. Geographically, the ARB is located between 9°02' N and 9°19' N latitude and 76°25' E and 76°75' E longitude (Fig. 1). Being situated in the humid tropics, the area experiences monsoon-dominated rainfall seasons, viz., the southwest monsoon from June to September and the north-east (retreating monsoon) from October to December. The study area receives a mean annual rainfall of 2000–3000 mm (CGWB, 2019), with ~80% of this rainfall during the southwest monsoon period. Rainfall exhibits a clear spatial gradient, generally increasing from south to north across the basin, reflecting the combined influence of monsoonal circulation and orographic effects (Prasad and Ramanathan, 2005).

Physiographically, the study area can be divided into three major units: highland, midland, and lowland. The eastern sector comprises the highland zone, characterised by rugged topography and steep slopes linked to the Western Ghats. The midland zone forms a transitional belt with moderate relief and undulating topography. The lowland zone, extending toward the western coastal margin, is generally flat and swampy, with poor natural drainage conditions. This low-lying coastal tract is highly susceptible to monsoon-induced inundation and frequently experiences flooding during periods of intense rainfall, owing to its low elevation, high groundwater levels, and backwater effects. During the extreme rainfall events of August 2024, the ARB was severely affected by intense flooding, specifically in the downstream portion.

2.2 Geo-database

In the present investigation, flood inventory mapping was conducted through intensive field surveys carried out immediately after the 2018 flood. Flood-affected locations were identified using a handheld GPS, and flood-water depths were measured and recorded at each site. In total, 677 flood locations were documented and utilised for the analysis. Flood susceptibility modelling is the integration of multiple geo-environmental factors through complex analytical procedures. In this study, independent variables influencing flood occurrence were selected based on their physical relevance, including geomorphology, soil texture, distance from streams, slope angle, rainfall, LU/LC (land-use/land-cover), VDCN, TWI, upslope curvature, and downslope curvature.

The geomorphology of an area explains its morphological features and evolution and plays a significant role in flood inundation. Hence, the geomorphology map in the study area is downloaded from the Geological Survey of India website and geomorphic units of the study area are illustrated in the Fig. 2a. Distance from stream is another significant parameter influencing flood susceptibility, as areas located near to streams are more susceptible to inundation during periods of heavy downpours and elevated discharge (Achu et al., 2025). Hence, in this investigation, the drainage network of the study area was digitised from Survey of India topographic sheets, and Euclidean distance analysis was applied to generate a continuous distance-to-stream layer (Fig. 2b).

LU/LC plays a significant role in regulating flood inundation by controlling overland runoff and surface infiltration within an area. Areas dominated by forests and other vegetated land-cover types enhance infiltration and reduce runoff, thereby exhibiting lower flood susceptibility. In contrast, urban, residential, and pasture lands are characterised by higher imperviousness or soil compaction, which restricts infiltration and promotes overland flow, resulting in increased runoff and greater flood susceptibility (Lappas and Kallioras, 2019). The land-use/land-cover (LU/LC) data for 2020 were obtained from the Kerala State Land Use Board. All raster files have a cell size of 30 m and a standard coordinate system of WGS84 UTM 43N. Soil texture significantly influences porosity and permeability and controls

ponding during intense rainfall. Owing to this, the soil texture dataset was sourced from the Kerala State Soil Survey Organisation at a scale of 1:50,000. The ARB is dominated by clay and gravelly clay soils (Fig. 2d), which exhibit low permeability and poor drainage, thereby enhancing runoff and increasing the likelihood of flooding during heavy rainfall.

Slope angle, which indicates terrain steepness, is one of the most critical parameters that control overland flow velocity and runoff concentration and significantly affect flood occurrence. The basin slope angle ranges from 0 to 67.7°, as shown in Fig. 2e. Steep slopes favour rapid runoff and reduced infiltration. In contrast, gentle slopes promote runoff concentration and increase the likelihood of flooding (Kazakis et al., 2015). Slope gradients were generated from the digital elevation model. Rainfall is a primary cause of flooding, as intense or prolonged precipitation over a given area can saturate soils, triggering widespread runoff and inundation (Rodda, 1970; Smith and Ward, 1998). The rainfall map for the study area is shown in Fig. 2f, and the data were obtained from the India Meteorological Department.

VDCN quantifies the elevation difference between a grid cell and the nearest stream, reflecting the terrain's vertical position relative to the drainage system (Feloni et al., 2020). It provides spatial information on the approximate depth of the base-level flow in a catchment at a point and is influenced by gully erosion. The VDCN of the study area varies from 0 to 786.6 and is shown in Fig. 2h. The TWI, by Beven (1979), represents topographic influences on hydrological processes and the spatial distribution of soil moisture concentration within a landscape (Lappas and Kallioras, 2019). TWI is estimated from SRTM DEM using Eq. (1)

$$TWI = \ln(\alpha/\tan\beta), \quad (1)$$

where α is the upslope contributing area per unit contour length (mm^{-1}), and β is the slope. Fig. 2h shows the spatial distribution of TWI values in the study area.

Curvature describes how slope steepness changes across the terrain and is an essential indicator of surface form, influencing flow concentration, runoff velocity, and erosion dynamics (Wang et al., 2015). As a result, the present study incorporated upslope and downslope curvatures as input variables for flood susceptibility modelling. These curvatures were derived from SRTM DEM using SAGA GIS software.

2.3 Machine-learning technique (MLT)

2.3.1 Maximum Entropy (MaxEnt)

The MaxEnt is a machine-learning model that uses presence-only data to evaluate flood susceptibility from recorded flood events. This approach is a widely applied technique for spatial distribution and susceptibility modelling. Its theoretical foundation is the principle of maximum entropy, proposed by Claude Shannon (1948). MaxEnt is a machine-learning-based approach that generates spatial predictions using presence-only data, making it particularly suitable for environmental applications (Rahmati et al., 2016). The method estimates the probability distribution of an event by identifying the distribution with the

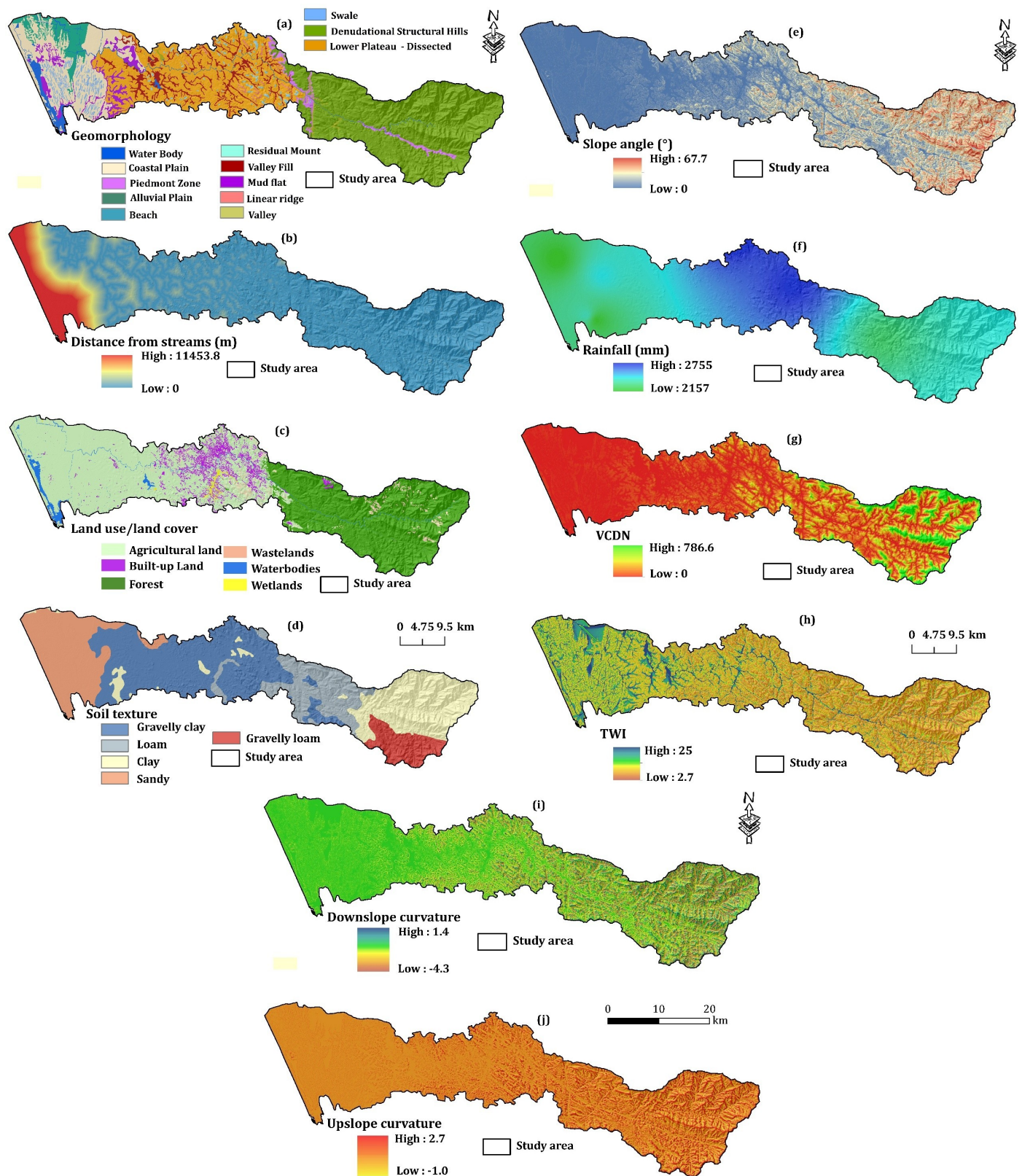


Fig. 2. Spatial distribution of indicators of flood hazard (a) geomorphic units, (b) distance from streams, (c) LU/LC, (d) soil texture, (e) slope angle, (f) annual average rainfall and (g) VCDN, (h) TWI, (i) downslope curvature, (j) upslope curvature.

highest entropy, subject to constraints imposed by the observed environmental variables and training data (Phillips et al., 2006). This optimisation ensures that the resulting probability density function is the least-biased representation consistent with the known occurrences. Consequently,

MaxEnt enables the estimation of event occurrence probabilities at unsampled or unknown locations. The model further computes the ratio between the probability density of environmental conditions at presence locations and that of the background, yielding an index of ecological suitability

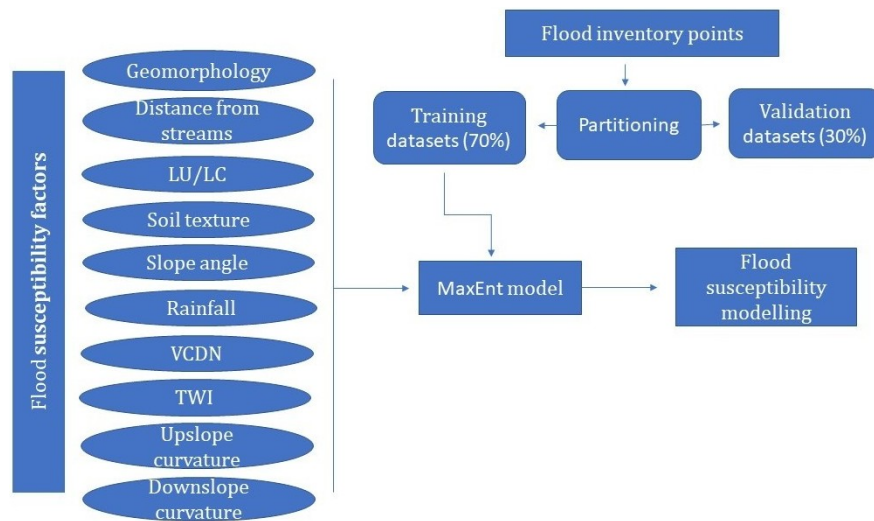


Fig. 3. Methodological flow chart.

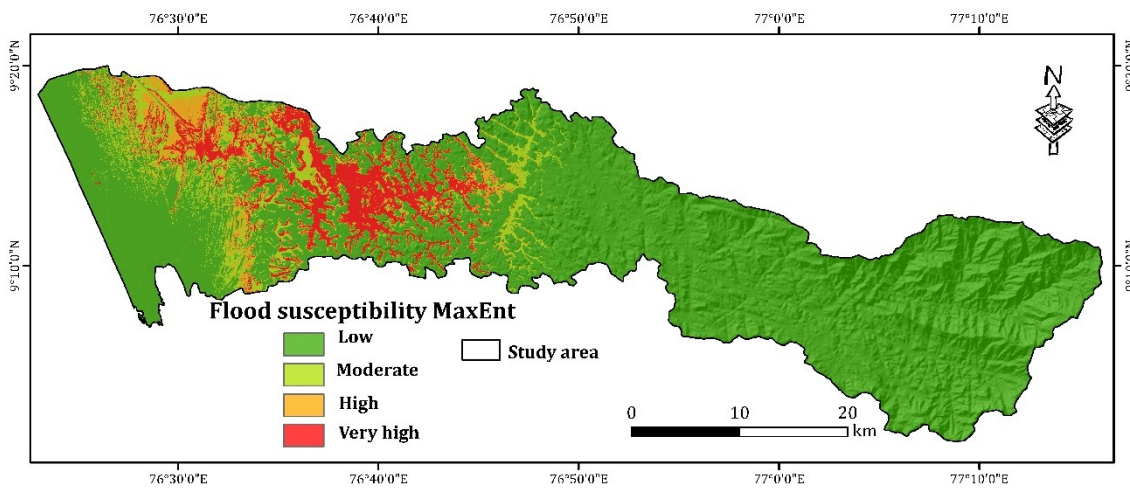


Fig. 4. Spatial distribution of predicted flood susceptibility in the study area.

for each spatial unit within the study area (Eq. (2); Achu et al., 2025).

The mathematical concept of MaxEnt is as follows;

$$\text{PrPr}(z) = \text{fl}(z)\text{PrPr}(Y = 1)/f(z), \quad (2)$$

where $\text{fl}(z)$ represents the probability density function of the environmental variables at known presence locations (flood-affected sites in this study), and $f(z)$ denotes the corresponding probability density of these variables across the entire study area. Given these distributions, estimation of the probability of flood event occurrence at unsampled locations requires only the proportion of occupied sites, $\text{Pr}(Y = 1)$. This framework enables spatial prediction by contrasting environmental conditions at observed presence locations with those available throughout the landscape. Detailed theoretical and mathematical descriptions of the MaxEnt approach are provided by Phillips et al. (2006).

2.3.2 Model validation

Model performance was measured as ROC AUC on the test data. The ROC curve was created by plotting sensitivity against the false-positive rate across a range of prob-

ability thresholds, allowing assessment of model skill independent of any single cutoff. The dataset was randomly split into 70% and 30% for training and validation, respectively, and ROC–AUC values were computed on the test dataset. The AUC provides a robust measure of predictive performance, with values approaching 1 indicating strong discriminatory power and values near 0.5 reflecting random classification (Hanley and McNeil, 1982; Fawcett, 2006).

3 Results

3.1 Flood susceptibility modelling

The predicted flood susceptibility map was in continuous probability values between 0 and 1. These probabilities were further categorized into four classes: low susceptibility (0.00–0.20), moderate susceptibility (0.20–0.40), high susceptibility (0.40–0.60), and very high susceptibility regions (0.60–1.00). The resulting spatial pattern across the Achankovil river basin is shown in Fig. 4. Both high and very high susceptibility regions are predominantly distributed in the western coastal regions and central low-land zones, particularly along the lower river courses and

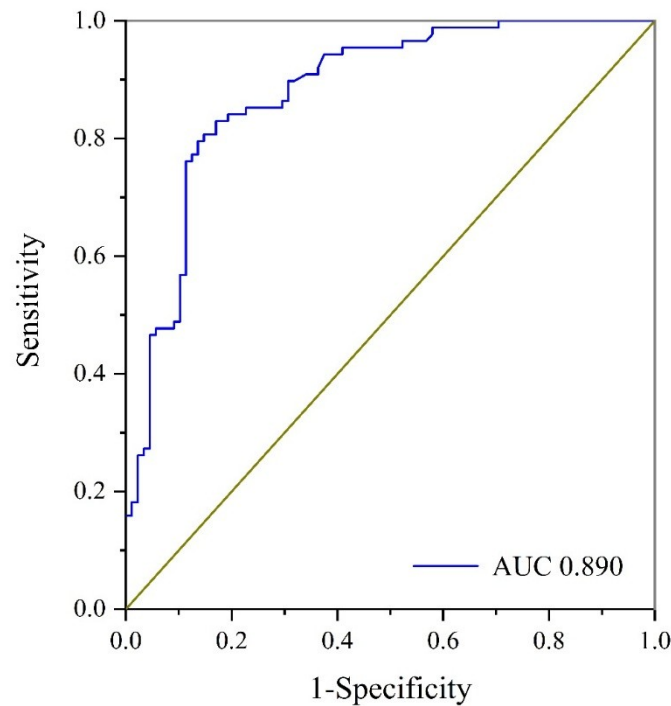


Fig. 5. ROC curve with AUC value with testing data.

adjacent floodplains. These regions are characterized by low relief, gentle topographic gradients, and close proximity to drainage networks, conditions that increase runoff concentration and elevate the likelihood of flood inundation during periods of intense downpour (Rahmati et al., 2016).

Moderate susceptibility zones occur predominantly in the midland regions, representing transitional terrain conditions. In contrast, the eastern highland region is largely characterized by low flood susceptibility, reflecting steep slopes and higher relief associated with the Western Ghats, which facilitate rapid runoff evacuation and limit flood persistence (Kazakis et al., 2015). Spatial pattern indicates an increasing flood susceptibility from upstream highlands toward downstream lowlands, highlighting the dominant role of topography and drainage proximity in flood occurrence across the basin (Rahmati et al., 2016; Allocca et al., 2022).

3.2 Performance evaluation

3.2.1 ROC–AUC result

The ROC–AUC is widely applied to assess predictive performance of binary classification problems by measuring how effectively a model distinguishes between true positive rate and false positive rate (Gorsevski et al., 2006). In this case, the ROC–AUC evaluates, how well the model discriminates between flooded region and non-flooded regions. In the present study, the MaxEnt produced an AUC value of 0.890, reflecting a strong discriminatory capability (Fig. 5). Based on the Hosmer and Lemeshow (2000) classification AUC values ranging from 0.7 to 0.8 show good accuracy, 0.8 and 0.9 indicate excellent accuracy, and values above 0.9 correspond to outstanding predictive power. The ROC curves generated from the testing dataset for the developed models are shown in Fig. 5.

4 Discussions

Kerala has recently experienced intense flooding episodes, most notably the extreme floods of 2018 that followed a triggering widespread inundation and landslides across several districts, and highlighting the higher flood susceptibility of the region under increasing hydro climatic extremes. The spatial prediction of flood susceptibility zones in the ARB shows a spatial heterogeneity of flood susceptibility within the region. About 7.33% of the ARB is identified as very high flood susceptible, reflecting locations with a strong probability of experiencing severe flooding. Areas classified as highly susceptible account for 7.15%, while 10.91% fall within the moderate susceptibility category. In contrast, nearly three-quarters of the basin (74.25%) lie within the low-susceptibility class, indicating comparatively lower flood risk. This distribution highlights the pronounced variation in flood vulnerability across different parts of the basin.

In this study, a variable contribution analysis was performed using the MaxEnt model to determine the relative influence of environmental factors on flood occurrence, and the overall model performance is presented in Table 1. Among the ten input variables, VDCN was the most influential, with a contribution of 0.29 ± 0.02 . This indicates that the vertical position of the land surface relative to nearby drainage channels plays a key role in governing flood susceptibility across the basin. Areas situated at lower elevations above the channel network are more prone to inundation because of their closer hydraulic connectivity to river flow, gentler gradients, and greater tendency to accumulate water during peak discharge conditions. This pattern is consistent with the findings of Feloni et al. (2020), who reported that relative topographic position with respect to drainage networks is a primary control on flood generation.

Table 1. The performance of the MaxEnt model for flood susceptibility.

Variables	Permutation Importance	Standard deviation
VDCN	0.29	± 0.02
Rainfall	0.22	± 0.01
Slope	0.10	± 0.00
Stream	0.03	± 0.00
Soil	0.03	± 0.00
TWI	0.02	± 0.00
Downslope curvature	0.01	± 0.00
LULC	0.01	± 0.00
Geomorphology	0.01	± 0.00
Upslope curvature	0.00	± 0.00

A comparable pattern was observed by [Achu et al. \(2025\)](#) in the Kadalundi River Basin of Kerala, where VDCN was recognized as a primary determinant of flood susceptibility. In the present study, rainfall emerged as the second most influential variable, with a contribution of 0.22 ± 0.01 . Numerous investigations have also reported a significant rise in both the regularity and intensity of extreme rainfall across different regions of India. [Das \(2019\)](#) and [Chattopadhyay et al. \(2017\)](#) observed a rising trend in high-intensity rainfall spells across multiple agro-climatic regions, corroborated by [Ahmed et al. \(2017\)](#), who observed similar patterns across fifteen agro-climatic zones in the country. Kerala has experienced pronounced impacts from extreme precipitation events. The unprecedented rainfall during August 2018 resulted in widespread flooding across the state ([Mishra et al., 2018](#)), followed by significant flood events in 2019, collectively placing the region under heightened geomorphic and hydrological risk. [Saravanan et al. \(2023\)](#) further confirmed that the August 2018 flood in the Idukki district represented one of the most extreme rainfall episodes ever recorded in Kerala. Moreover, [Kulithalai Shiyam Sundar and Kundapura \(2023\)](#) reported that exceptionally high rainfall caused rapid inflow into reservoirs, leading many of them particularly within the Vembanad Lake catchment to reach full reservoir level by the end of July. The forced release of stored water, together with continued heavy precipitation, substantially intensified downstream inundation and slope failures, thereby amplifying the overall severity of the disaster ([Parthasarathy et al., 2021](#); [Sudheer et al., 2019](#)). Such events underscore the sensitivity of the region to both short-duration, high-intensity rainfall and prolonged, moderate-intensity precipitation, both of which are capable of triggering severe flooding ([Shahabi et al., 2021](#)).

Recent investigations indicate that the increasing recurrence of flood events in India is closely linked to rising atmospheric temperatures and intensified southwest monsoon rainfall during the June–September season ([Chakraborty et al., 2022](#); [Kumar et al., 1999](#)).

Slope exerts a moderate control on flood susceptibility, with low-gradient terrain encouraging water retention and longer inundation periods, while steeper slopes facilitate faster drainage and limit the persistence of flooding ([Beven, 1979](#)). As slope gradient and altitude decrease, flood probability increases, with low-lying and nearly flat

terrains being particularly susceptible to inundation ([Norallahi and Seyed Kaboli, 2021](#)). Similar findings consistent in the Kadalundi River Basin, Kerala, and [Saravanan et al. \(2023\)](#) in the Idukki district of Kerala, all of whom identified slope as a significant factor influencing flood susceptibility. Under heavy rainfall conditions, flooding is further intensified by enhanced surface runoff and increased stream erosion ([Mishra et al., 2018](#)).

In contrast, distance from streams, soil type, LU/LC, geomorphology, Topographic Wetness Index (TWI), and curvature-related parameters exhibited comparatively low influence on flood susceptibility in the ARB. A similar pattern was observed by [Khan and Jhamnani \(2024\)](#) in the Idukki district, where these variables contributed marginally to flood susceptibility assessment. However, contrasting results have been reported in other basins. [Achu et al. \(2025\)](#) and [Saravanan et al. \(2023\)](#) identified geomorphology as a dominant control in the Kadalundi and Idukki basins, respectively. Previous studies indicate that flood susceptibility generally peaks around a TWI value of approximately 5 ([Maharjan and Dangol, 2024](#)). The ARB, however, is characterized by very low TWI values (~ 0.02), which explains its limited contribution in the present analysis. In contrast, [Das and Gupta \(2021\)](#) reported TWI as a dominant factor in the Subarnarekha River Basin, while [Das \(2019\)](#) found that higher TWI values corresponded to increased flood-prone areas in the Ulhas Basin. These discrepancies highlight the region-specific nature of TWI influence, governed by local topography, hydrology, and climatic conditions. Accordingly, in regions with higher TWI values and recurrent flooding, TWI-based hazard zoning can effectively delineate high-risk zones ([Riadi et al., 2018](#)).

Curvature-related parameters also showed minimal influence in the present study. Upslope curvature values range from -4.3 to 1.4 , while downslope curvature varies between -1.0 and 2.7 , indicating relatively gentle surface curvature and limited flow convergence. Similar observations were reported for the Kokcha River Basin in Afghanistan by [Qasim et al. \(2024\)](#). In contrast, [Achu et al. \(2023\)](#) identified curvature as a dominant influential factor in flood susceptibility mapping for the Kozhikode District, further reinforcing the spatial variability of controlling factors across different physiographic settings. The MaxEnt model established strong predictive capability, attaining an AUC value of 0.89 during the testing phase, which indicates high model

accuracy. This performance is comparable to that reported by Achu et al. (2025) for the Kadalundi River Basin (AUC = 0.84) and Mashao et al. (2023) for regions in Africa (AUC = 0.89). The predictive performance obtained in this study is higher than that reported by Davoudi Moghaddam and Haghizadeh (2020), who achieved an accuracy of 88.5%, and Darabi et al. (2020), who reported 76%, and it is broadly consistent with the near 90% accuracies documented by Azare (2021), Moradi et al. (2021), and Shreevastav et al. (2022). However, Javidan et al. (2021) reported a superior model performance, with an AUC of 97.2%. The performance of the present model confirms the robustness and reliability of the MaxEnt approach for flood susceptibility assessment in complex tropical river basins such as the Achankovil river basin.

5 Conclusion

The spatial likelihood of flood occurrence in the ARB was modelled using the MaxEnt approach with a set of environmental variables. The resulting susceptibility map delineated the basin into four categories such as low, moderate, high and very high susceptibility thereby clearly representing the spatial distribution of flood risk. Areas of high and very high susceptibility are largely confined to the western and central lowlands and to zones adjacent to major river channels and floodplains, while the eastern highland region of the Western Ghats is mainly comprised by low susceptibility owing to its elevated terrain and steeper slopes that facilitate rapid drainage. Model performance, assessed using the ROC–AUC criterion, produced a value of 0.89, reflecting excellent predictive capability. The variable contribution analysis indicated that the VDCN is the dominant control on flood susceptibility in the ARB, highlighting the essential role of terrain elevation relative to drainage channels in governing inundation processes. Rainfall ranked as the second most important factor, emphasizing the strong influence of intense precipitation in this monsoon-driven environment. Slope exhibited a moderate effect, whereas parameters such as distance to streams, soil characteristics, land-use/land-cover, geomorphology, Topographic Wetness Index, and curvature showed comparatively lower contributions, reflecting the site-specific nature of flood-generating mechanisms. Overall, the results demonstrate that the MaxEnt model provides a reliable framework for evaluating flood susceptibility in complex tropical catchments. The susceptibility map produced in this study offers critical spatial insights that can aid flood risk reduction, land-use regulation, and disaster preparedness in the Achankovil river basin under intensifying hydro-climatic extremes.

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Author contributions

Anjali. N: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft. Girish Gopinath: Supervision and reviewing the draft, writing, and editing.

Declaration of competing interest

The authors have no relevant financial or non-financial interests to disclose.

Data availability

The datasets used or analysed during the current study are available from the corresponding author on reasonable request.

AI-usage statement

The authors declare that no generative artificial intelligence (AI) tools were used in any stage of this research or manuscript preparation.

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