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PREDICTING FLOOD RISK WITH MACHINE LEARNING AND GIS: INSIGHTS FROM THE SAKTOLA RIVER, ASSAM, INDIA

Abstract: In Assam, India, flooding is among the most frequent and devastating natural disasters, bringing about significant social and economic disturbances in the Brahmaputra valley every year. Though floods occur quite frequently, a systematic assessment of flood susceptibility has not been extensively carried out in many secondary river basins, including the Saktola river Basin. This paper discusses the basin's first spatially defined flood susceptibility assessment using the Maximum Entropy (MaxEnt) machine learning method to facilitate informed management of flood risks. Field validation was combined with seven environmental variables that condition floods in order to model patterns of flood susceptibility. The produced susceptibility map classifies the basin into zones with low, moderate, and high susceptibility to floods; high-risk areas mostly lie along river channels and near floodplains. Validation of models through Area Under the Receiver Operating Characteristic Curve (ROC) reflects high predictive accuracy, which will confirm the MaxEnt algorithm's efficiency in flood susceptibility modeling. The study revealed the applicability of machine learning-based flood susceptibility assessment for data-scarce river basins in Northeast India and provided valuable insights for management of hazards like flood and associated problems in the state of Assam.

Keywords: Flood susceptibility, maximum entropy, environmental variable, ROC

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Introduction

Globally, floods have always been and still remain one of the top causes of death, destruction, and natural resource depletion among the major natural disasters (Lee & Fatemah, 2022; Gharakhanlou & Perez, 2023). In addition to property damage, floods also lead to a loss of natural environment and interruptions of human life for a long time period. The most prominent causes for the rise in flood frequency and intensity are climate change, land use changes, and extreme weather events (Mosavi et al., 2018; Hamidifar & Nones, 2023). The developing countries which fall under monsoon climate are more exposed to floods, as the high precipitation variability together with the vulnerable geomorphological condition of the area make them more susceptible to the flood hazard.

Flooding is one of the major environmental challenges in India and particularly so in the Brahmaputra Valley of Assam. This area is marked by vast low lying alluvial plains, a thick network of streams, high amounts of sediment, and very heavy monsoon rains, all of which have regularly caused flooding in the past (Gogoi et al., 2025; Borah et al., 2022). Seasonal floods often cause extensive damage to farm lands, roads, and houses, at the same time they displace huge numbers of people and limit economic growth of the region. Besides, frequent flood incidents will further increase the vulnerability of the area in the long run by changing river paths and degrading the resilience of the social and environmental systems.

Flood susceptibility mapping has become a key part of flood risk assessment as it helps to find out which areas have a higher probability of being flooded under certain environmental conditions (Malakeel et al., 2021). Besides, such spatial assessments facilitate the implementation of measures for land use planning, disaster preparedness, and mitigation based on solid evidence by changing management methods from reacting to risks to removing risks. On the other hand, creating dependable susceptibility maps is still a problem in places where hydrological observations and long, term monitoring datasets are scarce (Anees et al., 2020).

Traditional methods of flood risk assessment, such as detailed hydrological models and statistical methods that depend on historical data, usually need lots of field measurements and detailed calibration of model parameters, as well as continuous records of hydrological and meteorological variables (Sieg et al., 2023). Such requirements are hard to fulfill in data scarce areas like Northeast India. Besides that, the linear statistical methods may not properly represent the complex nonlinear relationships between the factors like topography hydrology climate, and human activities, which ultimately result in floods (Mangukiya & Sharma, 2024). Due to these reasons, data, driven modeling approaches have been sought and adopted because they are capable of taking complex environmental relationships into account.

Machine learning (ML) techniques have developed rapidly recently, and as a result, assessment of flood susceptibility has been substantially enhanced due to the possibility of considering multiple conditioning variables simultaneously and identifying complex, nonlinear relationships without imposing strict statistical assumptions. Random Forest, Support Vector Machine, and Artificial Neural Network, among other algorithms, have been able to achieve a high level of accuracy when performing predictive tasks in flood hazard studies conducted in different hydro-climatic regions (Zhang et al., 2025; Arora et al., 2025). In addition, using ML methods along with Geographic Information Systems (GIS) and remote sensing data could provide even better spatial prediction by enabling constant environmental monitoring and offering a more accurate representation of the changing hydrological processes (Tehrany et al., 2014; Pasang et al., 2025).

Maximum entropy or MaxEnt models are increasingly being considered one of the most powerful machine learning methods available for presence, only data analysis (Phillips et al., 2006). They were at first built for predicting the potential spatial distribution of species. The model uses the information from the environmental variables at the presence locations and tries to find the distribution of maximum entropy (i.e. closest to uniform) subject to these constraints (Elith et al., 2011; Merow et al., 2013). These features make the software suitable for water flood hazard studies when reliable absence data are hardly available. In addition, it has been recently emphasized that Maxent model can successfully be used for natural hazard applications by providing nonlinear environmental variable relationships and reliable susceptibility maps (Javidan et al. ,2021).

All over the World, MaxEnt has been used for preparing the species distribution modeling but it can be used in preparing flood susceptibility maps in different climatic and geomorphological locations (Harshasimha and Bhatt 2023,Arora et al., 2025). Such application in India reveal that it is quite effective in identifying the flood-prone areas in the monsoondominated environment and also helpful in the disaster risk management planning (Harshasimha and Bhatt 2023). Besides, floodrelated regional studies in Assam have also hinted that MaxEnt model offer better results than multi-criteria decision-making methods such as the Analytical Hierarchy Process in flood hazard assessments (Kalita et al., 2025a). Although these methods have been improved, there are still many areas where little research has been carried out and research is mainly concentrated in the major river basins.

Despite the increasing use of machine learning methods, comprehensive studies at the basin scale examining small and medium-sized tributary systems of the Brahmaputra valley are still relatively few. These tributary basins have complicated hydro-geomorphic dynamics and generally do not have thorough hydrological datasets, so they are perfectly suited for presence-only modeling techniques. As a result, the feasibility and effectiveness of the MaxEnt model for specific flood susceptibility evaluation in data-deficient riverine settings of Northeast India are still only limitedly investigated.

In this way, the study attempts to create the very first flood vulnerability map of the Saktola River Basin through the use of Maximum Entropy, a machine learning method. More precisely, the study intends to: (i) combine seven environmental variables leading to floods with a flood inventory that has been validated with ground based data, (ii) divide the river basin into several flood risk areas, and (iii) check the accuracy of the model by using a strong validation method based on the random division of data. In addition, the study measures the extent to which each conditioning factor individually contributes to providing insight into the spatial factors controlling the occurrence of floods.

This study is a significant contribution from the point of view of method and practice. From the methodology viewpoint, it shows the potential of the MaxEnt model used in ecological modeling can be extended for the purpose of flood susceptibility analysis in a river basin with limited data (Kalita et al., 2025 b; Anjali, N., & Gopinath, G. 2026). From the perspective of practice, the map of susceptibility produced by the study offers a decision-support tool for the local authorities to use for land-use regulation, flood mitigation planning, and disaster preparedness in central Assam. The suggested framework can be applied to other flood-prone catchments of Northeast India as well as hydro-climatic regions that are similar, and thus it can be a part of broader efforts in climate-resilient flood risk management.

Material and methods

Study area. Saktola river basin (Fig. 1) having a catchment area of 816.04 km^2 between 26^0 $22^/$ $30^{//}$ N to 27^0 $00^/$ N and 91^0 $50^/$ $40^{//}$ E to 92^0 $00^/$ $15^{//}$ E has its significantly differentiable morphometric details caused mainly by geological and fluvio-geomorphic processes. The Saktola river oozing from the Bhutan Himalaya in the north at an elevation of 450 meter above the mean sea level and flowing across the gently sloping Brahmaputra valley meets the mighty Brahmaputra in the south. The stage level and discharge very frequently caused flood havocs not only along the channel but also along and across the basin. Floods, riverbank erosion, and shifting have increasingly affected the region, especially after the great earthquake of 1950, and even more so since 1980. Flood problem become so intense that these three aspects of hydro-geomorphology have turned on to attaining the status of containing hazards to natural environment and human habitation. The basin being a significant one needs proper investigation in respects of its hydro-geomorphic characterization in terms of geomorphic and hydrologic bases.

Data used. A total of 150 real time flood occurrence data were collected from the study area with the help of GPS in different seasons repeatedly, including peak monsoon and non-monsoon phases. Flood occurrence points were chosen based on the basin area and spatial differences. They also met the basic requirements for presence-only machine learning models such as MaxEnt. These points are spread across flood-prone areas of the Saktola River Basin. This distribution ensures proper representation of the basin, reduces spatial bias, and fulfills the occurrence needs of the MaxEnt model. Observations were recorded systematically in a field notebook at each visit, and site conditions were photographed with an SLR camera (Canon SX 530 HS). Sampling locations' geographic coordinates were collected with a Garmin eTrex GPS device. Total 7 environmental variables (Table 1) were used for modeling. Elevation data, slope and Land use and land cover data is extracted from Google Earth Engine. All the environmental variables are resampled to 30 meter spatial resolution for better analysis in R studio and ArcGIS environment.

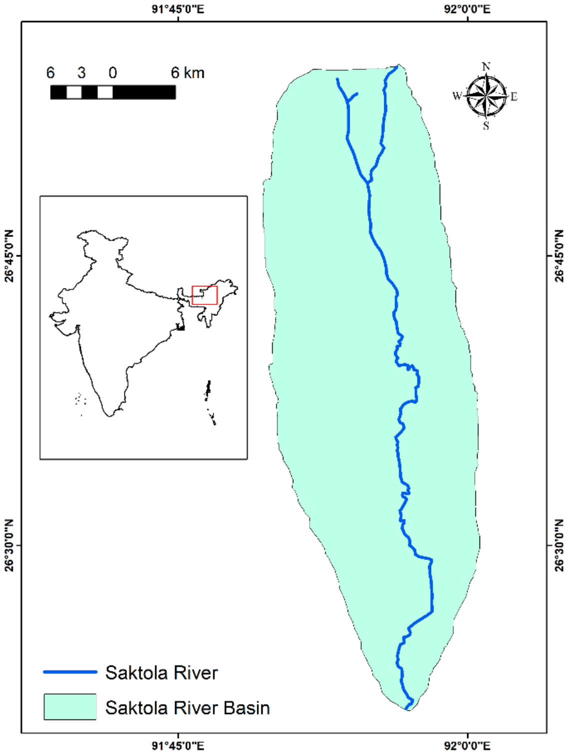

Fig. 1. Study area map showing the Saktola river
Source: own creation

Table 1. Data used and their sources

S.N.	Environmental Variables	Sources	Resolution Normalized
1	DEM	SRTM DEM ee.Image("USGS/SRTMGL1_003"	30M
2	Slope	Srtm DEM (ee.Image("USGS/SRTMGL1_003"))	30M
3	Precipitation	worldclim.org	30M
4	Topographic Wetness Index (TWI)	SAGA GIS (based on SRTM DEM)	30M
5	LULC	ee.ImageCollection("ESA/WorldCover/v100")	30M
6	Distance to Stream	HydroRIVERS	30M
7	Soil	www.fao.org	30M
8	Village shape files	https://search.earthdata.nasa.gov	Shape files

Source: own compilation

Multicolinearity test. Multicolinearity test is performed in R studio software to check if the environmental variables are highly correlated among themselves (Fig. 2). Several environmental variables exhibited strong Multi-co-linearity (r 0.8) as per the correlation matrix (Kumar et al., 2026). In particular, the high correlation values were noted between DEM and rainfall (r = 0.876), between DEM and soil (r = 0.834), and between soil and rainfall (r = 0.817).These are basically the relations where DEM, soil, and rainfall are very tightly connected with each other. Therefore, the variables have to be thoroughly examined to make a decision on which ones to eliminate for redundancy and a more stable model before applying Maxent modeling.

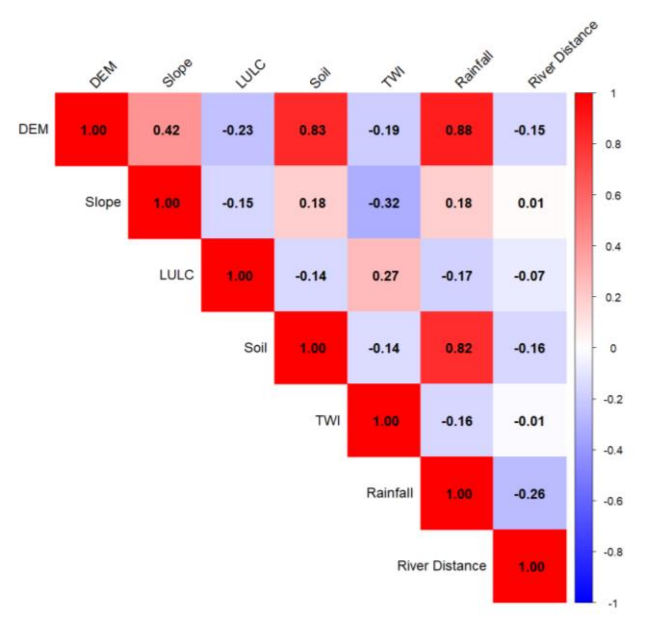

Fig. 2. Multicolinearity analysis in R studio
Source: own creation

A preliminary model was run in MaXent software to address the problem of multicollinearity where more emphasis was placed on Maxent permutation importance than on percent contribution, because permutation importance more truthfully shows how much the model depends on individual predictors when there is intercorrelation. This method made it possible to slightly more correctly analyse how each variable separately influenced the model performance.

The preliminary model run shows, rainfall was the most significant variable by far with the largest percent share of contribution (55.2%) and permutation importance (57.7%). River distance obtained a high permutation importance (16.4%) and it had a very weak correlation with other variables. Whereas, LULC, TWI, and slope each made only moderate contributions and were quite independent, hence, their presence is valid both from ecological and geomorphological points of view. Five variables, namely rainfall, river distance, LULC, TWI, and slope were kept in the final model after the assessment.

On the other hand, soil and DEM were dropped from the final Maxent model. Soil, despite being very closely linked with both DEM and rainfall, it hardly contributed (1.0%) and had zero permutation importance. DEM, while it had a moderate effect, it was very correlated with rainfall and thus it had a lower explanatory power than rainfall. Hence, dropping these variables not only helped to alleviate multicolinearitybut also resulted in retaining the most appropriate flood susceptibility predictors.

MaxEnt modelling. The Maxent model, developed by Steven J. Phillips and Miroslav Dudík (2008), was originally created at the American Museum of Natural History in collaboration with AT&T Research. First introduced in 2004 by Steven J. Phillips, Miroslav Dudík, and Robert E. Schapire, the model applies the principle of maximum entropy within a machine learning framework to predict species distribution probabilities using environmental variables. Owing to its strong predictive performance and flexibility, Maxent has become widely adopted in species distribution modeling studies (Kalita et al., 2025b). The principle of maximum entropy, as operationalized within the MaxEnt algorithm, is formally defined by the following mathematical expression.

$$P^*(z(x_i)) = \exp(z(x_i)l) / \sum_i \exp(z(x_i)l)$$

At location x_i, z represents a vector containing environmental variables, while l denotes the corresponding vector of regression coefficients.

Results and discussion

Model calibration and validation. Maximum Entropy (MaxEnt) modeling has been performed with the help of the program version 3.4.0. 70% of the flood occurrence records were randomly selected for the model calibration (training), whereas the remaining 30% were reserved for the independent validation (testing).To improve the model robustness and reduce uncertainty, ten independent runs were done. The maximum number of iterations was limited to 500 to make sure the algorithm converges (Kalita et al., 2025b).

To measure the model prediction rate, on the Receiver Operating Characteristic Curve (ROC) that has been turned into a measure of predictive accuracy, i.e., Area Under the Curve (AUC) (Fig. 3). Since the model produced results in logistic form, the model scores for suitability were in the range from 0 to 1, and values closer to 1 indicated a higher suitability. In order to make probability values easier to grasp, the later were divided into four intervals: 0 – 0.20 least potential, 0.20 – 0.40 moderate potential, 0.40 – 0.60 good potential, and 0.60 - 0.99 high potential. The model averaged a training AUC of 0.905 (Fig. 4) with a standard deviation of 0.023 across ten runs. Apart from the high mean AUC, the model also indicates the strong prediction power and the consistency of the effects demonstrated by the small variation between the runs. Maharajan et al., (2024) in their study on in the Mohana-Khutiya River of Nepal found an AUC value of 0.935 with a standard deviation of 0.018 and AUC values above 0.89 are considered to be excellent. likewise, Harshasimha and Bhatt (2023) also achieved AUC value of 0.83 for Kamrup metropolitan district of Assam (Maharajan et al., 2024).

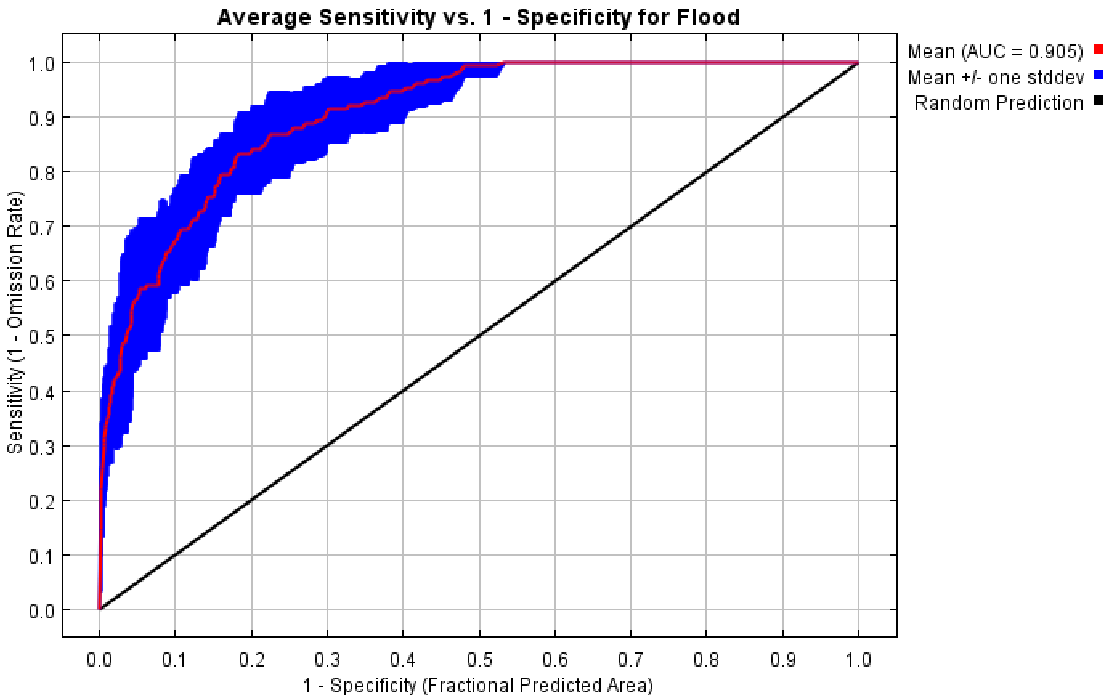

Fig. 3. Receiver operating characteristic (ROC) curve
Source: own creation based on MaxEnt

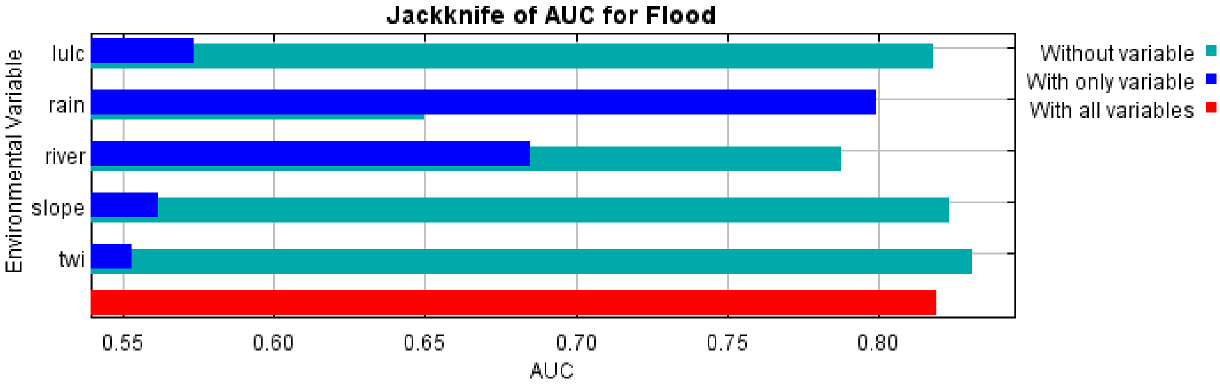

Fig. 4. Jackknife test of environmental variables
Source: own creation based on MaxEnt

Response of environmental variables to a flood event. The Maxent response curves illustrate the marginal influence of each environmental variable on predicted suitability while holding other predictors constant at their mean values (Fig. 5). Table 2 represents the analysis of variable contributions in the final model excluding the environmental variables i.e., soil and DEM.

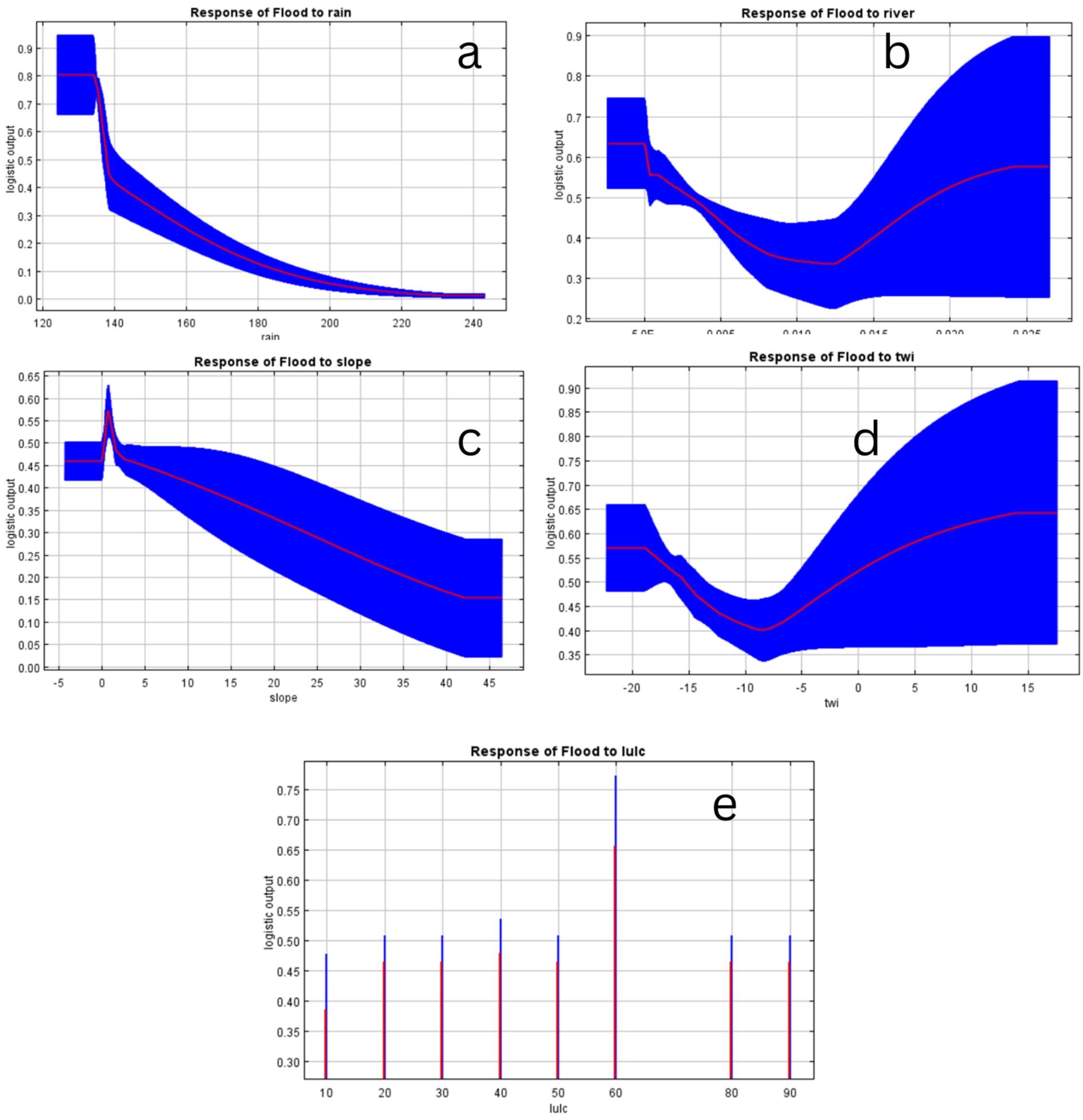

Fig. 5. Flood response a) rain, b) river, c) slope, d) TWI, e) LULC
Source: own creation based on MaxEnt

Table 2. Analysis of variable contributions in the final model

Variable	Percent contribution	Permutation importance
rain	70	76.2
river	9.9	3
lulc	9.7	8.3
twi	7.8	6.1
slope	2.6	6.4

Source: data generated using machine learning

Land use and Land cover. The categorical response of LULC indicates marked variation in predicted suitability across land-cover classes. Certain categories exhibit relatively higher predicted probabilities (as reflected by taller response bars), suggesting that specific land-use types provide more favorable environmental conditions for occurrence. This pattern highlights the importance of anthropogenic and surface characteristics in shaping spatial suitability.

Rainfall. According to the rainfall response curve, peak flood exposure aligns with moderate rainfall levels (120-135 mm), beyond which flood exposure rapidly decreases. This suggests that rainfall serves merely as an initiator; the other factors such as terrain characteristics and hydrological characteristics play the major role in causing the floods. Hence, in this paper, rainfall is regarded as a dependent driver conditioned by other factors and not a major driver of flooding.

Distance to river. The response of river distance is pretty clearly non, linear. The modelled habitat suitability is highest very near the rivers, falls off at intermediate distances, and goes up slightly at farther distances. Such a complicated relationship between the variables demonstrates that proximity to river networks greatly influences spatial prediction, which is likely a manifestation of the river, associated hydrological, and geomorphological factors.

Slope. Slope displays a gradual negative relationship with predicted suitability. As slope increases, suitability slightly declines, indicating that relatively flat or gently sloping terrains are more favourable compared to steep gradients. This pattern suggests that topographic stability and reduced gravitational influence contribute positively to predicted presence.

Topographic Wetness Index (TWI). The TWI, response relationship graphs show a nonlinear pattern. When the TWI values are low, the suitability score is quite high; then the score goes down at middle levels and finally, it goes up again with the increase of the TWI values. The environmental moisture and surface wetness are probably indirectly influencing the use of the flood through the suitability phases: Thus, both quite dry and very wet conditions could correspond to a higher level of suitability but in different ecological contexts.

Flood susceptibility mapping of the study area. The flood susceptibility map clearly shows the different levels of susceptibility of the different areas in the entire study area. A large part of the region is categorized as the least susceptible and extends over 568.44 Sq. km. In other words, practically majority of the land has a very low risk of flooding. The area with moderate susceptibility covers 174.48 Sq. km. and they are the zones influenced by terrain and drainage having an intermediate level of flood potential. Contrary to this, the areas that have been identified as good and high susceptibility are very small in size and they only cover 51.61 Sq. km and 21.51 Sq. km respectively (Table 3). These parts are mostly the lower parts of the basin and the downstream areas where the risk of flooding is naturally higher because of water accumulation and floodplain processes. Finally, although the high, risk part of the landscape is limited, the 73.12 Sq. km. under the good and high susceptibility that together still need to be the priority for flood management and planning (Fig. 6).

Table 3. Flood susceptible areas

Flood Susceptibility	Area (km^2)
Least	568.44
Medium	174.48
Good	51.61
High	21.51

Source: data generated using machine learning

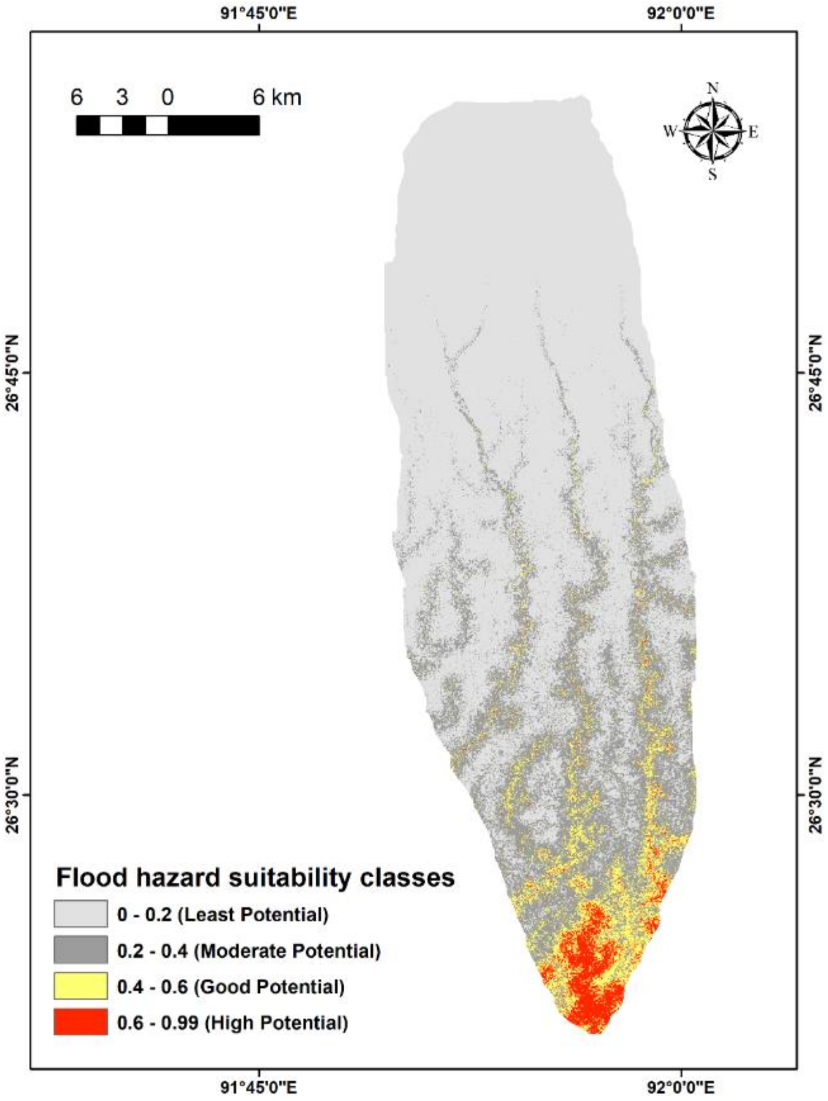

Fig. 6. Flood hazard suitability classes
Source: own creation

Flood susceptibility assessment of village. A village, level flood susceptibility analysis has been carried out, and the villages have been categorized into four susceptibility classes: high, good, moderate, and low susceptibility (Fig. 7). 14 villages are in the high susceptibility category, 27 are in the good susceptibility category, 89 are in the moderate susceptibility category, and 238 are in the low susceptibility category, respectively (Table 4).

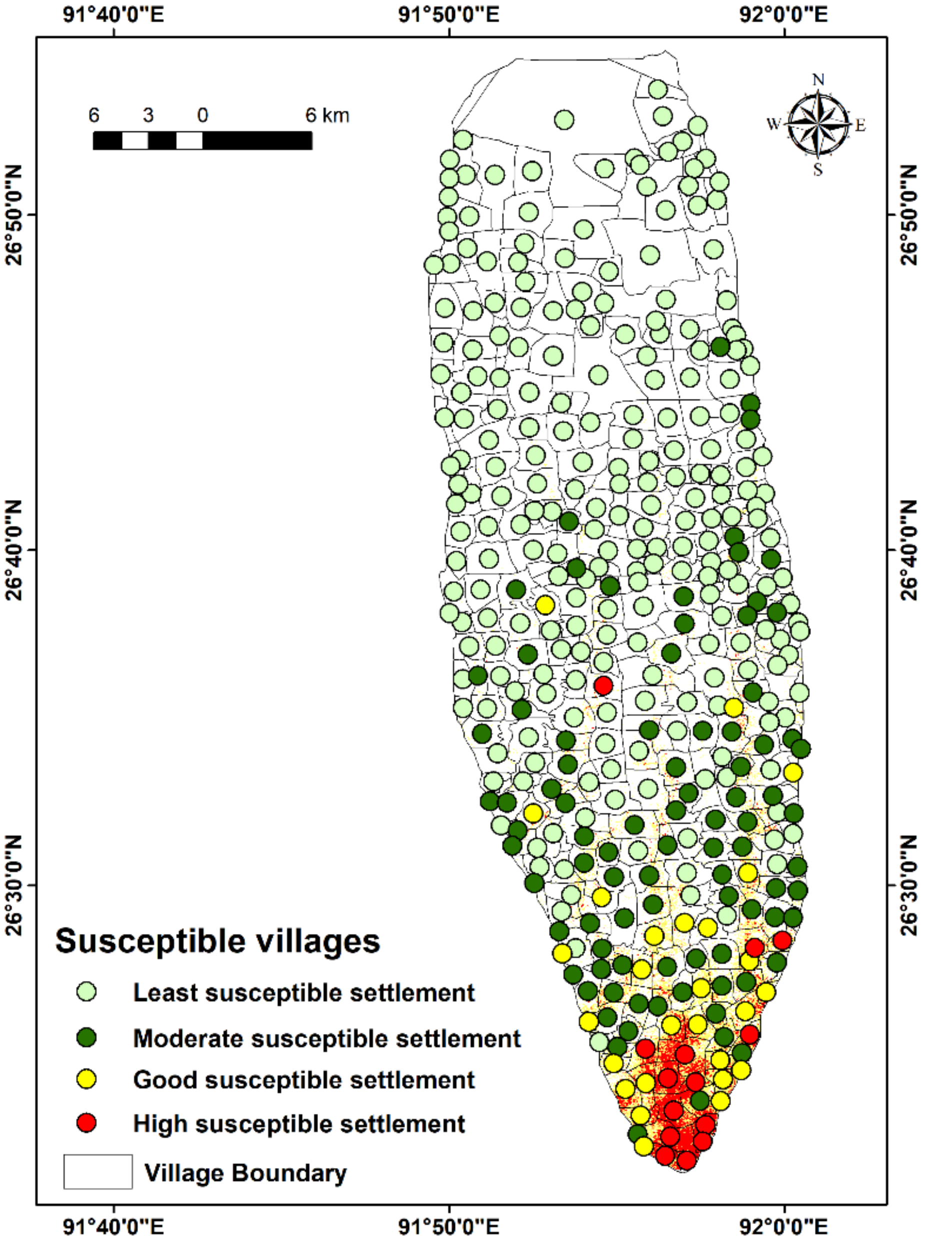

Fig. 7. Flood susceptible villages
Source: own creation

Table 4. Flood affected villages

Flood Susceptibility	**Flood Affected Villages**	**Total Villages**
Least	All the other villages within the river basin	**238**
Moderate	Bangali Gaon, Kochpara, Niz Harisinga, Khairabari, Pub-Futikbari, No. 2 Alikash, DakhinKuyabil, Rupa Khat, Harsapara, PachimJangalpara, Kachartali, Hapabari, Pakimuri, Balipara, Mahelkanda, Niz Dala, Atelia, Rangajuli Khat, Gerua Gaon, Saikiapara, No. 1 Kalaigaon, RanthaliBagicha, Ojhar Gaon, Borora Khat, Madeli Gaon, Habibhanga, No. 2 Kalaigaon, Napti Para, Dalai Para, Khas Ranthali, TengabariBagicha, JengeraJhar, Salaipara, Niz-Sarabari, Choudhuri Para, DakhinBokrajhar, Kamarpara, Hapamara, Garia Para, Bahjani, Nego Para, Durga Gaon, Jhakapara, Burahkhat, Baghbari, Mahaliapara, Bechimari, Kapili Satra, Gargari Chuba, Katahi, Ramgaon, Maja Chuburi, Naptapara, Nahar Bari, Kharkhowapara, Bareri, AhakaChuburi, Adhikari, Niz-Chopai, Hirapara, Patidarrang, Alekjhari, Kanai Chuba, Ghilakuri, Khatara, Athkuria, Nagaon, Tamulipara, Ramraipara, Baranga Bari, GakhirKhowa Para, Patharighat, Alikapaka, Niranchuba, Kabikara, Ganak Para, Bar-Satra, Kumarpara, No. 2 Chengapara, Batabari, Choto Athiabari, Barkalijhar, Muslimghopa, Patalsingpara, Ghatua Para, Hazarikapara, Mahariadal	**89**
Good	Hati Bandha, BholabariBagicha, Garubandha, Sakiapara, Jogipara, Potapukhuri, Lozora, Jhargaon, Kaikara, Maharipara, Pipirakuchi, Keot Para, Niz Dahi, Choto Athiabari, Barathiabari, Ghorasal, Ghopa, Barragaon, PachimChuburi, DakhinChuburi, Bhanguri-Chuba, Choto Nagaon, Bhutkabari, Barthekera Bari, Nizsipihar, Hatimura	**27**
High	Bangaon, Kumar Para, Kameipara, Boinaoja Para, Satgharia, PakabangiChuburi, Kabai Chuba, Satmadar, Pithakhowa, Debananda Satra, Jhakuwapara, Kachari Para, Satkhali, Ruperi Kash	**14**

Source: own compilation using village shapefiles from https://search.earthdata.nasa.gov

Conclusions

A Maximum Entropy machine learning approach was applied to analyze flood susceptibility in the Saktola River Basin of Assam. A field-based flood occurrence dataset combined with geospatial environmental variables has been used to produce an accurate susceptibility map for the basin. The study determined that rainfall and distance to river are the two most significant controlling factors, followed by land use and land cover, slope, and topographic wetness index in order of significance. The resultant susceptibility map indicated that areas along river corridors and low-lying floodplains have very high potentiality for floods. The model verified high predictive accuracy with an average AUC value of 0.905 which proves that the MaxEnt model is suitable for assessing flood susceptibility in regions with limited hydrological data.

This brings out the machine learning technique's efficiency when used with GIS and remote sensing data toward hazard assessment in a river basin where such data are scarce. The prepared susceptibility map is a useful tool for local authorities to implement flood risk management, planning of the land use and disaster mitigation. Besides, the methodological framework developed in this research could be applied to other basins of Northeast India which have similar hydro-climatic conditions and yet are susceptible to floodings. Future research might introduce hydrological variables along with finer resolution datasets and also climate change scenarios for enhanced flood prediction and resilience planning at regional level.

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Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data that support the findings of this study are available from the corresponding author, NK and NB, upon reasonable request.

Use of Generative AI and AI-Assisted Technologies

No generative AI or AI-assisted technologies were employed in the preparation of this manuscript.

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