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Flood Vulnerability Mapping Using MaxEnt Machine Learning Technique and Analytical Hierarchy Process (AHP) for Kamrup Metropolitan, Assam †

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Abstract: Addressing natural hazard's complexity is essential in preventing human fatalities and conserving natural ecosystems as natural hazards are varied and unbalanced in both time and place. So, the main objective of this study is to present a Flood Vulnerability Hazard Map and its evaluation for hazard management and land use planning. The inventory map of natural hazard- flood is generated for different Flood locations using multiple official reports. To generate the vulnerability maps, a total number of 9 geo-environmental parameters are chosen as predictors in Maximum Entropy (MaxEnt) machine learning technique and Analytical Hierarchical Process (AHP). The accuracy assessment of the predicted output models from MaxEnt are evaluated using Area under the curve. Similarly, for AHP outputs the accuracy was tested using the generated inventory map and AUC. It is observed that topographical wetness index, elevation, and slope are significant for assessment of flooded areas. Finally, Flood hazard maps are generated and a comparative analysis was performed for both methods. According to the study's findings, the flood map generated by MaxEnt was better with 0.83 AUC whereas 0.76 AUC of AHP flood map. From the study it can be concluded that, hazard maps could be a useful tool for local authorities to identify places that are vulnerable to hazards on a large scale.

Keywords: Vulnerability Mapping; Maximum Entropy (MaxEnt); Analytical Hierarchy Process (AHP); Area under the curve (AUC)

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1. Introduction

Around the world, natural catastrophes pose a major threat to property and human lives. Although it is impossible to prevent natural hazards, their negative impact can be reduced by creating effective planning strategies and mitigation techniques. Significant morphological changes in landforms brought on by active tectonics or climatic changes may affect human activity management. Events such as gully erosion, landslides, and floods are physical phenomena, active in geological times but uneven in time and space [1–4].

According to (NDMA, 2008), a flood is extra water that is flooded because rivers' capacity to transfer a large amount of water from the upstream area within their banks after significant rainfall is insufficient. Floods occur most frequently and are damaging to local social, economic, and environmental aspects of all the natural catastrophes that occur on a global scale. High intensity precipitation in the watershed, changes in river cross sections caused by sedimentation, sudden dam failure, release of high flow from dam, etc. are just a few of the causes of floods.

Floods can be broadly classified into four categories: fluvial (river) floods, ground water floods, pluvial floods, and surge (coastal) floods, depending on a variety of criteria including velocity, geography, and sources. Assam, which is in the monsoon climatic region, has been having an average yearly rainfall of 1600 mm to 4300 mm, causing flooding throughout the region (Assam State Disaster Management, n.d.). Overflowing tributaries of the Brahmaputra River also contribute to the volume of flood water in the valley.

Furthermore, this state has a unique hydrological, climatic, and unstable geological condition that intensifies the source of numerous geomorphic and geological dangers in the region. Considering all these conditions, the use of remote sensing techniques proves to be a viable solution.

2. Study Area

The Kamrup metropolitan district is located in the state of Assam which is situated in the north-eastern part of India, covering an area of 1528 km^2. The study stretches from 26.07° N latitude and 91.63° E longitude in the lower basin of Brahmaputra, which is prone to rapid flooding nearly every year.

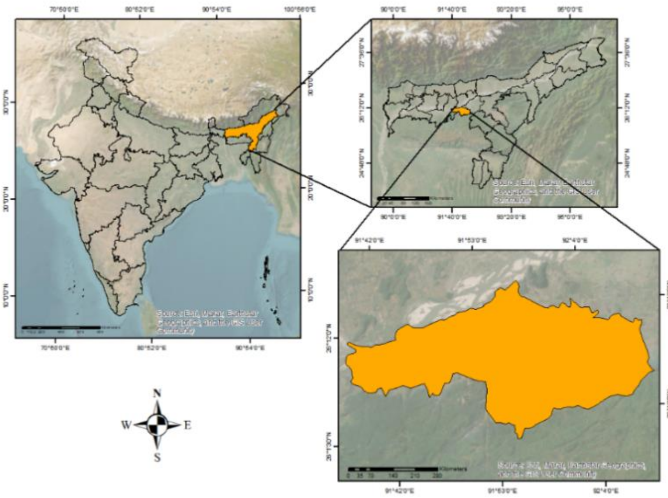
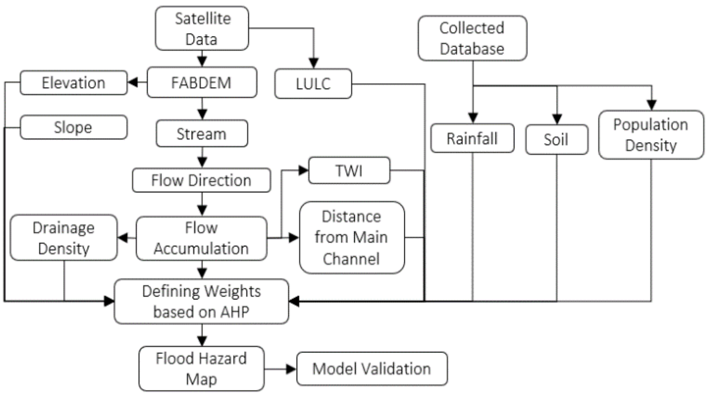


Figure 1. Research Study Area—Kamrup Metropolitan, Assam, India.

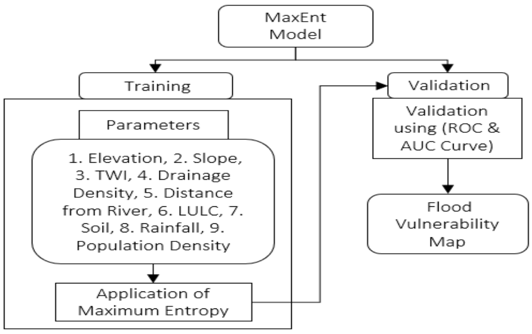
In 2021, the districts of Assam had an average annual temperature of 24 °C and an annual rainfall of over 2200 mm. Kamrup Metropolitan district is Assam's administrative center, with major cities.

3. Materials and Methods

Figure 2 Illustrates the methodology that was approached with AHP modelling and MaxEnt Modelling.



(**a**)



(**b**)

Figure 2. (**a**) AHP flowchart (**b**) MaxEnt flowchart.

3.1. Flood Inventory Mapping

A key step for susceptibility mapping is the preparation of an inventory of hazard landforms. The flood inventory for the Kamrup Metropolitan District (Assam, India) were compiled from national and regional documents from various organizations like Assam State Disaster Management Authority, North East Space Application Centre. About 53 flood areas are listed on the inventory map for floods. For training samples, a random partition approach is used. In the present study, 70% of each hazard was considered for model construction (training), and the remaining 30% were used for validation.

3.2. Flood Conditioning Factors

It is essential to determine the effective factors on different natural hazards and human-made fatalities to perform flood maps [5]. A good understanding of the main hazards-related factors is needed to recognize the susceptible areas.

For this aim, the conditioning factors for the hazard was selected [6–10]. In this study, ArcGIS 10.3 (ESRI, USA) is used to perform analysis of AHP, produce and display these data layers. All the factors were processed into a raster grid of 30 × 30 m grid cells. Entire conditioning factors were primarily continuous, and some of them were classified within different categories based on expert knowledge and literature review [11–14].

The geo-environmental parameters used in this study are as follows:

3.2.1. Elevation

The elevation parameter is of great significance for delineating flood hazards and mapping flood zones. During monsoon, downstream generates ideal flood conditions due to sedimentation and surge in river flow. Understanding elevation variation is critical for river basin generation and propagation of flood waters. In this study, FAB DEM(Forest and Building removed Copernicus DEM) data with a spatial resolution of 30 m is used.

3.2.2. Slope

The steepness and length of a region's topography greatly influence its discharge and flooding. The rapid velocity of precipitation runoff is caused by steep or high slopes. Low or flat slopes, on the other hand, are prone to waterlogging which can lead to high infiltration. The slope map was created using FABDEM (DEM) data.

3.2.3. Land Use Land Cover

Land use/land cover plays a significant role in the operation of hydrological and geomorphological processes by directly or indirectly influencing on processes such as evapotranspiration, infiltration, runoff generation and sediment dynamics. The land use/land cover product of 10 m spatial resolution is obtained from Sentinel 2 in Google Earth Engine (GEE) platform.

3.2.4. Soil Texture

Soil texture is generally recognized as a weighty controlling factor in the mechanism of infiltration and runoff generation and is effective on hazard occurrence. This layer was District acquired from the NBSSLUP. The soil texture in the study area comprises of loam and clay.

3.2.5. Topographic Wetness Index (TWI)

Moore and Grayson [15] and Grabs et al. [16] mention that TWI (Topographic wetness index) represents the tendency of gravitational forces and the spatial distribution of wetness conditions to move water to the downslope. The layer was generated using DEM. TWI is also important in the regulation of surface runoff since greater wet an area is, greater will be its runoff

3.2.6. Distance from River Channel

The distance from the river was estimated in ArcGIS using the Euclidean Distance tool, which displays the distance of the river basin region to the natural drainage. Natural drainage refers to all of the streams and rivers in the study region, which was categorised into five classes of 500 m, 1000 m, 1500 m, and 2000 m.

3.2.7. Drainage Density

The primary influencing factors that contribute to the occurrence of numerous risks is drainage density. A higher surface runoff ratio results from a high drainage density. To convert the drainage network pattern to measurable quantity, the drainage density was determined using an extension of "line density" in ArcGIS 10.3 software.

3.2.8. Rainfall

Rainfall is a key aspect in this study as floods most commonly occur during monsoon season, hence the term "rain-induced floods". The rainfall map of the study area is generated using the Inverse Distance Weighted approach (IDW) from Global Precipitation Measurement datasets. The map is generated considering annual total rainfall of year 2021 as 2021 was a flood year.

3.2.9. Population Density

One of the critical elements to consider while doing flood vulnerability research is population. This component is important in flood-vulnerable areas for analyzing the social loss and damage suffered by the community as a result of floods. The population density map for the study area were obtained from Google Earth Engine databases of population density gridded data of ≈1 km spatial resolution.

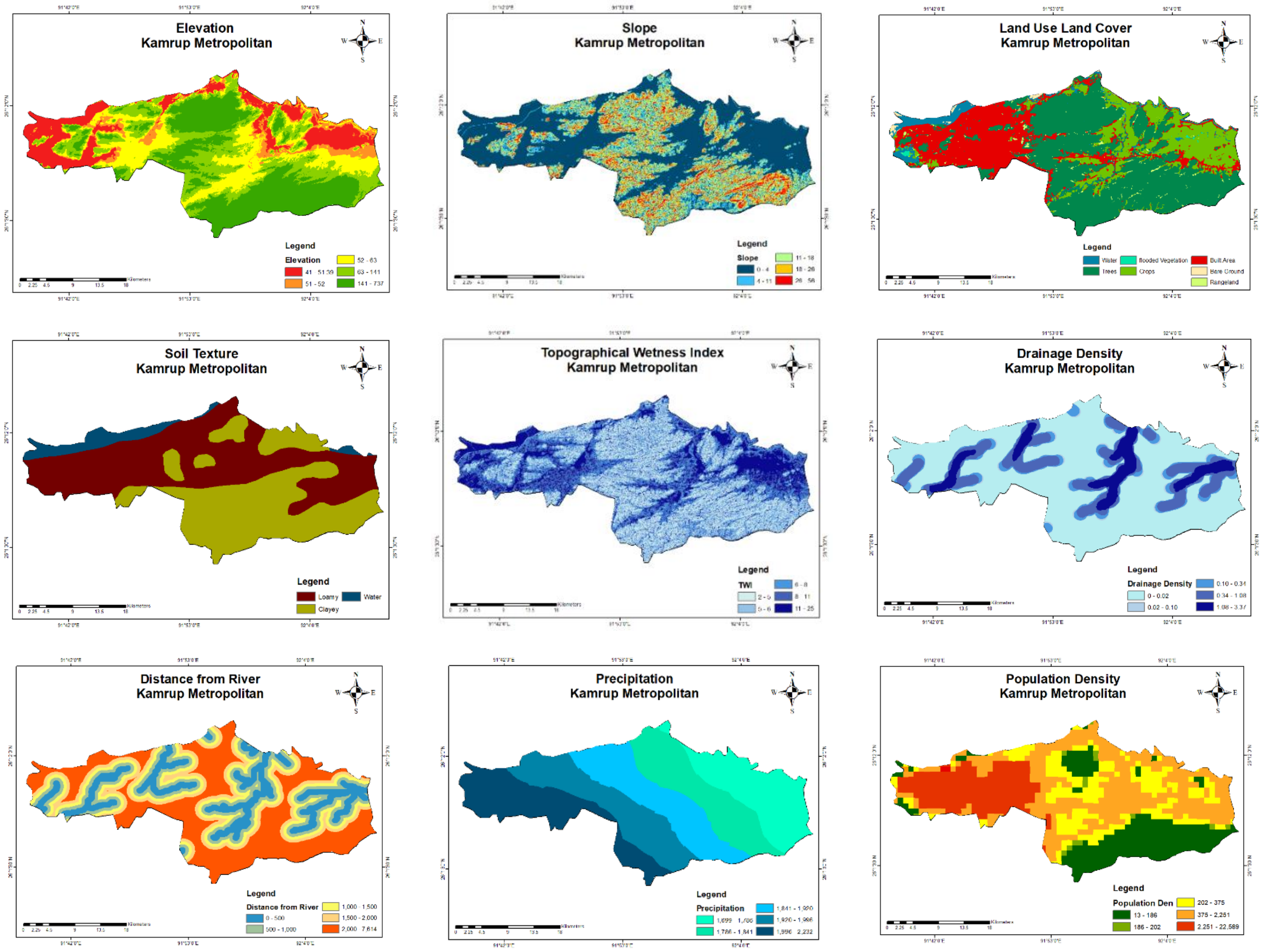


Figure 3. 9 geo—environmental conditioning factors.

4. Results

4.1. Maximum Entropy (MaxEnt)

The Maxent software uses the Maximum Entropy model, to calculate hazard estimates (version 3.4.4). MaxEnt model is usually used to estimate species distribution based on the most significant environmental condition. From a decision-theoretic perspective, we also interpret the maximum entropy estimation as a reliable Bayes estimation. The model relies on a machine learning reaction that generates hypotheses based on skewed data. The result from model is obtained in ASCII format. The conditioning factors are translated from raster into ASCII format, as required by the software. The most crucial phase in the modelling process is validation. The AUC curve has been used to assess the built-in hazard models' prediction accuracy, Figure 4.

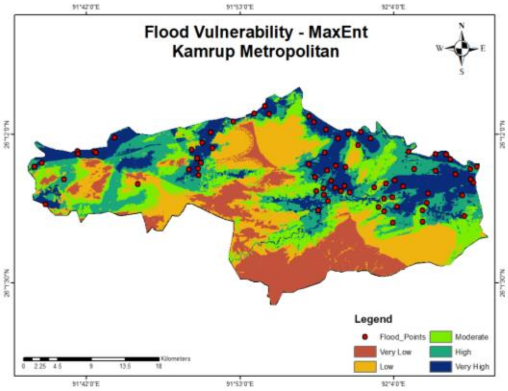


Figure 4. MaxEnt—Flood mapping.

4.2. Analytical Hierarchy Process (AHP)

The Table 1, shows the weights assigned for the nine geo-environmental parameters used to generate the flood hazard map. To obtain the spatial distribution of flood hazards, the parameters evaluated were mapped and normalized into five classes based on a rating scale of 1 to 5, with 1 being least vulnerable area and 5 being most vulnerable area. Figure 5.

Table 1. AHP weights**.**

Factor	Weight
Slope	0.22
Distance from River channel in meter	0.17
Land use land cover	0.05
Soil Texture	0.10
Elevation	0.07
Rainfall in mm	0.04
Population Density	0.02
TWI	0.21
Drainage Density	0.12

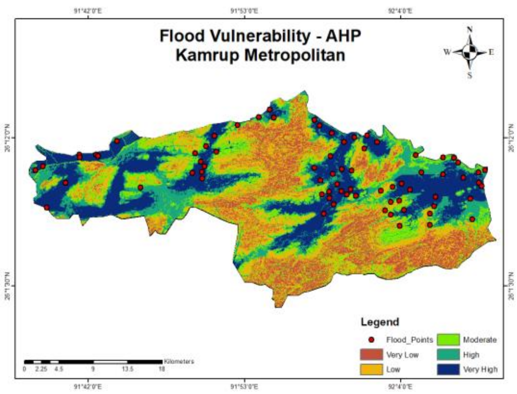


Figure 5. AHP—Flood Mapping**.**

4.3. Comparative Analysis of sensitivity and Response Curves

The relative influence of each predictor variable on the outcomes of predicted maps using the Jackknife test was examined using a sensitivity analysis from the AUC. On validating with respect to flood inventory points, we observe that MaxEnt slightly outperformed AHP modelwith the AUC of 0.83 Figure 6, over an AUC of 0.763, Figure 7.

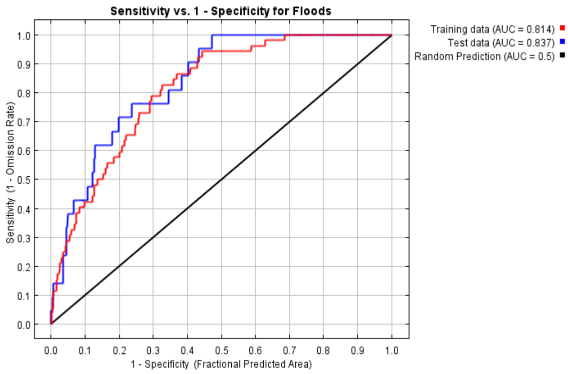


Figure 6. AUC—MaxEnt.

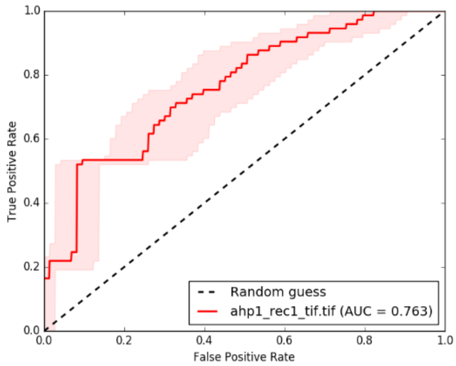


Figure 7. AUC—AHP.

4.4. Spatial Extent of Vulnerability

Flood vulnerability maps generated from the outputs of MaxEnt and AHP shows that the areas entitling the river, the surfaces with slopes of 0 degrees to 11 degrees and the land with the elevation range of 41 m to 52 m showed vulnerability to floods. Subsequently, on inspecting with Bhuvan—ISRO historical flood maps, we observe that, the flood map generated by MaxEnt and AHP, showed a reasonable resemblance with flood maps of Bhuvan, ISRO.

From the results we also observed that out of 1528 km^2 total area of the district, about 650 km^2 was found to be highly vulnerable to floods and major locations like Guwahati, Dispur, Sonapur Gaon of the Kamrup Metropolitan District showed a higher vulnerability to flooding.

5. Conclusions

In this study, a flood vulnerability map was generated for major district of Assam utilizing the AHP approach and MaxEnt machine learning technique. Given their ability to handle huge datasets, multi-criteria analysis using AHP and MaxEnt Technique was identified and proved beneficial for flood risk assessments.

Slope, Drainage density, TWI, and Elevation were the primary flood-causing geo-environmental parameters in the studied area. The AHP method and MaxEnt technique employed in this study are effective and enable the possibility of further research into flood vulnerabilities in various sections of the state or country. The AUC graphs is employed as a validation method in this work which demonstrates additional possibility for research validation and applicability in geospatial vulnerability assessment owing to extreme events.

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