



GIS-based frequency ratio model for flood susceptibility zonation in the state of Meghalaya, Northeast India

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Abstract

The flood is the most catastrophic natural hazard accounting for the loss of life and properties. The state of Meghalaya is very diverse in its topography. The landslides hit the mountainous region, and the floods create afraid in the low-lying areas of the state every year. Although flood is a major natural hazard in the region, no major research work has been carried out yet. In the current study, a flood susceptibility zone map was prepared for the blueprint. For this purpose, ten flood triggering factors were selected for estimating the weightage through the bivariate frequency ratio model and the predictive rate of flooding, subsequently. Based on the prediction rate, it was found that LandUse/LandCover, elevation, and topographic Wetness Index had been the maximum contribution, and the Drainage Density, Distance to River minimum contribution in flood occurrences in the study area. Finally, the flood susceptibility map was generated by using the Frequency Ratio raster image and their respective predictive rate of flooding. The generated flood susceptibility zonation map was classified into five susceptibility zones. The spatial distribution of floods has been classified into a very high flood susceptibility zone covering an area of 12.06 sq. Km., the high susceptibility zone covered 0.78 sq. Km., moderate susceptibility zone covered 135.72 sq. Km., low susceptibility zone covered 22204.99 sq. Km. and the very low susceptibility zone filled 0.09 sq. Km. Subsequently, the flood susceptibility zonation was evaluated by a predicative rate and success rate curves close to 0.906 and 0.984, respectively expressed as an excellent prediction accuracy. The current research contribution will act as a blueprint and be further helpful for policymakers.

Keywords Natural hazards · Flood frequency ratio · Predictive rate · Shillong Plateau · Meghalaya

Introduction

Flooding is an overflowing of water onto land that is normally dry. Floods can happen during heavy rains, when ocean waves come on shore, when snow melts quickly, or when dams or levees break. The floods are the most catastrophic events that can happen in an extensive area. The floods distress the land, dams, highways, and human infrastructures every year worldwide. Hence, the floods are also one of the most catastrophic natural disasters. A flood happens when a surplus amount of water overflows its regular boundaries, inundating river floodplains and creating

a temporal water stagnation (Samanta et al. 2018). It constitutes a major factor in the deterioration of the environmental ecosystem, the transportation network, crops and livelihood, sociocultural inheritance, and the existence of humanity (Khosravi et al. 2016). The flood-related losses impacted as an average of 99 million people between 2000 and 2008 (Tehrany and Kumar 2018), accounting for 32% of all human and environmental harm between 1963 and 1992. China has gained the first rank in accounting for the socioeconomic ramifications of floods (Munir et al. 2022). The prevention of floods is a crucial role in reducing the possible damages caused by floods. Therefore, early warning systems for preventing floods, flood mapping, flood mitigative measures, emergency services, and disaster risk reduction are important steps to reduce flood intensity (Samanta et al. 2018). The flood susceptibility zonation mapping is the first step toward flood mitigation. The term flood susceptibility is denoted as the zonation of homogeneous places for

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delineating the possible flood-affected areas under similar geo-environmental conditions.

The development of spatial technology like remote sensing and GIS opened a new era for flood susceptibility mapping throughout the world. Several GIS-integrated models like Artificial Neural Network (ANN), Frequency Ratio (FR), Weight of Evidence (WoE), Statistical Index (SI), Analytical Hierarchy Process (AHP), and Logistic Regression (LR) models are globally used by the Earth Scientists. However, different models have their prediction and accuracy based on the conditioning factors that vary from region to region. The frequency ratio (FR) model is one of the most widely used and highly accurate hazard assessment techniques. The FR is one of the bivariate statistical analyses, that evaluates the impact of each parameter on the occurrence of floods by giving values to each class of the parameters (Ghosh et al. 2022). It is a simple and sophisticated technique to apply through a GIS environment and could yield scientifically valid flood susceptibility maps (Pawar et al. 2022; Ghosh et al. 2022).

The maximum rainfall (75%) occurs in the SW monsoon between June to September and flows through the Ganga, Brahmaputra, Narmada, Tapi, Mahanadi, Godavari, Krishna, and Cauvery Rivers (Pawar et al. 2022) in India. The NITI Aayog has estimated that 7.17 million hectares of land are affected by floods annually in India. Saravanan et al. (2023) have reported that 235 flood events occurred in India and lost the lives of about 126,286 populations and 1.93 billion people homeless during the period 1980 and 2017 which caused more than \$58.7 billion in damages in terms of money. The recent flood events in different parts of the Indian sub-continent like Uttarakhand (2013), Kashmir (2014), Chennai (2015), Patna (2019), and Kerala (2018 and 2019) pose a serious issue (Saravanan et al. 2023). The creation of flood risk assessments and flood susceptibility maps is essential for planners and government representatives to create effective flood control measures while implementing management strategies.

Materials and methods

Study area

The state of Meghalaya is one of the areas prone to disasters like landslides, earthquakes, floods, etc. The floods in the study area are mostly occurred in the low-lying regions of the Garo Hills and flash floods also noticed in some parts of the Khasi and Jaintia Hills districts due to the excessive rainfall occurring in short periods, less than 6 h duration (Saleh et al. 2022). The recent reports stated that floods occurred on 21st April 2017 and affected the low-lying regions of South-west Garo Hills district in the state of Meghalaya causing

around twenty people displaced from their homes and damaging the roads, agricultural fields, and fish farms (Flood list 2020). Another flood affected the five lives lost in the region on 22nd June 2020 and the population of 1.52 lakh were affected directly. The NDTV reported that on July 14, 2020, more than 89,000 people were affected in West Garo Hills, particularly in the border regions like Tikrikilla, Demdema, and Selsella blocks where the Jinjiram River, a tributary of Brahmaputra overflowed causing flood (NDTV 2020). As per the State Disaster Management Authority, a flood in the West Khasi Hills district caused 5 people to go missing and 13 people died in a flood due to heavy rainfall all over Meghalaya on 22nd September 2020 (Flood list 2020). In the same year 2020, another flood in the South Garo Hills district destroyed huge public properties like roads, bridges, mobile connectivity, and power supplies affecting the lives of around forty-thousand people in the area ([www.india today.in](http://www.india.today.in)). The disaster washed out a wooden bridge connected Jijika village to Megua village of South Garo and West Garo Hills districts, respectively (Scroll staff 2022). Another crucial wooden bridge was washed away by the flood water in Meghalaya's South Garo Hills district on 25th September 2020 which affected the day-to-day life of the local people (Flood list 2020).

Flood is a natural process and it cannot be completely mitigated, but it can be monitored and effective control measures implemented to reduce the extent of damage (Munir et al. 2022; Tehrany et al. 2015; Al-Juaidi et al. 2018). Satellite image analysis on the RS and GIS platforms offers an amazing environment to run and utilize a wide range of models to assess flood vulnerability with logical and accurate results. Therefore, to prevent the effects of flooding, local governments should identify the areas that are vulnerable to flooding and stop urbanization on the floodplains of active river courses. Before putting these measures into action, vulnerable areas should be identified using appropriate scientific techniques. (Munir et al. 2022). The present study aims to identify the flood susceptible zones with a map in Meghalaya by using the frequency ratio (FR) model, which is a bivariate statistical analysis method that can be helpful for researchers and local governments for future flood mitigation plans.

About the study area

Meghalaya, the “abode of the clouds,” is one of the Indian seven sister states in the northeastern region (Fig. 1). It is located between latitudes 25°02'N and 26°07'N and longitudes 89°49'E and 92°50'E with a geographical area of 22,429 km². It forms an international border with Bangladesh in the west and south and shares a boundary with Assam in the north and east. According to the Census of India (2011) statistics the total population of the state is

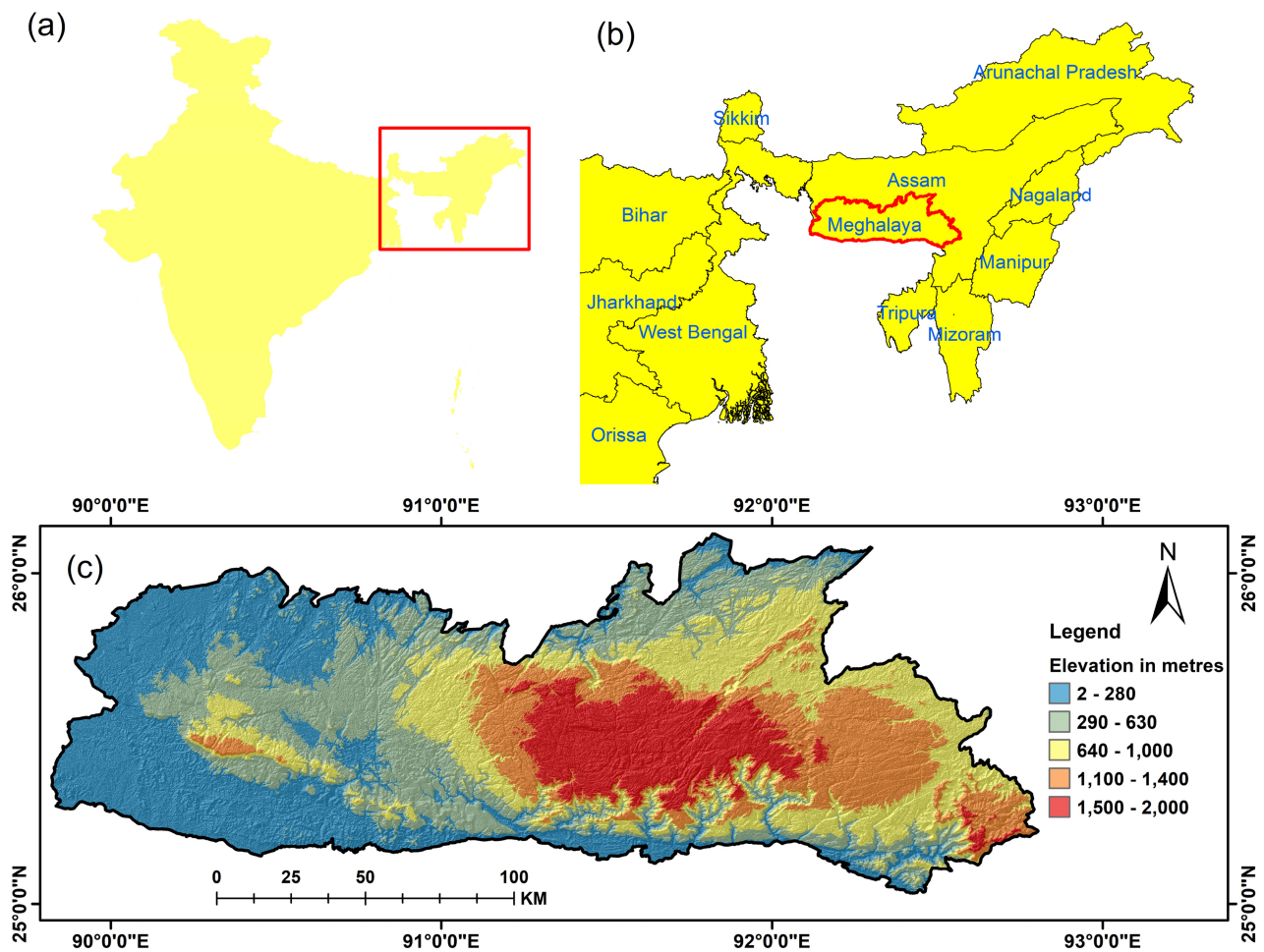


Fig. 1 Location of the study area, **a** Northeast India in the Indian context, **b** location of Meghalaya in the northeast India, and **c** Meghalaya along the elevation distribution of the state

2,966,889 persons. The Mosinram known as the wettest place in the world is located in the state of Meghalaya. Over the previous 30 years, the region has experienced 1234–7467 mm of annual rainfall on average (Indian Meteorological Department). As per the extent and distribution of geological formations, the region is a part of the Chotta Nagpur plateau and is separated by the Garo—Rajmahal gap (Grimaud et al. 2020). The Shillong Plateau in the western part of the state is the dominant geomorphologic feature like south-facing escarpments. The elevation of the state ranges between 2 and 2000 m above mean sea level. It abruptly rises along the southern escarpment in a short period, creating a steep slope of 70° to 76° in the south of the Khasi Hills region, and a slope angle as low as 0° to 5° is seen all along the southern parts and foothill regions of the Garo Hills. From the last few decades flood emerge as a serious issue on livelihood on the local residence (Fig. 2).

Preparation of thematic layers

There are numerous geo-environmental and man-made related factors, which influence flood occurrences in a region (Tehrany et al. 2015). The flood-triggering factors work with different intensities based on the local geo-environmental conditions (Sarkar and Mondal 2019). However, it is important to select reliable flood conditioning factors during flood susceptibility mapping from the appropriate sources. For this study, a total of 10 flood conditioning factors such as (1) Elevation, (2) Aspect, (3) Curvature, (4) Topographic Wetness Index (TWI), (5) Distance to River (DTR), (6) Drainage Density (DD), (7) Geology, (8) rainfall, (9) Land Use/Land Cover (LU/LC), and Normalised Difference Vegetation Index (NDVI) are taken into consideration (Fig. 3).

The ASTER 30 m digital elevation model was used to prepare the elevation, aspect, curvature, distance to rivers, and drainage density. The geological information was

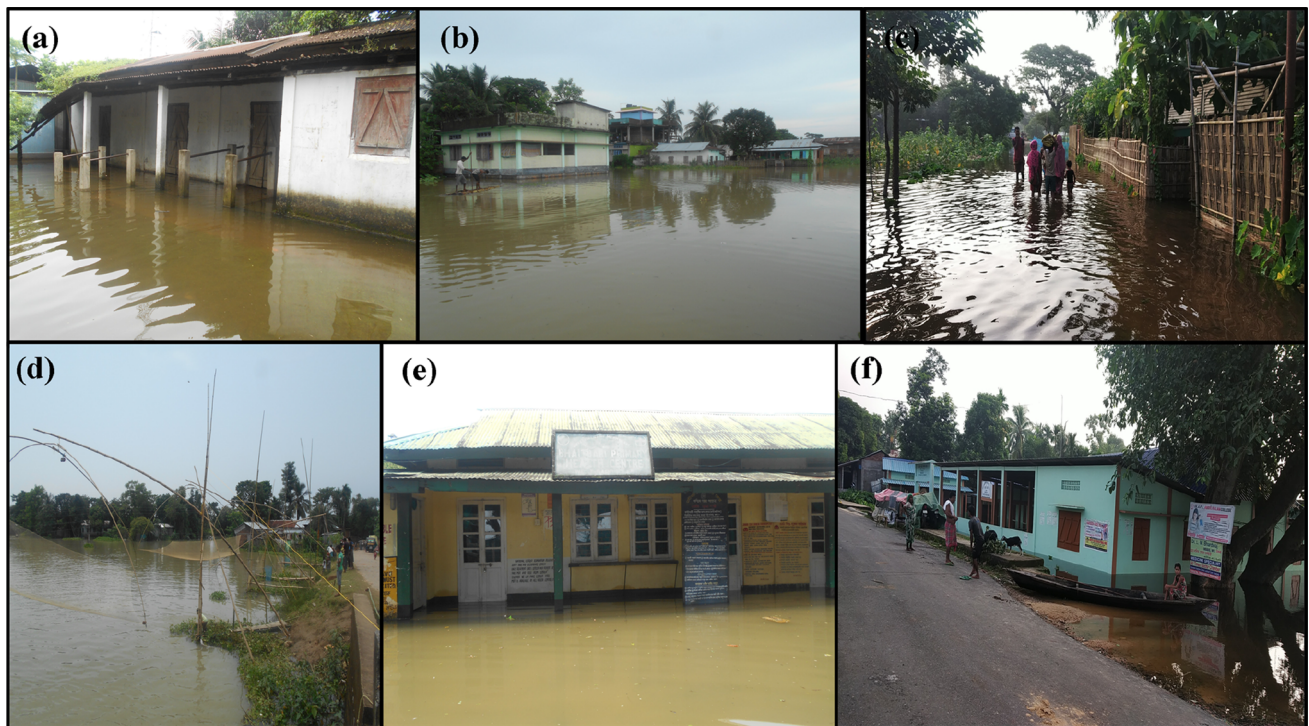


Fig. 2 The flood field scenarios during 2015–2019 in New Bhait Bari and Raja Bala and surrounding areas

gathered from the USGS geology database. Further, the spatial rainfall map was prepared by CRU (Climate Research Unit). The other two factors namely LULC and NDVI were prepared from the ESRI database and Landsat 8 OLI satellite imagery, respectively.

Elevation

The elevation is an important factor for flood susceptibility mapping (Janizadeh et al. 2019; Al-Juaidi et al. 2018; Samanta et al. 2018). The geographical elevation of an area and the flood events are inversely correlated. In brief, areas at lower elevations are more vulnerable to flooding and vice versa, due to long time water stagnation in the low-elevated areas (Mitra et al. 2022). The spatial distribution of elevation was prepared from filled 30 m ASTER DEM and categories into five classes (a) 2–283 m, (b) 283.01–631 m, (c) 631.01–1007 m, (d) 1007.01–1392 m, and (e) 1392.01–1974 m.

Aspect

Aspect denoted the slope facing direction and has a direct relationship with the water flow direction, the solar radiation, wind velocity, and the precipitation. Hence, the Aspect of an area plays a significant role in flood occurrence (Janizadeh et al. 2019; Liuzzo et al. 2019; Tehrani and Kumar

2018). Filled 30 m ASTER DEM was used for the present work to prepare the aspect map and was divided into ten classes namely, (a) Flat (-1), (b) North (1–23), (c) Northeast (24–68), (d) East (69–113), (e) Southeast (14–158), (f) South (159–203), (g) Southwest (204–248), (h) West (249–293), (i) Northwest (294–338), and (j) North (339–360).

Curvature

The curvature of an area is an imaginary line generated by connecting random points on the surface of the earth (Barman et al. 2023). It influences the runoff flow direction as well as velocity. The curvature map was prepared from the filled 30 m ASTER DEM. It was divided into three classes (a) < 1, (b) 1, and (c) > 1.

Topographic wetness index (TWI)

The Topographic Wetness Index is considered to be an important factor in flood susceptibility mapping (Mitra et al. 2022; Liuzzo et al. 2019). It denotes the total flow accumulation of a river basin and is related to the down flow of water under the action of gravity along the slope (Askar 2022). The TWI can be expressed in the form of an equation as Eq. 1.

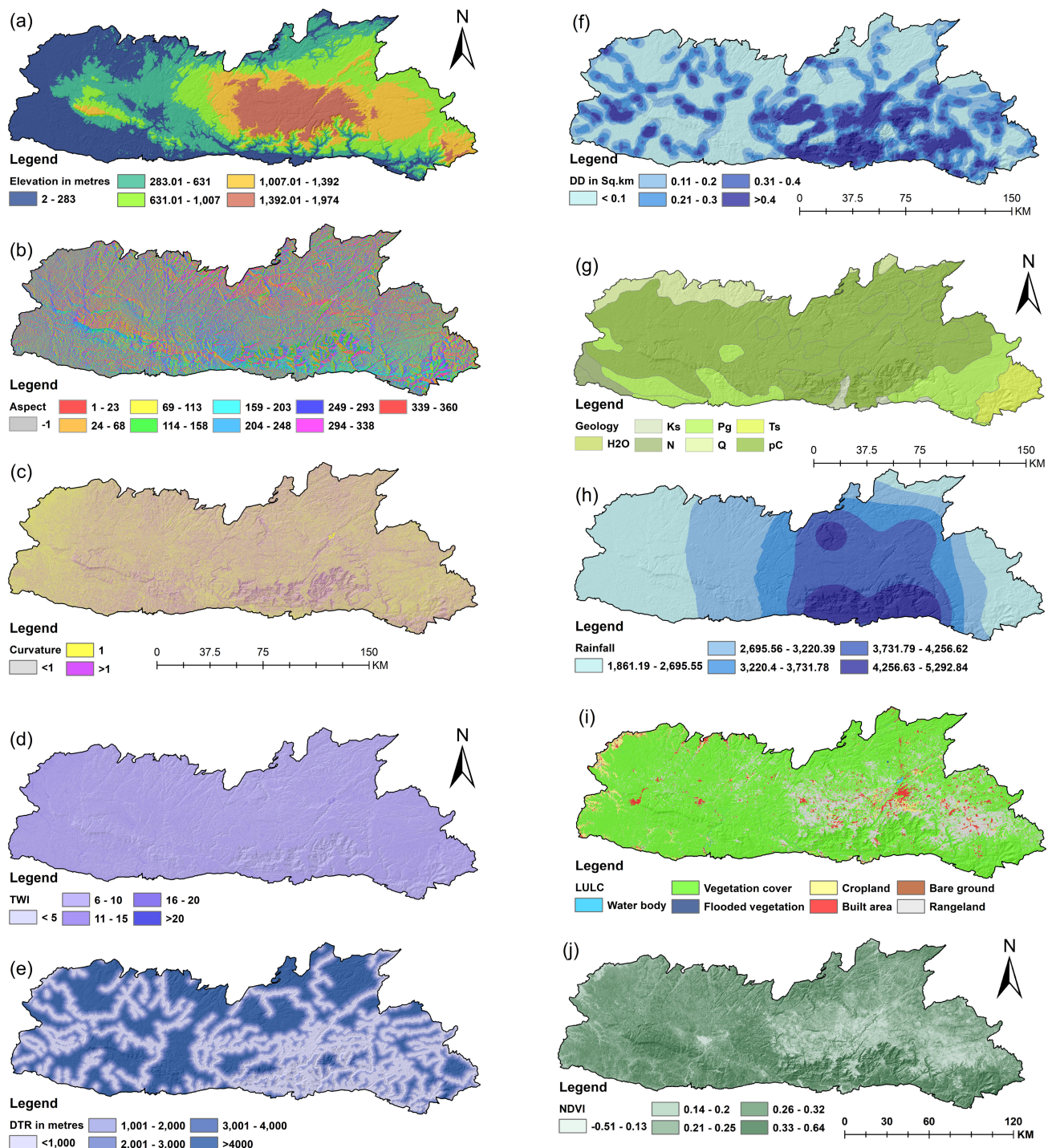


Fig. 3 The thematic map generation for flood conditioning factors, **a** elevation, **b** aspect, **c** curvature, **d** TWI (Topographic wetness index), **e** DTR (Distance to rivers), **f** DD (Drainage density), **g** geology, **h**

rainfall (Average annual from 2011 to 2020), **i** LU/LC (Landuse/land-cover), and **j** NDVI (Normalised differential vegetation index)

$$TWI = \ln \frac{A_s}{\tan \beta}, \quad (1)$$

where A_s signifies the upslope contributing area and β denotes the slope angle. The TWI of the study area ranges

between 1.79 and 23.36 which is divided into five classes: (a) <5, (b) 6–10, (c) 11–15, (d) 16–20, and (e) >20.



Distance to river (DTR)

The rivers are the natural path for water mobility and serve as the primary routes for flooding (Vojtek and Vojtekova 2019). The areas that are near the rivers experience the highest number of floods (Rincón et al. 2018). The DTR was prepared by using the Open Street Map (OSM) by Euclidean distance method and grouped into five sub-classes like (a) < 1,000 m, (b) 1,001–2,000 m, (c) 2,001–3,000 m, (d) 3,001–4,000 m and (e) > 4000 m.

Drainage density (DD)

The drainage density is the ratio between the total lengths of the channels per unit area (Barman and Biswas 2022; Ullah and Zhang 2020). The high drainage density values which always indicate the more chance of predicting a flood in an area indicate a high surface runoff (Rao et al. 2023; Vojtek and Vojtekova 2019; Sarkar and Mondal 2020). The drainage density is divided into five groups: (a) < 0.1, (b) 0.11–0.2, (c) 0.21–0.3, (d) 0.31–0.4, and (e) > 0.4.

Geology

The geology of an area is another important flood-controlling factor. The local geology can cause or contribute to flooding based on the makeup of the soil and landforms. Different types of soils and rocks handle water differently. A loose soil will hold more water than non-porous bedrock. The study area shows a variety of rock types ranging from the Precambrian gneissic complex being the oldest rock formation to the most recent deposits called alluvium, which is divided into older and newer alluvium. The majority of the flood-prone areas are mostly covered by the alluvium. The Geological formations observed in the study area are further classified into eight groups namely (a) Quaternary sediments, (b) undivided Precambrian rock, (c) Tertiary sedimentary rocks, (d) Palaeogene sedimentary rocks, (e) Neogene sedimentary rock, and (f) Cretaceous sedimentary rock (g) waterlogged area (USGS database).

Rainfall

India's northeast monsoon usually runs from October to December, bringing heavy rain, particularly to the south. The rainfall distribution in an area and the flood frequency have a direct relationship with each other as the rainfall intensity may be the main natural source for flooding (Askar et al. 2022). The rainfall data has been collected from Climate Research Unit (CRU) and is divided into five sub-factors: (a) 1861.19–2695.55 mm., (b) 2695.56–3220.39 mm., (c) 3220.4–3731.78 mm., (d) 3731.79–4256.62 mm., and (e) 4256.63–5292.84 mm.

Land use/land cover (LU/LC)

The LU/LC plays an important role in the occurrence of floods (Addis 2023; Sarkar and Mondal 2019). It is directly or indirectly affecting the infiltration, evapotranspiration, and surface runoff generation (Barman et al. 2023; Samanta et al. 2018). The LU/LC is divided into 7 classes (a) water body, (b) vegetation cover, (c) flooded vegetation, (d) cropland, (e) built area, (f) barren ground, and (g) rangeland.

Normalised difference vegetation index (NDVI)

In general, NDVI values range from – 1.0 to 1.0 with negative values indicating clouds and water, positive values near zero indicating bare soil, and higher positive values of NDVI ranging from sparse vegetation (0.1–0.5) to dense green vegetation (0.6 and above) (Barman et al. 2022). The Normalised Difference Vegetation Index (NDVI) indicates the green cover over an area and its effect on flooding in a basin, where its values vary between – 1 to + 1 (Addis 2023; Agrawal and Dixit 2022). Places with weak or no vegetation are more vulnerable to flooding, whereas dense vegetation helps prevent the effect of flooding (Askar et al. 2022).

$$NDVI = \frac{NIR - R}{NIR + R}, \quad (2)$$

where NIR (band 5) represents near-infrared and R (band 4) represents red. LANDSAT 8 imagery was downloaded from USGS and processed in the Arc GIS software to prepare an NDVI map. It is divided into five classes (a) 0.51–0.13, (b) 0.14–0.2, (c) 0.21–0.25, (d) 0.26–0.32, and (e) 0.33–0.64.

Frequency ratio model

The frequency ratio model is a popular quantitative and probability analysis method that has been widely applied with reliable results to create disaster-related susceptibility maps. The flood susceptibility mapping is crucial to determine the influence of variables in flooding. The relationship between flood incidents and the relationship of causative factors led to providing more insight into the flood conditions in an area (Biswas et al. 2023). The present study has used the Frequency Ratio (FR) model to construct a flood susceptibility zonation map of the Meghalaya Plateau using GIS techniques. The FR is a Bivariate Statistical Analysis (BSA) method that critically analyses the flood conditions to know the contributing factors for predicting the future floods in the area. It is a simple and widely used technique that involves rapid calculation processes (Tehrany et al. 2018). It is computed by examining the flood occurrences and the

contributing factors correlation. The FR values are calculated by using the following formula (Kumari and Goudar 2021; Tehrany et al. 2015; Tehrany et al. 2018).

$$FR = \frac{AB/CD}{EF/GH}, \quad (3)$$

where AB and CD are the area of flood pixels in that class and the study area, respectively, and EF and GH are the area of pixel distribution in the class and the study area. The FR value lower than 1 indicates a negative relationship between flood and conditioning factors; on the other hand, if, FR is greater than 1, it indicates a strong correlation between flood and conditioning factors.

In the next step, the frequency ratio FR was normalized in a range of values (0, 1) as relative frequency (FRr) using the following equation (Eq. 4).

$$FRr = \frac{\text{Factor class FR}}{\sum \text{factor classes FR}}. \quad (4)$$

After the normalization of relative flood frequency, the FRr has the disadvantage of assigning equal weightage to all the causative factors. To address this issue, a predictor rate (PR) or weightage was calculated by rating each flood causative factor by using the training data sets (Eq. 5).

$$PR = (FRr_{\max} - FRr_{\min}) / \text{Min}(FRr_{\max} - FRr_{\min}). \quad (5)$$

Ultimately, the flood susceptibility zonation (FSZ) was calculated by adding the FR of each class and the PR of each factor using Eq. 6.

$$FSZ = (PR \times Ele_{Fr} + PR \times Asp_{Fr} + PR \times Cuv_{Fr} + \dots + PR \times NDVI_{Fr}). \quad (6)$$

Results

The flood susceptibility of the Meghalaya plateau has been evaluated by using the integrated approach of the bivariate statistical method (FR) with the GIS technique (Table 1). The flood occurrences and flood-triggering factors were correlated by using the FR. In the present study, some 10 flood conditioning factors have been identified like elevation, aspect, curvature, topographic wetness index (TWI), distance to the river (DTR), drainage density (DD), geology, rainfall, land use/land cover (LU/LC), and normalised difference vegetation index (NDVI). In the FR method, all the conditioning factors were classified into their sub-classes by using different suitable classification techniques (natural breaking and manual), and in the ArcGIS environment, flood-affected areas under each sub-class were estimated with the help of tabulated area tool (Table 2). The relative importance of all the conditioning factors was calculated by using the predicted rate as Eq. 5.

In the study region, the elevation has the maximum contribution to flooding with a PR value of 11.92 closely followed by LU/LC and TWI with PR values of 11.73, and 10.71, respectively. The geology, rainfall, curvature, and NDVI have a medium influence on flood occurrence with PR values of 6.39, 5.42, 4.09, and 3.89 respectively, while the aspect, DTR, and DD are the least important factors with PR values of 2.34, 2.14, and 1.00 respectively, in determining flood susceptibility in the study region (Fig. 4). The water flow paths have always been indicating from the higher altitudes to low land areas and elevation in an area plays an important role in the occurrence of floods. The greatest FR value was obtained for the elevation class 2–283 m, followed by 0.17 for the elevation class 283.01–631 m. These two classes constitute 100% of the flood-affected area. The elevation of an area of more than 631 m has the least FR value (0.00). Regarding the slope aspect, the four sub-classes namely North (1–23),

Table 1 The various databases used for the present study

Product	Thematic layer	Source	Access date	Resolution	Data type
ASTER DEM	Elevation	https://search.earthdata.nasa.gov/	13th September, 2023	30 m	Raster
	Aspect				
	Curvature				
	TWI				
	Drainage density				
	Distance to rivers				
USGS	Geology	https://certmapper.cr.usgs.gov/data/apps/world-maps/	29th September, 2023	NA	Vector
CRU	Rainfall	High-resolution gridded datasets (uea.ac.uk)	21st October, 2023	0.5*0.5	Gridded
ESRI	LULC	Esri Land Cover (arcgis.com)	21st October, 2023	10 m	Raster
Landsat 8	NDVI	EarthExplorer (usgs.gov)	19th October, 2023	30 m	Raster



Table 2 The calculated results of all the factors with the FR and FRr

Factors	Sub factors	Count	F. count	Area ratio	Occurrence ratio	FR	FRr
Elevation	2–283	7,501,343	126459.25	0.29	0.96	3.34	0.95
	283.01–631	6,306,731	5343.3486	0.24	0.04	0.17	0.05
	631.01–1007	5,433,031	0	0.21	0.00	0.00	0.00
	1007.01–1392	4,064,936	0	0.16	0.00	0.00	0.00
	1392.01–1974	2,798,780	0	0.11	0.00	0.00	0.00
Aspect	– 1	0	0	0.00	0.00	0.00	0.00
	1–23	1,642,820	15139.488	0.07	0.12	1.77	0.19
	24–68	2,851,481	11577.255	0.11	0.09	0.78	0.08
	69–113	2,944,470	24045.069	0.12	0.18	1.57	0.17
	114–158	3,340,586	9796.139	0.13	0.07	0.56	0.06
	159–203	3,428,361	15139.488	0.14	0.12	0.85	0.09
	204–248	3,040,541	14248.93	0.12	0.11	0.90	0.09
	249–293	2,993,923	16920.604	0.12	0.13	1.09	0.11
	294–338	3,353,095	15139.488	0.13	0.12	0.87	0.09
	339–360	1,555,010	8905.581	0.06	0.07	1.10	0.12
Curvature	< 1	4,029,704	16030.046	0.16	0.12	0.76	0.32
	1	17,090,493	106866.97	0.68	0.81	1.19	0.50
	> 1	4,065,237	8905.581	0.16	0.07	0.42	0.18
TWI	< 5	4,586,181	4430.1501	0.18	0.03	0.19	0.00
	6–10	19,006,316	68224.312	0.75	0.52	0.69	0.01
	11–15	1,560,216	46959.592	0.06	0.36	5.81	0.04
	16–20	158,531	9746.3303	0.01	0.07	11.87	0.09
	> 20	3078	1772.0601	0.00	0.01	111.14	0.86
DTR	< 1000	8,066,527	56987.238	0.32	0.43	1.35	0.28
	1001–2000	5,194,211	29384.045	0.21	0.22	1.08	0.22
	2001–3000	3,361,067	12465.958	0.13	0.09	0.71	0.15
	3001–4000	2,675,730	16918.086	0.11	0.13	1.21	0.25
	> 4000	5,896,110	16027.661	0.23	0.12	0.52	0.11
DD	< 0.1	9,701,558	44,100	0.39	0.33	0.86	0.16
	0.11–0.2	4,870,435	27,900	0.20	0.21	1.08	0.21
	0.21–0.3	4,527,241	27,000	0.18	0.20	1.12	0.21
	0.31–0.4	2,794,571	18,900	0.11	0.14	1.27	0.24
	> 0.4	3,027,559	14,400	0.12	0.11	0.90	0.17
Geology	Q	1,616,261	22,500	0.06	0.17	2.62	0.20
	pC	17,496,876	44,100	0.70	0.33	0.47	0.04
	H ₂ O	470	0	0.00	0.00	0.00	0.00
	Ts	1,038,846	2700	0.04	0.02	0.49	0.04
	Pg	4,034,502	45,000	0.16	0.34	2.10	0.16
	N	484,554	17,100	0.02	0.13	6.65	0.51
	Ks	249,856	900	0.01	0.01	0.68	0.05
Rainfall	1861.19–2695.55	8,392,838	83,700	0.34	0.63	1.87	0.49
	2695.56–3220.39	6,000,048	33,300	0.24	0.25	1.04	0.27
	3220.4–3731.78	3,303,360	3600	0.13	0.03	0.20	0.05
	3731.79–4256.62	4,902,878	6300	0.20	0.05	0.24	0.06
	4256.63–5292.84	2,417,805	6300	0.10	0.05	0.49	0.13

Table 2 (continued)

Factors	Sub factors	Count	F. count	Area ratio	Occurrence ratio	FR	FRr
LULC	Water body	967,641	700	0.00	0.05	11.08	0.00
	Vegetation cover	173,420,161	7600	0.77	0.52	0.67	0.00
	Flooded vegetation	18,189	4300	0.00	0.29	3620.93	0.94
	Cropland	6,379,684	300	0.03	0.02	0.72	0.00
	Built area	7,098,435	200	0.03	0.01	0.43	0.00
	Bare ground	106,569	1600	0.00	0.11	229.96	0.06
	Rangeland	37,162,473	0	0.17	0.00	0.00	0.00
NDVI	– 0.51–0.13	1,803,349	18,900	0.07	0.14	1.97	0.35
	0.14–0.2	4,497,989	34,200	0.18	0.26	1.43	0.25
	0.21–0.25	5,696,933	41,400	0.23	0.31	1.37	0.24
	0.26–0.32	8,754,634	33,300	0.35	0.25	0.72	0.13
	0.33–0.64	4,168,286	4500	0.17	0.03	0.20	0.04

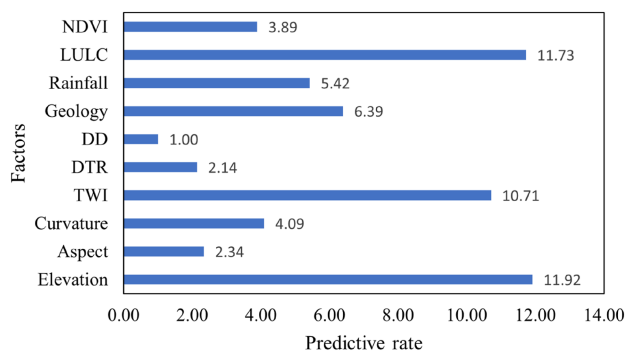


Fig. 4 The predictive rate of the flood conditioning factors

East (69–113), West (249–293), and North (339–360) were significantly influencing floods in the study area with the FR value 1.77, 1.57, 1.09, and 1.10, respectively.

Curvature plays a vital role in modeling flood risk because it affects the flow of water across the landscape. Hence, the curvature component is also an important significant contributor to flooding in the study area and comprises three classes. A convex surface is represented by > 1 , a flat surface by 1, and a concave surface by < 1 . The significant findings in the present study indicated that the convex surface has the lowest FR value at 0.42 and the flat surface shows the highest FR value at 1.19. It was found that the flat and 87% of the previous floods occurred on the concave surfaces in the area. In the case of TWI, the highest class (> 20) was found to exhibit the highest FR value of 111.14, with the class 16–20 showing the second-highest FR value of 11.87. The TWI class of < 5 has the lowest FR value at 0.19.

Generally, distance to the river has a high influence on the occurrence of floods and the class < 1000 m, the highest FR

value of 1.35. Similarly, the distance more than 4000 m has the lowest FR value of 0.52. The obtained results indicate that flood occurrence more in the areas near rivers and as the distance increases from the present river course, the chances of flooding decrease. The high drainage density of a stream always indicates more surface runoff, which is strongly correlated with a higher chance of flooding. This study employed the natural break method to classify the drainage density into five groups. A FR value of 1.27 indicates that the class 0.31–0.4 has the highest probability of flooding, while a FR value of 0.86 indicates that the class < 0.1 has the lowest probability.

The local geology can cause or contribute to flooding based on the makeup of the soil and landforms. The type of geological formations distributed in the study area also affects the likelihood of flooding as well. According to the study, the area of Neogene sedimentary rocks (N) distribution in the study area had the greatest impact on the flooding with a FR value of 6.65 followed by the sedimentary rocks of Quaternary-Q and Paleogene-PG with FR values of 2.62 and 2.10, respectively having a significant impact on the flooding. The highest FR (1.87) for the rainfall factor is found in class 1861.19–2695.55 mm. The increasing elevation factor is also one of the reasons why an increase in rainfall still does not affect flooding in the area, since flooding happens at lower elevations even with an increase in rainfall.

The land use patterns reveal the type of utilization of land by people and natural processes. For LU/LC, flooded vegetation had the highest FR value (3620.93) followed by barren land and water bodies with FRs equal to 229.96 and 11.08, respectively. In the study area, many croplands are severely affected by floods during the rainy season even though they have relatively low FR values when compared to the other three factors. The other crucial flooding



conditioning factor is the NDVI. The values of the index span from -1 to $+1$. By using the natural break method, the NDVI values in this study range from -0.51 to 0.64 , which were divided into five classes. The FR was highest for the class -0.51 to 0.13 , with a value of 0.34 , indicating a high likelihood of flooding in the study area.

After the preparation of all ten layers of flood triggering and causal factors and giving weights to each parameter by using the FR and FRr, a final hazard map was obtained by summation of each factor of PR and each class FRr in a raster calculator in ArcGIS 10.8 environment using Eq. 6. The FSZ values of the total area were divided into five subclasses using a natural break method: very low, low, medium, high, and very high and indicated in Fig. 5. The analysis illustrates that approximately 1% is in moderate, and 99% is in low area (Table 3).

Table 3 The spatial distribution of the flood susceptibility classes

Susceptibility classes	Area (Sq. Km)	Area (%)
Very low susceptibility	0.09	0.000
Low susceptibility	22204.99	0.993
Moderate susceptibility	135.72	0.006
High susceptibility	0.78	0.000
Very high susceptibility	12.06	0.001

Validation

The Receiver Operating Characteristic (ROC) method is frequently used for the validation of prediction maps. In this study, the ROC method was used to evaluate the success and prediction rate of the flood hazard map by comparing the existing flood data with developed flood susceptibility maps. The result of the success rate was calculated using the 75% training dataset (150 locations) and the prediction accuracy was calculated using the 25%

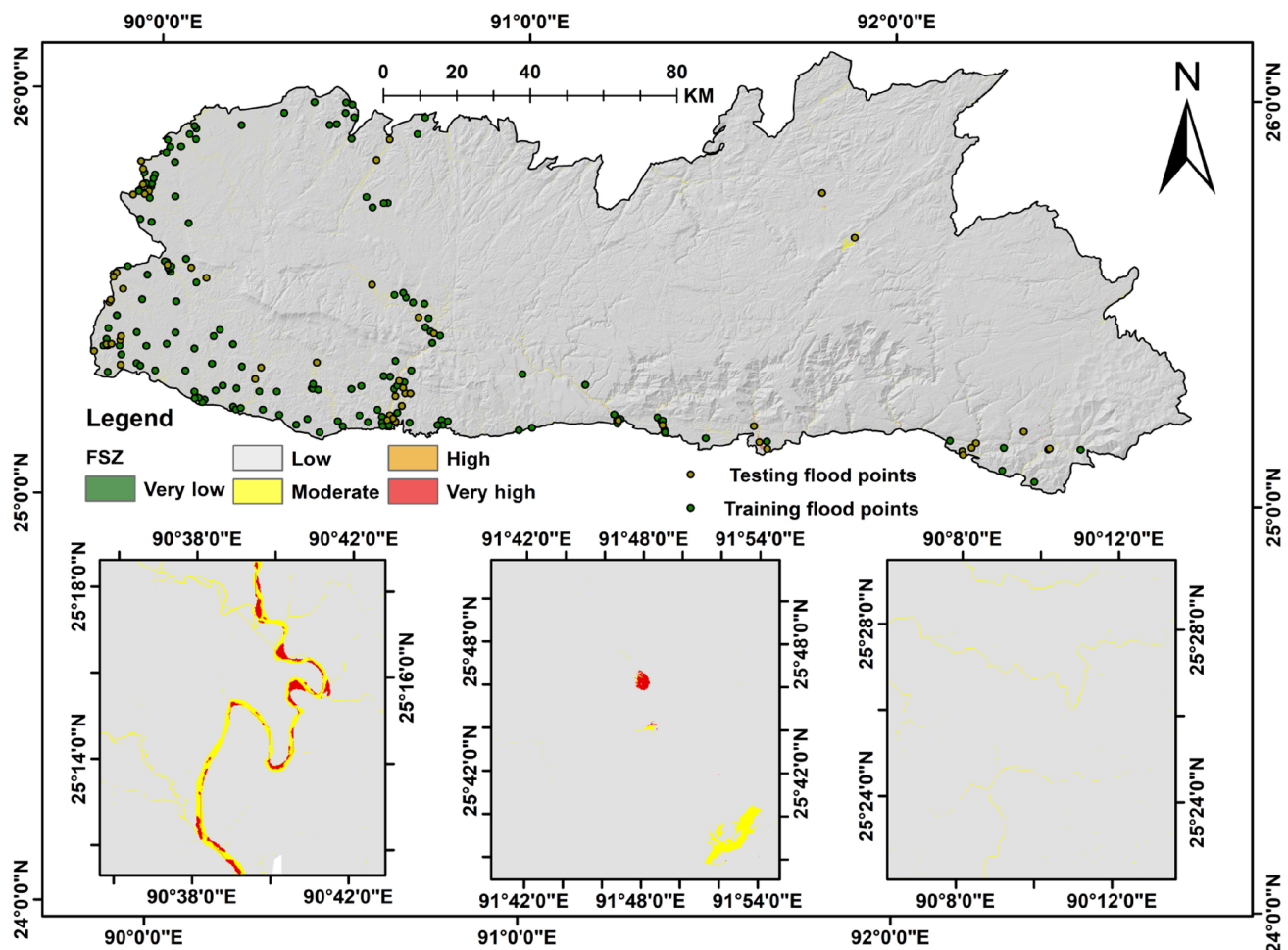


Fig. 5 The spatial distribution of the flood susceptibility zones

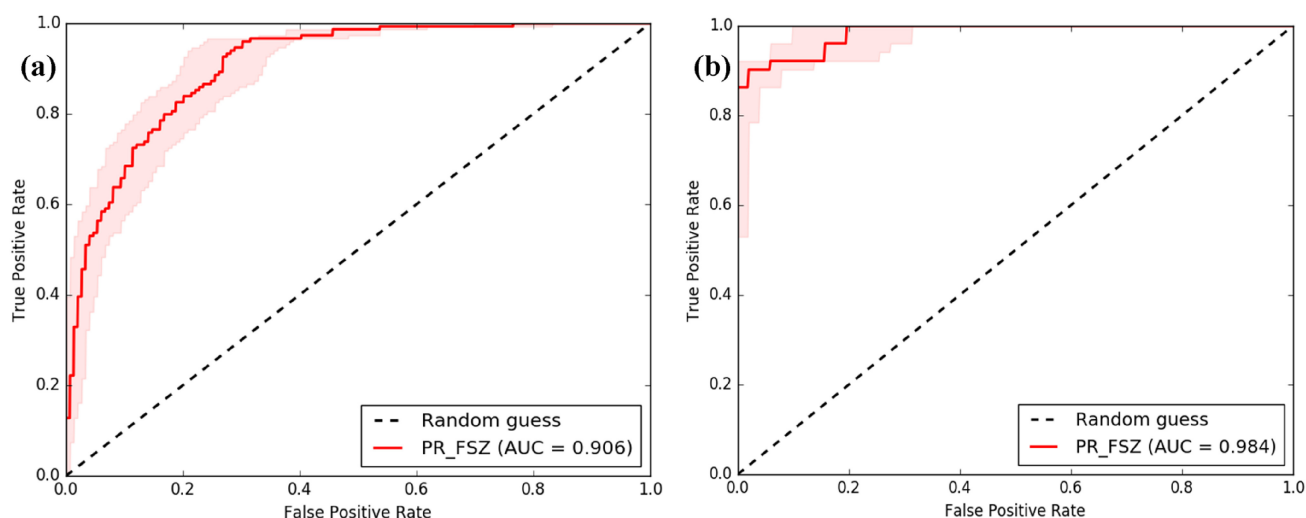


Fig. 6 The ROC plot and area under the curve, **a** predictive rate curve, and **b** success rate curve

testing dataset (50 locations). The ROC curve for this study is shown in (Fig. 6) with the AUC values of success and prediction accuracy of 98.4% and 90.6%, respectively.

Discussion

Meghalaya is land of diverse topography which consist of both highland plateau region also the flooded riverain valleys. As the steep slope and heavy down poor, the state faced frequent flood annually in low laying areas (Fig. 7). In this



Fig. 7 The field photographs show the damages and affecting areas, **a**, **b**, **c**, and **d** interaction with residents regarding the intensity of flood, **e**, and **f** impact of flood on the agriculture fields

regard, the Frequency Ratio method was used for flood susceptibility mapping and optimized conditioning factors. A total of ten conditioning factors were used for this study out of which seven were more significant for the incidence of flood. The elevation, LU/LC, TWI, geology, rainfall, curvature, and NDVI are dominant flood contributing factors. The AUC result gives a successful model prediction. In the present study, elevation played a major role in the flood susceptibility zonation using FR. Saleh et al. (2020) stated that due to water flowing down from higher elevations, the low-elevation regions have a high potential for flooding. The low-lying regions of Garo Hills suffer severe floods every year during the rainy season due to water flowing down from higher regions which gets accumulated as its velocity decreases with lower elevation.

The LU/LC is the second highest influencing factor in flood susceptibility zonation of the current study. The unscientific agriculture practices like vegetation burning, grazing, and barren ground restoration influence the hydrological cycle (Gao et al. 2017). Siswanto and Francés (2019) observed a reduction of evapotranspiration with LU/LC change with an increase of water yield during 1994–2014 and 2014–2029 by values of 15% and 40% respectively in Indonesia. The flooded vegetation area and bare ground have high FR values indicating a positive relationship with the occurrence of flood. Major floods occur in the cropland areas located in the low elevation in Meghalaya, flat surface regions which are significant factors for the occurrence of floods. The TWI has a direct relationship with flooding as higher TWI indicates higher chances of flooding in the watershed (Ullah and Zhang 2020). As the rocks found in the Garo Hills regions are mostly sedimentary and of the alluvium group (Lyngdoh et al. 1999), floods are more common as infiltration of water is very slow in those rock types. On the other hand, aspects DTR, DD, and NDVI were not found to be significantly influencing the flood susceptibility zonation. One of the reasons for the reduced role of DTR in FSZ is that the area ratio between flood occurrence and flood-safe region is very high and river flooding is not noticeable in the current study. In the present condition, the high drainage density was observed in the southwestern part of the region in which the maximum belongs to the first and second-order streams, while the south-eastern part having high drainage density showed high flood susceptibility.

Limitations and future trends

Information on the flood susceptibility zonation of the study area in Meghalaya was limited. Hence, in the present study, a bivariate model using ten flood conditioning factors was employed to calculate the Frequency Ratio. However, occasional errors may have occurred during the reclassification of classes, potentially impacting the

prediction and mapping. Additionally, the selection of conditioning factors also affected the final zonation like LU/LC where vegetation covers strongly affected the flooded areas by covering them up. Furthermore, a lack of detailed information in the flood inventories, such as volume, timing, length, area, and width, limited the proper validation of the results.

In future research, it would be beneficial to keep in mind all these effecting factors for creating FSZ maps and conducting comprehensive flood risk assessments in Meghalaya. The incorporation of additional conditioning factors like slope, MNDWI, etc., and comparative assessment using multiple models would enhance the accuracy of the predictions. Despite the above-mentioned limitations in the research procedure and estimation, the study's results can be used by researchers to do future flood zonation maps of Meghalaya more accurately.

Conclusions

Flooding is the most devastating natural disaster in the world, posing a serious threat to life. Thus, flood susceptibility maps are critical first steps in reducing flood damage. Furthermore, one of the most popular research topics is flood susceptibility zonation. The present study aims to assess flood hazards and map the flood-prone zones in the Meghalaya plateau. For this purpose, the FR method along with the extended FRr method was integrated with remote sensing and geospatial techniques to assess the flood hazard-prone areas and maps. The state faces severe flooding, especially in the low-lying regions of Garo Hills along the riverside and in croplands. Hence, the present study focuses on flood susceptibility zonation at the state level. The FR value successfully predicted the likelihood of a flood in Meghalaya with limited information and datasets. Students and researchers should take great interest in the floods of Meghalaya as every year it gets affected even though the state is thought to be a hilly region. The people of Meghalaya are suffering from flood is due to lack of awareness regarding flood mitigation which can be done only after proper zonation of the susceptibility area. Therefore, the present study can be useful for government planners, researchers, and administrators to carry out the mitigative measures, and create awareness among the public of which areas are affected and to minimize the flood effect in the state.

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Declarations

Conflict of interest No known conflict of interest among the authors.

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