A GIS-based flood risk mapping of Assam, India, using the MCDA-AHP approach at the regional and administrative level

Laxmi Gupta and Jagabandhu Dixit

Disaster Management Laboratory, Shiv Nadar University, Delhi NCR, Greater Noida, Uttar Pradesh, India

ABSTRACT
Floods are frequently occurring events in the Assam region due to the presence of the Brahmaputra River and the heavy monsoon period. An efficient and reliable methodology is utilized to prepare a GIS-based flood risk map for the Assam region, India. At the regional and administrative level, the flood hazard index (FHI), flood vulnerability index (FVI), and flood risk index (FRI) are developed using multi-criteria decision analysis (MCDA) – analytical hierarchy process (AHP). The selected indicators define the topographical, geological, meteorological, drainage characteristics, land use land cover, and demographical features of Assam. The results show that more than 70%, 57.37%, and 50% of the total area lie in moderate to very high FHI, FVI, and FRI classes, respectively. The proposed methodology can be applied to identify high flood risk zones and to carry out effective flood risk management and mitigation strategies in vulnerable areas.

1. Introduction
Natural hazards are caused by geological, hydrological, and meteorological events resulting in immeasurable loss of lives and property and natural landscape damage. Flood is the most frequent and expensive hydro-meteorological hazard due to its high intensity of damage (Shahiri Tabarestani and Afzalimehr 2021). Over the past few decades, the frequency of flood and its extent of destruction have increased significantly due to uneven distribution of rainfall, rapid snow melting, overflow of rivers, deforestation, uncontrolled urbanization, and unplanned human settlement along the coastal areas and riverbanks (Armenakis et al. 2017). From 2000 to 2019, floods contributed 44% of the total disaster worldwide, and Asia alone experienced 41% of the total flood events of the world, affecting approximately 1.5 billion people (CRED. 2019). Also, residual risk is always associated with the flood and it remains even after management actions have been taken to minimize the damage (Ridolfi et al. 2019). It mainly includes the failure of flood management structures like embankments, pumped drainage systems, reservoirs, etc. (Bischiniotis et al. 2020). Considering residual risk in flood management is essential even though its
probability is very low. The intensity of flood varies temporally and spatially, and its occurrence and negative consequences cannot be prevented altogether (Dewan et al. 2006). Many developed countries have adapted flood risk reduction strategies to minimize the damage like flood forecasting systems, structural engineering works like dikes and storm-surge barriers, restoration of the natural course of rivers, and many more (Bischiniotis et al. 2020; Du et al. 2020; Jongman 2018). As developing countries are more vulnerable to floods, there is an urgent need to assess and manage future flood events to minimize the adverse impact (Armenakis et al. 2017; Choubin et al. 2019; Dekongmen et al. 2021). Flood risk management at the regional or local scale begins with identifying vulnerable areas and a detailed understanding of interaction and relationships among the social, economic, and environmental factors to provide the rescue and mitigation response in an emergency.

According to United Nations International Strategy for Disaster Reduction (UNISDR. 2009), a hazard can be defined as any phenomenon, activity, or condition that may cause loss of life, injury, damage to property, or disruption of social and economic conditions or damage to the environment. The term vulnerability refers to the circumstances and characteristics of a community or society that make it susceptible to damaging effects (UNISDR. 2009). Risk can be defined as the combination of the probability of occurrence of an event and its negative consequences. It is expressed as the product of hazard and vulnerability (UNISDR. 2009).

Flood risk assessment involves detailed information about the hazard and vulnerable components of the concerned study area. Numerous studies are conducted on different aspects of flood risk assessment for various regional, national, and global regions using MCDA approaches and geoinformatics application (Armenakis et al. 2017; Dano 2020; Mishra and Sinha 2020.; Shivaprasad Sharma et al. 2018). Detailed flood hazard assessment has been carried out for the identification of main factors which contribute to the severity of flood occurrence (Chen et al. 2015; Kumar 2016; Toosi et al. 2019). Kourgialas and Karatzas (2017) performed a national scale flood hazard assessment for Greece using a combined approach of multicriteria analysis, artificial neural networks (ANNs) techniques, and GIS. Toosi et al. (2019) generated a modified Flood Hazard Index (mFHI) map using sensitivity analysis at the river basin scale for the Mashhad Plain basin in northeast Iran, emphasizing the importance of incorporating hydrological models and multicriteria analysis for comprehensive flood hazard study. Khosravi et al. (2020) developed a national scale flood susceptibility map for Iran using a deep learning convolutional neural networks (CNN) algorithm and showed that proper watershed management and prevention of uncontrolled urban expansion are the most effective way to control flood.

As vulnerability is one of the critical components in the flood risk assessment, researchers have provided comprehensive studies on the flood vulnerability aspect and developed flood vulnerability indices (Brito et al. 2018; Dandapat and Panda 2017; Dekongmen et al. 2021; Sarmah et al. 2020; Vignesh et al. 2021). Rashetnia and Jahanbani (2021) developed a GIS- fuzzy rule-based flood vulnerability index for Moreland city, Melbourne, considering social (Population density, age, % of disabled people, level of income and education), economic (business units and public facilities in flooded area or close to river, unemployment rate and quality of drainage system) and hydrological factors (Rainfall, permeability of areas, drainage network, DEM, LULC, flood extent and flood protection structures). Sadeghi-Pouya et al. (2017) developed an indexing method for the flood vulnerability assessment of the western coastal cities of Mazandaran Province, Iran, by classifying effective criteria into three indices, i.e. socio-economic, population-environmental, and technical, and the developed index was found to be
effective in Nowshahr city in Mazandaran. Sarkar and Mondal (2020) used parameters like elevation, surface slope, rainfall pattern, LULC, TWI, household, population density, and road density to delineate the flood vulnerable areas for the Kulik river basin by using the frequency ratio (FR) model and the final map was classified into five zones according to their degree of vulnerability to floods.

Many studies have been done on the flood risk assessment for rural and urban areas by incorporating hazard and vulnerability assessment and hydrological modeling (Armenakis et al. 2017; Chakraborty and Mukhopadhyay 2019; Lyu et al. 2018; Pathak et al. 2020; Vojtek and Vojtěková 2019; Zhang et al. 2020). Dandapat and Panda (2017) delineated the flood risk zone of Paschim Medinipur in West Bengal, India, using composite vulnerability index, which includes three indices i) Physical Vulnerability Index, ii) Social Vulnerability Index, and iii) Coping Capacity Index and estimated that 24.25% of the total population of the study area is in high to very high flood risk zones. Shivaprasad Sharma et al. (2018), using multicriteria analysis (MCA) and geospatial technique, carried out a flood risk assessment for Kopili River Basin (KRB) in Assam State, India, at village level and estimated that a significant portion of the crop and village land falls under high and moderate flood risk zones respectively. Cai et al. (2019) developed a multi-index fuzzy comprehensive evaluation model (MFCE model) for flood disaster risk, including all the three factors of risk, i.e. hazard, vulnerability, and exposure, and the method was found to be successfully applied for the urban area of Yifeng, Jiangxi Province, China. Zhang et al. (2020) developed a GIS-based model for flood risk assessment at a large basin scale, such as the Yangtze River Basin, China, and it accounts for different economic, social, and ecological indicators related to flood risk. Armenakis et al. (2017) developed a flood risk map for the Don River watershed, Toronto, with the help of high spatial resolution data and incorporated demographic indicators to enhance mitigation and preparedness planning. Rana and Routray (2018) carried out a flood risk assessment by combining hazard, vulnerability, and coping capacity for different communities from different urban areas in Pakistan and revealed that metropolitan cities are more vulnerable due to weak coping compared to the capacity of smaller cities. Arora et al. (2021) applied Shannon’s entropy (SE) and frequency ratio (FR) models to build a flood susceptibility model for Middle Ganga Plain using the 2008 Landsat 5TM image.

The above studies show that flood risk studies are associated with multidimensional characteristics and include spatial components. The studies have inherent challenges and limitations in identifying and quantifying flood hazard and vulnerability indicators like topographic, drainage, hydrology, meteorology, socio-economic, infrastructure, dealing with uncertainties, assigning a proper weightage of indicators, and validating the result (Arora et al. 2021; Shivaprasad Sharma et al. 2018). The indicators involved in the risk assessment are complex and consist of uncertainties in terms of temporal and spatial manner (Meyer et al. 2009). The main challenge is acquiring and collecting data of the selected indicators like hydrological, meteorological, LULC, etc., as it requires a workforce and is highly time-consuming for flood-prone areas (Cunha et al. 2011; Emanuelsson et al. 2014; Mishra and Sinha 2020).

Over the past few decades, remote sensing has played a crucial role in monitoring floods, and it has also solved the challenges related to the availability of data like DEM, LULC, hydro-meteorological data, etc (Rong et al. 2020; Sanyal and Lu 2004; Shivaprasad Sharma et al. 2018; Wang and Xie 2018). The data acquired by satellite imageries has its limitations in terms of accurate DEM data, flood depth determination, etc as a result, the desired accuracy is not achieved. To overcome these limitations, multi-sensor SAR imagery can be used (Sanyal and Lu 2004). The data acquired from the satellite and sensors
are further processed in a GIS environment to visualize and quantify the required parameters.

In recent times, GIS has been widely used as a decision support system for its database and analytical ability (Choubin et al. 2019; Danso et al. 2020; Lyu et al. 2018). GIS helps in the identification of vulnerable areas as well as acts as an early warning system by forecasting future events so that proper preparedness and planning can be executed during emergency scenarios. Another essential factor in flood risk analysis is to give appropriate weightage, rating, or ranking to the selected indicators of hazard and risk. To identify, integrate or rate the factors of flood risk assessment or other natural hazards, many studies have applied GIS-based Multi-Criteria Decision Analysis (MCDA) (Arabameri et al. 2019; Chen et al. 2015; Mishra and Sinha 2020; Toosi et al. 2019). Chakraborty and Mukhopadhyay (2019) found that the combination of Analytic Hierarchy Process (AHP) and GIS is a reliable method for the development of a flood risk map for Coochbehar district, West Bengal, India, by the quantification of flood risk index (FRI) together with flood hazard index (FHI) and flood vulnerability index (FVI). Hazarika et al. (2018) explained that the application of multicriteria analysis in the GIS environment provides flexibility in selecting significant indicators for the flood risk assessment for Dhemaji district in the Upper Brahmaputra River valley Assam, India. Arabameri et al. (2019) identified slope, distance to stream, and land use as the key indicators to increase flood susceptibility in the Kiasar watershed Northern Iran.

India is considered the second most flood-affected country globally, following China, and it experiences about 17 flood events per year on average, affecting approximately 345 million people (CRED. 2019). The vast river network system and the world’s most prominent monsoon system make about 5.74 million hectares of the total land area inundated by floods (Dhar and Nandargi 2004; Subrahmanyam 1988). The issue of flood risk is quite prominent in the Assam region of India due to the highly braided Brahmaputra River. It is mainly influenced by the southwest tropical monsoon, making the river experience high water levels and strong flows in the pre-monsoon season. Apart from topographic and meteorological factors, other factors like population settlement along the flood plains, erosion, and siltation of the banks accelerate the flood problem in the Brahmaputra basin. Every year the region suffers enormous losses and damage in terms of property and lives, so there is an urgent need to conduct a comprehensive flood risk assessment and identify vulnerable areas and triggering factors.

The flood-related study for the Assam region is limited only to one aspect like hazard, vulnerability, or risk focussing only on a small area, river basin, or district level with a limited number of indicators (Borah et al. 2018; Hazarika et al. 2018; Majumder et al. 2019; Pareta 2021; Pathan and Sil 2020; Sarmah et al. 2020; Shivaprasad Sharma et al. 2018). Considering hazard and vulnerability aspects, comprehensive flood risk assessment studies for the entire Assam region are limited. In the present study, a GIS-based comprehensive flood risk assessment of the Assam region at a regional scale and administrative level is conducted by integrating spatial, hydrological, and socio-economic indicators. The weightage of each indicator is determined by applying the MCDA technique. The final hazard and risk maps are validated by confusion matrix or error matrix, indirect methods of relative mean error (RME), and root of mean-square error (RMSE) based on historical flood events. The study framework provides an opportunity to understand the challenges associated with flood risk management and to implement effective and sustainable flood mitigation measures and policies for urban and rural areas located at flood risk zones.

The main objectives of the present study are as follows (i) to develop a GIS-based flood hazard, vulnerability, and risk index by the selection of suitable hazard and vulnerability
indicators, (ii) to produce high-resolution flood risk, hazard, and vulnerability maps by integrating MCDA and GIS to identify flood-prone areas, (iii) to analyze the flood risk scenario at the administrative level.

2. Study area

Assam lies in the north-eastern region (NER) of India, covering an area of approximately 78,438 km², extending from 24° 8' N to 28° 2’ N latitude and 89° 42’ E to 96° E longitude. The elevation of the Assam region ranges from 5–1964 m. The neighboring states of Assam are West Bengal, Arunachal Pradesh, Nagaland, Manipur, Mizoram, Tripura, and Meghalaya. Assam shares its boundary with neighboring countries, Bhutan in the north and Bangladesh in the south (Figure 1). The Guwahati city of Assam, the largest metropolis in NER, is known as the ’Gateway to Northeast India’ and connects the entire NER with the rest of India. The geographical feature of Assam contains three major physiographic divisions of India (i) the northern Himalayas as Eastern hills, (ii) Northern plains as Brahmaputra plain, and (iii) Deccan plateau as Karbi Anglong (Dikshit and Dikshit 2014).

The state of Assam can be divided into five administrative levels (i) Upper Assam, (ii) Lower Assam, (iii) Central Assam, (iv) North Assam, and (v) Barak Valley (Figure 1). According to the 2011 census, the population growth rate is 16.93%, and districts like Sonitpur, Cachar, Dhubri, Barpeta, Kamrup, Darrang, and Nagaon have high population density (Census 2011). The highest contribution to the economy of Assam is agricultural activities, and the majority of the population is rural involved in the agricultural sector (Figure 1). The climate of Assam is a tropical monsoon rainforest climate with heavy rainfall and high humidity. The summers are warm (temperature 32°–38°) and mild winters (temperature 8°–20°). The region experiences heavy annual rain ranging from 1500 to 3750 mm both in the plain and mountain areas due to the southwest monsoon, mainly in May to September, which causes floods (Figure 2) (Chaliha et al. 2012).

Two river systems, Brahmaputra and Barak, are present in the Assam region. In Assam, the Brahmaputra valley is bounded by Himalayan mountains, Patkai hill ranges,
and plains of Bangladesh in the northern, eastern, and southern parts, respectively (Deka et al. 2013). Due to the high flood frequency of the Brahmaputra river, it is known as ‘the river of sorrow’ in Assam (Dhar and Nandargi 2004). The tributaries of Brahmaputra River are rainfed in nature and classified as north bank tributaries namely Subansiri, Ronganadi, Dikrong, Buroi, Borgong, Jiabharali, Dhansiri (North) Puthimari, Manas, Beki, Aie, Sonkosh and south bank tributaries namely Noadehing, Buridehing, Desang, Dikhow, Bhogdoi, Dhansiri (South), Kopilli, Kulsi, Krishnai, Dhudhnoi, Jinjiran (Jain et al. 2007).

The Barak River system is present in the southern part of Assam, forming Barak valley, and it finally drains into Bangladesh (Deka et al. 2013). The main tributaries of Barak rivers are Katakhal, Jiri, Chiri, Modhura, Longai, Rukni, and Singla, mainly rainfed tributaries and are highly vulnerable to flooding during rainfall periods (Jain et al. 2007).

2.1. Flood scenario in Assam

In the Assam region, the Brahmaputra and Barak River system and more than 50 tributaries cause the flood event every year, predominantly in the monsoon (Shivaprasad Sharma et al. 2018). The area of Assam suffers an erosion problem that is very high compared to the rest of the country. The Assam region is considered a seismically active zone (Raghukanth et al. 2011), and the drainage pattern of the region is dendritic. Its unique physiographical setting mainly controls the river processes in Assam. The major area of the Assam region is covered by Brahmaputra valley, generally, a flat plain formed by the depositional processes of the river and its tributaries.

According to Rashtriya Barh Ayog (RBA), the total flood-prone area of Assam is 31.05 Lakh Hectares, constituting about 40% of the total area of Assam and 9.40% of the total flood-prone area of India (ADMA). In the year 2013, in June, more than 1,00,000 people in Assam were affected due to heavy rainfall triggered flood in the Brahmaputra valley, and 12 districts out of 27 in Assam were fully submerged. The 2015 Assam floods caused the deaths of 42 people, the destruction of major road networks, and affected 16.5 lakh people in 21 districts of Assam. It affected more than 2,000 villages, and 4,40,000 acres of standing crops were destroyed. In July 2016, the Assam flood displaced more than 17.5 lakh people. A large area of agricultural land was damaged. It also caused massive devastation to the wildlife of Kaziranga National Park. The overflowing of the Brahmaputra River caused the 2017 Assam floods, and it also affected neighboring states of Assam like Arunachal Pradesh, Nagaland, and Manipur. About 15 districts were highly affected, and
more than 5,00,000 were homeless. The 2018 Assam floods affected 4.5 lakh of the population, and 11,243 hectares of croplands were submerged in four districts. In 2019 approximately 3,024 villages were submerged, and 52,59,142 people were affected in 30 districts in Assam. In 2020, when the COVID-19 pandemic severely impacted the country, the floods in Assam were accelerating the damages of lives and livelihood. About 5 districts were severely affected, and more than 30,000 people were homeless. All the above past scenarios represent that flood in Assam is of significant concern, and all the possible efforts must be made to minimize its adverse impact.

3. Methodology

In the present study total of 24 indicators, i.e. 12 flood hazards and 12 vulnerability indicators, are selected based on literature review. The datasets are collected from various governmental organizations at a national and global platform (Table 1). The collected datasets are further processed to achieve the objectives of the study.

The methodology can be divided into the following sections: (1) preparation of spatial geodatabase for flood hazard and vulnerability indicator, (2) application of MCDA-AHP for weightage assignment of the indicators, (3) quantification of flood hazard index (FHI), flood vulnerability index (FVI), and flood risk index (FRI) at the regional and administrative level and (4) validation of flood hazard and risk models.

3.1. Flood hazard indicators

Flood hazard indicators are selected based on the literature review, and corresponding thematic layers are generated using GIS (ESRI ArcGIS 10.5).
3.1.1. Elevation and slope
The criteria of elevation and surface slope can delineate the regions having different flood hazard levels. The downstream areas at lower elevation and flat slopes are more prone to flooding than those with high elevation and steep slopes. The elevation and slope layers are created from SRTM 1 arc-second (30 m resolution) DEM. The void data was filled, mosaiced, and extracted by mask with the help of a spatial analyst tool, and the attributes were calculated using a zonal statistics tool (Souissi et al. 2020).

3.1.2. Drainage density
Drainage density can be defined as the length of river channels per unit area of the basin, and it represents flow accumulation pathways (Arora et al. 2021). The drainage network map of the study area is generated from DEM data using the hydrology tools, and drainage density is calculated by the line density tool in GIS (Vignesh et al. 2021).

3.1.3. Distance to river
Proximity to the river channels plays a critical role in flood hazard modeling. During the river’s overflow, the river’s volume will exceed its drainage capacity, and the water depth in the areas located near the riverbed will increase significantly. The flood inundation will not impact only the nearest river location, but the waterlogging and risk of flood will expand to the surroundings (Chakraborty and Mukhopadhyay 2019). A raster layer is created using the Euclidean distance tool in GIS (Toosi et al. 2019).

3.1.4. Distance to embankment breach locations
Embankments are man-made structures used as flood mitigation measures to protect the settlements around the riverbanks. The embankment’s breach can cause potential flood damage (Hazarika et al. 2018). The locations of embankment breaches are identified by the historical flood records, literature review, and Assam State Disaster Management Authority (ASDMA) reports. The coordinates of the locations are extracted from Google Earth and using the Euclidean distance tool, a raster layer is prepared (Chakraborty and Mukhopadhyay 2019).

3.1.5. Soil texture
Soil texture is a significant flood hazard indicator as the regional internal drainage system, surface runoff, and moisture contents are highly influenced by the prevailing soil texture (Arora et al. 2021). The soil data is obtained from the Food and Agriculture Organization of the United Nations Educational, Scientific and Cultural Organization (FAO-UNESCO) and classified into five soil classes (a) sandy clay loam, (b) loam, (c) clay loam, (d) clay, and (e) sandy loam (Pareta 2021).

3.1.6. Geology
Geology controls the hydraulic properties of the bedrock of a region. The bedrock with fractured, high porosity and permeability enhances the infiltration rate of rainwater, thus minimizing the risk of flood. The geology map is extracted from the National Geologic Map Database (NGMDB), USGS, and classified into four classes (a) sedimentary, (b) metamorphic, (c) Precambrian, and (d) Paleozoic rocks (Bhandari et al. 1973).

3.1.7. Geomorphology
Floods give rise to different landforms like erosional and depositional landforms. The geomorphological data is obtained from the Bhukosh-Geological Survey of India (GSI), and classified into (a) structural hills, (b) denudational hills, (c) alluvial plains, (d) pediplain, and (e) floodplain (Vignesh et al. 2021).
3.1.8. **Topographic wetness index (TWI)**

TWI is used to assess the effect of topography on the hydrological process of a watershed and allows delineation of flood inundated areas (Pourali et al. 2016). For TWI, slope and flow accumulation layers are generated from DEM data. TWI is calculated by the equation (1) given by Beven and Kirkby (1979)

$$TWI = \ln \left( \frac{A}{\tan \beta} \right)$$

where $A$ represents source contributing area and $\tan \beta$ is ground surface slope. Higher TWI indicates the area is more prone to flood, and lower value denotes the steepest slope and less flood-prone regions (Arora et al. 2021).

3.1.9. **Rainfall erosivity factor (REF)**

Soil erosion is a significant problem during floods, and its rate depends on rainfall intensity. With the help of REF, the impact of rainfall intensity on soil erosion can be quantified. REF is calculated by equation (2) developed by Singh et al. (1981) using the average daily rainfall data of 21 years from 2000 to 2020 (Pathan and Sil 2020).

$$R = 79 + 0.363 \times P$$

Here, $R$ and $P$ represent rainfall erosivity factors (MJ mm ha$^{-1}$ hr$^{-1}$ year$^{-1}$) and mean annual precipitation (mm), respectively.

3.1.10. **Rainfall intensity**

Rainfall intensity is a crucial parameter that induces the occurrence of floods. Rainfall data from 2000 to 2020 are collected from Indian Meteorological Department (IMD), and rainfall intensity is determined for 114 grid points using equation (3). Rainfall intensity map is developed using Modified Fournier Index (MFI) approach and interpolated by Inverse Distance Weighting (IDW) interpolation in GIS (Toosi et al. 2019).

$$MFI = \sum_{i=1}^{12} \frac{P_i^2}{P}$$

$P_i$ and $P$ are the mean monthly and annual precipitation (mm), respectively.

3.1.11. **Runoff coefficient**

In the present study, rainfall-runoff modeling is performed using the National Resources Conservation Services-Curve Number (NRCS-CN) method to estimate the surface runoff coefficient for 33 basins in the study area (Pathak et al. 2020). The required input datasets are DEM, soil data, land use land cover (LULC), and rainfall data of the study area (Toosi et al. 2019).

The runoff coefficient ($RC$) is calculated by the rational method using equation (4)

$$RC = \frac{Q}{P}$$

The surface runoff of an area is given by equations (5)–(10)

$$P = I + F + Q$$

$P$, $F$, and $Q$ signify precipitation, initial abstraction, actual retention, and direct runoff, respectively.
The ratio of actual rainfall retention to the potential maximum retention $S$ is equal to the ratio of direct runoff to rainfall minus initial abstraction.

$$\frac{(P - I - Q)}{S} = \frac{Q}{(P - I)}$$  \hspace{1cm} (6)

$$Q = \frac{(P - I)^2}{(P - I + S)}$$  \hspace{1cm} (7)

$$I = \lambda S$$  \hspace{1cm} (8)

$$Q = \frac{(P - \lambda S)^2}{P + (1 - \lambda)S} \text{ For } P > \lambda S$$  \hspace{1cm} (9)

$$Q = 0 \text{ For } P \leq \lambda S$$  \hspace{1cm} (10)

$\lambda$ is initial abstraction coefficient (ranging from 0 to infinity); in general, $\lambda = 0.2$ is recommended.

The value of $S$ for the derived curve number ($CN$) of the basin can be calculated by equation (11).

$$S = \frac{25400}{CN} - 254$$  \hspace{1cm} (11)

$CN$ is a dimensionless parameter ranging between 0 to 100 (USAD 2004; Al-Ghobari et al. 2020).

$CN_i$ values are determined for each sub-basin, with different land uses, soil types, and areas ($A_i$). The final composite curve number ($CN_w$) is estimated by weighting the resulting $CN$ values in equation (12).

$$CN_w = \frac{CN_i \times A_i}{A}$$  \hspace{1cm} (12)

3.2. Flood vulnerability indicators

Datasets for flood vulnerability indicators were collected from different global, national, regional platforms and processed in the GIS environment (ESRI ArcGIS 10.5) for further analysis.

3.2.1. Population density

Population density data are obtained from the Census 2011 (Census 2011). It directly relates to vulnerability because more people will be exposed to hazardous events in an area with a high population density (Chakraborty and Mukhopadhyay 2019).

3.2.2. Vulnerable population

The vulnerable population of the study area comprises females, children, and the old-aged population due to their low resilient capacity and high dependency. From the Census 2011, the data are extracted to estimate the spatial distribution of the vulnerable population (Shivaprasad Sharma et al. 2018).

3.2.3. Employment rate

The population’s economic status highly influences the coping capacity of an area. A well-defined income source of a community improves the living standard and increases
the community’s coping capacity. The employment status for the Assam region is acquired from Census 2011 (Agrawal et al. 2021).

### 3.2.4. Literacy rate
The literacy rate of an area is directly related to a community’s awareness about the hazard and helps in the preparedness during the hazardous event. Here, the literacy rate of Assam is obtained from Census 2011, and its thematic layer is generated (Shivaprasad Sharma et al. 2018).

### 3.2.5. Household with more than four family members
The household size directly influences the vulnerability component. A smaller household will be less vulnerable than a household with more family members. The data of households are collected from Census 2011 (Agrawal et al. 2021).

### 3.2.6. Dilapidated house
The condition of building structures determines their coping capacity towards any disaster. If the building, mainly a residential building, is dilapidated, its vulnerability will increase. From the Census 2011, data regarding the dilapidated houses are obtained (Agrawal et al. 2021).

### 3.2.7. Building density
Building density is considered an essential indicator for infrastructure vulnerability assessment, and it is positively correlated with the vulnerability index. For the present study, building density is calculated using the data obtained from the Census 2011 (Agrawal et al. 2021).

### 3.2.8. Distance to roads
A well-connected and maintained transportation system is one of the essential infrastructure components of a region. Road connectivity plays a critical role in relief and rescue operations during an emergency. Those settlements nearer to the roads are less vulnerable as they can be evacuated or rescued faster than the population residing in the remote areas (Hazarika et al. 2018). With the help of OpenStreetMap, major and minor roads are extracted and digitized in GIS. A raster dataset is generated by the Euclidean distance tool in GIS (Pareta 2021).

### 3.2.9. Distance to hospital
Proximity to hospitals and healthcare centers will facilitate emergency rescue operations and post-disaster health management activities. The locations of hospitals are obtained from the Department of Health & Family Welfare, Government of Assam. Coordinates of 624 government hospitals are extracted from Google Earth, and distance from hospitals is calculated using the Euclidean distance tool in GIS (Chakraborty and Mukhopadhyay 2019; Toosi et al. 2019).

### 3.2.10. Distance to stream confluence
The areas near the stream confluence are more prone to flood inundation because during the flood at the confluence point, the channel tends to carry combined discharge and load of two or more upstream tributaries (Chakraborty and Mukhopadhyay 2019). From the drainage network layer of the study area, confluence points are identified, and the
distance from the confluence point is determined using the Euclidean distance tool in GIS (Arora et al. 2021).

### 3.2.11. Flow accumulation

Flow accumulation is the flow concentration, and it is directly related to flood vulnerability (Vojtek and Vojteková 2019). It is lower upstream, but higher downstream as many tributaries join the main channel downstream. For the present study, flow accumulation raster is prepared by 30 m resolution of DEM data using hydrology tool in GIS.

### 3.2.12. Land use land cover (LULC)

LULC governs the relationship between different hydrological parameters like runoff, infiltration, and rainfall abstraction (Toosi et al. 2019). The urban and pasture land increase the overflow of water, whereas forest and dense natural vegetation increase water infiltration and abstractions. The land use land cover map with ten LULC classes for the study area is derived from Sentinel –2 imagery (10 m resolution) by ESRI (Kontgis et al. 2021). The map is further reclassified into five categories (a) water, (b) built-up area, (c) agricultural land, (d) natural vegetation, and (e) bare land and validated by calculating the kappa coefficient (Vignesh et al. 2021).

The accuracy of the LULC map is checked by overall accuracy ($A_{\text{OVERALL}}$) and Kappa ($K$) statistics, User’s and Producer’s accuracy ($A_{\text{USER}}$ and $A_{\text{PRODUCER}}$) using equations (13)–(16) (Gibril et al. 2017; Hishe et al. 2020). The detailed error matrix was computed for each classification image, as it allowed evaluation of $A_{\text{USER}}$ and $A_{\text{PRODUCER}}$ for each of the information classes included in our classification scheme (Table 2). For the present study, Google Earth was used to validate classification with $N=373$ points.

\[
K = \frac{N \sum_{i=1}^{r} m_{ii} - \sum_{i=1}^{r} (m_{i+})(m_{+i})}{N^2 - \sum_{i=1}^{r} (m_{i+})(m_{+i})}
\]  
\[
A_{\text{OVERALL}} = \left( \frac{1}{N} \right) \sum_{i=1}^{g} n_{ii}
\]  
\[
A_{\text{PRODUCER}} = \frac{n_{ii}}{n_{icolumn}}
\]  
\[
A_{\text{USER}} = \frac{n_{ii}}{n_{irow}}
\]

Where $r$ denotes the number of rows, $m_{ii}$ number of observations in row $i$ and column $i$, $m_{i+}$ and $m_{+i}$ are the marginal total of row ($r$) and column ($i$), respectively, $n_{ii}$ are the number of observations correctly classified.

The value of overall accuracy and Kappa coefficient are 90.88% and 0.885, respectively. The Kappa coefficient value close to 1 signifies that the classified image and reference

| LULC CLASS | Water | Natural Vegetation | Agriculture | Built-up | Bare Land | Total | User’s Accuracy (%) | Producer’s Accuracy (%) |
|------------|-------|--------------------|-------------|----------|-----------|-------|----------------------|-------------------------|
| Water      | 75    | 0                  | 0           | 0        | 3         | 78    | 96.15                | 96.15                   |
| Natural Vegetation | 0 | 65                | 6           | 0        | 3         | 74    | 87.84                | 91.55                   |
| Agriculture | 0   | 6                 | 60          | 4        | 3         | 73    | 82.19                | 88.24                   |
| Built-up   | 0    | 0                 | 1           | 67       | 2         | 70    | 95.71                | 91.78                   |
| Barren Land | 3   | 0                 | 1           | 2        | 72        | 78    | 92.31                | 86.75                   |
| Total Producer | 78 | 71                | 68          | 73       | 83        | 373   |                      |                         |
image shows perfect agreement, and hence the classification performed in the study is acceptable.

All the thematic layers of flood hazard and vulnerability indicators are resampled to a 30 m raster layer to minimize the error (Chakraborty and Mukhopadhyay 2019). Jenks Natural Breaks method is applied to classify flood hazard and vulnerability indicators, except for distance from rivers, roads, stream confluence, hospitals, embankment breach location, LULC, geology, geomorphology, and soil type (Toosi et al. 2019).

3.3. Analytical hierarchy process (AHP) as Multi-Criteria decision analysis (MCDA) technique

The weightage to flood hazard and vulnerability indicators are assigned using Analytical Hierarchy Process (AHP) as Multi-Criteria Decision Analysis (MCDA) technique (Dano 2021; Hazarika et al. 2018; Pathak et al. 2020; Toosi et al. 2019). During the application of AHP, the subjective evaluations can be converted into numerical values which can be processed to give ranks to each indicator of the study. It is considered a systematic, multi-objective, and reliable approach developed by Saaty (Saaty 2000; 2008), and for the present study Excel version, MS Excel 2013 is used. Uncertainties can be found among experts’ opinions or judgments in multi-criteria decision-making problems (Jankowski and Nyerges 2001; Jena et al. 2020; Meng and Malczewski 2015; Ouma et al. 2011). Therefore, the ranking of the indicators in the present study is performed by the critical analysis of the selected literature. The rank of each hazard and vulnerability indicators are assigned according to their significance in causing flood as reported in various literature (Chakraborty and Mukhopadhyay 2019; Lin et al. 2020; Pareta 2021; Pathak et al. 2020; Shahiri Tabarestani and Afzalimehr 2021; Shivaprasad Sharma et al. 2018; Souissi et al. 2020; Toosi et al. 2019; Vignesh et al. 2021). AHP decomposes a problem into a simple and subjective evaluated sub-problem hierarchy (Saaty 2000). The indicators are weighted according to relative importance on a scale from 1 to 9 (Saaty 2008). The steps of AHP are as follows:

Step 1. Decompose the complex unstructured problem into a hierarchy of goals, criteria, and indicators.

Step 2. Make a pairwise comparison of the indicators based on a qualitative scale (Table 3).

Step 3. Construct a square matrix of n x n where diagonal elements of the matrix are 1. If the indicator in the \( i^{th} \) row of the matrix is more important than the indicator in the \( j^{th} \) column, then the element \( (i, j) \) will be assigned a value greater than 1, and the element \( (j, i) \) will be its reciprocal.

Step 4. The weights of the pairwise comparison matrix are normalized by the eigenvector method using the equations (17) to (18).

\[
X_{ij} = \frac{C_{ij}}{\sum_{i=1}^{n} C_{ij}} \quad (17)
\]
\[
V_{ij} = \frac{\sum_{j=1}^{n} X_{ij}}{n} \quad (18)
\]
where $C_{ij}$ is the indicator value in the pairwise comparison matrix, $X_{ij}$ is the normalized score, and $V_{ij}$ is the priority vector representing the indicators’ weight ($W_{ind}$).

Finally, the assigned normalized weights are tested for consistency ratio ($CR$) using equation (19), where $CR$ must be less than 0.1 and consistency index ($CI$) is calculated by equation (20).

\[ CR = \frac{CI}{RI} \]  
\[ CI = \frac{\lambda_{\text{max}} - n}{n - 1} \]

$\lambda_{\text{max}}$, $RI$ (Table 4), and $n$ are principal eigenvector, random index, and the number of indicators, respectively.

### 3.4. Flood hazard, vulnerability, and risk index

Flood hazard index ($FHI$), flood vulnerability index ($FVI$), and flood risk index ($FRI$) are calculated in GIS using a raster calculator by equations (21)–(23). The index scores are normalized and converted into a raster of grid size 30 m × 30 m to minimize error (Chakraborty and Mukhopadhyay 2019).

\[
FHI = (W_{ELV} \times ELV) + (W_{SI} \times SI) + (W_{Dd} \times Dd) + (W_{Dr} \times Dr) + (W_{De} \times De) + (W_{St} \times St) + (W_{Geo} \times Geo) + (W_{Gm} \times Gm) + (W_{TWI} \times TWI) + (W_{MFI} \times MFI) + (W_{REF} \times REF) + (W_{RC} \times RC)
\]

\[
FVI = (W_{PD} \times PD) + (W_{VP} \times VP) + (W_{Emp} \times Emp) + (W_{LR} \times LR) + (W_{HHA} \times HHA) + (W_{DPH} \times DPH) + (W_{BD} \times BD) + (W_{DRd} \times DRd) + (W_{DH} \times DH) + (W_{DC} \times DC) + (W_{FA} \times FA) + (W_{LULC} \times LULC)
\]

Here, $W_{\text{indicator}}$ is the weight of respective indicators.

\[ FRI = FHI \times FVI \]
3.5. Flood hazard map validation

To validate the hazard map 478 historical flood location points are selected and used for the performance analysis based on the accuracy assessment of flood classification. The confusion matrix or error matrix is suitable to validate the accuracy (Arora et al. 2021; Cabrera and Lee 2019). Several parameters like overall accuracy (OA), true positive rate \((PR_{TRUE})\), false positive rate \((PR_{FALSE})\), true negative rate \((NR_{TRUE})\), and false-negative rate \((NR_{FALSE})\) are calculated using the equations (24) to (28):

\[
OA = \frac{P_{TRUE} + N_{TRUE}}{P + N} = \frac{P_{TRUE} + N_{TRUE}}{P_{TRUE} + N_{TRUE} + P_{FALSE} + N_{FALSE}}
\]

\[
PR_{TRUE} = \frac{P_{TRUE}}{P_{TRUE} + N_{FALSE}}
\]

\[
NR_{TRUE} = \frac{N_{TRUE}}{N_{TRUE} + P_{FALSE}}
\]

\[
PR_{FALSE} = \frac{P_{FALSE}}{P_{FALSE} + N_{FALSE}} = 1 - NR_{TRUE}
\]

\[
NR_{FALSE} = \frac{N_{FALSE}}{N_{FALSE} + P_{TRUE}} = 1 - PR_{TRUE}
\]

where \(P\), \(N\), \(P_{TRUE}\), \(N_{TRUE}\), \(P_{FALSE}\), and \(N_{FALSE}\) denote positive, negative, true positive, true negative, false positive, and false negative, respectively.

For the 478 points, elevations are extracted by using GIS tools. The elevation for the points ranged between 5 m to 135 m. The points are interpolated by the Kriging interpolation method and identified that points belonging to this elevation range are flood-prone areas.

3.6. Flood risk map validation

Due to a lack of data on flood depths, storm discharge at micro levels, the validation of the result was based on historical flood events and flood-prone areas reported by Disaster Management authorities at state and district levels. A total of 1263 inundation-prone settlements in the study area are identified and converted as georectified points in the GIS environment. From the settlement layer, a set of points are generated for very low to very high flood risk with the help of a spatial statistics tool. To validate the flood risk model (FRM), indirect methods of relative mean error \((RME)\) and root of mean-square error \((RMSE)\) are applied by considering observed locations \((OL)\) for reported sites and predicted locations \((PL)\) for modeled sites (Chakraborty and Mukhopadhyay 2019). The values of \(RME\), \(RMSE\), percentage of relative error \((RE_i)\), and standard error \((SE_i)\) for FRM are calculated using equations (29)–(32).

\[
RME = \frac{1}{n} \sum RE_i
\]

\[
RE_i = \frac{(OL - PL) \times 100}{OL}
\]

\[
RMSE = \sqrt{\frac{1}{n} (\sum SE_i)}
\]

\[
SE_i = (OL - PL)^2
\]
4. Result

In the present study, the flood hazard, vulnerability, and risk maps of Assam, at the regional and administrative level, are developed using different indicators. Weightage to each indicator is assigned by MCDA-AHP and integrated into GIS to obtain FIH, FVI, and FRI.

4.1. Spatial distribution of flood hazard and vulnerability indicators

The flood hazard and vulnerability indicators are classified into different classes, i.e. very low (1), low (2), moderate (3), high (4), and very high (5) (Chakraborty and Mukhopadhyay 2019; Pathak et al. 2020). A thematic layer of flood hazard indicators is generated in GIS (Figure 3a–l). Lower, North, Upper, and Barak valley of Assam are more flood-prone due to lower elevation, milder slopes, lower TWI, sedimentary rock structure, and sandy clay loam soil texture. The elevation ranges between 5 to 326 meters for 88.06% of the study area, milder slope ranging between 0°–3.07° constitutes about 48.83% of the study area, 52.54% of the study area is characterized by sandy clay loam, and 85.39% of the area is composed of sedimentary rock structure.

The drainage density is relatively low in Northern Assam and high in the Lower, Upper, Central, and Barak valleys of Assam, increasing its flood susceptibility. About 39.79% of the study area has drainage density ranging from 1.31 to 0.53 km/sq km, and 60.21% have drainage density lower than 0.53 km/sq km. The Lower, Northern, and Upper Assam are highly susceptible to flood due to alluvial and flood plains. The REF values in the Upper and Lower Assam range from very low to very high, very high to moderate in the Barak valley, very low to low in Central, and moderate to very low in Northern Assam. The rainfall intensity and runoff coefficient are moderate to very high for the Lower and Barak valley of Assam. The alluvial plains, pediplain, and floodplain constitute 73.98% aggregate of the study area. A total of 40.12% of the study area falls under very high to moderate runoff coefficient classes and 59.88% of the study area lies between low to very low runoff coefficient classes.

The vulnerability indicators can be grouped into four types of vulnerability (i) socio-economic (population density, vulnerable population, employment rate, literacy rate, and household with more than 4 family members), (ii) infrastructure (building density, distance to roads, distance to hospital, and several dilapidated houses), (iii) hydrological (flow accumulation and distance to stream confluences) and (iv) land use (LULC) (Figure 4a–l) (Shivaprasad Sharma et al. 2018). The population density ranges from very high to moderate for the Lower, Upper, and Barak valley of Assam and low to very low in Central and Northern Assam.

The vulnerable population is very high in some parts of the Lower, Central, Upper, and Barak valley of Assam. The employment rate is very high in the upper region of Assam due to the predominance of agricultural activities, and the majority of the population is self-employed. Very high to moderate literacy rates are found in the Upper, Central, and Barak valley of Assam and can be considered less vulnerable than those with low literacy rates. The housing condition of Central and Upper Assam lies in very low to low vulnerable class along with moderate to high building density. The LULC distribution is classified according to the flood hazard, vulnerability, and risk index for the Assam region (Figure 5a–d). The spatial distribution of population density shows that 21.67% of the study area is ‘very high to high’ densely populated, about 28.97% of the study area consists of moderate vulnerable class and more than 30% of the study area comprised of
**Table 5. Flood hazard indicators.**

| Indicator                        | $W_{nd}$ | Subclass       | % of area | Effective weight (EF) | Normalized EF |
|---------------------------------|----------|----------------|-----------|-----------------------|---------------|
| Elevation (ELV)                 | 0.10     | 5-135          | 73.69     | 5                     | 0.33          |
|                                 |          | 135.01-326     | 14.37     | 4                     | 0.27          |
|                                 |          | 326.01-600     | 6.11      | 3                     | 0.20          |
|                                 |          | 600.01-960     | 4.62      | 2                     | 0.13          |
|                                 |          | 960.01-1964    | 1.20      | 1                     | 0.07          |
| Slope (SI)                      | 0.14     | 0-3.07         | 48.83     | 5                     | 0.33          |
|                                 |          | 3.08-8.38      | 30.14     | 4                     | 0.27          |
|                                 |          | 8.39-15.92     | 12.46     | 3                     | 0.20          |
|                                 |          | 15.93-26.25    | 6.21      | 2                     | 0.13          |
|                                 |          | 26.26-71.21    | 2.35      | 1                     | 0.07          |
| Drainage Density (Dd)           | 0.09     | 0-0.26         | 30.28     | 1                     | 0.07          |
|                                 |          | 0.27-0.52      | 29.93     | 2                     | 0.13          |
|                                 |          | 0.53-0.79      | 23.32     | 3                     | 0.20          |
|                                 |          | 0.80-1.05      | 14.47     | 4                     | 0.27          |
|                                 |          | 1.06-1.31      | 2.00      | 5                     | 0.33          |
| Proximity to the river (Dr)     | 0.10     | 0-500          | 9.65      | 5                     | 0.33          |
|                                 |          | 501-1000       | 8.73      | 4                     | 0.27          |
|                                 |          | 1001-2000      | 15.44     | 3                     | 0.20          |
|                                 |          | 2001-4000      | 24.68     | 2                     | 0.13          |
|                                 |          | >4000          | 41.49     | 1                     | 0.07          |
| Proximity to embankment breach locations (De) | 0.05 | 0-500          | 0.09      | 5                     | 0.33          |
|                                 |          | 501-1000       | 0.27      | 4                     | 0.27          |
|                                 |          | 1001-2000      | 1.04      | 3                     | 0.20          |
|                                 |          | 2001-4000      | 3.74      | 2                     | 0.13          |
|                                 |          | >4000          | 94.86     | 1                     | 0.07          |
| Soil texture (St)               | 0.06     | Sandy clay loam| 52.54     | 5                     | 0.33          |
|                                 |          | Clay           | 3.72      | 4                     | 0.27          |
|                                 |          | Clay Loam      | 4.86      | 3                     | 0.20          |
|                                 |          | Clay Loam      | 6.01      | 2                     | 0.13          |
|                                 |          | Loam           | 32.87     | 1                     | 0.07          |
| Geology (Geo)                   | 0.02     | Metamorphic    | 0.60      | 2                     | 0.20          |
|                                 |          | Paleozoic      | 1.17      | 1                     | 0.10          |
|                                 |          | Precambrian    | 12.85     | 2                     | 0.20          |
|                                 |          | Sedimentary    | 85.38     | 5                     | 0.50          |
| Geomorphology (Gm)              | 0.03     | Alluvial plain | 43.74     | 5                     | 0.31          |
|                                 |          | Denudational hill| 1.53    | 2                     | 0.13          |
|                                 |          | Flood plain    | 25.75     | 5                     | 0.31          |
|                                 |          | Pediplain      | 5.89      | 3                     | 0.19          |
|                                 |          | Structural hill| 24.89     | 1                     | 0.06          |
| Topographic wetness index (TWI) | 0.05     | 2.35-8.06      | 65.30     | 2                     | 0.20          |
|                                 |          | 8.07-11.83     | 24.55     | 3                     | 0.30          |
|                                 |          | 11.84-28.33    | 10.14     | 5                     | 0.50          |
| Rainfall intensity (MFI)        | 0.19     | 148.45-254.22  | 28.68     | 1                     | 0.07          |
|                                 |          | 254.23-359.98  | 47.20     | 2                     | 0.13          |
|                                 |          | 359.99-465.75  | 14.89     | 3                     | 0.20          |
|                                 |          | 465.76-571.51  | 6.42      | 4                     | 0.27          |
|                                 |          | 571.52-677.28  | 2.81      | 5                     | 0.33          |
| Rainfall Erosivity Factor (REF) | 0.03     | 419.02-639.71  | 23.64     | 1                     | 0.07          |
|                                 |          | 639.72-786.84  | 29.56     | 2                     | 0.13          |
|                                 |          | 786.85-941.32  | 25.47     | 3                     | 0.20          |
|                                 |          | 941.33-1114.20 | 14.39     | 4                     | 0.27          |
|                                 |          | 1114.21-1356.96| 6.93      | 5                     | 0.33          |
| Runoff coefficient (RC)         | 0.12     | 0-0.04         | 30.87     | 1                     | 0.07          |
|                                 |          | 0.05-0.08      | 29.00     | 2                     | 0.13          |
|                                 |          | 0.09-0.13      | 26.63     | 3                     | 0.20          |
|                                 |          | 0.14-0.20      | 10.09     | 4                     | 0.27          |
|                                 |          | 0.21-30        | 3.40      | 5                     | 0.33          |
Table 6. Flood vulnerability indicators.

| Indicator                        | $W_{ind}$ | Sub class | % of area | Effective weight (EF) | Normalized EF |
|----------------------------------|-----------|-----------|-----------|-----------------------|---------------|
| Population density (PD)          | 0.21      | 43.65-91.79 | 19.54     | 1                     | 0.07          |
|                                  |           | 91.80-364.22 | 27.27     | 2                     | 0.13          |
|                                  |           | 364.23-530.01 | 31.53     | 3                     | 0.20          |
|                                  |           | 530.02-743.15 | 20.65     | 4                     | 0.27          |
|                                  |           | 743.16-1574.76 | 1.02      | 5                     | 0.33          |
| Vulnerable population (VP)       | 0.19      | 59.23-65.34 | 1.03      | 3                     | 0.14          |
|                                  |           | 65.35-69.34 | 38.03     | 4                     | 0.19          |
|                                  |           | 69.35-70.44 | 28.97     | 4                     | 0.19          |
|                                  |           | 70.45-71.19 | 10.01     | 5                     | 0.24          |
|                                  |           | 71.20-73.48 | 21.97     | 5                     | 0.24          |
| Employment rate (Emp)            | 0.03      | 32.49-33.17 | 6.91      | 5                     | 0.33          |
|                                  |           | 33.18-36.68 | 22.68     | 4                     | 0.27          |
|                                  |           | 36.69-40.21 | 33        | 3                     | 0.20          |
|                                  |           | 40.22-42.81 | 26.06     | 2                     | 0.13          |
|                                  |           | 42.82-46.17 | 11.34     | 1                     | 0.07          |
| Literacy rate (LR)               | 0.03      | 47.32-53.90 | 9.99      | 5                     | 0.33          |
|                                  |           | 53.91-58.75 | 32.56     | 4                     | 0.27          |
|                                  |           | 58.76-61.79 | 17.91     | 3                     | 0.20          |
|                                  |           | 61.80-70.68 | 34.9      | 2                     | 0.13          |
|                                  |           | 70.69-79.84 | 4.63      | 1                     | 0.07          |
| Household with more than 4 family members (HH4) | 0.06  | 64.72-68.32 | 7.53      | 3                     | 0.14          |
|                                  |           | 68.33-71.83 | 12.81     | 4                     | 0.19          |
|                                  |           | 71.84-75.57 | 39.4      | 4                     | 0.19          |
|                                  |           | 75.58-77.67 | 15.55     | 5                     | 0.24          |
|                                  |           | 77.68-81.83 | 24.7      | 5                     | 0.24          |
| Dilapidated house (DPH)          | 0.05      | 4.03-5.85  | 25.39     | 1                     | 0.07          |
|                                  |           | 5.86-7.46  | 11.3      | 2                     | 0.13          |
|                                  |           | 7.47-11.06 | 29.87     | 3                     | 0.20          |
|                                  |           | 11.07-14.12 | 23.26     | 4                     | 0.27          |
|                                  |           | 14.13-17.59 | 10.17     | 5                     | 0.33          |
| Building density (BD)            | 0.06      | 8.61-17.05 | 19.54     | 1                     | 0.07          |
|                                  |           | 17.06-85.78 | 20.53     | 2                     | 0.13          |
|                                  |           | 85.79-118.90 | 36.57     | 3                     | 0.20          |
|                                  |           | 118.91-149.74 | 18.82     | 4                     | 0.27          |
|                                  |           | 149.75-368.11 | 4.55      | 5                     | 0.33          |
| Proximity to roads (DRd)         | 0.05      | 0-500      | 9.72      | 1                     | 0.07          |
|                                  |           | 501-1000   | 11.2      | 2                     | 0.13          |
|                                  |           | 1001-2000  | 16.19     | 3                     | 0.20          |
|                                  |           | 2001-4000  | 22.67     | 4                     | 0.27          |
|                                  |           | >4000      | 40.22     | 5                     | 0.33          |
| Proximity to hospital (DH)       | 0.04      | 0-500      | 0.10      | 1                     | 0.07          |
|                                  |           | 501-1000   | 0.29      | 2                     | 0.13          |
|                                  |           | 1001-2000  | 1.14      | 3                     | 0.20          |
|                                  |           | 2001-4000  | 4.37      | 4                     | 0.27          |
|                                  |           | >4000      | 94.10     | 5                     | 0.33          |
| Distance to stream confluence (Dc)| 0.07  | 0-500      | 0.07      | 5                     | 0.33          |
|                                  |           | 501-1000   | 0.20      | 4                     | 0.27          |
|                                  |           | 1001-2000  | 0.78      | 3                     | 0.20          |
|                                  |           | 2001-4000  | 3.11      | 2                     | 0.13          |
|                                  |           | >4000      | 95.85     | 1                     | 0.07          |
| Flow accumulation (FA)           | 0.07      | 0-1000     | 97.77     | 1                     | 0.07          |
|                                  |           | 1001-2000  | 0.61      | 2                     | 0.13          |
|                                  |           | 2001-5000  | 0.56      | 3                     | 0.20          |
|                                  |           | 5001-12000 | 0.36      | 4                     | 0.27          |
|                                  |           | >12000     | 0.70      | 5                     | 0.33          |
| Land use land cover (LULC)       | 0.14      | Water      | 4.38      | 5                     | 0.33          |
|                                  |           | Natural vegetation | 43.74 | 2                     | 0.13          |
|                                  |           | Agricultural land | 34.10 | 3                     | 0.20          |
|                                  |           | Builtup area | 13.17 | 4                     | 0.27          |
|                                  |           | Bare land | 4.62      | 1                     | 0.07          |
high to a very high class of the vulnerable population. According to LULC classification, 77.84% of the study area consists of natural vegetation and agricultural land. The indicators are dynamic and vary spatially and temporally (Souissi et al. 2020).

4.2. Weightage assignment of indicators by AHP

In the present study AHP, a multi-criteria decision analysis approach is used to generate flood hazard index (FHI) and flood vulnerability index (FVI). The consistency ratio (CR) is 0.06 and 0.03 for flood hazard and vulnerability indicators, respectively, and the consistency index (CI) is 0.09 for flood hazard and 0.04 for vulnerability indicators. Highly
contributing factors for flood hazard are rainfall intensity, slope, runoff coefficient, elevation, distance to rivers, drainage density, and the least significant factors are erosivity factor, geomorphology, and geology (Table 7).

For flood vulnerability, highly contributing factors include population density, vulnerable population, land use landcover, whereas the least contributing factors are identified as employment and literacy rate (Table 8).

### 4.3. Mapping of FHI, FVI, and FRI

The resulting flood hazard map shows a substantial relationship with the controlling factors and FHI values. Areas with alluvial plains fall under very high to moderate FHI,
while regions with structural and denudational hills have very low to low flood hazard zonation (Vignesh et al. 2021). Upper and lower Assam have high TWI, and it comes under very high to high flood hazard zone. The Lower, Upper, and Barak valleys of Assam have very high FHI and low to very low FHI values observed for the Central Assam (Figure 6a).

The FVI ranges from low to very low for Central and Upper Assam, high to very high for Lower Assam, moderate to low for Northern Assam, and low to very high for the Barak valley. A large proportion of the area is in a very high vulnerable zone located
along West Bengal, Meghalaya, and Indo-Bangladesh border. These areas have very high to moderate population density, a very high percentage of the vulnerable population, low literacy and employment rate, and high building density (Chakraborty and Mukhopadhyay 2019). Very high to moderate FVI are observed for Lower and Barak valley of Assam. For Upper and Northern Assam, moderate to very low FVI values are identified, and a large part of Central Assam shows very low flood vulnerability (Figure 6b).
The FHI and FVI profiles of Assam are different because flood hazards represent real and existing physical elements that alter gradually, and the more dynamic indicators determine flood vulnerability (Shivaprasad Sharma et al. 2018).
The spatial distribution of FRI shows that both FHI and FVI contribute significantly to the generation of FRI, but their influences differ in many parts of the study area. Northern Assam has moderate to high FHI, and moderate to low FVI and FRI classes. For Upper Assam, the FHI ranges from moderate to very high, FVI and FRI range from very low to moderate. Barak valley has moderate to very high FHI values, low to high FVI and FRI classes. Lower Assam falls in the moderate to a very high flood risk category, and Central Assam has low to very low flood risk values. The spatial distribution of FRI indicates that flood vulnerability indicators contribute more to the estimation of risk than the hazard indicators (Figure 6c).

The spatial distribution of the three indices shows that more than 70%, 57.37%, and 50% of the total area lies in the moderate to very high FHI, FVI, and FRI classes, respectively (Figure 6d).

4.4. Mapping of FHI, FVI, and FRI at the administrative level

In lower Assam, the districts like Dhubri, Goalpara Barpeta, Bongaigaon, and Chirang lie in high to very high FHI, FVI, and FRI zones. The FRI class for the Kokrajhar district ranges from high to low, with moderate FVI and very high FHI. Nalbari lies in very high to high flood hazard zonation with moderate to high FVI resulting in high to moderate FRI. The area of Kamrup and Baksa falls under very high to low FHI and FVI class and high to low FRI class. The Kamrup metropolitan has very low to low FRI due to very low FHI and moderate FVI (Figure 7a–c). All the seven Upper Assam districts are in high FHI classes but moderate to very low FVI and FRI classes. (Figure 7d–f).
Northern Assam, Darrang district lies under high to very high flood hazards, vulnerability, and risk class. For Sonitpur, flood risk ranges from moderate to low due to lower flood hazards and vulnerability. Udalgiri district lies in a very high FVI zone but has moderate to low FHI, making it moderate towards flood susceptibility (Figure 7g–i).

The districts of Central Assam like Morigaon and Nagaon lie in moderate flood hazard and risk zones, having very high FVI due to high population density, low literacy rate, and agricultural lands and built-up areas. Similar variations are observed for FHI, FVI, and FRI classes for Karbi Anglong and Dima Hasao districts (Figure 7j–l). The FVI for
the Karimganj district of Barak valley is very high, with moderate to very high FHI and FRI classes. On the other hand, Hailakandi and Cachar districts lie in moderate to low FVI and FRI classes with very high FHI (Figure 7m–o).

The area-wise spatial distribution of FHI, FVI, and FRI show that for lower Assam, 90.29%, 86.03%, and 88.32% of the total area fall under moderate to very high FHI, FVI and FRI classes, respectively. More than 55% of the total area of Upper Assam falls under high to very high FHI class, and less than 10% lies in high to very high FVI and FRI class. Approximately 85%, 71%, and 63% of the total area of Northern Assam contribute very high to moderate FHI, FVI, and FRI classes, respectively (Figure 7p–r)). About 70% of the total study area of Central Assam falls under very low flood risk and vulnerability.
zone and more than 60% of the total area of Barak valley is observed under moderate to very high FRI zones (Figure 7r).

5. Result validation

5.1. Flood hazard index map

Based on 478 historical flood points, a resulting flood map was created by the interpolation method in GIS software and overlaid with the flood hazard index map, obtained by applying AHP. After performing the accuracy assessment by the confusion matrix or error matrix method, the number of pixels that matched correctly ($P_{TRUE}$) and mistakenly
are calculated (Table 9). The estimated accuracy is 90.75%. Calculated \( P_{\text{TRUE}} \), \( N_{\text{TRUE}} \), \( P_{\text{FALSE}} \), and \( N_{\text{FALSE}} \) values are 0.90, 0.92, 0.08, and 0.10, respectively.

### 5.2. Flood risk index map

Relative mean error (RME) and root of mean-square error (RMSE) were applied to validate the flood risk map of Assam, based on the selection of 1263 flood-prone locations. The model accurately predicted 1089 locations and has an accuracy of 86.22%, the overall efficiency of the model is found to be satisfactory, with RMSE equal to 0.105 and RME equal to 0.391. For the districts like Barpeta, Chirang, Cachar, Lakhimpur, Nalbari, Morigaon, Tinsukia, Karimganj, Golaghat, Jorhat, Udalguri, Naogaon, Sivasagar, Dima Hasao, Dhubri, Sonitpur, Darrang, Dhemaji, Goalpara, Bongaigaon, Kokrajhar shows accuracy level between 85–96% and district like Kamrup metropolitan, Kamrup rural, Baksa, Hailakandi, Dibrugarh, Karbi Anglong have accuracy level ranging from 78–85%.

### 6. Discussion

The detailed study on flood risk assessment is essential to create more comprehensive and integrated flood risk management practices for flood-prone regions like Assam. Many studies have considered MCDA to develop a flood risk model using hydrological, geological, demographical, and LULC indicators (Armenakis et al. 2017; Chakrabortty et al. 2021). The spatial distribution of the indicators has a critical impact on the variation of FHI, FVI, and FRI at the regional and administrative levels. In the present study, the extent of flood hazard and vulnerability depends on topographical, geological, drainage characteristics, hydrological, meteorological, demographical conditions of the Assam region (Arora et al. 2021; Hazarika et al. 2018; Pathak et al. 2020; Toosi et al. 2019). In the flood hazard assessment, rainfall intensity is given higher weightage, followed by slope and runoff coefficient (Toosi et al. 2019). Factors like elevation, slope, distance to river, geomorphology, soil type drainage density are used by many researchers for the flood hazard assessment of Assam and other areas (Kumar 2016; Pareta 2021; Pathak et al. 2020). But the selection of factors like TWI, REF, and runoff coefficient is minimal for Assam. For the FVI, more weightage is given to demographical indicators and LULC of the study area (Kourgialas and Karatzas 2017). LULC is considered an essential factor in determining runoff and hazard and vulnerability assessment (Arabameri et al. 2019; Chakrabortty et al. 2021). The results of the study are compatible with Hazarika et al. (2018) and Shivaprasad Sharma et al. (2018). The weightage assignment of the flood and vulnerability indicators is not constant, and it depends from region to region (Rashetnia and Jahanbani 2021; Sarkar and Mondal 2020).

The novelty of the present study lies in many facts; at first, it is conducted for the entire Assam region, and the flood risk scenarios are derived at the administrative level to have a better understanding and broader view. Secondly, the present study has considered...
all the vital flood risk management components that many researchers did not consider earlier for the Assam region (Majumder et al. 2019; Pareta 2021). Thirdly, the present studies include new explanatory factors like runoff coefficient calculated using the NRCS-CN method, topographic wetness index, rainfall erosivity factor, flow accumulation for the flood risk mapping of the Assam region. The novelty of the approach also lies in the fact that the study is based on the proper understanding of physical, social, economic, environmental, and infrastructural system behavior and how it affects the pattern of risk over the period. The validation of final flood hazard and risk maps by different approaches like confusion matrix or error matrix, indirect methods of relative mean error (RME), and root of mean-square error (RMSE) based on historical flood events provide identification of vulnerable zones. The study framework provides an opportunity to understand the challenges associated with flood risk management and to implement effective and sustainable flood mitigation measures and policies for urban and rural areas located at flood risk zones.

The present study holds significant importance on the global scale as the frequency of flood-related calamities is rising. There is a need for understanding the nature and dynamics of floods for proper flood risk management and sustainable water resources management is very important. The present work is based on a wide range of numerous research works conducted globally and hence it can be attributed as the immediate documentation of the flood risk of the Assam region. This work is of significant scientific value and it contributes towards effective decision making and policy interventions. The methodology adopted in the present study is flexible, reliable, and efficient and it can be applied to other flood-prone regions in the world at the local or national scale. The efficiency of the coupling of AHP and GIS is again found to be at good levels and can be suggested as a reliable tool for flood risk assessments, particularly for such data lacking regions. The main advantage of the indices is that it gives an overall estimation of the flood-prone areas of Assam and spatial variation of the indicators responsible for the occurrence of flood. As flood risk management includes four essential components, namely prevention, preparedness, response, and rehabilitation, all aspects should be considered.

7. Conclusion

In the present study, the flood hazard, vulnerability, and risk maps of Assam at the regional and administrative levels are developed by combining MCDA-AHP and GIS tools. The flood hazard and vulnerability layer are created using different indicators, and AHP is applied to assign weightage to the indicator. The final flood risk map is obtained by integrating hazard and vulnerability indices in GIS software and validated by confusion matrix, RME, and RMSE based on historical flood events. The results show that more than 70% of the total area lies in the moderate to very high FHI class, and it includes Lower, Upper, and Barak valley of Assam have very high FHI. About 57.37% of the total areas have moderate to very high FVI consisting of the Lower and Barak valley of Assam, whereas the Central Assam shows very low flood vulnerability. For more than 50% of the total study area, moderate to very high FRI are observed in the Lower, Upper, and Barak valley of Assam. The FHI, FVI, and FRI indices estimate the flood-prone areas of Assam and spatial variation of the indicators responsible for flood occurrence. The districts like Dhubri, Goalpara Barpeta, Bongaigaon, Darrang, Karimganj, and Chirang lie in high to very high FHI, FVI, and FRI zones. The study has inherent limitations related to the database, including soil, topography, meteorological, lithological, historical flood events,
weightage assignment, and accuracy of remote sensing data. To obtain more precise results and overcome the limitations, future research can be conducted for the vulnerable areas by using multi-sensor SAR imageries and incorporating highly advanced artificial intelligence (AI) and machine learning methods.

The results may provide the local governing authorities and stakeholders with a comprehensive tool for flood risk management. The methodology can be implemented in other locations to carry out a flood risk assessment with more accurate and precise data sources using time and cost-effective GIS-based tools.

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Disclosure statement

The authors declare that they have no known competing financial interests or non-financial interests or personal relationships that are directly or indirectly related to the work submitted for publication that could have appeared to influence the work reported in this paper.

ORCID

Laxmi Gupta http://orcid.org/0000-0003-4453-3119
Jagabandhu Dixit http://orcid.org/0000-0002-5450-578X

Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article and some of the raw data were generated at our laboratory and derived data supporting the findings of this study are available upon reasonable request.

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