Assessment of the performance of GIS-based analytical hierarchical process (AHP) approach for flood modelling in Uttar Dinajpur district of West Bengal, India

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\textbf{ABSTRACT}

Floods have received global significance in contemporary times due to their destructive behavior, which may wreak tremendous ruin on infrastructure and civilization. The present research employed an integration of the Geographic information system (GIS) and Analytical Hierarchy Process (AHP) method for identifying the flood susceptibility zonation (FSZ), flood vulnerability zonation (FVZ), and flood risk zonation (FRZ) of the humid subtropical Uttar Dinajpur district in India. The study combined a large number of thematic layers ($N = 12$ for FSZ and $N = 9$ for FVZ) to achieve reliable accuracy and included the multicollinearity analysis of these variables to overcome the issues related to highly correlated variables. According to the findings, 27.04, 15.62, and 4.59\% of the area were classified as medium, high, and very high FRZ, respectively. The ROC-AUC, MAE, MSE, and RMSE of the model exhibited a good prediction accuracy of 0.73, 0.15, 0.16, and 0.21, respectively. The performance of the AHP model has been evaluated using sensitivity analyses. It also highly recommends that persistent improvement in this subject, such as sensitivity studies on modifying criteria thresholds, changing the relative significance of criteria, and changing the desired matrix, will permit GIS and MCDA to be progressively adapted to real hazard-management issues.
1. Introduction

Floods have become one of the prominent natural disasters globally, leading to massive social and economic damages (Chen et al. 2020). Natural disasters are responsible for 40% of all socio-economic damages worldwide. Indeed, flooding is most frequent and devastating, specifically in south-east Asian countries (Bui et al. 2019). Floods can be effectively minimized or especially eliminated considering examining their spatial assessment. In recent times, the assessment of flood risk zonation (FRZ) has been an interesting and innovative task throughout the world for geographers, hydrologists, hydrogeologists, and policymakers to sustain long-term socio-economic growth (Souissi et al. 2020).

The FRZ relies on the susceptibility and vulnerability mapping of the concerned study area. Hence, modeling flood susceptibility zonation (FSZ) and flood vulnerability zonation (FVZ) is crucial for developing the FRZ assessment. One of the best suitable approaches is the multi-criteria decision analysis (MCDA), which was popularly used to modeling such kinds of FSZ, FVZ, and FRZ (Radwan et al. 2019; Hammami et al. 2019; Cabrera and Lee 2020; Abdelkarim et al. 2020; Roy et al. 2021; Pham et al. 2021). It performs a paramount role in determining which alternatives are optimum. The advantage of MCDA is that it can be used to quickly produce and rank all viable alternatives solely on their effectiveness (Radwan et al. 2019). Several scholars have recently assessed FRZ using the MCDA approaches with good accuracy integrating with remote sensing (RS) and GIS techniques globally. Several studies have been carried out to forecast the risk of flooding employing the MCDA approaches, viz.,
Analytical Hierarchy Process (AHP) (Das 2020; Roy et al. 2021; Das and Gupta 2021), Fuzzy Analytical Hierarchy Process (Hasanloo et al. 2019), Discrete Choice Analysis (Wassenaar and Chen 2003), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Sari 2021), Preference Ranking Organization Method (Chen 2021), Vise Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (Wang et al. 2019), Evaluation Based on Distance from Average Solution (EDAS) (Ghorabaee et al. 2017), Multi-Attributive Border Approximation area Comparison (Pamucar and Cirovic 2015), and Multi-objective Optimization on the basis Ratio Analysis (Karande and Chakraborty 2012). Various investigations (Radwan et al. 2019; Lyu et al. 2020; Roy et al. 2021; Bhattacharjee et al. 2021; Chakraborty and Mukhopadhyay 2019; Hammami et al. 2019; Cabrera and Lee 2020; Abdelkarim et al. 2020) had already adopted this method, which includes assigning weights to thematic layers and categorizing them relying on prior knowledge and site-specific circumstances. Natural calamities viz., floods, wildfires, earthquakes, and droughtiness are now predicted using machine learning techniques (Hong et al. 2018; Ahmadlou et al. 2019). The algorithms of this technique have been observed in the studies of Liu et al. (2022), Bot and Borges (2022), Ha et al. (2022) and Arabameri et al. (2022).

Floods in India have attracted more focus as flooding is more prevalent and severe in terms of human deaths, and it has an adverse impact on economic sectors. In the monsoon season, high-intensity rainfall for a shorter period of time generates an abrupt surge in runoff that exceeds the absorptive capacity of the drainage system and triggers flooding. Around 40 million hectares of land in the country are classified as flood-prone, and floods impact almost 8 million hectares of land each year (Das and Gupta 2021). Developing countries, notably from the Asian continent, incur around 90% of flood-induced disasters and 95 percent associated damages (Gupta et al. 2003; Mirza 2011). During the summer monsoon season, tropical disturbances such as cyclonic storms, depressions, and low-pressure systems encompass the country. Furthermore, orographic swings, local disturbances, and quick atmospheric fluctuations can induce localized to widespread aberrant rainfall in the Indian subcontinent (Sarkar and Singh 2017). The monsoon’s unpredictability generates torrential rainfall and flooding in the country’s rivers (Dhar and Nandargi 2003). Singh et al. (2009), in their study, specifically manifest the flooding conditions in the subcontinent due to variability of soil wetness using remote sensing data. During floods, there was a considerable rise in SWI values, which persisted high again for the period of the flood. In the studies of Sahana and Patel (2019), Chakraborty and Mukhopadhyay (2019), Sahana et al. (2020), Das (2020), Das and Gupta (2021), and Bhattacharjee et al. (2021), flood susceptibility, vulnerability, risk and hydro-geomorphologic changes of the river basin have been analyzed based on the Indian context.

West Bengal is the leading flood-prone state in India, and approximately 42.55% of its landmasses are susceptible to floods. The state has a significant threat to flood risk management and mitigation strategies (Annual Flood Report 2019). In the sub-Himalayan part of the state, the southern front of the Darjeeling-Bhutan Himalaya functions as the first orographic restriction to the south-west monsoon. It provides heavy rainfall in the rainy period. In this southern Himalayan margin, the study area is one of the richest in terms of the annual rainfall, usually 3000–6000 mm. It also
attains occasionally most regular severe rains up to 800 mm day\(^{-1}\) (Prokop and Walanus 2017). Thus, the Himalayan foothills are a renowned flood-prone area of the state (Ghosh and Ghosal 2021). The study area is located in the vicinity of the foothills of the eastern Himalayas in India. Due to its relief properties, drainage networks, and rainfall patterns, the region is susceptible to flood hazards annually. During the monsoon, the upper catchment area of the rivers attained a high amount of torrential rainfall; hence, in the lower reaches of the rivers, flood havoc occurred. As a result, low-lying human encroached riparian areas have been inundated, many standing crops have been damaged, and the livelihood of the people has been harmed (Chakraborty and Mukhopadhyay 2019).

The Uttar Dinajpur district is a humid subtropical region in West Bengal, India, where nine blocks (Chopra, Islampur, Goalpokhar-I, Goalpokhar-II, Karandighi, Raiganj, Hemtabad, Kaliaganj, and Itahar), and four municipalities (Kaliyaganj, Dalkhola, Islampur, and Raiganj) affected by flooding. Historically, the region has been wracked by floods since the district has seen extremely heavy torrential rains throughout the monsoon season, and water levels have been dangerously high in nearly all of the major rivers of this area. The aforementioned investigation was conducted dependent on the 12 susceptibility (elevation, slope, TWI, TPI, NDVI, MNDWI, drainage density, distance to river, SPI, STI, MFI, and lithology) and 11 vulnerability (distribution of population, population density, female population, child under 6 years, distance to flood shelter, LULC, distance to hospital, distance to road, road density, illiteracy, and employment rate) thematic layers to identify the FRZ of the study area. The study also includes multicollinearity analysis for detecting variables that were strongly correlated. The assigned weight for AHP assessment and mapping also was validated by employing the Stillwell ranking methods (Stillwell et al. 1981), single parameter sensitivity (Napolitano and Fabbri 1996), and map removal sensitivity (Lodwick et al. 1990) analyses. In addition, the model output was validated using the Receiver Operating Characteristic (ROC), MAE (Mean Absolute Error), MSE (Mean Square Error), and RMSE (Root Mean Square Error) cross-validation approaches (Hanley and McNeil 1982; Afolayan et al. 2020; Yaseen et al. 2022) and compared the final FSZ against the flood points and non-flood points data as determined by in-situ assessment.

Previous research shows that floods have had a substantial consequence on the study area’s residents’ social and economic lives (Ranjan 2017; Sarkar et al. 2021; Saha et al. 2021). However, there is a gap in consistent research that comprehensively investigates the severity of flood susceptibility, vulnerability, and risk of the study area in present times regarding contemporary issues. Along with there are also considerable research gaps in the cross verification of any model, particularly in the field of criteria ratings, which framework the model outputs. The current study has the prospects to play an important function in the long-term management of flood risk in the study region. The study is constructed based on the sensitivity studies of the AHP method, which can be employed in any other research area. It reflects the importance and novelty of the work. The major goals of the study are to (a) construct the GIS and AHP technique-based model for mapping the flood susceptibility zonation (FSZ), flood vulnerability zonation (FVZ), and flood risk zonation of the region after employing the multicollinearity assessment of the flood conditioning parameters,
(b) evaluation of the AHP method through sensitivity analyses, (c) examine the accuracy of the model by applying the ROC-AUC, MAE, MSE, and RMSE assessment. The findings may be useful to local governments and decision-makers in catastrophic risk mitigation.

2. Materials and methods

2.1. Study area

The present study has been confined to the Uttar Dinajpur district, which is situated in the extensive floodplain region of the state of West Bengal. After the split of West Dinajpur district on 1 April 1992, the district was formed. The district is lies between the extension of 25°11′N to 26°49′N and 87°49′E to 90°00′E. It entirely covers 3140 Km² (1212.36 sq. mi) area. The land is mostly flat, with a gradual inclination from north to south. The elevation ranges from –48 to 122 m, with a mean of 37 m. The slopes of nearly 90% of the studied area are found in <8°, with exceptional slopes ranging from 30° to 44° in some areas. The region is also divided into two physiographic units, namely, Islampur-Goalpokhar plain and Sudhani-Mahananda-Gamari plain. The major rivers are the Mahananda, Kulik, Tangan, Srimati, Nagar, and Gamari. Climatically, the region falls in the ‘Cwa’ category, with the highest temperature observed in May (approximately 290°C) and the lowest temperature observed in January (approximately 17°C). The rainy season lasts from June (316 mm) to September (303 mm), and annual rainfall (2007–2016) varies from 1169 mm to 1786.40 (DDMPUD 2020–2021). Administratively, the Uttar Dinajpur district is divided into 2 sub-divisions, 9 community development blocks, 9 police stations, 4 municipalities, and 98 gram panchayats. The population density of the district is 958 persons/km², while the country has 382 persons/km² (DCHUD 2011).

In terms of hazard, vulnerability, and risk, the district is historically affected by flooding in the rainy season, almost extremely and partially in all blocks and municipalities. In the years 1992, 1995, 1998, 2000, 2002, 2005, and 2017 heavy flood disasters has been occurred in and around the district. Mainly from July to September, floods occurred at several places in the district. The District Disaster Management Plan of Uttar Dinajpur District (DDMPUD) 2020–2021 estimated that during the 2017 flood, more than 17 lakhs people were affected, 4833 livestock were lost, 185,556 houses were damaged, 196.68 km of road networks were destroyed, embankment breached at 50 points, and 162,340 cropping areas were damaged. The district has 24 permanent flood shelters and 172 rescue shelters. The blocks and municipalities-wise flood-prone areas of the district have been illustrated in Table 1.

2.2. Flood inventory map

The preparation of flood inventory map is necessary for the accuracy assessment of flood susceptibility zonation. The flood inventory map of the study area was generated from the thematic services of Bhuban Portal (https://bhuvan-app1.nrsc.gov.in/thematic/thematic/index.php) from the historical flood events during 1999–2010. The flooded and non-flooded areas were obtained using the web map service (WMS) tool.
in ArcMap. The study considered flood areas; those areas flooded at least one time during these 12 years, and other areas were considered as non-flood areas. The flood inventory map is incorporated with the study area map in Figure 1(c). A total of 350 flood points and 163 non-flood points have been identified for further analysis.

### 2.3. Selection of the thematic layers for flood risk zonation (FRZ)

The GIS-based MCDA technique has been adopted to study the flood risk zone of the Uttar Dinajpur district. The multi-criteria technique of the concerned study adopted the criteria in two broad categories, i.e., flood susceptibility parameters and flood vulnerability parameters. Twelve parameters have been selected to study the flood susceptibility, whereas nine parameters have been considered for flood vulnerability analysis, as stated below.
2.3.1. Flood susceptibility parameters (FSP)

Elevation directly relates to the flood; hence, it has been considered an important flood susceptibility parameter. The lower elevated lands are mostly susceptible to floods due to higher river discharge and waterlogging conditions. The probability of flood depends on the slope of that region; as the slope decreases, the occurrences of flooding increase (Das and Gupta 2021). It directly relates to the flow velocity, surface runoff, and infiltration capacity (Ali et al. 2020). The topographic wetness index (TWI) is considered an important topographic FSP; hence it is considered in this

Figure 1. Location map of the study area (a) India, (b) West Bengal and (c) Uttar Dinajpur district with flood and non-flood point.
It denotes the quantity of flow accumulation as well as the water is probably downward slope due to gravity (Vafakhah et al. 2020). It mostly represents the spatial soil moisture patterns of a floodplain region (Shahabi et al. 2020). Topographic positioning index (TPI) generally denotes the altitudinal variation of each cell to the average altitude of adjoining cells in a specific radius (Weiss 2001; De Reu 2013; Rahmati et al. 2019). It was first postulated by Guisan et al. (1999). As the microtopographic variation is crucial for different hydrological parameters, i.e., water retention, flow velocity, hence TPI is selected for the flood susceptibility studies (Rahmati et al. 2019). The region with vegetation cover is generally detected through the normalized difference vegetation index (NDVI) analysis (Ali et al. 2020). The region with negative NDVI value is highly susceptible to flooding, while the positive NDVI region is associated with fewer chances of flooding. Instead of NDWI, the modified normalized difference water index (MNDWI) is selected as a vital flood susceptibility parameter for this study. The MNDWI has appropriately detected the water bodies than the NDWI. Therefore, to identify the areas with low-lying lands, the parameter MNDWI is very much useful. Drainage density (Dd) is related to the peak flow of the stream of any area (Rahmati et al. 2019). It has a direct influence on the runoff and infiltration capacity. Hence, it bears a strong connection with flood susceptibility. The regions with high Dd are associated with high flood susceptible zone and vice-versa. The selected flood susceptibility parameter distance to river has a significant role in preparing flood susceptibility zones. Flooding is more prevalent in areas closest to rivers (i.e., the active floodplain regions) than farthest from rivers (Rahmati et al. 2019). The erosive power of the streams is basically manifested through the stream power index (SPI) (Vafakhah et al. 2020). It has effects on the flood damages (Pei et al. 2010) and is utilized to know favorable locations for the soil protection strategies (Mojaddadi et al. 2017). Sediment transport index (STI) has the relationship with the runoff and quantity of sediment that has been transported through the streams of any region (Burrough and McDonnell 1998; Rahmati et al. 2019). Generally, lower STI value is related to the highly flood susceptible lands. Rainfall is a crucial parameter for detecting flood susceptibility. High intensifying rainfall in a short duration caused higher chances of surface runoff as well as flooding for any region. The spatial distribution of rainfall intensity is shown through the modified fournier index (MFI). A greater MFI value is linked to places that are extremely susceptible to flooding (Costache 2019; Souissi et al. 2020). Lithology is strongly related to soil permeability and hence affects flooding. The differences in rock types have caused variations in surface hydrology (Miller et al. 1990). The areas with non-permeable lithological structures enhance the runoff and can increase the occurrence of flooding phenomena (Das 2020). Therefore, the local lithological structure is taken as an essential flood conditioning parameter.

### 2.3.2. Flood vulnerability parameters (FVP)

The population is taken as an important parameter to assess flood vulnerability. The environmental vulnerability is accelerated due to the increasing number of populations. In developing countries or third world countries, due to excess population pressure, hazards and disasters frequently happen. The population density of an area
has been considered another important parameter, particularly for understanding the pressure on the area of the concerned region. It has been observed that the extreme population density regions are more vulnerable to flooding and vice-versa (Roy et al. 2021). Land use is also considered an essential component that influences infiltration, runoff, and evapotranspiration (Samanta et al. 2018). Thus, LULC has directly affected the hydrological parameters of any region. Specifically, in urban areas, the natural hydrological cycle has been disrupted by changing land-use patterns (Mahmoud and Gan 2018). The accessibility of flood shelters and medical facilities, as well as their proximity to people’s residences, play an important role in assessing the vulnerability of inhabitants (Hoque et al. 2019). Every vulnerable individual’s quick access ability to flood shelters and medical facilities can significantly reduce hazards consequences. When there are victims, an appropriate amount of hospital

Figure 2. Schematic flowchart illustrating the susceptibility, vulnerability and risk zonation methodology.
beds and professionally skilled employees are needed for optimal hazard control (Roy et al. 2021). Roads are the artificial obstacle to flooding; hence it affects the vulnerability of the region (Sarkar and Mondal 2020). Here two parameters related to roads are considered, i.e., distance to road and road density. Education is one of the significant variables for studying vulnerability. A higher literate population is adopted more strategies to cope with flooding; hence, they can better deal with floods (Salazar-Briones et al. 2020). As the literacy rate, the employment rate is another essential parameter when considering the vulnerability of any region. The greater employment ratio represents the strong economic strength to cope with a physical vulnerability like floods, droughts, landslides, etc. Figure 2 manifests the methodological framework used to delineate susceptibility, vulnerability and risk zonation.

### 2.4. Data acquiring and preparation of thematic maps

For preparing the thematic layers of the FSP and FVP, firstly, data is obtained from different authenticated sources, and all layers are represented using ESRI ArcGIS (version 10.4.1). The SRTM DEM (30 m resolution) of USGS is utilized for preparing the elevation, TWI, TPI, SPI, and STI thematic layers. Drainage network has been extracted from SRTM DEM. Parallely, the satellite images of USGS are used to prepare the NDVI, MNDWI and LULC. All the satellite images were radiometrically corrected and then further used for different calculations. The rainfall intensity map prepared using the MFI from the rainfall data (1986–2020) of IMD and lithology

| Parameters | Descriptions | Source |
|------------|--------------|--------|
| Elevation, Slope, TWI, TPI, SPI, STI, Drainage density and Distance to river | Derived from ASTER DEM (30m*30m) and prepared the thematic layer using ArcGIS | United States Geological Survey (USGS) Retrieved from: https://earthexplorer.usgs.gov |
| NDVI, MNDWI and LULC | Using Landsat 8 OLI/TIRS (30m*30m), all the layers were prepared after mosaicing and atmospheric correction of the image | United States Geological Survey (USGS) Retrieved from: https://earthexplorer.usgs.gov |
| MFI | Gridded rainfall (0.25 × 0.25) NetCDF file for the period 1986-2020 used to calculate the MFI | India Meteorological Department (IMD) Retrieved from: https://www.imdpune.gov.in |
| Lithology | Digital lithological map of the district | Geological Survey of India (GSI) Retrieved from: https://bhukosh.gsi.gov.in/ |
| Distribution of population, Population density, Illiteracy rate and Employment rate | Obtaining the village-level data from Census of India, 2011 | Office of the Registrar General & Census Commissioner, India Retrieved from: https://censusindia.gov.in/ |
| Distance to flood shelter | Adopting the data from DDMPUD (2020-21) | District Disaster Management Plan of Uttar Dinajpur District (DDMPUD), 2020-2021. West Bengal. Retrieved from: http://wbdmd.gov.in/pages/district_dm_plan.aspx. |
| Distance to hospital, Distance to road and Road density | Adopting the data from OpenStreetMap | OpenStreetMap Retrieved from: www.openstreetmap.org |
layers was prepared from obtaining the data from Bhukosh GSI. On other side, after obtaining the village-level data from the DCHUD (2011), on vulnerability parameters, i.e., distribution of population, population density, illiteracy and employment rate, spatial layers were prepared for each parameter. The spatial layers distance to hospital, distance to road and road density arranged from the data of OpenStreetMap website. Lastly, distance to flood shelter layer is prepared by adopting the data from DDMPUD (2020–2021). Table 2 shows the source and description of the parameters used in the susceptibility and vulnerability zonation.

The TWI layer is prepared from SRTM DEM using the Eq. 1 (Beven and Kirkby 1979):

\[
TWI = \ln\left(\frac{a}{\tan B}\right)
\]

where \(a\) and \(B\) represents the specific catchment area and slope of the region, respectively. Furthermore, here \(a = \frac{A}{L}\), where, \(A\) describe the total basin area, and \(L\) describe the length of the contour (Beven and Kirkby 1979). The TPI map used for flood susceptibility analysis by employing Eqs. (2) and (3). The 'land facet corridor designer tool' was also employing in ArcGIS software to analyze the TPI (Jenness et al. 2013).

\[
TPI = z_0 - \bar{z}
\]

\[
\bar{z} = \frac{1}{n_R} \sum_{i \in R} Z_i
\]

MNDWI and NDVI both are calculated from the satellite image using the following Eqs. 4 and 5 (Xu 2006):

\[
mNDWI = \frac{\text{Green} - MIR}{\text{Green} + MIR},
\]

\[
NDVI = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}},
\]

where \(MIR\) represents a middle infra-red band, \(NIR\) represents near-infrared band, and \(RED\) depicts red band. Another susceptibility parameters, the STI is computed through the Eq. (6) and the SPI is derived using the Eq. (7) (Moore et al. 1991), as stated below:

\[
STI = \left[\left(\frac{F_x}{\partial x}\right)^2 + \left(\frac{\text{Sig} n(S_z)}{\partial y}\right)^2\right]^{1/2}
\]

\[
SPI = Ai \ast \tan \beta,
\]
represents the constant, $A_i$ represents the specific area, and $\tan \beta$ represents the gradient.

MFI also used by obtaining the value from the Eq. (8) (Costache 2019; Souissi et al. 2020):

$$MFI = \sum_{i=1}^{12} \frac{P_i^2}{P_i},$$  \hspace{1cm} (8)

where $P_i$ describe the mean monthly precipitation, and $P$ describes the mean annual precipitation. Distance to river, distance to flood shelter, distance to hospital and distance to road all the spatial layers are generated using the 'Euclidean distance' tool of ArcGIS. The drainage and road density map has been prepared in the ArcGIS platform utilizing the 'line density' tool. Through using GIS platform’s 'resample' tool, all raster thematic layers were converted to a 30 m resolution (Tables 3 and 4).

### 2.5. Multicollinearity analysis

Since the multicollinearity test had no negative impact on the model’s predictability and reliability, it was found to be a useful tool. In the case of flood susceptibility modeling, the multicollinearity test incorporates the recognition of a linear relationship among the variables (Al-Juaidi et al. 2018). Statistically, a high degree of correlation persists between two or more independent variables (Mukherjee and Singh 2020); therefore, it is used to identify specific strongly correlated independent variables. Several methods were applied to analyze the multicollinearity among different independent variables, and in this study, the variance inflation factor (VIF) method is used. The following formula was used to compute the VIF (Myers et al. 2010):

$$\text{Tolerance of the ith predictor variable } (T_i) = 1 - R_i^2$$  \hspace{1cm} (9)

$$\text{VIF of the ith predictor variable } (VIF_i) = \frac{1}{T_i}$$  \hspace{1cm} (10)

where $R_i^2$ depicts the coefficient of determination of the regression equation.

| SP  | E  | S  | TWI | TPI | NDVI | MNDWI | DD | DR | SPI | STI | RI | L |
|-----|----|----|-----|-----|------|--------|----|----|-----|-----|----|---|
| T   | 0.17 | 0.66 | 0.40 | 0.56 | 0.86 | 0.77 | 0.72 | 0.73 | 0.17 | 0.17 | 0.79 | 0.86 |
| VIF | 5.96 | 1.51 | 2.48 | 1.78 | 1.17 | 1.29 | 1.38 | 1.38 | 5.82 | 5.81 | 1.27 | 1.16 |

| VP  | P  | FP | PD  | CD  | LR  | ILR | DFS | DH  | LULC | ER  | RD  | DTR |
|-----|----|----|-----|-----|-----|-----|-----|-----|------|-----|-----|-----|
| T   | 0.31 | 0.01 | 0.32 | 0.12 | 0.12 | 0.91 | 0.89 | 0.96 | 0.82 | 0.49 | 0.67 |
| VIF | 3.22 | 91.15 | 3.17 | 75.97 | 8.57 | 8.19 | 1.10 | 1.12 | 1.05 | 1.22 | 2.06 | 1.49 |

SP, Susceptibility parameters; E, elevation; S, slope; TWI, Topographic Wetness Index; TPI, Topographic Position Index; NDVI, Normalized Difference Vegetation Index; MNDWI, Modified Normalized Water Index; DD, Drainage Density; DR, Distance to river; RI, Rainfall Intensity Index; SPI, Stream power Index; STI, Sediment Transport Index; L, Lithology; VP, Vulnerability parameters; P, Total population; FP, Female population; PD, Population density; CD, Child under 6 year; LR, Literacy rate; ILR, Illiteracy rate; DFS, Distance to flood shelter, DH, Distance to hospital, LULC, Land use and land cover, ER, Employment rate; RD, Road density; DTR, Distance to Road.
2.6. Weighting and ranking by AHP

The Analytical Hierarchy Process (AHP) method was introduced by T. L. Saaty in the late 1970s, which is globally mostly used MCDA model in the contemporary time for ranking decision alternative (Saaty 1987; Saaty 1990). It is generally used in terms of weighting or rating the components and their categories (Kumar and Anbalagan 2016), and it is an effective approach to solve complex problems (Souissi et al. 2020). In case of flood susceptibility mapping, this MCDA technique is globally used as its importance and relevance in contemporary issues. Hence, in the present study AHP method has been employed for integrating the selected thematic layers of flood susceptibility and vulnerability. The weight of each layer varies in respect of their influence to prepare the susceptibility and vulnerability mapping. In AHP, the relative weight of each class within the same thematic layer and thematic layers are also compared to each other through the pair-wise comparison matrices (Fenta et al. 2015). Therefore, using Saaty’s scale of preference between 1 and 9 (Table 5), and based on literature review, field knowledge, and studies in similar geographical regions, the relative weight of each layer has been determined. It is the basic and necessary step of this technique and is called the knowledge-driven technique (Mukherjee and Singh 2020). Table SM1 and SM4 in the electronic supplementary material (SM) depicted the pair-wise comparison matrices, whereas Table SM2 and SM5 in the electronic supplementary material (SM) show the normalized vector for the flood susceptibility and flood vulnerability thematic layers, respectively.

| Table 4. Collinearity diagnostics of flood susceptibility and vulnerability parameters. |
| --- |
| Dimension | Susceptibility | | Vulnerability | |
| | Eigenvalue | Condition Index | Eigenvalue | Condition Index |
| 1 | 7.45 | 1.00 | 7.50 | 1.00 |
| 2 | 1.92 | 1.97 | 2.66 | 1.68 |
| 3 | 1.08 | 2.62 | 0.71 | 3.26 |
| 4 | 0.55 | 3.70 | 0.30 | 5.04 |
| 5 | 0.44 | 4.14 | 0.28 | 5.16 |
| 6 | 0.18 | 6.37 | 0.19 | 6.32 |
| 7 | 0.13 | 7.50 | 0.17 | 6.57 |
| 8 | 0.09 | 9.08 | 0.11 | 8.45 |
| 9 | 0.08 | 9.71 | 0.05 | 11.71 |
| 10 | 0.06 | 11.52 | 0.03 | 16.09 |
| 11 | 0.02 | 21.96 | 0.01 | 36.27 |
| 12 | 0.01 | 33.72 | 0.00 | 77.09 |

| Table 5. Saaty’s scale of relative importance. |
| --- |
| Numerical value | Definition |
| 1 | Equal importance |
| 2 | Equal to moderate importance |
| 3 | Moderate importance |
| 4 | Moderate to strong importance |
| 5 | Strong importance |
| 6 | Strong to very strong importance |
| 7 | Very strong importance |
| 8 | Very to extremely strong importance |
| 9 | Extreme importance |
According to the AHP technique, a square matrix \( A = (a_{ij}) \) is constructed when \( n \) criteria (for both FSP and FVP) are to be compared. The condition (Eq. 11) given below, which is satisfied regarding every \( a_{ij} \) of the matrix component.

\[
a_{ij} = \frac{1}{a_{ji}} \tag{11}
\]

In the case of the reciprocal matrix, \( a_{ij} \) follow the equality, i.e., \( a_{ij} = \frac{P_i}{P_j} \); where, \( P_i \) represent the preference of the alternative \( i \), as described in below (Eq. 12):

\[
A = \begin{pmatrix}
P_1 & P_1 & \ldots & P_1 & \ldots \\
P_1 & P_j & \ldots & \frac{P_i}{P_n} & \ldots \\
\frac{P_j}{P_1} & 1 & \ldots & 1 & \frac{P_i}{P_n} \\
\frac{P_i}{P_n} & \ldots & P_n & \frac{P_i}{P_n} & \ldots \\
P_1 & \ldots & P_j & \frac{P_i}{P_n} & \ldots
\end{pmatrix} \tag{12}
\]

In the present study, twelve matrices were constructed for flood susceptibility thematic layers and nine matrices for flood vulnerability layers. The matrices have been computed for each class of any thematic layer to determine the AHP rating. To assign the weights or rating, the relative ratio scale is calculated from the pair-wise comparison reciprocal matrix of judgments employing the following equations:

i. Summation of all the components of \( j \) column in matrix \( A \):

\[
\frac{P_1}{P_j} + \ldots + \frac{P_i}{P_j} + \ldots + \frac{P_n}{P_j} = \frac{\sum_{i=1}^{n} P_i}{P_j} \tag{13}
\]

ii. Computation of normalized value by dividing the comparison, i.e., \( a_{ij} = \frac{P_i}{P_j} \) by Eq. (14):

\[
\frac{P_i}{P_j} = \frac{P_i}{\sum_{i=1}^{n} P_j} \times \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} P_i} = \frac{P_i}{\sum_{i=1}^{n} P_i} \tag{14}
\]

iii. Assigned weight or rating of \( i \) row \( (W_i) \), which is determined by computing the average of the components (Eq. 15):

\[
W_i = \left( \frac{P_i}{\sum_{i=1}^{n} P_i} + \cdots + \frac{P_i}{\sum_{i=1}^{n} P_i} \right) \times \frac{1}{n} \tag{15}
\]
2.7. Consistency checks

The consistency ratio (CR) is used to judge the pair-wise comparison for each parameter and their sub-categories. For computing the CR following equation has been adopted:

\[ CR = \frac{CI}{RCI}, \]  

where CR is the consistency index, CI is the consistency index, and RCI is the random consistency index. The RCI values are constant as described based on Saaty and Vargas (1991) in Table 6 for different n values and CI is computed as follows:

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

where, \( \lambda_{\text{max}} \) represents the principal or largest eigenvalue of the pair-wise comparison matrix. The \( \lambda_{\text{max}} \) is calculated using the Eq. (18):

\[ \lambda_{\text{max}} = \frac{\sum_{i=1}^{n} W_i \times \sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} P_i} \]  

If the CR value is \( \leq 0.1 \), then the AHP result is acceptable. But if it is \( > 0.1 \), then the result is not consistent with pursuing the assessment and needs to be revised the method (Tables 7 and 9). The computed CR for flood susceptibility and vulnerability have been illustrated in Tables 8 and 10, respectively.

2.8. Mapping of flood susceptibility and vulnerability zonation

The important task of the study is to prepare the flood susceptibility and vulnerability zonation. Based on the priority of the parameters, AHP weights were given for flood susceptibility and vulnerability parameters. Both the mapping has been performed using these weights. In the ArcGIS platform, the weighted sum method has been applied using the Spatial Analyst tool. Equations (19) and (20) for computing the FSZ and FVZ are as follows:

\[ \text{FSZ} = \sum_{i=1}^{n} W_i^S \times S_i^S \]  

where FSZ is the flood susceptibility zonation, \( W_i^S \) is the weights of susceptibility parameters, \( S_i^S \) is the weightage of susceptibility sub-parameters.

### Table 6. Random index (RI) to check consistency ratio for different matrix (Saaty and Vargas, 1991).

|   | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|----|----|----|
|   | 0.00 | 0.00 | 0.58 | 0.90 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 | 1.49 | 1.51 | 1.48 |
Table 7. Selected parameters of flood susceptibility of Uttar Dinajpur district.

| Parameters                  | AHP Weight | Reclass Class | Class range          | Flood level | Area in SQ km | Area in % | Rating |
|-----------------------------|------------|---------------|----------------------|-------------|---------------|-----------|--------|
| Elevation                   | 0.267      | 1             | −48 to 28            | Very high   | 492.77        | 15.79     | 0.416  |
|                            |            | 2             | 29–37                | High        | 1121.87       | 35.95     | 0.262  |
|                            |            | 3             | 38–48                | Medium      | 715.29        | 22.92     | 0.161  |
|                            |            | 4             | 49–64                | Low         | 348.20        | 11.16     | 0.099  |
|                            |            | 5             | 65–122               | Very low    | 442.89        | 14.19     | 0.062  |
| Slope                       | 0.192      | 1             | 0–2                  | Very high   | 1449.32       | 46.44     | 0.444  |
|                            |            | 2             | 2–8                  | High        | 1558.73       | 49.94     | 0.262  |
|                            |            | 3             | 8–15                 | Medium      | 105.93        | 3.39      | 0.153  |
|                            |            | 4             | 15–30                | Low         | 6.85          | 0.22      | 0.089  |
|                            |            | 5             | 30–55                | Very low    | 0.19          | 0.01      | 0.053  |
| TWI                         | 0.087      | 1             | −3.62 to −1.15       | Very high   | 2.68          | 0.09      | 0.489  |
|                            |            | 2             | −1.49 to 0.00        | High        | 1960.15       | 62.60     | 0.261  |
|                            |            | 3             | 0                    | Medium      | 78.84         | 2.52      | 0.138  |
|                            |            | 4             | 0 to 2.50            | Low         | 1065.00       | 34.01     | 0.073  |
|                            |            | 5             | 2.50 to 5.29         | Very low    | 24.66         | 0.79      | 0.038  |
| NDVI                        | 0.028      | 1             | −0.07 to 0.01        | Very high   | 18.67         | 0.60      | 0.416  |
|                            |            | 2             | 0.01–0.14            | High        | 1747.61       | 55.99     | 0.262  |
|                            |            | 3             | 0.15–0.18            | Medium      | 702.62        | 22.51     | 0.161  |
|                            |            | 4             | 0.19–0.27            | Low         | 579.14        | 18.55     | 0.099  |
|                            |            | 5             | 0.28–0.37            | Very low    | 73.19         | 2.34      | 0.062  |
| MNDWI                       | 0.063      | 1             | −0.62 to −0.25       | Very low    | 1245.09       | 39.89     | 0.056  |
|                            |            | 2             | −0.24 to −0.1        | Low         | 1202.90       | 38.54     | 0.096  |
|                            |            | 3             | −0.09 to 0.11        | Medium      | 264.18        | 8.46      | 0.157  |
|                            |            | 4             | 0.12–0.33            | High        | 224.64        | 7.20      | 0.257  |
|                            |            | 5             | 0.34–0.94            | Very high   | 184.41        | 5.91      | 0.434  |
| Drainage density (km/km²)   | 0.123      | 1             | 0.00–0.15            | Very low    | 532.29        | 17.05     | 0.050  |
|                            |            | 2             | 0.16–0.28            | Low         | 801.07        | 25.67     | 0.088  |
|                            |            | 3             | 0.29–0.40            | Medium      | 852.64        | 27.32     | 0.151  |
|                            |            | 4             | 0.41–0.54            | High        | 661.58        | 21.20     | 0.259  |
|                            |            | 5             | 0.55–0.96            | Very high   | 273.65        | 8.77      | 0.451  |
| Distance from river (km)    | 0.122      | 1             | 0–200                | Very high   | 435.92        | 13.97     | 0.503  |
|                            |            | 2             | 201–500              | High        | 614.38        | 19.68     | 0.260  |
|                            |            | 3             | 501–1000             | Medium      | 927.28        | 29.71     | 0.134  |
|                            |            | 4             | 1001–2000            | Low         | 1028.60       | 32.96     | 0.068  |
|                            |            | 5             | 2001–3598            | Very low    | 115.04        | 3.69      | 0.035  |
| SPI                         | 0.015      | 1             | 0–0.01               | Very high   | 1298.05       | 41.59     | 0.503  |
|                            |            | 2             | 0.02–0.996           | High        | 1635.06       | 52.39     | 0.260  |
|                            |            | 3             | 99.66–193.3          | Medium      | 55.99         | 1.79      | 0.134  |
|                            |            | 4             | 193.31–498.25        | Low         | 51.63         | 1.65      | 0.068  |
|                            |            | 5             | 498.26–3262072.5     | Very low    | 80.29         | 2.57      | 0.035  |
| STI                         | 0.015      | 1             | 0–0.01               | Very high   | 1682.23       | 53.90     | 0.503  |
|                            |            | 2             | 0.02–3.69            | High        | 1122.99       | 35.98     | 0.260  |
|                            |            | 3             | 3.7–11.07            | Medium      | 223.42        | 7.16      | 0.134  |
|                            |            | 4             | 11.08–22.14          | Low         | 45.59         | 1.46      | 0.068  |
|                            |            | 5             | 22.15–16486.46       | Very low    | 46.79         | 1.50      | 0.035  |
| MFI (mm/year)               | 0.044      | 1             | 266–334              | Very low    | 1481.14       | 47.45     | 0.053  |
|                            |            | 2             | 335–402              | Low         | 426.48        | 13.66     | 0.089  |
|                            |            | 3             | 403–469              | Medium      | 510.75        | 16.36     | 0.153  |
|                            |            | 4             | 470–537              | High        | 331.14        | 10.61     | 0.262  |
|                            |            | 5             | 538–605              | Very high   | 371.72        | 11.91     | 0.444  |
| Lithology                   | 0.028      | 1             | Brown and Yellowish Color Highly Oxidized (Q1oad1) | Low | 1.37 | 0.04 | 0.070 |
|                            |            | 2             | Feebly Oxidized Sand, Silt and Clay (Q2najl) | Very high | 240.93 | 7.72 | 0.501 |
|                            |            | 3             | Sand, Silt and Gravel (Q2naml) | Medium | 487.51 | 15.62 | 0.159 |
|                            |            | 4             | Sand, Silt and Clay (Q2napr) | Very low | 1704.88 | 54.62 | 0.035 |
|                            |            | 5             | Sand, Silt, Clay with Calcareous Concretions (Q2oab1) | High | 686.54 | 22.00 | 0.235 |
Table 8. Consistency check of aggregated for flood susceptibility assessment in the Uttar Dinajpur district.

| Lambda max | N  | CI  | CR  |
|------------|----|-----|-----|
| 13.261     | 12 | 0.115 | 0.077 |

Table 9. Selected parameters of flood vulnerability of Uttar Dinajpur.

| Parameters                | AHP Weight | Class | Range          | Flood level | Area in SQ km | Area in % | Rating |
|---------------------------|------------|-------|----------------|-------------|---------------|----------|--------|
| Total Population          | 0.235      | 1     | 0              | Very low    | 10.62         | 0.34     | 0.044  |
|                           |            | 2     | 1–2000         | Low         | 1400.00       | 44.85    | 0.084  |
|                           |            | 3     | 2000–4000      | Moderate    | 882.16        | 28.26    | 0.148  |
|                           |            | 4     | 4000–10000     | High        | 576.87        | 18.48    | 0.256  |
|                           |            | 5     | >10000         | Very high   | 251.57        | 8.06     | 0.467  |
| Population density       | 0.235      | 1     | 0              | Very low    | 10.62         | 378.12   | 0.044  |
|                           |            | 2     | 1–500          | Low         | 652.16        | 23215.81 | 0.084  |
|                           |            | 3     | 500–1000       | Moderate    | 1667.85       | 59373.21 | 0.148  |
|                           |            | 4     | 1000–2000      | High        | 680.12        | 24211.38 | 0.256  |
|                           |            | 5     | >2000          | Very high   | 110.47        | 3932.59  | 0.467  |
| Illiteracy rate           | 0.038      | 1     | 0              | Very low    | 10.62         | 0.34     | 0.035  |
|                           |            | 2     | 1–20           | Low         | 0.85          | 0.03     | 0.068  |
|                           |            | 3     | 20–40          | Moderate    | 359.93        | 11.53    | 0.134  |
|                           |            | 4     | 40–60          | High        | 1865.21       | 59.76    | 0.260  |
|                           |            | 5     | 60–96          | Very high   | 884.61        | 28.34    | 0.503  |
| Distance to flood shelter (m) | 0.096     | 1     | 0–1000         | Very low    | 287.57        | 9.21     | 0.048  |
|                           |            | 2     | 1000–2000      | Low         | 729.24        | 23.36    | 0.085  |
|                           |            | 3     | 2000–3000      | Moderate    | 841.83        | 26.97    | 0.148  |
|                           |            | 4     | 3000–5000      | High        | 989.96        | 31.72    | 0.234  |
|                           |            | 5     | 5000–14603     | Very high   | 272.63        | 8.73     | 0.485  |
| Distance to hospital (m)  | 0.096      | 1     | 0–2000         | Very low    | 272.77        | 8.74     | 0.049  |
|                           |            | 2     | 2000–5000      | Low         | 1019.98       | 32.68    | 0.082  |
|                           |            | 3     | 5000–8000      | Moderate    | 939.45        | 30.10    | 0.149  |
|                           |            | 4     | 8000–10000     | High        | 393.27        | 12.60    | 0.267  |
|                           |            | 5     | 10000–19894    | Very high   | 495.75        | 15.88    | 0.454  |
| LULC                      | 0.153      | 1     | Water body     | Very low    | 63.68         | 2.04     | 0.035  |
|                           |            | 2     | Vegetation Cover| Moderate    | 199.17        | 6.38     | 0.134  |
|                           |            | 3     | Agricultural area| High       | 2136.73       | 68.46    | 0.260  |
|                           |            | 4     | Bare ground    | Low         | 53.35         | 1.71     | 0.068  |
|                           |            | 5     | Built-up area  | Very high   | 668.23        | 21.41    | 0.503  |
| Employment rate (%)       | 0.027      | 1     | 0              | Very high   | 10.62         | 0.34     | 0.467  |
|                           |            | 2     | 1–40           | High        | 2152.72       | 68.97    | 0.256  |
|                           |            | 3     | 40–50          | Moderate    | 710.58        | 22.77    | 0.148  |
|                           |            | 4     | 50–60          | Low         | 212.03        | 6.79     | 0.084  |
|                           |            | 5     | 60–85          | Very low    | 35.27         | 1.13     | 0.044  |
| Road density              | 0.060      | 1     | 0–0.34         | Very high   | 1739.63       | 55.74    | 0.426  |
|                           |            | 2     | 0.35–1.01      | High        | 1025.92       | 32.87    | 0.259  |
|                           |            | 3     | 1.01–1.96      | Moderate    | 240.77        | 7.71     | 0.159  |
|                           |            | 4     | 1.97–3.51      | Low         | 89.24         | 2.86     | 0.097  |
|                           |            | 5     | 3.52–6.58      | Very low    | 25.67         | 0.82     | 0.059  |
| Distance to road (m)      | 0.060      | 1     | 0–500          | Very low    | 1022.68       | 32.77    | 0.056  |
|                           |            | 2     | 500–1000       | Low         | 575.01        | 18.42    | 0.096  |
|                           |            | 3     | 1000–1500      | Moderate    | 423.30        | 13.56    | 0.157  |
|                           |            | 4     | 1500–2000      | High        | 330.26        | 10.58    | 0.257  |
|                           |            | 5     | 2000–8234      | Very high   | 769.96        | 24.67    | 0.434  |

Table 10. Consistency check of aggregated for flood vulnerability assessment in the Uttar Dinajpur district.

| Lambda max | N  | CI  | CR  |
|------------|----|-----|-----|
| 9.172      | 9  | 0.022 | 0.015 |
\[ FVZ = \sum_{i=1}^{n} W_i^V \times S_i^V \] 

(20)

where FVZ is the flood vulnerability zonation, \( W_i^V \) is the weights of vulnerability parameters, \( S_i^V \) is the weightage of vulnerability sub-parameters. Based on flood susceptibility and vulnerability, zones were categorized into five classes, i.e., very low, low, moderate, high, and very high.

2.9. Mapping of flood risk zonation

The main task of the research is the modelling of the flood risk zonation. For this, flood susceptibility zonation (FSZ) and flood vulnerability zonation (FVZ) maps were multiplied using the Equation (21) below:

\[ FRZ = FSZ \times FVZ \] 

(21)

where FRZ is the flood risk zonation, FSZ is the flood susceptibility zonation and FVZ is the flood vulnerability zonation. The final output of the flood risk zonation map is also divided five zones, i.e., very low, low, moderate, high and very high risk zones.

2.10. Evaluation of the AHP method

In the APH technique, the significant flaw is the computation of weight. Hence implication of sensitivity analysis is required to validate the assigned weightages for AHP. In this case study, the adopted sensitivity analysis techniques are: Stillwell ranking methods, single parameter sensitivity, and map removal sensitivity analysis.

2.10.1. Stillwell ranking methods

The Stillwell ranking methods two functions, i.e., rank sum weight and reciprocal rank have been used for comparison with AHP method. The rank sum weight \( W_i(RS) \) and reciprocal rank weight \( W_i(RR) \) using the Eqs. (22) and (23) (Stillwell 1981):

\[ W_i(RS) = (n - R_j + 1) / \sum_{k=1}^{n} (n - R_k + 1) \] 

(22)

\[ W_i(RR) = \frac{1}{\frac{1}{R_j}} / \sum_{k=1}^{n} \left( \frac{1}{R_k} \right) \] 

(23)

where \( W_i \) is the normalized weight of each attribute, \( n \) is the number of attributes, the attributes are ranked in ascending order, \( R_j \) is the direct rank of each attribute, then each weight normalized by \( \sum_{k=1}^{n} (n - R_k + 1) \).
2.10.2. Single parameter sensitivity analysis
This type of sensitivity analysis is adopted for examining the effectiveness of every thematic layer upon the FSZ and FVZ maps. This approach is utilized for distinguishing between the actual or effective weight and empirical weights assigned for every thematic layer in FSZ and FVZ maps (Fenta et al. 2015; Mukherjee and Singh 2020). The effective weighting factor for FSZ and FVZ maps is calculated using the Eqs. (24) and (25), respectively.

\[
W_{\text{FSZ}} = \frac{P_rP_w}{\text{FSZ}} \times 100
\]  
\[
W_{\text{FVZ}} = \frac{P_rP_w}{\text{FVZ}} \times 100
\]

Where \(W\) represents effective weight, \(P_r\) and \(P_w\) represents rate and weight value of every layer, FSZ represents flood susceptibility zonation, and FVZ represents flood vulnerability zonation.

2.10.3. Map removal sensitivity analysis
Another important sensitivity analysis is map removal sensitivity analysis, which is designed to investigate the consequences of eliminating any of the thematic layers used in the FSZ and FVZ maps generation. Using this approach, every thematic layer is erased and new FSZ and FVZ maps are constructed in every time through overlay analysis technique of remaining layers (Fenta et al. 2015; Mukherjee and Singh 2020). Here, sensitivity index is computed in every time using the Eqs. (26) and (27).

\[
SI_{\text{FSZ}} = \left| \frac{\left( \frac{\text{FSZ}}{N} \right) - \left( \frac{\text{FSZ}'}{n} \right) }{\text{FSZ}} \right| \times 100
\]  
\[
SI_{\text{FVZ}} = \left| \frac{\left( \frac{\text{FVZ}}{N} \right) - \left( \frac{\text{FVZ}'}{n} \right) }{\text{FVZ}} \right| \times 100
\]

Where SI depicted the sensitivity index associated with an excluded thematic layer, FSZ and FVZ depicted the flood susceptibility zonation and flood vulnerability zonation of all thematic layers, \(\text{FSZ}'\) and \(\text{FVZ}'\) depicted the flood susceptibility zonation and flood vulnerability zonation of one excluded thematic layer, \(N\) depicted the no of thematic layers of FSZ and FVZ maps, and \(n\) depicted the no of thematic layers of \(\text{FSZ}'\) and \(\text{FVZ}'\) maps.

2.11. Accuracy assessment of the model
Data validation is one of the most critical steps in ensuring the accuracy of any model after it has been developed; however, there are various ways for validating MCDA models. In this study, ROC-AUC, MAE, MSE and RMSE have been used to verify the FSZ map (Nachappa et al. 2020; Afolayan et al. 2020; Mitra and Roy 2022; Yaseen et al. 2022). ROC-AUC depicts the trade-off between specificity and sensitivity
In the two-dimensional ROC graph, the $x$-axis depicts 1-specificity (false positive rate) and the $y$-axis representing sensitivity (true positive rate) (Arabameri et al. 2019; Ali et al. 2020). Eq. 28 and 29 express the attributes of $x$ and $y$-axis, where TN represents true negative, FP represents false positive, TP represents true positive, and FN represents false negative (Swets 1988):

$$x = 1 - \text{specificity} = 1 - \left[ \frac{\text{TN}}{\text{TN} + \text{FP}} \right]$$

$$y = \text{sensitivity} = \left[ \frac{\text{TN}}{\text{TP} + \text{FN}} \right]$$

AUC (i.e., area under the ROC curve) was applied to quantitatively determine the performance of the AHP technique in the study region (Nguyen et al. 2021; Saha et al. 2021). The prepared FSZ model was verified against the flood point and non-flood point data of the district. Furthermore, MAE, MSE, and RMSE have been employed to identify the prediction accuracy. In all cases, the smaller value of MAE, MSE, and RMSE represents better the model fitness. The following equations were used for computing the MAE, MSE, and RMSE:

$$\text{MAE} = \frac{\sum_{i=1}^{n}|X_i - Y_i|}{n}$$

$$\text{MSE} = \frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{n}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{n}}$$

where $X_i$ is the observed value, $Y_i$ is the predicted value, $n$ is the number of data points.

### 3. Results

#### 3.1. Multicollinearity results

In the present study, 1000 random points were considered for both susceptibility and vulnerability parameters during the multicollinearity assessment. Collinearity statistics of the selected 12 flood susceptibility parameters revealed there has no existence of multicollinearity problem. The VIF and tolerance value for all susceptibility parameters is <10 and >.1, respectively (Table 3). The eigenvalue and condition index of all dimensions regarding susceptibility also depicts there has no multicollinearity. The only one predictor (i.e., MFI for dimension 12) in the variance proportion table
manifests a high value (> .90), which does not persist the multicollinearity, as shown in Table 4.

In the case of vulnerability parameters, a high correlation has persisted in the parameters 'female population' and 'child under 6 years'. The collinearity statistics stated that both parameters exhibit VIF, and tolerance value is >10 and <.1 (Table 3). The eigenvalue of dimensions 10 and 11 exist close to 0, which indicates multicollinearity. The observed condition index for both dimensions is above 15 and has variance proportions >.90 in more than one predictor (Table 4). Therefore, one strongly correlated parameter should be removed from two (i.e., 'female population' and 'child under 6 years') to overcome this collinearity problem.

3.2. Framework of the thematic layers

3.2.1. Flood susceptibility layers

In the present study area, the elevation ranges between -48 to 122 m. Based on elevation sub-classes, the maximum extent of the district is covered with high flood level category (15.79%), followed by medium (22.92%), very high (15.79%), very low (14.19%), and low (11.16%), as described in Table 7. The lower elevated lands are situated in the southern and south-eastern parts of the district (specifically Itahar, extreme southern portion of Karandighi) (Figure 3a). Elevation assigned 27% in AHP weight, and higher ratings were allocated to the elevation classes with lower ranges. Table SM3 in electronic supplementary material shows the corresponding rating, \( \lambda_{\text{max}} \), CI, and CR values for different elevation classes.

The slope of the district varies from 0° to 55° (Figure 3b), and it is prioritarily weighted (19%) in the AHP model. To prepare the flood susceptibility zonation flat (0°–2°), gentle (2°–8°), moderate (8°–15°), moderately steep (15°–30°), and steep (30°–55°) terrains are classified as the very high, high, medium, low, very low flood level category. According to the sloping category, most of the area (>96%) falls under high to very high flood level; hence the study area is considered highly susceptible to flood. Table SM3 in electronic supplementary material depicts the pair-wise comparison matrix of sub-criteria slope for flood susceptibility zonation.

The TWI values of the Uttar Dinajpur district vary from 3.62 to 25.13, which are further classified into five categories as illustrated in Figure 3(c). TWI has the positive relationship with flooding; hence, for rating, higher values are put for the higher TWI values and lower to the lower TWI values. Table SM3 in electronic supplementary material depicts the pair-wise comparison matrix of sub-criteria TWI for flood susceptibility zonation.

TPI of the study area ranges from -3.15 to 5.29 (Figure 3d). Mainly, flooding is associated with negative and zero TPI areas, as the negative TPI areas are the valleys, and zero TPI areas are the flat areas or constant sloping lands (Weiss 2001). Therefore, the higher rating is allocated to the low TPI sub-classes and vice versa. Table SM3 in electronic supplementary material shows the corresponding rating, \( \lambda_{\text{max}} \), CI, and CR values for different TPI classes.

The NDVI values of the district varied from -0.07 to 0.37, as depicted in Figure 3(e). The negative value of NDVI manifested the chances of flooding. As the overall
Figure 3. Selected flood susceptibility parameters of the Uttar Dinajpur district: (a) Elevation, (b) Slope, (c) Topographical wetness index (TWI), (d) Topographical positioning index (TPI), (e) Normalized difference vegetation index (NDVI), (f) Modified normalized difference water index (MNDWI), (g) Drainage density, (h) Distance to river, (i) Stream power index (SPI), (j) Sediment transport index (STI), (k) Modified fournier index (MFI) and (l) Lithology.
Figure 3. (Continued)
Figure 4. Selected flood vulnerability parameters of the Uttar Dinajpur district: (a) Distribution of population, (b) Population density, (c) Land use land cover (LULC), (d) Distance to flood shelter, (e) Distance to hospital, (f) Distance to road, (g) Road density, (h) Illiteracy rate (%) and (i) Employment rate.
NDVI value of the district is low, hence here probability of flooding is high. Higher weights were allocated to lower NDVI sub-classes areas and vice versa. Table SM3 in electronic supplementary material shows the corresponding rating, $\lambda_{\text{max}}$, CI, and CR values for different NDVI classes.

The MNDWI parameter has the positive relationship with flooding. In the district, it ranges from $-0.62$ to $0.94$ (Figure 3f). The higher rating is assigned for the high MNDWI sub-class and vice versa. Table SM3 in electronic supplementary material shows the corresponding rating, $\lambda_{\text{max}}$, CI, and CR values for different MNDWI classes.

The drainage density of the region varies from 0 to 0.96 km/km$^2$ (Figure 3g). Because higher drainage density indicates high runoff, the study provided higher drainage density areas with higher weight and vice versa. Drainage density values are observed high at the Mahananda, Kulik, Tangan, Srimati, Nagar, Gamari River basins. Table SM3 in electronic supplementary material shows the corresponding rating, $\lambda_{\text{max}}$, CI, and CR values for different drainage density classes.

The parameter distance to river is classified into five sub-classes, as depicted in Figure 3(h). The areas with the shortest distance to river primarily have a higher probability of flooding. Therefore, higher weights were assigned to lower sub-classes. Table SM3 in electronic supplementary material shows the corresponding rating, $\lambda_{\text{max}}$, CI, and CR values for different distance to river classes.

SPI values of the district ranged between 0 and $3262072.5$ (Figure 3i). Higher weights were allocated to lower SPI values and vice versa. Basically, lower SPI regions
are associated with flooding due to water flow being in a slow movement or stagnant condition. Table SM3 in electronic supplementary material shows the corresponding rating, $\lambda_{\text{max}}$, CI, and CR values for different SPI classes.

STI values vary from 0 to 16486.46, as illustrated in Figure 3(j). It is also grouped into five sub-categories based on flood level. Lower rating is assigned to the lower sediment transportation region and vice versa. Table SM3 in electronic supplementary material shows the corresponding rating, $\lambda_{\text{max}}$, CI, and CR values for different STI classes.

MFI is depicted to show the rainfall intensity of the district in Figure 3(k). As higher MFI values region has associated with very high flooding areas, hence higher rating is given to the higher classes. In this district, MFI varies from 266 to 605 mm/year. Table SM3 in electronic supplementary material shows the corresponding rating, $\lambda_{\text{max}}$, CI, and CR values for different MFI classes.

The lithological map of the district is shown in Figure 3(l). It is classified into five distinctive zones based on GSI. The very high flood hazard class is associated with feebly oxidized sand, silt and clay (Q2najl) class, while high flood hazard class is with sand, silt, clay with calcareous concretions (Q12oab1), medium flood hazard class is with sand, silt and gravel (Q2naml), low flood hazard class are with brown and yellowish color highly oxidized (Q1oad1), and very low flood hazard class is with sand, silt and clay (Q2napr). Table SM3 in electronic supplementary material shows the corresponding rating, $\lambda_{\text{max}}$, CI, and CR values for different lithology classes.

### 3.2.2. Flood vulnerability layers (FVL)

In terms of nine selected flood vulnerability parameters, the framework of the FVL has been assigned in the present study, which has been stated in detail in Table 9. The total population of the district is 3007134 (2011 census). The distribution of population map is produced using the village-wise population data of the district and found that it ranges from 0 to 430221, as depicted in Figure 4(a). For rating, maximum weightage is given to higher classes and vice versa. Table SM6 in electronic supplementary material shows the corresponding rating, $\lambda_{\text{max}}$, CI, and CR values for different distribution of population classes.

The vulnerability of flooding is also high in very high population density regions; hence higher weightage was assigned to higher population density sub-classes and vice versa. The village-wise population density of the district ranges from 0 to 2000 (Figure 4b). Table SM6 in electronic supplementary material shows the corresponding rating, $\lambda_{\text{max}}$, CI, and CR values for different population density classes.

LULC of the region is shown in five categories, i.e., water body (2.04%), vegetation cover (6.38%), agricultural area (68.46%), bare ground (1.71%), and built-up area (21.41%). The agricultural area largely occupies the Uttar Dinajpur district. Table SM6 in electronic supplementary material shows the corresponding rating, $\lambda_{\text{max}}$, CI, and CR values for different LULC classes.

Based on the distance to flood shelter, five zones are identified in the district, as manifested in Figure 4(d). The highest weights were allocated to the zones of maximum distance to flood shelter and vice versa. Table SM6 in electronic supplementary
material shows the corresponding rating, $\lambda_{\text{max}}$, CI, and CR values for different distance to flood shelter classes.

The distance to hospital map is represented in Figure 4(e) with five sub-classes. In terms of vulnerability, the maximum rating is given to the sub-classes having the longest distance to the hospital and vice versa. Table SM6 in electronic supplementary material shows the corresponding rating, $\lambda_{\text{max}}$, CI, and CR values for different distance to hospital classes.

According to the distance to road map, the highest weights were assigned to the classes having maximum distance to road and vice versa. Table SM6 in electronic supplementary material depicts the pair-wise comparison matrix of sub-criteria distance to road for flood vulnerability zonation.

The road density map is demonstrated in five sub-classes in Figure 4(g). It ranges from 0–0.34 (very low) to 3.52–6.58 (very high). The highest weights are allocated to lower classes and vice versa. The Uttar Dinajpur district has the least literacy rate compared to the other North Bengal districts. Table SM6 in electronic supplementary material depicts the pair-wise comparison matrix of sub-criteria road density for flood vulnerability zonation.

The literacy rate of the district was 59.10 in 2011, whereas the state has 76.30. It is slightly increased (11.20) from 2001 (47.90). The literacy rate of the rural area is 56, and the urban area was 80.30 in 2011; hence there is huge disparity observed in the district. The village-wise Illiteracy map is represented in Figure 4(h), where the
highest weights were allocated to the classes with higher illiteracy. The illiteracy rate ranges from 0 to 96%. Table SM6 in electronic supplementary material depicts the pair-wise comparison matrix of sub-criteria literacy rate for flood vulnerability zonation.

Lastly, the village-wise employment rate map is demonstrated of the district in Figure 4(i). In 2011, the percentage of total workers of the district was 35.80, while the state had 38.10. The highest weights were assigned to the lower sub-classes. Table SM6 in electronic supplementary material shows the corresponding rating, $k_{max}$, CI, and CR values for different employment rate classes.

### 3.3. AHP model outputs

#### 3.3.1. Flood susceptibility zonation (FSZ)

Before performing the model, the CR of each thematic layer and their sub-classes were computed, and observed that judgment matrices achieved satisfactory level ($<0.10$) in terms of consistency. Hence, twelve reclassified layers of flood susceptibility parameters have been integrated in the ArcGIS platform using their assigned weights. Therefore, the final FSZ map has been produced for the district by adopting the ‘weighted overlay method’. Based on pixel values, the Uttar Dinajpur district has been classified into five flood susceptibility classes, i.e., very low, low, medium, high, and very high (Figure 5a) (Table 11). The percentage-wise distribution of susceptibility classes manifested through the natural break, geometrical interval, quantile, and equal interval method (Figure 12a). Maximum areal coverage of very high and high flood susceptibility classes have been generated in the quantile deviation technique, whereas maximum medium and low classes were generated in the equal interval, and very low class were generated in the geometrical interval method. In this research, for the generation of the FSZ map of the district, the highest weight was allocated to elevation (27%), followed by the slope (19%), drainage density (12%), distance from river (12%), TWI (9%), MNDWI (6%), MFI (4%), NDVI (3%), lithology (3%), TPI (2%), SPI (2%) and STI (2%). In this floodplain region, floods have generally occurred along the riverside area; hence, the very high and high flood susceptibility classes are noticed along the rivers and their adjoining area. In association, the lower elevation, gentle slope, higher drainage density, TWI, and MNDWI were the flood conditioning indicators that help to produce the high to very high flood susceptible zones. In terms of susceptibility, Itahar, Kaliaganj, part of Hemtabad, Raiganj, Karandighi, Goalpokhar-II, and Islampur were highly susceptible to floods.

| Level         | FSZ Area in sq. km | FSZ Area in % | FVZ Area in sq. km | FVZ Area in % | FRZ Area in sq. km | FRZ Area in % |
|---------------|--------------------|---------------|--------------------|---------------|--------------------|---------------|
| Very low      | 571.97             | 18.39         | 602.91             | 19.36         | 614.44             | 19.76         |
| Low           | 885.13             | 28.46         | 964.20             | 30.96         | 1025.77            | 32.99         |
| Medium        | 846.64             | 27.22         | 843.21             | 27.08         | 840.78             | 27.04         |
| High          | 570.87             | 18.35         | 511.30             | 16.42         | 485.58             | 15.62         |
| Very high     | 235.56             | 7.57          | 192.38             | 6.18          | 142.77             | 4.59          |
| Total Area    | 3110.16            | 100.00        | 3114.01            | 100.00        | 3109.34            | 100.00        |

2210 R. MITRA ET AL.
3.3.2. Flood vulnerability zonation (FVZ)

Using the similar method adopted to produce the FSZ map, the FVZ map is generated in ArcGIS. Five vulnerability sub-classes have been assigned for the district, i.e., very low, low, medium, high, and very high (Figure 5b). In Figure 12(b), percentage-wise sharing of several vulnerability classes has been depicted using different methods. Very high and high flood vulnerability classes were observed highest in the quantile deviation technique, while medium and low classes were represented in the equal interval, and very low class were represented in the geometrical interval method. Among the nine parameters, five parameters (distribution of population, population density, LULC, distance to flood shelter, distance to hospital) contributes more than 80% to produce the FVZ map. High to very high flood vulnerability zones are found in the region having high population, population density, high built-up area, and agricultural areas besides the river. These zones are prominent in the central and northern portions of the district. Low to very low vulnerable zones are subsequently associated near the hospitals, flood shelters, major roads, and high road density prone regions. In terms of literacy rate, the district is very poor in the state, which enhances the vulnerability of the region. The Karandighi, Goalpokhar-II, Goalpokhar-I, Islampur, and Chopra blocks were found maximum area fall in high to very high vulnerability, whereas maximum parts of Raiganj, Hemtabad, Kaliaganj, and Itahar were less vulnerable.

3.3.3. Flood risk zonation (FRZ)

The final outcome of the study is the construction of the flood risk zonation (FRZ) map by integrating the FSZ and FVZ maps. Hence the produced FRZ map has been classified into five zones, i.e., very low, low, medium, high, and very high, as depicted in Figure 5(c). In the Uttar Dinajpur district, the high and very high flood risk zones covered 15.62 and 4.59% area, respectively. The very low, low, and moderate flood risk classes were observed in 19.76, 32.99, and 27.04% area. The high and very high risk-prone areas are found frequently in all the blocks of the district. However, the most risk-prone areas are fall in the Goalpokhar-II, Raiganj, Karandighi, and Itahar blocks, whereas Chopra, Islampur, Goalpokhar-I, parts of Raiganj and Hemtabad
blocks are least risk-prone. The high risk-prone areas are mainly dominated by low elevation (<37 m), high TWI (13.75–25.13), low NDVI (<0.14), high MNDWI (0.12–0.94), high drainage density, high population density, low employment rate, high illiteracy rate, higher distance from flood shelters and hospitals. Therefore, the higher risk areas are very much susceptible and vulnerable to floods regarding the existing physical environment and demographic, economic, and infrastructural characteristics.

### 3.4. Sensitivity analysis of the AHP method

The sensitivity analysis has been applied in this study to comprehend the significant thematic layers of the acquired FSZs and FVZs and the impact of the allocated rank and weights on every class and thematic layer (Mukherjee and Singh 2020). As a corollary, it also revealed which map(s) is (are) most or least important in deciding the output map’s values (Fenta et al. 2015).

#### 3.4.1. Stillwell ranking methods

Tables 12 and 13 depicted the comparison of weightage between Saaty (1980) and Stillwell (1981) for FSZ and FVZ. The output shows no substantial variations of the criteria ranking; even the weights were modified through Stillwell techniques for both FSZ and FVZ.

#### 3.4.2. Single parameter sensitivity analysis

In the case of susceptibility analysis, the parameter elevation gets the highest empirical weight (27%), but through the statistical output, it gets mean effective weight of 26.47% (Table 14). The slope represents the highest mean effective weight (30.65%), whereas it gets the empirical weight of 19%, hence maximum deviation has been observed. Lithology and TPI exhibit the lowest mean effective weight, i.e., 1.81% and 1.86%, respectively. The mean effective weights and empirical weights are more or less similar for the elevation, NDVI, SPI, and STI. Figure 6 represents the map of effective weight (W) of 12 flood susceptibility parameters.

In vulnerability analysis, maximum weights (23.5%) were assigned into two parameters, i.e., distribution of population and population density. The statistical result of
Table 14. Descriptive Statistics of single parameter sensitivity analysis of flood susceptibility.

| Thematic layers                  | Empirical weight (%) | Min   | Max   | Mean  | SD    |
|----------------------------------|----------------------|-------|-------|-------|-------|
| Elevation                        | 27                   | 5.04  | 69.35 | 26.47 | 10.77 |
| Slope                            | 19                   | 3.69  | 60.44 | 30.65 | 7.27  |
| TWI                              | 9                    | 1.25  | 30.27 | 5.32  | 3.63  |
| TPI                              | 2                    | 0.20  | 9.12  | 1.86  | 0.91  |
| NDVI                             | 3                    | 0.48  | 13.01 | 3.03  | 1.27  |
| MNDWI                            | 6                    | 0.85  | 23.67 | 3.22  | 2.27  |
| Drainage density (km/ km²)       | 12                   | 1.69  | 39.79 | 9.41  | 5.65  |
| Distance from river (km)         | 12                   | 1.37  | 47.63 | 10.12 | 6.95  |
| SPI                              | 2                    | 0.13  | 9.42  | 2.66  | 1.35  |
| STI                              | 2                    | 0.13  | 9.42  | 2.81  | 1.31  |
| MFI                              | 4                    | 0.56  | 22.03 | 3.31  | 3.34  |
| Lithology                        | 3                    | 0.24  | 13.61 | 1.81  | 1.86  |

Figure 6. Effective weight (W) of flood susceptibility parameters.

Table 15. Descriptive statistics of single parameter sensitivity analysis of flood vulnerability.

| Thematic layers                  | Empirical weight (%) | Min   | Max   | Mean  | SD    |
|----------------------------------|----------------------|-------|-------|-------|-------|
| Total population                 | 23.5                 | 4.33  | 65.39 | 18.17 | 8.79  |
| Population density (persons/km²) | 23.5                 | 4.50  | 64.03 | 19.29 | 6.93  |
| LULC                             | 15.3                 | 1.65  | 53.70 | 21.56 | 7.75  |
| Distance to flood shelter        | 9.6                  | 1.24  | 46.82 | 8.82  | 5.34  |
| Distance to hospital             | 9.6                  | 1.34  | 37.52 | 8.70  | 5.98  |
| Distance to road                 | 6                    | 0.80  | 21.25 | 5.59  | 4.33  |
| Road density                     | 6                    | 1.01  | 27.23 | 10.10 | 3.52  |
| Illiteracy rate                  | 3.8                  | 0.56  | 20.17 | 6.18  | 2.52  |
| Employment rate                  | 2.7                  | 0.41  | 18.69 | 3.28  | 1.21  |
each parameter sensitivity analysis for FVZ manifests that among the nine conditioning vulnerability factors, LULC gained the highest mean effective weight (21.56%), and the employment rate scored lowest (3.28%). The highest deviation (6.26%) between empirical and mean effective weights was observed in LULC (Table 15). Distance to flood shelter and distance to hospital implies relatively similar weights (Table 15). The map of effective weight (W) of 9 flood vulnerability parameters has been depicted in Figure 7.

Figure 7. Effective weight (W) of flood vulnerability parameters.

Table 16. Descriptive statistics of map removal sensitivity analysis of flood susceptibility.

| Thematic layers          | SI variation in % | Min     | Max     | Mean   | SD     |
|--------------------------|-------------------|---------|---------|--------|--------|
| Elevation                | SI variation in % | 7.4127E-06 | 4.343  | 1.412  | 1.047  |
| Slope                    | SI variation in % | 3.48401E-06 | 3.879  | 0.800  | 0.608  |
| TWI                      | SI variation in % | 0.379699081 | 1.381  | 0.998  | 0.123  |
| NDVI                     | SI variation in % | 0.060946576 | 1.372  | 0.961  | 0.130  |
| MNDWI                    | SI variation in % | 4.15558E-06 | 1.523  | 1.088  | 0.243  |
| Drainage density (km/km²) | SI variation in % | 1.51222E05  | 2.098  | 1.051  | 0.458  |
| Distance from river (km) | SI variation in % | 4.36905E-06 | 2.885  | 0.990  | 0.435  |
| SPI                      | SI variation in % | 0.056351319 | 1.238  | 0.845  | 0.135  |
| STI                      | SI variation in % | 0.201089114 | 1.291  | 0.826  | 0.128  |
| MFI                      | SI variation in % | 5.33904E-06 | 1.473  | 1.039  | 0.301  |
| Lithology                | SI variation in % | 0.001133207 | 1.544  | 1.060  | 0.182  |
3.4.3. Map removal sensitivity analysis

In the output, no significant variation was portrayed in removing single parameter sensitivity while considering the susceptibility layers (Table 16). The highest (mean SI variation = 1.41%) SI value has been noticed in removing the elevation layer, whereas the lowest (mean = 0.10%) is in the TPI layer. However, the highest and lowest SI difference is 1.31%; therefore, the susceptibility map is less sensitive to the selected parameters. The sensitivity Index (SI) of flood susceptibility parameters has been shown in Figure 8. Furthermore, the percentage of changes of FSZ with the removal of each thematic layer has been performed, as illustrated in Figure 9 and Table 17. The result of the removal of each thematic layer has significantly shown variation in the percentage of produced FSZ maps. The highest increases of the very low, low, medium, high, and very high flood susceptible area are observed in the exclusion of thematic layers elevation (28.57%), drainage density (4.09%), MNDWI (0.36%), TWI (8.77%), and distance from river (34.48%), respectively. The very low, low, medium, high, and very high flood susceptible area also decreases highest in removing the TWI (−7.11%), elevation (−13.29%), drainage density (−7.18%), drainage density (−15.10%), and slope (−10.73%) layer, respectively.

The map removal sensitivity study for vulnerability layers shows the highest variation (mean SI variation = 2.60) of SI in the distribution of population thematic layer, while the lowest (mean = 0.73%) in road density (Table 18 and Figure 10). Thus, the vulnerability map is also less sensitive, as the difference between the highest and lowest SI is only 1.87%. The percentage of change detection of flood vulnerability mapping with the removal of each thematic layer shows vast differences, as displayed
**Figure 9.** Flood Susceptibility Zonation each parameter removal.

**Table 17.** Percentage of changes of flood susceptibility zonation with removal of each thematic layer.

| Thematic layers | Very low | Low | Medium | High | Very high |
|-----------------|----------|-----|--------|------|-----------|
| Elevation (m)   | 28.57    | -13.29 | -3.86  | -8.05 | 14.01     |
| Slope (°)       | 18.03    | 2.42  | -6.23  | -8.08 | -10.73    |
| TWI             | -7.11    | -3.90 | -0.38  | 8.77  | 11.99     |
| TPI             | 0.05     | 2.14  | -2.14  | 0.22  | -0.70     |
| NDVI            | -2.05    | -0.07 | -2.05  | 3.21  | 5.03      |
| MNDWI           | -5.62    | -4.22 | 0.36   | 4.00  | 19.45     |
| Drainage density (km/km²) | 22.67 | 4.09  | -7.18  | -15.10 | -7.99     |
| Distance from river (km) | 18.87 | -4.01 | -13.18 | -7.34 | 34.48     |
| SPI             | 1.49     | 2.20  | -2.55  | -2.52 | 3.42      |
| STI             | 2.82     | 1.38  | -3.19  | 0.00  | -0.56     |
| MFI             | 0.38     | 0.35  | -4.63  | 1.93  | 9.73      |
| Lithology       | -5.10    | 0.69  | -0.60  | 2.91  | 4.93      |

'+' represents increased by area and '-' represents decreased by area.
in Figure 11 and Table 19. The very low, low, medium, high, and very high vulnerability areas have been increased highest in removing the road density (18.82%), distance from flood shelter (7.82%), distribution of population (32.34%), and LULC (35.08%) layers, respectively, while maximum decreases in their areas while removing the layers distribution of population (−22.58%), distribution of population (−16.93%), LULC (−6.05%), distance from road (−15.58%), distance from flood shelter (−30.48%), respectively.

Table 18. Descriptive statistics of map removal sensitivity analysis of flood vulnerability.

| Thematic layers                        | SI variation in % |
|----------------------------------------|-------------------|
|                                        | Min   | Max   | Mean | SD   |
| Total population                       | 0.0000808 | 5.252 | 2.596 | 1.109 |
| Population density (persons/km²)       | 0.0000808 | 5.025 | 2.322 | 0.985 |
| LULC                                   | 6.94E-05 | 4.474 | 1.019 | 0.741 |
| Distance from flood shelter            | 0.000438 | 3.392 | 1.723 | 0.606 |
| Distance from hospital                 | 0.000253 | 2.656 | 1.734 | 0.720 |
| Distance from road                     | 0.000798 | 1.998 | 1.281 | 0.576 |
| Road density                           | 0.000274 | 1.990 | 0.734 | 0.454 |
| Illiteracy rate                         | 0.000966 | 2.008 | 1.202 | 0.325 |
| Employment rate                        | 0.001337 | 2.694 | 1.565 | 0.162 |

Figure 10. Sensitivity Index (SI) of flood vulnerability parameters.
Figure 11. Flood Vulnerability Zonation each parameter removal.

Table 19. Percentage of changes of flood vulnerability mapping with removal of each thematic layer.

| Thematic layers                      | Very low | Low | Medium | High  | Very high |
|--------------------------------------|----------|-----|--------|-------|-----------|
| Total population                     | −22.58   | −16.93 | 8.98   | 32.84 | 28.97     |
| Population density (persons/km²)     | −8.13    | −6.87 | 1.63   | 10.85 | 23.82     |
| LULC                                 | −0.65    | −1.66 | −6.05  | 1.07  | 35.08     |
| Distance from flood shelter          | 0.56     | 7.82  | 5.69   | −13.31| −30.48    |
| Distance from hospital               | 11.13    | 6.30  | −4.11  | −13.24| −13.17    |
| Distance from road                   | 14.07    | 5.77  | −1.80  | −15.58| −22.62    |
| Road density                         | 18.82    | 3.71  | −6.02  | −14.18| −13.49    |
| Illiteracy rate                      | 3.01     | 4.70  | −0.67  | −8.74 | −6.81     |
| Employment rate                      | 4.29     | 3.69  | −4.00  | −2.58 | −6.82     |

‘+’ represents increased by area and ‘−’ represents decreased by area.
3.5. Validation of the model

The study quantitatively verified the AHP output with the flood inventory map through ROC-AUC, MAE, MSE, and RMSE assessments. The ROC-AUC has been performed by comparing the FSZ map with the flood point and non-flood point employing the ‘ArcSDM’ tool in the ArcGIS software. Figure 12(c, d) manifests the ROC curves and AUC with speedometer diagrams for the AHP model. The AUC displayed the accuracy rate of the FSZ model, which can be categorized into four groups, i.e., excellent (>0.9), accepted (0.8–0.9), good (0.7–0.8), and considerable (0.5–0.7). The study revealed that the observed accuracy of the AHP technique is 0.728 (72.80%). Therefore, according to the satisfaction scale, the model is efficiently performed to produce the FSZ map, and it is considered a good outcome. On the other side, MAE, MSE, and RMSE results show very good accuracy of the model as their computed value were 0.15, 0.16, and 0.21, respectively. It represents just only 15, 16, and 21% of error of the produced susceptibility map compared to the actual data.

4. Discussion

In this present study, an integrated RS and GIS approach-based AHP technique has been successfully applied to delineate the FSZ, FVZ, and FRZ of the high flood-affected Uttar Dinajpur district in eastern India. Flood susceptibility, vulnerability, and risk mapping are commonly utilized technique in modern times, and it is employed as a key resource for flood control research and the implementation of any development plans. The analytical hierarchy process (AHP) has been the most often employed for its effectiveness and reliability to demarcate the FRZ. It attempts to find an alternative solution. Recently, there has been a surge of attention in employing the AHP in natural hazard assessment and flood management, where the flood risk may...
be evaluated and mapped with acceptable precision using the AHP. The research identified the highly affected indices for mapping the flood susceptibility were elevation, slope, TWI, drainage density, and distance to river and for vulnerability were distribution of population, population density, LULC, distance to hospital, and distance to flood shelter. This study integrates the geomorphological and hydraulic features to the flood intensity, as well as social, economic, demographics, and infrastructural factors to the magnitude of vulnerability. Nachappa et al. (2020) demarcated the highly affected parameters for determining the flood susceptibility were elevation, slope, distance to drainage, rainfall, TWI, LULC, lithology, aspect, SPI, NDVI, and distance to roads. In their study, >60% weightages have been assigned to the three parameters, viz., elevation, slope, and distance to drainage. In other studies (Mehebub et al. 2015; Sahana and Patel 2019; Sahana et al. 2020) flood susceptibility and vulnerability have been analyzed based on several indices and different models, i.e., frequency ratio, support vector machine, fuzzy logic models. Rehman et al. (2019) provided a brief overview on methods used for flood vulnerability assessment and outlined the frameworked for future researches.

Recently GIS-based MCDA approaches have taken a crucial part in identifying behavior and constraints of the model. It’s important to remember that MCDA ranks are frequently uncertain. Uncertainty can arise from a variety of areas, including raw data, data processing, criterion selection, and thresholds. Criteria ratings or weights are usually the sources of the most debate and uncertainty. It could be due to the fact that decision-makers aren’t always completely aware of their preferences for the criteria or because the nature and scope of the criteria are unknown (Chen et al. 2010). In the APH technique, the significant flaw is the computation of weight. Hence implication of sensitivity analysis is required to validate the assigned weights for AHP (Fenta et al. 2015; Mukherjee and Singh 2020). It examines the connections between modelling application’s inputs and output. It’s performed to test the end result’s resiliency to small changes in the raw data (Zoras et al. 2007; Chen et al. 2010). Therefore, the present research employed three types of sensitivity analyses of the AHP method. Through Stillwell ranking methods, the assigned AHP weights in susceptibility and vulnerability assessment are subsequently validated. The deviation between the empirical and effective weights has been noticed while studying each parameter sensitivity analysis. The statistical results of map removal sensitivity analysis show the variation in sensitivity index (SI) among the parameters. The variation of SI has been obtained on the basis of rate, the weight of each layer, and the influence of other thematic layers (Fenta et al. 2015). The cross-verification outcome through ROC-AUC, MAE, MSE, and RMSE revealed the efficiency of the AHP technique for attending to the goals of the study.

Flooding is a big concern in every part of the world, and it is linked to significant losses in properties, economics, and people’s livelihoods. Various methods for evaluating flood susceptibility, vulnerability and risk have been established in this context. The basic aims of such approaches are just the equivalent, namely, to forecast this situation to a more appropriate degree. Floods cannot be totally prevented, but they can be reduced to a minimum by taking the necessary precautions. The proper diagnosis of susceptible, vulnerable, and risk areas is required for this goal, and it is the primary concern for design purposes.
5. Conclusions

In this research, the MCDA AHP technique has been performed and further utilized the sensitivity analysis of this method for flood modelling. Sensitivity evaluation is an essential aspect in assessing whether a solution is implementable and robust when employing the AHP. It gives evaluators or modellers more immediate feedback, which is easier to understand for non-experts, and provides a way to investigate the choice problem while understanding how changes in criteria weights affect evaluation outcomes spatially and quantitatively. Continuous progress in this field, including sensitivity study on adjusting criteria threshold levels, altering relative relevance of criteria, and thus preference matrix, would allow GIS and MCDA to be more successfully applied to practical land-management challenges.

The novelty of the research is the sensitivity studies of the AHP method, which can be further utilized for any other region of the world. An accurate flood susceptibility, vulnerability, and risk model is a useful asset for land-use planners and government authorities to implement successful risk-reduction strategies. The findings of this study could be useful in determining land use prior to flood control in this region. Thus, this study opens a new dimension in those studies which are employing several MCDA techniques for any kind of modelling. The identification of the high flood risk-prone areas is another important aspect of this research, which can help the local executive with the further implication of any monitoring and management plan of the concerned district. The high-risk prone areas were found at approximately 20%, which were identified mainly in the Goalpokhar-II, Raiganj, Karandighi, and Itahar blocks. In contrast, Chopra, Islampur, Goalpokhar-I, parts of Raiganj, and Hemtabad blocks were demarcated as least risk-prone, although approximately 27% area was delineated in the medium risk prone zone. Therefore, an adequate flood risk strategy is required for better improvement of the region. Furthermore, the adaptation of flood defense (both structural and non-structural) techniques is recommended for the high-risk-prone areas. The mitigation measures to decrease flood risk in this highly flood-affected region are prohibiting settlement expansion, increasing accessibility to flood shelters and hospitals, sustainable flood plain management, flood insurance, and, most importantly, public awareness should be prioritized. The resulting susceptibility, vulnerability, and risk maps will help local governments and public protection agencies assess regions that may be affected in the event of future floods.

The limitations of the study imply in MCDA technique, which can be further modified by using the high resolution data and alternative techniques which are suitable for this area. The model evaluation could be improved in the research by using other sensitivity analyses. The study also can make better decisions by applying the machine learning techniques for a better understanding the flood susceptibility, vulnerability, and risk-prone regions. Despite its flaws, the MCDA approach can be a powerful resource for investigating real problems in regions where data is limited, such as developing countries. The current study can be useful for policymakers, local administrative authorities, environmentalists, and engineers, and it can be applied to many flood-prone places around the world.
Disclosure statement
No potential conflict of interest was reported by the authors.

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Data availability statement
The data that support the findings of this study are openly available in various websites. The ASTER DEM (30 m*30 m) and Landsat 8 OLI/TIRS (30 m*30 m) data used in this manuscript were obtained from United States Geological Survey (USGS) portal (https://earthexplorer.usgs.gov), rainfall data collected from India Meteorological Department (IMD) portal (https://www.imdpune.gov.in), lithological map obtained from Geological Survey of India (GSI) portal (https://bhukosh.gsi.gov.in), village-level data for population distribution, population density, illiteracy rate and employment rate collected from Office of the Registrar General & Census Commissioner, India portal (https://censusindia.gov.in), adopting the distance to flood shelter data from District Disaster Management Plan of Uttar Dinajpur District (DDMPUD), 2020–2021 (http://wbdmd.gov.in/pages/district_dm_plan.aspx), distance to hospital and road networks data from OpenStreetMap portal (www.openstreetmap.org), and flood inventory map of the study area was generated from thematic services of Bhuban portal (https://bhuvan-app1.nrsc.gov.in/thematic/thematic/index.php).

References
Abdelkarim A, Al-Alola SS, Alogayell HM, Mohamed SA, Alkadi II, Ismail IY. 2020. Integration of GIS-based multi-criteria decision analysis and analytic hierarchy process to assess flood hazard on the Al-Shamal train pathway in Al-Qurayyat region, kingdom of Saudi Arabia. Water. 12(6):1702.
Afolayan AH, Ojokoh BA, Adetunmbi AO. 2020. Performance analysis of fuzzy analytic hierarchy process multi-criteria decision support models for contractor selection. Sci Afr. 9: e00471.
Ahmadlou M, Karimi M, Alizadeh S, Shirzadi A, Parvinnejhad D, Shahabi H, Panahi M. 2019. Flood susceptibility assessment using integration of adaptive network-based fuzzy inference system (ANFIS) and biogeography-based optimization (BBO) and BAT algorithms (BA). Geocarto International. 34(11):1252–1272. doi:10.1080/10106049.2018.1474276.
Ali SA, Parvin F, Pham QB, Vojtek M, Vojteková J, Costache R, Linh NTT, Nguyen HQ, Ahmad A, Ghorbani MA. 2020. GIS-based comparative assessment of flood susceptibility mapping using hybrid multi-criteria decision-making approach, naïve Bayes tree, bivariate statistics and logistic regression: A case of Topl’a basin, Slovakia. Ecol Indic. 117:106620.
Al-Juaidi AEM, Nassar AM, Al-Juaidi OEM. 2018. Evaluation of flood susceptibility mapping using logistic regression and GIS conditioning factors. Arab J Geosci. 11(24):1–10.
Annual Flood Report. 2019. West Bengal. Retrieved from: https://wbiwd.gov.in/uploads/annual_flood_report/ANNUAL_FLOOD_REPORT_2019.pdf.
Arabameri A, Rezaei K, Cerdà A, Conoscenti C, Kalantari Z. 2019. A comparison of statistical methods and multi-criteria decision making to map flood hazard susceptibility in Northern Iran. Sci Total Environ. 660:443–458.
Arabameri A, Seyed Danesh A, Santosh M, Cerda A, Chandra Pal S, Ghorbanzadeh O, Roy P, Chowdhuri I. 2022. Flood susceptibility mapping using meta-heuristic algorithms. Geomatics Nat Hazards Risk. 13(1):949–974.
Beven KJ, Kirkby MJ. 1979. A physically based, variable contributing area model of basin hydrology. Hydrol Sci J. 24(1):43–69.
Bhattacharjee S, Kumar P, Thakur PK, Gupta K. 2021. Hydrodynamic modelling and vulnerability analysis to assess flood risk in a dense Indian city using geospatial techniques. Nat Hazards. 105(2):2117–2145.
Bot K, Borges JG. 2022. A systematic review of applications of machine learning techniques for wildfire management decision support. Inventions. 7(1):15.
Bui DT, Ngo PTT, Pham TD, Jaaafari A, Minh NQ, Hoa PV, Samui P. 2019. A novel hybrid approach based on a swarm intelligence optimized extreme learning machine for flash flood susceptibility mapping. Catena, 179:179:184–196.
Burrough PA, McDonnell RA. 1998. Principles of geographical information systems. Oxford, NY: Oxford University Press.
Cabrera JS, Lee HS. 2020. Flood risk assessment for Davao Oriental in the Philippines using geographic information system-based multi-criteria analysis and the maximum entropy model. J Flood Risk Manag. 13(2):e12607.
Chakraborty S, Mukhopadhyay S. 2019. Assessing flood risk using analytical hierarchy process (AHP) and geographical information system (GIS): application in Coochbehar district of West Bengal, India. Nat Hazards. 99(1):247–274.
Chen TY. 2021. A likelihood-based preference ranking organization method using dual point operators for multiple criteria decision analysis in Pythagorean fuzzy uncertain contexts. Expert Syst Appl. 176:114881.
Chen W, Li Y, Xue W, Shahabi H, Li S, Hong H, Wang X, Bian H, Zhang S, Pradhan B, et al. 2020. Modeling flood susceptibility using data-driven approaches of naïve bayes tree, alternating decision tree, and random forest methods. Sci Total Environ. 701:134979.
Costache R. 2019. Flash-flood Potential Index mapping using weights of evidence, decision Trees models and their novel hybrid integration. Stoch Environ Risk Assess. 33(7):1375–1402.
Das S. 2020. Flood susceptibility mapping of the Western Ghat coastal belt using multi-source geospatial data and analytical hierarchy process (AHP). Remote Sens Appl: Soc Environ. 20:100379.
Das S, Gupta A. 2021. Multi-criteria decision based geospatial mapping of flood susceptibility and temporal hydro-geomorphic changes in the Subarnarekha basin, India. Geosci Front. 12(5):101206.
De Reu J, Bourgeois J, Bats M, Zwertvaegher A, Gelorini V, De Smedt P, Chu W, Antrop M, De Maeyer P, Finke P, et al. 2013. Application of the topographic position index to heterogeneous landscapes. Geomorphology. 186:39–49.
Dhar ON, Nandargi S. 2003. Hydrometeorological aspects of floods in India. Nat Hazards. 28(1):1–33.
District Census Handbook of Uttar Dinajpur District (DCHUD), Census of India. 2011. West Bengal. Retrieved from: https://www.censusindia.gov.in/2011census/dcb/WB.html.
District Disaster Management Plan of Uttar Dinajpur District (DDMPUD) 2020–2021. West Bengal. Retrieved from: http://wbmd.gov.in/pages/district_dm_plan.aspx.
Fenta AA, Kifle A, Gebreyohannes T, Hallu G. 2015. Spatial analysis of groundwater potential using remote sensing and GIS-based multi-criteria evaluation in Raya Valley, northern Ethiopia. Hydrogeol J. 23(1):195–206.
Gharabae MK, Amiri M, Zavadskas EK, Turskis Z, Antuacheviciene J. 2017. A new multi-criteria model based on interval type-2 fuzzy sets and EDAS method for supplier evaluation and order allocation with environmental considerations. Comput Ind Eng. 112:156–174.
Ghosh M, Ghosal S. 2021. Climate change vulnerability of rural households in flood-prone areas of Himalayan foothills, West Bengal, India. Environ Dev Sustain. 23(2):2570–2526.
Guisan A, Weiss SB, Weiss AD. 1999. GLM versus CCA spatial modeling of plant species distribution. Plant Ecol. 143(1):107–122.
Gupta S, Javed A, Datt D. 2003. Economics of flood protection in India. In Flood problem and management in South Asia. Dordrecht: Springer, p. 199–210.

Ha H, Bui QD, Khuc TD, Tran DT, Pham BT, Mai SH, Nguyen LP, Luu C. 2022. A machine learning approach in spatial predicting of landslides and flash flood susceptible zones for a road network. Model Earth Syst Environ. 1–17. https://doi.org/10.1007/s40808-022-01384-9

Hammami S, Zouhri I, Souissi D, Souei A, Zghibi A, Marzougui A, Dlala M. 2019. Application of the GIS based multi-criteria decision analysis and analytical hierarchy process (AHP) in the flood susceptibility mapping (Tunisia). Arab J Geosci. 12(21):1–16.

Hanley JA, McNeil BJ. 1982. The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology. 143(1):29–36.

Hasanloo M, Pahlavani P, Bigdeli B. 2019. Flood risk zonation using a multi-criteria spatial group fuzzy-ahp decision making and fuzzy overlay analysis. Int Arch Photogramm Remote Sens Spatial Inf Sci. XLII-4/W18:455–460.

Hong H, Panahi M, Shirzadi A, Ma T, Liu J, Zhu A-X, Chen W, Kougias I, Kazakis N. 2018. Flood susceptibility assessment in Hengfeng area coupling adaptive neuro-fuzzy inference system with genetic algorithm and differential evolution. Sci Total Environ. 621:1124–1141. doi:10.1016/j.scitotenv.2017.10.114. 29074239

Hoque MAA, Tasfia S, Ahmed N, Pradhan B. 2019. Assessing spatial flood vulnerability at Kalapara Upazila in Bangladesh using an analytic hierarchy process. Sensors. 19(6):1302.

Jenness J, Brost B, Beier P. 2013. Land facet corridor designer. USDA forest service rocky mountain research station.

Karande P, Chakraborty S. 2012. Application of multi-objective optimization on the basis of ratio analysis (MOORA) method for materials selection. Mater Design. 37:317–324.

Kumar R, Anbalagan R. 2016. Landslide susceptibility mapping using analytical hierarchy process (AHP) in Tehri reservoir rim region, Uttarakhand. J Geol Soc India. 87(3):271–286.

Liu R, Yang X, Xu C, Wei L, Zeng X. 2022. Comparative study of convolutional neural network and conventional machine learning methods for landslide susceptibility mapping. Remote Sensing. 14(2):321.

Lodwick WA, Monson W, Svoboda L. 1990. Attribute error and sensitivity analysis of map operations in geographical informations systems: suitability analysis. Int J Geogr Inf Syst. 4(4):413–428.

Lyub HM, Zhou WH, Shen SL, Zhou AN. 2020. Inundation risk assessment of metro system using AHP and TFN-AHP in Shenzhen. Sustain Cities Soc. 56:102103.

Mahmoud SH, Gan TY. 2018. Urbanization and climate change implications in flood risk management: Developing an efficient decision support system for flood susceptibility mapping. Sci Total Environ. 636:152–167.

Mehebub S, Raihan A, Nuhul H, Haroon S. 2015. Assessing flood inundation extent and landscape vulnerability to flood using geospatial technology: a study of Malda district of West Bengal, India. In Forum geographic, Vol. 14, No. 2. Craiova: University of Craiova, Department of Geography; p. 156.

Miller JR, Ritter DF, Kochel RC. 1990. Morphometric assessment of lithologic controls on drainage basin evolution in the Crawford upland, south-central Indiana. Am J Sci. 290(5):569–599.

Mirza MMQ. 2011. Climate change, flooding in South Asia and implications. Reg Environ Change. 11(S1):95–107.

Mitra R, Roy D. 2022. Delineation of groundwater potential zones through the integration of remote sensing, geographic information system, and multi-criteria decision-making technique in the sub-Himalayan foothills region, India. Int J Energ Water Res. 1–21. https://doi.org/10.1007/s42108-022-00181-5

Mojaddadi H, Pradhan B, Nampak H, Ahmad N, Ghazali AHB. 2017. Ensemble machine-learning-based geospatial approach for flood risk assessment using multi-sensor remote-sensing data and GIS. Geomatics Nat Hazards Risk. 8(2):1080–1102.

Moore ID, Grayson RB, Ladson AR. 1991. Digital terrain modelling: a review of hydrological, geomorphological, and biological applications. Hydroc Process. 5(1):3–30.
Mukherjee I, Singh UK. 2020. Delineation of groundwater potential zones in a drought-prone semi-arid region of east India using GIS and analytical hierarchical process techniques. Catena. 194:104681.

Myers JL, Well AD, Lorch Jr RF. 2010. Introduction to multiple regression. In Myers JL, Well AD, Lorch RF editors. Research design and statistical analysis. New York: Routledge; p. 528–547. https://doi.org/10.4324/9780203726631.

Nachappa TG, Piralilou ST, Gholamnia K, Ghorbanzadeh O, Rahmati O, Blaschke T. 2020. Flood susceptibility mapping with machine learning, multi-criteria decision analysis and ensemble using Dempster Shafer Theory. J Hydrol. 590:125275.

Nachappa TG, Piralilou ST, Gholamnia K, Ghorbanzadeh O, Rahmati O, Blaschke T. 2020. Flood susceptibility mapping with machine learning, multi-criteria decision analysis and ensemble using Dempster Shafer Theory. J Hydrol. 590:125275.

Napolitano P, Fabbri AG. 1996. Single-parameter sensitivity analysis for aquifer vulnerability assessment using DRASTIC and SINTACS. IAHS Publications-Series of Proceedings and Reports-Intern Assoc Hydrological Sciences. Vol. 235, p. 559–566.

Nguyen HD, Nguyen QH, Du QVV, Nguyen THT, Nguyen TG, Bui QT. 2021. A novel combination of Deep Neural Network and Manta Ray Foraging Optimization for flood susceptibility mapping in Quang Ngai province, Vietnam. Geocarto Int. 1–22.

Pamucar D, Cirovic G. 2015. The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC). Expert Syst Appl. 42(6):3016–3028.

Pei T, Qin CZ, Zhu AX, Yang L, Luo M, Li B, Zhou C. 2010. Mapping soil organic matter using the topographic wetness index: A comparative study based on different flow-direction algorithms and kriging methods. Ecol Indic. 10(3):610–619.

Pham BT, Luu C, Van Dao D, Van Phong T, Nguyen HD, Van Le H, von Meding J, Prakash I. 2021. Flood risk assessment using deep learning integrated with multi-criteria decision analysis. Knowl-Based Syst. 219:106899.

Prokop P, Walanus A. 2017. Impact of the Darjeeling-Bhutan Himalayan front on rainfall hazard pattern. Nat Hazards. 89(1):387–404.

Radwan F, Alazba AA, Mossad A. 2019. Flood risk assessment and mapping using AHP in arid and semi-arid regions. Acta Geophys. 67(1):215–229.

Rahmati O, Kalantari Z, Samadi M, Uuemaa E, Moghaddam DD, Nalivan OA, Destouni G, Tien Bui D. 2019. GIS-based site selection for check dams in watersheds: Considering geomorphometric and topo-hydrological factors. Sustainability. 11(20):5639.

Ranjan R. 2017. Flood disaster management. In River system analysis and management. Singapore: Springer; p. 371–417. https://doi.org/10.1007/978-981-10-1472-7_20.

Rehman S, Sahana M, Hong H, Sajjad H, Ahmed BB. 2019. A systematic review on approaches and methods used for flood vulnerability assessment: framework for future research. Nat Hazards. 96(2):975–998.

Roy S, Bose A, Chowdhury IR. 2021. Flood risk assessment using geospatial data and multi-criteria decision approach: a study from historically active flood-prone region of Himalayan foothill, India. Arab J Geosci. 14(11):1–25.

Saaty TL. 1980. The analytical hierarchy process, planning, priority. Pittsburgh: RWS publications.

Saaty RW. 1987. The analytical hierarchy process—what it is and how it is used. Math Modell. 9(3–5):161–176.

Saaty TL. 1990. How to make a decision: the analytic hierarchy process. Eur J Oper Res. 48(1):9–26.

Saaty TL, Vargas LG. 1991. Prediction, projection and forecasting: applications of the analytic hierarchy process in economics, finance, politics, games and sports. Boston: Kluwer Academic Publishers; p. 11–31.

Sahana M, Patel PP. 2019. A comparison of frequency ratio and fuzzy logic models for flood susceptibility assessment of the lower Kosi River Basin in India. Environ Earth Sci. 78(10):1–27.
Sahana M, Rehman S, Sajjad H, Hong H. 2020. Exploring effectiveness of frequency ratio and support vector machine models in storm surge flood susceptibility assessment: A study of Sundarban Biosphere Reserve, India. CATENA. 189:104450.

Saha A, Pal SC, Arabameri A, Blaschke T, Panahi S, Chowdhuri I, Chakrabortty R, Costache R, Arora A. 2021. Flood susceptibility assessment using novel ensemble of hyperpipes and support vector regression algorithms. Water. 13(2):241.

Saha S, Sarkar D, Mondal P. 2021. Ratio, entropy, and weights of evidence-information value models in flood susceptibility assessment: a study of Raiganj Subdivision, Eastern India. https://doi.org/10.1007/s00477-021-02115-9.

Salazar-Briones C, Ruiz-Gibert JM, Lomeli-Banda MA, Mungaray-Moctezuma A. 2020. An integrated urban flood vulnerability index for sustainable planning in arid zones of developing countries. Water. 12(2):608.

Samanta S, Pal DK, Palsamanta B. 2018. Flood susceptibility analysis through remote sensing, GIS and frequency ratio model. Appl Water Sci. 8(2):66.

Sari F. 2021. Forest fire susceptibility mapping via multi-criteria decision analysis techniques for Mugla, Turkey: A comparative analysis of VIKOR and TOPSIS. For Ecol Manage. 480:118644.

Sarkar D, Mondal P. 2020. Flood vulnerability mapping using frequency ratio (FR) model: a case study on Kulik river basin, Indo-Bangladesh Barind region. Appl Water Sci. 10(1):1–13.

Sarkar A, Saha S, Sarkar D, Mondal P. 2021. Variability and trend analysis of the rainfall of the past 119 (1901-2019) years using statistical techniques: a case study of Uttar Dinajpur, India. JCC. 7(2):49–61.

Sarkar S, Singh RP. 2017. June 19 2015 rainfall event over Mumbai: Some observational analysis. J Indian Soc Remote Sens. 45(1):185–192.

Shahabi H, Shirzadi A, Ghaderi K, Omidvar E, Al-Ansari N, Clague JJ, Geertsema M, Khosravi K, Amini A, Bahrami S, et al. 2020. Flood detection and susceptibility mapping using sentinel-1 remote sensing data and a machine learning approach: Hybrid intelligence of bagging ensemble based on k-nearest neighbor classifier. Remote Sensing. 12(2):266.

Singh RP, Kumar R, Tare V. 2009. Variability of soil wetness and its relation with floods over the Indian subcontinent. Can J Remote Sens. 35(1):85–97.

Souissi D, Zouhri L, Hammami S, Msaddek MH, Zghibi A, Dlala M. 2020. GIS-based MCDM–AHP modeling for flood susceptibility mapping of arid areas, southeastern Tunisia. Geocarto Int. 35(9):991–1017.

Stillwell WG, Seaver DA, Edwards W. 1981. A comparison of weight approximation techniques in multiattribute utility decision making. Org Behav Human Perform. 28(1):62–77.

Swets JA. 1988. Measuring the accuracy of diagnostic systems. Science. 240(4857):1285–1293.

Vafakhah M, Mohammad Hasani Loor S, Pourghasemi H, Katebikord A. 2020. Comparing performance of random forest and adaptive neuro-fuzzy inference system data mining models for flood susceptibility mapping. Arab J Geosci. 13(11):1–16.

Wang B, Song J, Ren J, Li K, Duan H, Wang X. 2019. Selecting sustainable energy conversion technologies for agricultural residues: A fuzzy AHP-VIKOR based prioritization from life cycle perspective. Resour Conserv Recycl. 142:78–87.

Wassenaar HJ, Chen W. 2003. An approach to decision-based design with discrete choice analysis for demand modeling. J Mech Des. 125(3):490–497.

Weiss A. 2001. Topographic position and landforms analysis. In Poster presentation, ESRI user conference, San Diego, CA (Vol. 200).

Xu H. 2006. Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. Int J Remote Sens. 27(14):3025–3033.

Yaseen A, Lu J, Chen X. 2022. Flood susceptibility mapping in an arid region of Pakistan through ensemble machine learning model. Stoch Environ Res Risk Assess. https://doi.org/10.21203/rs.3.rs-928677/v1

Zoras S, Triantafyllou AG, Hurley PJ. 2007. Grid sensitivity analysis for the calibration of a prognostic meteorological model in complex terrain by a screening experiment. Environ Modell Softw. 22(1):33–39.