Flood hazard mapping of Sangu River basin in Bangladesh using multi-criteria analysis of hydro-geomorphological factors

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Abstract
Flood havoc during 2019 in the Sangu River basin caused widespread damage to residents, crops, roads, and communications in parts of hills in Bangladesh. Developing flood hazard maps can play an essential step in risk management. For this purpose, this study assessed 12 hydro-geomorphological factors, namely, topographic wetness index, elevation, slope, extreme rainfall, land-use and land-cover, soil type, lithology, curvature, drainage density, aspect, height above the nearest drainage, and distance from streams. Maps prepared by individual application of the Analytical Hierarchy Process (AHP) and Analytical Network Process (ANP) exhibit validation scores ranging from 0.77 to 0.79. It is found that the ANP-based model under 1-day maximum rainfall denotes a reliable hazard map presenting comparable accuracy to the field results. The hazard map under 100-year return periods shows that a total of 0.71 million population living downstream is prone to "very high" flood because of its low-land morphology, mild slope, and high drainage density. Alarmingly, 39% of roads, 43% of farming lands, and 25% of education buildings are observed to lie in the highest flood-prone area. Details on subdistrict level exposures have the potential to serve the decision-makers and planners in site selection for flood management strategies and setting priorities for remedial measures.

KEYWORDS
analytical hierarchy process, analytical network process, Bangladesh, flood hazard map, hydro-geomorphological factors, sentinel data

1 | INTRODUCTION

Natural hazards have become one of the significant global issues facing humankind (Sui et al., 2018). Among all categories of natural hazards, flooding is one of the widespread, familiar, and regular events (Heidari, 2014; Foudi et al., 2015). Flood events have become more devastating and frequent in the rainy season, especially for subtropical and tropical regions of Asia (Islam and Dharianraj, 2017), where almost 80% of annual rain falls from June to September. Substantial rainfall along with massive river discharge overflow surrounding land area and initiate flood situation (Mohamed and El-Raey, 2019). A flood turns into a disaster when it results...
in massive damage to life, agricultural land, settlement area, and infrastructure (Dottori et al., 2016; Abebe et al., 2018). Every year flood comes with disaster in Bangladesh, typically in the Ganges-Brahmaputra-Meghna (GBM) basin (Bhuiyan and Al Baky, 2014) in any of the following five forms: (a) riverine, (b) rainfall-induced, (c) flash, (d) tidal, and (e) cyclonic/storm-surgical (Rahman and Salehin, 2013). Being situated at the outlet of GBM, Bangladesh has to bear the enormous volume of water flow in the monsoon season (starts from June and continues up to the end of October). All of the floods in the country are more prominent and common in flatlands (i.e., 79.1% by area) and accordingly get the main interest for study or planning purposes. The higher elevated areas that comprise 8.3% terraces and 12.6% hilly parts are often subjected to shallow flooding and flash floods from the hills but generally excluded or get less attention from flood analyses (e.g., Islam and Sado, 2000). For instance, the Sangu River basin of the Southeastern corner of the Chattogram Hill tract (CHT) has frequently been facing monsoon floods, including overflow of riverbanks. Several of these flood events and corresponding affected areas have previously been reported in Brakenridge (2018), ACAPS (2015), Reliefweb (2019), and Adnan et al. (2019). From 1981 until 2019, nine events (Table 1) either showed exceedance of danger levels (historically highest peaks) in the Sangu river or massive mudflows due to heavy rainstorms significantly affecting the basin. The socio-economic effects of these recurring floods are substantial. In particular, vulnerable groups are the indigenous ethnic people who need frequent shifting from one hill to another hill. Notably, during July 2019, most of the unions (i.e., smallest administrative units) under Bandarban city were inundated due to the overflow of the Sangu River (Figure 1). The situation became worse due to the continuously rising water level of the river. Mostly affected areas were low-lying lands of Bandarban city area. Around 35% of households in Bandarban city stayed under 3 to 5 ft (0.9–1.5 m) water level. All the low lying agricultural crop fields adjacent to the Sangu River were submerged and damaged. Flooded households in low lying areas were affected most. Considering severe damage to agricultural fields, settlement, and fisheries in Bandarban city, it is now an urgent need to identify or locate areas that are significantly prone to riverine flood.

| Year | Location          | Number of people affected | Source                                      | Cause                                      | Comment                                                                 |
|------|-------------------|---------------------------|---------------------------------------------|--------------------------------------------|------------------------------------------------------------------------|
| 1981 | Dohazari, Banigram | –                         | BWDB river stage data                       | Riverbank overflow                        | 0.22 m exceeding the Dohazari danger level (i.e., 7 m) and 1.11 m exceeding the Banigram danger level (i.e., 4.88 m) |
| 1983 | Dohazari          | –                         | BWDB river stage data                       | Riverbank overflow                        | 0.32 m exceeding the Dohazari danger level                             |
| 1997 | Dohazari, Bandarban | 230,000                   | Brakenridge (2018)                          | Heavy rain and Riverbank overflow         | 0.58 m exceeding the Dohazari danger level                             |
| 2011 | Dohazari          | –                         | BWDB river stage data                       | Riverbank overflow                        | 0.87 m exceeding the Dohazari danger level                             |
| 2015 | Banigram, Bandarban | 1,800,000                | ACAPS (2015) and BWDB river stage data     | Torrential rain and Riverbank overflow    | 1.00 m exceeding the Banigram danger level                             |
| 2016 | Dohazari, Banigram | –                         | BWDB river stage data                       | Monsoonal rain and Riverbank overflow     | 0.6 m exceeding the Dohazari danger level and 0.18 m exceeding the Banigram danger level |
| 2017 | Dohazari          | 60                        | BWDB river stage data and Brakenridge (2018)| Monsoonal rain and Riverbank overflow     | 0.4 m exceeding the Dohazari danger level                             |
| 2018 | Dohazari          | –                         | BWDB river stage data                       | Riverbank overflow                        | 0.5 m exceeding the Dohazari danger level                             |
| 2019 | Bandarban         | 50,000                    | BWDB river stage data and Reliefweb (2018) | Monsoonal rain                            | 3.05 m exceeding the Bandarban danger level (i.e., 15.25 m)           |

Abbreviation: BWDB, Bangladesh water development board.
hazards. Unfortunately, scarce or no high resolution monitored data, absence of field survey-based investigation like inundation depth information in CHT makes riverine flood evaluation relatively challenging at large Sangu Basin scale. Identification of flash flood susceptibility has recently been attempted by Adnan et al. (2019) but without any verification of observed flood points or satellite data.

FIGURE 1  (a) Location of the Sangu River basin in Bangladesh; (b) Location of Bandarban city within the Sangu River basin; (c–j) showing pictures of 2019 flood on 13 July in Bandarban city (Photo Sources: Mr. Tushit Chakma, Executive Engineer, Chattogram Hill Tract Development Board, Bangladesh)
To simplify such issues concerning flood data unavailability, remote sensing (RS) and Geographic information system (GIS) techniques are widely popular in demarcating or analysing natural hazards and vulnerability (de Moel et al., 2013; Pradhan et al., 2014). Remote sensing allows easy acquisition of topographic features, land surface, vegetation cover, and much more relevant information of a region. Using RS data GIS tools help in making spatial dataset for flood hazard mapping. So far, several statistical techniques have been developed that involve GIS making the mapping result more accurate, logical, and acceptable. They can be classified as (a) Expert knowledge-based models, for example, analytic hierarchy process (AHP) and Analytical Network Process (ANP); (b) Bivariate and statistical-based models, for instance, Information value, frequency ratio (e.g., Tehrany et al., 2014), Certainly factor, Logistic regression, Weights-of-evidence, and neuro-fuzzy logic; (c) Machine learning models, such as artificial neural network, Adaptive Neuro-Fuzz Inference System (ANFIS) and Differential Evolution, ANFIS and biogeography-based optimisation (BBO), Bat algorithms, Decision tree, support vector machine, k-nearest neighbour, Hybrid/evolutionary models, and random forest (RF); and (4) hydrological or hydraulic models (e.g., Ahmadisharaf et al., 2017) such as Hydraulic Engineering Centre-River Analysis System (HEC-RAS) and Soil Water Assessment Tool (SWAT; Raihan et al., 2020).

Recent approaches to assessing flood hazards are mentioned in Table S1. Among different multi-criteria decision analyses (MCDA) based flood hazard/risk mapping (e.g., Kubal et al., 2009; Meyer et al., 2009; Kourgialas and Karatzas, 2011; Tang et al., 2018), AHP (e.g., Sinha et al., 2008; Fernández and Lutz, 2010; Kandilioti and Makropoulos, 2012; Stefanidis and Stathis, 2013; Jia et al., 2019, Das, 2018, 2019, 2020), and Fuzzy logic (e.g., Wang et al., 2011; Zou et al., 2012; Yang et al., 2013; Papaoannou et al., 2015) type are popular, most widely used and recognized tools for analyzing complex decision problems (Malczewski, 2006). Further, the ANP approach is an extended method of the AHP that replace the hierarchy among elements with a network (Dano et al., 2019). An optimal decision can satisfactorily be achieved for a decision problem like ours in the study by using both the AHP and the ANP specifically for the flood hazard assessment. Thereby, in these circumstances, the aim of this research is set to demarcate areas prone to riverine flood in the Sangu river basin of Bangladesh by the integration of GIS and MCDA techniques, investigate the effects of extreme rainfall indices on hazard mapping, and finally identify riverine flood exposures at subdistrict levels on the existing demographic setting, settlements, and infrastructures and different land-use types. Past MCDA-based hill researches have not coupled riverine flood hazard mapping approaches with extreme rainfalls and their return periods or linked potential hazard effects to subdistrict levels beforehand. Resulted plots may serve the preliminary step towards a comprehensive susceptibility mapping, which can be beneficial to government, planners, and researchers in reducing the probability of potential adverse impacts of flooding and supervising flood prevention management.

2 STUDY AREA

The Sangu River basin of Bangladesh is originated from the Arakan Hills (situated between the border of the Arakan and the Chattogram Hill Tracts) of Myanmar and follows northerly in the Hill Tracts. After passing 90 km, this river enters Bangladesh near Remarki and Thanchi Upazilas (i.e., subdistrict) of Bandarban District and flows 173 km more down. This river further flows west across the Bandarban and four subdistricts of Chattogram district and finally falls into the Bay of Bengal at Kutubdia Channel. The Sangu is a meandering river, and its width varies from 91 to 136 m in the hills and 305 to 610 m in the flat/plain area. The main tributaries of the Sangu River are the Dolukhal, the Chandkhali, and the Kumira Khali. The Sangu River basin (Figure 1) encompasses an area of 3842.82 km². The basin mostly has brown hilly soils. Topographically, the catchment area is highly irregular, and the slope varies from 0 to 74°. The orientation of most of the slope is south to the west direction towards the downstream of the Bay of Bengal. The ground elevation varies from 0 to 1,053 m above the mean sea level. The Sangu River basin shows mostly a dendritic drainage system. The climate of CHT is mostly tropical, a monsoon regime of storms in summer with dry winter. The annual average temperature is ~29°C, and the annual rainfall ranges from ~2,540 to 3,810 mm (Ahmed, 2015). The rainfall mainly concentrates on the monsoon season, and its duration is June to October, which is warm, cloudy, and wet.

3 MATERIALS AND METHODS

3.1 Data

Conventional secondary data (i.e., soil texture, rainfall, land-use, and land-cover), remotely sensed raster data, such as digital elevation model (DEM) and primary field survey data were collated. The DEM data with a 30 m resolution was collected from a website (https://earthexplorer.usgs.gov) having satellite images, that is, shuttle radar topographic mission (SRTM) in a geographic coordinate system named WGS84. The meteorological daily rainfall data of five gauging stations, namely,
Chattogram, Cox’s Bazar, Rangamati, Sitakunda, and Teknaf, were collected from Bangladesh Metrological Department (BMD) for the years 1990 to 2018. The geological map was downloaded from the United States geological survey (USGS; Alam et al., 1990) to prepare the lithology classification of the Sangu River basin. Building and road length data were collected from the OpenStreetMap data website (https://extract.bbbike.org).

Table 2 represents the detail of the significant dataset, their sources, and the primary purpose of uses. Soil texture and land-use and land-cover (LULC) data of the study area were collected from Soil Resource Development Institute (SRDI) and Bangladesh delta plan online data portal, respectively.

### 3.2 Preparation of thematic maps

From literature reviews, as presented in Table S1, and consultation with water experts engaged in flood preventive measures, we chose the most widely used common 12 flood conditioning factors (shown in Figure 2), namely, Topographic wetness index (TWI), soil, slope, elevation, distance from streams, slope, curvature, rainfall, LULC, lithology, aspect, height above the nearest drainage (HAND), and drainage density (dd) to prepare 12 individual thematic maps. Here, TWI was calculated using Equation (1) provided by Beven and Kirkby (1979) and Qin et al. (2011).

\[
TWI = \ln \left( \frac{A_s}{\tan \beta} \right)
\]

where \(A_s\) represents catchment area (m\(^2\).m\(^{-1}\)) and \(\beta\) indicates a local slope in degree.

The thematic maps on elevation, slope, aspect, HAND, and combined curvature were produced from DEM. Inverse Distance Weighting (IDW) interpolation method with power coefficient two was used to prepare thematic maps on rainfall indices, namely, 1-day maximum rainfall (RX1) and maximum consecutive 5-day rainfall (RX5). For lithology map preparation, (a) first, the raster format of the USGS geological map was digitized with proper geo-referencing, (b) consequently, the digitized map was exported as the vector data; and (c) finally, the vector data was converted to a raster map of 30 m resolution. For stream network delineation, hydrological analysis (e.g., flow direction or flow accumulation) was performed in the ArcGIS platform. The thematic layers called “distance from streams” and dd were estimated using the euclidean distance tool and line density tool of ArcGIS. Thematic maps on Soil and LULC vector data were created using polygon to raster conversion tool for 30 m resolution.

### 3.3 Flood hazard mapping

Both AHP and ANP were applied in delineating hazard maps. First, AHP was applied to assigned weights to the classes of every thematic map based on their relative importance and influencing capacity on the flooding via approaching experts and reviewing published literature. It involves a pair-wise comparison method, with weights determined on a numerical scale developed by Saaty (1980). The method also aids in weight’s normalization of the influencing factors with the help of a preference matrix, where all relevant criteria are compared against each other with reproducible preference factors (as shown in Table S2; Saaty, 1980). In the cases of the ANP method,
derivation of weights was attained by a super decision-based software (https://www.superdecisions.com/index.php) that crisscrossed pair-wise comparison between decision elements, referred to as nodes or subclasses, for each cluster or influencing factor. Following the ANP methodology of Dano et al. (2019), a comparison matrix was used to check the validity of the output. Second, consistency index (CI) is calculated to get the consistency ratio (CR) in order to check the reliability of the obtained weights. CI can be expressed as:

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

where \(\lambda_{\text{max}}\) is the average number of consistency vector, and \(n\) is the number of factors considered.

For computing the consistency ratio (CR), the following formula was applied.

\[
CR = \frac{CI}{RI}
\]

where \(RI\) is the random index whose value depends on the number of factors (\(n\)) compared as provided in (Saaty and Vargas, 2012; Table S3). For the comparisons to be consistent and acceptable, the CR must be <0.1. Otherwise, it is necessary to revise the subjective judgments to locate the cause of inconsistency (Saaty and Vargas, 2012) and recalculate the weights. CR value equals zero means a perfect level of consistency is present in the pair-wise comparison. The threshold value not exceeding 0.1 represents the judgments matrix is reasonably consistent.

After preparing all the thematic maps, the quantile classification method was used in the GIS platform for assigning weight. Soil, LULC, and lithology maps were classified according to their subjective classes and ranked according to their potential capacities in the run-off generation. Finally, all thematic (input) maps with assigned weights were overlaid to determine the composite (output hazard) map layer by applying the Weighted Linear Combination (WLC) method in ArcGIS software. Please refer to Malczewski (2000) and Rahmati et al. (2016c) for detailed techniques.

A total of 16 flood hazard maps under both AHP and ANP were availed by replacing the extreme rainfall parameter with indices, namely, RX1 and RX5 for 2.33, 20, 50, and 100-year return periods calculated via probability distribution functions (PDF). Mainly, the best-fitted PDF was selected based on the highest probability plot correlation coefficient obtained from four types of distribution functions, namely, two-parameter log normal, Pearson type III, log Pearson type III, and Gumbel. Noticeably, flood frequency analyses of the said return periods have an enormous influence on determining the design of flood levels for flood managing structures like embankments, roads, or drainage systems for CHT areas.
3.4 | Reference flood event

It is well known that open source Sentinel-1B SAR is preferred in producing flood maps over other satellite imageries because of its cloud-free regular 6-day sample and high (20 m) spatial resolution. Further, Uddin et al. (2019) have confirmed its high accuracy in mapping the Bangladesh flood extent. For these reasons, the referenced flood map was generated by Sentinel 1 image as the secondary data and coupled with primary field visit locations. As mentioned in Section 1, the recent flood event occurred in Bandarban city during the second week of July 2019. Afterwards, three field visits were done to identify the exact flood location points and record corresponding flood depths. The locations and attributes of the 2019 flood event for Bandarban city and its surrounding areas were collected during the field visits. The rest of the flooded (and unflooded) locations were selected using a systematic random approach from the satellite (Sentinel 1) image derived flood map. This flood map was derived by analyzing pre (July 2, 2019) and post (July 14, 2019) flood satellite (Sentinel 1, Level −1) images of the Sangu River basin. The flood map was prepared in the open-access ESA's Sentinel Application Platform (SNAP), specifically implementing the following preprocessing steps: data import, radiometric calibration, speckle filtering, radiometric terrain correction, linear-to-backscattering coefficient decibel scaling transformation, and data export. Especially, the methodologies described by Uddin et al. (2019) was followed in detail. The flood map had contained a total of 100 (flooded 53 and non-flooded 47) locations that were selected from every sub-watershed of the Sangu River basin.

Afterwards, the AHP and ANP model-based outputs of flood hazard maps for extreme rainfall events that occurred in the second week of July were compared with this referenced flood map using the statistical model verification technique viz., Receiver Operating Characteristic (ROC) curve method (Shafapour Tehrany et al., 2019). The areas beneath the ROC curve (AUC-ROC) are considered as the best indicator of distinguishing the areas with high flood probability from those with low flood probability (Lee, 2005). In the AUC method, the value regarding the area beneath the ROC curve varies between 0 and 1. According to (Yesilnacar, 2005), the qualitative relationship between AUC-ROC and efficiency of model can be classified into the following categories: 0.5–0.6 (poor); 0.6–0.7 (average); 0.7–0.8 (good); 0.8–0.9 (very good); and 0.9–1 (excellent; Yesilnacar, 2005). Note that while validating with Sentinel imagery, we used observed extreme rainfall indices, namely, RX1 and RX5, respectively, during 12–14 July 2019 (Figure 3e) and during 8–14 July 2019 (Figure 3j). Subsequently, the output map with the highest AUC-ROC value is considered in selecting the final model type among 16 hazard maps produced under Section 3.3. Finally, the total number of exposed people, settlements and infrastructures under different flood hazard zones for the chosen model type under each said return periods are calculated for different subdistricts of the Sangu River basin.

4 | RESULTS

4.1 | Details on thematic maps

4.1.1 | Topographic wetness index

A higher TWI value symbolizes a higher probability of flood occurrences (Rahmati et al., 2016b). Figure 4a shows the spatial database on calculated TWI that is categorized into five classes (0 2.29 – 5.1, 5.11 – 5.89, 5.9 – 6.94, 6.95 – 9.49, and 9.5 – 24.6). Here, the downstream of the basin shows the highest TWI.

4.1.2 | Elevation

Generally, higher elevated areas have less probability of occurring flood, and the lower elevated places (e.g., flat areas) have a higher probability of flood occurrences (Das and Pardeshi, 2018). Here, the highest elevation is found along the foothills of Arakan mountain located at the south and the lowest part is exposed to the Bay of Bengal (Figure 4b).

4.1.3 | Slope

Slopes are dictated by elevation contours having a direct relationship with the flow velocity, lithology, structure, type of soil, and drainage (Das, 2018). Steeper slopes (region having high gradient at the south) reduces the infiltration process but increases the process of surface run-off, and flat terrains (region having low gradient at the northwest) are susceptible to water stagnant (Figure 4c). As a result, low gradient slopes are highly vulnerable to flood occurrences compared to high gradient slopes (Ouma and Tateishi, 2014). In the study area, the slope gradient varies from 0 to 74°.

4.1.4 | Drainage density

The drainage density (dd) represents the ratio of the total length of rivers within an area to the size of the area...
(Greenbaum, 1989). If the drainage density is high, a significant run-off rate causes a higher flood (Shekhar and Pandey, 2015). Five classes of dd (0–0.062 km²/km, 0.06231–0.1986 km²/km, 0.1987–0.3193 km²/km, 0.3194–0.44 km²/km, and 0.4401–0.993 km²/km) are displayed in Figure 4d.

4.1.5 Curvature

Curvature is the rate of slope change in a particular direction (Wilson and Gallant, 2000; Das, 2018). The Sangu Basin is characterized by a more concave curvature profile than others comprising 1801.97 km² of areas. The
convex and flat profile covers an area of 938.78 and 520.68 km², respectively (Figure 4e).

4.1.6 | Distance from streams

The shortage distance from the stream network is highly affected by the flood hazard. On the contrary, distance is inversely proportional to the flood spreading and flood magnitude (Fernández and Lutz, 2010). Generally, a flood occurs nearby the bank of rivers and inundates adjoining low-lying areas (Samanta et al., 2018). As the distance increases, the slope and elevation become higher. In this article, distance from streams was divided into five classes (0–387.2 m, 387.3–903.4 m, 903.5–1,549 m, 1,550–2,388 m, and 2,389–8,228 m) as shown in Figure 4f.

4.1.7 | Rainfall

Rainfall has a significant influence on flooding when natural river channels cannot convey excess water. Hence, riverbanks overflow resulting in riverine floods. All extreme rainfall indices for each said return period commonly are noticed to have heavy rainfalls in the southwest upstream and the northeast downstream part, with an exception in the RX1 plot for 2.33-year return periods (see Figure 3). Interestingly, the spatial distribution of observed extremes during 2019 flood events under consideration (Figures 3e and 3j) matches with this RX1 of 2.33-year return periods. Again, few spatial differences are observed among maps, namely, RX1 for 100-year return periods (Figure 3d) and RX5 for 2.33, 50, and 100-year return periods. On the contrary, an inverse spatial pattern is observed for RX1 under 20 and 50-year return periods and RX5 under 20-year return periods.

4.1.8 | Land-use and land-cover

The components of hydrological processes, including evapotranspiration, infiltration, and run-off, are influenced by different types of land uses (Rahmati et al., 2016c). For instance, residential areas made of impermeable surfaces increase run-off and surface water flow. On the other hand, vegetation increases infiltration capacity. Hence, densely vegetated areas are less likely to flooding (Tehrany et al., 2013). Figure 4h displays dense settlements and farming land occurrences at the western downstream and forest at the rests of the hilly zones.

4.1.9 | Soil

The Sangu River basin is mostly covered by clay loam which comprises 78% of the total area (Figure 4i). The
rest of the area is enveloped with sand, sandy loam, and loam type of soils which occupy 3%, 11%, and 8% areas, respectively. Here, different soil types have different capacities of infiltration, hence, assigned with a different weight in Table 3.

4.1.10 | Lithology

The lithological formation is mainly considered as a critical factor for its site-specific and spatio-temporal variation. The permeable formations, that is, coarse-sand and sand, are perfect for rainwater infiltration and subsequently decrease the flood hazard. On the other hand, the impermeable factors, that is, clay and silt, increase the run-off rate, which amplifies the flood probability (Çelik et al., 2012). The Main lithological features in the Sangu river basin area are divided into seven classes as follows: Girujan Clay (Pleistocene and Neogene), Boka Bill Formation (Neogene), Dihing and Dupitila Formation Undivided, Bhuban Formation (Miocene), Tipam Sandstone (Neogene), Valley alluvium and colluvium, and the Beach and dune sand (Figure 4j). The most massive (50%) extent of the basin area is covered with the Bhurban (30%) and Boka Bill (20%) formations. The down-stream of this basin belongs to a coastal region showing coastal mixed sediment. Other formations (i.e., Valley alluvium and colluvium, Neogene type Boka Bill Formation, Neogene type Tipam Sandstone) follow a linear fashion with mixed coarse sediments.

4.1.11 | Aspect

The aspect commonly refers to the horizontal direction of the mountain facing and influences local climatological conditions (i.e., received the amount of rainfall and sunshine). Figure 4k represents the spatial distribution of aspects in the study area where a sizeable downstream portion displays mostly flat category.

4.1.12 | Height above nearest drainage

As areas having lower heights and short distances from streams has more likelihood to be flooded rather than the higher lands, the lower value range of the factor, called height above nearest drainage (HAND), is assigned to a higher weight and vice versa (Table 3). Figure 4l depicts the spatial patterns of the study area for HAND.

4.2 | Flood hazard mapping

Summary of the pair-wise comparison between every subclasses of the said 12 thematic layers and the corresponding relative weights that are finally assigned are presented in Table 3. The resultant flood hazard map values obtained from integrating 12 thematic maps are classified into five distinctive (quantile) divisions: “very low”, “low”, “moderate”, “high”, and “very high” (Figure 5). Extreme lowlands and areas adjacent to the riverbanks (mainly concentrated in the west and south plains) were labeled as a “high” to “very high” hazard zone. These particular locations have high elevation with a slope of more than 40° but a flat aspect, are far located from the stream, and the value of TWI is also low.

Potential “high” flood locations are found to be situated in the south part of the Sangu basin, where the river has a steep slope and elevation change at the foot of the mountains. Similarly, the regions with higher slope are less susceptible to flood, as the slope and elevation play a vital role in flood occurrence. According to Zaharia et al. (2017), areas with slopes exceeding 15° show less accumulation of water. Hence, they have a low probability of occurring flood or water stagnation. On the other hand, regions that have an extensive cover of dense vegetation and flat surface topography are in favor of the retention of the excess surface water during a flood event. The area having slope ranging from 0% to 5%, RX1 ranging from 203.8 to 286.5 mm, elevation varies from 0 to 19 m, LULC is mainly settlement, agricultural land, and soil type is clay loam, loam, this type of area is subject to “high” to “very high” flood hazard zone. The geological structure of this region includes Valley alluvium and colluvium, which are found highly prone to flooding with drainage density ranges from 0.4401 to 0.44 km/km². These types of zones are mainly dominant in the down-stream, which is located west part of the basin area.

Notably, 65% of Bandarban city areas are vulnerable to “high” up to “very high” flood hazard (Figure 5h). In fact, the location of this city is within very low elevation, having a riverbank on one side and a steep hill on the other side. Thereby, in monsoon season, heavy rainfall from the upstream and surrounding elevated hills generate massive run-off creating overflow, hence, flood in this area. Apart from Bandarban city, about 1962 km of roads and 81.79% of residential buildings are prone to “high” and “very high” flood (Figure 6). This implies that the construction of temporary flood shelters demands immediate attention to these zones. Besides, such hazard-prone zones should get priority for the extra healthcare services to avoid flood-linked common illnesses like cholera, typhoid, infections, or snakebite. Otherwise, floods can
| Serial | Factors                          | Subclasses of features | Consistency ratio (CR) | Weight AHP | Weight ANP |
|--------|----------------------------------|------------------------|------------------------|------------|------------|
| 1      | Topographic wetness index        | 9.5–24.6               | 0.0328                 | 0.521      | 0.910      |
|        |                                  | 6.95–9.49              |                        | 0.252      | 0.035      |
|        |                                  | 5.9–6.94               |                        | 0.119      | 0.270      |
|        |                                  | 5.11–5.89              |                        | 0.067      | 0.020      |
|        |                                  | 2.29–5.1               |                        | 0.041      | 0.010      |
| 2      | Elevation                        | 0–19                   | 0.0396                 | 0.471      | 0.718      |
|        |                                  | 19.01–70               |                        | 0.254      | 0.131      |
|        |                                  | 70.01–154              |                        | 0.155      | 0.082      |
|        |                                  | 154.1–309              |                        | 0.079      | 0.054      |
|        |                                  | 309.1–1,053            |                        | 0.041      | 0.039      |
| 3      | Slope                            | 0–1.43                 | 0.0799                 | 0.476      | 0.706      |
|        |                                  | 1.44–6.31              |                        | 0.235      | 0.170      |
|        |                                  | 6.32–12                |                        | 0.159      | 0.077      |
|        |                                  | 12.1–19.5              |                        | 0.094      | 0.042      |
|        |                                  | 31.47–74.27            |                        | 0.037      | 0.014      |
| 4      | Curvature                         | –26.13 to –0.7167      | 0.0506                 | 0.415      | 0.711      |
|        |                                  | –0.7166 to –0.3166     |                        | 0.314      | 0.161      |
|        |                                  | –0.3165 to –0.1165     |                        | 0.148      | 0.083      |
|        |                                  | –0.1164 to 0.4837      |                        | 0.083      | 0.035      |
|        |                                  | 0.4838–24.89           |                        | 0.040      | 0.018      |
| 5      | Distance from stream             | 0–387.2                | 0.0382                 | 0.465      | 0.751      |
|        |                                  | 387.3–903.4            |                        | 0.245      | 0.114      |
|        |                                  | 903.5–1,549            |                        | 0.160      | 0.076      |
|        |                                  | 1,550–2,388            |                        | 0.088      | 0.038      |
|        |                                  | 2,389–8,228            |                        | 0.042      | 0.021      |
| 6      | 1-day maximum rainfall, RX1      | 198.59–198.62          | 0.0581                 | 0.495      | 0.771      |
|        | (median)                         | 198.63–198.67          |                        | 0.233      | 0.110      |
|        |                                  | 198.68–198.75          |                        | 0.154      | 0.072      |
|        |                                  | 198.76–198.91          |                        | 0.079      | 0.330      |
|        |                                  | 198.92–199.27         |                        | 0.039      | 0.140      |
| 7      | Lithology                        | A                      | 0.0325                 | 0.361      | 0.722      |
|        |                                  | B                      |                        | 0.238      | 0.117      |
|        |                                  | C                      |                        | 0.155      | 0.062      |

(Continues)
accelerate further death and sickness of local inhabitants. Furthermore, ~83.34% of government buildings that include Police station, Post office, and Court and ~62.14% of agricultural lands are at risk of falling into “high” to “very high” flood hazard zone (Figure 6). Interestingly, even having substantial differences in rainfall patterns

| Serial | Factors                        | Subclasses of features | Consistency ratio (CR) | Weight | AHP | ANP |
|--------|--------------------------------|------------------------|------------------------|--------|-----|-----|
| 8      | Land use and land cover        |                        |                        | 0.0278 |     |     |
|        | Water body                     | 1 2 5 7                |                        | 0.530  | 0.775 |
|        | Agricultural land              | 1 2 5                  |                        | 0.270  | 0.129 |
|        | Forest                         | 1 3                    |                        | 0.140  | 0.067 |
|        | Settlement                     | 1                      |                        | 0.060  | 0.300 |
| 9      | Soil                           |                        | 0.0387                 |        |     |     |
|        | Clay Loam                      | 1 2 5 7                |                        | 0.541  | 0.782 |
|        | Loam                           | 1 2 3                  |                        | 0.247  | 0.112 |
|        | Sandy Loam                     | 1 3                    |                        | 0.143  | 0.070 |
|        | Sand                           | 1                      |                        | 0.069  | 0.031 |
| 10     | Drainage density               |                        | 0.0173                 |        |     |     |
|        | 0.4401–0.993                   | 1 3 5 7 9              |                        | 0.538  | 0.781 |
|        | 0.3194–0.44                    | 1 2 3 5                |                        | 0.217  | 0.102 |
|        | 0.1987–0.3193                  | 1 2 3                  |                        | 0.125  | 0.066 |
|        | 0.06231–0.1986                 | 1 2                    |                        | 0.075  | 0.037 |
|        | 0–0.0623                       | 1                      |                        | 0.045  | 0.019 |
| 11     | Height above nearest drainage  |                        | 0.0286                 |        |     |     |
|        | 0–3                            | 1 2 5 7 9              |                        | 0.497  | 0.767 |
|        | 3–24                           | 1 2 4 6                |                        | 0.258  | 0.120 |
|        | 24–66                          | 1 2 3                  |                        | 0.124  | 0.056 |
|        | 66–156                         | 1 3                    |                        | 0.090  | 0.042 |
|        | 156–853                        | 1                      |                        | 0.031  | 0.014 |
| 12     | Aspect                         |                        | 0.0877                 |        |     |     |
|        | Flat (−1)                      | 1 2 2 4 3 3 3 2 3 5    |                        | 0.209  | 0.590 |
|        | North (0–22.5)                 | 1 2 3 4 2 2 2 2 2     |                        | 0.154  | 0.090 |
|        | Northeast (22.5–67.5)          | 1 2 3 4 3 3 2 3 3     |                        | 0.146  | 0.080 |
|        | East (67.5–112.5)              | 1 2 3 3 1 2 4         |                        | 0.102  | 0.060 |
|        | Southeast (112.5–157.5)        | 1 2 3 2 1 3           |                        | 0.087  | 0.050 |
|        | South (157.5–202.5)            | 1 3 2 3 4             |                        | 0.081  | 0.040 |
|        | Southwest (202.5–247.5)        | 1 3 2 2               |                        | 0.710  | 0.030 |
|        | West (247.5–292.5)             | 1 3 3                 |                        | 0.670  | 0.020 |
|        | Northwest (292.5–337.5)        | 1 2                   |                        | 0.510  | 0.019 |
|        | North (337.5–360)              | 1                     |                        | 0.330  | 0.010 |

Note: A, Girujan Clay (Pleistocene and Neogene); B, Boka Bill Formation (Neogene); C, Dihing and Dupitila Formation Undivided, D, Bhuban Formation (Miocene); E, Tipam Sandstone (Neogene); F, Valley alluvium and clullvium; and G, Beach and dune sand.
for RX5, no notable variation is observed in the outputs of flood hazard maps among AHP-based maps (Figure 5d–f) or ANP-based plots (Figure 5g–i). On the other hand, upstream southern hill parts in ANP derived hazard maps display more areas prone to “high” or “very high” flood in comparison to AHP-based plots with...
exceptions in Figure 5e,f under RX1 for the 2.33- and 20-year return periods, respectively.

4.3 Validation of flood hazard map

In flood hazard analysis, it is crucial to assess the accuracy and to validate the output result. Accuracy measurement is an essential step for validating the study result and is a must to apply (Shafapour Tehrany et al., 2019). The primary goal of the accuracy assessment is to find areas that are actually affected by floods and thus compare them with the known flood locations (Rahmati et al., 2016a). Among various techniques of assessing the accuracy and validation (Ali et al., 2019), the area under the ROC curve (AUC) is widely used in natural hazard studies due to its comprehensive, reasonable, and visually understandable method of validation (Nefeslioglu et al., 2010). The AUC values obtained by comparing with the Sentinel image (Figure 7a) are found to vary between 0.77 and 0.79 (Figure 7b,c), which correspond to the validation accuracy of 77% and 79%, respectively. AUC-ROC curves for RX1 and RX5 indices prepared by both AHP and ANP have been shown in Figures 7b,c, respectively. Interestingly, ANP-based AUC scores are always higher than those of AHP-based maps. The ANP-based flood hazard map derived by RX1 shows the best match with the Sentinel image of Figure 7a with the highest (79%) AUC score. Hence, it is selected for the latter analyses (see Section 4.2). The ANP output for 1-day maximum rainfall under 100-year return periods presented in Figure 5h is finally used in exposure assessments for flood design, management planning, and policymaking purposes.

5 DISCUSSION ON EXPOSURE TO FLOOD HAZARDS

The Sangu River basin is comprised of 13 subdistricts with different numbers of people exposed to different categories of flood hazards. In Figure 8, a total of 0.4 and 0.31 million population in Satkaniya and Lohagara subdistricts are lying in “high” to “very high” flood hazard zones, respectively. Likewise, the very low population in Belai chari (0.003 million), Lama (0.02 million), Ruma...
(0.04 million), Thanchi (0.02 million) subdistricts are mostly (~60% area) exposed to “very low” riverine flood category but are previously being detected as a “very high” zone for flash flood events (Adnan et al., 2019). Being located downstream of a river, 71% area of Anwara and 58% area of Boalkhali subdistricts are susceptible to “very high” flood. This region of CHT is mostly famous for touristic places with high mountain scenarios and indigenous/tribal ethnic groups. In particular, out of a total of 45 ethnic groups in Bangladesh, 11 tribes with a population of 1.79 million (BBS, 2011) are living in the Bandarban district alone. Among them, the Bwam, the Marma, the Murang, and the Tanchangya are the dominant indigenous ethnic groups constituting a 70% hill population of this district (Khan et al., 2007). Note that most of their houses are made of fragile material like bamboo, timber, and mud. Hence, their tipping points are close to being reached. Policymakers should provide a specific plan to improve roads, communication, and network coverage of remotely affected areas (i.e., Ruma, Thanchi, and Rowangchhari) to minimize risks. Especially pregnant or lactating mothers need intensive care in flood situations, particularly in remotely affected areas. Immediate management activities should provide more concern about (a) road network services of 1,237 km at risk, exclusively that connect community health clinics in Satkania, Lohagara, and Anwara, (b) provision of postflood relief items for the 502 km² flood-prone farming lands, and (c) allocating reconstruction/repairing budget for (87.5%) hazard-prone education buildings under “high” and “very high” zones (See Figure 6). Such hazard-based analysis undertaken at subdistrict levels will specifically benefit CHT council to develop plan for management and disaster preparedness, CHT

**Figure 7**  (a) Derived flood map from Sentinel 1 satellite image and Receiver Operating Characteristic (ROC) curves for flood hazard maps based on (b) Analytical hierarchy process (AHP) and (c) Analytical network process (ANP) in the Sangu River basin. Here, RX1 and RX5 denote 1-day and 5-day maximum rainfalls, respectively, and AUC represents the area under the curve.
Development Board (CHTDB) and Local Government Engineering Department (LGED) to improve infrastructures under the rationalizing water resource management program of Bangladesh Delta Plan 2100, Department of Public Health Engineering (DPHE), international/local nongovernmental organizations and others to understand better the place-based critical needs and Bangladesh Water Development Board (BWDB) in strengthening embankments projects.

6 | CONCLUSIONS

Flooding becomes a significant environmental threat for South Asia, which is evidenced by frequent flood events. The Sangu River basin situated at the Chattogram hill tracts of Bangladesh is no exception. Lack of proper flood management for flood-prone areas can hinder sustainable socio-economic development. On the contrary, a right and proper hazard map can become handy in reducing probable damage dangers. However, considerable data gaps in high-resolution long-term monitored sites and the absence of field investigations make it challenging to produce the flood hazard map with complete satisfaction, especially in hard to reach hill zones like CHT. Further, considering cost and time effectiveness, in recent times, MCDA-based hazard maps have become practical to provide a guideline to administrators and planners to address flood management issues on the ground. Thereby, this article critically assesses a case-study on the riverine flood fostering two RS-GIS based MCDA techniques, namely AHP and ANP, through validation and comparison of each hazard maps against the recent 2019 flood event using primary field surveys and Sentinel based satellite images. Drawing insights from the validation score, that is, AUC-ROC value of 0.79, the article infers that ANP-based flood hazard mapping under rainfall factor RX1 denotes a reliable hazard map showing close to the field results. A visual comparison between AHP and ANP outputs indicates that they have more or less similar patterns with minor discrepancies. For example, in the case of the Sangu river basin, discrepancies are observed in the southeast and northeast attributed to extreme rainfall differences in spatial distribution.

For the Sangu case-study, this article categorized five flood hazard zones, of which the “high” and “very high” hazard zones are observed to be mainly distributed in the northern and central parts of the basin. Alarmingly, the highest (i.e., 0.4 million) number of people in Satkaniya and maximum (i.e., 94%) area in Anwara subdistricts are noted to have more exposures to “high” and “very high” flood hazard categories. All the 11 indigenous tribes with a population of 1.79 million in the Bandarban district are located living in the low to moderate flood hazard zones. Network disruptions of 39% of roads at risk can threaten the ability to provide medical care during the flood. Immediate attention is required to speed up postflood

![Figure 8](image-url)
rehabilitation methods for 43% and 25% of flood-prone agricultural land and education buildings, respectively. Likewise, detailed information on subdistrict level exposures is expected to help decision-makers and planners in setting priorities and assessing specific budget plans for district-wise prevention programs. The case study lessons provided by this study serve as a preliminary step in this regard for other deltas around the world.

However, some limitations to our study still exist. It does not account for the sensitivity analysis, considers equal weightage for all 12 factors while applying the WLC method, employed a fixed clustering technique (i.e., quantile), validation accounted only one single flood event instead of considering a composite layer of extreme flood events, and limit the exposures to only people and physical elements. Further, uncertainties are involved in (a) determining the weights in AHP by expert’s subjective/biased preferences and in ANP while performing comparisons between subclasses at the same hierarchical level, (b) expanding interpolation methods, and (c) using a lower number of observation points for interpolation. The accuracy of the study can further be enhanced by the use of higher-resolution DEM, flooding depth, and flow data for flood routing and model simulations (Merwade et al., 2008) by accounting orographic correction in IDW and by incorporating socio-economic parameters. However, as mentioned earlier, very good accordance between the AHP/ANP-based hazard maps and field-based flood map ascertains a reasonable basis for discussions on disaster reduction measures.

To date, flood prevention plans in mountain zones are based mainly on a previous events inventory of information, in part due to the limited number of inspections. Also, holistic (scientific) consideration of all flood controlling geomorphological factors is rarely considered. Hence, success was partial. In such circumstances, the outcomes of a study like ours can add scientific values to the evolving MCDA process and benefit current plans/programs through revising via RS-GIS. Furthermore, relevant organizations can assign priority, for example, where further constructions should be restricted (i.e., “very high” and “high” hazard-prone areas) and where they should not (i.e., “very low” and “low” hazard-prone areas). Responsible authorities may wish to consider this guide for effective flood management plans in a number of ways, for example, (a) in emergency preparedness, including flood relief and aid operations, (b) determining safe and unsafe areas for sustainable development, (c) doing construction and development plans for flood defense, (d) to control development especially in “high” hazard-prone area, (e) to provide proper land use planning, (f) to priorities subdistricts for flood management based on hazard-prone people/area, and (g) to prevent migration by motivating for alternative livelihood strategies which are less sensitive to flood (i.e., flood-tolerant agriculture, cattle farming, etc.).

DATA AVAILABILITY STATEMENT
The data that support the findings of this study are available from the corresponding author upon reasonable request.

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