SPATIAL ANALYSIS AND IDENTIFICATION OF FLOOD RISK ZONES IN MYMENSINGH DIVISION USING AN INTEGRATED GIS-AHP FRAMEWORK

Sishir Das *[1], SM Rifdu Rafee [2], Swadheen Md. Masum Reza[3] and Md. Shagor Hossain[4]

[1] *Student, Department of Civil Engineering, Mymensingh Engineering College, Bangladesh, e-mail:* sishir05.ce@gmail.com

[2] *Student, Department of Civil Engineering, Mymensingh Engineering College, Bangladesh, e-mail:* rifduabd@gmail.com

[3] *Student, Department of Civil Engineering, Mymensingh Engineering College, Bangladesh, e-mail:* swadheenmasum@gmail.com

[3] *Student, Department of Civil Engineering, Mymensingh Engineering College, Bangladesh, e-mail:* hossainshagor6969@gmail.com

***Corresponding Author**

ABSTRACT

Due to changing climate conditions and geomorphological vulnerabilities, the low-lying and riverine areas of Mymensingh Division regularly experience frequent and severe flood events, which cause significant damage to livelihoods and infrastructure. This emphasizes the necessity of effective flood management and mitigation initiatives. The initial step to achieving these goals is the identification of flood-prone areas. In response, the present study aimed to delineate the flood risk zones of the Mymensingh Division by integrating the Analytical Hierarchy Process (AHP) with Geographic Information System (GIS). AHP was chosen for its ability to handle complex decision-making problems by incorporating both qualitative and quantitative data. This study adopted the most relevant and widely used flood conditioning factors commonly applied in numerous recent studies. Each factor has been systematically compared with the others through pairwise comparisons within the AHP framework to determine its relative weight, based on expert judgment. The weighted layers have been overlaid in a GIS environment to create the flood risk map with five categories as very low, low, moderate, high, and very high. The results show that 27.82% of a total of 10043.66 sq.km. area was under very high and highly vulnerable zones, and Netrokona is the most vulnerable district in that region, with 65.13% of its area identified as highly susceptible to flooding. Using the ROC–AUC curve, the flood risk map has been validated with a score of 0.86 based on a flood inventory map derived from historical flood event data and satellite imagery. The findings of this study will help policymakers in formulating effective strategies to mitigate flood risks in the region.

Keywords: *Flood; Vulnerable Zone; Analytical Hierarchy Process (AHP); Geographic Information System (GIS); Risk mapping.*

1. INTRODUCTION

Flood is considered as one of the most severe natural disasters worldwide, which is responsible for massive social, economic and environmental damages (Hoque et al., 2019). Nearly 2.4 million deaths and an estimated USD 82 billion in economic losses globally between 1950 and 2021. This impact was most devastating in Asia, which accounted for more than half of the global flood-related losses during 1990–2021(Jones et al., 2022). Several recent studies have predicted that the frequency and intensity of flood disasters are expected to rise substantially (Chen et al., 2015). Since the climate is changing continuously, developing nations with weak infrastructure and limited disaster preparedness are finding it more challenging to anticipate and reduce the damage caused by floods. Bangladesh is a highly flood-prone area because of its geographical location at the confluence of the Ganges, Brahmaputra, and Meghna (GBM) rivers, along with these basins' hydro-meteorological and topographical characteristics. Every year, about 20–25% of the country's area is submerged, and in extreme cases, up to 80% becomes inundated (Kundzewicz et al., 2014; Mirza, 2002). Mymensingh Division lies in the north-central region of Bangladesh with an average elevation of 25m above the mean sea level. The climate of this area is predominantly influenced by heavy monsoon rainfall. During summer, south-westerly winds from the Bay of Bengal ascend along the Meghalaya Hills and result in heavy rainfall. The region is surrounded by some of the major river streams like the Brahmaputra, Kangsha, and Jamuna. During the monsoon period, the rivers overflow due to heavy rainfall and the upstream flow. As a result, it increases the area's susceptibility to flooding. The hydrological and geological nature of this location is changing rapidly. Therefore, it is crucial to implement effective planning and measures to mitigate future catastrophes. The effective management of disasters involves strategies that are oriented to preventing and mitigating the possibility of floods (Dewan, 2013). The first step is to identify these flood-prone areas to make sure communities in the most vulnerable areas are better prepared and receive early warnings. In recent years, Geographic Information Systems (GIS) and remote sensing have become essential technologies for assessing flood risk. Flood-prone locations can be identified more accurately by using multiple flood-influencing factors in a GIS framework (Chakraborty & Mukhopadhyay, 2019; Tehrany et al., 2014; Zaharia et al., 2017). Additionally, integrating hydrological data with demographic and socioeconomic data enables more accurate results (Sanyal & Lu, 2005). There are various methods used to generate flood risk maps. Multicriteria Evaluation (MCE) is one of the most suitable methods among them to map flood-prone areas with precision(Danumah et al., 2016; Santos et al., 2019). AHP is the most common MCE method, which has been applied in various studies. By using the weighted overlay or the weighted sum technique in a GIS environment, this evaluation can be achieved (Radwan et al., 2019). Therefore, the goal of the current study is to evaluate the flood-prone regions within the Mymensingh Division by integrating AHP with GIS techniques.

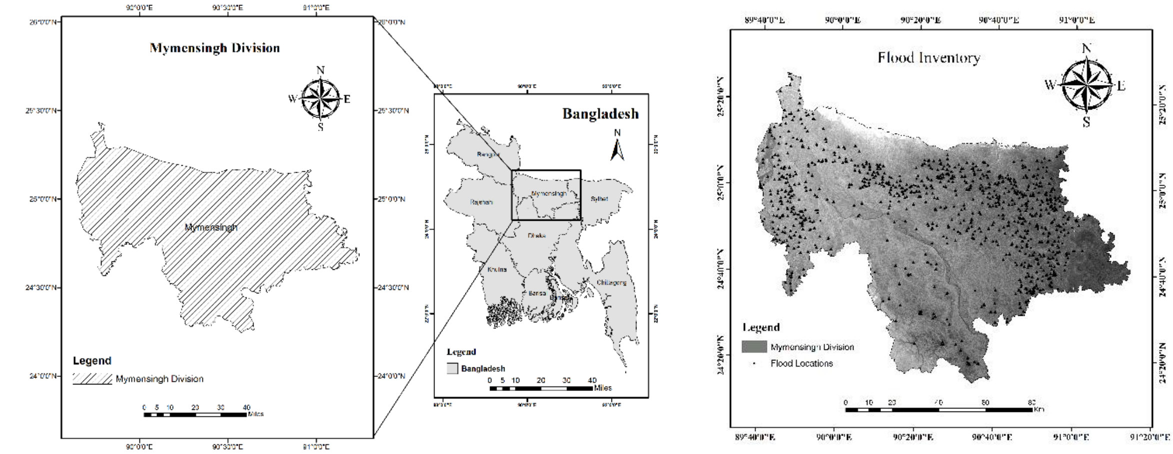
2. MATERIALS AND METHODS

2.1 Study area

Mymensingh Division is located in the north-central region of Bangladesh with an area of 10,584 km². As seen in Figure 1(a), the division lies between latitudes 24°15' N and 25°12' N and longitudes 90°04' E and 90°49' E. It is predominantly composed of low-lying areas situated at the foothills of the northeastern Himalayas, encompassing the Garo Hills and the Meghalaya state of India. It has four districts and a total land area of 10,485 square kilometres. All four districts of this division lie on the same delta formed by the Brahmaputra River. Almost every year, the region faces severe riverine flooding due to its flat terrain, and it is also more vulnerable to flash flooding (Akter et al., 2016).

2.2 Flood Inventory Mapping

The flood inventory map is essential for the validation of the vulnerability model and identified flood risk zones. In this study, the 2022 monsoon flood event that occurred across the study area was mapped using Sentinel-1 SAR imagery within the Google Earth Engine (GEE) platform. The Sentinel-1 images provide four types of polarization modes, and for this study, we have used the VH polarization due to its high sensitivity. The Refined Lee filter was used to improve the accuracy of flood detection by reducing the speckle noise in the image. A change-detection approach was then used to quantify the backscatter ratio between pre-flood and flood-period photos, where a decrease in VH backscatter was identified as flooding (Martinis et al., 2013).



(a) (b)

Figure 1: (a) Study Area; (b) Flood Inventory Map

2.3 Data collection and processing

The datasets used in this study were obtained from various sources, and geospatial techniques were employed to generate spatial layers from these datasets. The integration of hazard and exposure with social vulnerabilities provides valuable insights for developing effective flood risk management (Koks et al., 2015). Besides, the flood vulnerability and its effect on the community largely depend on the joint effect of social and physical factors(Hoque et al., 2019). Therefore, this study utilized both indicators for a better understanding of the region's vulnerability to flooding. Figure 2. shows the overall methodological framework for the flood risk assessment. For the integration of physical indicators, a total of nine key factors have been selected based on prior studies. The datasets have been obtained from multiple sources. The Shuttle Radar Topography Mission (SRTM) DEM data have been collected from the USGS freely available data resources to extract elevation, slope, topographic wetness index (TWI), and drainage density. The land-use and land-cover map was produced through supervised classification of the Landsat-8 image, and it was classified into five distinct classes. In addition, Copernicus climate data sources were utilized to extract the annual rainfall data, which was then converted into a suitable format for analysis in the GIS environment. For social vulnerability, six types of factors were selected, including population density, female population, agriculture-dependent population, literate population, dependent population, and disabled population. District-wise population for all those criteria was collected from the Bangladesh Bureau of Statistics (BBS) Population Census 2022. Table 1. presents the essential data information. All of the factors for both criteria were classified into five classes using the Natural Breaks (Jenks) classification algorithm in ArcGIS and resampled to a 30 m x 30 m resolution for uniform spatial resolution, as shown in Figures 3 and 4.

Table 1: Data types and sources used in this study.

Datasets	Year	Description	Resolution	Source
Digital Elevation Model	2019	SRTM	30m	USGS
LULC	2025	Sentinel-2 L2A	10m	Esri
Lithology	2023	Extracted from the Map	1:1,000,000	FAO
Rainfall	2003-2024	Annual Rainfall	0.05˚	CHRS
Social factors data	2022	Derived in tabulation format	30m	BBS 2022
Distance to Roads & River	2025	Line shape file format	30m	OpenStreetMap

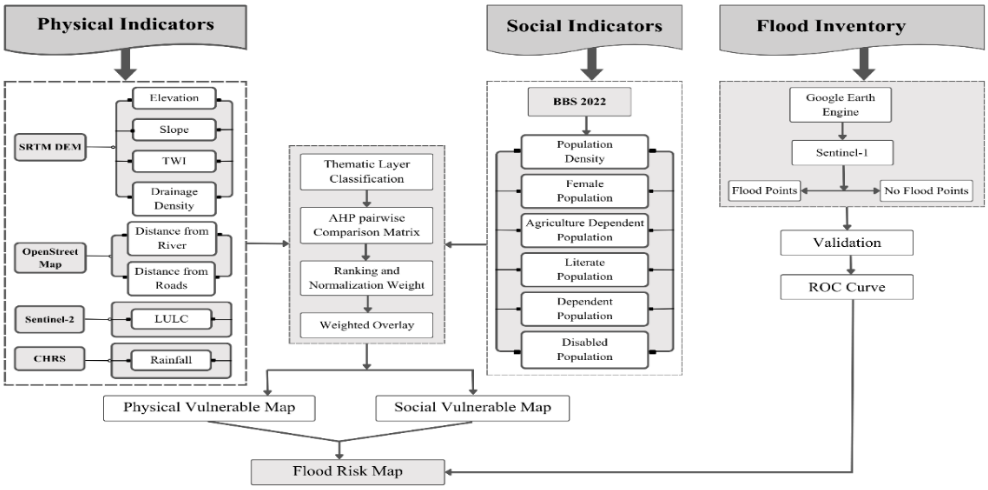


Figure 2: Methodological flowchart of the flood risk assessment.

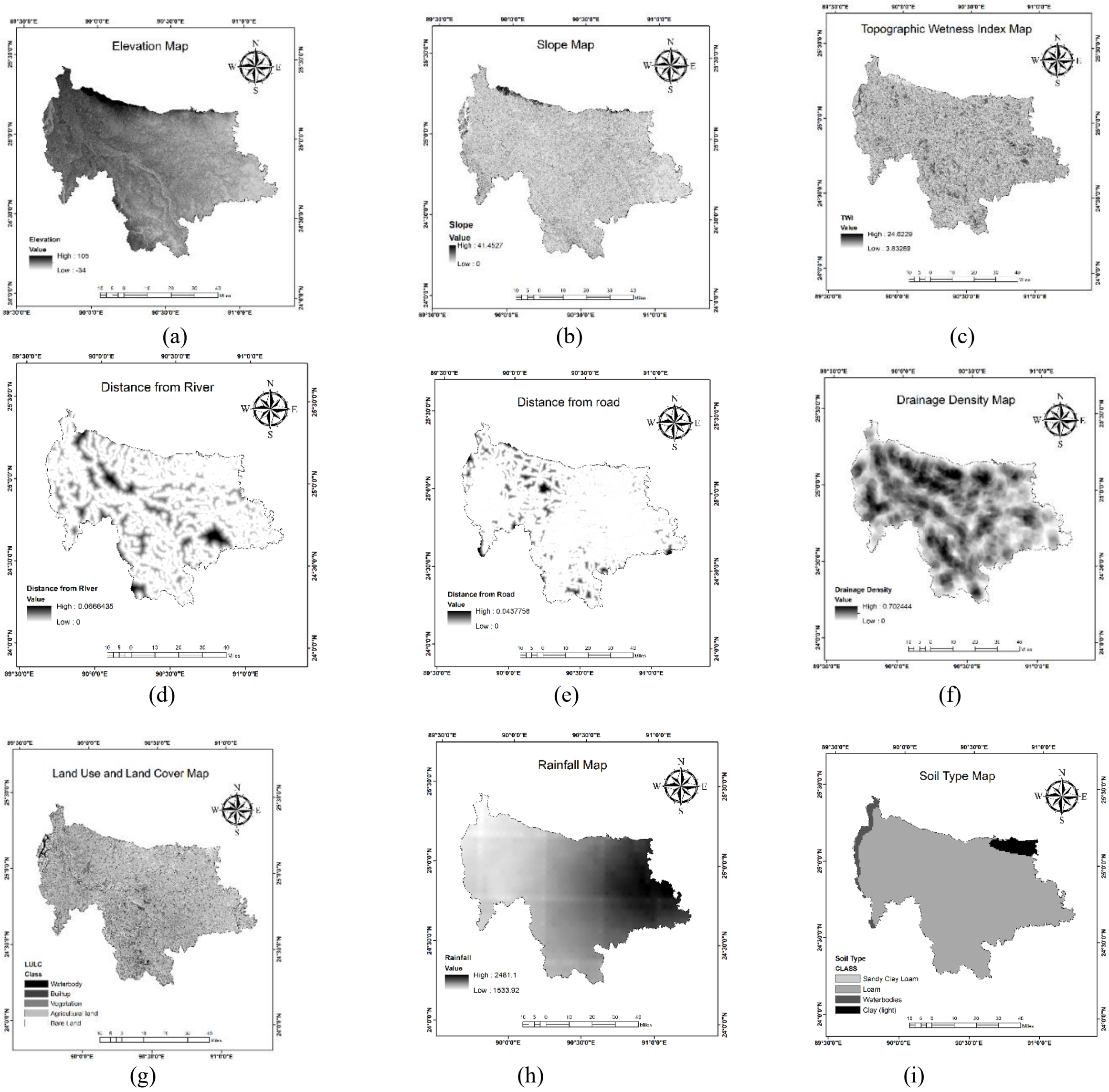


Figure 3: Physical Vulnerable Factors- (a) Elevation; (b) Slope; (c) TWI; (d) Distance from river; (e) Distance from road; (f) Drainage Density; (g) LULC; (h) Rainfall; (i) Soil Type

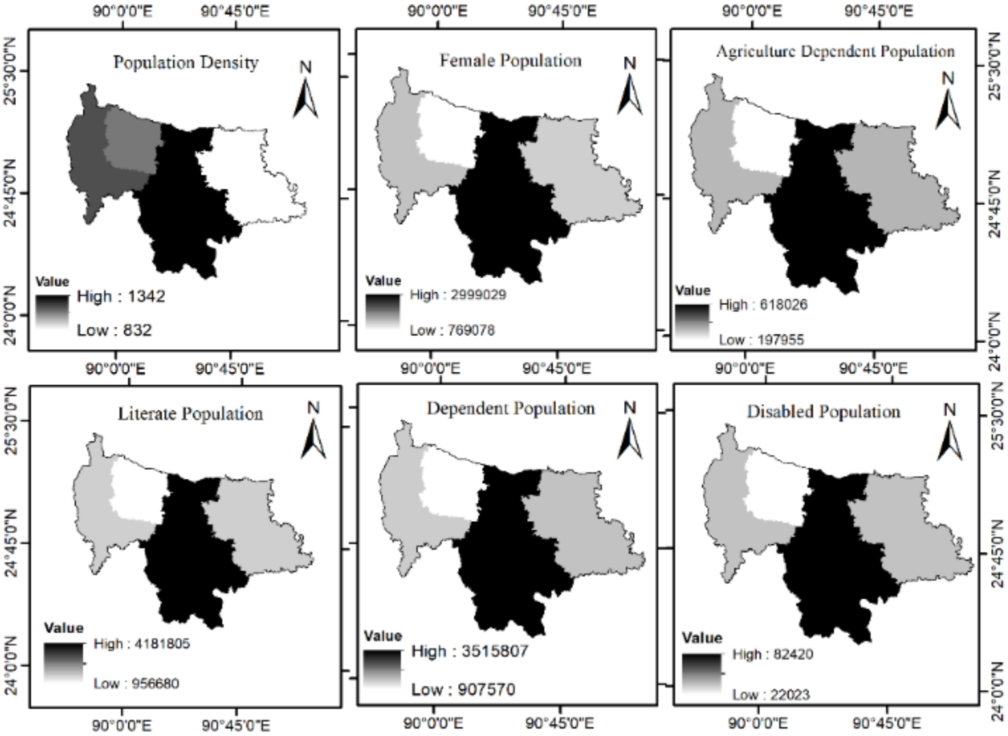


Figure 4: Social Vulnerability Factors

2.4 AHP Framework and Criteria Weighting

The Analytical Hierarchy Process (AHP) is a multi-criteria decision-making technique used for assessing an area's susceptibility to flooding. Multiple flood conditioning factors can be integrated by pairwise comparison to give preferences to the most important one through this method. A structured procedure has to be followed to rank multiple criteria and assign appropriate weights based on their relative importance. The standardized scale of relative importance ranges from 1 to 9, as detailed in Table 2, where 1 indicates equal importance and 9 represents extreme importance (Saaty, 2004). The Analytical Hierarchy Process (AHP) is a multi-criteria decision-making method used to identify an area's susceptibility to flooding. For this study, a pairwise comparison matrix was constructed based on expert opinion for both physical and social vulnerability indicators. These matrices were then normalized to convert the assigned scores into a comparable scale. The mean value of each row in the normalized matrix provided the weight or priority score for each parameter.

Table 2: Saaty's scale of relative importance

Importance Intensity	Degree of preference	Explanation
1	Equal importance	Both elements equally contribute to the objective
2, 4, 6, 8	Intermediate values	Parameters are very close in importance
3	Moderate importance	Moderately favorable to one another.
5	Strong or essential importance	Strongly or essentially favorable to one another.
7	Very strong importance	One parameter is significantly superior to another
9	Extreme importance	Highest possible evidence favors one parameter as superior

Finally, the consistency ratio was calculated to ensure the judgments are logically consistent and acceptable. The following equation was used to calculate the consistency ratio:

$$CR = \frac{CI}{RI} \tag{1}$$

Here, *CR* = Consistency ratio, *RI*= Random index, and *CI*= Consistency index which was computed as:

$$CI = \frac{\lambda_{max} - \eta}{\eta - 1} \quad (2)$$

Where, λ_{max} is the principal Eigen value and n is the number of factors.
If the CR value is less than 0.1, then the AHP model is acceptable, and the value for RI is identified by Saaty, as shown in Table 3.

Table 3: Random coherence index values

N	1	2	3	4	5	6	7	8	9	10	11
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.59

2.5 Flood Risk Analysis

After calculating the weight for each factor from both criteria, all generated thematic layers were integrated and processed within the GIS platform. Before combining the layers, each factor was standardized to a common 1–5 scale, where a value of 1 indicates the lowest susceptibility and 5 indicates the highest. Then, using the Weighted Overlay Analysis tool in ArcGIS, these standardized layers were combined to produce the criterion-specific vulnerability map. The same approach was applied to both physical and social indicators. After obtaining the vulnerable map for each criterion, an equal weight of 0.50 was assigned to create the final optimized flood risk map.

3. RESULT AND DISCUSSION

3.1 Physical Index analysis

This study incorporates nine flood conditioning physical elements to assess the flood-vulnerable zones. A 9 × 9 formation matrix was generated through the inducing variables for the preparation of the AHP model analysis, as shown in Table 4. Then Saaty's importance intensity scale was utilized for the pairwise comparison of each element, and the Consistency Ratio (CR) was found to be 0.083, which is less than 1. This indicates the model set-up for this analysis is well-balanced. The relative weight was calculated by normalizing the pairwise comparison values. These weights are further used in GIS environments. The results indicated that rainfall has the highest weight of 0.214, and distance from rivers and drainage density also have higher weights compared to others. Rainfall is a crucial parameter that directly influences riverine flooding. Typically, the Mymensingh Division receives an annual rainfall of around 1,500-2,500 mm. During the monsoon season, it becomes heavier. On the other hand, proximity to the river also has a larger connection to flood risk. According to Norman et al.(2010), areas near rivers are affected mostly during floods due to overflow. After obtaining weights for all the physical factors, these weights are assigned to the reclassified layers by using the weighted overlay tools in ArcGIS. Finally, the physical vulnerable map has been generated with five distinct susceptible classes as very low, low, moderate, high, and very high. The map indicates that nearly 60% of the region falls under moderate to high risk zone, as shown in Figure 5. It can be seen that locations that are highly vulnerable are mostly situated close to drainage channels, which increases the risk of flooding during the monsoon season. The north-eastern, south-eastern, and central parts of the area are particularly prone to this heightened risk.

Table 4: Weightage of Physical Indicators

Criteria ↓ vs →	**Slp**	**Elv**	**TWI**	**ST**	**Rf**	**LC**	**DR**	**DRO**	**DD**	**CI**	**CR**	**Weightage**
Slp	1	2	3	2	2	2	3	2	2	0.12	0.083	0.101
Elv	1/2	1	2	2	3	2	3	2	2			0.049
TWI	1/3	1/2	1	2	3	3	3	2	2			0.122
ST	1/2	1/2	1/2	1	2	2	3	2	2			0.042
Rf	1/2	1/3	1/3	1/2	1	2	3	3	3			0.214

LC	1/2	1/2	1/3	1/2	1/2	1	2	2	2			0.076
DR	1/3	1/3	1/3	1/3	1/3	1/2	1	3	2			0.206
DRO	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1	1			0.059
DD	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1	1			0.131

Here, Slp= Slope, Elv= Elevation, TWI= Topographic Wetness Index, ST= Soil Texture, Rf= Rainfall, LC= Land Use Land Cover, DR= Distance from River, DRO= Distance from Road, DD= Drainage Density, CI= Consistency Index, CR= Consistency Ratio.

3.2 Social Index analysis

A total of six social criteria, which are more crucial for that area, were selected for the analysis. The factors are Population Density, Dependent Population, Agriculture Dependent Population, Literate Population, Female Population, and Disabled Population. A 6×6 matrix based on expert judgment and prior studies was used for the pairwise comparison to create the AHP model. The CR value is found to be 0.044, which is below 0.1 and falls within the acceptable range. As shown in Table 5, Population density has the highest weightage, suggesting that the more densely populated an area is, the greater the risk of that area being vulnerable to flooding. Vulnerable groups, especially those dependent on agriculture, are the most affected by flooding. Therefore, these criteria were also assigned relatively high weights. In contrast, the female population and the disabled population received lower weightage values compared to others. After conducting weights for all the criteria, a similar approach was taken to generate the social vulnerability map. The map is classified into five vulnerable classes, ranging from very high to very low levels, as shown in Figure 5.

Table 5: Weightage of Social Indicators

Criteria ↓ vs →	PD	DeP	ADP	LP	FP	DP	CI	CR	Weightage
PD	1	3	3	5	5	7			0.29
DeP	1/3	1	3	5	5	5			0.23
ADP	1/3	1/3	1	3	5	5			0.20
LP	1/5	1/5	1/3	1	3	5	0.054	0.044	0.14
FP	1/5	1/5	1/5	1/3	1	3			0.09
DP	1/7	1/5	1/5	1/5	1/3	1			0.05

Here, PD= Population Density, DeP= Dependent Population, ADP= Agriculture Dependent Population, LP= Literate Population, FP= Female Population, DP= Disabled Population.

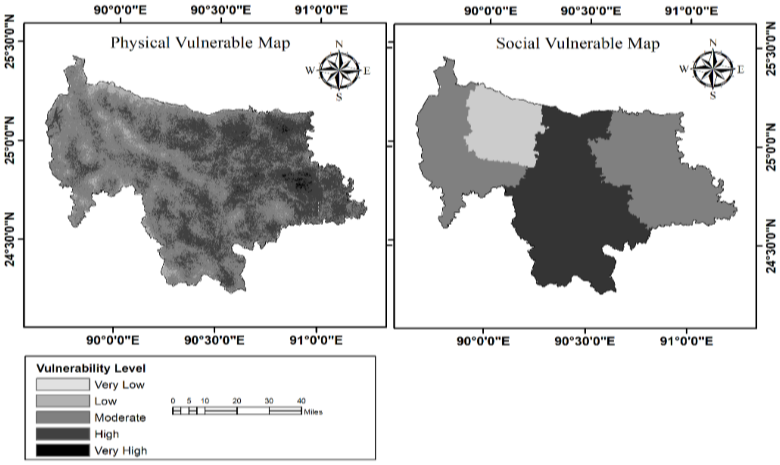
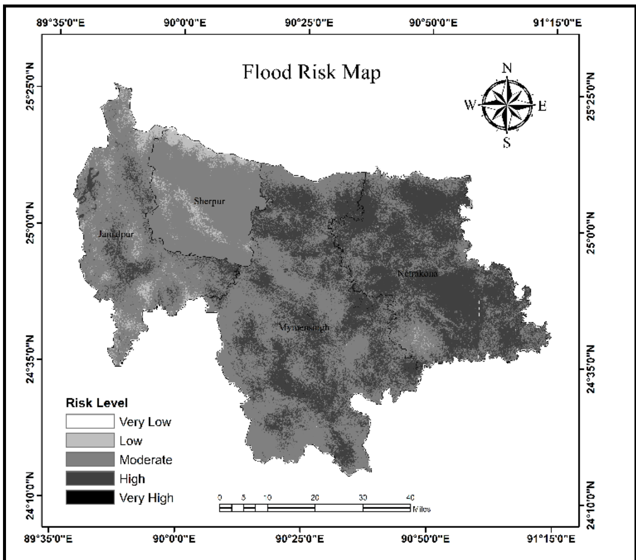


Figure 5: Physical & Social Vulnerability Map.

3.3 Spatial Distribution of Flood Risk Zonation

After incorporating both physical and social vulnerability maps, an equal weight of 0.50 was used to generate the final flood risk map. To understand the vulnerability level, the map has been classified into five classes, as shown in Figure 6. The results show that only 0.014% and 3.24% of the area are classified as very low and low-risk areas. On the other hand, moderate, high, and very high vulnerable areas are 60.32% (6275.05 sq.km), 36.41% (3788.31 sq.km), and 0.02% (2.2 sq.km), respectively. From this perspective, it is evident that the majority of the region falls within the moderate to high risk zone for flooding. The results further indicate that regions in low-lying areas, particularly around the lower part of the river, are at an extremely high level of susceptibility and have higher exposure of rural communities to floods, as well as a lack of core capacities. Moreover, densely populated areas are depicted as more vulnerable to flooding, especially in urban regions where infrastructure may be overwhelmed.

3.4 District-wise Flood Susceptibility



Vulnerability Class	Area (sq.km)	Area (%)
Very Low	1.4481	0.0139
Low	336.5595	3.2350
Moderate	6275.0547	60.3163
High	3788.3142	36.4136
Very High	2.1969	0.0211

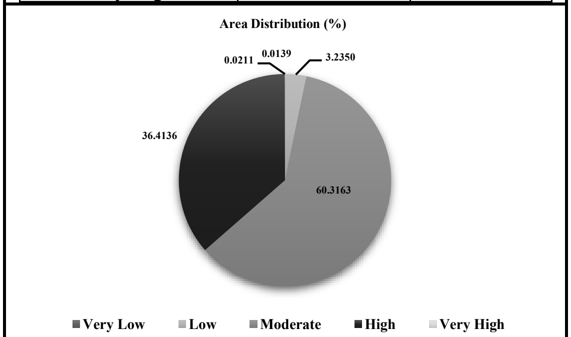
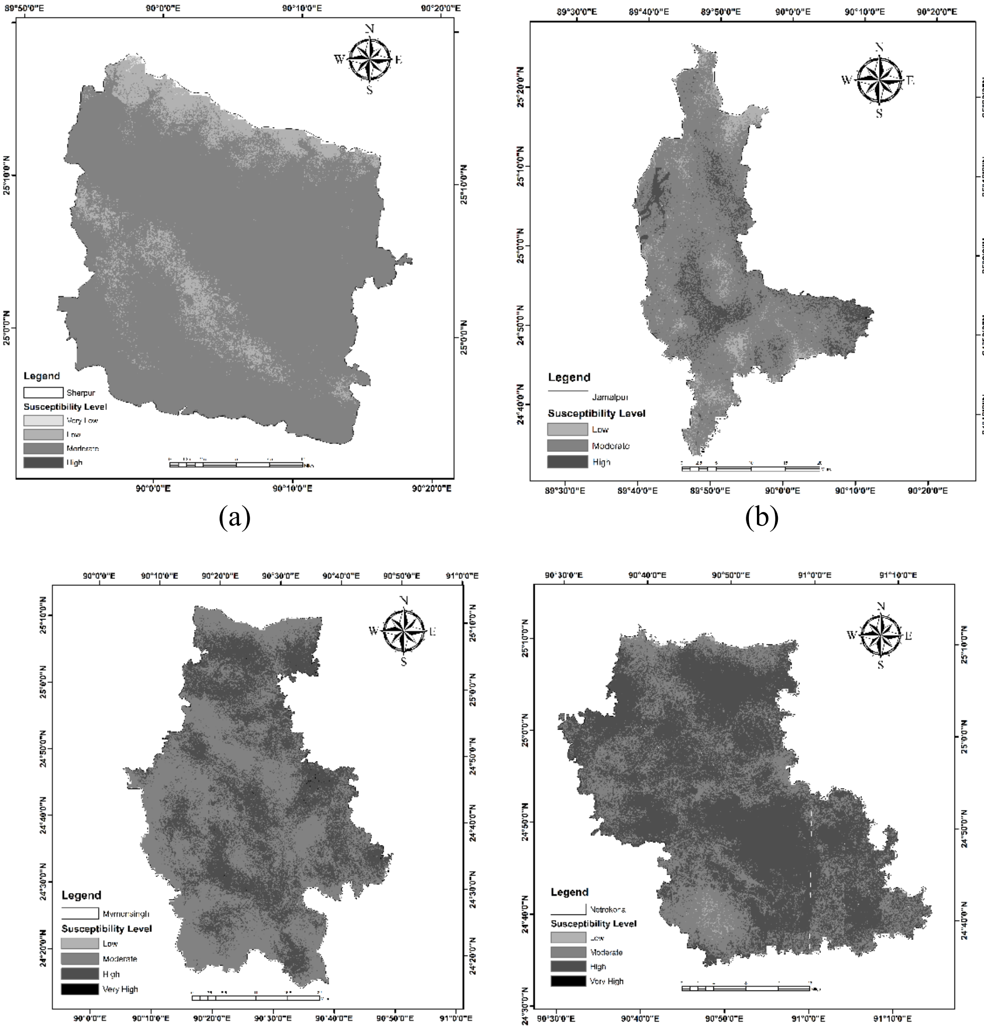


Figure 6: Flood Risk Map.

To understand the region's vulnerability more specifically, the distribution of flood risk across four districts: Jamalpur, Sherpur, Mymensingh, and Netrokona has been extracted from the final risk map. The maps clearly show how flood risks vary across these districts, as demonstrated in Figure 7. Across the districts, Netrokona stands out as the most vulnerable district to flooding. Meanwhile, a large portion of the area of Mymensingh district falls under moderate to highly vulnerable zones. An area-wise distribution is further shown in Table 6. For instance, a study conducted by Nahin et al., 2023 showed that 17.33% area in Jamalpur is highly vulnerable, while in this study, we found that 8.37% (169.89 sq.km) of the area is under low vulnerability, 78.34% (1590.96 sq.km) is moderately vulnerable, and 13.3% (270.05 sq.km) is highly vulnerable. Sherpur's low vulnerability covers only 7.77% (155.63 sq.km), while 87.91% (1161.58 sq.km) is categorized as moderately vulnerable, and 2.07% (2.73 sq.km) is highly vulnerable. In Mymensingh, 60.49% (2581.68 sq.km) is moderately vulnerable, with 39.90% (1715.22 sq.km) in the high vulnerability category. Very low and low vulnerabilities are almost nonexistent in Mymensingh. Netrokona falls into the high vulnerability category, accounting for 65.42% (1800.31 sq.km), with 34.19% (940.82 sq.km) in the moderate vulnerability category, and only 0.39% (10.82 sq.km) under low vulnerability. These results highlight significant flood risks in Mymensingh and Netrokona, particularly in areas with moderate to high susceptibility levels.



(a) (b) (c) (d)

Figure 7: District-wise flood risk map- (a) Sherpur; (b) Jamalpur; (c) Mymensingh; (d) Netrokona

Table 6: Area and Percentage of District-wise Flood-Susceptible Zones

Vulnerability Level	Jamalpur		Sherpur		Mymensingh		Netrokona	
	Area (sq.km)	Area (%)	Area (sq.km)	Area (%)	Area (sq.km)	Area (%)	Area (sq.km)	Area (%)
Very Low	0.00	0.00	1.45	0.11	0.00	0.00	0.00	0.00
Low	169.89	8.37	155.63	11.78	0.22	0.01	10.82	0.39
Moderate	1590.96	78.34	1161.58	87.91	2581.68	60.05	940.82	34.19
High	270.05	13.30	2.73	0.21	1715.22	39.90	1800.31	65.42
Very High	0.00	0.00	0.0027	0.0002	2.19	0.05	0.01	0.0003

3.5 Validation of the Model

The accuracy of the AHP result was validated using the flood inventory map. Based on previous flood records, flooded and non-flooded locations were identified. Those points were used for training and testing purposes. The final flood risk map was compared to the identified sample points by calculating the Area Under the Curve (AUC) using the ROC method in Python. AUC can evaluate the accuracy of the model's output. The higher the AUC value, the more accurate the model and vice versa. (Mitra et al., 2022). An AUC value of less than or equal to 0.5 indicates that the model is not suitable for the study, while an AUC value close to 1 indicates an ideal model with maximum accuracy. For this study, the AUC value was found to be 0.86 (86%), indicating that the model effectively generated the flood risk map and can be considered successful, as shown in Figure 8.

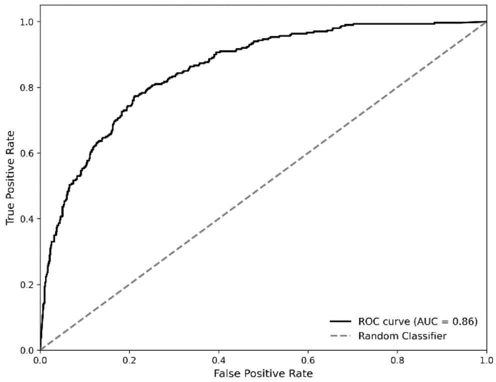


Figure 8. ROC-AUC Validation Curve.

4. CONCLUSION

An effective flood susceptibility management system is crucial for developing a resilient and sustainable community that can adapt to future uncertainties and evolving environmental conditions. Therefore, this study integrates AHP with Geospatial techniques for a robust and accurate flood-prone area delineation in the Mymensingh Division of Bangladesh. Based on expert opinions and prior research, both physical and social factors have been incorporated to run the AHP model. To ensure the reliability of the model, the final flood risk map was validated using the Receiver Operating Characteristic - Area Under the Curve (ROC-AUC) method. The map achieved a high ROC-AUC value of 0.86, confirming its accuracy and suitability. The results have highlighted a complex combination of geological, climatic, and socioeconomic factors that have contributed to the region's susceptibility to floods. The findings demonstrated that the eastern part of the study area is more vulnerable to flooding, and about 36.41% of the total area falls under the high-risk zone. The low-lying and riverine areas are detected as the most susceptible zone. Among the factors, it is evident that monsoon rainfall has a direct influence on this region's flood vulnerability. Additionally, socioeconomic factors such as population density and agricultural dependence also have a substantial impact on this. Since rural people have limited access to resources and preparedness for disasters, they face heightened vulnerability during flood events. This lack of preparedness and access to essential services such as early warning systems, healthcare, and infrastructure significantly hampers their ability to respond to and recover from floods. Overall, the study will help people understand the flood risks in the area, raising awareness of the vulnerabilities they face. It will also assist the government and policymakers in creating more effective plans and policies to manage flood risks and protect the community. Although this study offers valuable insights into flood risk areas, it is crucial to know certain drawbacks. The use of high-resolution Digital Elevation Models (DEM) and satellite imagery could have further enhanced the accuracy and precision of the analysis. Moreover, a ground-based evaluation, such as surveys or interviews with local citizens, would have provided essential on-site insights into the immediate effects of the flooding and the issues that the affected communities were experiencing.

DECLARATION OF USE OF AI

During the preparation of this manuscript, we utilized "SciSpace" to assist in searching for relevant literature, summarizing technical articles, and explaining complex research findings. Additionally, we used "Grammarly" to refine the language, ensure grammatical accuracy, and maintain a consistent academic tone throughout the document.

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