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GIS-based Multi-criteria evaluation using AHP for landslide susceptibility zoning in Chattogram Hill Districts, Bangladesh

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Abstract: GIS-based multi-criteria approach for landslide susceptibility zoning, providing a comprehensive understanding of spatial vulnerability patterns. By integrating a diverse range of geospatial datasets, including variables like soil permeability, elevation, land use and land cover, rainfall distribution, and proximity to key features such as roads, fault lines, and streams, this approach provides a holistic assessment of factors influencing landslide occurrences in Chattogram Hill Districts (CHD). Through the implementation of the Analytical Hierarchy Process (AHP), which assigns appropriate weights to each criterion based on their relative importance and the weighted overlay tool within ArcMap integrates every factor of landslide susceptibility and generates a comprehensive susceptibility map. The map reflects the distribution of 25.48% in the low susceptible class, 71.71% in the moderate susceptible class, and 2.81% in the high susceptible class. The Area Under Curve (AUC) of the Receiver Operating Characteristic (ROC) is used to validate the landslide susceptibility zoning. The calculated value of AUC is 0.828, indicating an 83% success rate of landslide mapping. Identifying areas at higher risk of landslides, developing targeted strategies for disaster preparedness, and formulating land use policies that account for potential hazards can be possible.

Keywords: Multi-criteria, Geospatial, Analytical Hierarchy Process (AHP), Landslide Susceptibility Zoning, Receiver Operating Characteristic (ROC)

1. Introduction

Landslide is a geological phenomenon that is characterized by the movement of earth, rocks, debris, and mud that is caused by gravitational forces (Highland & Bobrowsky, 2008). This is a highly typical occurrence in mountainous places, which can be primarily attributed to the interaction of natural processes and human activities (Islam et al., 2017). Landslides endanger people's lives and cause significant property damage (Dastranj et al., 2021). A landslide catastrophe is now a growing national concern due to an increase in extreme precipitation events. (Khan, et al., 2020). Landslides have become a common

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hazard in Bangladesh's southeastern mountainous areas (Chowdhury, 2023) as a result of excessive rainfall (40 mm/day) in a short period of time (2 -7 days) (Khan et al., 2011) caused by climate change (Alam, 2020; Sultana & Tan, 2021). Over the past decade, Bangladesh has witnessed several devastating landslides, with the highest toll recorded in 2017 at 163 casualties, followed by 2007 with 135, 2015 with 94, and 2010 with 60, highlighting the recurring and pressing need for robust mitigation measures and proactive risk management strategies (Islam & Islam, 2020). The likelihood of a landslide happening at a certain location at some point in the future is referred to as the area's susceptibility to landslides. An analysis of the relationship between the causes of landslides and their geographic locations can be used to quantify the risk. (Dai & Lee, 2002). A well-established practice that frequently compares various predictive methodologies, such as multivariate and bivariate analysis (Fernández et al., 2012; Ahmed & Dewan, 2017; Chowdhury & Hafsa, 2022), is assessing and mapping landslide susceptibility. This practice provides the opportunity for a dynamic, integrated, and ongoing management of the territory and its unforeseen changes (Devkota et al., 2013; Ullah, 2021).

Research on landslides has, over the duration of the past decade, made extensive use of Remote Sensing (Prabu & Ramakrishnan, 2009; Sonker et al., 2022) and Geographic Information Systems (GIS) (Gupta & Joshi, 1990; Mersha & Meten, 2020; Beheshtifar, 2021) both of which are effective techniques for determining the risk of landslides. Aerial photographs and high-resolution satellite data can be helpful when attempting to detect, track, and monitor the processes involved in landslide activity (Nichol et al., 2009; Li et al., 2012). The advancement of geospatial technologies has made it possible to evaluate the risks posed by landslides in a manner that is both precise and comprehensive (Pardeshi et al., 2013). AHP is a method that is used as a systematic approach to landslide susceptibility zoning (Kumar & Anbalagan, 2016; El Jazouli et al., 2019; Saha, 2021; Panchal & Shrivastava, 2022). Its purpose is to determine the weight and geometric mean of the factors (Saaty, 1980).

The prior literature placed an emphasis on landslide zoning in a particular region or a particular district (Ahmed & Dewan, 2017; Begum et al., 2020; Rabby et al., 2021; Humayain & Biplob, 2021). Therefore, it is necessary to construct a landslide zoning of hilly regions in Bangladesh in order to understand the overall scenario of landslides in Bangladesh. The main objective of this study is to develop a landslide susceptibility map for the Chattogram Hill Districts. This will be achieved by employing a weighted combination of multiple factors, including slope, NDVI, elevation, soil permeability, rainfall, LULC, proximity to fault lines, proximity to roads, and proximity to streams. This study discussed the Landslide Susceptibility Zoning with a Multi-criteria approach.

2. Selection of the Study Area

Landslides are a common geological hazard in southeastern Bangladesh, particularly in the Chattogram Division (Bandarban, Chattogram, Cox's Bazar, Khagrachhari, and Rangamati Districts). This region has the steepest average slopes in the country (Bangladesh Landslide Disaster Summary Sheet - 5 June 2018 - Bangladesh, 2018). The Chattogram Hill Districts (CHD) have comprised with five administrative districts: Chattogram, Cox's Bazar, Bandarban, Khagrachari, and Rangamati (Ahmed, 2021). This region is located at 91° 31′ N to 92° 68′ N and 23° 74′ E to 20° 59′ N (Figure 1).

The natural slope angle of landslide zones ranges from 34 to 84°, with the majority of slopes above 40°, which is more than the average angle of internal friction of slope materials (26-34°). As a result, most of the tertiary hill slopes in Bangladesh are unstable in natural settings (Ali et al., 2018). The climate is classified as tropical monsoon, and the yearly temperature ranges from 10° to 35°, with a mean minimum of 24° and a mean maximum of 34° at sea level (Bai, 2006). During the wet season, high temperatures are typically accompanied by very high humidity levels. The mean annual rainfall ranges from 2540 to 3810 millimetres (Bai, 2006). Most of the mountainous parts of these regions face these occurrences which made these areas vulnerable to landslides.

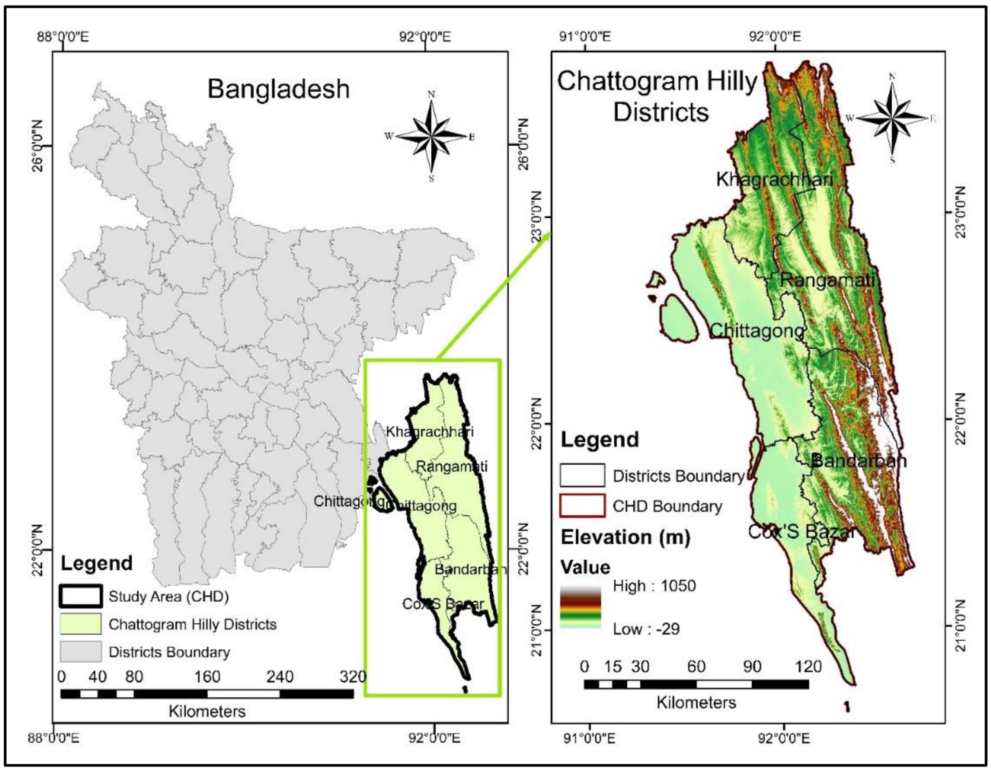

Figure 1: Study Area (*Source: Compiled by Authors, 2023)*

3. Materials and Methods

Utilizing a multi-criteria approach, the research was conducted with the intention of producing a Landslide Susceptibility Zoning map. The present investigation was divided into three stages: the first was the gathering of data, the second was the building of a database (thematic maps), and the third was the landslide susceptibility zoning.

The study studied how much the conditioning factors influenced the frequency of landslides. ArcMap version 10.8 was utilized throughout the process of the development of the conditioning factors layers. Applying the AHP approach for analyzing and assigning weights to each component in the decision-making process.

The natural breaks categorization method is used to identify how these characteristics should be categorized based on how closely they are associated with the likelihood of a landslide occurring.

The AHP method involves creating a hierarchy of criteria, conducting pairwise comparisons to determine importance, calculating priority weights, normalizing them, aggregating factor values into a susceptibility map, and thus systematically integrating diverse factors for a comprehensive understanding of landslide susceptibility. This was accomplished by making use of the weighted overlay tool that is available within ArcMap.

The equal interval classification method is used to classify the landslide susceptibility zoning using natural factors map. This method divides the landslide susceptibility into three different categories: high susceptibility, moderate susceptibility, and low susceptibility. The high susceptibility category has the highest likelihood of a landslide occurring. Using the ROC curve validation method, both the validity of the maps and their performance are examined.

This study's flow chart outlines the processes taken to measure landslide susceptibility and validate the model using AUC (Figure 2).

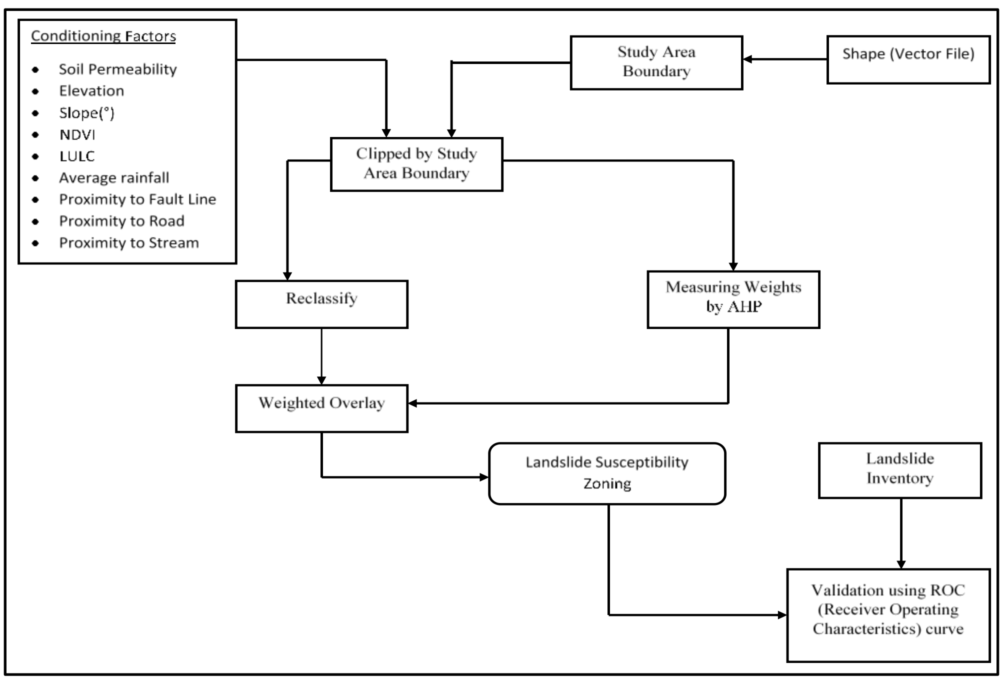

Figure 2: Methodological Workflow Diagram (*Source: Compiled by Authors, 2023)*

3.1 Data Acquired and Sources:

The necessary data were obtained from various secondary sources (Table 1). The thematic layers of causal factors were generated by Euclidean distance, IDW interpolation method, image classification or by direct means.

Table 1: Data Sources of the parameters

	Parameters	**Sources**	**Data**
Conditioning Factor	Soil Permeability	https://www.barc.gov.bd/	Polygon
	Elevation	https://earthexplorer.usgs.gov/	SRTM DEM
	Slope		
	NDVI	https://earthexplorer.usgs.gov/	Landsat 8 Image (February, 2021)
	LULC		
	Rainfall	https://bmd.gov.bd/	
	Fault Line	https://doi.org/10.2113/2022/6058346	Polyline
	Road Network	https://lged.gov.bd/	
	Stream Data	https://data.humdata.org/	

Source: Compiled by Authors, 2023

3.2 Conditioning Factors

Conditioning factors of landslides refer to the geological, environmental, and hydrological conditions that contribute to the increased susceptibility of a terrain to experience landslides (Highland & Bobrowsky, 2008). These factors set the stage for the occurrence of landslides by creating conditions that make the slope more prone to failure (Panchal & Shrivastava, 2020). The decision to consist of landslide-influencing factors has a substantial effect on the ultimate Landslide Susceptibility Zoning (Ozer et al., 2019; Dastranj et al., 2021).

The statistical approaches for landslide susceptibility mapping do not have strict rules, but rather, the chosen factors should be operational and measurable based on a specific area's characteristics (Ayalew & Yamagishi, 2005).

This study examines nine parameters that contribute to the predisposition of landslides.

The study proceeded to assess these factors by determining their respective weights based on the correlation between landslides and their causal factors. As a result, the accuracy of these findings was confirmed.

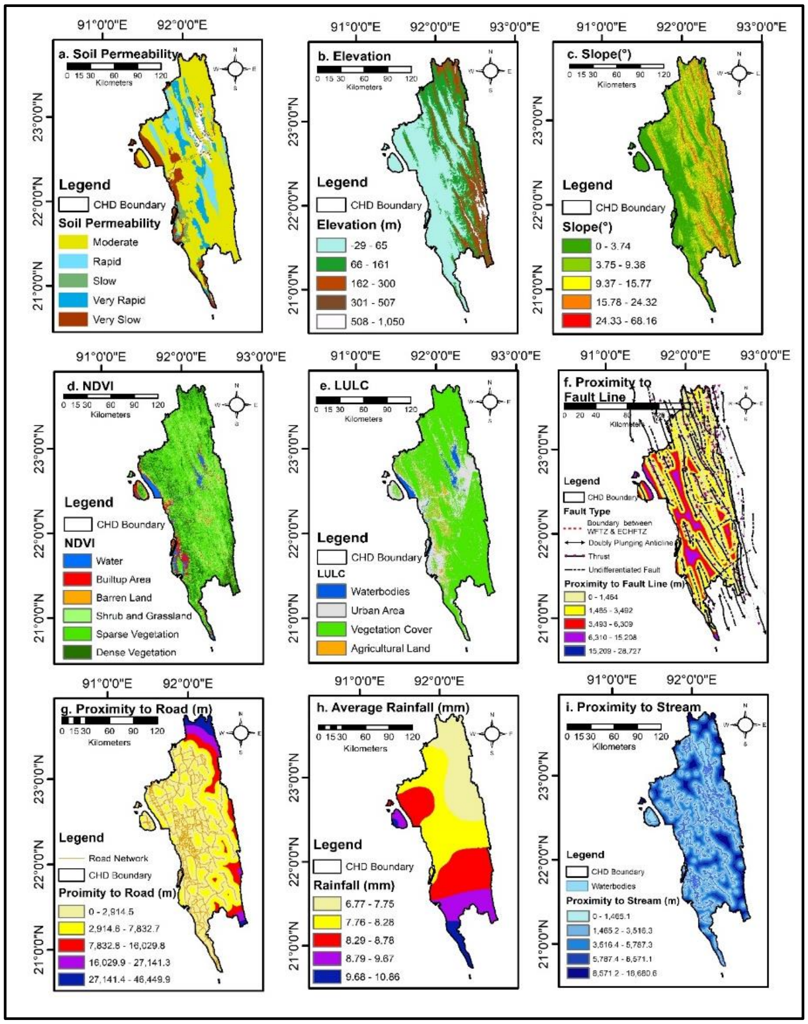

Figure 3: Landslide Conditioning Factors- a. Soil Permeability, b. Elevation, c. Slope, d. NDVI, e. LULC, f. Proximity to Fault Line, g. Proximity to Road, h. Average Rainfall, i. Proximity to stream *(Source: Compiled by authors, 2023)*

Soil Permeability: Landslides predominantly occur in soil types characterized by a significantly lower permeability and lower porosity (Ahmed et al, 2018). Soil permeability plays a pivotal role in landslide occurrences as it influences how water is absorbed and drained within the soil (Oliveira et al., 2022). Low soil permeability, which means the soil has poor drainage and retains water, is indeed more likely to contribute to landslide occurrences (Xiaran, 2017). This retained water increases the weight and reduces the stability of the soil, making it susceptible to sliding during heavy rainfall or other triggering events (Rachman & Jamie, 2021).

In this study, the soil permeability (Figure 3a) divides into 5 classes (Ahmed et al, 2018)- (1) very rapid permeability, (2) rapid permeability, (3) moderate permeability, (4) slow permeability and (5) very slow permeability

Elevation: Another commonly employed parameter in landslide susceptibility studies is elevation. It is asserted that landslides are more likely to occur at greater elevations (Ercanoglu et al.2004). In this study, the study area is divided into five classes of elevation (Figure 3b): (1) -29m to 65m, (2) 66m to 161m, (3) 162m to 300m, (4) 301m to 507m, (5) 508m to 1050m (Table 3).

Slope*:* The relationship between the slope angle and mass movement, as well as gravitational energy, is closely linked to the occurrence of landslides (Wen et al., 2017). The study area is divided into five classes of slope (Figure 3c): (1) 0 to 3.7, (2) 3.8 to 9.4, (3) 9.5 to 15.8, (4) 15.9 to 24.3 and (5) 24.4 to 68.2.

NDVI: The utilization of the Normalized Difference Vegetation Index (NDVI) is frequently observed in the investigation of landslide susceptibility (Tubog et al., 2023). This is due to the fact that the existence of thriving vegetation plays a crucial role in slope stabilization and serves as a preventive measure against landslide occurrences (Liu et al., 2018). The greenness or health of plants can be quantified via a method that involves the comparison of reflectance values between red and near-infrared light within the electromagnetic spectrum (Gao, 1996).

The formula used to calculate the NDVI is given below

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (1)$$

In this study, the NDVI (Figure 3d) classes were divided into six classes- (1) -0.17 to -0.01, (2) -0.02 to 0.15, (3) 0.16 to 0.27, (4) 0.28 to 0.34, (5) 0.28 to 0.36, (6) 0.37 to 0.58.

Land Use and Land Cover: The stability of a slope is significantly influenced by land use patterns. The presence of vegetation plays a crucial role in the regulation of water flow and infiltration. In contrast, cultivated land has been observed to impact slope stability as a result of soil saturation (Devkota et al., 2013). In this study, LULC (Figure 3e) is divided into four classes- waterbodies, urban areas, vegetation cover and agricultural land.

Average Rainfall: Rainfall is a trigger for the occurrence of landslides (Skilodimou et al., 2018). Rainfall triggers landslides by supplying water, which subsequently increases the levels of subsurface hydrostatics and pore water pressures (Desalegn et al., 2022). In this study, daily average rainfall quantity from 1948 to 2017 (Figure 3f) is divided into five classes – (1) 6.77mm to 7.75mm, (2) 7.76mm to 8.28mm, (3) 8.29mm to 8.78mm, (4) 8.79mm to 9.67mm and (5) 9.68mm to 10.86mm.

Proximity to Fault Line: Rock loses strength along fault lines, which represent tectonic breakdowns (Origins of Earthquakes - Plate Tectonics - Climate Policy Watcher, 2023). In general, a region nearer to the fault line is more vulnerable to landslides than a region farther away (Netra et al. 2014). For estimating the proximity to fault line the Euclidean method was used in the study. The study area is divided into five classes (Figure 3g) of distance from the fault line (1) 0m to 1464.5m, (2) 1464.6m to 3492.2m, (3) 3492.3m to 6308.6m, (4) 6308.7m to 15208.2m and (5) 15208.3m to 28726.5m.

Proximity to Road: Streams that possess drainage networks have an increased likelihood of experiencing landslide occurrences due to the excessive deposition of sedimentary materials by streams located away from the base of the slope (Mersha & Melen, 2020). Landslides within the research area show a consistent association with stream order. The maps were made using the Euclidean distance technique with the spatial analyst tool of ArcGIS 10.8. The study area is divided into five classes (Figure 3h) in proximity to road layer (1) 0m to 1464.5m, (2) 1464.6m to 3492.2m, (3) 3492.3m to 6306.6m, (4) 6306.7m to 15208.2m, (5) 15208.3m to 25726.5m.

Proximity to Stream: Rivers and streams have a significant impact by reducing shear strenth (Wicher-Dysarz, 2019) on the erosion of adjacent slopes of water bodies and might indirectly affect the occurrence of landslides (Rahman et.al, 2017). Here, the Proximity to the Stream (Figure 3i) is classified into five classes (1) 0m to 1465.1m, (2) 1465.2m to 3516.3m, (3) 3516.4m to 5787.3 m (4) 5787.3m to 8571.1m, (5) 8571.1m to 18680.6m.

3.3 Analytical Hierarchy Process

The Analytical Hierarchy Process (AHP) is a decision-making methodology used to address complicated problems (Sharma & Mahajan, 2018). It is a semi-qualitative method in which the weightages to the components are awarded depending on the judgments of the expert, and the weightage values range anywhere from 1 to 9 (Saaty, 1980; Saaty & Vargas, 2001; Saaty, 2005).

AHP involves pairwise comparisons where elements are compared to one another using a scale of relative importance. The 9-point scale, often referred to as Saaty's scale, assigns values from 1 to 9 (Table 2) to express how much more one element is preferred over another.

Table 2: Nine-point preference table by Saaty, 1980

Preference Scale	Degree of Preference	Description
1	Equal	Equal contribution is inherited by factors
3	Moderate	One factor exhibits a moderate degree of preference over others.
5	Strong	One factor exhibits a strong degree of preference over others.
7	Very Strong	One factor exhibits a very strong degree of preference over others.
9	Extreme	One factor exhibits an extreme degree of preference over others.
2, 4,6, 8	Intermediate Values	Intermediate values between1,3,5, 7 and 9

Source: Saaty, 1980

After the weightage assignment has been finalized, the factor maps will be reclassified and then included into GIS.

One of the crucial components of the Analytic Hierarchy Process (AHP) approach is the computation of the consistency index (CI) and consistency ratio (CR). If the consistency ratio (CR) exceeds 0.1, it indicates that the comparison matrix is inconsistent and hence requires revision (Kayastha et al., 2013). The Consistency Ratio required a Random Index table (Table 3) for calculating it.

$$CI = \lambda_{Max}\text{-}(N/\ (N\text{-}1)) \quad (2)$$

$$CR = CI/RI \quad (3)$$

The RI indicated the Random Index.

Table 3: Random Index table

n	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Source: Saaty, 1980

3.4 Model Validation

One of the methods employed for the validation of the landslide susceptibility map involves the utilization of the Area Under Curve (AUC) (Pourghasemi et al., 2018).

The calculation of the area under the curve (AUC) provides a reliable assessment of the model's performance, with values ranging from 0.5 to 1. A higher proximity of AUC values to 1 is indicative of superior performance in prediction models (Dastranj et al., 2021).

LSZ was spatially correlated with the landslide validation datasets, and rate curves were produced, and finally, the AUC was estimated.

4 Results and Discussion

This study investigated the connection between nine different factors and the occurrence of landslides. The relative weighted values were determined through the use of the AHP method. The factors were classified and assigned weights based on their relative importance as shown in Table 4. A numerical scale ranging from 1 to 9 was employed to assign weights (Table 4) to various criteria. These weights used to create the comparison matrix of the conditioning factors.

4.1 Analytical Hierarchy Process (AHP)

Table 4: Comparison matrix of factors for the Analytical Hierarchy Process (AHP) method

	Soil Permeability	**Elevation**	**Slope**	**NDVI**	**LULC**	**Average Rainfall**	**Proximity to Fault**	**Proximity to Road**	**Proximity to Stream**
Soil Permeability	1	2	2	6	5	8	7	9	8
Elevation	1/2	1	1	4	3	7	5	8	7
Slope	1/2	1	1	4	5	3	5	6	7
NDVI	1/6	1/4	1/4	1	1/2	3	2	5	5
LULC	1/5	1/3	1/5	2	1	4	3	6	6
Average Rainfall	1/8	1/7	1/3	1/3	1/4	1	1/3	2	4
Proximity to Fault	1/7	1/5	1/5	1/2	1/3	3	1	3	2
Proximity to Road	1/9	1/8	1/6	1/5	1/6	1/2	1/3	1	3
Proximity to Stream	1/8	1/7	1/7	1/5	1/6	1/4	1/2	1/3	1

Source: Compiled by Authors, 2023

The Comparison Matrix table provides information on the relative information of conditioning factors of the landslides according to the Saaty Scale. From the comparison matrix, the weights (Table 5) of each criterion are evaluated, followed by a normalized comparison matrix.

Table 5: Weights of each landslide conditioning factors

Landslide Factors	**Criteria Weight**	**Weighted (%)**
Soil Permeability	0.304	30
Elevation	0.197	20
Slope	0.190	19
NDVI	0.074	7
LULC	0.099	10
Average Rainfall	0.040	4
Proximity to Fault	0.049	5
Distance to Road	0.027	3
Distance to Stream	0.020	2
Total	1.000	100

Source: Compiled by Authors, 2023

After computing the weight of each factor and the rate of each class using AHP method, the Landslide Susceptibility Zoning (LSZ) was calculated by summing up each factor's weight. The comparative weights of soil permeability, elevation, slope, NDVI, LULC, average rainfall, proximity to fault, proximity to road and proximity to stream has been founded (Table 5).

The comparison matrix needs to be updated if CR is more than 0.1 because it is inconclusive. Using formula (2) and (3) CI and CR are founded-

$$CI = \lambda_{Max}\text{-}(N/(N\text{-}1))$$

$$= 9.82\text{-}9/8$$

$$=0.10$$

$$CR = CI/RI$$

$$=0.10/1.45$$

$$=0.70$$

The matrix was utilized to assess the class rating of each constraint and thereafter employed to compute the weight value of the criteria using Excel application from Microsoft Office packages. As shown in Table 5, soil permeability was the most influential factor, with a value of 0.304. The elevation and slope also have a significant value of 0.197 and 0.191, followed by LULC value of 0.099; NDVI has a value of 0.074; proximity to fault is 0.049; rainfall 0.040; Proximity to the road is 0.027 and proximity to streams has the value of 0.020. For the landslide susceptibility zoning in GIS, the weights achieved from the Analytical Hierarchy Process (AHP) in each layer class have to be reclassified for the weighted overlay tool within ArcGIS.

From the criteria weight (Table 5), the reclassification value and weights of the factor for the ArcGIS 10.5 is given in the Table 6.

Table 6: Conditioning factors layers, values, and influence of each sub-class

Factors	**Subclasses**	**Reclassified Values**	**Reference**
Soil Permeability	Very Slow	5	Xiaran, 2017
	Slow	4	
	Moderate	3	
	Rapid	2	
	Very Rapid	1	
Elevation	-29 to 65	1	Ercanoglu et al.2004
	66 to 161	2	
	162 to 30	3	
	301 to 507	4	
	508 to 1050	5	
Slope	0 to 3.7	1	Wen et al., 2017
	3.8 to 9.4	2	
	9.5 to 15.8	3	

Factors	**Subclasses**	**Reclassified Values**	**Reference**
	15.5 to 24.3	4	
	24.4 to 68.2	5	
NDVI	-0.17 to -0.01	1	Liu et al., 2018
	-0.02 to 0.15	3	
	0.16 to 0.27	5	
	0.28 to 0.34	4	
	0.35 to 0.58	2	
LULC	Waterbodies	1	Devkota et al., 2013
	Urban Area	4	
	Vegetation Cover	3	
	Agriculture land	2	
Proximity to Fault Line	0 to 1464.5	5	Netra et al. 2014
	1464.6 to 3492.2	4	
	3492.3 to 6306.6	3	
	6306.7 to 15208.2	2	
	15208.3 to 25726.5	1	
Proximity to Road	0 to 2914.5	5	Mersha & Melen, 2020
	2914.6 to 7832.7	4	
	7832.8 to 16029.8	3	
	16029.9 to 27141.3	2	
	27141.4 to 46449.9	1	
Average Rainfall	6.77 to 7.75	1	Desalegn et al., 2022
	7.75 to 8.28	2	
	8.28 to 8.78	3	
	8.78 to 9.67	4	
	9.67 to 10.86	5	
Proximity to streams	0 to 1465.1	5	Rahman et.al, 2017
	1465.2 to 3516.3	4	
	3516.4 to 5787.3	3	
	5787.4 to 8571.1	2	
	8571.2 to 18680.6	1	

Source: Compiled by Authors, 2023

When it comes to landslide susceptibility, a higher reclassified value of each conditioning factor indicates a greater likelihood of landslide occurrence, whereas a lower reclassified value indicates a reduced likelihood of landslide occurrence. If the value is high, it indicates that the area is at a high risk for landslides, if it is low, it indicates that the area is at a low risk for landslides, and if it is intermediate, it indicates that the area is at a moderate risk for landslides (Figure 6).

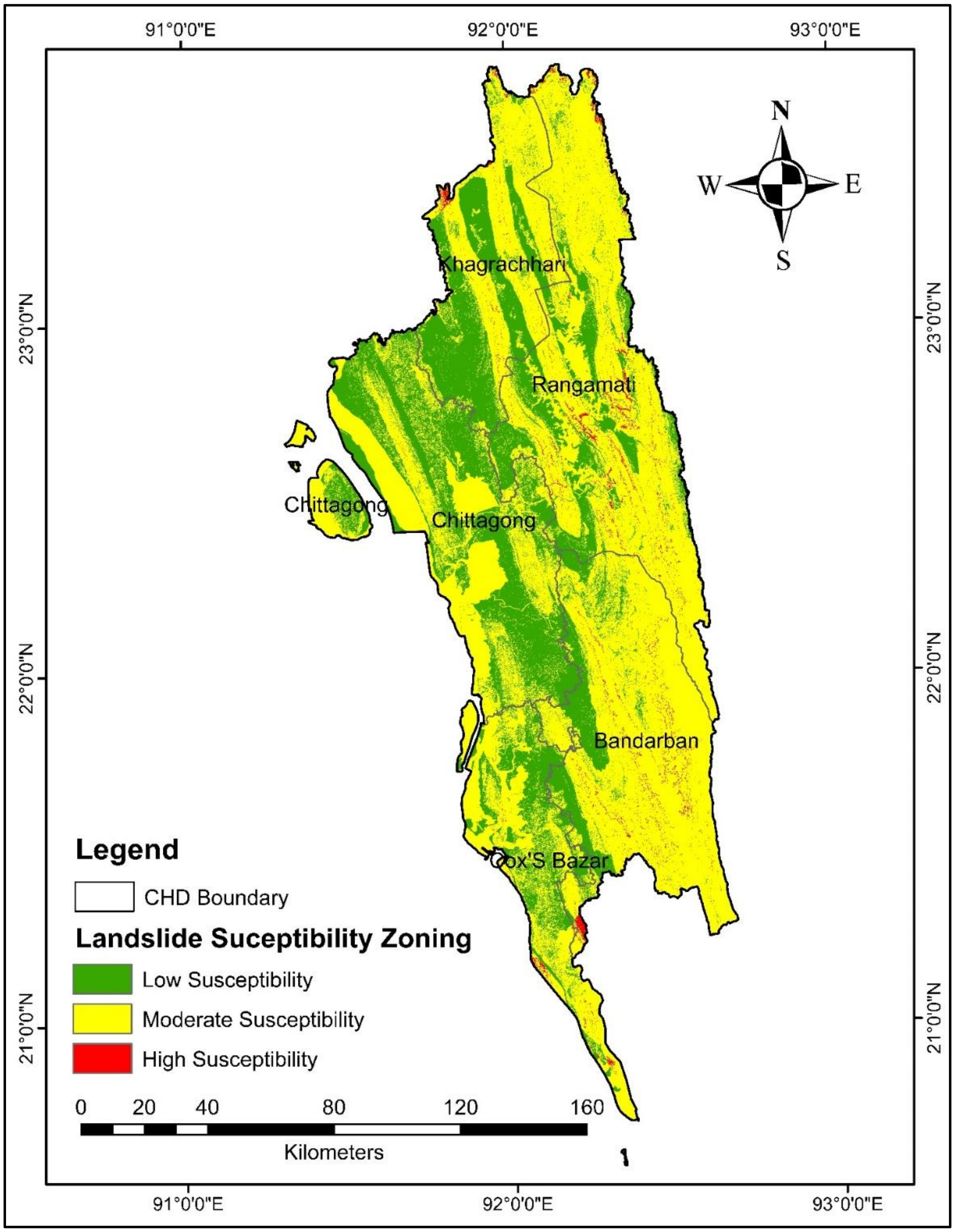

Figure 6: Landslide Susceptibility Zoning (*Source: Compiled by Authors, 2023)*

Table 7: Landslide Susceptibility Zoning

Class	Area (sq.km)	Percentage
Low Susceptible	5186	25.48%
Moderate Susceptible	14592	71.71%
High Susceptible	572	2.81%

Source: Compiled by Authors, 2023

This map presents the distribution of land in terms of three different susceptibility classes (Table 7): Low Susceptible class covers an area of 5,186 square kilometers, which accounts for approximately 25.48% of the total area. These areas are characterized as having a relatively low likelihood of experiencing landslides.

Moderate Susceptible class encompasses 14,592 square kilometers, this category constitutes about 71.71% of the entire area. These regions have a moderate susceptibility to landslides, indicating a somewhat higher potential for such events compared to the low susceptible areas.

High Susceptible class covers an area of 572 square kilometers, making up roughly 2.81% of the total area. These are the areas with the highest vulnerability to landslides, implying a significant likelihood of landslide occurrence.

Table 8: Susceptibility class distribution of the study area

Districts	**Low Susceptible Class**		**Moderate Susceptible Class**		**High Susceptible Class**	
	Area (sq.km)	Percentage (%)	Area (sq.km)	Percentage (%)	Area (sq.km)	Percentage (%)
Bandarban	595.93	13.01%	3775.40	82.40%	210.24	4.59%
Chattogram	1884.72	38.80%	2966.25	61.06%	6.96	0.14%
Cox's Bazar	644.46	28.19%	1603.52	70.19%	37.77	1.65%
Khagracchari	1106.38	37.23%	1804.20	60.71%	61.13	2.06%
Rangamati	897.13	15.94%	4476.70	79.52%	255.97	4.55%

Source: Compiled by Authors, 2023

In Bandarban District the low susceptible class, covers an area of 595.93 square kilometers (13.01% of the district's total area), the moderate susceptible class accounts for 3775.40 square kilometers (82.40%) and the high susceptibility regions span 210.24 square kilometers (4.59%) (Table 8).

In Chattogram District 1884.72 square kilometers (38.80% of the district's area) categorized as low susceptible, the moderate susceptible class encompasses 2966.25 square kilometers (61.06%) and high susceptibility areas cover 6.96 square kilometers (0.14%) (Table 8). The result is almost similar to the previous study (Chowdhury & Hafsa, 2022), which was conducted in the whole Chattogram district, where High and very high susceptible zone covers 35.46% of the area using the Frequency ratio method. Chattagram

District experiences a tropical monsoon climate, characterized by heavy rainfall during the monsoon and torrential rain in pre and post-monsoon seasons (Pham, 2018).

In Cox's Bazar District 644.46 square kilometers (28.19% of the district's area) are considered low susceptible, the moderate susceptible class includes 1603.52 square kilometers (70.19%) and high susceptibility regions span 37.77 square kilometers (1.65%) (Table 8). This result is slightly dissimilar to previous study (Adnan et al., 2020) where by using Random Forest method 23% of the area are considered high susceptibility zone. The rapid urbanization and Land use pattern (Ahmed et al., 2020) of this area caused the landslide susceptibility.

In Khagrachhari District, 1106.38 square kilometers (37.23% of the district's area) in the low susceptible class, the moderate susceptible class encompasses 1804.20 square kilometers (60.71%) and high susceptibility regions cover 61.13 square kilometers (2.06%) (Table 8).

In Rangamati District 897.13 square kilometers (15.94% of the district's area) are categorized as low susceptible, the moderate susceptible class covers 4476.70 square kilometers (79.52%) and the high susceptibility areas span 255.97 square kilometers (4.55%) (Table 8).

4.2 Model Validation

The accuracy of a landslide susceptibility zoning refers to its capacity to accurately identify and distinguish between areas that are free from landslides and areas that are prone to landslides. The correctness of the landslide susceptibility map was determined through a process of model validation (Kumar & Anbalagan, 2016; Mersha & Meten, 2020). In this research, to validate the landslide susceptibility zoning, a total of 817 landslide occurrences was used in the Reciever Operating Characteristics (ROC) Curve. The area under the curve (AUC) was calculated to be 0.828, indicating that the landslide susceptibility zonation map had an overall success rate of 82.8% (Figure 7).

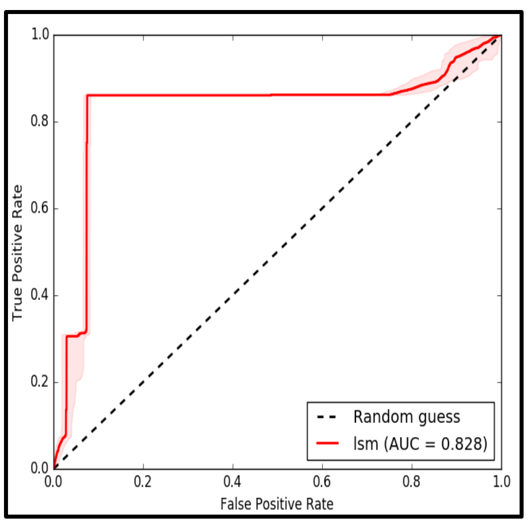

Figure 7: Area Under Curve of Landslide Zoning Map
(*Source: Compiled by Authors, 2023)*

4. Conclusion

Given the significant risks that landslides present to both human life and property, the development of susceptibility zoning can serve as an initial measure in mitigating the resulting damages. A landslide susceptibility map classifies an area into different categories based on its stability, ranging from stable to unstable conditions. The conditioning factors soil permeability, digital elevation model (DEM), slope, NDVI, LULC, proximity to roads, proximity to fault line, average rainfall and proximity to streams of landslide occurrences have a great impact on landslide. The application of a GIS-based multi-criteria approach for landslide susceptibility zoning in Bangladesh signifies a noteworthy progression in the realm of geospatial analysis and the reduction of hazards. The present study has effectively highlighted the capacity to incorporate diverse spatial, geological and natural, in order to provide complete and precise landslide susceptible zones.

The primary factors contributing to landslide occurrences in the study region include the steep gradient of the hills, deforestation activities, hill-cutting practices, heavy rainfall, and human settlement on the hill slopes. In this study, the association of factors with landslide produces a susceptible zones in Bangladesh.

The results of this study emphasize the significance of adopting a comprehensive viewpoint while tackling the intricate issue of landslide threats. The aforementioned data is of utmost importance for urban planners, legislators, and authorities responsible for disaster management in order to make well-informed decisions that emphasize the safety and overall welfare of individuals. Landslides are a prevalent natural hazard observed in the Chattogram Hill Districts, particularly in the wet season.

In summary, the utilization of a GIS-based multi-criteria method for the purpose of landslide susceptibility zoning is a significant and beneficial contribution to the domain of geospatial analysis and disaster management. As the nation persists in confronting natural hazards, this particular approach stands as a symbol of advancement, demonstrating the capacity of inventive techniques to protect lives, infrastructure, and the environment amidst the difficulties presented by landslides.

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