Landslide Susceptibility Mapping using Bivariate Statistical Models and GIS in Chattagram District, Bangladesh

Md. Sharafat Chowdhury (✉ sharafat.44@geography-juniv.edu.bd)

Jahangirnagar University Faculty of Social Science

Bibi Hafsa

Jahangirnagar University Faculty of Social Science

Research Article

Keywords: Remote sensing, Geographic Information System, Bivariate Statistical Model, Landslide Susceptibility Map, Area Under Curve

Posted Date: June 2nd, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-531858/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Declarations

Funding

Not Applicable

Conflict of Interest /Competing interests

All authors declare no conflicts of interest in this paper

Availability of data and material

Data presented in the article will be available on request

<https://download.geofabrik.de/>

<http://www.gsb.gov.bd/site/view/commondoc/Geo-scientific%20Map/-?page=3&rows=20>.

<https://earthexplorer.usgs.gov/>

<https://doi.org/10.3390/data5010004>

Code availability

Not Applicable

Authors' contributions

Md. Sharafat Chowdhury analysed the data and writes up the manuscript. Bibi Hafsa writes up the manuscript and proof reading.

Ethics approval

Not Applicable

Consent to participate

Not Applicable

Consent for publication

Not Applicable

Acknowledgement

We are grateful to Yasin Wahid Rabby for providing the landslide inventory data.

Landslide susceptibility mapping using bivariate statistical models and GIS in Chattagram District, Bangladesh

Md. Sharafat Chowdhury*, Bibi Hafsa

Department of Geography and Environment, Jahangirnagar University, Dhaka, Bangladesh.

*corresponding author: sharafat.44@geography-juniv.edu.bd

Abstract

This study attempts to produce Landslide Susceptibility Map for Chattagram District of Bangladesh by using five GIS based bivariate statistical models, namely the Frequency Ratio (FR), Shannon's Entropy (SE), Weight of Evidence (WofE), Information Value (IV) and Certainty Factor (CF). A secondary landslide inventory database was used to correlate the previous landslides with the landslide conditioning factors. Sixteen landslide conditioning factors of Slope Aspect, Slope Angle, Geology, Elevation, Plan Curvature, Profile Curvature, General Curvature, Topographic Wetness Index, Stream Power Index, Sediment Transport Index, Topographic Roughness Index, Distance to Stream, Distance to Anticline, Distance to Fault, Distance to Road and NDVI were used. The Area Under Curve (AUC) was used for validation of the LSMs. The predictive rate of AUC for FR, SE, WofE, IV and CF were 76.11%, 70.11%, 78.93%, 76.57% and 80.43% respectively. CF model indicates 15.04% of areas are highly susceptible to landslide. All the models showed that the high elevated areas are more susceptible to landslide where the low-lying river basin areas have a low probability of landslide occurrence. The findings of this research will contribute to land use planning, management and hazard mitigation of the CHT region.

Key Word: Remote sensing; Geographic Information System; Bivariate Statistical Model; Landslide Susceptibility Map; Area Under Curve.

Introduction

Landslide is a very common and devastating natural disaster occurred in all mountainous areas of the world (Hong et al., 2015; Khan et al., 2019). Asia is more prone to landslide than any other continent. In the hilly areas of Bangladesh frequency of landslide is increased tremendously and almost every year it causes huge damage to life and property (Sultana, 2020; Al-Kafy et al., 2019). From 2000-2018 landslides caused 727 deaths and 1017 injuries in this country (Sultana, 2020). The complex topography of Chittagong with rapid urbanization, hill cutting, agricultural activity, road construction makes it extremely vulnerable to landslide during monsoon season when heavy rainfall can easily triggers landslide (Khan et al., 2012; Alam, 2020).

Remote sensing and GIS along with statistical models plays a significant role in landslide hazard zonation which is very important to reduce loss and damage in an area (Dahal et al., 2008; Ozioko and Igwe, 2020). There are many popular statistical methods frequently been using for landslide susceptibility mapping for case studies at local scale using GIS environment. These can produce more accurate and reliable results in the complex topographic environments (Youssef et. al., 2015; Youssef et al., 2016; Yang et al., 2019). Present study employed Frequency Ratio (FR), Weight of Evidence (WofE), Shannon's Entropy (SE), Information Value (IV) and Certainty Factor (CF)

models in GIS environment for landslide susceptibility mapping. Still now these models are used extensively and many researcher had get reliable and acceptable result using these models (Park et al., 2012; Youssef et al., 2015; Ba et al., 2017; Wen et al., 2017; Passang and Kubicek, 2018; Elmoulat and Brahim, 2018; Nohani et al., 2019; Silalahi et al., 2019; Wang et al., 2019).

In this research thematic layers of landslide causative factors such as Slope Aspect, Slope Angle, Geology, Elevation, Plan Curvature, Profile Curvature, General Curvature, Topographic Wetness Index (TWI), Stream Power Index (SPI), Sediment Transport Index (STI), Topographic Roughness Index (TRI), Distance to Stream, Distance to Anticline, Distance to Fault, Distance to Road and Normalized Difference Vegetation Index (NDVI) were used and correlate with landslide events. Though landslides of this region got attention of many researchers but no attempt had been taken to implement Bivariate statistical models and analysing so many causative factors for landslide susceptibility mapping in this region. As the result of Bivariate Statistical models varies from region to and model to model so that five models were employed to produce landslide susceptibility map and the accuracy of these maps were calculated using Area Under Curve. So the objectives of the research goes to calculate the degree of relationship between landslide conditioning factors and previous landslides by using five GIS based bivariate statistical models, identify the areas vulnerable to landslide according to the models, and calculate the prediction rate of these models in the CHT hilly area.

Materials and Methods

Study Area

Chattagram District is located in between 21°54' and 22°59' North latitudes and in between 91°17' and 92°13' East

Figure 1: Spatial distribution of landslide points over study area

longitudes (Figure 1). The Chittagong Hill Tracts were uplifted during Miocene period as a result of collision between the Indian and Eurasian Plates. Soils of the hills are composed of Tertiary and Quaternary sediments and there are many anticlines and synclines exist in this hilly region. The surface strata of this region have easily-weatherable feldspar and unconsolidated sedimentary rocks (yellowish-brown to reddish-brown loams). Geologically these Hill ranges are underlain by rocks of Tipam and Surma formation. The hill ranges have low height below 300 meter but there are steep slopes which are disconnected by rills and gullies (Brammer, 1996; Sarkar and Rashid, 2013; Brammer, 2016). Surface soils of the region are dominated by Cambisols (Moderately developed soils) and Gleysols (Groundwater affected soils) (FAO, 1988). Climatologically CHT region belongs to tropical monsoon climate with mean yearly rainfall 2540 mm to 3810 mm which is the main triggering factor of landslide (Ahmed, 2014).

Methodological Summary

Flow chart of the broad steps followed in this research for deriving results of landslide susceptibility assessment and the model used for validation (AUC) are given below (Figure 2).

Figure 2: Methodological Flow Diagram

Data Acquired and Source

Historical landslide data (Figure 1) were acquired from Rabby and Li (2019) (Link: <http://www.mdpi.com/2306-5729/5/1/4/s1>, Dataset License: CC-BY). Geological map of Bangladesh was collected from Geological Survey of Bangladesh (GSB) server (Link: <http://www.gsb.gov.bd/site/view/commondoc/Geo-scientific%20Map/-?page=3&rows=20>). For road network OpenStreetMap data were collected from GEOFABRIK server (Link: <https://download.geofabrik.de/>) a popular data source used globally. Landsat-8 OLI images and SRTM dem images

of the study area were acquired from USGS server (Link: <https://earthexplorer.usgs.gov/>). Data of Anticline are adopted from Khan et al. (2017).

Data Processing

In this section, authors describe data processing and preparation method of the landslide conditioning factors including the background theory where necessary. Data were processed by using ArcMap 10.5 software to generate the spatial database of the conditioning factors.

Slope aspect mainly affects the amounts of sunlight and rainfall. Again wind can negatively impact slope equilibrium and indirectly influence landslides (Demir et al 2013 Wen et al 2017). Slope aspects of the study area were derived from DEM images by using ArcMap 10.5 software. They are classified into nine groups (Figure 3.a): flat (-1°), north (0° - 22.5° ; 337.5° - 360°), northeast (22.5° - 67.5°), east (67.5° - 112.5°), southeast (112.5° - 157.5°), south (157.5° - 202.5°), southwest (202.5° - 247.5°), west (247.5° - 292.5°), and northwest (292.5° - 337.5°). The slope angle controls the mass movement and gravitational energy and is directly connected to the landslide occurrence (Wen et al 2017). DEM images were employed to calculate the slope angle of the study area and they are categorized as 0 - 1.29° , 1.29° - 3.44° , 3.44° - 6.02° , 6.02° - 8.82° , 8.82° - 11.83° , 11.83° - 15.27° , 15.27° - 19.57° , 19.57° - 25.81° and 25.81° - 54.85° (Figure 3.b).

Three types of curvature were calculated, namely general curvature profile curvature and plan curvature. The curvatures significantly control the distribution of stresses plan curvature and the shrinking and expansion of the saturated landslide materials according to the landslide motion direction (Carson and Kirkby 1972; Guo et al 2015). As a result, increase in convexity and concavity of any slope curvature enhances the likelihood of landslide occurrence (Lee and Talib 2005 merchant and Meten 2020). The slope curvatures were categorized into three classes namely: convex, concave and flat figure (Figure 3.d, e and f).

High elevated mountains contain weathered rock and intermediate or close to the ground are covered by thin colluvium materials which are more susceptible to landslide (Youssef et al 2015). The elevation raster of the study area was directly derived from DEM processing by ArcMap 10.5 software (Figure 3.c). In the analysis of landslide susceptibility distance to lineaments (faults folds joints and fractures) is considered as an effective factor (Yousuf et al 2015). In this research distance to faults (Figure 3.h) and distance to anticline (Figure 3.i) were used.

Road construction and inappropriate cut slope and drainage from road adversely impact slope stability as a result landslide occurs along roads (Dahal et al 2008). Raster data of distance to the road (Figure 3.j) was computed by using Euclidean distance. Drainage is another major cause of landslides (Elmoulat and Brahim 2018). This casual factor was derived from DEM by using hydrology tool of ArcMap 10.5 software. DEM raster analysis was executed to generate data of flow direction flow accumulation and then vector stream network data were extracted. Then the distance to drainage (Figure 3.g) was computed by using the Euclidean distance tool.

Geological units of the study area (Figure 3.k) are Tipam Sandstone (Tt), Boka Bil Formation (Tbb), Bhuvan Formation (Tb), Girujan Clay (QTg) Dupi Tila Formation (QTdt), Dihing Formation (QTdi), Dihing and Dupi Tila

Figure 3: Landslide Conditioning Factors: a) slope aspect, b) slope degree, c) elevation, d) general curvature, e) plan curvature, f) profile curvature, g) distance to stream, h) distance to fault and i) distance to anticline

Figure 3: Landslide Conditioning Factors j) distance to road, k) geology, l) ndvi, m) TWI, n) STI, o) TRI and p) SPI

Formation Undivided (QTdd), Beach and dune sand (csd) and Valley alluvium and colluviums (ava).

Topographic Wetness Index (TWI) (Figure 3.m) and Stream Power Index (SPI) (Figure 3.p) were calculated by equation 1 and 2 respectively. The high TWI value negatively impacts the slope durability causes landslide (Beven and Kirkby 1979). SPI impacts the debris flow development and this factor is extensively applied to landslide susceptibility assessment (Tehrany et al 2019).

$$TWI = \ln \left(\frac{\alpha}{\tan \beta} \right) \dots \dots \dots (1)$$

Where α is the local upslope area draining through a certain point per unit of contour length, and β is the local slope gradient in degrees.

$$SPI = A_s \times \tan \beta \dots \dots \dots (2)$$

Where A_s indicates the catchment area that is studied and β indicates the local slope gradient measured in degrees.

The Sediment Transport Index (STI) (Figure 3.n) is another index of measuring erosive power of the overland flow (Moor et al., 1993). To calculate it by using Universal Soil Loss Equation instead of 1D slope length the 2D catchment area is used (Kumar and Singh, 2016).

$$STI = \left(\frac{A_s}{22.13} \right)^{0.6} \left(\frac{\sin \beta}{0.0896} \right)^{1.3} \dots \dots \dots (3)$$

Where, A_s is the area (m²/m) of specific catchment and β is the measurement of slope gradient (degree).

The Topographic Roughness Index (TRI) (Figure 3.o) is measured as an output of surface ratio provides an index of topographic roughness. It is a very effective tool used for assessing slope stability (Jenness, 2013). TRI was calculated by the Equation 4,

$$TRI = \sqrt{\|x\|(max^2 + min^2)} \dots \dots \dots (4)$$

Normalized Difference Vegetation Index (NDVI) was analysed from Landsat 8 OLI image by using AcrMap 10.5 software and classified into five classes (Figure 3.l). General equation of NDVI analysis is $NDVI = (NIR-RED)/(NIR+RED)$.

GIS Based Bivariate Models

Frequency Ratio (FR)

Frequency ratio is the possibility of occurrence of an event for a given characteristics (Bonham-Carter, 2014). By calculating the bivariate relationship between the landslide and their conditioning factors it reveals the statistical correlation among them (Lee and Talib, 2005). Equation (5) shows the FR algorithm,

$$FR_{ij} = \frac{\frac{Lc}{Lt}}{\frac{Af}{At}} \dots \dots \dots (5)$$

Where FR is the frequency ratio of a class i of a conditioning factor j , Lc is the number of landslide points of a class of a conditioning factor, Lt is total landslide point of the study area, Af is the number of pixel of a class of a conditioning factor and At is the total number of pixel in that conditioning factor.

Shanon's Entropy (SE)

It calculates the bi-variate relationships among the component of a system with the degree of disorder. This method can separate the most significant impact factor from less significant one. In landslide study entropy of a landslide indicates the degree of influence of factors to occur landslide. By using the following Equations value of the parameter is computed (Arabameri et al., 2019),

$$FR_{ij} = \frac{Lc}{Lt} / \frac{Af}{At} \dots \dots \dots (7)$$

$$P_{ij} = \frac{FR_{ij}}{\sum FR_{ij}} \dots \dots \dots (8)$$

Where, E_{ij} is the ratio between number of landslide occurrence in a specific class and total pixel within that class.

$$H_j = - \sum_{i=1}^{M_j} FR_{ij} \log(FR_{ij}), \quad j = 1, \dots, n \dots \dots \dots (9)$$

$$H_{jmax} = \log_2 M_j, \quad M_j - \text{number of class} \dots \dots \dots (10)$$

$$I_j = (H_{jmax} - H_j / H_{jmax}), \quad I = (0,1), j = 1, \dots \dots \dots (11)$$

$$W_j = I_j FR \dots \dots \dots (12)$$

Where H_j and H_{jmax} are the entropy of a class of a conditioning factor, I_j is the coefficient of information value, M_j is the number of classes in each conditioning factor, and W_j is the achieved weight value for the given factor. The value of W_j ranges 0-1. The entropy of W_j close to 1 has higher probability to be inconsistent and imbalanced (Khosravi et al., 2016 and Nohani et al., 2019).

Weight of Evidence (WofE)

After Bonham-Carter et al. (1988) used this method for gold exploration, still now it has been used for mineral exploration integrating with GIS and also had become popular in landslide susceptibility assessment (Elmoulat and Brahim, 2018; Wang et al., 2019). Statistically, WofE can be expressed by Equation 13.

$$WofE = \left[\ln \left(\frac{Relative\ Frequency\ of\ Goods}{Relative\ frequency\ of\ Bads} \right) \right] * 100 \dots \dots \dots (13)$$

WofE model calculates the positive weight (W^+) and negative weight (W^-) of the indicator where W^+ indicates the presence of the event and W^- indicates the absence of the event as follows (Bonham-Carter et al. 1994). The original equation was rewritten in pixel format to calculate weights of landslide as follows:

$$W^+ = \ln \frac{\frac{Npix_1}{Npix_1 + Npix_2}}{\frac{Npix_3}{Npix_3 + Npix_4}} \dots \dots \dots (14)$$

$$W^- = \ln \frac{\frac{Npix_2}{Npix_1 + Npix_2}}{\frac{Npix_4}{Npix_3 + Npix_4}} \dots \dots \dots (15)$$

Where Npix1 indicates previously occurred landslide point is specific factor class, Npix2 indicates the existence and non-existence of landslide point in the factor map, Npix3 s the existence of predictive factor but non-existence of landslide in the factor class, Npix4 is the non-existence of both causative factor class and the landslide point.

Weight of contrast (C) is measured by substituting W^+ and W^- . It is the degree of spatial association of causative factor class and the corresponding landslides. C is calculated by Equation 16.

$$C = W^+ + W^- \dots \dots \dots (16)$$

The weighted value of C was assigned to create factor map (Equation 17) and LSM was prepared by combining all the factor map (Equation 18):

$$Wmap = \sum C \dots \dots \dots (17)$$

$$Cmap = \sum Wmap \dots \dots \dots (18)$$

Information Value (IV)

The information value method can calculate the probability of landslide occurrence in an unbiased way as it is considered as an indirect statistical approach (Zezere 2002). In this method, the ratio of landslide point density in a class of a factor and the landslide density of the entire map is employed and the natural logarithm of this ratio is considered as the Information of Value of that parameter class (Bui et al 2011). IV is calculated by using equation 19.

$$I_i = \ln \left(\frac{Densclass}{Densmap} \right) = \ln \left(\frac{N_{pix}(S_i)}{N_{pix}(N_i)} / \frac{\sum_{i=1}^n N_{pix}(S_i)}{\sum_{i=1}^n N_{pix}(N_i)} \right) \dots \dots \dots (19)$$

where, I_i is the weight of a given class of a factor; Densclass is the density of landslide of a given class; Densmap is the landslide density of the factor; $N_{pix}(S_i)$ is the number of landslides in a certain factor class; $N_{pix}(N_i)$ is the number of pixels in a certain factor class; N is all of the landslide points in the database; and n is the total number of classes. Finally all the factor maps were combined to produce the LSM using Equation 20.

$$LSM = \sum_{i=1}^m I_i \dots \dots \dots (20)$$

Where, m = number of thematic layers.

Certainty Factor (CF)

Certainty factor is the function of probability (Sujatha et al., 2012) that is modified by Heckeman in 1986 from the original version. The modified equation is as follows (Equation 21):

$$CF = \begin{cases} \frac{PPa - PPs}{PPa(1 - PPs)}, & \text{if } PPa > PPs \\ \frac{PPa - PPs}{PPs(1 - PPa)}, & \text{if } PPa < PPs \end{cases} \dots \dots \dots (21)$$

Where PPa is the ratio between the number of landslide point and the number of pixel within class a, and PPs is the ratio between the total landslide point and all the pixel in the entire factor layer. The value of CF varies between 1 to -1. Positive value indicates the increasing certainty and negative value indicates decreasing certainty of landslide occurrence while the 0 value means initial probability is very similar to the conditional probability (Wang et al. 2019). Finally the LSM produced by combining all the factor map (Equation 22):

$$LSM_{cf} = \sum_{i=1}^n CF \dots \dots \dots (22)$$

Where, n= number of factor map layers.

Model Verification

The AUC (Area Under Curve) is a popular method used to identify the model's accuracy which shows the success rate of the model. The AUC indicates the ability of a model for predicting future probability of landslide occurrence and non-occurrence. If AUC value ranges between 0.5 and 1 it is considered that the model can predict future landslide perfectly. AUC value of 1 indicates perfect prediction and the more closely the value to 1 the better the accuracy of the model (Youssef et al. 2015; Nohani et al. 2019; Vakhshoori et al. 2019).

Results

Frequency Ratio

Results of weights of all the conditioning factors and their subclasses obtained for Frequency Ratio model tabulated in Table 1. Probability ratio of each map was used with every subclass for LSM. Equation 6 used in GIS environment to prepare the susceptibility map as follows:

$$\begin{aligned}
 LSM_{FR} = & 1.232 * FR_{Aspect} + 3.031 * FR_{Slope} + 1.810 * FR_{Geology} + 2.149 * FR_{Elevation} \\
 & + 2.788 * FR_{Plan\ Curvature} + 2.466 * FR_{Profile\ Curvature} + 2.372 * FR_{General\ Curvature} \\
 & + 4.186 * FR_{TWI} + 5.171 * FR_{SPI} + 1.913 * FR_{STI} + 2.822 * FR_{TRI} + 1 * FR_{Dis_Stream} \\
 & + 3.082 * FR_{Dis_Anticline} + 3.364 * FR_{Dis_Fault} + 1.895 * FR_{Dis_Road} \\
 & + 1.578 * FR_{NDVI} \dots \dots \dots (23)
 \end{aligned}$$

Results of frequency ratio showed that SPI has the highest correlation with landslide occurrence. Results of SPI indicated that all the landslide points are in one class (0 - 26,376,673.13) and it got the highest probability ratio of 5.171. The Second highest correlation was found for TWI, the probability ratio is 4.2. Slope, distance to anticline and distance to fault had the probability ratio above 3. Among the classes, the Southwest facing slope (FR= 2.48) had a great contribution to the landslides and the other two important slopes are South (FR=1.68) and Southeast (FR=1.53). Elevation, General Curvature, Plan Curvature, Profile Curvature and TRI had probability ratio above 2 where TRI and Plan Curvature had probability ratio nearly 3. Concave and convex curvatures were more unstable and susceptible to the landslide. But between them convex slopes were relatively more vulnerable to landslide as FR for Plan, Profile and General Curvature were 1.965, 1.184 and 1.689. Geology, STI, Distance to Road had a probability ratio above 1.8 and NDVI had 1.6. The Geological Units of Tb, Tbb, Tt QTdt showed correlation values of 6.321, 5.826, 2.566 and 2.687 respectively and had the highest impact on landslides in the region. Among these three geological subgroups Tb, Tbb and Tt contained 80% landslide point. The lowest probability ratio was found for Distance to Stream which was 1 and the second-lowest for Aspect which was 1.2.

Shanon's Entropy

The results of Shanon's Entropy for the relationship of the effective factors with the occurrence of landslides are presented in Table 1. Shanon's weight Wj was calculated for all the factors. Wj value is the relative percentage of the importance of each map. Finally Equation 11 and GIS environment used to prepare susceptibility map according to following formula:

$$\begin{aligned}
 LSM_{FR} = & 0.071 * FR_{Aspect} + 0.062 * FR_{Slope} + 0.062 * FR_{Geology} + 0.065 * FR_{Elevation} \\
 & + 0.066 * FR_{Plan\ Curvature} + 0.067 * FR_{Profile\ Curvature} + 0.070 * FR_{General\ Curvature} \\
 & + 0.052 * FR_{TWI} + 0.038 * FR_{SPI} + 0.070 * FR_{STI} + 0.062 * FR_{TRI} + 0.073 * FR_{Dis_Stream} \\
 & + 0.052 * FR_{Dis_Anticline} + 0.055 * FR_{Dis_Fault} + 0.066 * FR_{Dis_Road} \\
 & + 0.069 * FR_{NDVI} \dots \dots \dots (24)
 \end{aligned}$$

This model showed slope aspect, general curvature, STI, distance to stream and NDVI had the highest correlation with landslide occurrence and the Wj value of these variables are ≥ 0.07 . Slope, elevation, geology, plan curvature, profile curvature, TRI and distance to road had Wj value > 0.06 . TWI, distance to anticline and distance to fault had

Wj value >0.05 and SPI got the lowest value of 0.038 in this model. Wj value is the relative percentage of the importance of each map.

Table 1: Summary results of Frequency ratio, Shanon's Entropy Weight of evidence, Information Value and Certainty Factor method

Factors	Class	Class Pixel (Nclass)	Class Pixel (%)	Landslide Point (Nclass)	Landslide Point (%)	FR			SE		WofE	IV	CF
						FR	RF (%)	PR	Pij	Wj			
Slope Aspect	Flat	733691	15.71	0	0.00	0.00	0.00	1.23	0.00	0.07	-0.17	0.00	-1.00
	North	279409	5.98	9	4.64	0.78	7.45		0.08		-0.27	-0.11	-0.23
	Northeast	469039	10.04	11	5.67	0.57	5.43		0.05		-0.62	-0.25	-0.44
	East	477990	10.23	19	9.79	0.96	9.20		0.09		-0.05	-0.02	-0.05
	Southeast	504472	10.80	32	16.50	1.53	14.68		0.15		0.49	0.18	0.35
	South	486935	10.43	34	17.53	1.68	16.16		0.16		0.60	0.23	0.41
	Southwest	524255	11.23	54	27.84	2.48	23.83		0.24		1.12	0.39	0.60
	West	513108	10.99	15	7.73	0.70	6.76		0.07		-0.39	-0.15	-0.30
	Northwest	498658	10.68	11	5.67	0.53	5.10		0.05		-0.69	-0.28	-0.47
	North	182922	3.92	9	4.64	1.19	11.39		0.11		0.18	0.07	0.16
Slope (degree)	0 – 1.291	1981360	42.42	5	2.58	0.06	0.10	3.03	0.00	0.06	-3.33	-1.22	-0.94
	1.291 – 3.442	1373550	29.41	16	8.25	0.28	0.45		0.00		-1.53	-0.55	-0.72
	3.442 – 6.023	498019	10.66	30	15.46	1.45	2.33		0.02		0.43	0.16	0.31
	6.023 – 8.819	329940	7.06	39	20.10	2.85	4.56		0.05		1.20	0.45	0.65
	8.819 – 11.830	225710	4.83	41	21.13	4.37	7.01		0.07		1.66	0.64	0.77
	11.830 – 15.272	142818	3.06	25	12.89	4.21	6.76		0.07		1.55	0.63	0.76
	15.272 – 19.574	77501	1.66	15	7.73	4.66	7.47		0.08		1.60	0.67	0.79
	19.574 – 25.812	33691	0.72	11	5.67	7.86	12.61		0.13		2.11	0.90	0.87
	25.812 – 54.849	7890	0.17	12	6.19	36.62	58.72		0.59		3.66	1.56	0.97
Geology	Tb	102835	2.20	27	13.92	6.32	35.02	1.81	0.35	0.06	1.97	0.80	0.84
	Tbb	260332	5.57	63	32.47	5.83	32.27		0.32		2.10	0.77	0.83
	Tt	525395	11.25	56	28.87	2.57	14.21		0.14		1.16	0.41	0.61
	ava	1685895	36.10	4	2.06	0.06	0.32		0.00		-3.29	-1.24	-0.94
	csd	849812	18.20	21	10.83	0.60	3.30		0.03		-0.61	-0.23	-0.41
	Qtdi	452437	9.69	0	0.00	0.00	0.00		0.00		-0.10	0.00	-1.00
	QTdt	206056	4.41	23	11.86	2.69	14.89		0.15		1.07	0.43	1.69
	QTg	148109	3.17	0	0.00	0.00	0.00		0.00		-0.03	0.00	-1.00
	QTdd	410109	8.78	0	0.00	0.00	0.00		0.00		-0.09	0.00	-1.00
Elevation (meter)	-5 – 15	2525570	54.08	0	0.00	0.00	0.00	2.15	0.00	0.07	-0.78	0.00	-1.00
	15.001 – 31	996875	21.34	42	21.65	1.01	5.56		0.06		0.02	0.01	0.01
	31.001 – 50	616360	13.20	78	40.21	3.05	16.70		0.17		1.49	0.48	0.67

Factors	Class	Class Pixel (Nclass)	Class Pixel (%)	Landslide Point (Nslclass)	Landslide Point (%)	FR			SE		WofE	IV	CF
						FR	RF (%)	PR	Pij	Wj			
	50.001 – 74	303720	6.50	27	13.92	2.14	11.73		0.12		0.84	0.33	0.53
	74.001 – 108	140430	3.01	26	13.40	4.46	24.44		0.24		1.61	0.65	0.78
	108.01 – 159	66688	1.43	21	10.83	7.58	41.56		0.42		2.13	0.88	0.87
	159.01 – 320	20836	0.45	0	0.00	0.00	0.00		0.00		0.00	0.00	-1.00
Plan Curvature	Concave	1172409	25.10	62	31.96	1.27	37.66	2.79	0.38	0.07	0.34	0.11	0.22
	Flat	2028005	43.42	12	6.19	0.14	4.21		0.04		-2.45	-0.85	-0.86
	Convex	1470065	31.48	120	61.86	1.97	58.13		0.58		1.26	0.29	0.49
Profile Curvature	Concave	1407305	30.13	90	46.39	1.54	53.34	2.47	0.53	0.07	0.70	0.19	0.35
	Flat	1332051	28.52	9	4.64	0.16	5.64		0.06		-2.10	-0.79	-0.84
	Convex	1931123	41.35	95	48.97	1.18	41.03		0.41		0.31	0.07	0.16
General Curvature	Concave	1803327	38.61	69	35.57	0.92	31.25	2.37	0.31	0.07	-0.13	-0.04	-0.09
	Flat	1356428	29.04	19	9.79	0.34	11.44		0.11		-1.33	-0.47	-0.66
	Convex	1510724	32.35	106	54.64	1.69	57.31		0.57		0.92	0.23	0.41
TWI	3.109 – 6.828	1472620	31.53	162	83.51	2.65	80.95	4.19	0.81	0.05	2.40	0.42	0.62
	6.828 – 8.940	1558495	33.37	25	12.89	0.39	11.80		0.12		-1.22	-0.41	-0.61
	8.940 – 11.392	710749	15.22	7	3.61	0.24	7.25		0.07		-1.57	-0.63	-0.76
	11.392 – 14.518	764043	16.36	0	0.00	0.00	0.00		0.00		-0.18	0.00	-1.00
	14.519 – 24.659	164572	3.52	0	0.00	0.00	0.00		0.00		-0.04	0.00	-1.00
SPI	Very Low	4669995	99.99	194	100	1.00	100	5.17	1.00	0.038	0.00	0.00	0.00
	Low	306	0.007	0	0.00	0.00	0.00		0.00		0.00	0.00	-1.00
	Medium	130	0.003	0	0.00	0.00	0.00		0.00		0.00	0.00	-1.00
	High	38	0.001	0	0.00	0.00	0.00		0.00		0.00	0.00	-1.00
	Very High	10	0.000	0	0.00	0.00	0.00		0.00		0.00	0.00	-1.00
STI	0 – 50.41	3868095	82.82	86	44.33	0.54	3.96	1.91	0.04	0.07	-1.80	-0.27	-0.47
	50.41 – 176.43	559076	11.97	73	37.63	3.14	23.26		0.23		1.49	0.50	0.68
	176.43 – 378.08	164973	3.53	20	10.31	2.92	21.60		0.22		1.14	0.47	0.66
	378.08 – 697.34	60894	1.30	14	7.22	5.54	40.96		0.41		1.77	0.74	0.82
	697.34 – 2,142.44	17441	0.37	1	0.52	1.38	10.22		0.10		0.32	0.14	0.28
TRI	No Roughness	705575	15.11	0	0.00	0.00	0.00	2.82	0.00	0.06	-0.16	0.00	-1.00
	0.111 – 0.340	1324660	28.36	16	8.25	0.29	8.54		0.09		-1.48	-0.54	-0.71
	0.340 – 0.526	1605779	34.38	124	63.92	1.86	54.57		0.55		1.22	0.27	0.46
	0.526 – 0.889	1034465	22.15	54	27.84	1.26	36.89		0.37		0.30	0.10	0.20
Distance to Stream (meter)	0 – 151.9	1211622	25.94	24	12.37	0.48	5.35	1.00	0.05	0.07	-0.91	-0.32	-0.52
	152 – 334.2	1126360	24.12	39	20.10	0.83	9.36		0.09		-0.23	-0.08	-0.17
	334.3 – 516.6	966711	20.70	34	17.53	0.85	9.51		0.10		-0.21	-0.07	-0.15
	516.7 – 698.9	661711	14.17	41	21.13	1.49	16.75		0.17		0.49	0.17	0.33

Factors	Class	Class Pixel (Nclass)	Class Pixel (%)	Landslide Point (Nslclass)	Landslide Point (%)	FR			SE		WofE	IV	CF
						FR	RF (%)	PR	Pij	Wj			
	699 – 921.7	459667	9.84	42	21.65	2.20	24.70		0.25		0.93	0.34	0.55
	921.8 – 1,276	203249	4.35	11	5.67	1.30	14.63		0.15		0.28	0.12	0.23
	1,277 – 2,583	41159	0.88	3	1.55	1.76	19.70		0.20		0.57	0.24	0.43
Distance to Anticline (meter)	0 – 2,016.48064	714317	15.29	67	34.54	2.26	38.97	3.08	0.39	0.05	1.07	0.35	0.56
	2,016.48 – 3,969.95	864511	18.51	124	63.92	3.45	59.60		0.60		2.05	0.54	0.71
	3,969.95 – 5,860.40	870552	18.64	3	1.55	0.08	1.43		0.01		-2.68	-1.08	-0.92
	5,860.40 – 7,750.85	820691	17.57	0	0.00	0.00	0.00		0.00		-0.19	0.00	-1.00
	7,750.85 – 9,704.31	603998	12.93	0	0.00	0.00	0.00		0.00		-0.14	0.00	-1.00
	9,704.31 – 11,783.81	492906	10.55	0	0.00	0.00	0.00		0.00		-0.11	0.00	-1.00
	11,783.81 – 16,068.83	303504	6.50	0	0.00	0.00	0.00		0.00		-0.07	0.00	-1.00
Distance to Fault (meter)	0 – 3,512.25	922937	19.76	50	25.77	1.30	25.85	3.36	0.26	0.06	0.34	0.12	0.23
	3,512.25 – 7,375.73	1004845	21.52	137	70.62	3.28	65.06		0.65		2.17	0.52	0.70
	7,375.73 – 11,239.21	761457	16.30	0	0.00	0.00	0.00		0.00		-0.18	0.00	-1.00
	11,239.21 – 14,985.62	681098	14.58	0	0.00	0.00	0.00		0.00		-0.16	0.00	-1.00
	14,985.62 – 18,732.02	615420	13.18	3	1.55	0.12	2.33		0.02		-2.27	-0.93	-0.88
	18,732.02 – 22,712.58	402739	8.62	0	0.00	0.00	0.00		0.00		-0.09	0.00	-1.00
	22,712.58 – 29,854.16	281983	6.04	4	2.06	0.34	6.77		0.07		-1.12	-0.47	-0.66
Distance to Road (meter)	0 – 322.103	2584589	55.34	142	73.20	1.32	36.65	1.90	0.37	0.07	0.79	0.12	0.24
	322.103 – 901.89	975509	20.89	24	12.37	0.59	16.41		0.16		-0.63	-0.23	-0.41
	901.89 – 1,610.52	501979	10.75	18	9.28	0.86	23.92		0.24		-0.16	-0.06	-0.14
	1,610.52 – 2,480.20	309718	6.63	9	4.64	0.70	19.39		0.19		-0.38	-0.16	-0.30
	2,480.20 – 3,510.93	183858	3.94	1	0.52	0.13	3.63		0.04		-2.07	-0.88	-0.87
	3,510.93 – 5,282.50	94862	2.03	0	0.00	0.00	0.00		0.00		-0.02	0.00	-1.00
	5,282.50 – 8,213.65	19964	0.43	0	0.00	0.00	0.00		0.00		0.00	0.00	-1.00
NDVI	-0.140 – 0.104	216703	4.64	0	0.00	0.00	0.00	1.58	0.00	0.07	-0.05	0.00	-1.00
	0.104 – 0.236	356334	7.63	9	4.64	0.61	16.13		0.16		-0.53	-0.22	-0.39
	0.236 – 0.326	894505	19.15	32	16.50	0.86	22.85		0.23		-0.18	-0.07	-0.14
	0.326 – 0.396	1653347	35.40	79	40.72	1.15	30.52		0.31		0.23	0.06	0.13
	0.396 – 0.575	1549590	33.18	74	38.14	1.15	30.50		0.31		0.22	0.06	0.13

Legend: Nsclass = landslide point in class, nClass = pixel in the class, FR = frequency ratio, RF = relative frequency, PR = probability ratio, Pij = ratio of FR, Wj = weights of shanon's entropy, C = weight of contrast, IV = weights of Information Value model, CF = weights of certainty factor

Weight of Evidence

Results of weights of evidence model were tabulated in Table 1. Equation 18 and GIS used to integrate the values to produce the final map according to Equation 25.

$$\begin{aligned}
 LSM_{WofE} = & Aspect_{WofE} + Slope_{WofE} + Geology_{WofE} + Elevation_{WofE} + Plan\ Curvature_{WofE} \\
 & + Profile\ Curvature_{WofE} + General\ Curvature_{WofE} + TWI_{WofE} + SPI_{WofE} + STI_{WofE} \\
 & + TRI_{WofE} + Dis_Stream_{WofE} + Dis_Anticline_{WofE} + Dis_Fault_{WofE} + Dis_Road_{WofE} \\
 & + NDVI_{WofE} \dots \dots \dots (25)
 \end{aligned}$$

In terms of individual factor Slope, Elevation and Geology had a strong correlation with landslide and in terms of individual class slope degrees between 25° and 54 ° degrees had a strong positive impact on the landslide. But in this subclass, both the number of class pixels and the number of landslides were smaller than other subclasses. Geological subgroups of Tb (C = 2.0), Tbb (C = 2.1) and Tt (C = 1.2) were more unstable than other subgroups. After the previous three causative factors STI, distance to stream and slope aspect had a relatively more positive relation with landslide occurrence. Distance to anticline the subclass of <4000 meter had a strong correlation with the landslide. Results showed that in the case of distance to anticline, the subclass of 0-2000 meter had a correlation value of 1 and 2000-4000 meter had a correlation value of 2. Comparing and considering the three curvature it was evident that flat curvature had no impact on landslide occurrence where concave curvature (C = 1.26 for plan, 0.31 for profile and 0.92 for general curvature) were relatively more susceptible to landslide than convex curvature (C = 0.34 for plan, 0.7 for profile and -0.131 for general curvature). In the case of NDVI it was seen that a relatively high value showed more strong correlation to landslide occurrence which means in terms of the whole Chattagram district landslide occurred not only in the populated area but in vegetated areas of the hills. But the most devastating landslides have occurred in the Chattagram Municipality area (Ahmed, 2015 and Sultana, 2020). Subclass 3500-7400 of distance to fault line has a high correlation value of 2.2 and 95% of the landslide occurred in a distance between 0-7400 meter.

Information Value

The Information Value method was utilized to calculate the relationship between landslide location and the landslide conditioning factors. The results of weights of each class of landslide conditioning factors of this model tabulated in Table 1. The final LSM is produced by using GIS and Equation 22.

$$\begin{aligned}
 LSM_{IV} = & Aspect_{IV} + Slope_{IV} + Geology_{IV} + Elevation_{IV} + Plan\ Curvature_{IV} + Profile\ Curvature_{IV} \\
 & + General\ Curvature_{IV} + TWI_{IV} + SPI_{IV} + STI_{IV} + TRI_{IV} + Dis_Stream_{IV} + Dis_Anticline_{IV} \\
 & + Dis_Fault_{IV} + Dis_Road_{IV} + NDVI_{IV} \dots \dots \dots (26)
 \end{aligned}$$

This model showed that slope degree was the most important factor in landslide occurrence. Like the weight of evidence model slope class of 25- 54 showed a strong positive impact on the landslide and slopes above 3.5° were marked as more susceptible to the landslide. With increasing slope degree it has become unstable. In the case of geological factors 87% landslide occurred in four subgroups namely Tb, Tbb, Tt and Qdt and they had a correlation

value of 0.80, 0.77, 0.41 and 0.43 respectively. Elevation indicated that landslides started to occur above 15 meters height and 60% of the landslides occurred within 15-50 meter range and 75% of landslides occurred within a range of 15-75 meter and no landslide occurred above 160 meters. It indicates hills of the intermediate position were more unstable and more prone to landslide as they were composed of loose material. In terms of distance to stream, 50% of the landslides occurred within the subclass of 0-500 meter but this subclass showed a negative correlation with landslide occurrence. Comparing the landslide conditioning factors slope degree, elevation and geology had a more positive impact on landslide and STI and distance to stream and slope aspect had the second-highest impact.

Certainty Factor

Results of Certainty Factor were tabulated in Table 1. Certainty factor, Information value and weight of evidence method showed similarities in weighting values of landslide conditioning factor. Equation 27 and GIS finally used to prepare the map according to the following procedure:

$$LSM_{CF} = Aspect_{CF} + Slope_{CF} + Geology_{CF} + Elevation_{CF} + Plan\ Curvature_{CF} + Profile\ Curvature_{CF} + General\ Curvature_{CF} + TWI_{CF} + SPI_{CF} + STI_{CF} + TRI_{CF} + Dis_Stream_{CF} + Dis_Anticline_{CF} + Dis_Fault_{CF} + Dis_Road_{CF} + NDVI_{CF} \dots \dots \dots (27)$$

Considering the values of the slope aspect, the Southwest facing class had the most significant impact (0.597) on the landslide. Other important classes having a positive impact on landslides are sequentially South (0.405), Southeast (0.345) and North (0.156) facing slope. Among the factors slope was the most significant impact on the landslide. With the increase of slope angle, the impact of it to landslide was also increased. Such as classes of 3.44-6.022, 6.022-8.819, 8.819 - 11.830, 11.830 - 15.272, 15.272 - 19.574, 19.574 - 25.811 and 25.811 - 54.849 had a correlation value of 0.310, 0.649, 0.771, 0.763, 0.785, 0.873 and 0.973 respectively. In the case of Geology Tb, Tbb and Tt had shown a positive impact on landslide and the rest of the class showed a negative impact on the landslide. After slope, another important factor was Elevation. Five subclasses out of seven had shown a positive correlation with landslide and the class 1008.01-159 had the greatest impact (0.868) on landslide. Among curvature, the concave and convex slope had a positive impact on landslide and the convex slope had a relatively high impact on the landslide. In the case of SPI only one class showed no relation with landslide and the rest of the class showed a negative impact on the landslide. Among the other factors, STI and Distance to Stream showed a more positive impact on landslide and Distance to Road showed a very little impact as the only class (0-322.103) had a value of 0.244. In the case of NDVI the higher value showed a more positive impact and the medium to very low value showed a negative impact on the landslide.

Finally five LSM were prepared for FR, SE, WofE, IV and CF models (Figure 4). The LSM of the study area were categorized into five classes according to landslide vulnerability level, namely Very Low, Low, Medium, High and Very High. Percentage of areas containing these classes illustrated Figure 6.

Figure 4: Landslide Susceptibility Maps

Model Verification

Model verification was completed by using Area Under Curve (AUC) techniques. Prediction rate for AUC of the

Figure 5: Model Validation for Chattagram District (Prediction Rate)

models FR, SE, WofE, IV and CF are 76.11%, 70.11%, 78.93%, 76.57% and 80.43% respectively (Figure 5). Considering the results of evaluation of the five models CF showed most accurate prediction rate for identification of landslide susceptible areas in the Chattagram District. The least accurate prediction in identification of landslide found for SE model. The second best prediction rate showed WofE model. The FR and IV models had AUC of 76.11% and 76.57% respectively showed similar prediction rate in the study area.

Discussion

In the present study CF (80.83%) model produced excellent prediction of the landslide occurrence (Figure 5). Other models also produced acceptable result and SE produced the

Figure 6: Area (%) of different landslide susceptible classes for all models

lowest accuracy among the models. The CF model showed 15% areas are at very high risk for future landslide occurrence in the study area (Figure 6 and Figure 4). Very high landslide susceptible area found for other four models are FR, SE, WofE, IV and CF are 14.93%, 12.67%, 13.94%, 13.49% and 15.04% respectively (Figure 6). Results are slightly dissimilar to the previous study conducted by Mourin et al. (2018) and Chakraborty (2019). Low and very low susceptible area calculated from the present study was 40-48% where in previous study marked 60%.

Conclusion

In this research bivariate statistical models of FR, SE, WofE, IV and CF was employed integrating with GIS software (ArcMap 10.5) for landslide susceptibility mapping. The causative factors of slope degree, slope aspect, elevation, geology etc. have great influence on landslide occurrence in Chattagram District. The excellent prediction rate found for CF model of 80.43%. The prediction rates of other models are also acceptable. CF model indicates 18.17%, 24.67%, 24.85%, 17.26% and 15.04% areas are very low, low, high and very high vulnerable respectively. All the models showed that only the high elevated areas are more vulnerable to landslide but the low-lying river basin areas have low probability of landslide occurrence. LSM produced in this research will be helpful for policy makers and development planners to avoid more damaging areas suggested in the susceptible maps (Figure 4). Forest resource management authority and environmental conservation unit will also be benefited from this research. If more precise and high resolution remote sensing data can be used accuracy of the model will be increased.

Declarations

Funding

Not Applicable

Conflict of Interest /Competing interests

All authors declare no conflicts of interest in this paper

Availability of data and material

Available on request

Code availability

Not Applicable

Authors' contributions

Md. Sharafat Chowdhury analysed the data and writes up the manuscript. Bibi Hafsa writes up the manuscript and proof reading.

Ethics approval

Not Applicable

Consent to participate

Not Applicable

Consent for publication

Not Applicable

References

Ahmed B (2014) Landslide susceptibility mapping using multi-criteria evaluation techniques in Chittagong Metropolitan Area, Bangladesh. *Landslides* 12(6):1077–1095. <https://doi.org/10.1007/s10346-014-0521-x>

Ahmed B (2015) Landslide susceptibility modelling applying user-defined weighting and data-driven statistical techniques in Cox's Bazar Municipality, Bangladesh. *Nat. Hazards* 79:1707–1737. <https://doi.org/10.1007/s11069-015-1922-4>

Al-Kafy A, Hasan MM, Ferdous L, Ali MR, Uddin MS (2019) Application of Artificial Hierarchy Process for Landslide Susceptibility Modelling in Rangamati Municipality Area, Bangladesh. *Proceedings, International Conference on Disaster Risk Management, Dhaka, Bangladesh, January 12-14, 2019*. <https://www.researchgate.net/publication/331008711>

Alam E (2020) Landslide Hazard Knowledge, Risk Perception and Preparedness in Southeast Bangladesh. *Sustainability* 12 (6305): 1-12. <https://doi.org/10.3390/su12166305>

Arabameri A, Cerda A, Tiefenbacher JP (2019) Spatial Pattern Analysis and Prediction of Gully Erosion Using Novel Hybrid Model of Entropy-Weight of Evidence. *Water* 11(6):1129. <https://doi.org/10.3390/w11061129>.

Ba Q, Chen Y, Deng S, Wu Q, Yang J, Zhang J (2017) An Improved Information Value Model Based on Gray Clustering for Landslide Susceptibility Mapping. *ISPRS Int. J. Geo-Inf.* 8. <https://doi.org/10.3390/ijgi6010018>

Beven K, Kirkby M (1979) Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin versant (A physically based, variable contributing area model of basin hydrology). *Hydrol. Sci. J.* 24:43–69.

Bonham-Carter GF (1994) Geographic information systems for geoscientists: modelling with GIS, comp. Meth. Geos., vol. 13, Pergamon, New York, p 398

Bonham-Carter GF (2014) Geographic Information Systems for Geoscientists: Modelling with GIS. vol 13. Elsevier: Amsterdam, The Netherlands, 2014. <https://doi.org/10.1016/C2013-0-03864-9>

Bonham-Carter GF, Agterberg FP, Wright DF (1988) Integration of geological data sets for gold exploration in Nova Scotia. Photogram Eng Remote Sens. 54:1585–1592. <https://doi.org/10.1029/SC010p0015>

Bui DT, Lofman O, Revhaug I, Dick O (2011) Landslide susceptibility analysis in the Hoa Binh province of Vietnam using statistical index and logistic regression. Nat. Hazards. 59(3):1413–1444. <https://doi.org/10.1007/s11069-011-9844-2>

Carson MA, Kirkby MJ (1972) Hillslope form and process. Cambridge University Press, London. Pp-475

Chakraborty T, Islam MD, Alam MS (2019) Landslide Susceptibility Mapping Using Xgboost Model in Chittagong District, Bangladesh. Proceedings on International Conference on Disaster Risk Management, Dhaka, Bangladesh, January 12-14, 2019. pp: 431-434. Link: https://jidpus.buet.ac.bd/ICDRM2019/resources/proceedings-papers/73_ICDRM_2019_Proceedings.pdf

Dahal RK, Hasegawa S, Nonomura A, Yamanaka M, Masuda T, Nishino K (2008) GIS-based weights-of-evidence modelling of rainfall-induced landslides in small catchments for landslide susceptibility mapping. Environ. Geol. 54: 311–324. <http://dx.doi.org/10.1007/s00254-007-0818-3>

Demir G, Aytekin M, Akgun A et al. (2013) A comparison of landslide susceptibility mapping of the eastern part of the North Anatolian Fault Zone (Turkey) by likelihood-frequency ratio and analytic hierarchy process methods. Nat Hazards. 65(3):1481-1506. [10.1007/s11069-012-0418-8](https://doi.org/10.1007/s11069-012-0418-8)

Elmoulat M, Brahim LA (2018) Landslides susceptibility mapping using GIS and weights of evidence model in Tetouan-Ras-Mazari area (Northern Morocco). Geomat Nat Haz and Risk 9(1):1306-1325. [10.1080/19475705.2018.1505666](https://doi.org/10.1080/19475705.2018.1505666)

FAO, 1988. Land resources appraisal of Bangladesh for agricultural development. Vol 2, Rome.

GEOFABRIK, [Online], Link: <https://download.geofabrik.de/>

Geological Survey of Bangladesh (GSB), [Online] Link: <http://www.gsb.gov.bd/site/view/commondoc/Geoscientific%20Map/-?page=3&rows=20>.

Guo C, Montgomery D, Zhang Y, Wang K, Yang Z (2015) Quantitative assessment of landslide susceptibility along the Xianshuihe fault zone, Tibetan Plateau, China. Geomorphology 248:93-110. [10.1016/j.geomorph.2015.07.012](https://doi.org/10.1016/j.geomorph.2015.07.012).

Heckeman D (1986) Probabilistic interpretation of MYCIN's certainty factors. In: Kanal LN, Lemmer JF (ed) Uncertainty in artificial intelligence. New York: Elsevier. p. 298–311. <https://doi.org/10.1016/B978-0-444-70058-2.50017-6>

Hong H, Xu C, Bui TD (2015) Landslide susceptibility assessment at the Xiushui area (China) using frequency ratio model. Procedia Earth and Planet Sci. 15(2015):513–517. DOI: [10.1016/j.proeps.2015.08.065](https://doi.org/10.1016/j.proeps.2015.08.065)

Hugh Brammer (1996) The geography of the soils of Bangladesh. University Press, Dhaka.

Hugh Brammer (2016) Bangladesh's diverse and complex physical geography: implications for agricultural development. Int J Environ Stu., doi: <https://doi.org/10.1080/00207233.2016.1236647>

Jenness J (2013) DEM Surface Tools. Jenness Enterprises. Available at: http://www.jennessent.com/arcgis/surface_area.htm

Khan H, Shafiq M, Khan MA, Bacha MA, Shah SU, Calligaris C (2019) Landslide susceptibility assessment using Frequency Ratio, a case study of northern Pakistan. *Egypt J Remote Sens Space Sci.* 22(2019):11–24. <https://doi.org/10.1016/j.ejrs.2018.03.004>

Khan MSH, Hossain MS, Chowdhury KR (2017) Geomorphic Implications and Active Tectonics of the Sitapahar Anticline -CTFB, Bangladesh. *Bangladesh Geosci J.* 23:1-24. <https://www.researchgate.net/publication/335365724>.

Khan YA, Lateh H, Baten MA, Kami, I AA (2012) Critical antecedent rainfall conditions for shallow landslides in Chittagong City of Bangladesh. *Environ Earth Sci.* 67(1):97-106. <https://doi.org/10.1007/s12665-011-1483-0>

Khosravi K, Nohani E, Maroufinia E, Pourghasemi HR (2016) A GIS-based flood susceptibility assessment and its mapping in Iran: A comparison between frequency ratio and weights-of-evidence bivariate statistical models with multi-criteria decision-making technique. *Nat. Hazards* 83:947–987. <https://doi.org/10.1007/s11069-016-2357-2>

Kumar S, Singh RP (2016) Spatial distribution of soil nutrients in a watershed of Himalayan landscape using terrain attributes and geostatistical methods. *Environ Earth Sci.* 75:473 (2016). <https://doi.org/10.1007/s12665-015-5098-8>

Lee S, Talib JA (2005) Probabilistic landslide susceptibility and factor effect analysis. *Environ Geol.* 47:982–990. <https://doi.org/10.1007/s00254-005-1228-z>

Mersha T, Meten M (2020) GIS-based landslide susceptibility mapping and assessment using bivariate statistical methods in Simada area, northwestern Ethiopia. *Geoenviron Disasters* 7:20 (2020). <https://doi.org/10.1186/s40677-020-00155-x>

Moore ID, Grayson RB, Ladson AR (1991) Digital terrain modeling—a review of hydro-hydrological, geomorphological, and biological application. *Hydrol. Process* 5:3–30

Mourin MM, Ferdous AA, Hossain MJ (2018) Landslide Susceptibility Mapping in Chittagong District of Bangladesh using Support Vector Machine integrated with GIS. 2018 International Conference on Innovation in Engineering and Technology (ICIET). 1-5. <https://doi.org/10.1109/CIET.2018.8660782>

Nohani E, Moharrami M, Sharafi S, Khosravi K, Pradhan B, Pham BT, Lee S, Melesse AM (2019) Landslide Susceptibility Mapping Using Different GIS-Based Bivariate Models. *Water.* 11(1402):1-22. <https://doi.org/10.3390/w11071402>

Ozioko OH, Igwe O (2020) GIS-based landslide susceptibility mapping using heuristic and bivariate statistical methods for Iva Valley and environs Southeast Nigeria. *Environ Monit Assess.* 192:119 (2020). <https://doi.org/10.1007/s10661-019-7951-9>

Park S, Choi C, Kim B, Kim J (2012) Landslide susceptibility mapping using frequency ratio, analytic hierarchy process, logistic regression, and artificial neural network methods at the Inje area, Korea. *Environ Earth Sci.* 68:1443–1464. <https://doi.org/10.1007/s12665-012-1842-5>

Passang, Kubicek (2018) Information Value Model based Landslide Susceptibility Mapping at Phuentsholing, Bhutan. AGILE 2018 – Lund pp 1-7. https://agile-online.org/conference_paper/cds/agile_2018/shortpapers/107%20ShortPaper%20ID%20107.pdf

Rabby YW, Li Y (2019) Landslide Inventory (2001–2017) of Chittagong Hilly Areas, Bangladesh. *Data.* 5(1):4. <https://doi.org/10.3390/data5010004>

Rashid H (1991) Geography of Bangladesh. University Press Ltd.

Sarkar AA, Rashid AKMM (2013) Landslide and Flashflood in Bangladesh. Shaw R et al. (eds.) Disaster Risk Reduction Approaches in Bangladesh, Disaster Risk Reduction. Springer Japan. https://doi.org/10.1007/978-4-431-54252-0_8

Silalahi FES, Arifianti, YP, Hidayat F (2019) Landslide susceptibility assessment using frequency ratio model in Bogor, West Java, Indonesia, Silalahi et al. Geosci. Lett. 6(10):1-17. <https://doi.org/10.1186/s40562-019-0140-4>

Sujatha ER, Rajamanickam GV, Kumaravel P (2012) Landslide susceptibility analysis using Probabilistic Certainty Factor Approach: a case study on Tevankarai stream watershed, India. J. Earth Syst. Sci. 121(5):1337–1350. <https://doi.org/10.1007/s12040-012-0230-6>

Sultana S (2020) Analysis of landslide-induced fatalities and injuries in Bangladesh: 2000-2018. Cogent Soc Sci. 6(1):1737402. <https://doi.org/10.1080/23311886.2020.1737402>

Tehrany MS, Jones S, Shabani F (2019) Identifying the essential flood conditioning factors for flood prone area mapping using machine learning techniques. Catena, 175:174–192. <https://doi.org/10.1016/j.catena.2018.12.011>.

USGS. [Online], Link: <https://earthexplorer.usgs.gov/>.

Vakhshoori V, Pourghasemi HR, Zare M, Blaschke T (2019) Landslide Susceptibility Mapping Using GIS-Based Data Mining Algorithms. Water 11(2292):1-30. <https://doi.org/10.3390/w11112292>

Wang Q, Guo Y, Li W, He J, Wu Z (2019) Predictive modeling of landslide hazards in Wen County, northwestern China based on information value, weights-of-evidence, and certainty factor. Geomat Nat Haz Risk 10(1):820-835. <https://doi.org/10.1080/19475705.2018.1549111>

Wen F, Xin-sheng W, Yan-bo C, Bin Z (2017) Landslide susceptibility assessment using the certainty factor and analytic hierarchy process. J Mt Sci. 14(5):906-925. <https://doi.org/10.1007/s11629-016-4068-2>

Yang Y, Yang J, Xu C, Xu C, Song C (2019) Local-scale landslide susceptibility mapping using the B-GeoSVC model. Landslides 16:1301–1312. <https://doi.org/10.1007/s10346-019-01174-y>

Youssef AM, Pourghasemi HR, Pourtaghi ZS, Al-Katheeri MM (2016) Landslide susceptibility mapping using random forest, boosted regression tree, classification and regression tree, and general linear models and comparison of their performance at Wadi Tayyah Basin, Asir Region, Saudi Arabia. Landslides 13:839–856. <https://doi.org/10.1007/s10346-015-0614-1>

Youssef AM, Pradhan B, Pourghasemi HR, Abdullahi S (2015) Landslide susceptibility assessment at Wadi Jawrah Basin, Jizan region, Saudi Arabia using two bivariate models in GIS. Geosciences J. 19:449–469. <https://doi.org/10.1007/s12303-014-0065-z>

Zezere JL (2002) Landslide susceptibility assessment considering landslide typology: A case study in the area north of Lisbon (Portugal). Nat Haz Earth Sys Sci. 2:73–82. <https://doi.org/10.5194/nhess-2-73-2002>.

Figures

Figure 1

Spatial distribution of landslide points over study area Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 2

Methodological Flow Diagram

Figure 3

Landslide Conditioning Factors: a) slope aspect, b) slope degree, c) elevation, d) general curvature, e) plan curvature, f) profile curvature, g) distance to stream, h) distance to fault and i) distance to anticline
 Landslide Conditioning Factors j) distance to road, k) geology, l) ndvi, m) TWI, n) STI, o) TRI and p) SPI
 Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 4

Landslide Susceptibility Maps Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 5

Model Validation for Chattagram District (Prediction Rate)

Figure 6

Area (%) of different landslide susceptible classes for all models