ANALYZING THE IMPACTS OF CLIMATIC AND TOPOGRAPHICAL DETERMINANTS ON LANDSLIDE SUSCEPTIBILITY IN CHATTOGRAM CITY CORPORATION AREA: A 28-YEARS RETROSPECTIVE (1990-2018)

Rizbina Reduan Rayma[*1], Abdur Rahman Zihad[2], Tanvir Ahmed[3], Md. Ali Hassan Tuhin[4],
Mohammad Belayet Hossain Raihan [5]
Chittagong University of Engineering & Technology, Bangladesh
***Corresponding Author:** u1905027@student.cuet.ac.bd

Abstract

During the monsoon season, landslides frequently threaten the residents residing on the hazardous hillslopes in Chattogram City Corporation (CCC) area of Bangladesh. Due to excessive rainfall over a few days, landslides are becoming more frequent and intense over time. Moreover, hill-cutting and rapid urbanization are two other factors that are thought to significantly affect the frequency of landslides by reducing the soil stability. This study aims to recommend planning control and mitigation measures by assessing the impact of numerous climatic and topographic factors on landslide susceptibility in Chattogram City Corporation during a 28-year period. For this, statistical techniques have been used, such as Multiple Regression Analysis and Bivariate Statistical Analysis. Five climatic and topographic factors (i.e., elevation, slope, aspect, NDVI, and rainfall) were selected based on their association with historical landslide events. A landslide inventory was prepared through both primary and secondary data for a time period of 28 years listing a total of 43 landslide events in different locations of CCC area. By applying the mentioned statistical techniques, the study identified the most influential factor contributing to landslide occurrences. NDVI, in particular, had a significant negative correlation with landslide occurrences, indicating that areas with more vegetation were less prone to landslides, while areas with less or no vegetation experienced more frequent landslide events. This further underscore the importance of vegetation in preventing landslides. The findings will help guide the implementation of targeted planning measures and disaster management strategies, with an emphasis on addressing critical environmental and infrastructural vulnerabilities that contribute to landslide risk in Chattogram.

1. Introduction

Natural disasters cause catastrophic levels of property damage, people displacement, and fatalities worldwide. Approximately 45% of the 1388 disasters that were reported globally between 2013 and 2015 took place in Asia (ESCAP, 2015). Landslides are among the most damaging natural disasters, causing major damage to infrastructure such as roads, bridges, and buildings, as well as loss of life (Bopche & Rege, 2021; Sarkar & Kanungo, 2004). Landslides are projected to become more frequent and impactful as urbanization and infrastructure development continue in many vulnerable locations (Bopche & Rege, 2021). In the past, landslide tragedies were rare in Bangladesh's highly populated areas, but in recent years, a number of landslides have been caused by growing human activities including careless hill cutting for the construction of settlements and residential housing (Ahmed, 2017). Chattogram City Corporation area is bound with natural resources including hills. Landslide in Chattogram City Corporation occurs almost every year. Human activities such as unplanned development, inappropriate land use, illegal hill cutting and deforestation have increased the risk, making metropolitan areas like CCC more exposed to such risks. In the hilly areas of Chattogram city, where inhabitants are especially vulnerable to landslide disasters due to the area's steep slopes, devastating and deadly landslides have occurred repeatedly (Rahman et al., 2017). Devastating landslides have frequently affected CCC in recent years, resulting in losses, damages, and fatalities. For instance, on June 11, 2007, landslides caused by excessive rainfall (610 mm) for eight days in a row resulted in the deaths of nearly 128 persons and the injuries of about 100 others near many hills. Another eight days of nonstop rain (889 mm) caused landslides on June 26, 2012, which resulted in 90 fatalities and 150 injuries (Ahmed & Dewan, 2017).
Landslide impacts can be reduced by predicting future occurrences (Budha et al., 2016). Implementing effective planning and development policies for avoiding landslide disasters can help to reduce approaching landslide dangers, but this necessitates a thorough assessment of this underappreciated

risk. Thus, mapping landslide susceptibility is an important step before landslide evaluation, planning, management, and catastrophe mitigation (Maqsoom et al., 2022). Several factors influence landslide susceptibility, including topography, geology, and meteorology (Farooq & Akram, 2021). Key factors influencing landslide occurrences include rainfall intensity, slope gradient (Farooq & Akram, 2021), land use and land cover, soil type (Shit et al., 2016), hill-cutting (Ahmed, 2015), population pressure in flat lands (Ahmed, 2021) and plant cover. Over the past 20 years, many landslide susceptibility approaches have been proposed and successfully implemented, based on the idea that in conditions similar to past landslides, the occurrence of landslides can be predicted as long as the causal relationship among causative factors is established (Farooq & Akram, 2021). Despite the two main approaches for measuring landslide susceptibility being generically classified as the qualitative and the quantitative methods (Corominas et al., 2013).

The overall processes for assessing landslide susceptibility are identical. Some of these stages include creating a landslide inventory, identifying and evaluating the relationship between the qualitative and quantitative landslide causative elements, and producing a landslide susceptibility map that illustrates different vulnerable zones. Among the most helpful quantitative methods for studying landslides at a regional level are statistically based landslide susceptibility mapping methodologies (Farooq & Akram, 2021). These are data-driven methods that incorporate historical slope movement and knowledge other factors. Using mathematical equations and the weight coefficients of specific causal components that are crucial to the development of slope movement. Using geospatial tools including geographic information systems (GIS) and remote sensing (RS) applications, landslide susceptibility maps are produced in these methods (Kelarestaghi & Ahmadi, 2009; Shahabi et al., 2013). Remote sensing data, integrated with digital elevation models (DEMs) and satellite imagery, give a high degree of objectivity and reproducibility in estimating landslide risk when compared to traditional field-based methods (Farooq & Akram, 2021). The use of sophisticated GIS and Remote Sensing tools in conjunction with bivariate statistical techniques has resulted in better delineation of areas susceptible to landslides. They also support the integration of varied types of datasets such NDVI and digital elevation models that enable better assessment of the role of vegetation cover and the terrain in landslide occurrence (Kelarestaghi & Ahmadi, 2009). Besides, the integration of historical landslide inventories over a significant time frame increases the reliability of the models as it allows one to look back in order to make forward projections regarding possible hazards. Such approaches tend to be more useful in places which are prone to disasters due to rapid environmental and demographic changes (Corominas et al., 2013).

In CCC area, landslides are a challenging, multifaceted issue that combines social (community vulnerability) and physical (building materials and dwelling patterns) aspects. Few research has been conducted to date despite the high level of landslide hazard and susceptibility in CCC. Though the number of landslide occurrences are increasing rapidly over the years along with the severe consequences and damages, there is a gap in proper planning control and mitigation measures for ensuring the safety of the citizens of CCC by the concerned authorities. To address this issue, this study aims to recommend planning control and mitigation measures by assessing the impact of numerous climatic and topographic factors on landslide susceptibility in Chattogram City Corporation during a 28-year period. Using multiple statistical methods, the study will examine historical landslide data for determining the influence of significant causative factors in landslide susceptibility, such as elevation, slope, aspect, NDVI, and rainfall.

1. Materials and Methods

1.1 Description of the Study Area

Chattogram City Corporation (CCC) is located in Chattogram district of Bangladesh, bounded by the Bay of Bengal in the west and Karnaphuli River in the east. Geographically, it lies between 22.13° and 22.28° N latitude and between 91.45° and 91.54° E longitude as shown in [Fig. 1].

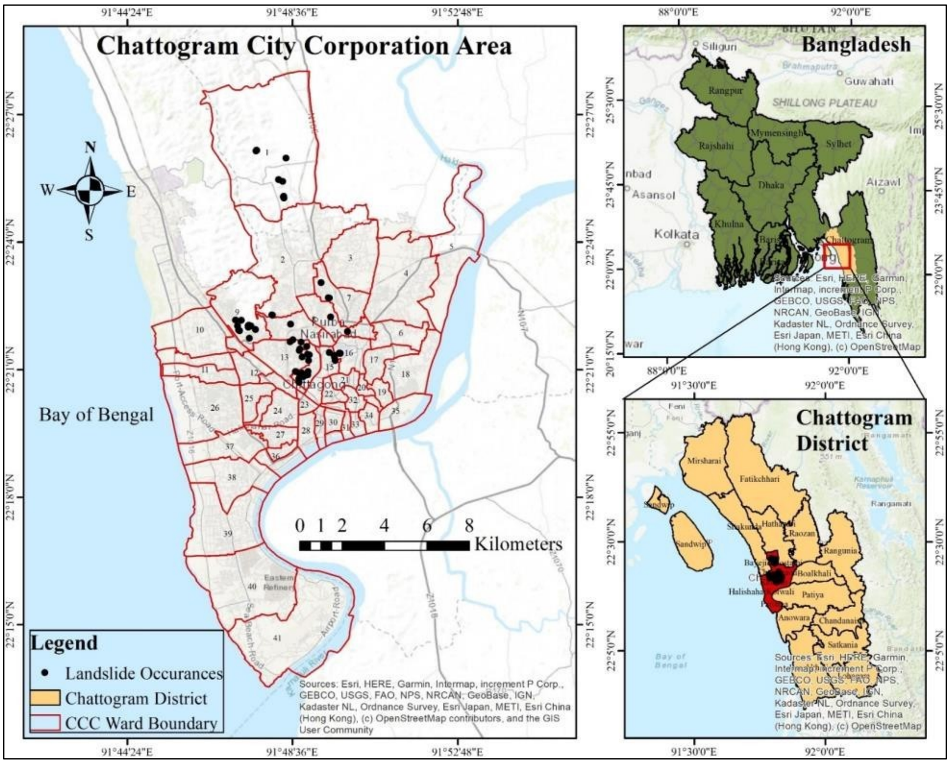

Fig. 1: Location map of Chattogram City Corporation area

The total area of CCC is about 170.41 sq. km and is administratively divided into 41 wards. The urban population of CCC area was around 2.58 million in 2011 which increased to around 3.23 million in 2022, representing an increase of the urban population by approximately 25.19% from 2011 to 2022.

1.2 Description of Landslide Causative Factors

1.2.1 Elevation

The Earth's climate system is unquestionably warming, and this warming is exacerbated at higher elevations (Pepin et al. 2015; Yao et al. 2016). Global warming causes changes in the quantity, size, and causes of landslides at high elevations (Hock et al. 2019). Since elevation is influenced by a number of geology and geomorphological processes, it is an important landslide conditioning element (Gritzner et al 2001). Elevation changes can affect the geomorphology, vegetation, and rate of erosion in a region, changing the likelihood of landslides (Chen et al. 2017). For data where feature identification mostly relies on relative changes, normalization performs admirably. For accurate analysis, slope, aspect, NDVI, rainfall, and elevation are all normalized. Normalizing such input data to ensure that all features are suitably weighted will help to mitigate this (A. Fafard et al 2020).

1.2.2 Slope

Slope is defined by many researchers as an input parameter in susceptibility studies, and it is the expression of the rate of the vertical distance to the horizontal distance between two specified points with the tangent angle. Slope is significant in terms of the formation, development, and susceptibility to landslides (Güler & Yomralıoğlu, 2017). Stated differently, slope, which is expressed in degrees, is a measurement of surface steepness. Its range is 0-90 degree, where a vertical area is represented by 90 and a horizontal area by 0 (Yüksel & Avci, 2017). Slope is a derivative of the digital elevation model and is evaluated in the topographical parameter classification. One of the most significant causative elements influencing slope stability is slope aspect (Kayastha, 2015). This parameter controls the progression speed and motion distance to test material transportation because the propensity of slope is the component strength of gravity. It dictates the direction of impressions, slope regulates the magnitude and extent of landslides (Sadr et al., 2014). Slope morphometry is the steepness of the slope, which influences surface runoff and weathering layer depth in addition to controlling the strain distribution within the slope mass.

1.2.3 Aspect

The influence of aspect on the sun-light, wind and rainfall exposure also has an indirect effect on other factors that cause soil movement such as wetness of the soil, growth of plants and depth of the soil. Aspect is usually expressed and understood as a class of compass direction. Which is usually given in degrees to, 0 clockwise to 360 degrees. Some of the climatic conditions such as the angle at which rain falls, the duration of sunshine, the topographical features of the region have slope stability effects whereby the slopes subjected to heavy rains reach saturation quicker (Mohammady et al., 2012).

1.2.4 Rainfall

In the hilly regions of Chattogram, Bangladesh, rainfall is one of the most significant triggers for landslides, particularly during the monsoon season. Because of its steep slopes, deforestation, and fast development, this area is vulnerable to landslides. Heavy rains during the monsoon season quickly saturate the soil, resulting in slope collapses that can have catastrophic effects on nearby towns. Intense rains, the properties of the soil, and human activity all combine to make Chattogram a high-risk area for landslides.

1.2.4.1 Monsoon Rainfall and Soil Saturation

Chattogram receives significant rainfall during the monsoon season, typically from June to October. The average annual rainfall in the region is about 2,800 mm, with most of it concentrated during the monsoon months (Baten et al., 2018). The earth gets quite wet during these times of heavy rains. Water fills the holes between soil particles when it seeps into the ground, decreasing the cohesiveness of the soil and increasing its weight. This process reduces the slopes' stability and increases the likelihood of landslides, particularly in places where vegetation has been removed. The rapid urbanization of Chattogram, particularly in hillside areas, has further exacerbated the situation. With less vegetation to absorb rainwater, surface runoff increases, leading to quicker soil saturation and a higher risk of landslides (Ahmed & Dewan, 2017).

1.2.4.2 Increased Pore Water Pressure

Rainfall increases pore water pressure, which is a key factor in landslides, especially in Chattogram's hilly areas. As rain saturates the soil, water fills the gaps between soil particles, reducing the friction that holds the soil together. This decrease in friction, or effective stress, weakens the slope. When pore water pressure exceeds a critical point, the slope can no longer support its own weight, leading to a landslide (Rahardjo et al., 2007).

In Chattogram, the combination of high-intensity rainfall and steep slopes accelerates this process. For instance, in 2012, after heavy rains, a landslide near Chattogram city claimed several lives. Studies have shown that landslides in this region often occur after continuous rainfall for several days, which leads to high pour water pressure and slope failure (Baten et al., 2018).

1.2.4.3 Rainfall Intensity and Duration in Chattogram

The intensity and duration of rainfall are critical factors in determining the likelihood of landslides. In Chattogram, short but intense rainfall events can trigger shallow landslides, while prolonged rainfall saturates deeper layers of the soil, leading to deeper landslides. Research shows that rainfall thresholds in Chattogram for triggering landslides are around 100 mm in 24 hours, with landslides more likely when this threshold is exceeded (Ahmed & Dewan, 2017). In 2017, Chattogram had more than 300 mm of rain in a few days, which was more than enough to cause a landslide. The already unstable slopes were overwhelmed by the heavy rains, which resulted in numerous landslides in both urban and rural regions.

1.2.5 Vegetation

Vegetation is a significant factor in decreasing the amount of erosion on slopes. Slope instability results from bare slopes, which are typically more vulnerable to erosional activity. On the other hand, a well vegetated slope lessens the impact of erosion due to the natural anchorage that tree roots give. The hills of CCC were once covered in a closed Dipterocarp rainforest, but shifting (Jhum) farming and deforestation have severely damaged most of it. Large tracts of land are now covered in secondary forest or shrub regrowth, or coarse grasses and bamboos, which are prone to burning during the dry season (Ahmed & Dewan, 2017). Vegetation indices derived from satellite imagery can be used to track vegetation-related changes over time. The reflective bands of satellite data are used to estimate vegetation cover using the normalized difference vegetation index (NDVI). Mostly expressing greenness, this index produces values between -1.0 and 1.0. Values close to zero are primarily produced by rock and bare soil, while any negative values are primarily produced by clouds, water, and snow. Bare patches of rock or sand are associated with very low NDVI values (0.1 and lower). Shrub and grassland are represented by moderate values (0.2 to 0.3), whilst temperate and tropical rainforests are indicated by high values (0.6 to 0.8) (Ahmed, 2015).

1.3 Landslide Inventory

Landslide inventories are one of the significant bases for assessing the landslide susceptibility of an area (Aleotti & Chowdhury, 1999). They are necessary for susceptibility models that forecast landslides based on historical data. Future landslides are predicted by analyzing the conditions under which they occurred in the past and using particular combinations. It is necessary to comprehend the relationship between causal variables and landslides. Depending on the type of landslide, these conditions vary. Estimating the frequency of landslides requires temporal information. Additionally, landslide inventories are used to verify risk, hazard, and susceptibility maps for landslides (Jetten et al., 2014). In this study, a landslide inventory has been prepared based on the historical data of landslide occurrences during the period 1990 to 2018 in CCC area as shown in Appendix I. From the inventory, most significant causal factors triggering landslide occurrences shall be determined by using various statistical techniques.

1.4 Methods

In this study, five climatic factors – NDVI, Elevation, Slope, Aspect, and rainfall were chosen to demonstrate the landslide prone areas in CCC area and the relationship between the factors and the historical data of landslide occurrences. To assess these factors and their relationship with landslide occurrences, remote sensing data were utilized. Landsat images were employed to derive the NDVI, providing a measure of vegetation health and density over the study area. MERIT-DEM (Multi-Error-Removed Improved-Terrain Digital Elevation Model) was used to extract Elevation, Slope, and Aspect data, which are crucial topographic parameters. The specific bands from these datasets were used in combination to calculate and generate the necessary basic remote sensing evaluation datasets for each factor. The NDVI, Elevation, Slope and Aspect were derived by band calculation to obtain the basic remote sensing evaluation datasets by using the Google earth Engine. Further, the normalization of each data for each factor was done. Using the constructed dataset, a multiple linear regression analysis has been done to understand the relationship between the factors and landslide occurrences and how the factors influence the landslide occurrence. Fig. 2 illustrates the overall framework mentioned above.

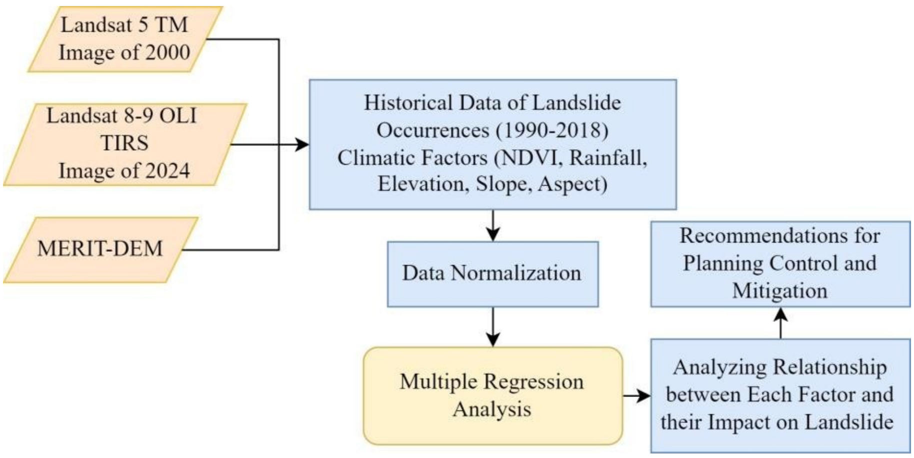

Fig. 2: Methodological framework of the study

2.3.1 Multiple Regression Analysis

Multiple regression (MR) is a least-square approach in which a linear relationship is assumed between dependent and independent variables. For example, in the case of three independent variables, the form of MR equation can be-

$$Y = a + (b1 \times x1) + (b2 \times x2) + (b3 \times x3) \quad \text{an equation (1)}$$

Here, the dependent variable is Y, the independent variables are x1, x2, and x3, the intercept is a, and the coefficients of the independent variables of x1, x2, and x3 are b1, b2, and b3, respectively. When the values of the independent variables get closer to zero, the intercept shows the value of Y. The parameter coefficients show how Y changes as the relevant independent variable increases by one unit. To determine the significance level, the F-test (for the overall regression) and t-test (for the single variable and intercept) tables were reviewed (Eastman, 2012). The significant impact of the selected causative factors on the frequency of landslide occurrences can be determined by using the MR method.

2.3.2 *Bivariate Statistical Analysis*

Bivariate analysis is a statistical analysis where two variables (dependent Y, and independent X) are observed and the changes that took place between the two variables and their respective magnitudes are examined. The strength of the linear relationship between two quantitative variables is commonly described by Pearson's r, also known as bivariate correlation. These two variables are frequently referred to as Y (dependent) and X (independent). The range of values for Pearson's r is -1.00 to +1.00. The direction of the link between X and Y can be inferred from the sign of r. A positive correlation means that when X scores rise, Y scores tend to rise as well; a negative correlation means that Y scores tend to fall as X scores rise; and a correlation close to 0 means that X scores do not decrease or rise linearly as Y scores do. The magnitude of the linear relationship between scores on X and Y can be determined from the absolute magnitude of Pearson's. There is no linear correlation between X and Y for values of r around 0. There is a perfect negative linear correlation when r = -1.00 and a perfect positive linear association when r = +1.00. The relationship's intermediate strength is indicated by intermediate values of r (Warner, 2013). The relationship between the causative factors and the frequency of landslide occurrences can be examined by applying the bivariate analysis in this study.

2. Results and Discussion

2.1 Correlation ship between Causative Factors

The inter-item correlation matrix reveals the Pearson correlation coefficients between several normalized factors that may influence landslide occurrences, including Normalized Elevation, Slope, Aspect, NDVI, and Rainfall. A moderate positive correlation (0.405) between Normalized Elevation and NDVI suggests that areas with higher elevation tend to have more vegetation cover. Similarly, the correlation between Normalized Elevation and Rainfall (0.330) indicates that higher elevations are associated with increased rainfall. In contrast, the slope shows weak correlations with other variables, implying limited direct linear relationships. Additionally, a moderate positive correlation (0.322) between Normalized Aspect and NDVI suggests that the direction a slope faces may influence vegetation cover, possibly due to factors like sunlight exposure or local microclimate.

Table 1: Correlation Matrix of Normalized Causative Factors

Inter-Item Correlation Matrix					
	Normalized Elevation	Normalized Slope	Normalized Aspect	Normalized NDVI	Normalized Rainfall
Normalized Elevation	1.000	0.100	0.189	0.405	0.330
Normalized Slope	0.100	1.000	0.219	-0.047	0.019
Normalized Aspect	0.189	0.219	1.000	0.322	0.081
Normalized NDVI	0.405	-0.047	0.322	1.000	0.240
Normalized Rainfall	0.330	0.019	0.081	0.240	1.000

2.2 Multiple Regression Results

The multiple linear regression results indicate that out of the various factors considered (Elevation, Slope, Aspect, NDVI, and Rainfall), only Normalized NDVI has a significant impact on landslide occurrences, with a negative relationship (B = -2.939, p = 0.001). This suggests that areas with higher vegetation cover (NDVI) are less susceptible to landslides. Normalized Aspect has a moderately significant positive impact (B = 1.563, p = 0.034), suggesting that changes in slope direction increase the likelihood of landslides, while Normalized Slope has a negative influence (B = -1.427, p = 0.065) and its effect is only marginally significant, indicating a possible link between steeper slopes and landslide risk. On the other hand, Normalized Elevation (B = -0.471, p = 0.594) and Normalized Rainfall (B = -0.181, p = 0.826) do not show significant impacts on landslide occurrences.

Table 2: Multiple Linear Regression Results for Factors Influencing Landslide Occurrence

Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Normalized Elevation	-0.471	0.877	-0.081	-0.537	0.594
Normalized Slope	-1.427	0.750	-0.261	-1.903	0.065
Normalized Aspect	1.563	0.709	0.317	2.204	0.034
Normalized NDVI	-2.939	0.819	-0.549	-3.587	0.001**
Normalized Rainfall	-0.181	0.814	-0.031	-0.222	0.826
a. Dependent Variable: Landslide Occurrences					

2.3 Bivariate Analysis Results

The NDVI has a significant negative correlation (-0.475) with the frequency of landslide occurrences, which indicates that the areas with vegetation had been less prone to landslide events over the last 23 years whereas the areas with less or no vegetation has faced landslide events. The vegetation loss in the hilly areas of CCC are mainly due to the hill cutting, which contributes to the landslide hazard. This correlation highlights the protective role that vegetation plays in stabilizing soil and reducing landslide risks. As hill cutting intensifies, the loss of vegetation exacerbates soil erosion, making the terrain more vulnerable to landslides, especially during heavy rainfall events.

Table 3: Correlation Matrix of Landslide Occurrences and NDVI

		Landslide Occurrences	Normalized NDVI
Landslide Occurrences	Pearson Correlation	1	-.475**
	Sig. (2-tailed)		0.001
	N	43	43
Normalized NDVI	Pearson Correlation	-.475**	1
	Sig. (2-tailed)	0.001	
	N	43	43
**. Correlation is significant at the 0.01 level (2-tailed).			

2.4 Recommendations

2.4.1 *Implementation of Strict Hill-Cutting Regulations*

Unregulated hill-cutting is a primary cause of vegetation loss and increased landslide susceptibility. Enforcing strict regulations on hill-cutting and construction activities, particularly in high-risk zones, is essential. The government should develop a framework that ensures compliance with land-use policies and mandates environmental impact assessments (EIAs) before any development is approved in hilly areas.

2.4.2 *Afforestation and Reforestation Programs*

Afforestation and reforestation initiatives should be prioritized in areas that have experienced vegetation loss. Replanting native species and increasing green cover can stabilize the soil, reducing erosion and landslide risks. The introduction of social forestry programs could incentivize local communities to participate in reforestation efforts, similar to existing programs facilitated by the Forest Department.

2.4.3 Enforcement of Zoning Laws and Urban Planning

Adopt and enforce strict zoning regulations in urban areas, restricting construction on steep slopes. Urban planners should work with geologists and environmental scientists to create landslide susceptibility maps, identifying the most vulnerable areas. Construction permits should only be granted in areas deemed safe after thorough environmental and geological assessments.

2.4.4 Community Awareness and Involvement

Awareness campaigns should be organized to educate local communities about the importance of vegetation in preventing landslides. Encouraging community participation in environmental conservation projects, such as reforestation and slope maintenance, is key. This participatory approach ensures long-term compliance and sustainable land-use practices.

2.5 Discussion and Future Work

There are a number of shortcomings with this study that require more investigation. The first is the absence of a detailed historical landslide inventory map. Only data pertaining to significant landslide incidents were gathered from multiple secondary sources and verified after fieldwork and only the areas where significant repercussions, such as documented human casualties or damaged or destroyed homes and roads, could be identified. The analysis was unable to include locations of other smaller landslide threats, such as those where the hill was physically damaged or partially collapsed but no casualties or damage were documented. This is a significant drawback in this study. There is no monitoring system to assess the entire study area and identify landslide-hit areas (with or without human settlement), even for recent landslides. Following any landslide incident, the Government of Bangladesh (GoB) ought to promptly assemble a specialized team to carry out the required surveying and create inventory maps. Second, the Bangladesh Meteorological Department (BMD), which is only in charge of gathering historical rainfall data in Bangladesh, does not provide any information on rainfall intensity (mm/h). There is only limited access to daily rainfall data. Two solar-powered automated weather monitoring and rainfall forecast stations were set up in Chattogram City by the GSB in 2015, although the data is not made available to the public. The rainfall thresholds should be updated on a regular basis by evaluating the impacts of regional climate change, cyclone intensities, and resultant rainfall patterns as recommended by the UN Intergovernmental Panel on Climate Change (IPCC). Finally, CCC must pay particular attention to initiatives pertaining to the integration and dissemination of landslide warnings, protective measures like sheltering or evacuation, public and stakeholder response, community vulnerability assessment, integrating indigenous knowledge, and general emergency management (Ahmed et al., 2018).

3. Conclusion

Landslides are not currently considered to be a major threat in Bangladesh since they are overshadowed by storm surges, cyclones, and flooding. In CCC, the rate of urbanization is concerning because of the high population density, rural-urban movement, and lack of available land for shelters. Nowadays, unlawful hill cutting is being done to create residential zones in order to accommodate the growing demand. Landslides will literally cause catastrophic destruction in the coming years, especially in metropolitan agglomerations, given the threat of global warming, the rate of urbanization, the rise in extreme precipitation events, and population pressure.

The study of landslide susceptibility in the Chattogram City Corporation (CCC) area underscores the critical relationship between vegetation loss and increased landslide risk. The findings reveal that unregulated hill-cutting, deforestation, and rapid urbanization are primary drivers of vegetation loss, which, in turn, exacerbates soil instability and makes hillslopes more prone to landslides, particularly during the monsoon season. The strong negative correlation between NDVI (Normalized Difference Vegetation Index) and landslide occurrences highlights the protective role of vegetation in maintaining slope stability and reducing the likelihood of landslides. To mitigate the growing risk of landslides, a combination of planning controls and mitigation measures is essential. Strict enforcement of hill-cutting regulations, afforestation, the development of green buffer zones, and the implementation of slope stabilization techniques can help restore lost vegetation and stabilize vulnerable slopes. Additionally, adopting robust urban planning practices, which include the enforcement of zoning laws and building codes, will ensure safer construction practices in high-risk areas. Public awareness and community involvement play a key role in sustaining these efforts, as local populations can actively contribute to reforestation and slope management. The establishment of an early warning system will also help minimize loss of life and property during landslide events by providing timely alerts.

Overall, the study demonstrates that a multi-pronged approach combining ecological restoration, engineering solutions, and community participation is vital for reducing landslide susceptibility in the CCC area. By addressing both natural and human-induced factors, these strategies can promote a more resilient and sustainable urban environment, capable of withstanding future landslide risks.

APPENDIX-A

Table A1: Major Historical Landslide Events of CCC area from 1990-2018

Serial No.	Date	Location Name	Normalized Elevation	Normalized Slope	Normalized Aspect	Normalized NDVI	Normalized Rainfall
1	August,2013	Motijhorna, Chattogram	0.7883	0.7835	0.0596	0.2983	0.7501
2	2013	Motijhorna, Chattogram	0.7125	0.6680	0.0649	0.8544	1.0000
3	11June ,2007	Tankir Pahar, Motijhorna, Chattogram	0.5617	0.0727	0.6581	0.9832	1.0000
4	22 June,2012	Chanmari Bi Lane, Motijhorna	0.4841	0.0605	0.0900	0.8019	0.6659
5	1998 and 2010	Tankir Pahar, Motijhorna, Chattogram	0.9767	0.1899	0.5136	0.6855	0.8334
6	23 August,2008	Batila hill, Motijorna,Chattogram	0.9518	0.6067	0.0152	0.3065	0.7501
7	2011	Batila hill, Motijorna,Chattogram	0.7969	0.7050	0.9681	0.6968	0.7501
8	1 July,2011	Tiger Pass, Motijorna,Chattogram	0.3894	0.3030	0.6064	0.8255	0.5999
9	11 June ,2007	Lebu Bagan, Chattogram Cantonment	0.6535	0.6895	0.6451	0.9865	0.9962
10	11 June ,2007	Lebu Bagan, Chattogram Cantonment	0.8553	0.5822	0.7910	0.7262	0.9962
11	11 June ,2007	Lebu Bagan, Chattogram Cantonment	0.8553	0.5782	0.7924	0.6517	0.9962
12	11 June ,2007	Kaicchaghona, Chattogram Cantonment	0.6945	0.5764	0.4759	0.9234	0.9962
13	11 June ,2007	Kaicchaghona, Chattogram Cantonment	0.3434	0.3349	0.0643	0.5760	0.9962
14	11 June ,2007	Lebu Bagan, Chattogram Cantonment	0.0448	0.1412	0.0318	0.0343	0.9962

Serial No.	Date	Location Name	Normalized Elevation	Normalized Slope	Normalized Aspect	Normalized NDVI	Normalized Rainfall
15	11 June ,2007	Sekandar Para, Chattogram Cantonment	0.5978	0.9826	0.2207	0.4623	0.9962
16	11 June ,2007	Sekandar Para, Chattogram Cantonment	0.5978	0.9826	0.2207	0.5057	0.9962
17	11 June ,2007	Sekandar Para, Chattogram Cantonment	0.6907	0.9844	0.2500	0.4623	0.9962
18	2013	Ispahani Hill, Kushumbagh	0.8563	0.8634	0.9852	0.2648	1.0000
19	2013	Kushumbagh Housing	0.3183	0.4900	0.0592	0.0243	1.0000
20	2013	Goribullah Shah, Kushumbagh	0.6328	0.5028	0.0599	0.4363	1.0000
21	1990	Gol Pahar, Foy'z lake	0.8570	0.9026	0.7894	0.8567	1.0000
22	1990	Gol Pahar, Foy'z lake	0.9843	0.6146	0.5920	0.6747	1.0000
23	1990	Gol Pahar, Foy'z lake	0.9679	0.5562	0.4916	0.6816	1.0000
24	11 June ,2007	Akbar shah mazar hill	0.4455	0.0455	0.4390	0.0489	1.0000
25	2013, August	Lal Pahar, Foy'z Lake	0.8033	0.1281	0.0349	0.3343	0.7501
26	2013, August	Foy'z Lake Observation Tower Hill	0.5407	0.6634	0.4139	0.6808	0.7501
27	2014, July	Foy'z Lake Zoo Hill	0.5407	0.7752	0.4715	0.7440	0.4286
28	2014, July	Foy'z Lake Zoo Hill	0.6171	0.5793	0.4286	0.9432	0.4286
29	2013	Foy'z Lake Zoo Hill	0.7603	0.6474	0.4479	0.9353	1.0000
30	2013	Foy'z Lake Zoo Hill	0.8540	0.7750	0.4714	0.6899	1.0000
31	2013	Jakir Hossain Road, South Khulshi	0.6043	0.5551	0.0870	0.8300	1.0000
32	2013	Holy Crescent,Khulshi	0.3208	0.8921	0.8512	0.3519	1.0000
33	2013	Holy Crescent,Khulshi	0.1393	0.8369	0.8259	0.5289	0.9991
34	May, 2014	Medical Hill, Goachi bagan, Panchlaish	0.3895	0.5550	0.0126	0.1522	0.2858
35	May, 2014	Medical Hill, Goachi bagan, Panchlaish	0.2559	0.9109	0.2482	0.3070	0.2858
36	July, 2013	The king of Chattogram hill, Panchlaish	0.4044	0.6365	0.1537	0.3433	0.7501
37	July, 2011	Medical Hill, Goachi Bagan	0.2032	0.5544	0.0542	0.3784	0.5999
38	July, 2011	Medical Hill, Goachi Bagan	0.2393	0.5544	0.0542	0.2183	0.5999
39	2013	AK Khan Hill	0.8801	0.0845	0.3204	0.8530	1.0000
40	14 October, 2018	Feroze Shah Colony	0.2589	0.5883	0.7861	0.2778	0.3684
41	19 July, 2015	Amin colony	0.7519	0.2741	0.0609	0.6226	1.0000
42	19 July, 2015	Lalkhan Bazar	0.2378	0.2393	0.5190	0.8912	1.0000
43	3 February, 2014	Bayezid, Shantinogor	0.4294	0.3507	0.6048	0.3621	0.0000

References

Ahmed, B. (2015). 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. (2017). *Community vulnerability to landslides in Bangladesh*. UCL (University College London). Ahmed, B. (2021). The root causes of landslide vulnerability in Bangladesh. *Landslides*, *18*(5), 1707–1720.
https://doi.org/10.1007/s10346-020-01606-0

Ahmed, B., & Dewan, A. (2017). Application of Bivariate and Multivariate Statistical Techniques in Landslide Susceptibility Modeling in Chittagong City Corporation, Bangladesh. *Remote Sensing*, *9*(4), 304. https://doi.org/10.3390/rs9040304

Ahmed, B., Rahman, Md. S., Islam, R., Sammonds, P., Zhou, C., Uddin, K., & Al-Hussaini, T. M. (2018). Developing a Dynamic Web-GIS Based Landslide Early Warning System for the Chittagong Metropolitan Area, Bangladesh. *ISPRS International Journal of Geo-Information*, *7*(12), 485. https://doi.org/10.3390/ijgi7120485

Aleotti, P., & Chowdhury, R. (1999). Landslide hazard assessment: Summary review and new perspectives. *Bulletin of Engineering Geology and the Environment*, *58*(1), 21–44. https://doi.org/10.1007/s100640050066

Bopche, L., & Rege, P. P. (2021). Feature-based model for landslide susceptibility mapping using a multi-parametric decision-making technique and the analytic hierarchy process. *Sādhanā*, *46*(3), 122. https://doi.org/10.1007/s12046-021-01648-7

Budha, P. B., Paudyal, K., & Ghimire, M. (2016). Landslide susceptibility mapping in eastern hills of Rara Lake, western Nepal. *Journal of Nepal Geological Society*, *50*(1), 125–131. https://doi.org/10.3126/jngs.v50i1.22872

Corominas, J., Van Westen, C., Frattini, P., Cascini, L., Malet, J.-P., Fotopoulou, S., Catani, F., Van Den Eeckhaut, M., Mavrouli, O., Agliardi, F., Pitilakis, K., Winter, M. G., Pastor, M., Ferlisi, S., Tofani, V., Hervás, J., & Smith, J. T. (2013). Recommendations for the quantitative analysis of landslide risk. *Bulletin of Engineering Geology and the Environment*. https://doi.org/10.1007/s10064-013-0538-8

Eastman, J. (2012). IDRISI selva: Guide to GIS and image processing. *Clark Labratories, Clark University, Worcester, Massachusetts, USA*.

ESCAP, U. (2015). *Disasters in Asia and the Pacific: 2015 year in review*.

Farooq, S., & Akram, M. S. (2021). Landslide susceptibility mapping using information value method in Jhelum Valley of the Himalayas. *Arabian Journal of Geosciences*, *14*(10), 824. https://doi.org/10.1007/s12517- 021-07147-7

Güler, D., & Yomralıoğlu, T. (2017). Alternative suitable landfill site selection using analytic hierarchy process and geographic information systems: A case study in Istanbul. *Environmental Earth Sciences*, *76*(20), 678. https://doi.org/10.1007/s12665-017-7039-1

Jetten, V., Alkema, D., van Westen, C., & Brussel, M. (2014). *Development of the Caribbean handbook on disaster risk information management*. International Conference on Analysis and Management of Changing Risks for Natural Hazards 2014.

Kayastha, P. (2015). Landslide susceptibility mapping and factor effect analysis using frequency ratio in a catchment scale: A case study from Garuwa sub-basin, East Nepal. *Arabian Journal of Geosciences*, *8*(10), 8601–8613. https://doi.org/10.1007/s12517-015-1831-6

Kelarestaghi, A., & Ahmadi, H. (2009). Landslide susceptibility analysis with a bivariate approach and GIS in Northern Iran. *Arabian Journal of Geosciences*, *2*(1), 95–101. https://doi.org/10.1007/s12517-008-0022- 0

Maqsoom, A., Aslam, B., Khalil, U., Kazmi, Z. A., Azam, S., Mehmood, T., & Nawaz, A. (2022). Landslide susceptibility mapping along the China Pakistan Economic Corridor (CPEC) route using multi-criteria decision-making method. *Modeling Earth Systems and Environment*, *8*(2), 1519–1533. https://doi.org/10.1007/s40808-021-01226-0

Mohammady, M., Pourghasemi, H. R., & Pradhan, B. (2012). Landslide susceptibility mapping at Golestan Province, Iran: A comparison between frequency ratio, Dempster–Shafer, and weights-of-evidence models. *Journal of Asian Earth Sciences*, *61*, 221–236. https://doi.org/10.1016/j.jseaes.2012.10.005

Rahardjo, H., Ong, T. H., Rezaur, R. B., & Leong, E. C. (2007). Factors Controlling Instability of Homogeneous Soil Slopes under Rainfall. *Journal of Geotechnical and Geoenvironmental Engineering*, *133*(12), 1532– 1543. https://doi.org/10.1061/(ASCE)1090-0241(2007)133:12(1532)

Rahman, M. S., Ahmed, B., & Di, L. (2017). Landslide initiation and runout susceptibility modeling in the context of hill cutting and rapid urbanization: A combined approach of weights of evidence and spatial multi- criteria. *Journal of Mountain Science*, *14*(10), 1919–1937.

Sarkar, S., & Kanungo, D. P. (2004). An Integrated Approach for Landslide Susceptibility Mapping Using Remote Sensing and GIS. *Photogrammetric Engineering & Remote Sensing*, *70*(5), 617–625. https://doi.org/10.14358/PERS.70.5.617

Shahabi, H., Ahmad, B. B., & Khezri, S. (2013). Evaluation and comparison of bivariate and multivariate statistical methods for landslide susceptibility mapping (case study: Zab basin). *Arabian Journal of Geosciences*, *6*(10), 3885–3907. https://doi.org/10.1007/s12517-012-0650-2

Shit, P. K., Bhunia, G. S., & Maiti, R. (2016). Potential landslide susceptibility mapping using weighted overlay model (WOM). *Modeling Earth Systems and Environment*, *2*(1), 21. https://doi.org/10.1007/s40808-016- 0078-x

Warner, R. M. (2013). *Applied statistics: From bivariate through multivariate techniques: From bivariate through multivariate techniques*. Sage.

Yüksel, A., & Avci, V. (2017). Landslide susceptibility analysis of Yamaç Basin in Bingol through the index method. *Kastamonu Üniversitesi Orman Fakültesi Dergisi*. https://doi.org/10.17475/kastorman.309474

Yao, J., Yang, Q., Mao, W., Zhao, Y., & Xu, X. (2016). Precipitation trend–Elevation relationship in arid regions of the China. Global and Planetary Change, 143, 1–9. https://doi.org/10.1016/j.gloplacha.2016.05.007