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LANDSLIDE MODELLING AND RISK ASSESSMENT: EVIDENCE FROM CHATTOGRAM CITY OF BANGLADESH

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ABSTRACT

Landslide causes human casualties, property damage, and economic losses in hilly area of Chattogram City. The aim of the research was to produce the landslide susceptibility and risk maps for the city. By considering nine causal factors of landslide six susceptibility maps were prepared by analytic hierarchy process, weighted linear combination and logistic regression method. Vulnerability index was calculated by 11 indicators under 4 vulnerability components. Road and structure density were used for exposure assessment. Finally, risk map was prepared by multiplying most accurate susceptibility map with exposure index and vulnerability index. Inventory analysis stated that multiple casual factors were responsible for devastating landslide. According to model performance assessment, logistic regression models were more accurate and highly susceptible zones were found within 28-31%. The ward wise overall vulnerability index values were within 0.42 to 0.59. Ward wise minimum and maximum exposure was 949 and 1757 respectively. Finally, about 18% area was found under high-risk zone in spatial risk zoning map. The findings of the research might be used for planning and decision making on landslide risk reduction.

Keywords: *Hill Tracts; Susceptibility Map; Analytical Hierarchy Process; Weighted Linear Combination; Logistic Regression; GIS*

1. INTRODUCTION

Landslide became one of the most occurring geological hazards in the hilly regions especially during the monsoon. Landslide can be defined as the down slope movement of rock, earth and organic material under the force of gravity (Marrapu and Jakka, 2014; Highland and Bobrowsky, 2008; Cruden, 1991). When the force of gravity exceeds the strength of material then the landslide occurs (Washington Geological Survey, 2017). Various external factors (i.e., rainfall, seismic activity etc.) can reduce the strength of soil and can create landslide (Zhendong and Jiachun, 2013; Romo *et al.*, 2000). Every year landslide causes loss of life, injuries, damage of various physical properties and affects the natural resources (Marrapu and Jakka, 2014). As cited in EM-DAT (2014), worldwide 7612 people lost their life between 2000 and 2014 and annually USD 4 billion property worth were damaged by the landslide.

Bangladesh is the biggest delta in the world, which has 82% of flat land with 18% of hilly area (Ahmed *et al.*, 2014). Geographically the country is more vulnerable to various disasters like flood, cyclone, drought, earthquake and landslide (Denissen, 2017; Sarwar, 2008). According to the statistics of EM-DAT (2007), 306 natural disasters occurred in the country in between 1950 to 2014. Those affected at least 40 million people and stranded at least 14 million people. More than 300 people have been dead in the country by landslide since 2000 (Sarwar, 2008).

Chattogram Metropolitan Area (CMA) is a highly urbanized area with 10% of hilly land. The area was developed in tertiary age and that made the city more vulnerable to landslide hazard (Ayala *et al.*, 2006; CDA, 2017). Chattogram Development Authority (CDA) has identified 30 risky hills (i.e., Gol Pahar, Matijhorna, Lalkhan Bazar, Tankir Pahar, Batali Hill, and AK Khan Pahar etc.) (Ahmed *et al.*, 2014), where people were living on the slope of hills with high risk of landslide event. Since 1997, nearly 235 people were died by landslide who lived in various informal settlements within the Chattogram City Corporation (CCC) area and adjacent urban centers (Chattogram Divisional Office, 2008). On 11 June 2007, a landslide disaster occurred in CCC, which resulted more than 128 people death and 150 people injure (SDMC, 2007). Again, on 21 July 2017, landslide killed six people in Sitakunda (The Independent, 2017).

A landslide susceptibility map might be an important landslide disaster risk reduction tool. Landslide susceptibility means the likelihood of occurrence of a landslide event in a certain region (Brabb, 1984). It provides the probability of landslide for a given set of geo-environmental condition (Guzzetti, 2005). Moreover, for proper disaster management and land use planning of a particular area, susceptibility map is exigent. Therefore, preparation of accurate susceptibility map is inevitable to develop disasters risk reduction strategies. There exist several methods for landslide susceptibility zoning (i.e., Analytical Hierarchy Process, Conditional

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Analysis Method, Geomorphological Mapping and Investigation, Rough Set Theory, Geotechnical or Physically Based Models, Frequency Ratio Approach, Logistic Regression Model, Multinomial Regression Model, Weighted Linear Regression Model, Artificial Neural Network and many more). But GIS based susceptibility modelling by using GPS and Remote Sensing (RS) provide most accurate result among other methods (Chaplow, 1983; Waltham and Dixon, 2000; Brunsden, 2002; Clayton *et al.*, 2002; Duman *et al.*, 2005; Federici *et al.*, 2007; Gorservski and Jankowski, 2008; Zieher *et al.*, 2017; Solaimani *et al.*, 2012; Komac, 2006; Ahmed, 2015; Ahmed *et al.*, 2014). The method typically uses causal factors such as precipitation, slope, soil types, seismic activities, elevation, aspect, distance to stream, distance to road etc. for preparing susceptibility map. The objective of this study was to examine the existing condition of various environmental components associated with landslide and to investigate landslide susceptibility by different techniques and prepare a landslide risk zoning map of the study area. The result of the research might be very useful for decision making process by the development authority so that they can minimize the damage caused by landslides.

2. DATA AND METHODOLOGY

Chattogram is highly populated and the second largest city of Bangladesh with a population density of 16618 per sq. km (BBS, 2011). Topologically Chattogram is a hilly city with diversified natural resources surrounded by Karnaphuly River on east and by Bay of Bengal on west. By considering the frequency rate of previous landslide events, the research was conducted on ward 8, 9, 13, 14 and 15 of CCC (Figure 1). The extent of study area is 2° 23' 29'' N to 22° 20'24'' N and 91° 46'37" E to 91° 50'48''E that covers an area of 4101.49 acres.

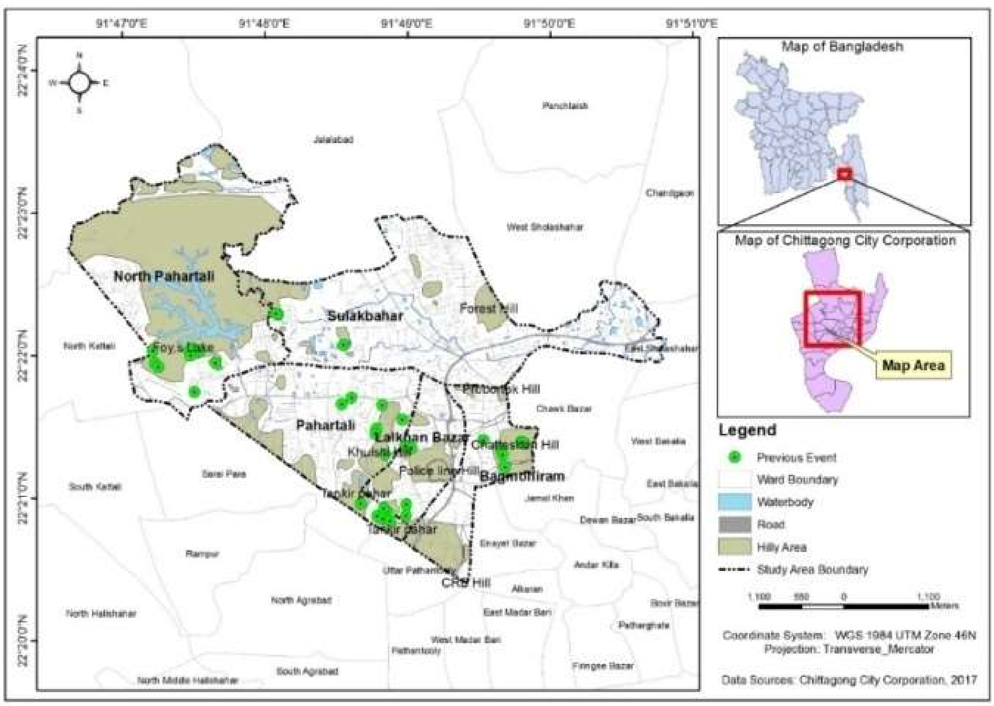

Figure 1: Study Area Map

The study was mostly based on secondary data and results were validated through ground truthing. To prepare the landslide susceptibility map, the research team also carried out an extensive field survey within the study area from 26 March 2018 to 30 March 2018. The research identified thirty-eight previous landslide zones (Figure 1) and analyzed. Android software (GPS logger) was used to identify the locations of the landslides during field survey. The research collected the location of the event, information on landslide width and length, vegetation types, number of affected houses and landslide occurrence history for each identified landslide event. Digital Elevation Model (DEM) and slope of study area was extracted from ASTER data through ArcGIS. For preparation of rainfall pattern analysis, the research collected past 50 years (1963-2013) rainfall data from Bangladesh Meteorological Department (BMD). For rainfall pattern analysis six precipitation indices calculated through Rclimdex. The land cover map of study area was prepared from Landsat 7 ETM+ (8 spectral bands with 30 meters spatial resolution) imagery by using maximum likelihood supervised classification technique through image processing software ERDAS Imagine 14. The land cover was classified in four types as buildup area, vegetation, bare soil, and water body. After the classification, kappa coefficient (equation 1) was calculated for accuracy assessment of the classified image. According to Landis, if the kappa coefficient is greater than 0.6 then it agrees which means for further research purpose can use the classified image (Landis & Koch, 1977).

$$Kappa\ Coefficient\ (k) = (Observed\ Accuracy\text{-}Change\ Agreement)/\ (1\text{-}Change\ Agreement) \quad (1)$$

$$NDVI= (NIR\text{-}RED)/\ (NIR+RED) \quad (2)$$

For the research, kappa coefficient was found 0.73 which is greater than 0.6. This result concluded that the classified image can be useful for further analysis. NDVI was calculated at 5-year interval (2002, 2007, 2012, and 2017) by using Equation 2 in GIS environment to understand the changes rate of forest cover. For the research, soil data at 5 meters depth, road network, drain and stream network from CCC were collected as shape file format. Euclidean distance tool was used for producing distance to road, distance to drain, distance to stream map. After the preparation of these 9-causal factor maps, six Susceptibility maps were prepared by using three different techniques (i.e., one by Analytic Hierarchy Process (AHP), three by Weighted Linear Combination (WLC_1, WLC_2, WLC_3) method and two by Logistic Regression (LR_1, LR_2) method). Then the research classified each susceptibility map into four categories: Very Low Susceptibility (0-0.01), Low Susceptibility (0.01-0.25), Moderate Susceptibility (0.25-0.5), and High Susceptibility (0.5-1) (Australian Geomechnic Society, 2017).

To prepare susceptibility map by Analytic Hierarchy Process (AHP), a pair wise comparison matrix for all sub criteria and main criteria was constructed. A total of 15 people (i.e., 9 local people and 6 experts) gave the weight of a criterion or sub criterion against others. According to Saaty's pair wise comparison scale, the factors weight follows a range between 1 to 9 where 1 represent equal important, greater than 1 represent more importance and less than 1 represent less importance (Ahmed *et al.*, 2014). Consistency Ratio (CR) was calculated by using Equation 3 to check the consistency of the weights.

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

Where, RI = average consistency index, CI = the consistency index. When CR value is less than 0.1 then the weights are consistent (Ahmed *et al.*, 2014). Equation 4 was used for calculating the CI.

$$CI= (\gamma\_max\text{-}n)/\ (n\text{-}1) \quad (4)$$

Here, γ_{max} = the largest eigenvector of the matrix, n = the order of the matrix (Reis *et al.*, 2012)
In this research, all Consistency Ratio (CR) were found less than 0.1. So, the given weights were consistent which indicates that further research can use the weights. Finally, Equation 5 was used for preparing susceptibility map.

$$LSI = \sum x_i y_i \quad (5)$$

Here, x = the Eigen value of each main factor, y = the Eigen value of sub factor of x.

In Weighted Linear Combination (WLC) method, three different combinations of weights of main criterion were used for preparing susceptibility maps. In this method, the weight of sub criteria was used same as AHP. For preparing susceptibility map by Logistic Regression (LR) method, the research conducted a correlation analysis between landslide and its causal factors. Then two susceptibility maps were prepared by using logistic regression method, one by considering only statistically correlated variables and another by considering all variables. Here, Landslide was used as dependent variable or binary variable and causal factors were used as independent variables.

Finally, model performance assessment for six susceptibility maps were done through ROC curve by using 25% stratified sample. The higher area under the ROC Curve (AUC) indicates the more accurate model (Mas *et al.*, 2013). After determining the most accurate susceptibility map, ward wise vulnerability index was calculated through indicator base approach by considering 11 indicators under 4 vulnerability components (Social, Economic, Environmental, and Physical). Road and Structure density were used for exposure (i.e., element at risk) assessment. It was assumed that, the road and structure density was proportional to exposure of landslide. Equal weight was given to road and structure density for calculating exposure index. Each indicator of vulnerability and exposure assessment was normalized to a range between 0 to 1 by considering their functional relationship with exposure and vulnerability according to Human Development Index (HDI) developed by UNDP in 2006, (Behanzin *et al.*, 2015). Normalized value 1 indicated the highest exposure or vulnerability where 0 indicated the lowest exposure or vulnerability. For positive or proportional relationship of indicators with vulnerability or exposure equation 6 was used and for negative or decreasing functional relationship equation 7 was used.

$$Eij= (Xij\text{-}MinXi)/\ (MaxXi\text{-}MinXi) \quad (6)$$

$$Eij= (MaxXi\text{-}Xij)/\ (MaxXi\text{-}MinXi) \quad (7)$$

Where, Eij = the normalized score regarding component (i) for ward (j), Xi = the observed value of the same component for the same ward; MaxXi and MinXi stand for the maximum and minimum value of the observed range of values of the same component. Then the normalization of data, the average index (AI) for exposure and vulnerability was calculated by giving equal weighted to all indicators. The equation 8 is used for calculating the values of AI.

$$\overline{AI} = \frac{1}{N}\sum_{i=1}^{n} Xi \qquad (8)$$

Here, AI = the average index, N = the sum of the index and Xi = the value of the index.

Finally, AI of exposure and vulnerability were graphically represented in two separate maps with their spatial extent. And then, landslide risk was calculated in GIS environment by multiplying the most accurate susceptibility map with exposure and vulnerability map. The research classified the risk into three categories which are low risk zone (0-0.1), moderate risk zone (0.1-0.5) and high-risk zone (0.5-1).

3. RESULTS AND DISCUSSION

3.1 Inventory Analysis

Spatial location of total 38 previous landslide events showed that around 34% landslide occurred in Pahartali (Ward 13) whereas only 8% in Suklabahar (Ward 8). Rather 58% occurred in other three ward (21% in Bagmoniram, 11% in Lalkhan Bazar, and 26% in North Pahartali). After the spatial joining of previous landslide location and nine causal factors of landslide, it was found that most of the landslide occurred at 20-40 m elevation and 3˚-10˚ slope, in vegetation cover and within 200 m distance from road and drain. Moreover, silty sand was more vulnerable to landslide as it covered only 18% of area but 34% landslide occurred in this zone. Table 1 showed the inventory information of previous landslides.

Table 1: Inventory Information of Previous Landslides

Slope (Degree)	%	**Distance to Drain (m)**	%	**Distance to Road (m)**	%
0-2	10.53	0-200	81.58	0-200	100
3-6	34.21	201-450	18.42	201-400	0
7-10	26.32	451-650	0.00	401-550	0
11-20	28.95	651-875	0.00	551-770	0
Grand Total	100.00	Grand Total	100	Grand Total	100
Distance to Stream (m)	%	**Precipitation(mm)**	%	**Land Cover**	%
0-200	28.95	2700-2736	0.00	Buildup Area	28.95
201-450	39.47	2723-2808	73.68	Vegetation	55.26
451-700	31.58	2736-2772	23.68	Bare Soil	15.79
701-1250	0	2809-2850	2.63	Water Body	0.00
Grand Total	100	Grand Total	100	Grand Total	100
DEM (m)	%	**Permeability (cm/hr)**	%	**NDVI Value**	%
10-20	7.89	0.18	28.95	0-0.14	7.89
21- 30	28.95	0.22	10.53	0.15-0.39	36.84
31-40	18.42	0.25	13.16	0.4-1	55.26
41-50	28.95	0.37	34.21	–	–
51-60	15.79	0.39	13.16	–	–
Grand Total	100	Grand Total	100	Grand Total	100

3.2 Rainfall Pattern Analysis

Previous 50 years daily rainfall data was used for rainfall pattern analysis. The output of rainfall pattern analysis showed that the average precipitation rate of Chattogram was increasing with 5.287% estimated slope (Figure 2c). But maximum number of consecutive days with daily precipitation ≥1 mm was decreasing with a decreasing slope rate of 0.053 (figure 2 (b)). On the other hand, maximum number of consecutive days with daily precipitation <1 mm was increasing with an increasing slope rate of 0.657 (Figure 2a). These increasing average precipitation rate and consecutive dry days and decreasing consecutive wet days indicate that the precipitation frequency was decreasing day to day, but precipitation intensity was increasing. As a result, the rate of number of days having ≥10 mm, ≥20 mm and ≥25 mm rainfall was found with an increasing slope rate of 0.079, 0.071 and 0.053 (Figures 2 d, e and f) respectively. Pearson correlation coefficient (PCC) between intensity of rainfall and occurrence of landslide was 0.150. So, from the indices, it can be concluded that the intensity of rainfall was increasing continuously which might resulting landslide as the highly intensive precipitation make the soil more vulnerable to landslide by decreasing the soil strength.

3.3 Susceptibility Maps

Figure 3(a) showed the susceptibility map prepared by AHP method. Green to red color gradient represented the different value of landslide susceptibility (i.e., red color for high susceptible to landslide event and green color for low susceptible to landslide event). According to the map, most of the previous events were located on the highly susceptible zones. Similarly, Figure 3(b), Figure 3(c) and Figure 3(d) showed three different susceptibility maps (i.e., WLC_1, WLC_2, WLC_3 respectively) using three different combinations of factor weights in WLC method. Among the three maps, areas under highly susceptible to landslide were more in WLC_2 map. In the three maps, most of the previous events were also located on the highly susceptible zones. Figure 3(e) and Figure 3(f) represented the two susceptibility maps using Logit Model or Logistic Regression (i.e., one by only statistically correlated variables and another by all variables respectively). The correlation among landslide event and causal factors was given in Table 2. According to the result, 3 causal factors (i.e., slope, NDVI and land cover) have no significant correlation with landslide event. According to expert opinion, many interrelated factors worked behind the landslide and these 3 factors might have partial relation with landslide events.

Table 2: Correlation Analysis between Landslides and Its Causal Factors

	Land Cover	Permeability	Slope	Rainfall	Elevation	Stream	Road	Drain	NDVI
Pearson Correlation	-0.008	0.119^{**}	0.006	0.150^{**}	0.033^{**}	0.014^{**}	-0.040^{**}	-0.048^{**}	-0.013
Sig. (2-tailed)	0.479	0	0.603	0	0.003	0.004	0	0	0.233

Table 3 showed the odds ratio of two logit models. The results of both logistic regressions stated that the permeability has higher influence on landslide hazard. Equation 9 and Equation 10 were derived from Table 3 with 10% significant level. The Nagelkerke R Square value for these models were found 0.776 and 0.77 respectively stated that the models were good and the significant. Both susceptibility maps using LR models illustrated less highly susceptible zones than previous two models. But the previous landslide events were also found on the highly susceptible zones.

*Logit (landslide) = - 1033.760 +2.110*Pemeability+0.073*Rainfall+0.064*Elevation-0.027*Distance to Road+.010*Distance to Drain-0.014*Distance to Stream* (9)

*Logit (landslide) = - 1037.977 -0.073*Land Use + 2.082*Permeability -0.038*Slope + 0.009*Rainfall + 0.071*Elevation + 1.911*NDVI - 0.028* Distance to Road - 0.010*Distance to Drain - 0.014 * Distance to Stream* (10)

Table 3: Odds Ratios of Logistic Regression Analysis

Variables in the Equation	Odds Ratios of Logistic Regression Analysis (By only statistically significant variables)				Odds Ratios of Logistic Regression Analysis (By all variables)			
	B	S.E.	Sig.	Exp (B)	B	S.E.	Sig.	Exp (B)
Permeability	2.11	5.586	0.706	8.246	2.082	5.686	0.714	8.024
Rainfall	0.073	0.041	0	1.452	0.009	0.061	0	1.454
Elevation	0.064	0.032	0.048	1.066	0.071	0.034	0.035	1.075
Stream	-0.014	0.003	0	0.986	-0.014	0.003	0	0.986
Road	-0.027	0.008	0.001	0.974	-0.028	0.008	0.001	0.973
Drain	0.01	0.004	0.02	1.01	0.010	0.005	0.027	1.01
Land Use					-0.073	0.473	0.731	0.85
NDVI					1.911	3.417	0.576	6.763
Slope					-0.038	0.075	0.612	0.963
Constant	-1033.76	166.906	0	0	-1037.977	168.152	0	0

3.4 Comparison between Susceptibility Maps

Comparison between three methods showed that the high susceptible zones were grater in WLC method than other two methods. Table 4 showed the percentage of area cover by different level of susceptibility according to each susceptibility map. According to AHP, it was found that 67.73% areas were highly susceptible to landslide event and only 0.06% areas were very low susceptible to landslide. As per WLC, WLC_1 has 81.64% high susceptible areas where WLC_2 and WLC_3 have 88.29 % and 84.27% of high susceptible areas for landslides event respectively. 30.89% and 28.73% areas were under high susceptible zones for LR_1 and LR_2 models respectively.

Table 4: Different Level Susceptibility of Different Methods

Susceptibility Level	AHP (%)	WLC_1 (%)	WLC_2 (%)	WLC_3 (%)	LR_1 (%)	LR_2 (%)
Very Low Susceptibility	0.06	0.0002	0.0038	0.0002	0.0038	0.0112
Low Susceptibility	7.06	0.51	1.17	0.92	19.93	11.51
Moderate Susceptibility	25.16	17.84	10.54	14.81	49.18	59.76
High Susceptibility	67.73	81.64	88.29	84.27	30.89	28.73
Grand Total	100	100	100	100	100	100

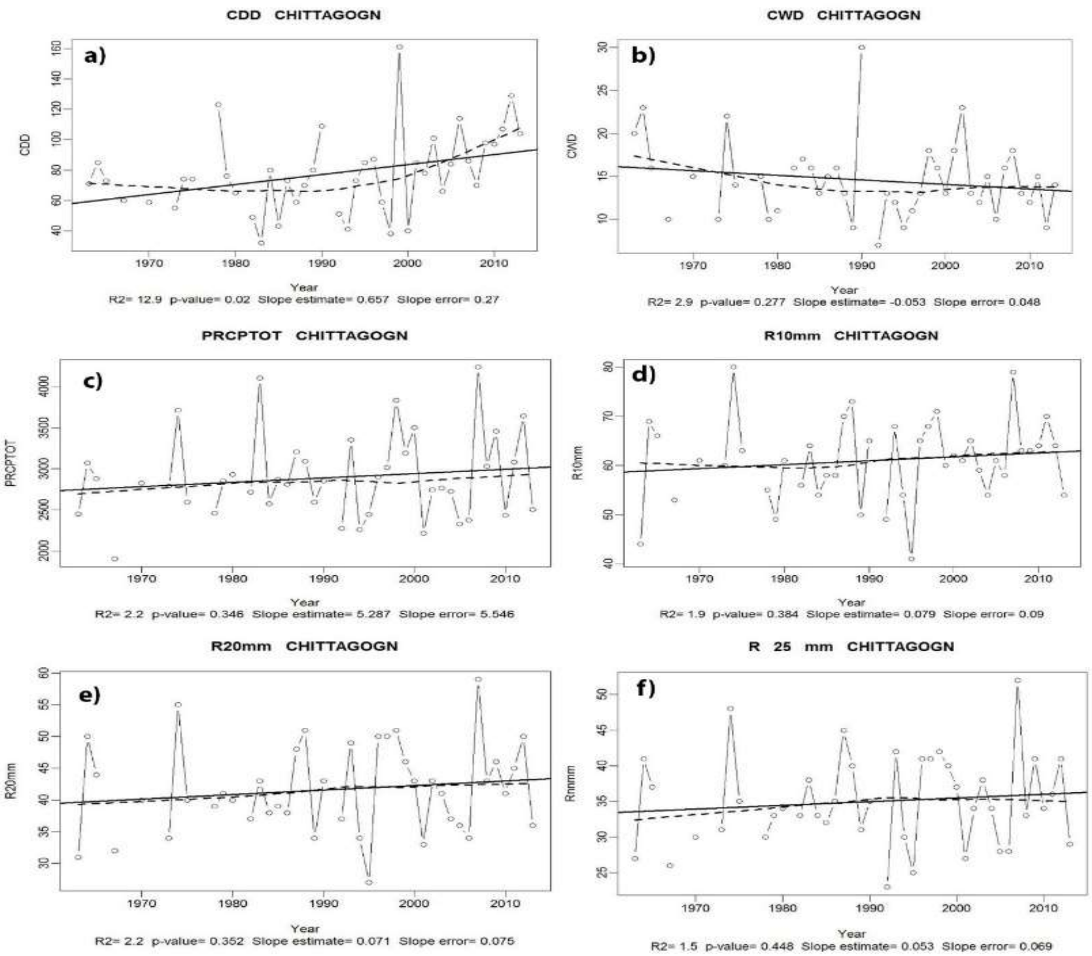

Figure 2: Precipitation Indicators a) Consecutive Dry Days; b) Consecutive Wet Days; c) Annual Total Wet-day Precipitation; d) Moderate Rainy Days; e) High Rainy Days; f) Very High Rainy Days

3.5 Performance Assessment for Susceptibility Model

Both two logistic regressions gave more accurate results as they have higher AUC value. The AUC of LR_1 and LR_2 were found 0.804 and 0.847 respectively. The AUC of AHP was 0.638 which indicated that the accuracy of susceptibility map produced by Analytical Hierarchy Procedure (AHP) was lower than other methods. Moreover, out of total 3 combination of Weighted Linear Combination Method, Combination 3 (WLC_3) provided more accurate result than Combination 2 (WLC_2) and combination 1 (WLC_1). The comparison of performance assessment between various models was in Figure 4 as a line graph.

3.6 Vulnerability Assessment

Four vulnerability components (i.e., Social, Economic, Environmental, and Physical) and their functional relationship were analyzed to assess the vulnerability of the study areas. According to social vulnerability indicators, population density was maximum in Lalkhan Bazar ward and female population and household number was maximum in Sulakbahar ward. Bagmoniram was found highly vulnerable to economic condition (i.e., lower average household income and higher unemployment rate). Around 60% land of North Pahartali ward was covered by hills so job opportunity and average household income was also minimum in the ward. According to environmental vulnerability, Suklabahar ward was relatively flat land with maximum percentage of buildup area and minimum percentage of vegetation cover. According to physical vulnerable component, North Pahartali ward was more vulnerable due to maximum katcha roads and buildings.

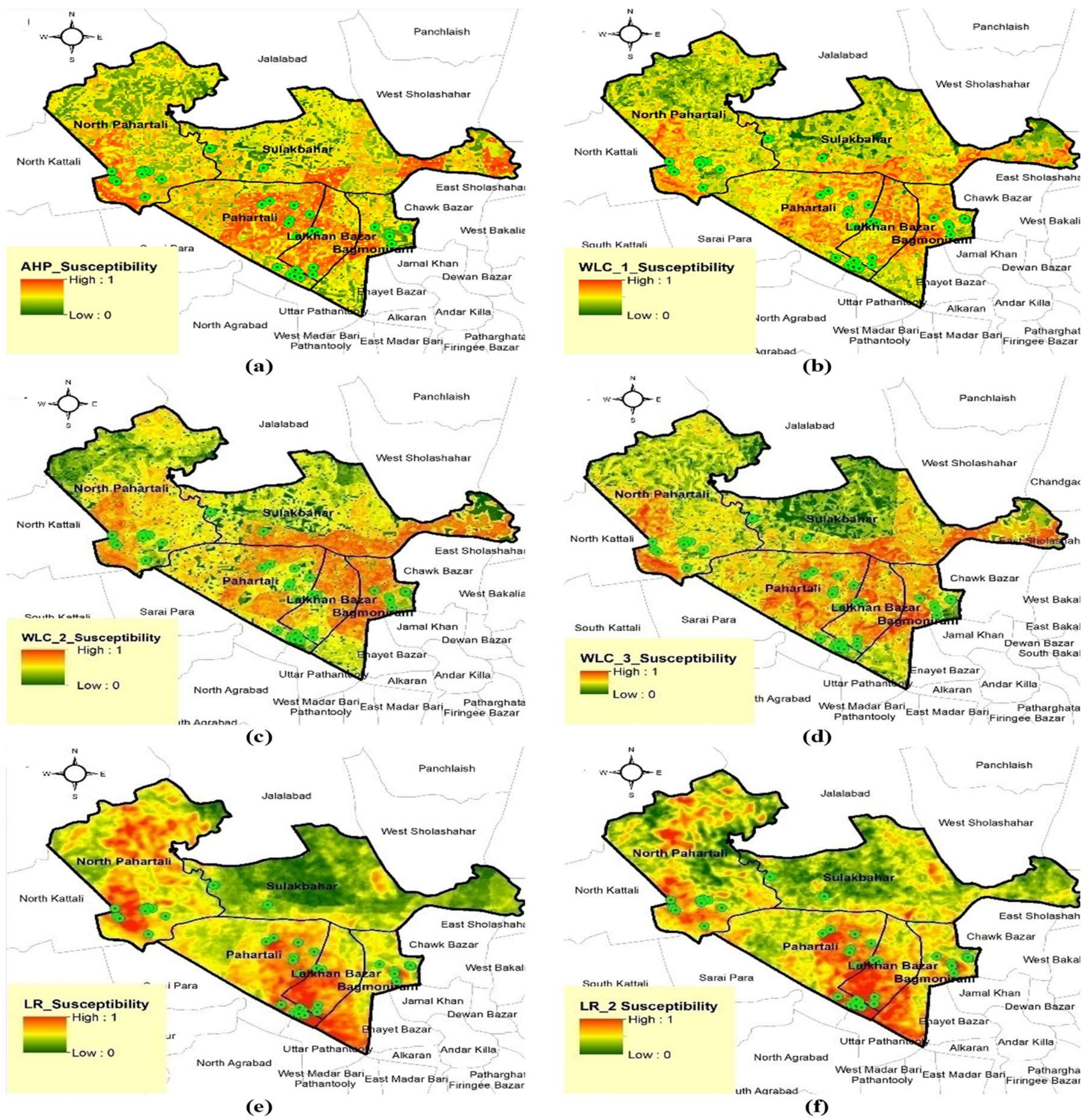

Figure 3: a) Susceptibility Map by AHP b) Susceptibility Map by WLC_1 c) Susceptibility Map by WLC_2 d) Susceptibility Map by WLC_3 e) Susceptibility Map by LR_1 f) Susceptibility Map by LR_2

The result of overall indictor base vulnerability index showed that North Pahartali (0.59) was the most vulnerable ward to landslide hazard where Lalkhan Bazar ward (0.42) was under lowest vulnerable zone. Bagmoniram and Lalkhan Bazar ward have almost same value of vulnerability index. The difference of vulnerability index between these two wards was only 0.01 (0.43-0.42). Pahartali and Sulakbahar ward have same value of vulnerability index (0.52). Figure 5 (b) illustrated the ward wise vulnerability index.

3.7 Exposure Index

Exposure (i.e., element at risk) assessment was based on two indicators (i.e., road density and structure density). It was observed that ward wise population was increasing with the increase of structure density. The result of exposure index indicated that North Pahartali has a lower exposure (949) as this ward has a few road and structure where Lalkhan Bazar has maximum exposure of 1757. Bagmoniram, Pahartali has almost same average exposure. Bagmoniram and Pahartali have average exposure of 1631 and 1689, respectively. The remaining Sulakbahar has an exposure of 1560. Figure 5(a*)* showed the normalized value of exposure index.

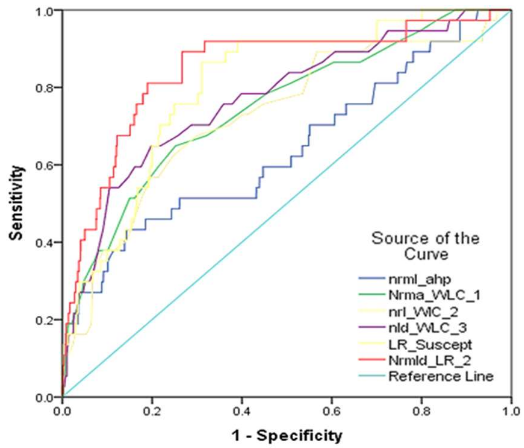

Figure 4: ROC Curve of Susceptibility Models

Table 5: Overall Vulnerable Index

Name of the Ward		Bagmoniram	Lalkhan Bazar	Pahartali	North Pahartali	Sulakbahar
Social Component	Population density	0.38	1	0.24	0	0.23
	Female population	0	0.27	0.36	0.35	1
	Adult literacy rate	0	0.7	1	0.71	0.24
	Household	0	0.34	0.32	0.41	1
	Head count ratio	0.68	0.74	0.89	1	0
Social vulnerability		0.21	0.61	0.56	0.49	0.49
Economical Component	Average income	1	0.5	0.75	1	0
	Unemployment rate	1	0	0.12	0.7	0.15
Economical vulnerability		1	0.25	0.44	0.85	0.08
Environmental Component	Vegetation (%)	0.45	0.68	0.61	0	1
	Build Up Area (%)	0.56	0.67	0.69	0	1
Environmental vulnerability		0.5	0.68	0.65	0	1
Physical Component	Katcha building (%)	0	0.12	0.52	1	0.39
	Katcha road (%)	0	0.2	0.32	1	0.6
Physical Vulnerability		0	0.16	0.42	1	0.5
Vulnerability Index		0.43	0.42	0.52	0.59	0.52

3.8 Risk Assessment

This research investigated risk through GIS mapping. The inputs of risk mapping were susceptibility map, vulnerability map and exposure map (i.e., element at risk). Risk wise zone was the output of the risk assessment procedure showed in Figure 5(d). North Pahartali ward has the lowest exposure (i.e., element at risk) among the five which might lead it to low risky ward. It can be said that exposure or element at risk showed an influence on risk zoning in this research. About 18% of area was found under high-risk zone at 10% threshold. Around 51% area was under moderate risk zone whereas around 30% area was found under low risk zone. Table 6 showed the percentage of land by different level of risk. Using the spatial risk zoning site specific risk elements might be found easily and decision can be made efficiently.

Table 6: Percentage of Land Covered by Different Risk Level

Risk Types	Risk Value	Area (Acres)	Percentage
Low Risk Zone	0-0.1	1225.20	29.87
Moderate Risk Zone	0.1-0.5	2133.05	52.01
High Risk Zone	0.5-1	743.24	18.12
Total		4101.49	100

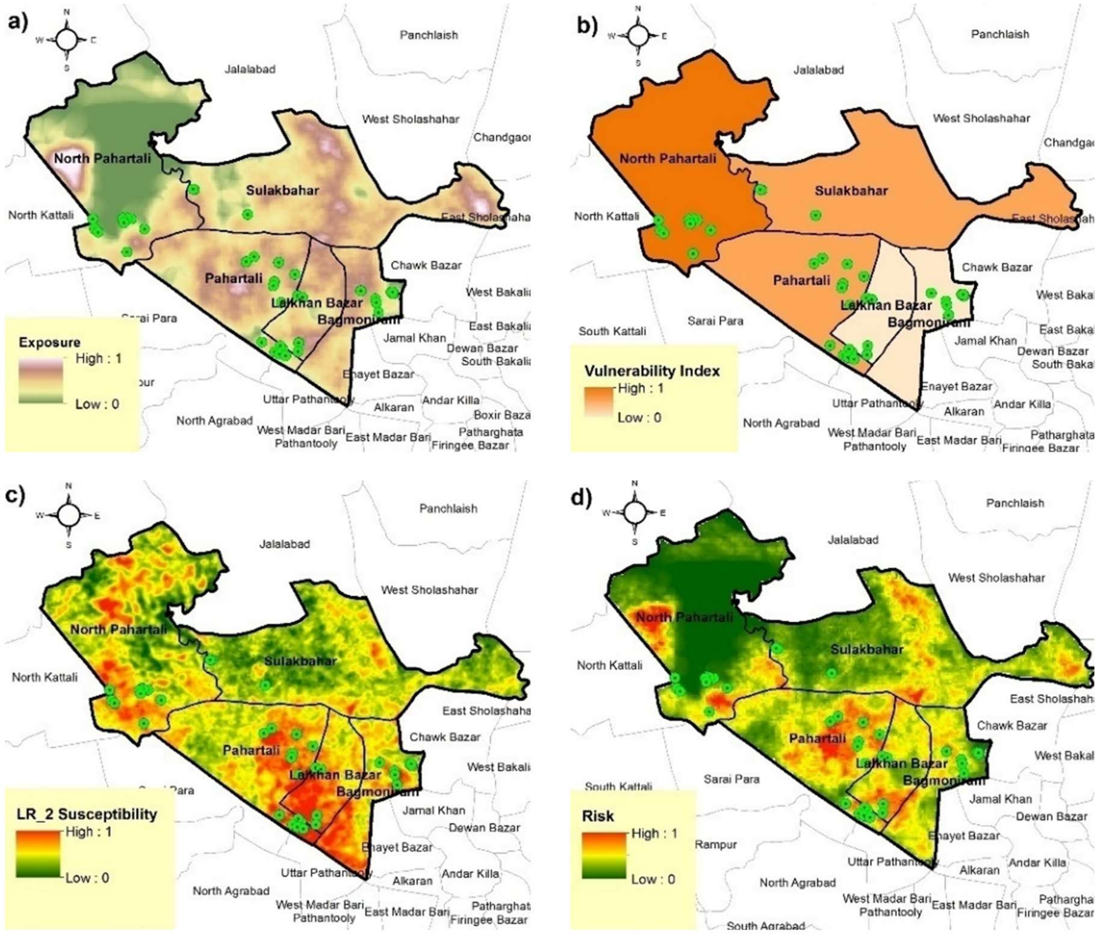

Figure 5: a) Exposure Index; b) Vulnerability Index; c) Most Accurate Susceptibility Map; d) Risk Map

4. CONCLUSIONS

Multiple casual factors were responsible for devastating landslide in the urbanized hilly areas of Chattogram city. The research prepared different landslide susceptibility maps, vulnerability map and exposure map for generation risk zoning map of the study area. As found by inventory analysis, elevation (20-40 m), slope (3˚-10˚), vegetation cover and proximity to road and drain (within 200 m) were responsible for landslide occurrence. Rainfall pattern analysis showed the intensity of rainfall was increasing continuously in this region which might make the soil more vulnerable to landslide. GIS and Remote Sensing based weighted Multi Criteria Evaluation (MCE) methods (i.e. AHP, and WLC), and one data-driven statistical models (Logistic Regression) ware used for preparing susceptibility maps. WLC_2 showed 88.29 % area was under highly susceptible to landslide event. On the other hand, high susceptible zones for LR_1 and LR_2 models were only 30.89 % and 28.73%. According to ROC curve, performance of susceptibility models using logistic regression (i.e., LR_1 and LR_2) were more accurate (i.e., AUC values = 0.804 and 0.847 respectively). The ward wise overall vulnerability index based on four vulnerability components (i.e., social, economic, environmental, and physical) were within 0.42 to 0.59. Exposure index indicated that ward wise minimum exposure (i.e., element at risk) was 949 and maximum was 1757. Finally, about 18.12 % (i.e., 743.24 acres) of area was found under high-risk zone in spatial risk zoning map. The result of the research might be used for landslide hazard risk reduction planning. Moreover, the outcome of this research might help the endangered local inhabitants/communities, urban planners, and engineers to reduce losses caused by future landslides by means of prevention, mitigation, and avoidance. The results will also be useful for explaining the driving factors of the known historical landslides, for supporting emergency decisions, and for upholding the efforts on the mitigation of future landslide hazards in Chattogram, Bangladesh.

However, the result helps to find the level of landslide hazard risk there exists some limitations too. Firstly, indicator-based approach is taken for this study, but the indicators are not constant. Therefore, future change in indicators may change the risk and vulnerability level. Moreover, the research used ward boundary for vulnerability assessment, but community boundary might show a more accurate result. This research creates scope for further research to address these limitations to make a more accurate risk mapping.

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