Chapter 23
Landslide Susceptibility and Risk Assessment in Hilly Regions of Bangladesh: A Geostatistical and Geospatial Modeling Approach for Sustainability

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Abstract Landslides significantly threaten human life, infrastructure, and environmental balance. In the hilly regions of Bangladesh, including Sylhet and Rangamati, landslides are frequent, causing 727 deaths and 1017 injuries between 2000 and 2018. The northeastern section of Bangladesh is projected to receive over 500–600 mm of precipitation in 2023, breaking records over the past 122 years, according to the European Centre for Medium-Range Weather Forecasts (ECMWF). With an elevation range of 0 to 195 m above sea level and 18% of its total land area covered by water bodies, Rangamati is particularly vulnerable to landslides. Despite the devastating impact of landslides, susceptibility assessment and risk management strategies are lacking. This research aims to address this gap by developing a comprehensive framework for sustainable landslide risk mitigation using geostatistical and geospatial modeling techniques. Factors such as land use and land cover (LULC), elevation, slope, topographic wetness index (TWI), precipitation, lithology, soil type, normalized difference vegetation index (NDVI), and distance from roads are used to create a frequency ratio (FR) model and identify landslide susceptibility and risk zones. The resulting high-resolution landslide susceptibility map (LSM) and risk assessment models provide valuable insights for policymakers, land-use planners, and stakeholders involved in disaster risk reduction and sustainable development. By applying geostatistical and geospatial modeling techniques to assess landslide susceptibility, manage risk, and promote sustainability, this research enhances resilience to landslides and highlights the importance of proactive planning and informed decision-making in mitigating the impact of landslides for promoting sustainable development in hilly regions.

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23.1 Introduction

A landslide is a geological phenomenon encompassing various ground movements, such as rock falls, deep slope failures, and shallow debris flows (Rahman 2012). Unplanned development activities, overpopulation, settlement along hill slopes, and ineffective disaster risk reduction efforts are the anthropogenic contributors accompanying climate-change-induced increased torrential rainfall are the main reasons for the increase in landslide occurrence (Alam 2020). Over the past five decades, the United Nations (UN) has prioritized implementing disaster risk reduction initiatives. The United Nations officially designated 1990 to 1999 as the "International Decade for Natural Disaster Reduction" (Alexander 1993). Additionally, the United Nations' Sustainable Development Goals for 2015–2030 have established a precise aim to substantially reduce the number of fatalities and the overall impact on individuals affected by disasters worldwide (UN 2015). From 2004 to 2013, 115 of the 173 global landslides resulted in around 7098 fatalities and impacted 3 million people in Asia alone (Ahmed et al. 2014; IFRC 2014). Bangladesh has been a prime susceptible zone for landslides for the last decades. Most of Bangladesh's land is floodplain, while only 18% is hilly and mountainous (Islam and Uddin 2002). In Bangladesh, 17 persons perished in 1999, 13 perished in 2000, 91 perished in 2007, 54 perished in 2010, and 17 perished in 2011 (BWDB 2005). Over the last three decades, there have been around 200 fatalities and considerable economic and property damages. The unconsolidated sedimentary rocks in the hill tracts by the rivers and streams are the reasons for high landslide-susceptible areas (Rashid 1991; Brammer 1996).

In recent years, this landslide has been a significant concern in the Chittagong and Chittagong Hill Tracts regions of Bangladesh's southeast. Chittagong has experienced approximately 12 landslides over the past five decades (BWDB 2005). Kutupalong Rohingya Camp (KRC) in Cox's Bazar District (CBD), Bangladesh, saw roughly 257 landslides or slope collapses, resulting in five fatalities and the destruction of over 5000 shelters (Kamal et al. 2022). Sylhet is also a vulnerable location for landslides because of its topographic condition where about 10,000 households live in hazardous conditions due to deforestation and hillocks being chopped down. These families are not on a government list, and there are no overt efforts to help them get back on their feet. The number of individuals living in danger is unknown to the district administration (Debu 2022).

The most vulnerable locations to landslides in Sylhet are built-up areas and vegetation to built-up land use and land cover (LULC) change types, and primary economic activities like jhum cultivation and fishing are the worst affected by landslides, according to the characteristics, causes, and consequences of landslides in Rangamati District where the urbanized Bengali and Rohingya refugee communities are highly vulnerable to landslide (Abedin et al. 2020; Ahmed 2021). That's why an assessment of landslide vulnerability in hilly areas in Bangladesh is needed to understand the risk, improve preparedness, and reduce the impact of landslides (Edris and Alam 2020). Sylhet and Rangamati are essential from an environmental and economic standpoint. The selection of these areas is based on differences in the landslide situation and variables impacting natural hazards supporting the new range of research in geography.

The occurrence of any natural catastrophe may be traced mostly to the interaction of political and economic variables, insufficient adaptation to natural circumstances, and human activity. To have a comprehensive understanding of the constituents of a disaster, it is imperative to thoroughly examine both exceptional natural occurrences and societal development over time (Quarantelli 1998; Alexander 2000). So, the chapter aims to address this gap by developing a comprehensive framework for sustainable landslide risk mitigation using geostatistical and geospatial modeling techniques to assess landslide susceptibility, manage risk, and promote sustainability, this research enhances resilience to landslides on Sylhet and Rangamati.

The assessment methodology indeed includes numerous factors. In Bangladesh, slope angle aspect, LULC, elevation, geology, normalized difference vegetation index (NDVI), distance from the road, rainfall, and distance from stream have been given the highest importance in landslide susceptibility mapping (Chowdhury 2023). A multidisciplinary approach was used to research landslides in Bangladesh, focusing on the Chittagong region (Kafy et al. 2017). Also, the frequency ratio (FR) approach is used to assess landslide susceptibility because it possesses a success and prediction rate of 75% to 80% (Pratap and Vikram 2021). The FR value is one metric to assess the relationship between various causes and landslides. A moderate link with land sliding is shown by an FR value of less than 1, while a strong correlation is indicated by a value of more than 1 (Samanta et al. 2018). A more accurate map of vulnerable landslide sites is what the FR method's landslide susceptibility map (LSM) will provide (Mahdi et al. 2023). The comparative analysis between two locations (Sylhet and Rangamati) will add an immense dimension to the research that will help the policymakers build a comprehensive recommendation for capacity building against landslides. The mitigation of landslides in southeast Bangladesh is insufficient due to financial constraints (Rabby and Li 2019).

The main objective of this chapter is to analyze landslide susceptibility and risk assessment using geostatistical and geospatial modeling techniques to provide guidelines for policymakers and planners for the development of Sylhet and Rangamati. The chapter has provided specific guidance for each location. As the influencing factor for landslides in each location varies, the research will be beneficial for cost-efficient development. The order of upazilas and other parameters will be useful in determining the location and other aspects that will enhance landslide mitigation and protection. The overall research will provide an inventory of landslides and a comparison examination of two important locations with different topographies, environments, and climates. The research findings will provide qualitative assistance to improve the development process in Sylhet and Rangamati.

23.1.1 Study Location

The hill tracts of Bangladesh, including the Chittagong hilly regions and Sylhet hilly sides, are indeed considered landslide susceptible areas. Sylhet is situated in the northeastern region of Bangladesh at coordinates 24°32′0″ N and 91°52′0″ E on the northern side of the river Surma, encompassed by the Jaintia, Khasi, and Tripura hills. The physiography of Sylhet mainly consists of hill soils, which include many significant depressions referred to as "Haors" by the local population (Bangladesh Metrological Department 2009). A total of 27 wards in Sylhet are estimated to have a population density of 250.26 per square kilometer (Habibur et al. 2011). Its immense rainfall increase over the years from May to September is the prime factor for landslides (Bangladesh Metrological Department 2009). Rangamati is situated within the southeastern part delimited by India to the north and east, Bandarban district to the south, and Khagrachari and Chittagong districts to the west. It covers an expansive area of 6116.19 km^2, making it the largest district in the country in terms of geographical expansion with 10 administrative upazilas (Rangamati Hill District Council 2011). The research region encompasses 1145 km^2, specifically including landslide-vulnerable locations Rangamati Sadar, Kawkhali, and Kaptai, which individually cover 547 km^2, 339 km^2, and 259 km^2, respectively. This region is more significant and fragile in terms of biodiversity since 497 km^2 of it is covered in forest flora, whilst 218 km^2 of it is distinguished by riverine characteristics (BBS 2012). According to Rangamati district government, about 12,450 people experienced losses (UNPO 2017). Additionally, 1,500 dwellings were demolished, while 2,000 residences sustained partial damage due to landslides (UNDP 2017) (Fig. 23.1).

23.2 Methods and Materials

The research follows the FR method for analyzing the landslide susceptibility in Sylhet and Rangamati. These significant economic hubs of Bangladesh significantly influence the country's development. The previous year's landslide record and NASA landslide inventory data prepared the map. The workflow diagram represents the conditioning factors and procedures for the FR method to prepare LSM. The data sources required to conduct FR calculation are illustrated in (Table 23.1) for LSM (Fig. 23.2).

Elevation, topographic wetness index (TWI), LULC, slope, rainfall, lithology, NDVI, soil type, and distance from the road are the prime conditioning factors for the suitable method calculation. In landslide susceptibility research, slope, curvature, and aspect variables are commonly regarded as critical characteristics related to landslide conditions. These variables are typically derived using a digital elevation model (DEM) with a spatial resolution of 30 m. The research region was categorized into five distinct groups based on the significance of elevation and slope as primary determinants of landslide incidence. As the elevation height and slope angle drop,

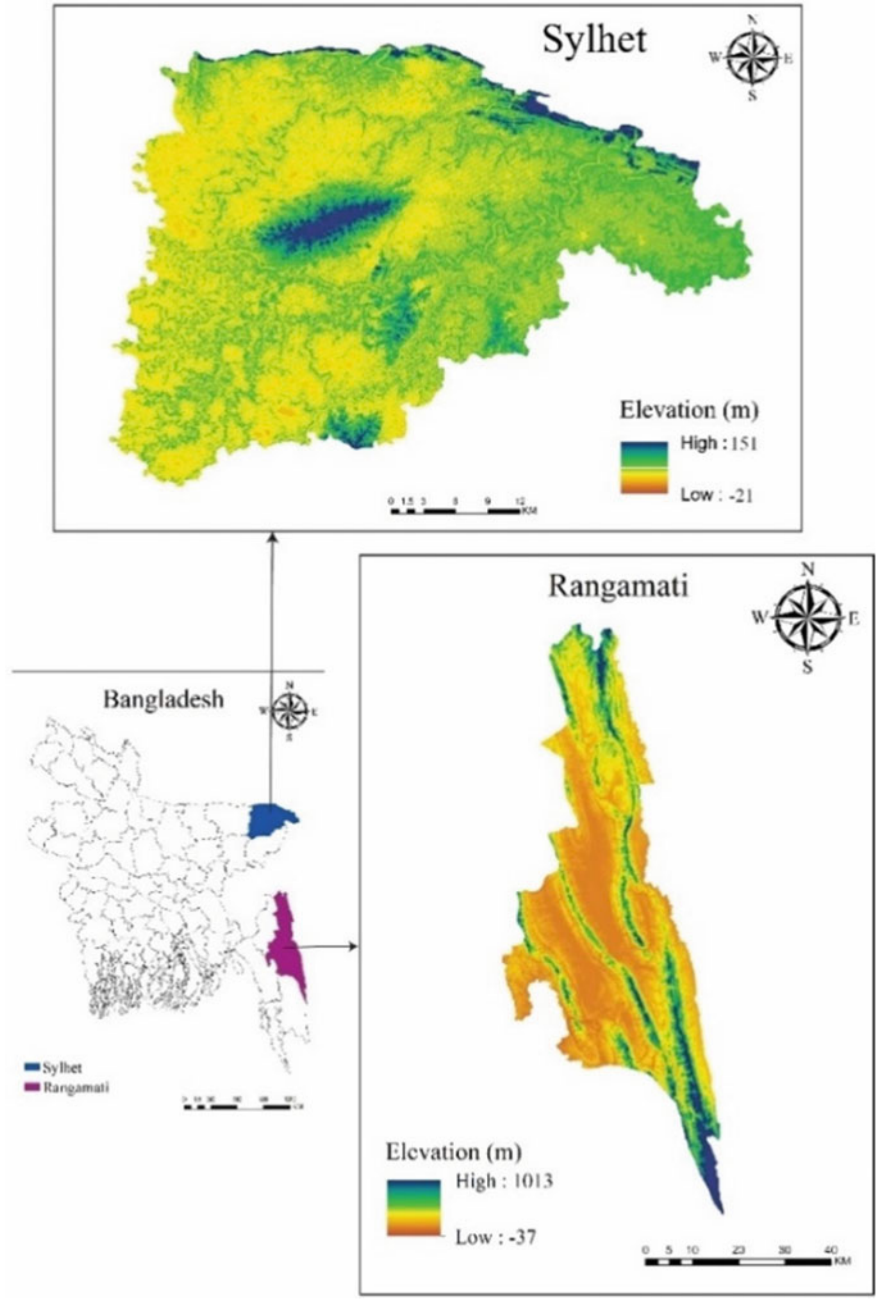

Fig. 23.1 Study area (Sylhet & Rangamati, Bangladesh)

Table 23.1 Data source for landslide influence factors

Factor	File type	Source
Elevation	DEM (30 m × 30 m)	USGS
TWI	DEM (30 m × 30 m)	USGS
LULC	Sentinel-2, Landsat 8 (10 m × 10 m)	ESRI
Slope	DEM (30 m × 30 m)	USGS
Rainfall	IDW	Bangladesh metrological Department
Lithology		USGS
NDVI	(30 m × 30 m)	USGS
Soil Type		BARC
Distance from Road		BARC

there is an increased likelihood of landslide events, resulting in a more significant incidence of landslides in low-lying and flat regions. Conversely, it is improbable for it to transpire at higher altitudes. Steep slopes accelerate the velocity of surface run-off, reducing the duration during which the soil can absorb the water. The influence of curvature is a significant component in the study of landslides. It has been categorized into three types: concave (negative), convex (positive), and flat (zero) surfaces. The amount of rainfall and sunshine received by terrain is influenced by conditioning factors (Jebur et al. 2014).

The conditioning factor for TWI was derived using DEM with a spatial resolution of 30 m, using Eq. (23.1), resulting in the following expression:

$$\mathrm{TWI} = \ln\left(\frac{A_s}{\tan\beta}\right) \tag{23.1}$$

The specific catchment area (m^2/m) and slope angle in degrees (β) are defined as variables in the study conducted by Regmi et al. (2010). TWI measures the water accumulation at various locations within a watershed and the inclination of water to move downslope due to gravitational forces (Moore et al. 1991). Typically, higher TWI values are observed in places prone to landslides.

Another influential element that affects landslides is rainfall data collected from the Meteorological Agency of Ethiopia over 30 years (1990–2021), especially from June to August. The rainfall map was generated using the IDW interpolation technique on the yearly average precipitation data obtained from the station sites within the research region.

NDVI is a popular and frequently utilized index. The vegetation index is commonly used in global climate and environmental change studies. Vegetation's sensitivity to the environment helps protect against natural disasters by influencing ecological balance and climate. Distance to Road: One factor that affects the likelihood of a landslip is the distance from a road. This factor refers to a road network

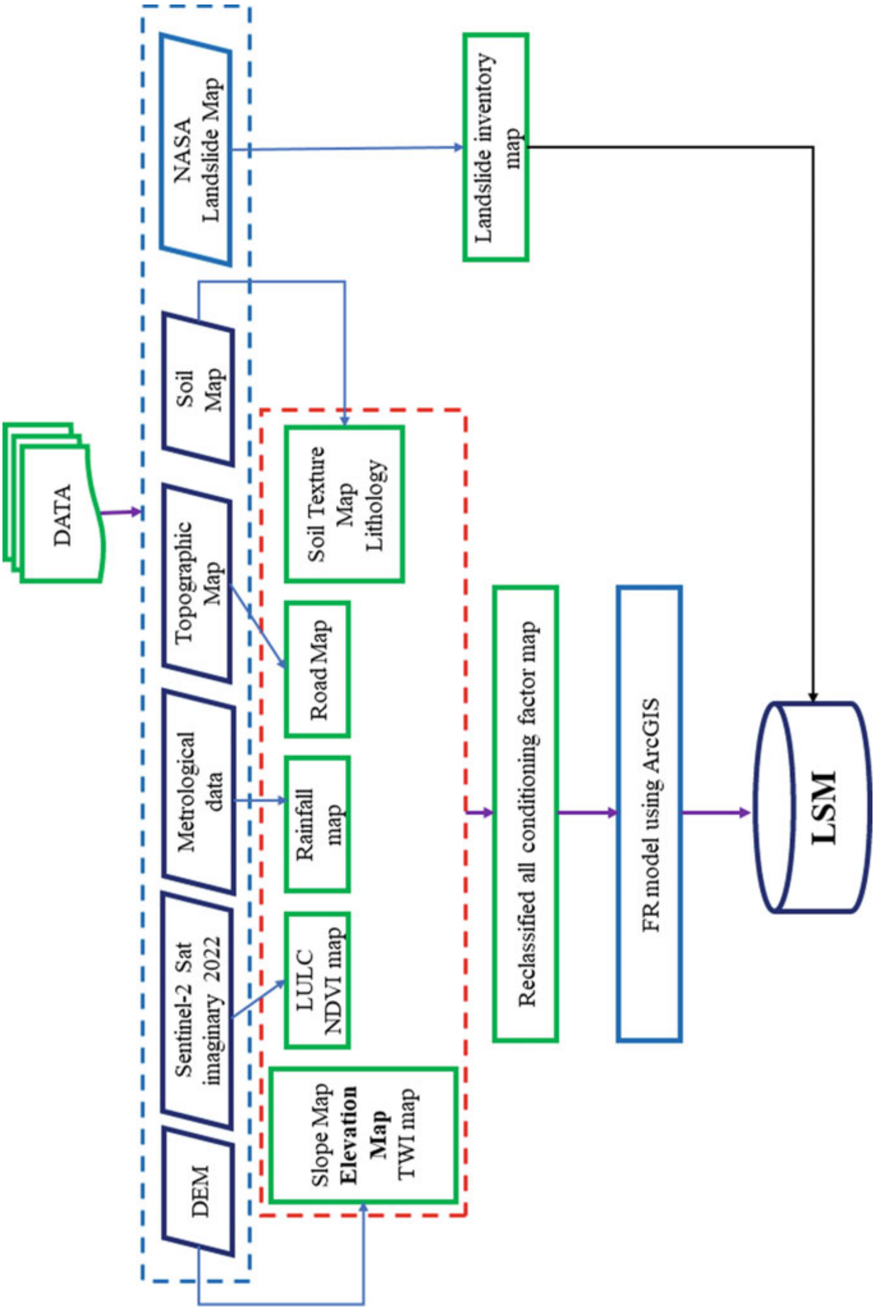

Fig. 23.2 Methodological framework

that serves as a dam or water barrier for a particular area. It has a reverse relationship with land sliding. Organizing mountain roadways needs construction projects such as cutting or digging slopes that will change and weaken the primary geological structure (Sofa et al. 2021). The road distance is a primary factor in planning landslide zone projections. Roads in the hilly region may be one of the reasons for the occurrence of landslides (Catena 2008); in due time, the road changes into a different topographic structure.

The NDVI is a metric used to assess the vegetation properties of a given region and its influence on landslides within a basin. The NDVI values range from -1 to $+1$, exhibiting variability. The NDVI conditioning factor was derived using Sentinel-2 satellite images with a spatial resolution of 30 m, using Eq. (23.2) as described (Pradhan et al. 2010).

$$\mathrm{NDVI} = \frac{IR - R}{IR + R}. \tag{23.2}$$

In this context, "IR" refers to the infrared bands, while "R" refers to the red bands within the electromagnetic spectrum.

The soil type data were acquired from Bangladesh's Soil Resource Development Institute (SRDI) (Haque 2006). The study areas contain diverse soil types including clay loam, sandy loam, and sandy clay loam. Soil characteristics like texture and moisture retention capacity influence landslide susceptibility, and were incorporated in the analysis (Rahman et al. 2018; Petley et al. 2005).

The occurrence of landslides is significantly influenced by land use, which serves as a crucial conditioning element. The land use map was generated using Sentinel-2 satellite images and a supervised classification methodology within the ArcGIS software. The land use map was categorized into six distinct types. The presence of cultivated land and shrub vegetation primarily characterizes the research region. The proximity of river and road networks is a significant determinant in the incidence of landslides. The distances from the Road and river were measured and shown on a map scale of 1:500,000. This was done by digitizing the topographic map of the research region and using the Euclidean distance technique in the ArcGIS tool. Soil type and lithology are significant conditioning elements that influence the occurrence of landslides. The lithology and soil type of the research region was determined by utilizing a geological map and a soil map, respectively. The geology and soil data were acquired from the Ethiopian Minister of Water and Energy in Addis Ababa, Ethiopia. The research region has a dominating soil type known as dystric nitisols, which falls under one of the eight soil type classifications. The lithology in the research region is categorized into four distinct classes. Tertiary extrusive and intrusive rocks are the most prevalent lithological types.

The LSM is prepared by summing the factors contributing to landslides for both Sylhet and Rangamati.

$$\begin{aligned}\mathrm{LSM} = \sum \mathrm{FR} * (&\mathrm{Elevation} + \mathrm{TWI} + \mathrm{LULC} + \mathrm{Slope} + \mathrm{Rainfall}\\ &+ \mathrm{Lithology} + \mathrm{NDVI} + \mathrm{Soil\ Type} + \mathrm{Distance\ from\ road}).\end{aligned}$$

23.3 Results

A spatial mapping and statistical database were created for all nine influencing factors in landslide susceptibility, including LULC, elevation, slope, TWI, rainfall, lithology, soil type, NDVI, and distance from roads, along with their respective subcategories for both Sylhet and Rangamati district (Fig. 23.3).

23.3.1 Sylhet

Based on this spatial mapping of all nine factors, a statistical database was derived, which is illustrated in (Table 23.2 and Fig. 23.4).

LULC classification categorized the land into seven distinct classes: water, vegetation, flooded vegetation, cropland, buildup area, bare land, and range land. 'Crop Land' covers the majority of the land about 64.61%, and it has a low correlation to landslides with a FR of only 0.26. Surprisingly, even though the 'Buildup Area' covers a smaller land area of 13.85%, it exhibits a much higher FR value of 4.21, which is highly correlated with landslides. This is because the buildup of areas contributes to landslide susceptibility by clearing vegetation, disrupting natural drainage, altering soil properties, and increasing surface runoff (Quevedo et al. 2023). These changes weaken slope stability and enhance the risk of landslides, making them more likely in urbanized environments.

The study area displayed an elevation range spanning from −21 m to 151 m into five classes. Higher elevation may increase landslide hazards by intensifying slope steepness and terrain instability (Rabby et al. 2022). Conversely, lower altitudes, notably in flat or gently sloping regions, can foster landslide vulnerability as water accumulation raises pore pressure and diminishes soil stability. Notably, the class labeled '13.4 m to 47.8 m' showed a high FR value of 1.20, covering 62.56% of the land area.

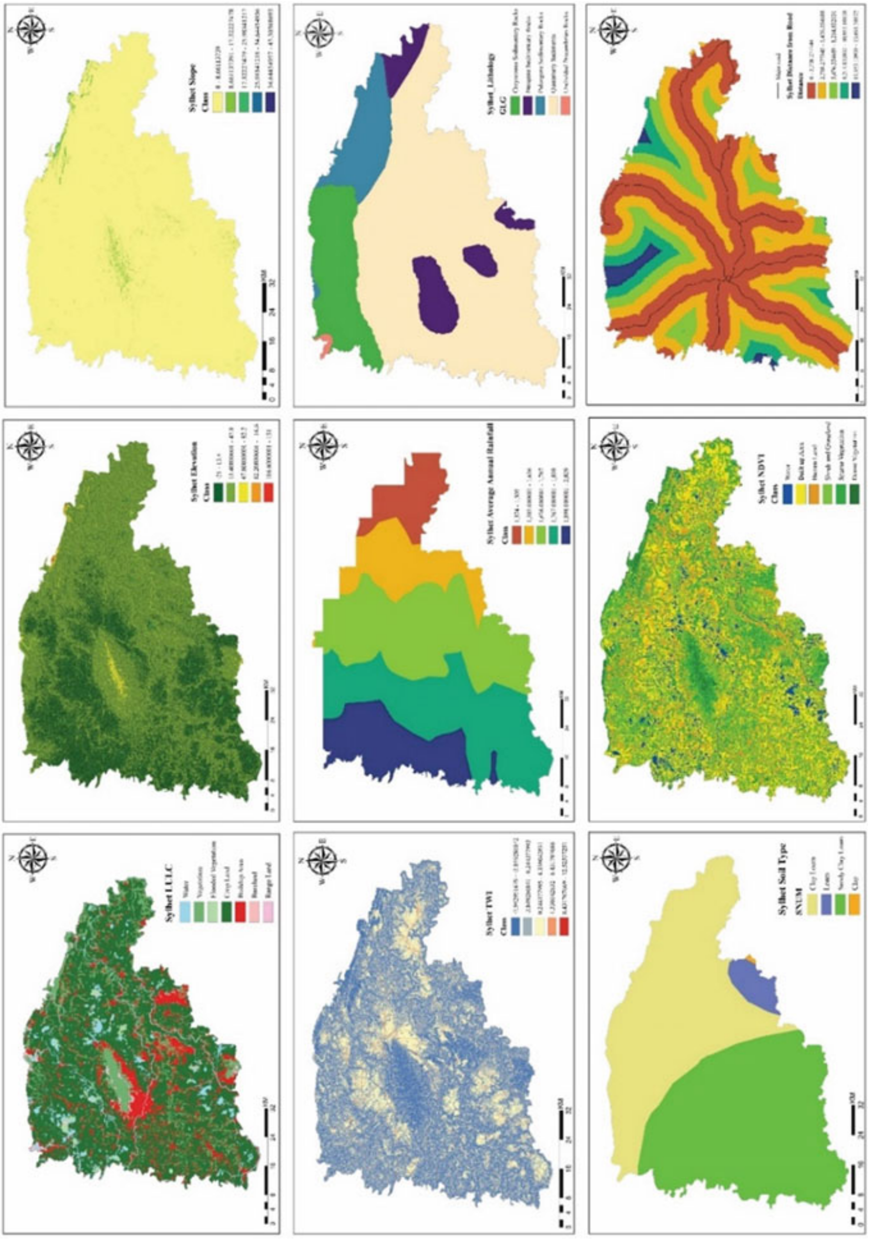

Fig. 23.3 Factors used for FR modeling (Sylhet)

Table 23.2 Conditioning factors used for Landslide susceptibility mapping through FR model (Sylhet)

Parameter	Class name or description	Histogram	% of histogram	Landslide number	% of Landslide number	FR
LULC	Water	2,252,687	6.59	2	16.67	2.53
	Vegetation	4,298,888	12.58	0	0.00	0.00
	Flooded vegetation	444,939	1.30	0	0.00	0.00
	Crop land	22,070,993	64.61	2	16.67	0.26
	Buildup area	4,729,986	13.85	7	58.33	4.21
	Bare land	39,226	0.11	0	0.00	0.00
	Range land	324,384	0.95	1	8.33	8.78
Elevation	−21–13.4	1,443,450	36.46	3	25.00	0.69
	13.4–47.8	2,476,386	62.56	9	75.00	1.20
	47.8–82.2	36,040	0.91	0	0.00	0.00
	82.2–116.6	2408	0.06	0	0.00	0.00
	116.6–151	342	0.01	0	0.00%	0.00
Slope (in degree)	0–8.66	3,821,341	98.34	11	91.67	0.93
	8.66–17.32	59,984	1.54	1	8.33	5.40
	17.32–25.91	4193	0.11	0	0.00	0.00
	25.91–34.64	358	0.01	0	0.00	0.00
	34.64–43.30	30	0.00	0	0.00	0.00
TWI	−7.93–3.84	1,552,684	39.36	4	33.33	0.85
	−3.84–0.24	1,347,342	34.16	4	33.33	0.98
	0.24–4.33	945,563	23.97	4	33.33	1.39
	4.33–8.43	88,942	2.25	0	0.00	0.00
	8.43–12.52	10,074	0.26	0	0.00	0.00
Rainfall	3749.34–4246.49	1,118,082	29.55	0	0.00	0.00
	4246.49–4743.64	1,456,208	38.49	4	33.33	0.87
	4743.64–5240.79	552,827	14.61	4	33.33	2.28
	5240.79–5737.94	380,005	10.04	1	8.33	0.83
	5737.94–6235.10	276,537	7.31	3	25.00	3.42
Lithology	Creyaceous sedimentary rocks	7543	14.22	7	58.33	4.10
	Neogene sedimentary rocks	4980	9.39	3	25.00	2.66
	Paleogene sedimentary rocks	5131	9.68	0	0.00	0.00
	Quaternary sediments	35,190	66.36	1	8.33	0.13
	Undivided Precambrian rocks	186	0.35	1	8.33	23.76

(continued)

Table 23.2 (continued)

Parameter	Class name or description	Histogram	% of histogram	Landslide number	% of Landslide number	FR
Soil type	Clay loam	24,713	46.94	5	41.67	0.89
	Loam	1682	3.19	0	0.00	0.00
	Sandy clay loam	26,211	49.78	7	58.33	1.17
	Clay	47	0.09	0	0.00	0.00
NDVI	Water	246,293	6.42	1	8.33	1.30
	Buildup area	907,229	23.66	4	33.33	1.41
	Barren land	689,540	17.98	2	16.67	0.93
	Shrub and grassland	1,166,047	30.41	5	41.67	1.37
	Sparse vegetation	747,499	19.49	0	0.00	0.00
	Dense vegetation	78,025	2.03	0	0.00	0.00
Distance from road	0–2738.27	15,757	41.98	12	100.00	2.38
	2738.27–5476.55	12,068	32.15	0	0.00	0.00
	5476.55–8214.83	6354	16.93	0	0.00	0.00
	8214.83–10,953.11	2524	6.72	0	0.00	0.00
	10,953.11–13,691.38	830	2.21	0	0.00	0.00

The susceptibility of a slope to landslides is impacted by its height and steepness. High, steep slopes are more prone to landslides due to increased gravitational forces, while gentle, low slopes have lower landslide risk because of better stability and reduced gravitational impact (Ramesh 2021). A spatial database on slope map (In Degree) was reclassified into five classes ranging from 0 to 43.30^0. The class labeled '0–8.66^0' stands out with a low FR ratio of 0.93, covering a significant 98.34% of the land area and being associated with 91.67% of landslide occurrences. On the other hand, the class '8.66^0–17.32^0' exhibits a high FR ratio of 5.40 but covers only 1.54% of the land, with 8.33% of landslide occurrences.

The TWI data is divided into five classes (−7.93 to −3.84, −3.84 to 0.24, 0.24 to 4.33, 4.33 to 8.43, 8.43 to 12.52), with the class '0.24 to 4.33' having a high FR value of 1.39 and all the landslide events occurred in the range of −7.93 to 4.33. According to (Różycka et al. 2017), low TWI values have the potential to affect slope stability, particularly in the top areas and on the steep head scarps of landslides, making them more susceptible to landslides. High TWI values also signify regions prone to water accumulation, escalating landslide risk. They often denote concentrated drainage paths, suggesting potential erosion and instability. In contrast, lower TWI values imply improved drainage, reducing landslide vulnerability.

Rainfall data is categorized into five classes spanning from 3749.34 mm to 6235.10 mm. The class '5737.94–6235.10' exhibits a high FR value of 3.42 as heavy rainfall in Bangladesh, particularly during the monsoon season, escalates the risk of landslides (Hossain 2020). Urban development on hillsides and settlement at their

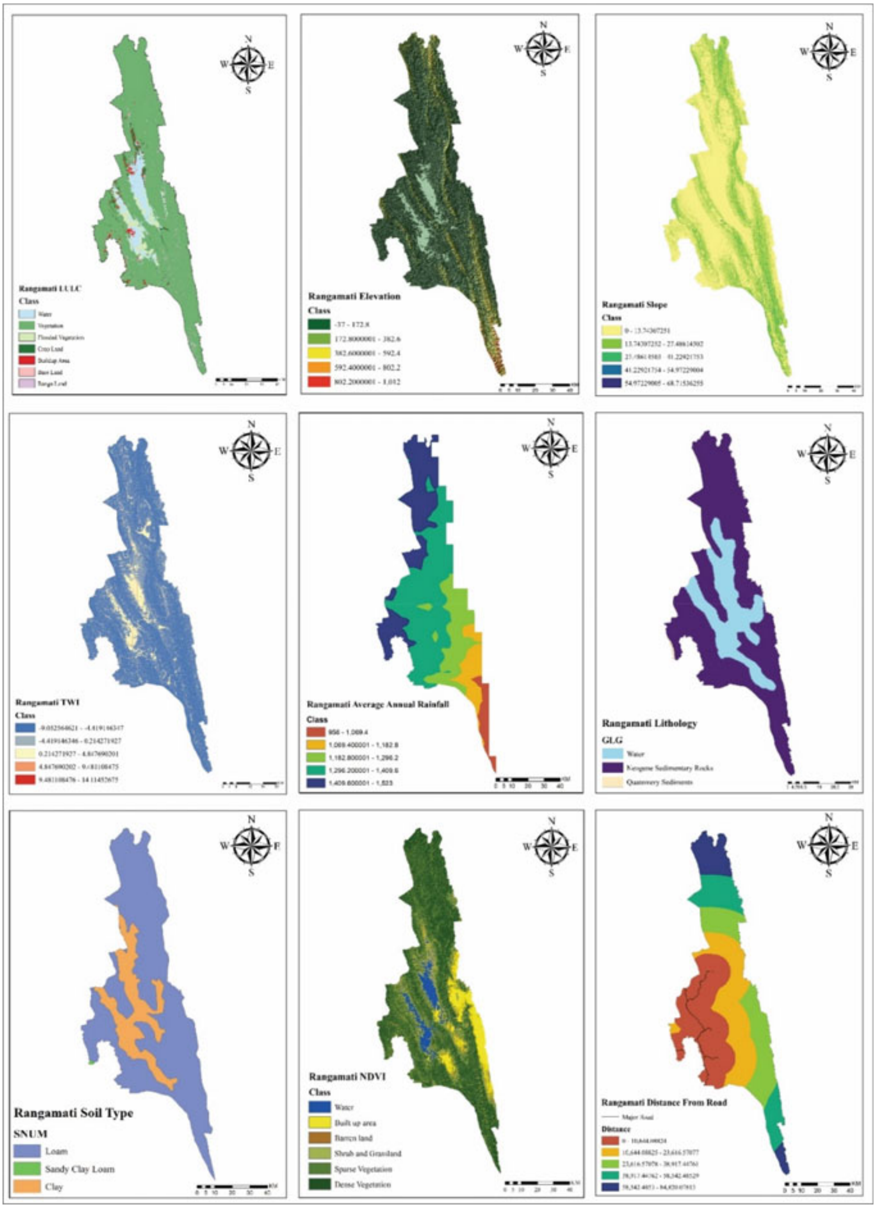

Fig. 23.4 Factors used for FR modeling (Rangamati)

bases worsens susceptibility. Rainfall impacts soil's pore water pressure, altering landslide danger, and emphasizing the importance of understanding rainfall patterns for effective hazard management. The type of rocks in the area is also classified into 5 categories.

The lithological composition of the basin plays a crucial role in influencing slope stability and the occurrence of landslides. Stronger rock formations offer greater resistance to external forces, making them less susceptible to landslides, while weaker rock types are more vulnerable to such events (Yalçın 2008). From a lithological perspective, areas with prevalent marl, limestone, shale, gypsum, and marly conglomerate formations are at a higher risk of landslides. Therefore, assessing the density of landslides within different geological structures is essential to understand their propensity for such events better (Abedini and Tulabi 2018). 'Undivided Precambrian Rocks' has a notably high FR value of 23.76, covering only 0.35% of the land area but being associated with 8.33% of landslides.

Soil type data includes clay loam, loam, and sandy clay loam. 'Sandy Clay Loam' stands out with a high FR value of 1.17 and covers 49.78% of the land area, with 58.33% of landslide occurrences. However, the susceptibility of different soil types to landslides is influenced by factors like composition, permeability, and shear strength, and sandy clay loam soils with a higher sand content exhibit better drainage and higher shear strength, rendering them less susceptible to landslides (Han et al. 2019a, b). The reason is that landslide susceptibility does not solely depend on soil characteristics; rainfall, distance from road factors, etc. influence it. As we see on the soil type map, most of the sandy clay loam portion is placed in the north-western and south-western zones. But at the same time, more rainfall happens in that zone, and the main road linkages are there in that zone. Clay loam soils, with a high clay content, are more prone to landslides due to poor drainage and high-water retention, leading to increased pore pressure and reduced shear strength. That's why this zone has a low FR but it has witnessed almost 42% of landslide occurrences.

The NDVI is a valuable tool for identifying landslide scars, tracking post-landslide changes, and assessing landslide susceptibility (Qu et al. 2020). NDVI data is categorized into 6 classes which 'Shrub and Grassland' has a relatively high FR value of 1.37 with 41.67% of landslide occurrences. Roads play a crucial role in concentrating runoff, which is evident from experience and existing landslide statistics observed during road reconstruction and widening projects (Abedini and Tulabi 2018).

The distance from the road is categorized into five classes (0–2738.27 m, 2738.27–5476.55 m, 5476.55–8214.83 m, 8214.83–10,953.11 m, 10,953.11–13,691.38 m). The class '0–2738.27' stands out with a high FR value of 2.38, covering 41.98% of the land area and being associated with 100.00% of landslide occurrences. This indicates a strong correlation between landslides and proximity to roads in this class as the proximity of roads to areas at risk of landslides, especially near rivers, heightens the landslide risk (Zhou et al. 2023).

23.3.2 Rangamati

Based on this spatial mapping of all nine factors, a statistical database was derived which is illustrated in (Table 23.3).

LULC is characterized by 7 distinct classes in which flooded vegetation, covering 3.08% of the area, exhibits a higher correlation of sporting an FR of 9.27. Flooded vegetation can make landslides more severe by reducing slope strength and root stability (Mirus et al. 2017). Slopes become more susceptible to collapse when floods sweep away vegetation. Because of the flooded vegetation, the soil is less cohesive and has higher pore pressures, which increases the risk of sliding. It also modifies the dynamics of water, impacting the stability of slopes. On the other hand, water plays a key role in triggering landslides by saturating and destabilizing soil as infiltration raises pore pressure, reducing soil strength, and causing slope failure (Abebe et al. 2021). Changes in land use like deforestation disrupt the natural water balance, increasing landslide risk. Steep terrain and poor land management compound this vulnerability, making water a critical factor in landslides. That's why, water occupies 6.17% of the total coverage area and is associated with a high FR of 2.32, which is highly correlated with landslide events.

Moving on to the elevation assessment, the Rangamati region displays an elevation range spanning from −37 to 1012 m. Notably, the class of −37 to 172.8 m, covering 74.12% of the area, is highly correlated with landslides, boasting an 85.71% correlation and an FR of 1.16. Other elevation classes exhibit lower or negligible correlations with landslide occurrences.

Slope, measured in degrees, is another crucial factor. The analysis categorizes slope data into five classes. The class spanning 13.7 to 27.4 degrees, covering 30.35% of the area, displays a strong correlation with landslides and a high FR of 3.30. In contrast, other slope classes show lower or no significant correlations with landslides.

TWI is divided into five classes and the class from −4.41 to 0.21 exhibits a higher FR of 2.43.

Rainfall data is also taken into account, and segmented into five distinct classes. The class within the range of 2488.14 to 2592.69 mm shows a high correlation with six landslide occurrences, resulting in a high FR of 3.11. Heavy rainfall is more susceptible to landslides but low rainfall can also indirectly cause landslides by drying up the soil, diminishing its cohesiveness, and increasing the susceptibility of slopes to collapse, particularly in steep places where constant rainfall is essential for soil stability (Ray and Lazzari 2020). Prolonged periods of low rainfall can cause soil desiccation and decreased moisture content, which raises the risk of landslides during periods of heavy rainfall.

The lithological composition is an influential factor, with Neogene Sedimentary Rocks covering 74.52% of the area and displaying a strong correlation with seven landslide occurrences, resulting in an FR of 1.34.

Soil type is another critical consideration, and the analysis reveals that Clay covers only 19.29% of the region, but is highly correlated with landslides at 85.71% landslide occurrence with an FR of 4.44. According to (Chen et al. 2010), clay content

Table 23.3 Conditioning factors used for landslide susceptibility mapping through FR model (Rangamati)

Parameter	Class name or description	Histogram	% of histogram	Landslide number	% of landslide number	FR
LULC	Water	4,787,643	6.17	1	14.29	2.32
	Vegetation	47,091,419	60.69	3	42.86	0.71
	Flooded vegetation	2,390,951	3.08	2	28.57	9.27
	Crop land	21,217,917	27.35	0	0.00	0.00
	Buildup area	894,206	1.15	1	14.29	0.19
	Bare land	83	0.00	0	0.00	0.00
	Range land	1,209,344	1.56	0	0.00	0.00
Elevation	−37–172.8	4,869,669	74.12	6	85.71	1.16
	172.8–382.6	1,302,929	19.83	1	14.29	0.72
	382.6–592.4	272,837	4.15	0	0.00	0.00
	592.4–802.2	111,246	1.69	0	0.00	0.00
	802.2–1012	13,692	0.21	0	0.00	0.00
Slope (in degree)	0–13.7	4,100,448	66.08	0	0.00	0.00
	13.7–27.4	1,883,125	30.35	7	100.00	3.30
	27.4–41.2	210,154	3.39	0	0.00	0.00
	41.2–54.9	10,953	0.18	0	0.00	0.00
	54.9–68.7	571	0.01	0	0.00	0.00
TWI	−9.05–4.41	4,496,591	63.80	3	42.86	0.67
	−4.41–0.21	1,240,896	17.61	3	42.86	2.43
	0.21–4.84	741,375	10.52	0	0.00	0.00
	4.84–9.48	560,589	7.95	1	14.29	1.80
	9.48–14.11	8663	0.12	0	0.00	0.00
Rainfall (in mm)	2383.60–2488.14	1,108,924	17.43	1	14.29	0.82
	2488.14–2592.69	1,753,364	27.56	6	85.71	3.11
	2592.69–2697.24	2,782,028	43.73	0	0.00	0.00
	2697.24–2801.79	600,009	9.43	0	0.00	0.00
	2801.79–2906.34	116,992	1.84	0	0.00	0.00
Lithology	Water	16,351	25.29	0	0.00	0.00
	Neogene sedimentary rocks	48,182	74.52	7	100.00	1.34
	Quaternary sediments	127	0.20	0	0.00	0.00
Soil type	Loam	50,299	80.61	1	14.29	0.18
	Sandy clay loam	63	0.10	0	0.00	0.00
	Clay	12,038	19.29	6	85.71	4.44
NDVI	Water	380,302	5.93	0	0.00	0.00

(continued)

Table 23.3 (continued)

Parameter	Class name or description	Histogram	% of histogram	Landslide number	% of landslide number	FR
	Buidup area	721,854	11.26	0	0.00	0.00
	Barren land	219,522	3.43	0	0.00	0.00
	Shrub and grassland	803,263	12.53	2	28.57	2.28
	Sparse vegetation	1,925,790	30.05	2	28.57	0.95
	Dense vegetation	2,358,592	36.80	3	42.86	1.16
Distance from road	0–10,644.08	19,602	30.69	6	85.71	2.79
	10,644.08–23,616.57	15,828	24.78	1	14.29	0.58
	23,616.57–38,917.44	13,171	20.62	0	0.00	0.00
	38,917.44–58,542.58	9116	14.27	0	0.00	0.00
	58,542.58–84,820.07	6160	9.64	0	0.00	0.00

significantly impacts soil mass failure, with moderate clay (5–10%) causing quick failures in short rainfall while low (2.5–5%) and high clay (>10%) soils need longer rain to fail. High clay reduces cohesion, aiding failure. Research suggests >2.5% clay is needed for landslides (Liu et al. 2021). Other soil type categories exhibit no or low correlations with landslide occurrences.

NDVI is categorized into six classes, a prominent factor causing landslides. According to (Asada and Minagawa 2023), dense vegetation, such as forests, can cause landslides by absorbing rainfall and blocking it, which results in runoff and soil saturation. Compared to forests, grasslands, and shrubs are more susceptible to landslides because of their weaker and less stable root systems than dense vegetation. That's why we can see that shrub and grassland demonstrate a relatively high correlation of 28.57% with two landslide occurrences and an FR of 2.28. Dense vegetation also exhibits high correlations with landslide events with an FR of 1.16.

Lastly, the distance from roads is examined and segmented into five classes where the class covering 0–10,644.08 m displays a strong correlation of 85.71% landslide events and an FR of 2.79 as areas closer to roads increase higher landslide occurrence (Zhou et al. 2023).

23.3.3 Comparison of Factors Between Sylhet and Rangamati

In both Sylhet and Rangamati regions, various factors contribute to landslide susceptibility, but the significance of these factors and their correlations differ between the two areas.

In Sylhet, 'Buildup Area' and 'Crop Land' significantly impact landslide susceptibility as urbanization disrupts natural drainage and soil properties, and also increase in deforestation increases susceptibility. Elevation influences susceptibility as steep slopes increase the chances of landslides. Heavy rainfall and certain geological formations increase susceptibility. Road proximity is a critical factor, with areas closer to roads showing a strong correlation with landslides. On the other hand, in Rangamati, features like 'Flooded Vegetation' and 'Water' exacerbate landslide susceptibility due to their effects on soil cohesion and slope stability. Slope, TWI, and heavy rainfall also contribute to susceptibility. 'Clay' soil type is a significant factor, with high clay content increasing cohesion and the risk of landslides. Dense vegetation and proximity to roads also play roles in landslide susceptibility. The key differences between the two regions lie in the factors influencing susceptibility. Sylhet's susceptibility is affected by land use changes and urbanization, while Rangamati experiences higher susceptibility due to flooded vegetation and water. Both areas share common factors like slope, TWI, and road proximity, highlighting their significance in landslide risk assessment.

23.3.4 FR Factors Ranking for Sylhet and Rangamati

Landslides are a common risk in terrain with slopes, resulting in fatalities in transportation routes, rural industrial sites, and urban areas (Froude and Petley 2018). Seismic activity, prolonged periods of heavy rain, creep fault occurrences, etc. are the prime reasons for landslides (Barbano et al. 2014). Risk assessment for landslides includes environmental, topographic, and social-based data sources. So, the factor-based analysis in the FR model provides immense details about the landslide susceptibility. Landslide databases of the highest caliber are necessary for assessing the danger of landslides where this landslide inventory is a fundamental tool for risk analysis and land planning, it represents a foundation of information and greatly aids the local authorities in making decisions (Froude and Petley 2018; Colombo et al. 2005). These NASA databases aid in the computation of the FR technique for Bangladesh's Sylhet and Rangamati during vulnerability assessments.

In Sylhet and Rangamati, the FR study details landslide vulnerability using nine parameters. In contrast to Sylhet, which is located in northeast Bangladesh, Rangamati symbolizes the southeast. The landslide causes at these two locations change depending on factors, as seen by the disparity in height and topographic conditions.

23.3.5 Comparing the Susceptibility Level of Landslide Between Sylhet and Rangamati

In comparing landslide susceptibility between Sylhet and Rangamati districts, it's evident that Sylhet has a greater number of villages and populations in the 'Moderate' zone compared to Rangamati (Fig. 23.5).

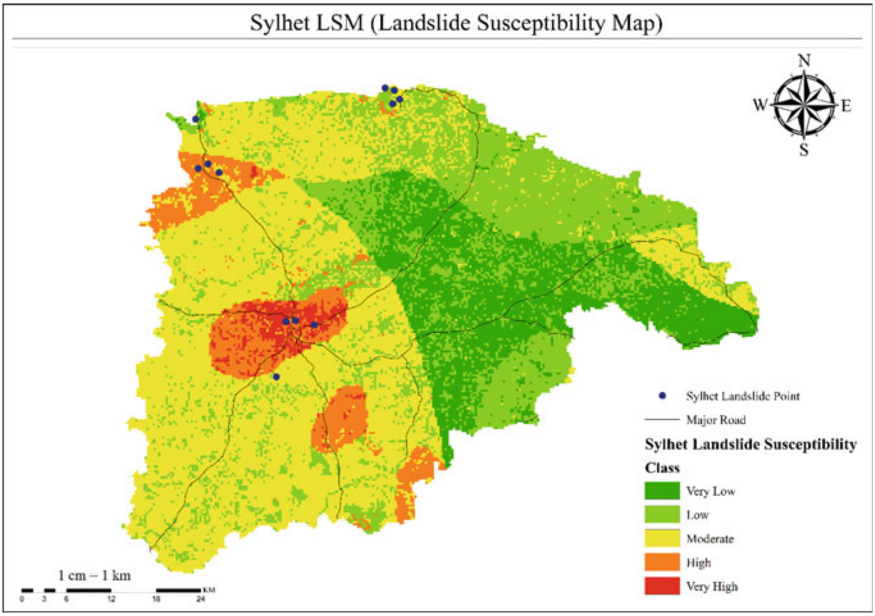

Fig. 23.5 Landslide susceptibility map (Sylhet)

Massive hill cutting in Sylhet has increased the risk of landslides (Islam et al. 2013). The problem is exacerbated by widespread hill damage brought on by housing firms breaking anti-hill cutting rules and misunderstanding the environmental effects. With its smaller land area and higher population density, Sylhet faces a more concentrated impact of land-use changes, deforestation, and construction activities that increase the risk of landslides. On the other hand, Rangamati has a higher percentage of villages with 'High' and 'Very High' ranges that are susceptible to landslides, and a higher number of people reside in these high-risk areas (Fig. 23.6).

Urbanization, forest conversion, uncontrolled hill cutting, and home-building on unstable slopes all increase the risk of landslides in hilly areas (Ahmed 2021). Especially in urbanized hill settlements, flash floods can be exacerbated by heavy monsoon rainfall. Furthermore, the topographical differences in these districts make it inherently more susceptible to landslides, especially during heavy rainfall. The statistics indicate the pronounced disparities in landslide susceptibility, highlighting the importance of considering geographical factors in disaster risk assessment and management.

The percentage of sensitive places varies according to the circumstances and FR factors in Sylhet and Rangamati. According to (Table 23.4), Rangamati has a high landslide vulnerability due to soil type, LULC, and TWI factors. The most vulnerable locations to landslides are those with vegetation to built-up LULC transition types, while the worst-affected industries include primary economic activities like fishing and jhum farming (Abedin et al. 2020). Meanwhile, lithology, LULC, and rainfall are

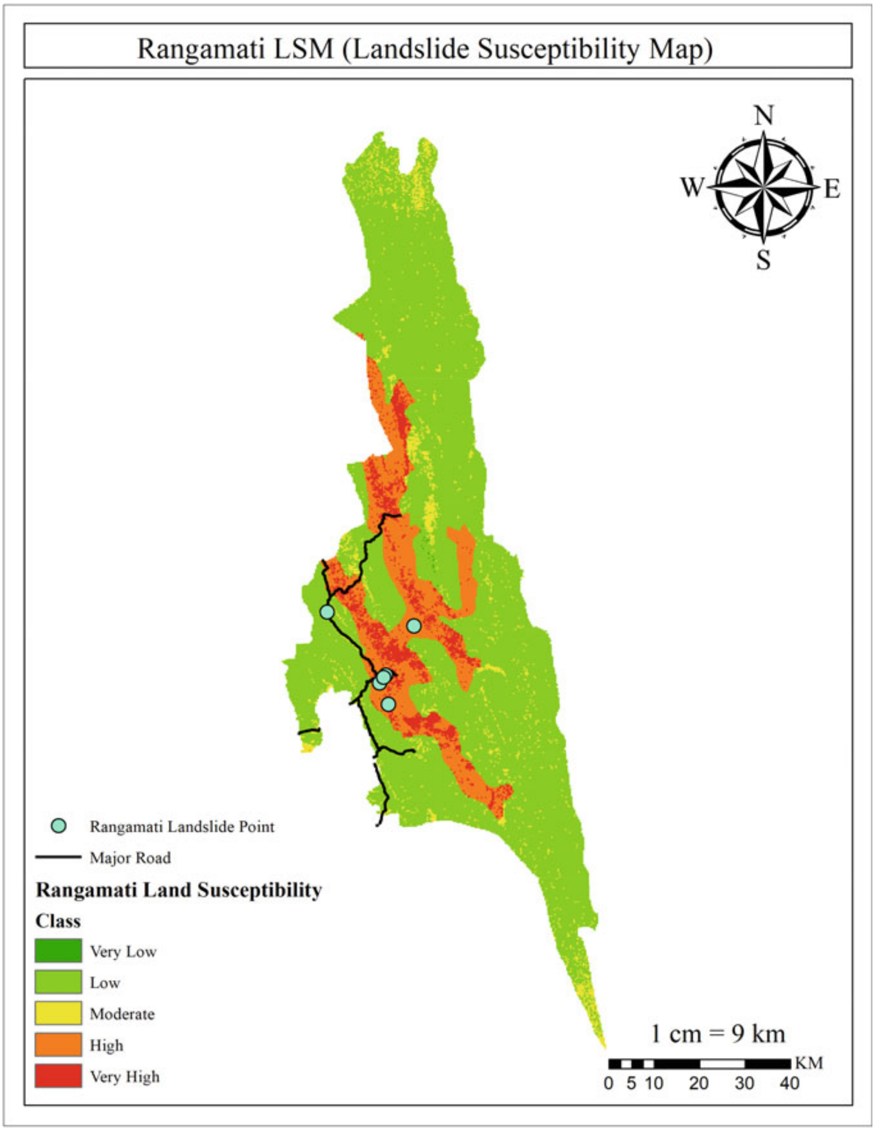

Fig. 23.6 Landslide susceptibility map (Rangamati)

major definers for the highly susceptible areas in Sylhet. The Surma River's discharge pattern is altering in tandem with the rainfall patterns in the northeastern region of Bangladesh which is an influential reason for disasters like floods, landslides, and so on (Akter et al. 2019). In Sylhet, the high landslide-prone zones are around 300 km^2 or nearly 10% of the total area; in Rangamati, the size is above 1000 km^2.

Table 23.4 FR ranking of factors between two regions

Parameter	Sylhet FR	Ranking	Rangamati FR	Ranking
LULC	15.77 (21.12%)	2	12.49 (31.05%)	1
Elevation	1.88 (2.52%)	9	1.88 (4.67%)	8
Slope (in degree)	6.33 (8.48%)	4	3.30 (8.2%)	7
TWI	3.21 (4.3%)	6	4.90 (12.18%)	2
Rainfall (mm)	7.40 (9.91%)	3	3.93 (9.77%)	5
Lithology	30.65 (41.04%)	1	1.34 (3.33%)	9
Soil type	2.06 (2.76%)	8	4.62 (11.48%)	3
NDVI	5.00 (6.70%)	5	4.40 (10.94%)	4
Distance from road	(3.19%)	7	3.37 (8.38%)	6

Table 23.5 Landslide susceptibility zone

Ranges	Sylhet villages	Rangamati villages	Sylhet population	Rangamati population	Sylhet area (km^2)	Rangamati area (km^2)
Very Low	473 (13.89%)	1 (0.07%)	495,349 (15.66%)	363 (0.07%)	588.44 (17.23%)	2.14 (0.04%)
Low	797 (23.4%)	1115 (73.6%)	820,129 (25.92%)	367,219 (71.24%)	999.21 (29.26%)	4363.79 (75.72%)
Moderate	1713 (50.29%)	81 (5.35%)	1,466,157 (46.35%)	27,620 (5.36%)	1505.10 (44.07%)	317.85 (5.52%)
High	311 (9.13%)	225 (14.85%)	285,510 (9.03%)	86,093 (16.7%)	257.77 (7.55%)	787.56 (13.67%)
Very High	112 (3.29%)	93 (6.14%)	96,348 (3.05%)	34,159 (6.63%)	64.48 (1.89%)	291.67 (5.06%)

Source Directorate General of Family Planning, MIS Unit (2014)

Roughly twenty villages in Sylhet and ten in Rangamati are located in the risk zones (Table 23.5).

To integrate policies and deliver services, the LSM offers comprehensive information on the people and locations that are vulnerable to landslides.

23.4 Discussion

This study provides important insights into landslide susceptibility and risk assessment in Bangladesh's Sylhet and Rangamati hilly regions using geostatistical and geospatial modeling techniques. The results highlight key differences in landslide causative factors between the two regions, with implications for targeted risk mitigation strategies.

In Sylhet, the FR analysis identified built-up areas, crop lands, lithology, rainfall, slope, and proximity to roads as key factors influencing landslide occurrence. Built-up areas exhibited the highest FR value (4.21), indicating significantly increased landslide susceptibility from urbanization, land use changes, and anthropogenic activities like deforestation and unplanned construction (Han et al. 2019a, b; Rahman et al. 2013). Rahman et al. (2013) noted that rapid and uncontrolled urban growth on slopes overlooking the Surma River basin escalates landslide risks in Sylhet City. Crop lands also contribute to landslides by replacing natural vegetation, disrupting drainage patterns, and increasing surface runoff (Quevedo et al. 2023). Specific lithological formations like cretaceous sedimentary rocks (FR 4.10) further increase susceptibility in Sylhet (Rabby and Li 2019). Areas of high rainfall, steep slopes, and proximity to roads likewise raise landslide hazards. These findings align with prior research on landslide conditioning factors in Bangladesh (Jebur et al. 2014; Kirschbaum et al. 2015).

In contrast, Rangamati's landslide susceptibility is strongly influenced by flooded vegetation, water, clay soils, slope, and road proximity. Flooded vegetation showed the highest FR (9.27), reflecting increased instability from soil saturation, loss of root cohesion, and altered drainage (Mirus et al. 2017). Water bodies also destabilize slopes, especially on steep terrain (FR 2.32) (Dahal and Hasegawa 2008). Heavy rainfall further elevates pore water pressure and reduces shear strength, making Rangamati's wet, vegetated slopes more prone to failure (Kirschbaum et al. 2015). Clay content is another critical factor, with clay soils exhibiting a high landslide correlation (85.71%) and an FR of 4.44. Louati et al. (2023) noted that clayey soils have higher moisture retention, lower permeability, and increased risk of sliding. Besides topographical and hydrological factors, proximity to roads remained influential in Rangamati like Sylhet.

The comparative FR analysis thus highlights the distinct landslide causation patterns based on the unique geographical settings of each region. While some common factors like roads exist, region-specific elements like lithology in Sylhet and flooded vegetation in Rangamati are major determinants of susceptibility. Integrating these differences is vital for targeted risk management (Reichenbach et al. 2014; Kirschbaum et al. 2015). Structural measures like retaining walls and improved drainage infrastructure in built-up areas can mitigate landslide impacts in Sylhet City (Rahman 2013). In Rangamati, restoring natural vegetation, avoiding developments on unstable clayey slopes, and regulating anthropogenic changes to hydrology are priority interventions (Mirus et al. 2017). Petley (2012) noted that susceptibility models should guide context-specific mitigation strategies.

The landslide susceptibility maps generated using the FR model also showcase the spatial patterns of landslide vulnerability across Sylhet and Rangamati. In Sylhet, the moderate risk zone covers the highest share of villages (50.29%) and population (46.35%), clustered around Sylhet City and other urbanized areas. In Rangamati, villages (73.60%) and people (71.24%) are predominantly concentrated in low landslide susceptibility areas, with the high risk zone accounting for 20.99% of villages and 22.46% of the population. These maps provide actionable information to local authorities for targeted disaster risk reduction planning based on vulnerability levels (Guzzetti et al. 2012).

Several limitations of this study provide avenues for future research. First, the analysis considered only past landslide locations. Using satellite data could strengthen it by integrating landslide triggering factors like rainfall thresholds (Kirschbaum et al. 2015; Petley 2012). Second, the FR model could include more landslide conditioning factors like geology and curvatures (Jebur et al. 2014). Lastly, different modeling techniques like logistic regression and machine learning can be used alongside FR for comparison and validation (Khosravi et al. 2018; Jebur et al. 2014). Nonetheless, this study delivers valuable insights into landslide susceptibility patterns in two major hilly regions of Bangladesh using robust geospatial analytics. The findings can guide evidence-based policies for landslide risk reduction and sustainable development.

23.5 Conclusion

This chapter delves into the complex realm of landslide susceptibility, with a focus on the various factors that influence this natural hazard, particularly in the Sylhet and Rangamati districts of Bangladesh. The analysis considers nine influential factors: LULC, elevation, slope, TWI, precipitation, lithology, soil type, NDVI, and distance from roads. By employing the FR model, the chapter provides valuable insights into the factors that shape landslide susceptibility in these regions.

The findings reveal that both regions are prone to landslides, but the underlying causes differ significantly. In Sylhet, susceptibility is tied to urbanization, land-use changes, and features such as 'Built-up Area' and 'Crop Land.' Conversely, Rangamati's susceptibility is largely due to elements like 'Flooded Vegetation' and 'Water,' which are influenced by unique topographical and environmental features, among other factors. Additionally, both regions' landslide susceptibility is influenced to varying degrees by elevation, slope, heavy rainfall, lithology, TWI, soil type, NDVI, and proximity to roads.

A comparative analysis between Sylhet and Rangamati underscores the importance of geographical and environmental factors in determining landslide susceptibility. Factors such as concentrated urbanization and deforestation in Sylhet, and unique topographical features in Rangamati, inherently increase their susceptibility to landslides. The Landslide Susceptibility Map (LSM) indicates that 18.73% of Rangamati's areas and 9.44% of Sylhet's areas are classified as highly to extremely susceptible to landslides.

This chapter plays a crucial role in identifying areas prone to landslides, enabling a swift determination of which regions are more susceptible to various factors. For instance, the Sylhet region is more vulnerable to changes in land use and urbanization, while Rangamati is more susceptible due to its topography. The comprehensive analysis provided in this chapter allows for a targeted approach to understanding the factors contributing to vulnerability in different regions. By pinpointing the specific challenges each region faces, we can devise effective strategies and take necessary measures to minimize landslide risks. This organized approach ensures a more effective and appropriate response to the specific vulnerabilities caused by different geographical and environmental conditions.

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