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Climate Change Induced Landslide Susceptibility Assessment - for Aiding Climate Resilient Planning for Road Infrastructure: A Case Study in Rangamati District, Chittagong Hill Tracts, Bangladesh

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Abstract. Climate change induced extreme hydro-meteorological conditions have increased the prevalence of landslides in the hilly and geologically fragile region of Chittagong Hill Tract districts (including Rangamati) in Bangladesh. These landslides have attributed to significant damages to transportation infrastructures such as roads and bridge. In this study, we investigated the susceptibility of landslides due to extreme rainfall events under different climate change scenarios in Rangamati district. We developed high-resolution 1km x 1km downscaled extreme rainfall projections under RCP 4.5 and RCP 8.5 scenarios for baseline period 1976-2005 and for future time horizons 2030s, 2050s, and 2080s. Based on these extreme rainfall scenarios, the combination of the Frequency Ratio (FR) and Analytical Hierarchy Process (AHP) techniques were applied to map and analyse the landslide susceptibility maps. Nine multi-variate factors contributing to the landslides were considered including terrain slope, aspect, elevation, lithology, soil, distance from the lineaments, distance from the stream, land use and mean annual rainfall in four different time periods for scenario RCPs. Further, an Area Under the Curve (AUC) approach was used to evaluate the quality of the model A total of seven landslide susceptibility maps were developed and classified into five susceptible classes. The models were validated using the Receiver Operating Characteristic curve (ROC) approach, which showed a satisfactory result of 80-86 percent accuracy.

1. Introduction

In 2017, a landslide in Rangamati district caused severe damage and degraded the region's geomorphology, increasing the danger of future slope failure. The risk of slope failure has been further exacerbated due to the extreme rainfall events caused by climate change. We developed high-resolution 1km x 1km downscaled extreme rainfall projections under selected extreme GCMs from the Coupled Model Inter-comparison Project Phase 5 (CMIP5), Global Climate Models (GCMs), with representative concentration pathways (RCP 4.5 and RCP 8.5) scenarios for baseline period 1976-2005 and future time horizons 2030s, 2050s and 2080s. Based on these extreme rainfall scenarios, we modelled and mapped landslide susceptibility by merging the Frequency Ratio (FR) and Analytical Hierarchy Process (AHP) techniques. The developed approach applies Geographic Information System (GIS) as a tool along with open data to develop the landslide susceptibility models. The study aims to obtain a better understanding of the controlling and triggering factors of landslides and the mutual relationships among controlling, triggering factors and the spatial distribution of landslide susceptibility level for current climate condition and future time horizons, i.e., the 2030s, 2050s and 2080s with RCP 4.5 and RCP 8.5 scenarios.

1.1. Description of the study area

Rangamati district is situated at the South-eastern side of Bangladesh. Rangamati is located in between latitudes of 22°27′ and 23°44′ N, and the longitudes of 91°56′ and 92° 33′ E. Rangamati district encompasses 6116.11 km^2 which is considered to be the biggest district in the country, in relation to land size [1]. Geologically, the study area is part of folded belt area and regionally is dominated by two major geological group formations: Surma Group and Tipam Group [2]. Rangamati district (zila) consists of 10 sub-district (upazila, Figure 1). The rural roads in Bangladesh are divided into three types i.e., upazila, union, and village roads, and the spatial distribution of rural roads are shown in Figure 1. There are two types of pavements for rural roads in Rangamati District, 4310.27km of earthen roads and 629.92km of paved roads with grand total of 4940.19km [3].

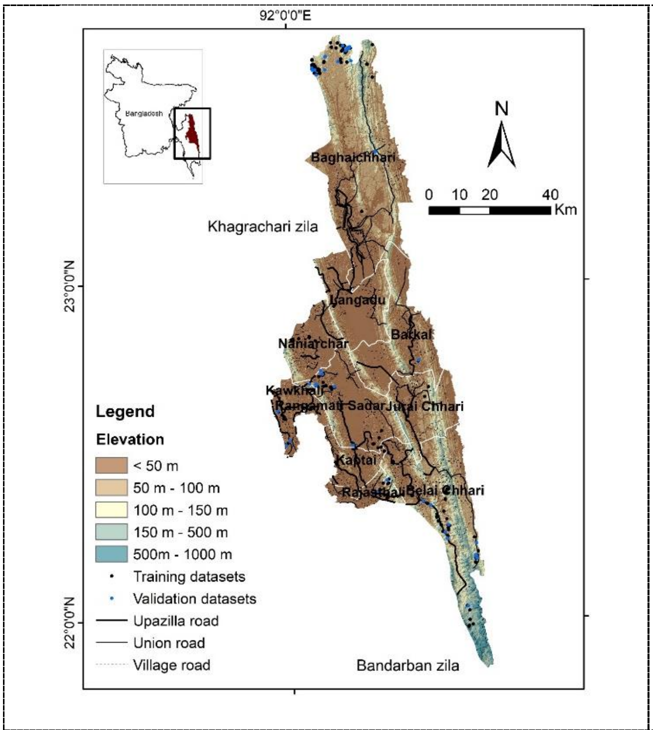

Figure 1. The digital map shows the location, topography and distribution of rural roads of study area.

1.2. General description of the landslides in Rangamati District

The majority of landslides in Bangladesh occurred during the monsoon season as a result of heavy rainfall (> 40 mm/day) in a short period of time (2–7 days, [4]). Based on [1], ± 40% of landslide type in Rangamati was the debris flow. [2] mentioned that there were two dominant types of landslides in this area, which were slide and flow. Based on [1], 60 percent of the landslide's size in Rangamati district was 100 m^2. In accordance with Hungr's categorization [5], most of the landslide types in Rangamati district can be categorized into slides and flows.

2. Datasets and Method

2.1. Landslide inventory map

The preparation of inventory map is an important part for landslide susceptibility mapping. The landslide inventory map aids in determining the link among previous landslide occurrences and various controlling and triggering parameters. In this study, the observations and digitation of landslide areas were collected through visual interpretations of existing landslides on high resolution satellite imagery, using Google Earth images and references from available studies including [1] and [6].

The change of morphological surface and the presence of debris were considered to identify landslides. 237 landslides were mapped in study area. The distribution of landslides in landslide inventory was randomly divided into two subsets, the training set area (80 percent) and the test/validation set area (20 percent) as suggested by [7], Figure 3. The landslide size in study area varied from 163 m^2 to 0.04 km^2. The existing landslides mapped through visual interpretation covered an area of about 0.62 km^2.

2.2. Extreme rainfalls projections under climate change scenarios

The process of proposed climate impact modeling for identification of extreme events at the study area comprise of six methodological stage as shown in the Figure 2.

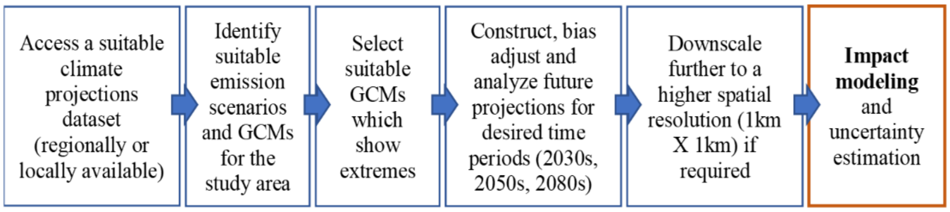

Figure 2. Schematic of climate impact modeling for assessing risk from extreme landslides at the watershed scale using downscaled GCMs.

Future climate scenarios for 2030 (averaging 2016-2045), 2050 (averaging 2036-2065), and 2080 (averaging 2066-2095) are developed in the research area based on present climate (rainfall and mean temperature from 1976-2005) across the same study region during the wet season. Because landslides are more common during the rainy (monsoon) season, it is found to be an excellent time to pick suitable GCMs. The pattern of rainfall projections under different future time horizon and climate change scenarios are shown in Figure 3.

2.3. Landslide controlling and triggering factor maps

With the combination of the aforementioned work of literatures and the nature of the study area, nine different thematic layers together with terrain slope (°), distance from lineaments (m), distance from streams (m), elevation (m), lithology, soil, land use, aspect, and mean annual rainfall in different climate change scenarios were taken into consideration. The landslide controlling and triggering factor's maps were rasterized with 12.5 m x 12.5 m pixels and each raster was reclassified into appropriate thematic classes.

2.4. Frequency ratio method

Frequency ratio (FR) values represent the relationship between landslide event and the classes of every single controlling and triggering parameters. The landslide susceptibility can be evaluated from the spatial relationship between the controlling, triggering factors and landslides occurrences. The greater the FR ratio, the stronger the link among the landslide causing parameter and the incidence of the landslide [8]. The frequency ratio value is computed like described in the following formula:

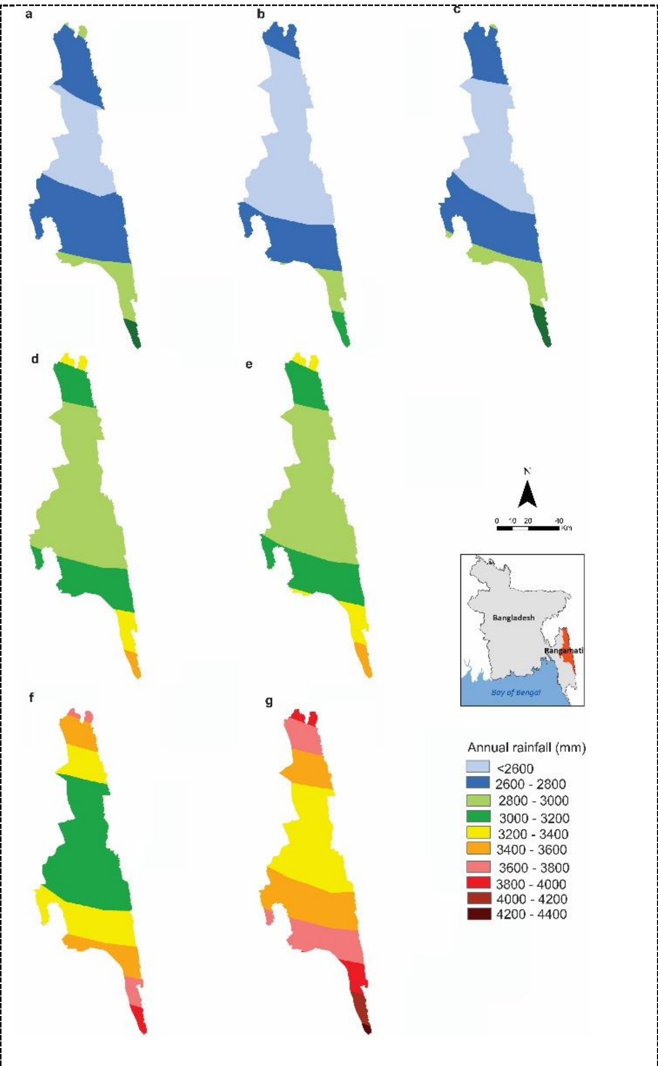

Figure 3. Mean annual rainfall for baseline (1976-2005, a), future time horizon 2030s with RCP 4.5 (b) RCP 8.5 (c). Time horizon 2050s, with RCP 4.5 (d) and 8.5 (e). Time horizon 2080s, with RCP 4.5 (f) and 8.5 (g).

$$FRi = \frac{Ncell\ (Si)/Ncell\ (Ni)}{\sum Ncell\ (Si)/\sum Ncell\ (Ni)}$$

where Ncell (Si) is the amount of grid cells in class I that have been recognized as landslides and Ncell (Ni) is the total amount of grid cells in class I in the area. The overall amount of grid cells identified as landslides in the entire region is ∑Ncell (Si), whereas the overall amount of grid cells in the entire region is ∑Ncell (Ni).

2.5. Analytical and hierarchy process method

The analytical hierarchy process avoids the difficulties associated with random weights and ratings systems by allowing judgment to influence relative importance features or weights rather than randomly assigning those features [9]. In this study, the AHP method was used for creating a map of landslide susceptibility zonation.

The AHP technique used the consistency ratio (CR), that is a ratio between the matrix's consistency index and the random index. CR stands for the likelihood that the matrix judgments were created at random, as follows:

$$CR = \frac{\mathrm{CI}}{\mathrm{RI}}$$

based on the arrangement of Malczewski's matrix [10], RI is the average of the resultant consistency index, and CI is the consistency index.

2.6. Integrated weighted index

There are three important processess in the integrated weighted index method. The first step is to determine the relative importance of landslide controlling and triggering parameters by using AHP technique (Figure 4). The second step is by describing the mutual relationship between the location of landslide and the controlling & triggering parameters using the FR method. The third step, by using the weighted overlay tool in GIS environment, the landslide susceptibility maps were created. By combining the FR and AHP techniques, the integrated weighted model examined the connection among the conditioning parameters as well as the effect of each landslide conditioning parameter on landslide frequency (Figure 4). The following formula can be used to obtain the integrated weighted index:

$$I = \sum_{i}^{m} (\mathrm{W}i \text{ x } \mathrm{FR}i)$$

where m is the number of controlling and triggering factors, Wi denotes the weight assigned to each conditioning factor using the AHP method, and FRi denotes the FR value assigned to the conditioning factor using the FR method.

2.7. Validation method

Validation of the model predictions is critical for landslide susceptibility mapping. The receiver operating characteristics curve (ROC) approach [11] was adopted to evaluate the performance of the integrated weighted index model. The ROC curve is a plot of the model prediction's sensitivity (percent of true positives) against the complement of its specificity (proportion of false positives). The true positive rate (TPR) was plotted in contradiction of the false positive rate (FPR) on the ROC curve, with TPR on the y-axis and FPR on the x-axis (Figure 6). The area under ROC curve AUC ranged between 0.5 and 1.0, where value of 1.0 suggested that the model performed perfectly, but a value near 0.5 indicated that the model performed poorly.

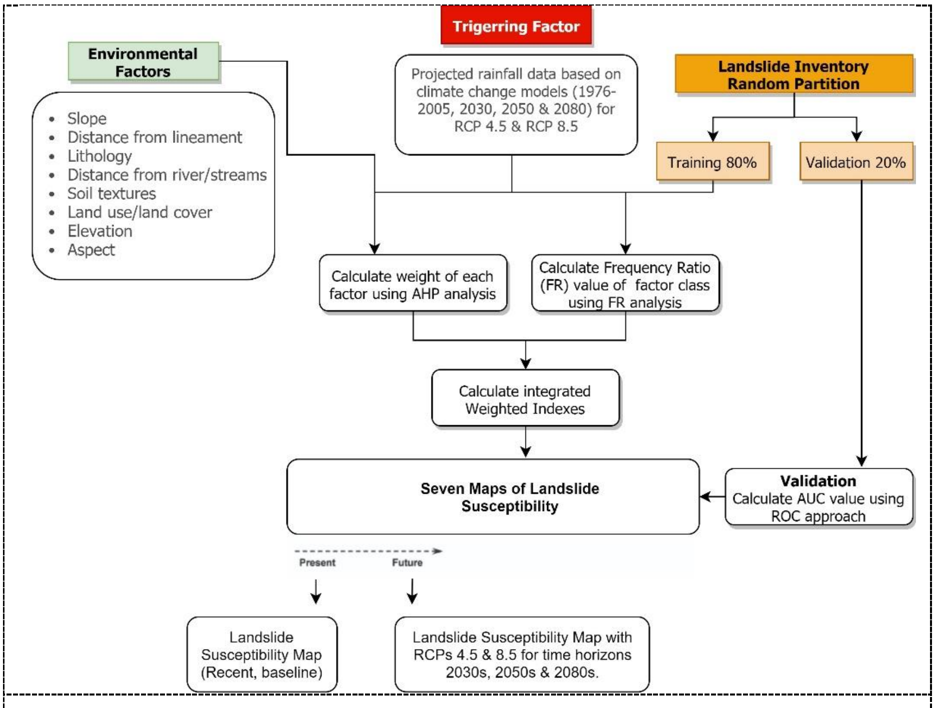

Figure 4. The flow chart depicted the study approaches.

3. Results

3.1. Landslide susceptibility maps

Based on the pairwise comparison matrix of AHP, the weight of slope was the highest (0.205 suggesting that slope has the greatest effect on the frequency of landslides, the weight of distance from lineaments and rainfall the second and third highest (0.198 and 0.174, respectively), followed by lithology (0.134), soil (0.067), distance from streams (0.061) and finally the weights of aspect, elevation, and land use were the lowest (0.054), This suggested that these three parameters had the lowest impact on the prevalence of the landslide. The consistency ratio (CR) of the matrix of paired comparisons between the 9 controlling and triggering factors in susceptibility map is 0.012. A consistency ratio of 0.10 or less is a reasonable degree of consistency [12].

Based on FR analysis, the highest frequency of landslide occurred on the slope class 30° to 60° (2.216), distance from lineaments class <500 m (1.075), mean annual rainfall class 3800-3850 (7.734), Lithological type is the yellowish-brown to brown, fine to medium grained pebbly and cross-bedded sandstone (2.503), soil type is the deep brown soil (3.307), distance from stream class <500 m (1.154) the east terrain aspect (2.410), elevation range 100-150 m (2.317), and the land use type is trees (1.137). With the help of weighted overlay tools in GIS environment, a total of seven landslide susceptibility maps were generated from two RCP 4.5 and RCP 8.5 for time horizons 2030s, 2050s, and 2080s and baseline (1976-2005). The landslide susceptibility maps were classified into five susceptible classes using the natural breaks classification in GIS environment *viz.* very low , low, moderate, high, and very high (Figure 5). The total area of landslide susceptibility was quantified by calculating the area geometry in GIS environment. Based on the acquired landslide susceptibility maps, the area for each level of susceptibility in scenarios shows different values (Table 1). Based on RCP scenario 4.5 for time horizon 2030, 2050, and 2080, the very high and high susceptibility level zones, occupied approximately 42%, 49%, and 53 % of study area, respectively. The highest area value (3477 km^2) of the high to very high susceptibility level was achieved by the susceptibility map of RCP scenario 8.5 for time horizon 2080. Concerning the susceptibility map of RCP 4.5 and 8.5 for time horizon 2030, 2050, and 2080, most parts of high to very high-level susceptibility zones are mainly distributed in the North part of Baghaichhari Upazila, East part of Naniarchar, Kawkhali and Rangamati sadar Upazila, Northeast part of Kaptai Upazila, center, North, Southeast part of Belai Chhari Upazila, West part of Rajasthali and Jura Chhari upazila, East and North part of Barkal Upazila and the almost entire area of Rajasthali and Bella Charri upazila (only for time horizon 2080 with RCP 4.5 and 8.5 cases, Figure 5).

3.2. Validation of landslide susceptibility maps

A sample subset of 44 landslides were used as a validation subset from the total (237 landslides sample set) to validate the reliability of the landslide susceptibility model. To examine the integrated weighted index model's predictive accuracy, a validation dataset (i.e., 44 landslides) was used to to calculate predictions percentages. The AUC values for landslide susceptibility map (current climate and future projected scenarios) varied from 80 – 86%, which indicated a reliable predicting capability of the integrated weighted index model adopted for this study. Figure 6 showed two examples of ROC of landslide susceptibility map for time horizon 2080s with RCP 4.5 and RCP 8.5.

Table 1. The total area of landslide susceptibility in Rangamati district for current climate (baseline), future time horizons with different RCPs scenarios.

Susceptibility area	Baseline (km^2)	RCP 4.5 (km^2)			RCP 8.5 (km^2)		
	1976-2005	2030s	2050s	2080s	2030s	2050s	2080s
Very low	261	261	213	210	261	213	173
Low	533	529	405	384	526	403	330
Moderate	2511	2496	2241	2023	2483	2236	1668
High	1791	1808	2068	2116	1824	2061	2294
Very high	540	554	721	914	553	733	1183

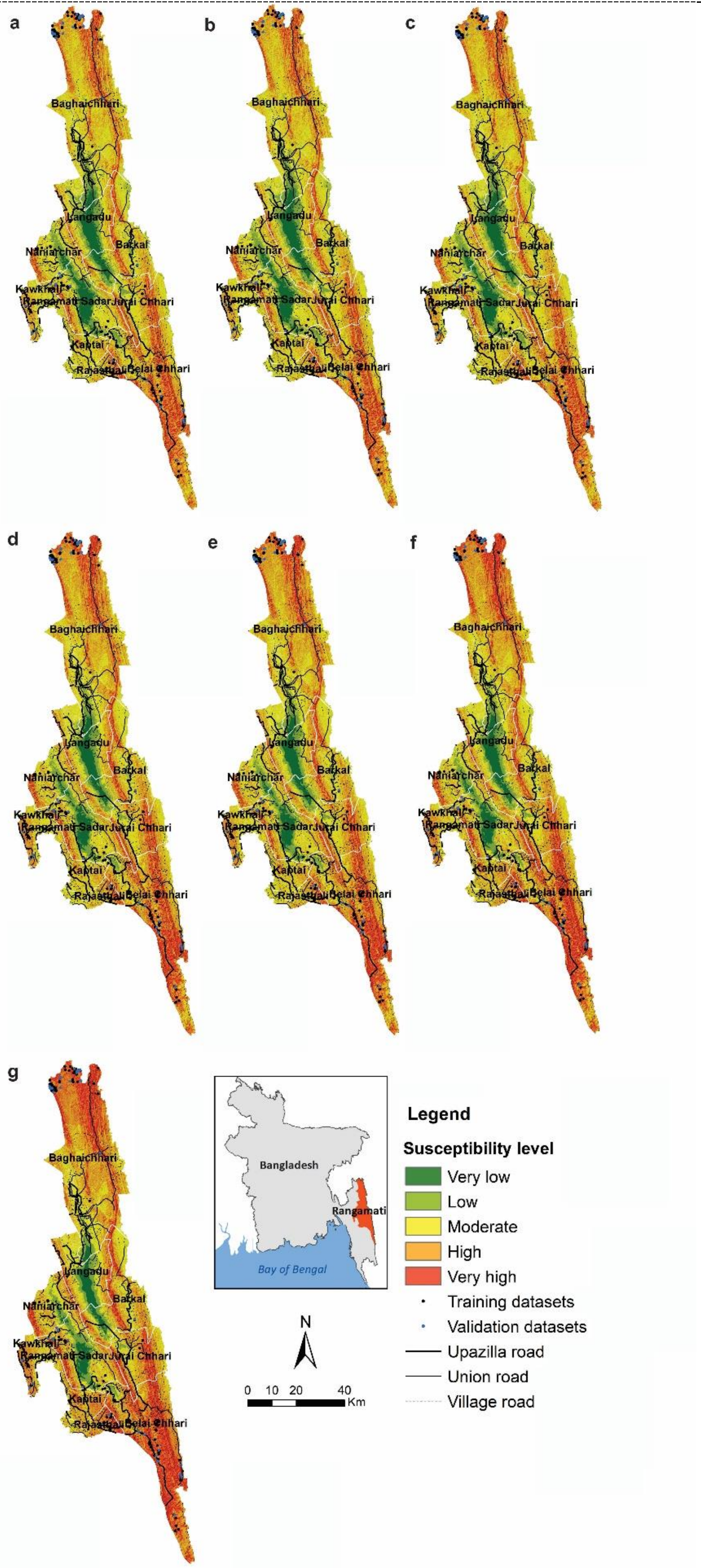

Figure 5. a) Recent landslide susceptibility map, projected landslide susceptibility map for time horizon 2030s, with RCP 4.5 (b) and 8.5 (c). Time horizon 2050s, with RCP 4.5 (d) and 8.5 (e). Time horizon 2080s, with RCP 4.5 (f) and 8.5 (g).

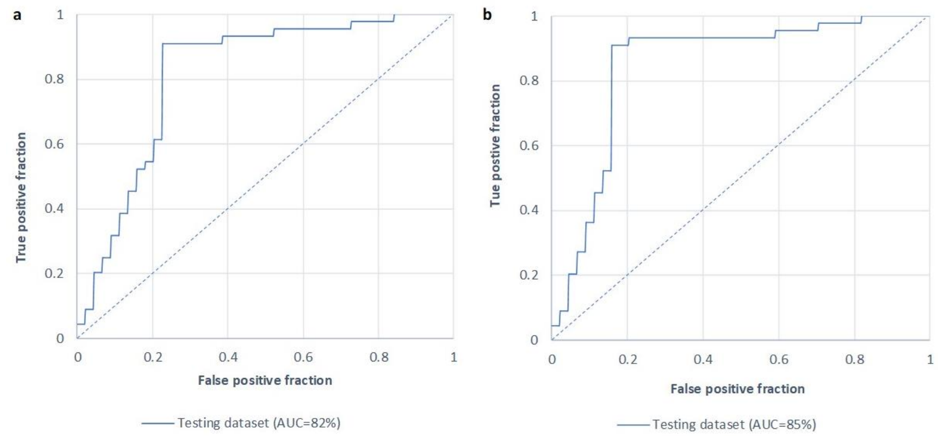

Figure 6. The integrated weighted index model's forecast effectiveness. Two examples of ROC of landslide susceptibility map for time horizon 2080s with RCP 4.5 (a) and RCP 8.5 (b).

4. Discussion

Compared to the landslide susceptible areas modelled for the current baseline climate conditions (1976-2005), the landslide susceptible areas are significantly increased in extreme rainfall conditions for the future climate change scenarios for both RCP 4.5 and RCP 8.5. Results revealed that the regions with "Very High" landslide susceptibility increased from 374km^2 to 643 km^2 in the 2080s. Thus, it is predicted that landslide susceptibility will increase in future time horizons (in 2030s, 2050s, and 2080s). RCP 8.5 showed larger susceptible areas than RCP 4.5 for the future time horizons, as RCP 8.5 models predicted heavier rainfall than RCP 4.5. In future periods, the southern part of Rangamati is likely to have higher landslide susceptibility area compared with the same under current condition. In particular, it is predicted that landslide susceptibility in the northern area would increase in the 2050s (2036-2065) and 2080s (2066-2095) in both RCP scenarios. In both scenarios, the landslide susceptible areas for 2080s were predicted to expand significantly to the area adjacent to Bella Charri upazila. In the case of future time horizon 2080 with RCP 8.5, significant landslide susceptibility was expected to occur at Baghaichhari Upazila.

The susceptibility map for time horizon 2080 with RCP 8.5 represents the worst-case scenario for the landslide. Although the majority of the study area (43-44%) was predicted to be located on "Moderate" susceptible to future landslides, (32%) was indeed on "High" susceptible category. The unsafe areas mentioned in the previous section, require immediate mitigation action. Reactivation of existing landslide sites and new landslide may occur particularly along lineaments. The findings revealed the dependability (indicated by the AUC value that showed a satisfactory result of 80 – 86 percent accuracy) and practicality of the integrated weighted index model in regional landslide susceptibility mapping.

Based on those results, it showed that under climate change scenarios, exposures to landslides would substantially increase for all rural roads in Rangamati district. Thus, the next step, further studies will be conducted in 2022. The overall maximum kilometers (km) of rural road networks exposed to landslide susceptibility levels under climate change scenarios will be analysed. A detailed landslide hazard assessment was planned for future studies, including landslide magnitudes analysis along representative road segments to better understand the landslide types and their physical processes (volume, flow direction, size, run out distance, & impact area of the landslide) to support designing the landslide mitigation measures.

Finally, the landslide susceptibility maps produced in the study is useful for planners and engineers for planning and designing roads and other infrastructures to obtain a better understanding of future climate-induced landslide and their potential impacts on road networks for planning new roads and rehabilitation/retrofitting of the existing roads in Rangamati district.

5. Conclusion

The landslide susceptibility modelling and mapping spatially locates the regions susceptible to landslides due to multi-variate factors under the extreme rainfall conditions for the current and projected future time horizons. Seven landslide susceptibility maps were developed representing scenarios for RCP 4.5 and RCP 8.5 for future time horizons 2030s, 2050s, and 2080s and the current (1976-2005) baseline period. The significant increase between 374km^2 to 643 km^2 in "Very High" landslide susceptible area between the baseline period and the long-term horizon in 2080 (for RCP 8.5 scenario) indicates that the extreme rainfall due to climate change will attribute to substantial increase in landslides at Rangamati district. Higher proportion of the land falling under "High" landslide susceptibility under future climate change scenarios also indicate limited available land for planning and development of road infrastructure. These landslide susceptibility models and maps enables decision making in planning of road infrastructure through relatively safer areas indicated by "Very Low", "Low" and/or "Moderate" susceptible areas. Planning, designing and construction of road infrastructure in the "Moderate" susceptible areas may require considerations of road design parameters to adapt and/or mitigate the impacts of landslide hazards. The "Moderate" susceptible areas may also be managed through climate adaptive measures including green-grey infrastructures such as incorporation of Nature based Solutions (NbS) along with engineering solutions. These landslide susceptibility maps will further support vulnerability assessment of rural roads in the district and identification of critical road segments for planning and implementing climate adaptation measures and activities to enhance the climate resilience of the road infrastructure in the district.

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