Proceedings of International Conference on Planning, Architecture and Civil Engineering, 12 - 14 October 2023,
Rajshahi University of Engineering & Technology, Rajshahi, Bangladesh

Paper ID: CE 0144

Soil Erosion Assessment in Rangamati District: Comparing Hydrological Conditions & Geospatial Data Before & After the 2017 Landslide Event

H. Moulik[1], M. Saleh[2], A. P. Bonna[3], T. I. Illin[4]

[1]Department of Water Resources Engineering, BUET, Bangladesh (1916012@wre.buet.ac.bd)
[2]Department of Water Resources Engineering, BUET, Bangladesh (2016002@wre.buet.ac.bd)
[3]Department of Water Resources Engineering, BUET, Bangladesh (1816004@wre.buet.ac.bd)
[4]Department of Water Resources Engineering, BUET, Bangladesh (1816018@wre.buet.ac.bd)

Abstract

Landslides are mostly caused by heavy rainfall, earthquake, volcanic eruption, etc. Despite being a naturally occurring phenomenon, man-made factors like deforestation, hill-cutting, etc. sometimes play a vital role. Being situated in a wind-risk area, Rangamati faces a massive amount of rainfall every year. The elevation, soil texture, and vegetation pattern of the area are quite different from other areas of Bangladesh. A significant landslide occurred in Rangamati on 12 June 2017. The following year, another similar incident took place in the same district. This study aims to determine the probable causes of the event by figuring out the changes in the considered parameters like rainfall, NDVI, and slope using GIS during the years 2013-2017. The changes in these factors afterward (2018-2022) are also observed to assess whether the current situation has deteriorated or not. RUSLE is used to find out the soil erosion caused by water or particularly rainfall. So, if the quantification of soil erosion can account for the landslide is another significant purpose of this study. Along with the background study, the post-analysis of the associated parameters will be of use to concerned authorities to take sustainable measures to prevent the calamity as well as alleviate the aftereffects.

Keywords: *Soil Erosion; Risk Factor; Geo-Spatial Data Comparison; Chattogram Hill Tracts; Spatio-Temporal Analysis.*

1 Introduction

Landslide disasters pose significant threats in various regions around the world. The major causes of Rangamati landslides were heavy rainfall (37%), hill morphology (26%), hill cutting (21%), deforestation (10%), and unplanned road construction (06%) (Sarwar & Muhibbullah, 2022.)

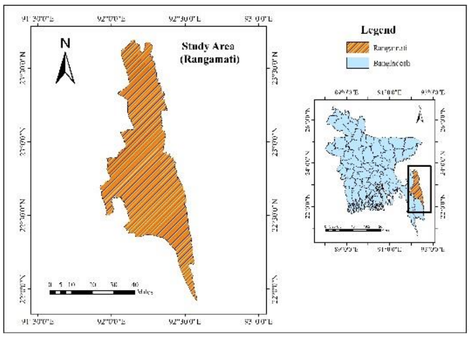


Figure 1. Location of the Study Area

This study utilizes comparative analysis of data from 2013-2017 and 2018-2022 to understand the pre- and post-landslide situation, identify potential causes, and evaluate changes in parameters such as rainfall patterns, vegetation indices and slope characteristics using Geographic Information System (GIS). The research employs the Revised Universal Soil Loss Equation (RUSLE) to assess if soil erosion can correspond to the landslides in the Rangamati district. RUSLE is an empirical equation that quantifies gross soil erosion mainly by water although the impact of vegetation, slope is incorporated within the equation. By applying this model, the investigation aims to analyze the extent of soil erosion in Rangamati over a specific period.

2 Methodology

The Revised Soil Loss Equation (RUSLE) is used for this study to determine the soil loss in Rangamati of Bangladesh. Five parameters are needed for the equation as input, and they are calculated with ArcGIS 10.8.

$$A\ (\text{ton/ha/year}) = R*K*LS*C*P \quad \text{(Renard et al., 1991)} \tag{1}$$

2.1 Calculation of the Factors for RUSLE

The calculation of each factor of the equation are explained in detail in the following sections.

2.1.1 Rainfall Erosivity Factor (R Factor)

The input data needed is Annual Rainfall (mm) for the equation.

$$R = 81.5 + 0.38*\text{Annual Average Precipitation (mm)} \quad \text{(Babu et al., 2004.)} \tag{2}$$

The rainfall data were collected from Earth Data, NASA. As the collected data was monthly average precipitation (mm) in raster format it was multiplied by 12 to get a fair assumption of the annual precipitation.

2.1.2 Soil Erodibility Factor (K Factor)

The digital soil map of the world was collected from FAO (Food and Agriculture Organization) Map Catalog for the soil type of the study area. Using the SWAT (Soil & Water Assessment Tool) 2012 database, soil type was determined. The K factor varies from 0.19 to 0.63 for loam depending on the pH & percentage of sand, silt and clay (David, 1988). As Rangamati mostly has loam, K was assumed to be 0.24 for the areas excluding water bodies. For water bodies, K=0.

2.1.3 Slope Length & Steepness Factor (LS Factor)

$$L=(m+1)\left(\frac{\lambda}{22.13}\right)^{m} \quad \text{(Pelton et al., 2012)} \tag{3}$$

$$S=\left(\frac{\sin(0.01745\theta}{0.09}\right)^{n} \quad \text{(Pelton et al., 2012)} \tag{4}$$

λ is the area of upland, m depends on soil's erosion susceptibility and is taken to be 0.4 in this study. L is the Slope length Factor & S is the Steepness Factor. θ is the slope in degree & n depends on the soil's erosion susceptibility and is taken to be 1.4. For the LS factor, Digital Elevation Model of each year is needed and was collected by taking more than 15000 points on the study area on Google Earth Pro. The points were interpolated using the IDW interpolation method and further slope, flow direction and flow accumulation raster files were created. The following equation was used in Raster Calculator to directly calculate the LS factor.

Power("flow accumulation"*[cell resolution]/22.13,0.4)*Power(Sin("slope in degree"*0.01745))/0.09,1.4)*1.4 (5)

2.1.4 Cover Management Factor (C Factor)

For the C factor, satellite images from USGS Earth Explorer were collected. Landsat 8-9 OLI/TIRS C2 L2 images for 2013-2022 were collected. The C factor was computed from NDVI (Normalized Difference Vegetation Index) values using the formula of as the study area is under a tropical climate and faces a huge rainfall every year.

$$NDVI=\frac{NIR-Red}{NIR+Red} \tag{6}$$

$$C= \frac{1-NDVI}{2} \quad \text{(Durigon et al., 2014)} \tag{7}$$

2.1.5 Conservation Practice Factor (P Factor)

This factor depends on the agricultural practices of the concerned area. As Rangamati does not practice any specialized techniques for soil conservation like Contour Farming, Terracing, Stripped Cropping, etc., the value of P factor was taken to be 1 for the entire region for a conservative estimate.

2.2 Change in Raw Parameters Through the Years

NDVI, Slope & Rainfall were the raw data used for calculating the factors for RUSLE. So, to examine the impact of these parameters, change in them were tabulated and observed.

2.2.1 Change in NDVI

The NDVI of each year was reclassified (Rafa et al., 2021) indicating the land coverage type. The following classification showed in Table 1 is an unsupervised one.

Table 1. NDVI Classification

NDVI Range	-1-0.2	0.2-0.35	0.35-0.5	0.5-1
Type of Land Coverage	Others	Sparse Vegetation	Medium Vegetation	Dense Vegetation

Then the percentage of area that covers the specific type of land coverage according to the classification, was calculated by finding out the corresponding type's number of cells and the total number of cells using MS Excel & further plotted for 2013-2022 (Figure 2).

2.2.2 Change in Slope

The slope was reclassified (Sinshaw et al., 2021) in Table 2 for each year to represent the erosion susceptibility.

Table 2. Slope Classification

Slope Range (%)	0-5	5-10	10-15	15-20	>20
Erosion Susceptibility	Very Low	Low	Moderate	High	Very High

Afterward, the percentage of area that is susceptible to erosion of a kind was computed and plotted for 2013-2020 (Figure 3). As the slope was calculated using DEM (Digital Elevation Model) prepared from Google Earth Pro, the slope of 2021-2022 could not be calculated due to data unavailability.

2.2.3 Change in Rainfall

To check the change in rainfall throughout the years, average and maximum rainfall from 2013-2020 were tabulated and observed graphically (Figure 4).

2.3 Calculation of Mean Soil Erosion

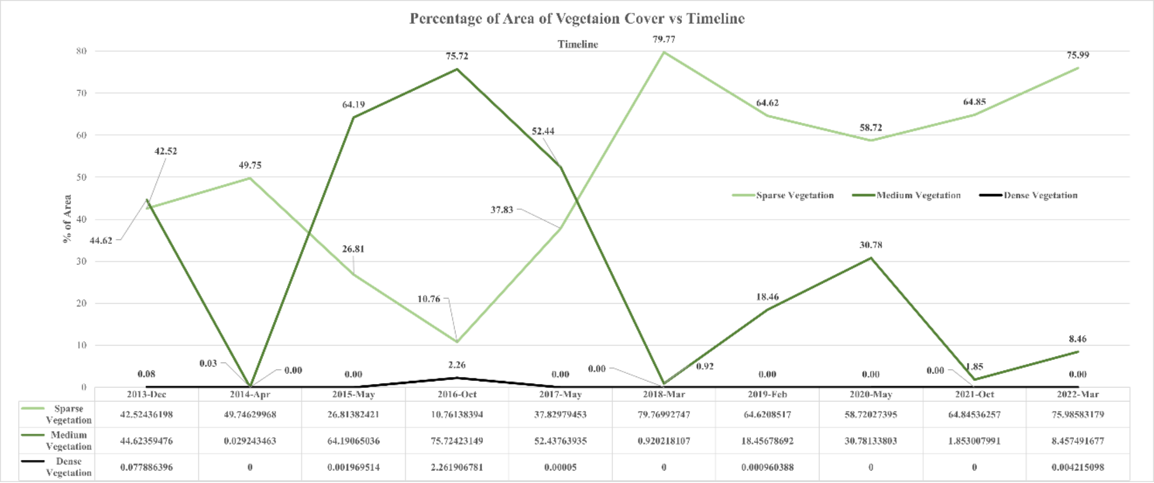
The soil erosion raster files found using RUSLE for 2013-2022 had different cell values representing the erosion in a particular cell. To observe the pattern of change with year, a single mean value for a particular year was calculated and the change was observed graphically (Figure 6). A point file was generated from the raster and transferring the tabular data of that point shape file to MS Excel, the mean value was calculated for a year.

3 Results & Discussion

The vegetation cover type and erosion susceptibility were interpreted using NDVI and Slope, respectively. The percentage of sparse vegetation was in an increasing trend from 2016 (10.76%) to 2017 (37.83%) and it went up to 79.77% in 2018 but the medium vegetation was exactly the opposite: 75.72% in 2016, 52.44% in 2017, 0.92% in 2018. Dense vegetation was about 2.26% in 2016 but it decreased to nearly 0% in 2017, 2018 & even ahead of that. This trend might have influenced the landslide. After 2018 the medium vegetation showed an increasing rate, respectively 18.46% and 30.78% in 2019 and 2020 but it jumped to 1.85% in 2021 (Figure 2).

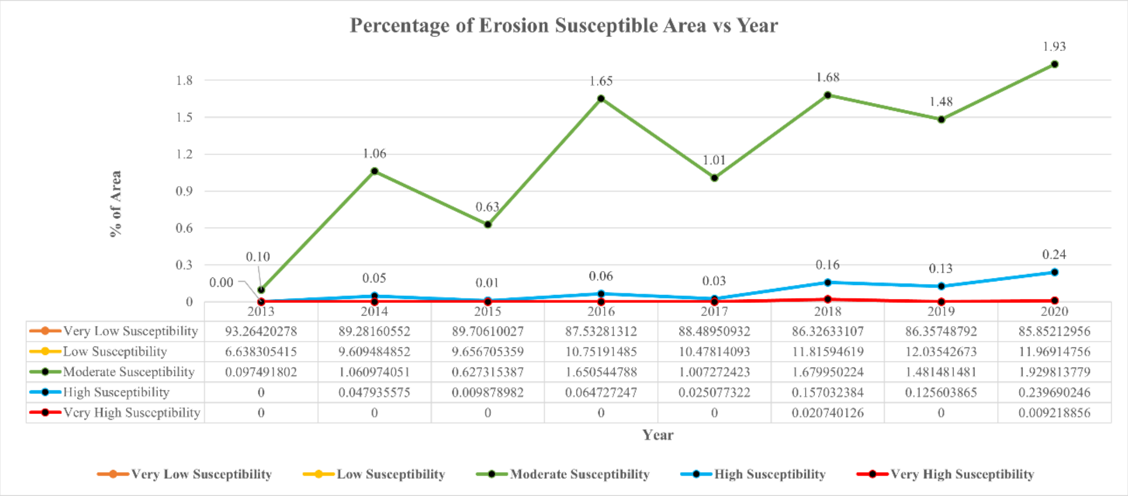
The erosion susceptibility fluctuated a lot throughout the years. As the slope was calculated for the month of December for every year, the slope of 2016 can account for the erosion in 2017 because in December 2016, 1.65% of the area as moderately susceptible and 0.06% area was highly susceptible to erosion. An alarming situation can be observed in the values of 2020 since 1.93% of the area was moderately susceptible and 0.24% of the area was highly susceptible (Figure 3).

The average rainfall from 2013 to 2015 was almost the same but it showed an increasing trend from 2016 to 2020. Although the maximum rainfall suddenly increased in 2017 in comparison to 2016. This could have been a critical reason behind the event as well (Figure 4).



	2013-Dec	2014-Apr	2015-May	2016-Oct	2017-May	2018-Mar	2019-Feb	2020-May	2021-Oct	2022-Mar
Sparse Vegetation	42.52436198	49.74629968	26.81382421	10.76138394	37.82979453	79.76992747	64.6208517	58.72027395	64.84536257	75.98583179
Medium Vegetation	44.62359476	0.029243463	64.19065036	75.72423149	52.43763935	0.920218107	18.45678692	30.78133803	1.853007991	8.457491677
Dense Vegetation	0.077886396	0	0.001969514	2.261906781	0.00005	0	0.000960388	0	0	0.004215098

Figure 2. Change in Vegetation Cover from 2013 to 2022



	2013	2014	2015	2016	2017	2018	2019	2020
Very Low Susceptibility	93.26420278	89.28160552	89.70610027	87.53281312	88.48950932	86.32633107	86.35748792	85.85212956
Low Susceptibility	6.638305415	9.609484852	9.656705359	10.75191485	10.47814093	11.81594619	12.03542673	11.96914756
Moderate Susceptibility	0.097491802	1.060974051	0.627315387	1.650544788	1.007272423	1.679950224	1.481481481	1.929813779
High Susceptibility	0	0.047935575	0.009878982	0.064727247	0.025077322	0.157032384	0.125603865	0.239690246
Very High Susceptibility	0	0	0	0	0	0.020740126	0	0.009218856

Figure 3. Change in Percentage of Erosion Susceptible Areas from 2013 to 2020

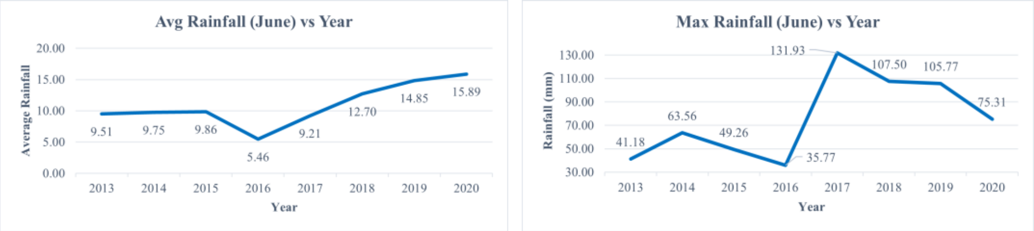


Figure 4. Change in Average & Maximum Rainfall from 2013 to 2020

The five factors of RUSLE were calculated for 2013-2022. Due to the data unavailability, the DEM of 2020 was used for calculation purposes in 2021 & 2022. K factor for all the years was taken to be the same. The primary objective was to compute soil erosion for the month of June for each year, but the Landsat data for June was not available for every year. Therefore, the C factor was calculated for different months of the year to get a fair assumption of the soil erosion. The initial anticipation was that the soil erosion computed from RUSLE will account for the landslide, but it did not. Two consecutive landslides occurred in 2017 & 2018, agreeing to which, the value of soil erosion should have been the most in these two years among all the years from 2013 to 2022.

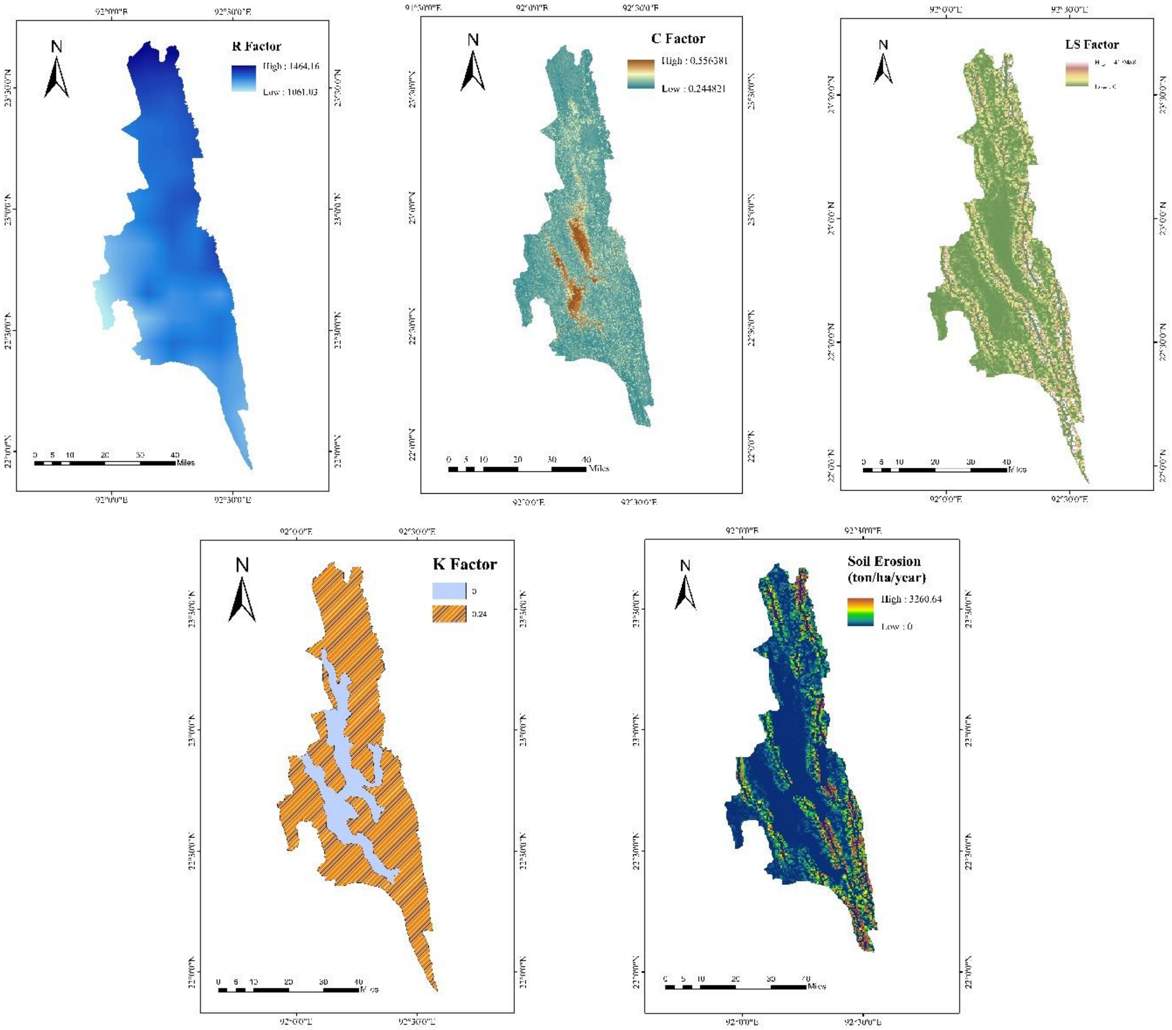


Figure 5. RUSLE Factors & Soil Erosion for 2017

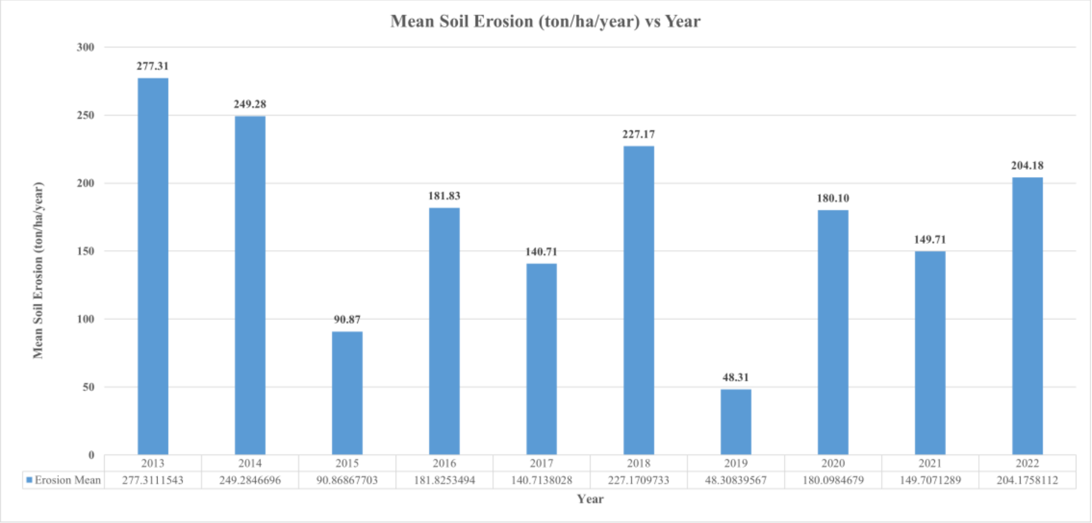


Figure 6. Change in Mean Soil Erosion from 2013 to 2022

4 Conclusion

Evaluation of the change in raw parameters which was done in this study, can be crucial in determining vulnerability to landslides. NDVI can indicate the stability of slopes and the potential for landslides (Wang et al., 2010). Similarly, the analysis of slope data can provide insights into the steepness and stability of the terrain (Kumar et al., 2020). Rainfall analysis is crucial in understanding the role of precipitation in triggering landslides and other natural disasters (Abbate et al., 2021). Excessive rainfall can saturate the soil, reducing its stability and increasing the likelihood of landslides (Prancevic et al., 2020). By incorporating rainfall data into the analysis, it becomes possible to identify periods of heightened risk and establish connections between rainfall patterns and calamities.

In this study the change in crucial parameters like NDVI, Rainfall and Slope were assessed. Some of the patterns before 2017 even can account for the landslide event. But the soil erosion and landslide did not agree with each other (Figure 6). It might be because RUSLE predicts net soil erosion mainly due to rainfall. Although the landslide occurred in 2017 after massive rainfall, the amount of soil erosion did not conform to that as landslide depends on gravity, wind, vegetation pattern, agricultural practices, etc. too. An attempt to assess the impact of vegetation, gravity (slope) and rainfall was made in this study to correlate landslide and soil erosion, but the effect of the wind was not considered here which is a limitation. There were some limitations of the study in calculating the parameters for some years due to data unavailability. Further studies can be carried out using up-to-date data considering the impact of wind and other possible parameters to establish a proper relation between the landslide and soil erosion.

References

Abbate, A., Papini, M., & Longoni, L. (2021). Analysis of meteorological parameters triggering rainfall-induced landslide: a review of 70 years in Valtellina. Natural Hazards and Earth System Sciences, 21(7), 2041-2058.

Babu, R., Dhyani, B. L., & Kumar, N. (2004). Assessment of erodibility status and refined Iso-Erodent Map of India. Indian Journal of Soil Conservation, 32(2), 171-177.

David, W. P. (1988). Soil and water conservation planning: policy issues and recommendations (No. JPD 1988 Vol. XV No. 1-c). Philippine Institute for Development Studies.

Durigon, V. L., Carvalho, D. F., Antunes, M. A. H., Oliveira, P. T. S., & Fernandes, M. M. (2014). NDVI time series for monitoring RUSLE cover management factor in a tropical watershed. International Journal of Remote Sensing, 35(2), 441-453.

Kumar, A., Sharma, R. K., & Mehta, B. S. (2020). Slope stability analysis and mitigation measures for selected landslide sites along NH-205 in Himachal Pradesh, India. Journal of Earth System Science, 129, 1-14.

Prancevic, J. P., Lamb, M. P., McArdell, B. W., Rickli, C., & Kirchner, J. W. (2020). Decreasing landslide erosion on steeper slopes in soil-mantled landscapes. Geophysical Research Letters, 47(10), e2020GL087505.

Pelton, J., Frazier, E., & Pickilingis, E. (2012). Calculating slope length factor (LS) in the revised Universal Soil Loss Equation (RUSLE).

Rafa, N., Nuzhat, S., Uddin, S. M. N., Gupta, M., & Rakshit, R. (2021). Ecotourism as a forest conservation tool: An NDVI analysis of the Sitakunda Botanical Garden and Ecopark in Chattogram, Bangladesh. Sustainability, 13(21), 12190.

Renard, K. G., Foster, G. R., Weesies, G. A., & Porter, J. P. (1991). RUSLE: Revised universal soil loss equation. Journal of soil and Water Conservation, 46(1), 30-33.

Sarwar, M. I., & Muhibbullah, M. (2022). Vulnerability and Exposures to Landslides in the Chittagong Hill Region, Bangladesh: A Case Study of Rangamati Town for Building Resilience. In Climate, Environment and Disaster in Developing Countries (pp. 391-399). Singapore: Springer Nature Singapore.

Sinshaw, B. G., Belete, A. M., Tefera, A. K., Dessie, A. B., Bizuneh, B. B., Alem, H. T., ... & Moges, M. A. (2021). Prioritization of potential soil erosion susceptibility region using fuzzy logic and analytical hierarchy process, upper Blue Nile Basin, Ethiopia. Water-Energy Nexus, 4, 10-24.

Wang, F., Huang, J., & Chen, L. (2010). Development of a vegetation index for estimation of leaf area index based on simulation modeling. Journal of plant nutrition, 33(3), 328-338.