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Research Article

Landslide susceptibility zonation in the Nepalese Siwaliks using GIS and the frequency ratio model

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ABSTRACT

Landslides are recurrent and destructive hazard in Nepal's geologically young and fragile Siwalik (Chure) Hills, where the lack of systematic susceptibility assessments limits effective land-use planning and disaster risk reduction. This study aimed to evaluate and map landslide susceptibility in Rajpur Rural Municipality, Dang District, using Geographic Information System (GIS) and bivariate Frequency Ratio (FR) model. A spatially explicit landslide inventory of 151 historical events was prepared from high-resolution Google Earth imagery. Nine landslide conditioning factors-slope, aspect, elevation, plan curvature, land use/land cover (LULC), geology, soil type, mean annual precipitation, and proximity to rivers—were processed and analyzed within a GIS framework. Class-wise FR values were calculated to quantify relationship between each factor and past landslide occurrences, and these values were integrated to produce Landslide Susceptibility Map (LSM) that classified the area into five susceptibility zones. The FR analysis revealed strong association between landslide occurrence and water bodies within the LULC parameter (FR=1.52), highlighting the role of fluvial erosion and slope undercutting. Soil emerged as the most influential factor, exhibiting the highest prediction rate (PR = 2.57). Model validation using the Area Under the Curve (AUC) method yielded an AUC value of **0.545**, indicating a marginal but positive predictive performance above random classification. The resulting LSM provides scientifically grounded decision-support tool for local authorities, planners, and disaster management agencies to identify priority areas for targeted mitigation measures, including bio-engineering, community-based afforestation, and risk-sensitive infrastructure development, demonstrating the practical utility of the FR model in data-scarce mountainous environments of Nepal.

Keywords: Land Hazard, Siwalik Hills, Nepal, Disaster Risk Reduction, Maps

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INTRODUCTION

Landslides are a persistent and often devastating natural hazard in mountainous regions, where fragile geological conditions and steep terrain interact with intense climatic forces. Across the world, these events repeatedly threaten human lives, damage infrastructure, disrupt livelihoods, and impose long-lasting economic burdens on affected communities (Guzzetti, 2012). Nepal, situated within the young and tectonically active Himalayan orogenic belt, experiences landslides as a regular and widespread phenomenon rather than as isolated disasters (Dahal et al., 2008). The country's rugged topography, weak and unconsolidated rock formations, intense

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monsoonal rainfall, and increasing human pressure on slopes together create conditions that are highly conducive to slope instability (Paudel et al., 2016). Consequently, landslides in Nepal frequently result in loss of life, destruction of transportation corridors, degradation of agricultural land, and prolonged socio-economic disruption, particularly in rural and mountainous areas (Petley, 2012).

Given the recurrent nature of landslide disasters, a shift from reactive response to proactive risk management is essential. Landslide Susceptibility Mapping (LSM) plays a central role in this transition by providing a spatial framework for identifying areas that are more prone to landslide occurrence under prevailing environmental conditions (Brabb, 1984). Importantly, susceptibility maps do not aim to predict the timing of landslides; rather, they focus on identifying where landslides are more likely to occur based on the spatial association between past landslide events and a set of conditioning factors such as slope, geology, land use, and hydrology (Fell et al., 2008). When developed carefully, LSM serves as a critical input for land-use planning, infrastructure siting, disaster risk reduction strategies, and the formulation of early warning and mitigation measures (Reichenbach et al., 2018).

The Rajpur Rural Municipality of Dang District, located within Nepal's Siwalik (Chure) range, exemplifies the challenges associated with landslide-prone landscapes. The Siwalik Hills are characterized by soft, loosely consolidated sedimentary rocks, highly dissected terrain, and an extensive network of rivers and streams. These inherent geological and geomorphological characteristics, combined with intense seasonal rainfall, make the region particularly vulnerable to erosion and slope failures. Despite this evident susceptibility, systematic and scientifically grounded landslide susceptibility assessments at the local scale remain limited for Rajpur. The absence of such spatial information constrains effective land-use planning and weakens local disaster preparedness and mitigation efforts.

A variety of quantitative approaches have been developed to assess landslide susceptibility, ranging from expert-based qualitative methods to advanced statistical and machine-learning techniques (Pourghasemi et al., 2018). Among these approaches, the Frequency Ratio (FR) model has been widely applied due to its conceptual simplicity, transparency, and relatively modest data requirements. The FR model evaluates the statistical relationship between historical landslide occurrences and individual classes of conditioning factors, allowing for a clear and interpretable assessment of their relative contributions to landslide susceptibility (Lee & Pradhan, 2007). Its applicability and effectiveness have been demonstrated in several studies conducted in geomorphologically complex and data-limited regions similar to the Siwalik Hills (Lee & Sambath, 2006).

In this context, the present study seeks to address the lack of localized landslide susceptibility information for Rajpur Rural Municipality by applying the Frequency Ratio model within a GIS environment. The specific objectives of this research are to: (1) prepare a detailed landslide inventory and thematic maps of key landslide conditioning factors; (2) quantify the spatial relationship between landslide occurrence and these factors using Frequency Ratio and Prediction Rate analysis; and (3) generate and validate a landslide susceptibility map that can support land-use planning, infrastructure development, and disaster risk reduction initiatives at the local level.

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MATERIALS AND METHODS

Data Collection and Preparation

A reliable and comprehensive landslide inventory is the foundational layer for any statistically based susceptibility analysis (Guzzetti et al., 2012). In this study, a total of 151 landslide polygons were visually identified, interpreted, and manually digitized using high-resolution multi-temporal imagery from Google Earth Pro (circa 2023). This landslide inventory map (Figure 1) was then randomly partitioned into two subsets: 70% (106 landslides) for training the FR model and 30% (45 landslides) for validating its predictive performance. Data sources and types used in the research are presented in Table 1.

Table 1: **Data sources and types used in the research**

Database	Data Type	Source	Resolution/Scale	Purpose
Landslide Inventory	Polygon	Google Earth Pro	-	Inventory & Model I/O
Digital Elevation Model (DEM)	Raster (GeoTIFF)	USGS (SRTM)	30 m	Derive Topographic Factors
Land Use/Land Cover	Raster (GeoTIFF)	USGS	10 m	Causative Factor
Geology	Polygon (Shapefile)	ICIMOD	1:250,000	Causative Factor
Soil	Polygon (Shapefile)	ICIMOD (SOTER)	1:50,000	Causative Factor
Precipitation	Point (Excel)	Dept. of Hydrology & Metrology	-	Interpolated to Raster
Rivers & Streams	Polyline (Shapefile)	Dept. of Survey	-	Proximity Analysis

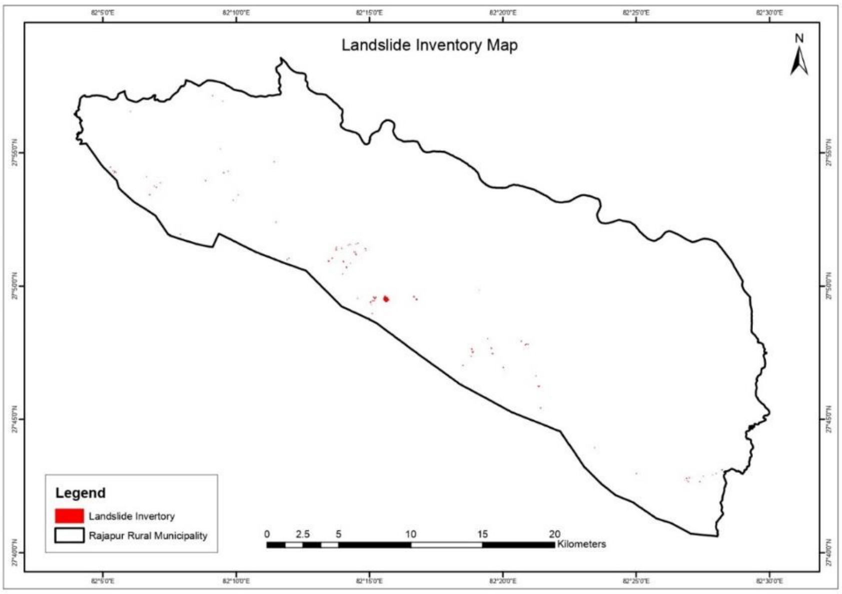

Figure 1: Landslide Inventory map of the study area

Based on an extensive review of the literature and the principle of data availability, nine primary landslide causative factors were selected. All vector data were converted to raster

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layers, and all datasets were harmonized to a common spatial resolution of 30 x 30 meters and projected into the WGS 1984 UTM Zone 45N coordinate system. The factors are:

Slope: Measured in degrees, derived from the SRTM DEM (Figure 2).

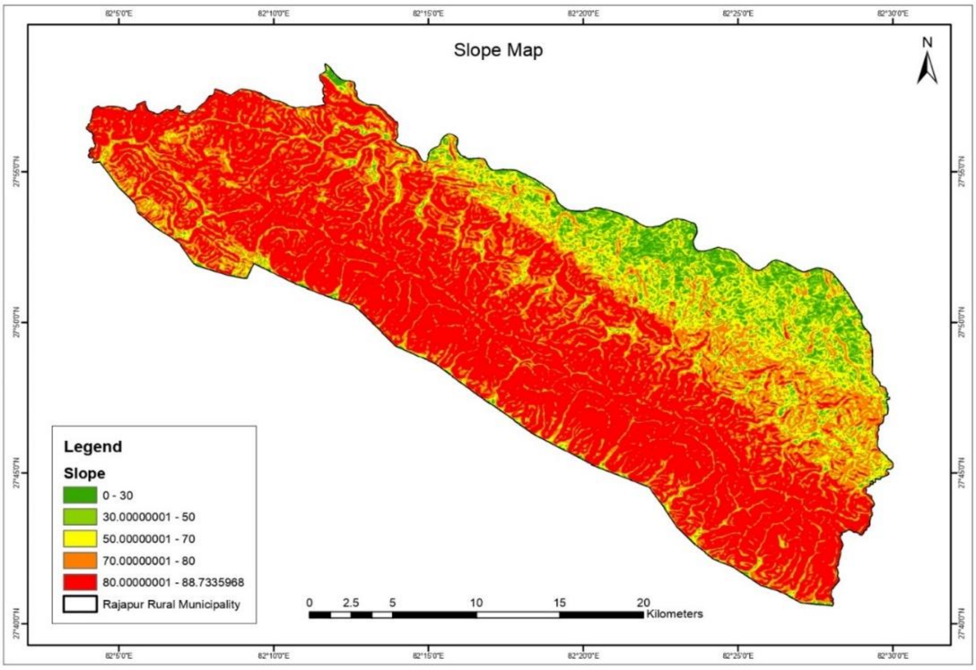

Figure 2: Slope Map

Aspect: The direction of the slope face, derived from the DEM (Figure 3).

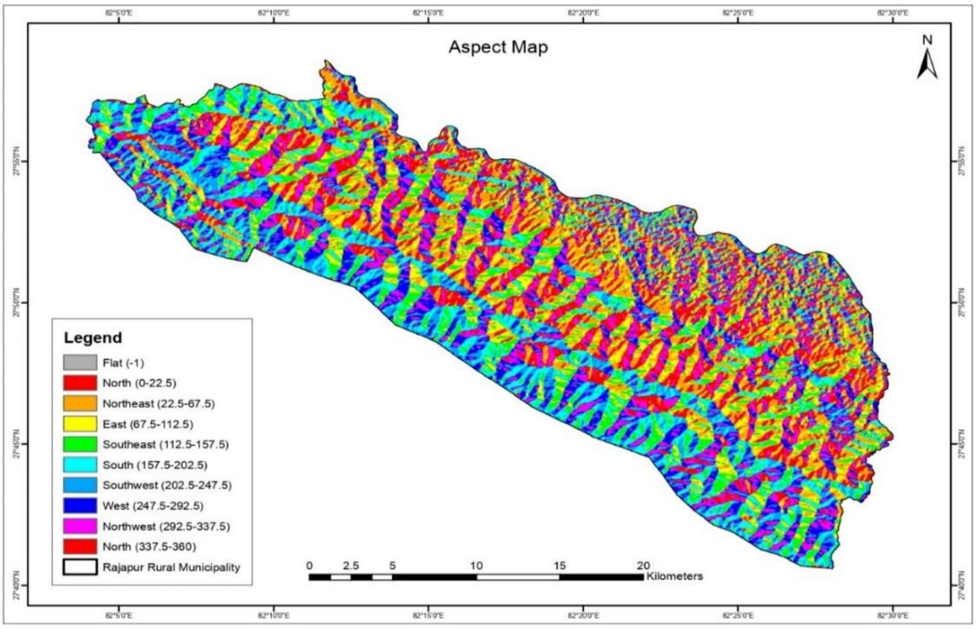

Figure 3: Aspect Map

Elevation: In meters above sea level, derived from the DEM (Figure 4).

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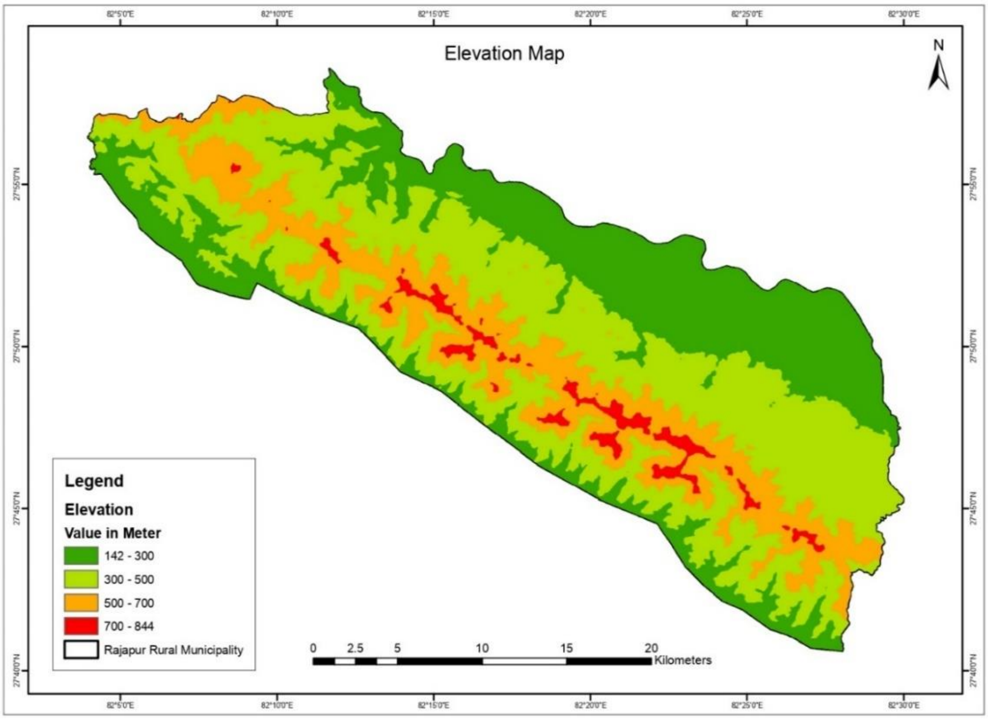

Figure 4: Elevation Map

Plan Curvature: Indicating terrain convergence/divergence, derived from the DEM (Figure 5).

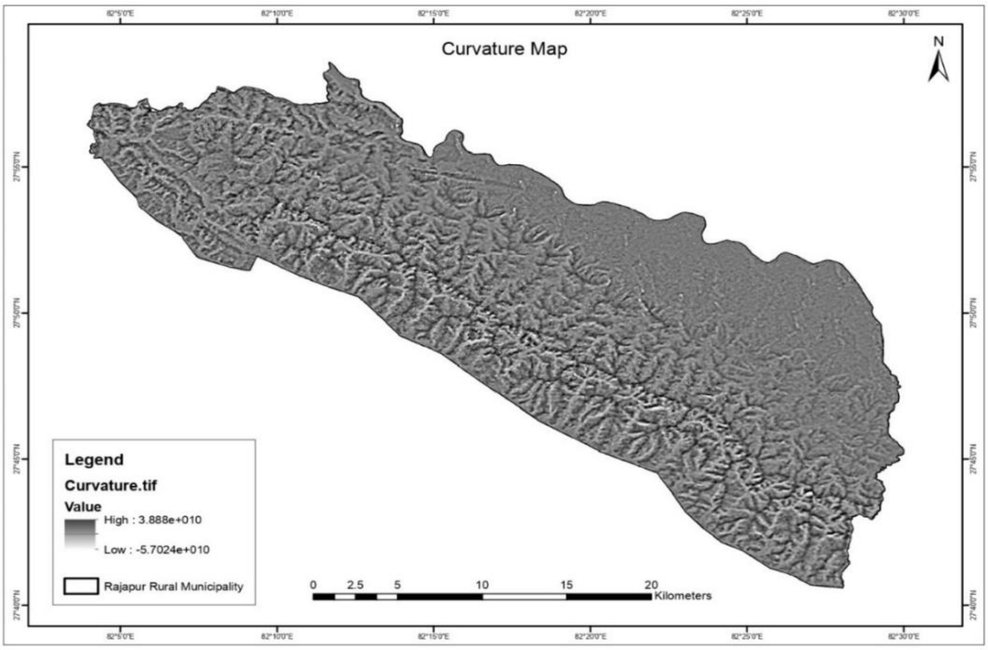

Figure 5: Curvature Map

Land Use/Land Cover (LULC): Classified into Forest, Cultivation, Other Land (built-up, bare), and Water Body (Figure 6).

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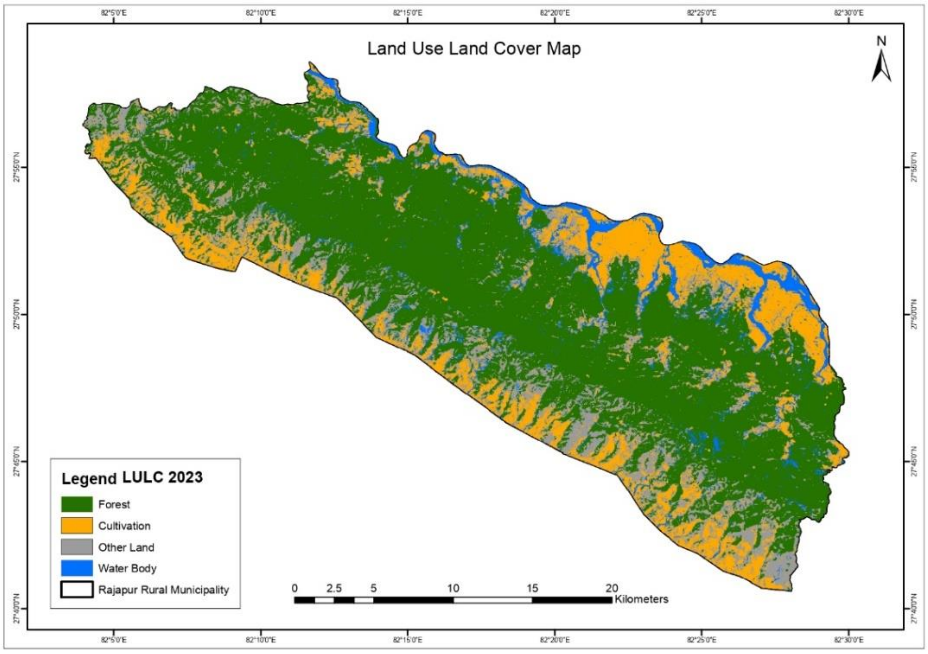

Figure 6: Land Use Land Cover Map

Geology: Classified into Middle Siwalik 1, Middle Siwalik 2, Lower Siwalik, Upper Siwalik, and Quaternary deposits (Figure 7).

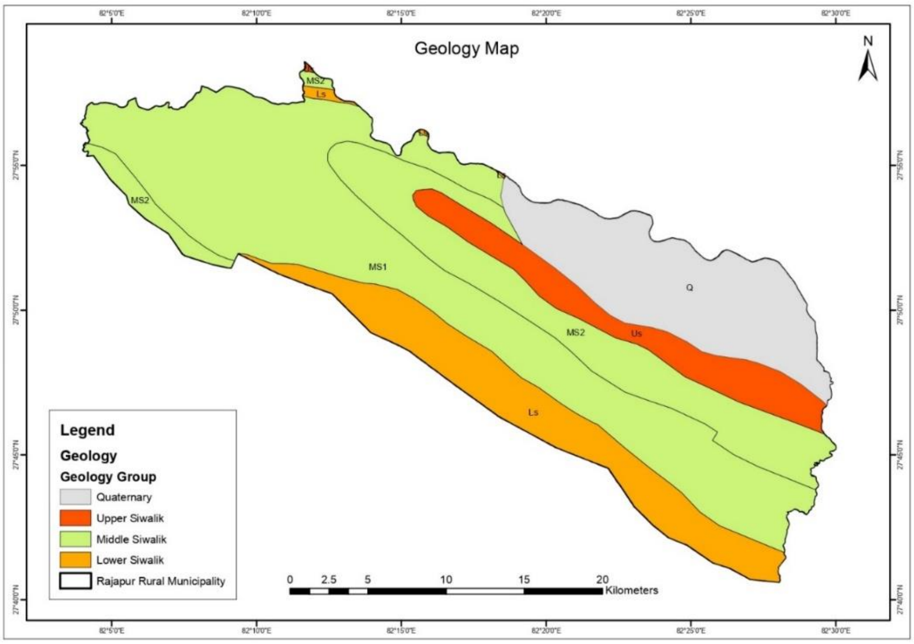

Figure 7: Geology Map

Soil Type: Classified into two dominant units: Udipsamments, Dystrochrepts, Rhodustalfs (UDR) and Dystrochrepts, Eutrochrepts, Argiudolls (DEA) (Figure 8).

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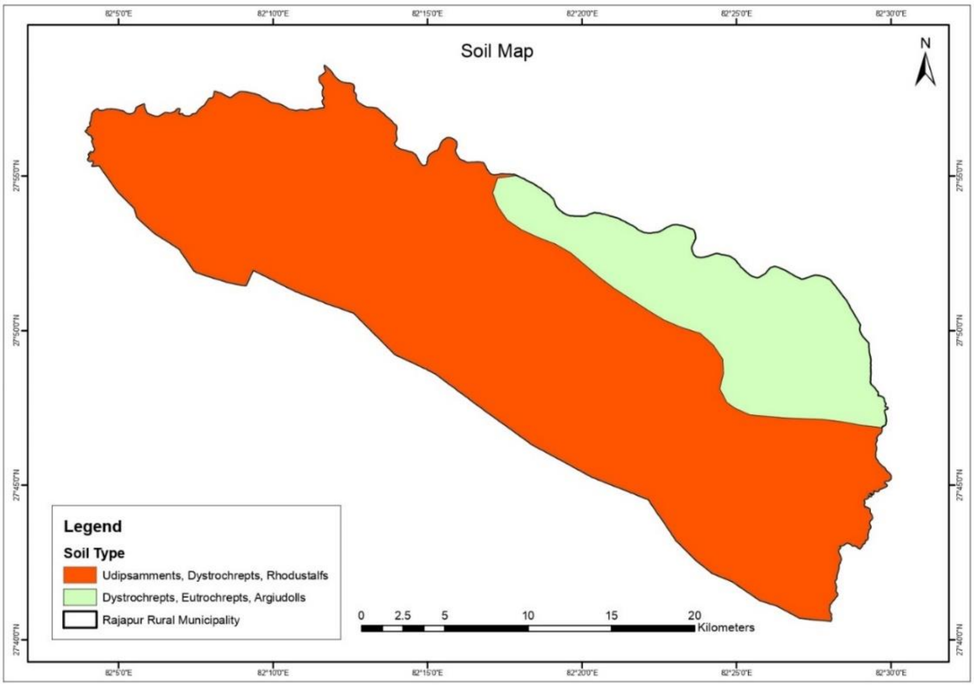

Figure 8: Soil Map

Precipitation: Mean annual rainfall (1990-2020) was interpolated using the Inverse Distance Weighting (IDW) method to create a continuous raster surface (Figure 9).

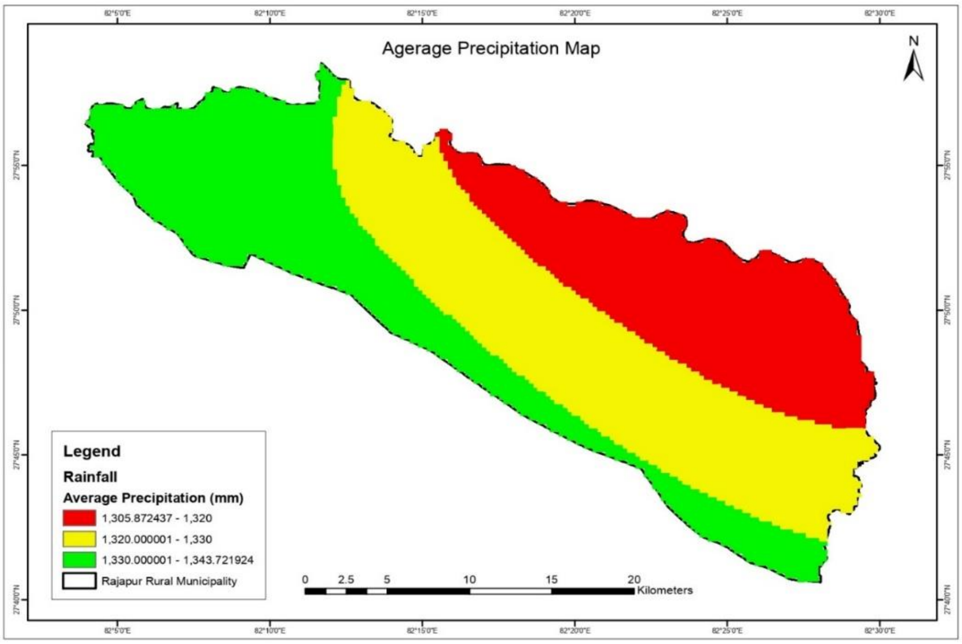

Figure 9: Average Precipitation Map

Proximity to Rivers: A Euclidean distance map was created from river and stream networks (Figure 10).

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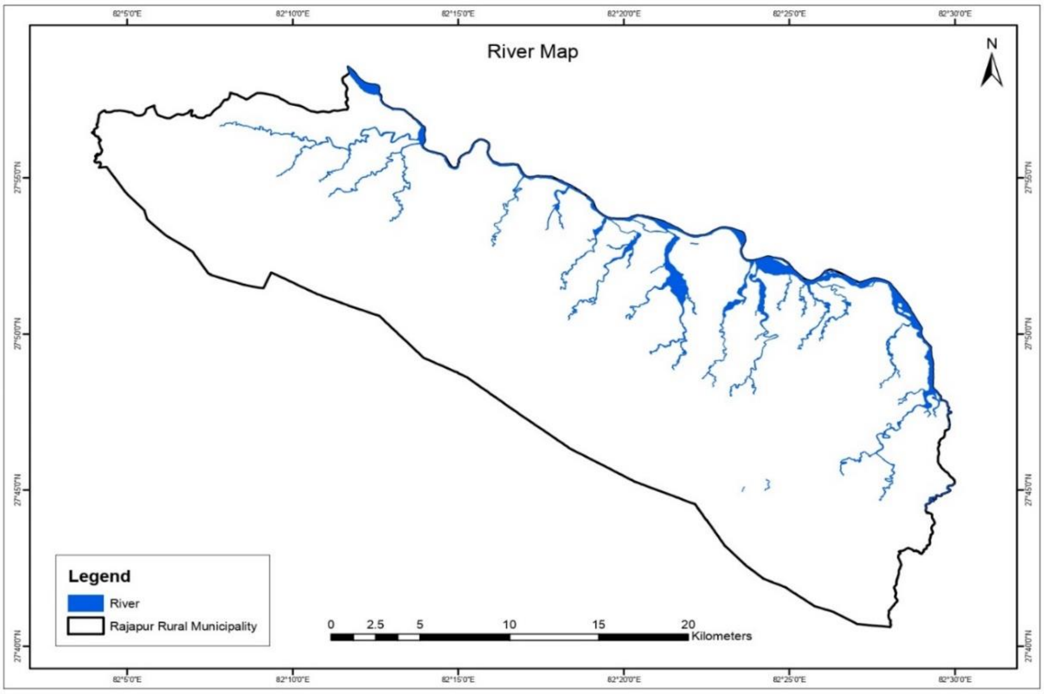

Figure 10: River Map

Frequency Ratio Model

The Frequency Ratio (FR) is a simple bivariate statistical model that quantifies the probabilistic relationship between the occurrence of landslides and each class of a causative factor (Lee & Sambath, 2006). The FR for a given class is calculated using Equation 1:

$FR = N_{\text{pix}}(LS_i) / N_{\text{pix}}(LS_{total}) \div N_{\text{pix}}(C_i)/N_{\text{pix}}(C_{total})$……………Eq.1

Equation 1. Frequency Ratio calculation

Where:

- Npix(LSi) is the number of landslide pixels in class *i* of a factor.
- Npix($LStotal$) is the total number of landslide pixels in the study area.
- Npix(Ci) is the total number of pixels in class *i*.
- Npix($Ctotal$) is the total number of pixels in the study area.

An FR value greater than 1 indicates a strong correlation and high probability of landslide occurrence within that specific class, while a value less than 1 indicates a weaker correlation. The Prediction Rate (PR) for each factor, calculated as the sum of the FR values for all its classes, was used to rank the overall importance of the factors.

The Landslide Susceptibility Index (LSI) for each pixel in the study area was computed by summing the FR values of all nine factors (Equation 2). A higher LSI value indicates a higher probability of landslide occurrence.

$LSI = i=1 \sum nFRi$………………Eq.2

Equation 2. Landslide Susceptibility Index calculation.

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The final continuous LSI raster was classified into five relative susceptibility classes using the natural breaks (Jenks) classification method, which minimizes variance within classes and maximizes variance between classes. The resulting zones are: Very Low, Low, Medium, High, and Very High susceptibility.

Model Validation

The predictive performance of the susceptibility model was rigorously validated using the Receiver Operating Characteristic (ROC) curve analysis. The area under the ROC curve (AUC) was calculated by comparing the locations of the validation (30%) landslide dataset against the predicted susceptibility map. The AUC value ranges from 0.5 to 1.0, where 0.5 suggests a model performance no better than random chance, and 1.0 indicates a perfect fit (Yesilnacar, 2005).

RESULTS

Analysis of Landslide Causative Factors

The FR values for each class of the nine causative factors were calculated, and the Prediction Rate (PR) for each factor was determined to assess their relative importance (Table 2).

Table 2: Frequency Ratio and Prediction Rate for landslide causative factors

Factor	Class	Class Pixels	Landslide Pixels	Frequency Ratio (FR)	Prediction Rate (PR)
LULC	Forest	394,804	42	0.11	1.78
	Cultivation	103,937	3	0.03	
	Other Land	107,790	53	0.49	
	Water Body	34,860	53	1.52	
Soil	UDR	516,516	151	0.29	2.57
	DEA	124,875	0	0.00	
Geology	Middle Siwalik 1	266,843	33	0.12	2.28
	Middle Siwalik 2	116,612	2	0.02	
	Lower Siwalik	90,495	116	1.28	
	Upper Siwalik	54,646	0	0.00	
	Quaternary	112,795	0	0.00	
Slope (°)	0-30	24,769	0	0.00	2.52
	30-50	42,020	0	0.00	
	50-70	90,211	2	0.00	
	70-80	138,006	7	0.01	
	>80	346,385	142	0.41	
...(Aspect, Elevation, etc.)...					

Key findings from the FR and PR analysis include (Figure 11):

- **LULC:** The 'Water Body' class had the highest individual class FR value (1.52), indicating a very strong spatial correlation with landslides, primarily due to riverbank erosion and slope undercutting.
- **Soil:**The 'UDR' soil unit, despite a moderate FR (0.29), had the highest overall PR (2.57), identifying it as the most critically influential factor across the entire study area.
- **Geology:**The 'Lower Siwalik' formation showed a very high FR (1.28), confirming its inherent weakness and high susceptibility compared to other, more stable geological units.

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- **Slope:** As expected, the steepest slope class (>80°) had a significantly higher FR (0.41) compared to all gentler slope classes, which had values near or at zero.
- **Aspect:** South-east (112.5-157.5°) and south-facing (157.5-202.5°) slopes had higher FR values, potentially related to higher moisture evaporation and soil weathering patterns. Aspect had the lowest overall PR (1.00), indicating it was the least discriminatory factor.

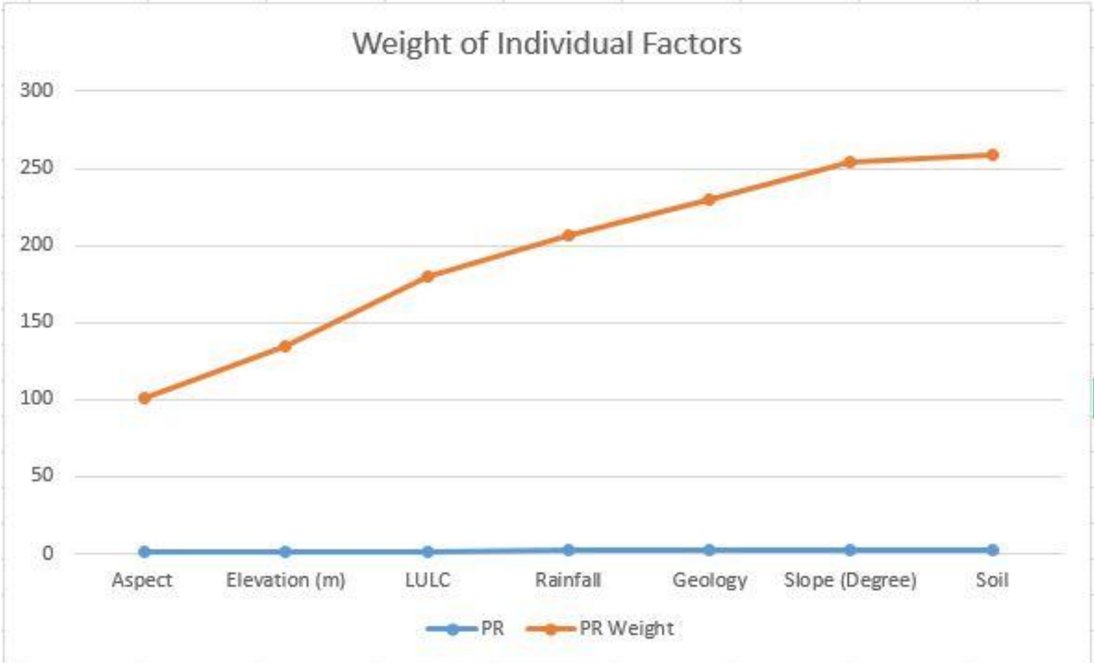

Figure 11: Relative weight of individual causative factors based on Prediction Rate (PR)

Landslide Susceptibility Map and Validation

The final Landslide Susceptibility Map (LSM) is presented in Figure 12. The area coverage for each susceptibility class was calculated as follows:

- **Very Low:** 15.12% (~ 26.5 km²)
- **Low:** 19.45% (~ 34.0 km²)
- **Medium:** 28.40% (~ 49.7 km²)
- **High:** 28.63% (~ 50.1 km²)
- **Very High:** 8.40% (~ 14.7 km²)

This distribution reveals that over **37%** of the municipality's total area falls within the High and Very High susceptibility zones. These areas are predominantly concentrated in the topographically steeper, central and northern parts of the municipality, exhibiting a strong spatial coincidence with the Lower Siwalik geology, UDR soil type, and close proximity to river networks.

The validation of the model using the ROC curve (Figure 13) produced an AUC value of 0.545**,** suggesting the model captures basic spatial patterns but has low discriminatory power. This result suggests that the model captures the general spatial pattern of landslide occurrence but has low discriminatory power between landslide and non-landslide areas. While this is a modest accuracy, it confirms that the model performs significantly better than a random

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classification (AUC = 0.545) and is acceptable for a regional-scale, first-order assessment using a bivariate method.

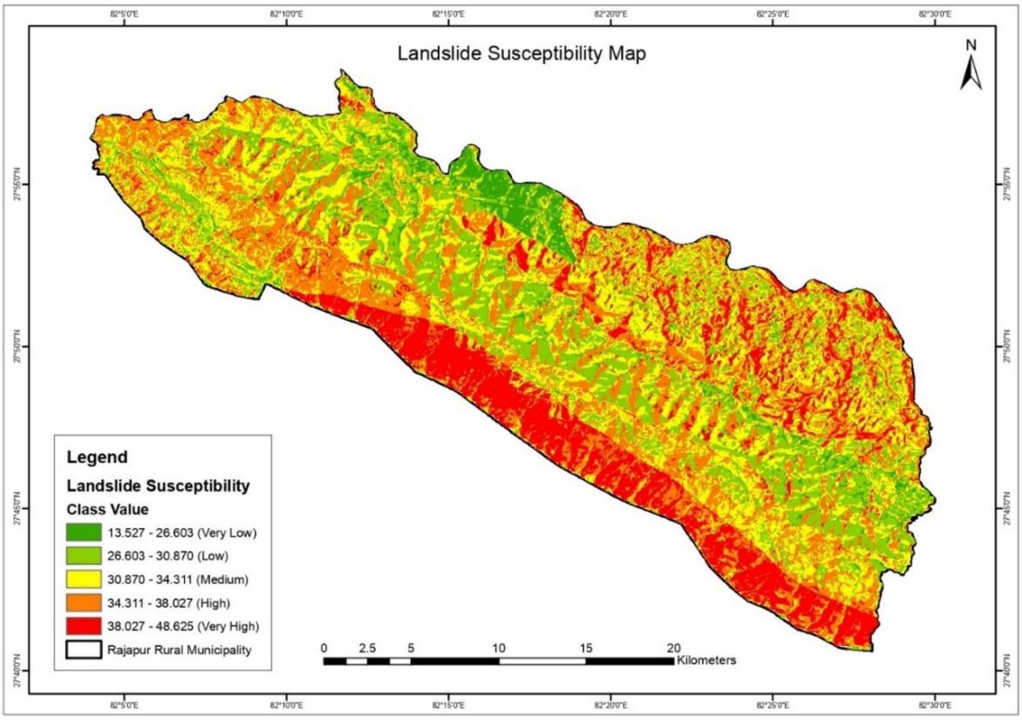

Figure 12: Landslide Susceptibility Map of Rajpur Rural Municipality.

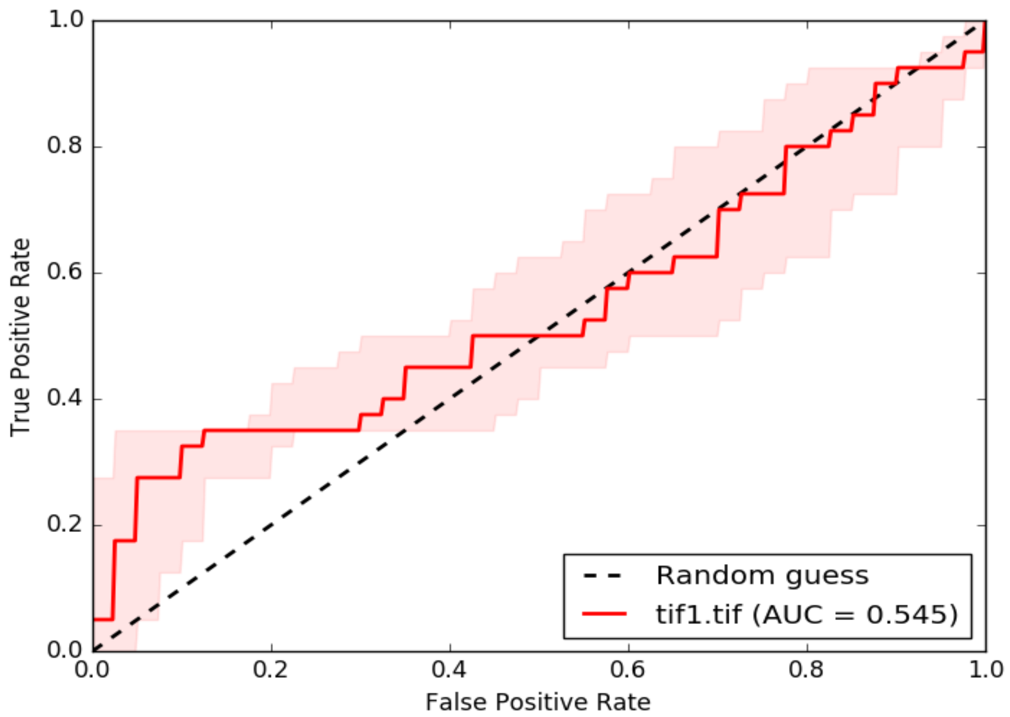

Figure 13: Receiver Operating Characteristic (ROC) curve for model validation (AUC = 0.545)

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DISCUSSION

The results of this study illustrate the practical applicability of the Frequency Ratio model, integrated with GIS, for landslide susceptibility assessment in a data-scarce setting such as Nepal's Siwalik region. The relatively high FR value associated with the Water Body class (1.52) clearly highlights the importance of hydrological processes in both triggering and preconditioning slope failures. In many parts of the study area, fluvial erosion at the base of slopes leads to progressive undercutting and steepening, which reduces slope stability and promotes failure initiation (Korup, 2005). In addition, the presence of nearby water bodies facilitates saturation of slope materials, increasing pore-water pressure and reducing effective stress and shear strength, conditions that are well known to favor landslide initiation (Vakhshoori & Zare, 2016).

Among the evaluated conditioning factors, soil exhibited the highest Prediction Rate (2.57), indicating its strong overall contribution to landslide susceptibility across the study area. The dominant UDR soil unit in the Siwalik region is typically shallow, coarse-textured, and weakly developed on highly erodible parent materials. Such soils tend to have low cohesion and high permeability, characteristics that make them particularly susceptible to failure during periods of intense rainfall. The observed concentration of landslides within the Lower Siwalik geological formation (FR = 1.28) further emphasizes the controlling role of lithology. This formation, composed mainly of interbedded sandstone and mudstone, is highly prone to weathering. When saturated, the relatively impermeable mudstone layers can act as preferential slip surfaces, facilitating translational landslides (Dahal et al., 2008).

The spatial clustering of high and very high susceptibility zones within steep and rugged terrain is consistent with well-established geomorphological understanding of landslide processes. At the same time, the model's AUC value of 0.545 reflects the inherent limitations of bivariate statistical approaches when applied in complex mountainous environments with limited landslide inventory data, a challenge also reported in other Himalayan studies (Regmi et al., 2014). Although this level of predictive performance is adequate for broad regional planning and prioritization, it underscores the need for cautious interpretation of the results. The model primarily represents static, predisposing environmental conditions and does not explicitly capture dynamic triggering mechanisms such as rainfall intensity–duration thresholds, seismic activity, or localized anthropogenic disturbances, including unplanned road construction and deforestation, which play an important role in slope instability within the study area.

CONCLUSION

This study presents a systematic and replicable approach for assessing landslide susceptibility in the geologically fragile Siwalik region of Nepal. The findings indicate that landslide occurrence in Rajpur Rural Municipality follows clear spatial patterns and is strongly influenced by a combination of interrelated geoenvironmental factors rather than occurring randomly across the landscape. By applying the Frequency Ratio model within a GIS framework, the study successfully delineated areas of varying landslide susceptibility, providing a clear spatial representation of relative landslide-prone zones.

The main conclusions of the study can be summarized as follows:

- Landslide occurrence in the study area is primarily controlled by soil characteristics—particularly the Udipsamments, Dystrochrepts, and Rhodustalfs unit—together with proximity to river networks that promote erosion and slope undercutting, and the inherently weak and weathering-prone lithology of the Lower Siwalik formation.
- More than 37% of the total area of Rajpur Rural Municipality falls within the High and Very High landslide susceptibility classes. These zones represent areas of elevated risk to local communities, infrastructure, and natural resources, highlighting the need for focused and prioritized intervention by planners, engineers, and policy-makers.
- Despite its limited predictive accuracy, the generated Landslide Susceptibility Map serves as a first-order, scientifically grounded decision-support tool for regional-scale planning. It provides a useful baseline for guiding land-use decisions, infrastructure development, and proactive disaster risk reduction measures within the municipality.

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Authors' contribution

P. Bhattarai designed the research, conducted the field work, and analyzed the data. P.Bhattarai and G. Kafle prepared the manuscript. G. Kafle supervised the overall research, report, and article preparation. All authors read and approved the final manuscript.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

Ethics Approval Statement

This study is based on secondary geospatial data and field observations. It did not involve humans or animals. All data were used in accordance with the ethical guidelines, institutional policies and applicable regulations.

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