

Landslide Susceptibility Mapping and Rainfall Threshold Analysis of Chishankhugadhi Rural Municipality Wards 1, 4, 5 and 7, Eastern Nepal: A Gis Based Frequency Ratio Approach

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LANDSLIDE SUSCEPTIBILITY MAPPING AND RAINFALL THRESHOLD ANALYSIS OF CHISHANKHUGADHI RURAL MUNICIPALITY WARDS 1, 4, 5 AND 7, EASTERN NEPAL: A GIS BASED FREQUENCY RATIO APPROACH

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ABSTRACT

Chishankhugadhi Rural Municipality, located in Koshi Province, eastern Nepal, lies within the geologically active Lesser Himalaya, where complex geology, rugged topography, intense monsoonal rainfall, and frequent seismic activity contribute to slope instability. This study presents a GIS-based landslide susceptibility assessment of Chishankhugadhi Rural Municipality, focusing on Wards 1, 4, 5, and 7. A landslide inventory was compiled through field verification, historical records, and satellite and Google Earth interpretation, and susceptibility was modeled using seven conditioning factors: slope angle, aspect, curvature, geology, distance from streams, distance from roads, and distance from faults. Land use/land cover (LULC) was mapped separately to support interpretation. The study area was classified into five susceptibility zones using the natural-breaks classification method, and model performance was evaluated using a receiver operating characteristic (ROC) curve, yielding a success-rate area under the curve (AUC) of 0.734. High and very high susceptibility zones were predominantly associated with slopes within the 12°–30° class, weathered phyllitic materials of the Kuncha Formation, and areas near road cuts, drainage channels, and colluvial deposits. Geotechnical testing at eleven representative landslide sites recorded low cohesion (2.4–6.1 kPa) and moderate friction angles (20°–28°), providing supporting site-scale evidence of relatively weak slope materials. Rainfall records from the Okhaldhunga station for 2014–2024 show a mean annual rainfall of 1668 mm, with 80.3% concentrated during the monsoon season. Comparison of short-duration rainfall intensities (1–5 days) with the global intensity–duration envelope of Caine (1980) indicates that some observed rainfall extremes fall within or exceed portions of the envelope. The observed multi-day rainfall maxima, including RX5day and RX7day, provide useful reference conditions for future event-based analyses of rainfall-triggered landslides. Overall, the susceptibility assessment provides a quantitative basis for regional-scale susceptibility screening, land-use planning, infrastructure prioritization, and identification of locations requiring detailed geotechnical investigation.

Keywords: Landslide Susceptibility; GIS; Rainfall Characteristics; Lesser Himalaya; ROC-AUC; Chishankhugadhi

1 INTRODUCTION

Landslides represent one of the most destructive natural hazards in Nepal, posing severe threats to human life, infrastructure, agricultural land, and overall socioeconomic development. Varnes (1978) defined landslides as the downward and outward movement of slope-forming materials composed of natural rock, soil, artificial fills, or a combination of these materials under the influence of gravity. Similarly, Cruden et al. (1993) defined landslides as the downward movement of rock, sediment, debris, or earth along a slope. Landslides are among the most frequent geohazards in the hilly and mountainous terrain of Nepal, where approximately 83% of the total land area is covered by hills and mountains (Regmi et al., 2014a). The combination of rugged topography, complex and fragile geological structures, high-intensity rainfall, thick colluvial and residual soil cover, and frequent seismic activity makes Nepal one of the most landslide-prone countries in the world.

Chishankhugadhi Rural Municipality lies within the Lesser Himalaya of Koshi Province, eastern Nepal, a region characterized by pronounced geological and topographical heterogeneity that gives rise to a wide range of slope-failure processes and related hazards (Dhakal, 2014). Recent infrastructure development, particularly road construction, has contributed to the occurrence of landslides in the area. Despite increasing exposure to landslide

hazards, no comprehensive scientific assessment of landslide susceptibility has been carried out for this rural municipality.

Landslide susceptibility mapping is the process of identifying and spatially delineating areas that are prone to slope failure based on the relationship between causative conditioning factors and historical landslide occurrences (Brabb, 1984). Over the past three decades, a wide range of statistical, probabilistic, and machine-learning methods have been developed and applied for landslide susceptibility mapping, including frequency ratio (FR), weight of evidence (WoE), Shannon entropy, logistic regression, and artificial neural networks (Guzzetti et al., 1999; Bhandari et al., 2024). Among these, the FR method has been applied extensively across the Nepal Himalaya (Khadka et al., 2018; Gadtaula and Dhakal, 2019; Ghimire, 2011) and has demonstrated useful predictive performance while remaining computationally simple and relatively interpretable compared with machine-learning alternatives (Lee and Talib, 2005; Cen et al., 2018).

Landslide susceptibility mapping conventionally integrates static conditioning factors and proximity to structural discontinuities with dynamic triggering factors, among which rainfall is a dominant trigger in the monsoon-influenced Nepal Himalaya. Chishankhugadhi Rural Municipality is characterized by steep terrain, weathered phyllitic and schistose bedrock, and heavy monsoon rainfall, which together may predispose the landscape to slope failure. Most susceptibility models in Nepal, including studies conducted in Dailekh, Benighat-Rorang, and Jugal Rural Municipalities (Pradhan and Dahal, 2023;), incorporate rainfall primarily as a static mean annual or mean monsoon rainfall layer. Therefore, a dedicated analysis of rainfall variability, long-term trends, extreme precipitation indices, and comparisons with established intensity–duration thresholds can strengthen the hydroclimatic context of landslide susceptibility assessment. Such an analysis helps place the susceptibility map within a more comprehensive and defensible hydroclimatic framework.

Geographic Information System (GIS) technology plays a central role in modern landslide susceptibility mapping by enabling the efficient integration, processing, and spatial analysis of multiple thematic layers derived from remote sensing data and field investigations (Van Westen, 1993). The integration of GIS with statistical methods allows the generation of spatially continuous susceptibility maps that can directly inform land-use planning, disaster risk reduction, and infrastructure decision-making (Van Westen et al., 2003).

This study aims to: (i) develop a comprehensive landslide inventory for Wards 1, 4, 5, and 7 of Chishankhugadhi Rural Municipality through field surveys, remote sensing, and Google Earth analysis; (ii) identify and screen key landslide causative factors using statistical correlation analysis; (iii) generate a landslide susceptibility map in a GIS environment; (iv) validate the susceptibility model using ROC curve analysis; (v) characterize the geotechnical properties of slope materials at identified landslide sites; and (vi) analyze historical rainfall variability, trends, and extremes and compare observed short-duration rainfall with established landslide-triggering intensity–duration thresholds. The findings are intended to provide a baseline scientific resource for local and national authorities engaged in disaster risk reduction, land-use planning, and sustainable development in the rural municipality.

1.1 STUDY AREA

Chishankhugadhi Rural Municipality is located in Okhaldhunga District of Koshi Province, eastern Nepal, approximately 250 km from Kathmandu (Fig. 1). The municipality covers an area of approximately 111.7 km² and is bounded by 27°14'59"N–27°23'15"N and 86°32'11"E–86°41'11"E, with elevations ranging from approximately 376 to 3,014 m above mean sea level, reflecting the highly variable topography of the Lesser Himalaya. The main road corridor connecting the municipality to the national highway network passes through steep hillslopes and several geomorphologically sensitive zones, creating artificial cut slopes that may further destabilize already vulnerable terrain. Land cover is predominantly agricultural, with forest patches on steep slopes, built-up areas concentrated along valley floors and terraces, and bare ground associated with active landslides and recent road cuts.

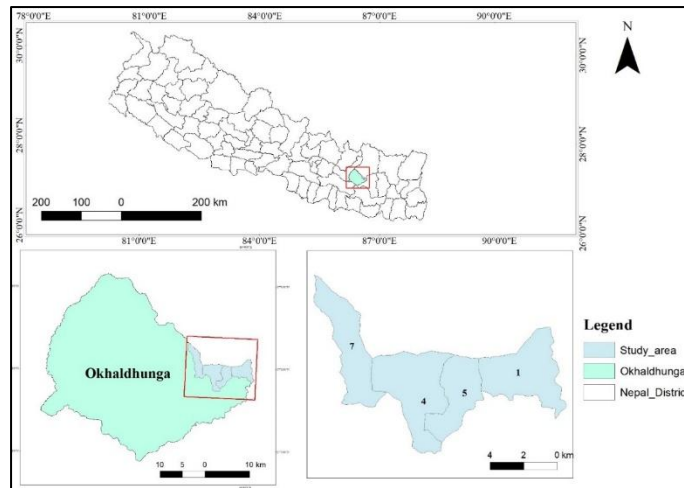


Figure 1 Administrative map of Okhaldhunga District Representing Study Area

2 REGIONAL GEOLOGICAL AND TECTONIC SETTING

2.1 TECTONIC FRAMEWORK

Geologically, Okhaldhunga District lies in central-eastern Nepal within the Lesser Himalayan Zone and forms part of the Okhaldhunga Tectonic Window (OTW), a structural culmination where erosion and tectonic exhumation expose a rare cross-section of deeper Himalayan tectonostratigraphic units. The window is bounded by the southward thrusting of Higher Himalayan Crystalline (HHC) rocks over the Lesser Himalayan Sequence (LHS) along the Main Central Thrust (MCT), with additional structural complexity associated with the Ramgarh and Dhad Khola thrusts (Sherpa et al., 2024). The LHS within this window comprises low- to medium-grade metasedimentary units, including the Para Khola Formation, Halesi Dolomite, Madhavpur Slates, and Harkapur Formation, and is interpreted as an antiformal stack of thrust sheets containing a locally intense shear zone, approximately 50–70 m thick, along the Dudhkoshi River (Sherpa et al., 2024). This intense thrusting and shearing has left the Lesser Himalayan Sequence pervasively fractured and foliated, providing a structural precondition relevant to the widespread slope instability discussed below.

Chishankhugadhi Rural Municipality (Wards 1, 4, 5, and 7) lies within this tectonic framework and is dominated by Paleo- to Mesoproterozoic metasedimentary rocks, principally phyllite, with subordinate slate and quartzite. These rocks belong chiefly to the Kuncha Formation, with lesser occurrences of Fagfog Quartzite and the Nourpul Formation, as well as a small outcrop of the Ulleri Formation (augen gneiss) in the northwest. The area is strongly influenced by the MCT and Ramgarh Thrust. These rocks have undergone multiple phases of Himalayan folding and faulting, producing structurally complex, heavily jointed, and mechanically weak rock masses that may be susceptible to slope failure. These lithologies are also susceptible to weathering under intense monsoonal precipitation, while colluvial cover on hillslopes and alluvium on valley floors may further contribute to terrain instability. Balanced cross-sections across the wider Okhaldhunga Window indicate several hundred kilometers of Himalayan shortening accommodated largely within Lesser Himalayan rocks since the Middle–Late Miocene, with duplex growth active at approximately 12–5 Ma (Sherpa et al., 2024). This protracted deformation history is consistent with the concentration of present-day failures in phyllite-dominated terrain documented elsewhere in the Lesser Himalaya (Dhital, 2015; Thapa et al., 2023), presenting serious challenges for land-use planning and landslide-susceptibility management.

3 DATA AND METHODS

3.1 LANDSLIDE INVENTORY MAP

Landslide inventory mapping constitutes a fundamental prerequisite for any susceptibility assessment, as it provides the empirical basis against which causative factors are calibrated and models are validated (Guzzetti et al., 2012). The inventory for this study was prepared using a combined approach comprising: (i) interpretation of high-resolution satellite imagery obtained from Google Earth; (ii) review of historical records maintained by local government authorities; and (iii) systematic ground truthing and field mapping conducted during 2025.

A total of 20 landslides were identified and mapped within the study area (Fig. 2), encompassing both historical events and those actively documented during the 2025 field campaign. Landslides were delineated as polygons representing their mapped areal extent from crown to toe rather than as single points, and these polygons were subsequently rasterized at the native 12.5 m DEM resolution for the FR analysis. For the susceptibility modelling procedure, a 70/30 split was initially defined for exploratory model assessment; however, because the resulting test subset contained only six landslides, the reported AUC was calculated as a success-rate curve using the complete inventory and should not be interpreted as independent predictive validation. Given the very small resulting test subset, all validation results reported in Section 4.4 should be interpreted with appropriate caution. The separation of the training and testing datasets was performed using the Subset Features geostatistical tool in ArcGIS. The landslide inventory (Table 1) lists the identifier, coordinates, type, activity state, and source of identification for each landslide identified during the field investigation. Disturbed and undisturbed soil samples were collected from representative locations within the identified landslides during the field investigation for geotechnical laboratory analysis (Table 5). Field observations of landslide type, depth, geometry, material composition, and triggering conditions were systematically recorded using standardized data sheets.

Table 1 Field identified and field verified landslide inventory of the study area

Landslide / Site	Latitude/ Longitude	Landslide Type / Movement	Activity	Lithology/ Material	Data Source
Rato Mate Pahiro	27°19'10.93"N, 86°40'17.40"E	Slope Failure; Creep/Reactivation	Active Left Side; Right Side Stabilized	High-Plasticity Lateritic Soil	Field Survey
Odhare Landslide	27°19'14.70"N, 86°39'49.40"E	Planar Sliding / Structurally Controlled Failure	Active/Unstable	Highly Weathered Phyllite, Kunchha Formation; Colluvium , Clay- Rich "Kamero Mato"	Field Survey
Gahate Pahiro	27°19'17.48"N 86°39'05.64"E	Complex Slope Failure; Toppling At Crown	Dormant With Periodic Reactivation	Highly Weathered/Crushed Phyllite	Field Survey
Jyamire (Hilechhap) Landslide	27°18'22.85"N, 86°40'14.95"E	Wedge + Planar + Creep Movement	Ongoing Creep / Unstable	Highly Fractured Greenish Phyllite, Kunchha Formation	Field Survey
Amare (Kalimati) Landslide	27°18'32"N, 86°39'19"E	Active Soil Creep	Active	Thick Colluvium;	Field Survey
Landslide At 27°19'14"N, 86°37'01"E	27°19'14"N, 86°37'01"E	Potential Wedge Failure	Unstable / High- Risk	Greyish, Heavily Deformed , Fractured Phyllite	Field Survey
Thumki Landslide	27°19'57"N, 86°36'59"E	Creep; Potential Wedge/Structural Failure	Ongoing Creep Indicated By Drunken Trees And Cracks	Greenish-Grey- Greyish Phyllite; Colluvial Deposits	Field Survey

Khani Khola Landslide	27°18'59"N, 86°38'11"E	Wedge / Toppling Failure	Progressive / Unstable	Highly Deformed Greenish–Greyish Phyllite	Field Survey
Kalimati Pahirol	27°18'48.62"N, 86°35'59.44"E	Active Landslide	Highly Active	Loose Sediments + Weathered Phyllite	Field Survey
Ratamate Pahirol	27°19'01.74"N, 86°35'36.38"E	Slow-Moving Landslide / Creep	Slow-Moving, Persistent	Red Clay	Field Survey
Diyale Pahirol	27°18'07.60"N, 86°37'22.31"E	Shallow Rotational Slide / Active Detachment	Increasing Activity / Active	Crushed/Weathered Phyllite, White Cohesive Clay	Field Survey
Simpani Landslide	27°19'17"N, 86°33'30"E	Plane + Wedge Failure	Active/Unstable	Greenish- Grey, Gritty Phyllite, Kuncha Formation	Field Survey
Bhandare Danda Pahirol	27°19'23.50"N, 86°33'41"E	Rotational Or Translational Movement	Ongoing Degradation / Unstable	Highly Weathered Phyllite Degraded, Clay-Rich Soil	Field Survey
Chihane Landslide	27°20'02"N, 86°33'32"E	Plane + Wedge Failure	Unstable	Rock Mass with Pre-Existing Weak Planes/Fractures	Field Survey
Thuldhunga Creep	27°20'12"N, 86°33'24"E	Slow-Moving Creep	Slow-Moving; Accelerates During Monsoon	Colluvial Deposits / Unconsolidated Weathered Materials	Field Survey

3.2 SELECTION AND SCREENING OF CAUSATIVE FACTORS

Causative factors were selected on the basis of (i) direct field observations of landslide-conditioning environments within the study area and (ii) a thorough review of published literature from comparable Lesser Himalayan settings in Nepal. Seven factors were ultimately included in the quantitative Frequency Ratio (FR) model: slope angle, aspect, curvature, geology, stream distance, road distance, and fault distance. This factor set is consistent with those used in comparable studies across Nepal (Dahal et al., 2008; Regmi et al., 2014b; Bhandari et al., 2024).

An additional thematic layer, land use/land cover (LULC), was also mapped for the study area (Fig. 3h) and used to support interpretation of the results, for example, in identifying rice cultivation on steep terrain as a potential anthropogenic amplifier of instability (Section 5.1). LULC was not included in the quantitative FR weighting because land-cover classes within the four wards are strongly correlated with terrain steepness and are not independent of the slope and curvature layers already included in the model. Including LULC alongside these factors could therefore risk double-counting the same underlying spatial signal. Further refinement of the model could formally evaluate LULC using a multicollinearity diagnostic, such as the variance inflation factor (VIF), before determining whether it should be included.

3.3 LANDSLIDE SUSCEPTIBILITY ASSESSMENT USING THE FREQUENCY RATIO METHOD

The Frequency Ratio (FR) method is a bivariate statistical approach that evaluates the spatial relationship between landslide occurrences and environmental conditioning factors (Lee and Talib, 2005). It quantifies the relative likelihood of landslide occurrence within different classes of each conditioning factor by comparing the frequency of landslides within a given class with the corresponding proportion of that class in the study area. The fundamental principle of the FR method is therefore to assess whether landslides occur more or less frequently than expected under a random spatial distribution. An FR value greater than 1 indicates a positive association between a factor class and landslide occurrence, whereas an FR value less than 1 indicates a relatively lower association. The method provides statistical weights for individual classes of each conditioning factor, which are subsequently used to generate the landslide susceptibility index by integrating the contributions of the selected factors.

Mathematical Formulation: The FR calculation follows this relationship:

$$FR = (N_{ij} / A_{ij}) / (N_T / A_T)$$

Where the components represent:

- N_{ij} : Number of landslides within class j of factor i
- A_{ij} : Area coverage of class j within factor i
- N_T : Total landslide count in the study area
- A_T : Total study area extent

This formula essentially computes the ratio of landslide density within a specific factor class to the overall landslide density of the study area. Values greater than 1.0 indicate a higher-than-expected landslide occurrence and, therefore, a positive association with landslide susceptibility, whereas values below 1.0 indicate a lower-than-expected occurrence and a relatively lower association with landslide susceptibility. As a worked example, for the 0–50 m stream-distance class (Table 1), the class contains $A_{ij} = 12,277$ pixels out of $A_T = 348,026$ total pixels (3.53% of the study area) and $N_{ij} = 420$ landslide pixels out of $N_T = 17,188$ total landslide pixels (2.44% of mapped landslide pixels). The full ratio is therefore $FR = (420/12,277) / (17,188/348,026) = 0.0342/0.0494 = 0.69$, i.e., this class hosts about 69% of the landslide density expected under a random spatial distribution. Because N_T/A_T is a single constant value for a given factor (it does not vary between that factor's classes), it cancels out when FR values are subsequently normalized into a percentage weight within each factor. For this reason, Table 2 reports the class wise landslide density N_{ij}/A_{ij} directly in its "FR" column (0.03 for the class above) rather than the fully normalized ratio shown in the worked example; the two are proportional to one another within a given factor, so the final normalized class weights (Table 2, "Weight (%)") column) are unaffected and remain equivalent to conventional FR-based weights. This normalization procedure follows the same class-weighting logic used in earlier bivariate statistical landslide models (e.g., Yin and Yan, 1988) and in FR applications across the Nepal Himalaya (Regmi et al., 2014a). The class-wise weights (expressed as percentages of the total FR density within each factor) were then summed across all seven factors on a pixel-by-pixel basis to produce a continuous Landslide Susceptibility Index (LSI). The resulting LSI was subsequently classified into five susceptibility zones using the Natural Breaks (Jenks) method.

3.4 CAUSATIVE FACTOR MAP

Causative factors (CFs) are characteristics that affect the balance between driving and resisting forces influencing the movement and direction of landslides. At a broader regional level, these factors are shaped by diverse geological, geomorphological, and environmental conditions, which essentially provide the foundational conditions for landslide occurrence. In landslide studies, the selection of CFs is typically based on the type of landslide and the specific characteristics of the study area. The choice of these factors often depends on their relevance to the study and the availability of data. There is no universal standardized procedure for CF selection; most studies, including the present study, select factors by analyzing the spatial association between past landslides and relevant influencing variables, informed by prior work conducted in comparable settings (Dahal and Hasegawa, 2008; Shrestha, 2021).

All seven causative-factor layers used in the quantitative landslide susceptibility model were prepared in ArcGIS (Fig. 3) using spatial datasets from the ALOS PALSAR Radiometric Terrain Correction (RTC) DEM, Department of Survey, Department of Mines and Geology (DMG), and ESRI Land Cover. The 12.5 m ALOS PALSAR RTC DEM, representing observations acquired during 2006–2011, was projected to WGS 1984 UTM Zone 45N (EPSG:32645), clipped to the study area, and used to derive slope, aspect, and curvature; the resulting raster comprised 1183×1216 cells. Road and stream networks from the Department of Survey were projected to the same coordinate system, rasterized to the common 12.5 m grid, and converted to Euclidean-distance raster. Fault traces and geological data from DMG were digitized and standardized to the same projection and grid; fault-distance raster was generated using Euclidean distance, while geological units were reclassified into the Kuncha and Ulleri units. Because the mapped fault traces represent interpreted geological structures at the source-map scale, their positional accuracy is subject to mapping- and scale-related uncertainty; therefore, fault-distance values are interpreted as regional-scale spatial proxies rather than exact measures of subsurface structural distance. Land-use/land-cover data from the ESRI 10 m Land Cover dataset (2020) were reclassified into five classes—waterbody, forest, cropland, built-up, and grassland and resampled to the common 12.5 m grid using the nearest-neighbor method to preserve categorical values. All factor layers were standardized to a common projection, spatial extent, cell size, and raster alignment before frequency-ratio analysis.

3.5 GEOTECHNICAL CHARACTERIZATION

Representative soil samples were collected from each identified landslide site and subjected to standard laboratory testing to determine key geotechnical parameters governing slope stability. The tests performed included direct shear tests to determine cohesion (c) and internal friction angle (ϕ), determination of moisture content following ASTM D2216 procedures, calculation of bulk density and dry density from undisturbed samples, and determination of specific gravity using the pycnometer method. The results from these tests informed the physical interpretation of failure mechanisms at each site and provided quantitative parameters for slope stability assessment (Section 4.5; Table 5).

Direct shear testing was conducted following the general procedures of ASTM D3080/D3080M-04 to determine the shear strength parameters of the soil samples. The specimens were prepared and placed in the direct shear apparatus while maintaining their natural moisture condition. For each sampling site, one specimen was tested sequentially under three different normal stresses of 0.5, 1.0, and 2.0 kg/cm². Initially, a normal stress of 0.5 kg/cm² was applied to the specimen and allowed to stabilize. The specimen was then sheared horizontally at the specified shearing rate, while shear load and horizontal displacement were recorded. After completion of the first shearing stage, the normal stress was increased to 1.0 kg/cm², and the same specimen was sheared again. Finally, the normal stress was increased to 2.0 kg/cm², and the specimen was subjected to a third shearing stage. The specimen was maintained under its natural moisture condition throughout the testing procedure. The recorded shear load was converted to shear stress based on the shearing area of the specimen. Shear stress–horizontal displacement curves were prepared for each normal stress, and the peak shear stress was identified from each curve. The peak shear stresses corresponding to the three normal stresses were then plotted to establish the shear-strength relationship using the Mohr–Coulomb failure criterion: The intercept of the fitted failure envelope was used to determine cohesion, while the slope of the envelope was used to calculate the friction angle. The resulting values represent the apparent peak shear-strength parameters of the samples under natural moisture conditions.

$$\tau = c + \sigma_n \tan \phi$$

where:

τ = shear stress at failure

c = cohesion

σ_n = normal stress

ϕ = angle of internal friction

The intercept of the fitted failure envelope was used to determine cohesion, while the slope of the envelope was used to calculate the friction angle. The resulting values represent the apparent peak shear-strength parameters of the samples under natural moisture conditions.

3.6 RAINFALL

Daily 24 hour accumulated rainfall records for Okhaldhunga Station Index 1206; 27.308°N, 86.504°E; elevation 1,731m, the meteorological station nearest to Chishankhugadhi Rural Municipality were used for the period of 1 Jan 2014 to 31st December 2024 (4023 daily observation values).

3.6.1 ANALYTICAL METHODS

- I. Trend detection: The non-parametric Mann–Kendall test (Mann, 1945; Kendall, 1975) was applied to annual rainfall totals to test for a monotonic trend, with the magnitude of change estimated using Sen’s slope estimator (Sen, 1968).
- II. Seasonal characterization: Daily totals were aggregated into four locally relevant seasons pre monsoon (Mar–May), monsoon (Jun–Sep), post-monsoon (Oct–Nov), and winter (Dec–Feb).
- III. Extreme precipitation indices: Standard indices recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI; Zhang et al., 2011) were computed, including RX1day, RX5day, R10mm, R20mm, SDII, CWD, CDD, R95p, and R99p. A wet day was defined as a day with rainfall ≥ 1 mm. The 95th- and 99th-percentile thresholds underlying R95p and R99p were calculated from the distribution of all wet-day rainfall totals over the full 2014–2024 record, rather than from a longer 1961–1990-type climatological baseline, which is not feasible given the 11-year record length. R95p and R99p represent the percentage of total rainfall contributed by days exceeding the respective station-specific percentile thresholds.
- IV. Rainfall intensity duration threshold comparison: Rather than defining discrete rainfall events with an explicit inter event dry period separation criterion, this analysis extracted the maximum n-day rolling cumulative rainfall directly from the continuous daily series, for durations of 1, 3, 5, 7, 10 and 15 days, and converted each to a mean intensity (mm/hr). These intensity duration (I-D) pairs were compared against the global empirical threshold of Caine (1980), $I = 14.82 \cdot D^{-0.39}$ (I in mm/hr, D in hours), as a comparison of observed rainfall extremes against an established global threshold rather than as a locally calibrated, event based triggering threshold.

4 RESULTS

4.1 LANDSLIDE INVENTORY

A total of 20 landslides were identified and mapped within Wards 1, 4, 5, and 7 of Chishankhugadhi Rural Municipality (Fig. 2), reflecting the spatial diversity of failure mechanisms across different topographic and geological settings. The majority of the mapped failures are transitional and rotational slides occurring on colluvial slopes and hillsides adjacent to road cuts. A subset of these failures is associated with local- and regional-scale faulting and folding, where deformed rock masses have failed along pre-existing structural weaknesses.

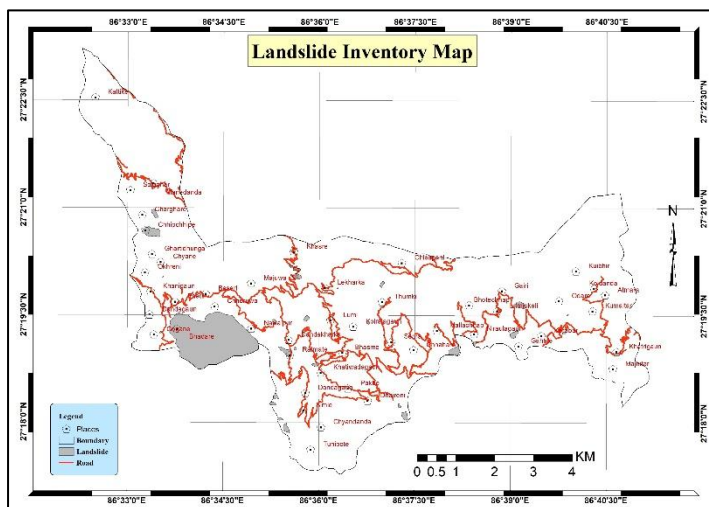


Figure 2 Landslide Inventory Map of the study area.

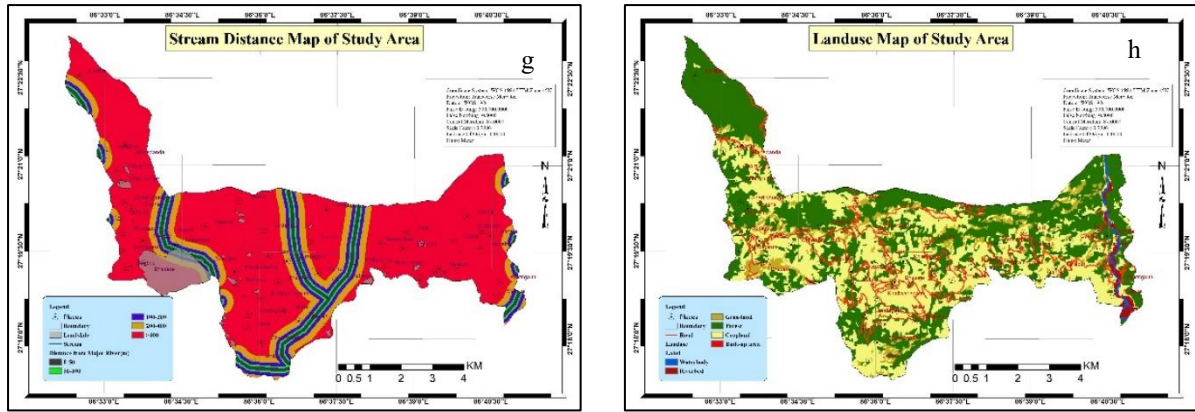


Figure 3 a) Slope, b) Aspect, c) Curvature, d) Fault Distance, e) Geology, f) Road Distance, g) Stream Distance, h) Landuse map of study area.

4.3 LANDSLIDE SUSCEPTIBILITY MAP

The Landslide Susceptibility Index (LSI) values computed using the seven factors were classified into five susceptibility zones using the Natural Breaks (Jenks) method (Fig. 4). The spatial distribution and proportional coverage of each susceptibility zone, along with the corresponding percentage weight of each contributing factor, are presented in Table 2 and Fig. 4. The prediction rate for each susceptibility class is presented in Table 3.

Table 2 Frequency Ratio (FR) and normalized weight for each class of the seven causative factors used in the quantitative model.

S N	Data Layers	Classes	Pixel Count of Classes	%Pixel Count of Classes	Pixel Count in Landslide	%Pixel Count in Landslide	FR	RF (normalized%)
1	Stream Distance	0-50	12277	3.53%	420	2.44%	0.03	16.92
		50-100	11606	3.33%	324	1.89%	0.03	13.81
		100-200	23170	6.66%	917	5.34%	0.04	19.58
		200-400	45839	13.17%	2213	12.88%	0.05	23.88
		>400	255134	73.31%	13314	77.46%	0.05	25.81
	Total		348026		17188		0.20	100.00
2	Road Distance	0-50	54642	15.70%	429	2.50%	0.01	4.40
		50-100	37767	10.85%	309	1.80%	0.01	4.59
		100-200	56842	16.33%	1185	6.89%	0.02	11.70
		200-400	74503	21.41%	3449	20.07%	0.05	25.97
		>400	124272	35.71%	11816	68.75%	0.10	53.34
	Total		348026		17188		0.18	100.00
3	Fault Distance	0-50	7715	2.22%	2061	11.99%	0.27	30.41
		50-100	6997	2.01%	1665	9.69%	0.24	27.09
		100-200	14084	4.05%	2983	17.36%	0.21	24.11
		200-400	27888	8.01%	3869	22.51%	0.14	15.80
		>400	291342	83.71%	6610	38.46%	0.02	2.58
	Total		348026		17188	100.00%	0.88	100.00
4	Curvature	Concave	32417	9.33%	1106.00	6.41%	0.03	25.71
		Plane	219859	63.28%	11922.00	69.12%	0.05	40.87
		Convex	95169	27.39%	4220.00	24.47%	0.04	33.42
	Total		347445		17248		0.13	100.00
5	Slope	0-5	4583	1.33%	108.000	0.64%	0.02	12.09
		5-12	15850	4.61%	793.000	4.69%	0.05	25.67
		12-30	158360	46.10%	9946.000	58.78%	0.06	32.22
		30-45	133583	38.89%	5543.000	32.76%	0.04	21.29
		>45	31118	9.06%	530.000	3.13%	0.02	8.74
	Total		343494		16920		0.19	100.00
6	Aspect	North	12072	3.51%	3030	17.91%	0.25	38.69
		Northeast	27759	8.08%	6476	38.27%	0.23	35.96
		East	42214	12.29%	2120	12.53%	0.05	7.74
		Southeast	62516	18.20%	1494	8.83%	0.02	3.68
		South	74832	21.79%	1555	9.19%	0.02	3.20
		Southwest	73595	21.43%	1114	6.58%	0.02	2.33
		West	39437	11.48%	736	4.35%	0.02	2.88
		Northwest	11069	3.22%	395	2.33%	0.04	5.50
	Total		343494		16920		0.65	100.00
7	Geology	Ulleri Formation	23762	6.83%	0	0.00%	0.00	0.00
		Kuncha Formation	324264	93.17%	17188	100.00%	0.05	100.00
	Total		348026		17188		0.05300619 2	100.00

Note on Table 2 column definitions: "Pixel Count of classes" and "%Pixel Count of classes" give the area (in DEM pixels) of each factor class and its share of the total study area pixels (AT); "Pixel count in Landslide" and "%Pixel count in Landslide" give the number of landslide affected pixels within that class and its share of all mapped landslide pixels (NT), following the polygon-to-pixel rasterization. "FR" is the class wise landslide density (N_{ij}/A_{ij} ; see Section 3.3 for the worked example and its relationship to the full frequency ratio equation). "RF" is FR normalized to sum to 1.0 within each factor, and "RF(INT)"/"Weight (%)" express this normalized value as a percentage; these percentage weights, not the raw FR column, are the values summed pixel by pixel across the seven factors to build the susceptibility index. "PR" (renamed Class Weight Ratio, CWR, in Table 4) is their ratio, used descriptively in this study as an indicator of how unevenly a factor discriminates between its own classes; it is not a standardized, independently validated statistical index and should not be read as equivalent to the ROC based prediction rate discussed in Section 4.4. Total pixel counts differ slightly between factors (e.g., 348,026 for Stream/Road/Fault/Geology versus 347,445 for Curvature and 343,494 for Slope/Aspect) because the curvature and slope/aspect raster derived directly from the DEM, exclude a small number of edge and no data cells that are present in the Euclidean distance and geology layers; this does not materially affect the class wise percentages reported.



The high- and very-high-susceptibility zones are predominantly concentrated along steep slopes adjacent to road corridors, in areas underlain by colluvial and residual soils, and in zones receiving above-average annual rainfall. Although approximately 80% of mapped landslide pixels occur within the high- and very-high-susceptibility classes, these classes also cover approximately 90% of the study area. Therefore, the map provides only limited spatial discrimination at the present inventory size and should primarily be interpreted as a regional screening product. The low- and very-low-susceptibility zones are largely confined to the upper parts of the study area, where bedrock-dominated ridgelines, gentle slopes, low topographic moisture accumulation, and relatively stable geological substrates limit the conditions conducive to slope failure. Even within these relatively stable zones, isolated landslide occurrences are recorded, underscoring that susceptibility should be interpreted probabilistically rather than deterministically.

Table 3 Descriptive class-weight spread among the seven conditioning factors.

SN	Data Layers	Classes	Prediction Ratio	Relative Frequency	Weightage
1	Stream Distance	0-50	1.00	16.00	16.00
		50-100		13.00	13.00
		100-200		19.00	19.00
		200-400		23.00	23.00
		>400		25.00	25.00
2	Road Distance	0-50	4.08	4.00	16.31
		50-100		4.00	16.31
		100-200		11.00	44.84
		200-400		25.00	101.92
		>400		53.00	216.06
3	Fault Distance	0-50	2.32	30.00	69.56
		50-100		27.00	62.60
		100-200		24.00	55.65
		200-400		15.00	34.78
		>400		2.00	4.64
4	Curvature	Concave	1.26	25.00	31.56
		Plane		40.00	50.50
		Convex		33.00	41.66
5	Slope	0-5	1.96	12.00	23.47
		5-12		25.00	48.91
		12-30		32.00	62.60
		30-45		21.00	41.08
		>45		8.00	15.65
6	Aspect	North	3.03	38.00	115.10
		Northeast		35.00	106.02
		East		7.00	21.20
		Southeast		3.00	9.09
		South		3.00	9.09
		Southwest		2.00	6.06
		West		2.00	6.06
		Northwest		5.00	15.15
7	Geology	Ulleri Formation	8.33	0.00	0.00
		Kuncha Formation		100.00	407.67

Table 4 reports, for each factor, the ratio of its highest to lowest normalized class weights, termed the Class Weight Ratio (CWR), rather than the “prediction ratio,” to avoid confusion with the ROC-based prediction rate discussed in Section 4.4. The CWR is a simple descriptive measure of how unevenly a factor discriminates among its classes and is not, by itself, a validated statistical index. By this measure, geology, aspect, and distance from roads show the widest spread between their strongest and weakest classes, whereas stream distance and curvature vary comparatively little across classes.

Two results in Table 4 require caution in interpretation. First, the geology CWR (8.33) is substantially influenced by the extreme area imbalance between its two classes. The concentration of the mapped landslide inventory within the Kuncha Formation is consistent with an important geological association; however, because the Kuncha

Formation occupies approximately 93% of the study area and the inventory contains no mapped failures within the Ulleri Formation, the strength of this lithological association cannot be independently distinguished from the underlying area imbalance. Second, the road-distance result, which shows increasing class weights with increasing distance from roads and the strongest weight beyond 400 m, appears at first glance to contradict the qualitative field observation (Section 5.1) that road cuts can destabilize slopes. These findings operate at different spatial scales and are not necessarily in conflict. The road-distance layer in the FR analysis reflects the areal distribution of landslide density relative to the sparse road network across the entire study area. Because the constructed road network tends to preferentially follow gentler and graded alignments, it may avoid many of the steepest and potentially more landslide-prone terrain classes, thereby weakening the spatial correlation between distance-from-road classes and landslide density. The qualitative observation, by contrast, concerns site-specific failures directly attributable to individual unsupported cut slopes. These represent distinct processes operating at different spatial scales; therefore, the road-distance FR result should not be interpreted as evidence against road cuts acting as local triggers.

Table 4 Class Weight Ratio (CWR), a descriptive measure of the spread between each factor's highest and lowest normalized class weight for each causative factor

Factor	Class Weight Ratio (CWR)	Interpretation
Stream Distance	1.00	Negligible discriminatory power on its own
Road Distance	4.08	Landslide density rises with distance from mapped roads (highest beyond 200 m); reflects the road network's alignment along gentler grades rather than an absence of road-cut effects (see Section 5.1 for site-specific road-cut failures)
Fault Distance	2.32	Strong spatial association, concentrated within 200 m of mapped faults
Curvature	1.26	Weak to moderate control
Slope Angle	1.96	Moderate to relatively high class-wise association, peaking at 12–30°
Aspect	3.03	Strong spatial association with north and northeast aspects; physical mechanism remains uncertain because rainfall observations were available from only one station
Geology	8.33	All mapped landslides occur in the Kuncha Formation, but this unit also covers ~93% of the study area; the high CWR partly reflects this area imbalance and should not, on its own, be read as proof of an unusually strong lithological control (see caveat above)

4.4 MODEL PERFORMANCE ASSESSMENT

Validation of the FR-based susceptibility model was carried out using the Receiver Operating Characteristic (ROC) curve and the area under the curve (AUC) metric, which provides a threshold-independent measure of the model's discriminatory capability (Rahaman et al., 2024). AUC values range from 0.5, indicating performance equivalent to random assignment, to 1.0, indicating perfect discrimination. Given the very small size of the held-out test subset (approximately six landslides), a prediction-rate curve computed from that subset alone would be

highly unstable. The single ROC curve reported here (Fig. 5; AUC = 0.734) is therefore a success-rate curve, computed using the full set of 20 mapped landslides against the susceptibility index, and should be interpreted as a measure of model fit rather than independent predictive performance on unseen data.

An AUC of 0.734 indicates that there is approximately a 73.4% probability that a randomly selected landslide location will receive a higher susceptibility score than a randomly selected non-landslide location. The AUC therefore provides an assessment of the model's discriminatory ability across all possible classification thresholds. The value of 0.734 falls within the range reported by several FR-based studies in comparable terrain; however, differences in inventory size, sampling strategy, factor selection, and validation procedures limit direct comparison (Singh and Kumar, 2017; Bhandari et al., 2024; Manopkawee and Mankhemthong, 2025), placing the model fit within the fair-to-good category.

Nevertheless, given the small underlying inventory (20 landslides in total, with only 14 available for training and 6 for testing once the dataset is split), and because the AUC reported here is based on a success-rate curve rather than an independent test-based prediction-rate curve, this value should be treated as an indicative measure of model fit rather than as confirmed evidence of independent predictive skill. This limitation is further discussed in Section 5.5. Reporting separate training (success-rate) and test (prediction-rate) curves, together with repeated random train-test splits to assess the sensitivity of AUC to sample selection, is recommended once a larger landslide inventory becomes available for the study area.

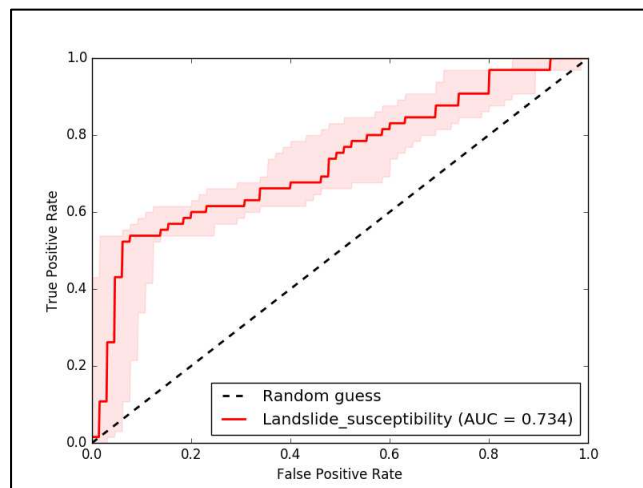


Figure 5 ROC success rate curve for landslide susceptibility model.

4.5 GEOTECHNICAL CHARACTERIZATION

Laboratory analysis of soil samples collected from the landslide sites revealed consistently low cohesion values and moderate friction angles across the study area, indicating relatively limited shear resistance. The geotechnical parameters determined for each sampling site are presented in Table 5.

Table 5 Geotechnical properties of representative landslide materials

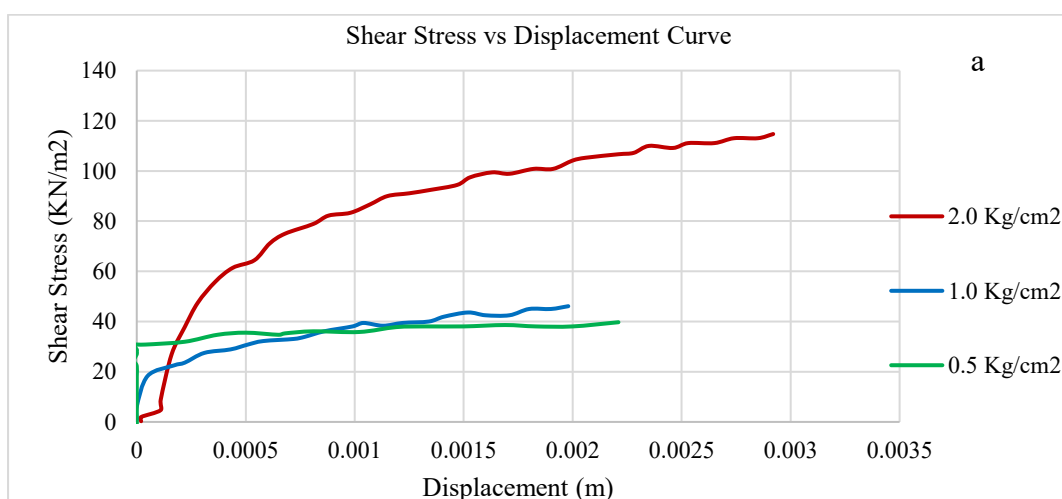
Site	Cohesion c (kPa)	Friction Angle ϕ ($^{\circ}$)	Bulk Density (Undisturbed Sample) (g/cm ³)	Dry Density (Undisturbed Sample) (g/cm ³)	Moisture Content (%)	Specific Gravity
TL	3.1	28.0	2.79	2.60	19.1	2.73
RL	6.1	25.4	2.33	2.25	15.9	2.43
KK	2.4	28.0	2.89	2.68	7.1	2.83

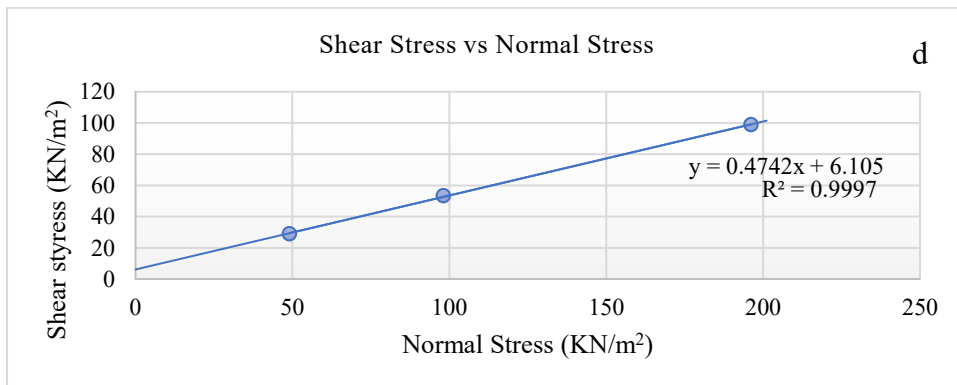
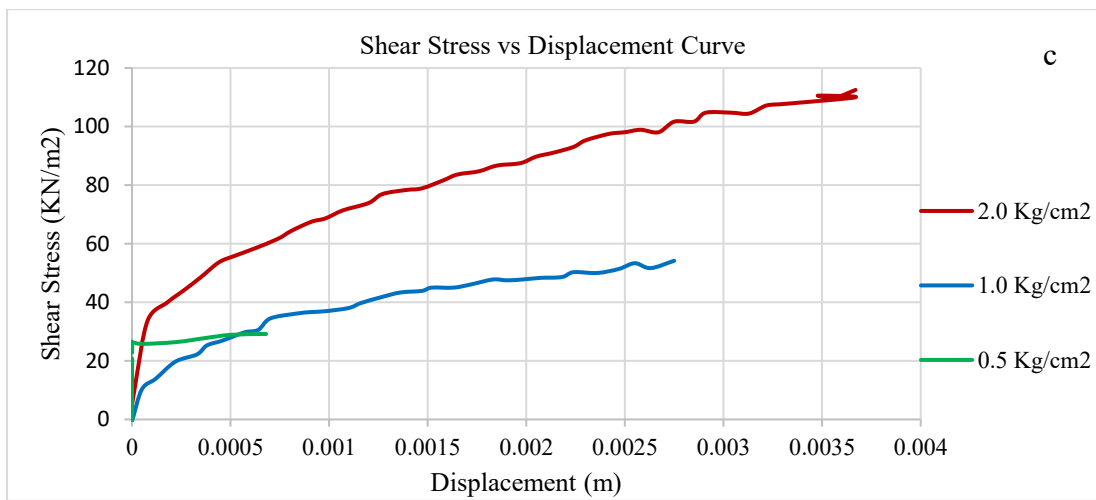
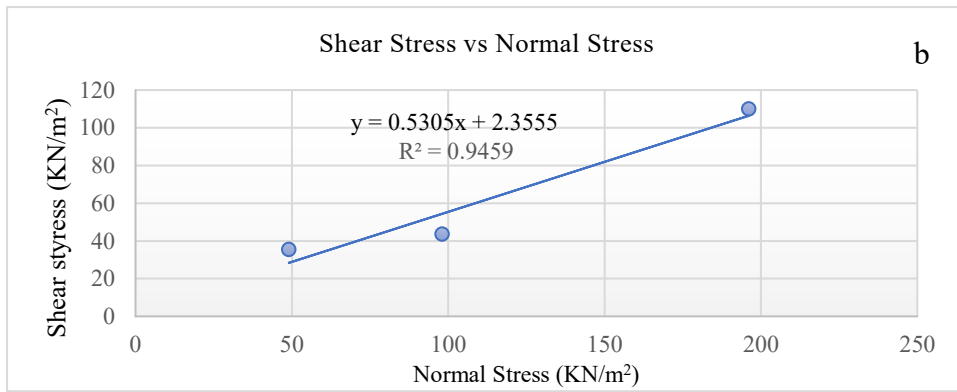
BP	5.1	22.5	2.74	2.52	15.2	2.83
KL	6.1	25.4	2.35	2.25	15.2	4.03
AL	2.6	27.0	2.87	2.67	12.3	3.95
DL	3.1	28.0	2.81	2.60	20.0	2.46
OL	2.39	27.0	2.88	2.69	17.5	2.27
Site 01	2.39	27.0	2.75	2.57	20.3	2.99
TK	4.9	20.1	2.31	2.22	18.6	2.94
RAM	5.9	24.3	2.30	2.23	18.4	3.48

Notes: Thumki Landslide (TL), Odhare Landslide (OL), Amare Landslide (AL), 27°19'14"N and 86°37'1"E (site 01), Khani Khola Landslide (KK), Kalimati Pahirol (KL), Ratamate Pahirol (RL), Diyale Landslide (DL), Bhandare Danda Pahirol (BP), Thuldhunga Creep (TK), Jyamire Landslide (RAM)

The values reveal a consistent pattern: cohesion is uniformly low, ranging from 2.4 kPa at Khani Khola to 6.1 kPa at two sites provisionally identified as Kalimati and Ratamate, pending verification of the site labels as noted in Table 5, while friction angles cluster within the range of 20–28°. The combination of low cohesion and relatively high in-situ moisture contents, reaching 20.0% at Diyale and 20.3% at Site 01, is consistent with potentially reduced effective shear strength during monsoon-season infiltration. However, directly confirming this mechanism would require measurements of pore-water pressure, matric suction, or effective stress, which were not collected in this study. The site currently labelled “TK” in Table 5 (attributed to Thuldhunga creep; see Table 5 note) exhibits the lowest friction angle (20.1°) among all sites, consistent with its field characterization as a slow-moving deformation zone.

The measured specific gravity values also varied among the investigated soil samples. Relatively high values were recorded at KL, AL, and RAM and were retained as reported in the laboratory sheets, as these values represent the properties of the materials actually subjected to laboratory testing. The direct-shear test results are illustrated by representative plots showing the shear stress–displacement responses and the corresponding relationships between peak shear stress and applied normal stress (Fig. 6). These relationships were used to establish the Mohr–Coulomb failure envelopes and determine the apparent cohesion (c) and friction angle (ϕ) under natural moisture conditions.





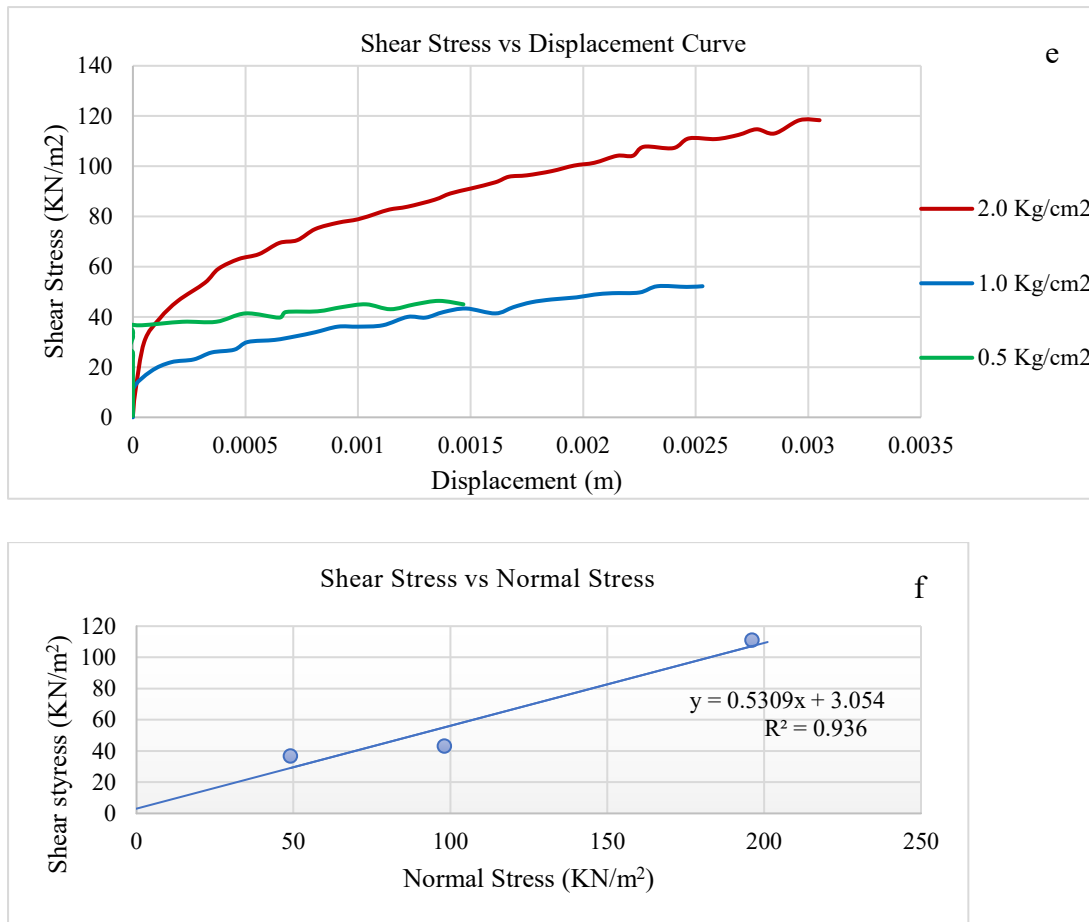


Figure 6 Representative direct shear test results (a)shear stress–displacement curves and (b) corresponding Mohr–Coulomb failure envelopes for Bhandare Danda ; (c) shear stress–displacement curves and (d) corresponding Mohr–Coulomb failure envelope for Khani Khola; (e) shear stress–displacement curves and (f) corresponding Mohr–Coulomb failure envelope for Ratamate Landslide.

4.6 TEMPORAL RAINFALL PATTERNS AND RAINFALL THRESHOLD ANALYSIS

4.6.1 RAINFALL REGIME AND SEASONAL DISTRIBUTION

Okhaldhunga station recorded a mean annual rainfall of 1,668 mm over 2014–2024, ranging from 1,310 mm in 2018 (the driest year) to 2,223 mm in 2024 (the wettest year on record). Rainfall is strongly concentrated in the monsoon season: over four-fifths (80.3%) of the mean annual total of 1,668 mm falls between June and September, with July and August alone contributing approximately 48% of the annual rainfall, averaging 408 mm and 398 mm, respectively (Table 6; Fig. 7). This pronounced monsoon concentration provides context for the observation that north- and northeast-facing slopes host a disproportionate 56% of the mapped landslides. A plausible explanation is that these aspects receive more direct monsoon precipitation while experiencing limited solar heating, thereby sustaining elevated soil moisture during the failure season. However, the single-station rainfall record used here provides no spatial or aspect-dependent information on precipitation or wind-driven loading. Therefore, this mechanism remains a hypothesis consistent with the seasonal timing of failures rather than a finding directly demonstrated by the rainfall data; testing it would require spatially distributed rainfall and wind observations.

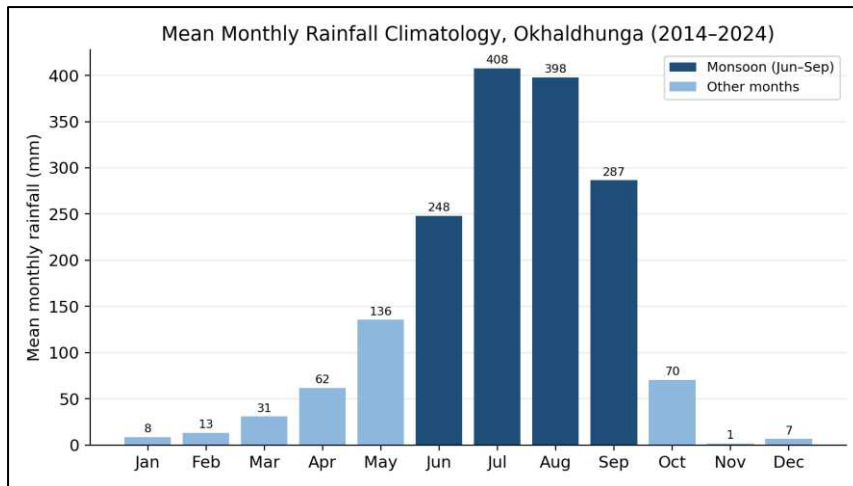


Figure 7 Mean monthly rainfall at Okhaldhunga station (2014–2024). Monsoon months (June–September) are shaded dark and align with the period of elevated failure activity on north/northeast facing slopes discussed in Section 5.1.

Table 6 Seasonal rainfall distribution at Okhaldhunga station (2014–2024).

Season	Months	11- Year Total (mm)	Share of Annual Rainfall
Monsoon	June–September	14,737.6	80.3%
Pre-monsoon	March–May	2,508.5	13.7%
Post-monsoon	October–November	791.0	4.3%
Winter	December–February	308.8	1.7%

4.6.2 TREND ANALYSIS (MANN–KENDALL AND SEN’S SLOPE)

The Mann–Kendall test applied to annual rainfall totals (2014–2024) returned $Z = 0.62$ and $p = 0.53$ (Kendall’s $\tau = 0.16$), indicating no statistically significant monotonic trend over the 11-year record. The Sen’s slope estimator nonetheless indicates a positive tendency of approximately $+26.8$ mm/year (Fig. 8), consistent with 2024 being the wettest year on record. Given the short record length, this result should be interpreted as indicative rather than as evidence of a confirmed climatic trend and is broadly consistent with the increasing rainfall intensity perceived by local residents of Chishankhugadhi Rural Municipality, as reported by Phuyal et al. (2022).

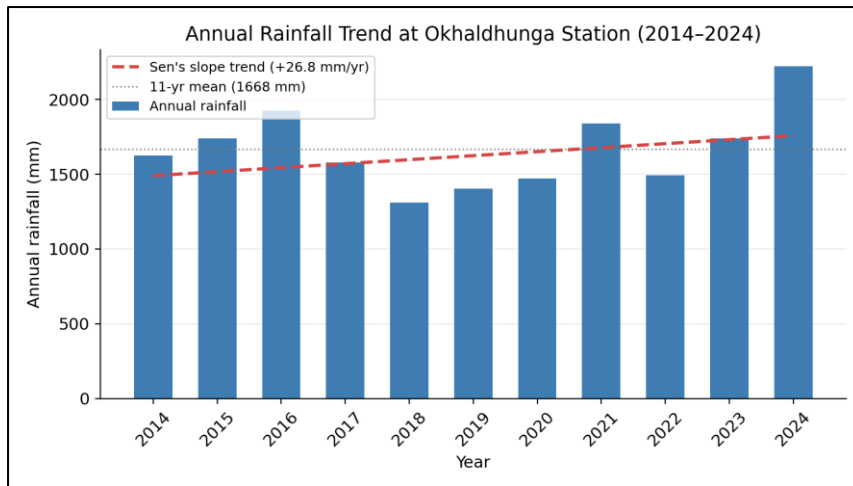


Figure 8 Annual rainfall totals at Okhaldhunga station (2014–2024) with Sen's Slope trend line.

4.6.3 EXTREME PRECIPITATION INDICES

Extreme precipitation indices computed for the record (Table 7) show that rainfall in the study area, while highly seasonal, is also intense. The Simple Daily Intensity Index (SDII) of 10.8 mm per wet day indicates that individual rainfall events, when they occur, are typically substantial. Very wet days exceeding the 95th-percentile threshold (45.4 mm/day) contribute nearly one-third (30.6%) of the total annual rainfall, underscoring the outsized role of a relatively small number of extreme events in the overall water balance and slope hydrology. The maximum single-day rainfall (RX1day) recorded was 110.6 mm on 3 September 2015, while the maximum 5-day cumulative rainfall total (RX5day) was 276.4 mm, ending on 21 August 2015.

Table 7 ETCCDI-based extreme rainfall indices, Okhaldhunga station (2014–2024).

Index	Definition	Value
RX1day	Maximum 1-day rainfall	110.6 mm
RX5day	Maximum cumulative 5-day rainfall	276.4 mm
R10mm	Mean amount of days/year with rainfall ≥ 10 mm	46.8 days/yr
R20mm	Mean amount of days/year with rainfall ≥ 20 mm	26.3 days/yr
SDII	Simple Daily Intensity Index (rainfall per wet day)	10.8 mm/day
CWD	Maximum consecutive wet days	22 days
CDD	Maximum consecutive dry days	136 days
R95p	Contribution of very wet days (>95 th percentile, >45.4 mm) to total rainfall	30.6%
R99p	Contribution of extremely wet days (>99 th percentile, >82.0 mm) to total rainfall	8.2%

The five largest single-day and five-day cumulative rainfall events recorded during 2014–2024 are listed in Table 8, while Fig. 9 presents the daily rainfall series for the same period, highlighting extreme rainfall events exceeding the R95p threshold of 45.4 mm/day. These dates represent the highest-priority windows for cross-referencing rainfall events against landslide occurrence records. However, precise onset dates are not available for most of the 20 mapped landslides in the current inventory, as many represent historical failures or features documented as active during the 2025 field campaign without a recorded onset date. Consequently, systematic cross-referencing has not yet been possible, and no landslide-triggering threshold specific to Chishankhugadhi should be inferred from Table 8 alone. Establishing a robust local rainfall threshold would require a revised inventory containing accurately dated landslide occurrences paired with the corresponding rainfall events, which is identified as a priority for future work (Section 5.5).

Table 8 Top five RX1day and RX5day rainfall events, Okhaldhunga station (2014–2024).

Rank	Date	RX1day (mm)	Date (RX5day window ending)	RX5day (mm)
1	3 Sep 2015	110.6	21 Aug 2015	276.4
2	31 Jul 2024	108.7	13 Jul 2019	253.8
3	12 Jul 2019	106.6	15 Jul 2019	237.7
4	28 Sep 2024	104.4	29 Sep 2024	223.9
5	25 Aug 2023	97.6	14 Jul 2019	223.6

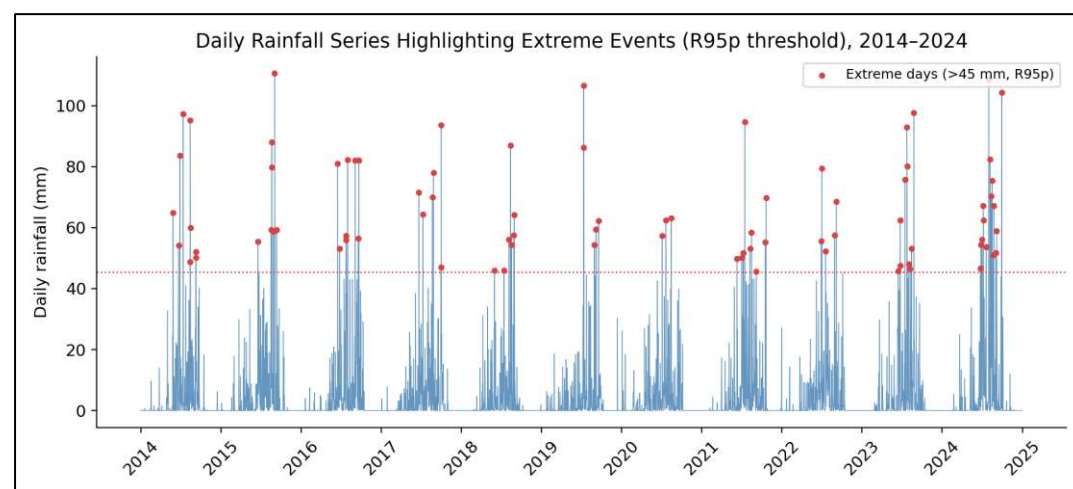


Figure 9 Daily rainfall series (2014–2024) with extreme events (R95p threshold, >45.4 mm/day) highlighted in red.

4.6.4 RAINFALL INTENSITY – DURATION THRESHOLD COMPARISON

Fig.10 compares the maximum observed rainfall intensity at Okhaldhunga, for durations ranging from 1 to 15 days, against the global rainfall intensity–duration (I–D) threshold for shallow landslide and debris-flow initiation proposed by Caine (1980), $I = 14.82D - 0.39I = 14.82D^{-0.39}$, and subsequently updated by Guzzetti et al. (2008). Because the available rainfall dataset consists of daily 24-hour accumulated observations, the Caine (1980) comparison was performed using fixed-duration rolling rainfall windows rather than individually delineated rainfall events. No inter-event dry-period separation criterion was therefore applied. Maximum cumulative rainfall was extracted from the continuous daily series for durations of 1, 3, 5, 7, 10, and 15 days. For each duration, the cumulative rainfall was divided by the corresponding duration in hours to obtain the mean rainfall intensity (mm h^{-1}). These maximum intensity–duration pairs were then compared with the global empirical Caine (1980) relationship, $I = 14.82D - 0.39I = 14.82D^{-0.39}$, where I is rainfall intensity (mm h^{-1}) and D is duration (h).

This analysis represents a comparison of observed rainfall extremes with a published global threshold and does not constitute a locally calibrated rainfall-triggering threshold. Because occurrence dates were unavailable for the inventoried landslides, the rainfall extremes could not be systematically paired with individual landslide events. Consequently, the rainfall analysis is treated as contextual rather than as an event-based triggering analysis.

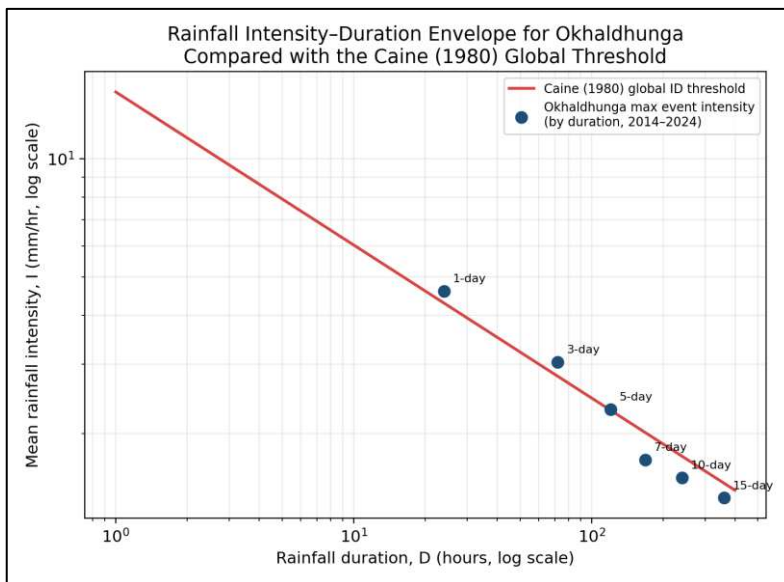


Figure 10 Rainfall intensity–duration envelope for Okhaldhunga station (2014–2024) with the Caine (1980) global threshold.

5 DISCUSSION

5.1 CONTROLLING FACTORS ON FAILURE MECHANISMS

The FR analysis, together with the geotechnical characterization and field observations, indicates that landslide susceptibility in Chishankhugadhi results from the interaction of geological, topographic, structural, hydrological, and anthropogenic conditions. The FR results identify spatial associations between mapped landslides and the conditioning factors, whereas the geotechnical and field investigations provide supporting evidence for the material and site conditions under which slope instability may develop. The results should therefore be interpreted as evidence of susceptibility associations and plausible mechanisms rather than as proof that any individual factor acts independently or causally.

Among the conditioning factors, geology shows a particularly strong association with the mapped landslide inventory. Most mapped landslide occurrence is concentrated within the phyllite-dominated Kuncha Formation. Phyllitic materials may be susceptible to failure because pronounced foliation can provide preferential planes of weakness, while weathering and clay-mineral development may reduce the shear resistance of discontinuities and weathered materials. Under monsoonal conditions, progressive weathering may further weaken the near-surface material and facilitate shallow failure. These characteristics are consistent with observations from other parts of

the Kuncha Formation and the Lesser Himalaya. Silwal et al. (2024) reported that increasing weathering intensity in Kuncha Formation phyllite, metasandstone, and gritty phyllite, manifested by microcracking, loss of mica pleochroism, and progressive alteration of muscovite to illite, was associated with shallow landslide occurrence. Similarly, Halder et al. (2025) documented the potential role of hydrophilic clay minerals, including illite and chlorite, in reducing the frictional strength of weathered materials and sliding surfaces in the Lesser Himalaya. Comparable relationships between weathering, clay-mineral development, and landslide instability have also been reported from central Nepal (Regmi et al., 2013; Hasegawa et al., 2009).

The geological association identified by the FR analysis is nevertheless subject to an important limitation. The Kuncha Formation occupies approximately 93% of the study area, whereas the Ulleri Formation represents a much smaller area and contains no mapped landslides in the present inventory. Consequently, the high FR value and large class-weight contrast for geology partly reflect the strong imbalance in the spatial extent of the geological classes. The results therefore support a strong association between the mapped landslide inventory and the Kuncha Formation, but they do not independently establish that lithology alone is responsible for the observed concentration. The geological interpretation is strengthened by the documented structural and weathering characteristics of phyllite and by the field and geotechnical observations, but the relative contribution of lithology, weathering, topography, and other interacting controls cannot be separated quantitatively using the present dataset.

The geotechnical results provide site-specific evidence of the mechanical characteristics of materials associated with the investigated failures. Cohesion values were consistently low, ranging from 2.36 to 6.11 kPa, while the measured friction angles were generally within approximately 20–28°. The low cohesion values indicate limited apparent cohesive resistance in the tested materials, making frictional resistance an important component of their measured shear strength. These results are compatible with the presence of weak and weathered near-surface materials, but the laboratory measurements should be regarded as supporting site characterization rather than independent validation of the FR susceptibility model. In particular, the measured friction angles cannot be interpreted as critical slope-stability thresholds because actual slope stability also depends on slope geometry, material thickness, discontinuity orientation, groundwater conditions, pore-water pressure, and failure-surface configuration.

The moisture-content measurements provide additional evidence regarding the hydrological condition of the sampled materials. Moisture contents reached 20.0% at Diyale and were relatively elevated at several other investigated sites. Such conditions are consistent with the possibility that prolonged monsoonal wetting may reduce available shear resistance; however, the present data do not directly demonstrate rainfall-induced strength reduction. Confirmation of this mechanism would require measurements of pore-water pressure, matric suction, or effective stress. Thus, the moisture measurements are interpreted as supporting evidence for the presence of relatively wet slope materials rather than as direct evidence of a quantified rainfall–strength relationship. The combination of low measured cohesion, moderate friction angles, and elevated moisture contents nevertheless provides a plausible geotechnical basis for the observed susceptibility where prolonged seasonal wetting occurs.

The relatively high specific gravity values measured at KL, AL, and RAM require separate qualification because of the composition of the tested specimens. During field sampling, the collected materials contained appreciable amounts of naturally occurring and crushed phyllitic fragments that were not completely separated from the soil before laboratory testing. These denser mineral fragments may have contributed to the elevated measured specific gravity. Accordingly, the reported values represent the specific gravity of the composite soil–phyllite materials subjected to laboratory testing rather than that of a strictly isolated soil fraction. Because the soil and phyllite fractions were not separately characterized, their individual contributions cannot be quantitatively distinguished. The reported values have therefore been retained as measured, but they should be interpreted as properties of the tested composite materials rather than as definitive specific-gravity values for the soil fraction alone.

Topographic controls further modify the spatial distribution of susceptibility. The concentration of mapped landslide pixels within the 12–30° slope class should not be interpreted as a universal critical slope angle. Rather, it represents a characteristic of the present inventory and may result from the combined effects of slope geometry, material availability, surface cover, and landslide size. Moderate to steep slopes may retain relatively continuous soil or colluvial cover that can become unstable during prolonged monsoonal wetting, whereas parts of the steepest terrain may have thinner surficial materials, exposed bedrock, or more competent rock masses, reducing the area available for shallow soil failures. In addition, the landslide inventory was converted from polygons to raster pixels, meaning that larger landslides occupying moderate slopes contribute more pixels to the corresponding slope classes. Accessibility and mapping limitations may also influence the representation of failures in steep and

inaccessible terrain. The 12–30° concentration is therefore interpreted as an inventory-specific spatial association rather than a universal slope-stability threshold.

Aspect provides an additional directional component of susceptibility. Aspect influences solar exposure, evaporation, soil-moisture retention, and, depending on local climatic conditions, the spatial distribution of rainfall and wind exposure (Cellek, 2021). The observed concentration of landslide occurrence in particular aspect classes suggests that slope orientation contributes to the spatial pattern of susceptibility in the study area. For northeast-facing slopes, one plausible explanation is that relatively greater effective monsoonal moisture combined with comparatively limited solar heating may promote prolonged soil-moisture retention. This interpretation, however, remains a hypothesis rather than a demonstrated mechanism. As discussed in Section 4.6.1, the rainfall analysis is based on a single rainfall station and therefore cannot resolve spatial variations in rainfall or wind exposure between different slope aspects. Spatially distributed rainfall, radiation, evaporation, and/or wind observations would be required to test this mechanism. Accordingly, aspect is interpreted here as a susceptibility-related spatial factor rather than evidence of a confirmed directional rainfall mechanism.

Fault proximity represents an important structural component of the susceptibility pattern. The 0–50 m fault-distance class contains 11.99% of the mapped landslide occurrence while representing only 2.22% of the study area. This disproportionate concentration is consistent with the potential influence of structurally weakened zones, where increased fracturing and deformation may reduce rock-mass competence. Recent characterization of Himalayan fault-damage zones has shown systematic variations in joint density, block characteristics, and shear strength toward fault cores, supporting the interpretation that fault-related damage can create mechanically weaker corridors that are more susceptible to failure (Ahmed et al., 2026). The spatial association observed in Chishankhugadhi is therefore compatible with the expected influence of tectonic structures on slope instability.

The fault-distance result should nevertheless be interpreted at the scale of the available geological mapping. The fault traces used in the analysis were derived from regional geological mapping and are subject to positional uncertainty. At distances of only tens of metres, this uncertainty can influence the assignment of landslides to individual fault-distance classes. Therefore, the concentration of landslides within the 0–50 m class should not be interpreted as evidence that 50 m represents a precise fault-influence or damage-zone width. Instead, it indicates a spatial association between mapped landslides and the vicinity of mapped fault traces. Detailed field-scale structural mapping, including fracture density, discontinuity orientation, weathering state, and damage-zone width, would be required to establish the actual spatial extent and mechanical significance of individual fault zones.

A field example consistent with this interpretation occurs at Bhandare Danda Pahi, where a large-scale translational or rotational failure threatening twelve households is located along an inferred fault zone mapped by the Department of Mines and Geology (DMG). The structural complexity associated with the mapped setting provides a plausible explanation for the weakened ground conditions observed at the site. However, because the mapped fault position is subject to the uncertainty inherent in regional geological mapping, the relationship should not be interpreted as definitive evidence that the inferred fault directly controls the failure. Field-scale structural investigation would be necessary to determine the exact fault trace, damage-zone extent, and relationship between the structural discontinuities and the observed failure surface.

Anthropogenic factors provide an additional layer of interpretation because they can locally modify slopes that are already predisposed to instability. Although anthropogenic variables were not included as primary conditioning factors in the FR model, field investigations identified road construction, inadequate drainage, irrigation, and steep-slope cultivation as potential local triggers or amplifiers of natural susceptibility. This distinction is important: the FR analysis evaluates regional spatial associations, whereas field observations can identify localized modifications to slope geometry, drainage, and water input that may initiate or accelerate individual failures.

Road construction was associated with slope instability at several investigated sites, particularly where road cuts lacked adequate toe support or drainage management. This field evidence does not necessarily contradict the distance-from-road FR result. The FR analysis describes the distribution of landslides relative to the regional road network, whereas an individual road cut produces a localized change in slope geometry and drainage conditions. Roads may also preferentially follow gentler and more accessible terrain, which can weaken the regional spatial relationship between road distance and landslide density. Consequently, the distance-from-road FR pattern should not be interpreted as evidence that roads are non-contributory to local slope failure; rather, it indicates that regional

distance from roads does not adequately represent the localized mechanical and hydrological effects of individual road cuts.

At Kalimati Pahi, unmanaged irrigation channels appear to have enhanced an already unstable slope through persistent seepage and infiltration. The observed progression from slow deformation to more active failure suggests that sustained anthropogenic water input may have amplified pre-existing susceptibility. Similarly, rice cultivation on steep terrain may contribute to instability by maintaining elevated soil-moisture conditions through repeated water application. These observations provide field-based evidence that human modification of drainage and water availability can locally amplify natural susceptibility. Nevertheless, because pore-water pressures and subsurface hydraulic conditions were not measured, the inferred hydrological mechanisms cannot be quantitatively established from the present dataset.

Taken together, the results indicate that landslide susceptibility in Chishankhugadhi is controlled by the interaction of predisposing terrain and material conditions with localized triggering processes. The geological setting, particularly the association with phyllite of the Kuncha Formation, provides an important material and structural predisposition, while slope and aspect influence the spatial distribution of potentially unstable terrain. Fault proximity indicates an additional structural association, although the exact extent of fault influence remains uncertain because of the resolution of regional geological mapping. Geotechnical results provide supporting evidence for the weak mechanical characteristics of sampled materials, while moisture measurements and field observations indicate that seasonal and anthropogenic water inputs may further promote instability. Anthropogenic activities, particularly road cutting, drainage modification, irrigation, and steep-slope cultivation, therefore appear to act primarily as local triggers or amplifiers rather than as independently quantified susceptibility factors. Overall, the FR model identifies spatial associations, while the geotechnical and field evidence provides process-based context; neither dataset alone is sufficient to establish causality. This integrated interpretation provides a more defensible basis for susceptibility zonation while recognizing the limitations imposed by the small inventory, geological class imbalance, limited geotechnical sampling, single-station rainfall record, and positional uncertainty of regional structural mapping.

5.2 SITE SPECIFIC FAILURE MECHANISM

The integration of field observations, geotechnical data, and joint analysis across the inventoried sites reveals three primary failure-mode categories. Planar and wedge failures (Fig. 11) dominate at sites where foliation planes or intersecting joint sets provide kinematically feasible sliding surfaces that daylight out of the slope face. Representative examples include Odhare Pahi, where the foliation attitude is 245/38 and the foliation planes daylight on a northeast-facing slope, and Jyamire, where foliation with an attitude of 275/60 is associated with clay-filled joints. These failure modes are particularly hazardous because they can mobilize rapidly once initiated, potentially generating high-velocity debris with limited warning time.

Toppling failures are documented at the crown portions of steep exposures, where unfavorably oriented joint planes allow blocks to rotate. This failure mode is most prominent at Gahate Pahi and the Thumki Landslide, where the crown geometry facilitates progressive block detachment. Creep phenomena affect a distinct subset of sites, including Amare, Thuldhunga, and Ratamate, where thick colluvial mantles or cohesive, clay-rich deposits undergo gradual viscoplastic deformation under sustained gravitational loading and seasonal variations in moisture. Although creep rates are typically slow, the geotechnical data from Thuldhunga, including the lowest friction angle (20.14°), relatively high moisture content (18.64%), and a failure-line slope of 0.319, indicate conditions that may warrant priority field monitoring, particularly during periods of intense or prolonged rainfall and, especially, during extreme rainfall events.

276.4 mm, respectively) represent observed rainfall maxima and provide useful local reference conditions for future event-based rainfall-triggering analyses.

Comparison of the observed rainfall intensity–duration envelope with the global threshold proposed by Caine (1980) shows that some short-duration rainfall extremes exceed portions of the Caine (1980) envelope. However, because these rainfall extremes were not systematically paired with dated landslide occurrences, this comparison cannot establish that the observed rainfall events triggered landslides in Chisankhugadhi. Similarly, none of the individual daily rainfall totals during 2014–2024 reached the 144 mm/day regional threshold reported for the Nepal Himalaya by Dahal and Hasegawa (2008); the highest recorded daily total of 110.6 mm represents approximately 77% of this benchmark. This does not imply an absence of landslide susceptibility or rainfall-triggered failures, because regional thresholds may vary with local geology, soil depth, land use, and antecedent moisture conditions (Dahal and Hasegawa, 2008; Guzzetti et al., 2007). Rather, the absence of a threshold exceedance suggests that the documented failures, particularly those described as chronic or progressively destabilized, such as Bhadaure Danda and Kalimati, may involve cumulative multi-day antecedent wetting rather than isolated extreme-intensity rainfall. This interpretation is also consistent with the potential influence of anthropogenic factors, including road cuts, irrigation seepage, and paddy cultivation on steep terrain, which may interact with rather than replace the influence of a persistently wet monsoon climate.

These findings highlight the need for locally calibrated rainfall thresholds for future early-warning and susceptibility applications in Chisankhugadhi Rural Municipality. Cumulative antecedent rainfall indices, including RX5day and RX7day, may provide useful reference variables for future event-based analyses in which rainfall conditions are systematically paired with accurately dated landslide occurrences.

5.5 LIMITATIONS

- Inventory size: with only 20 mapped landslides, the 70/30 training/test split leaves a small test subset (approximately six events). Larger, regularly updated inventories ideally incorporating a wider historical record would materially strengthen future validation.
- Single method design: this study applies the bivariate FR method only. Benchmarking against weight-of-evidence, logistic regression, or machine learning approaches is recommended as a next step, consistent with recent comparative work in similar settings (Chen et al., 2018; Dou et al., 2020; Bhandari et al., 2024).
- Factor independence: LULC was excluded from the quantitative model due to its likely correlation with slope and curvature; a formal multicollinearity checks across all candidate factors is recommended before any future model expansion.
- Validation reporting: The reported AUC of 0.734 was derived from a success-rate curve using the full 20-landslide inventory and therefore represents discriminatory performance on the mapped inventory rather than independent predictive performance on unseen landslides. Given the small inventory, a single 70/30 split would provide only approximately six testing events and could produce an unstable prediction-rate estimate. Future studies should therefore use larger inventories together with repeated random resampling, bootstrap validation, or other cross-validation strategies to quantify model performance and uncertainty more reliably.
- Event based rainfall calibration: the rainfall analysis (Section 4.6) compares observed rainfall extremes against global/regional thresholds but does not pair specific rainfall events with dated landslide occurrences, since precise trigger dates are not available for most of the current inventory. A genuine local rainfall triggering threshold for Chishankhugadhi would require an inventory of dated landslide events paired with the corresponding rainfall record, which we recommend as a priority for future monitoring.

6 CONCLUSION

This study presents a systematic GIS-based landslide susceptibility assessment of Chishankhugadhi Rural Municipality, eastern Nepal, using the Frequency Ratio (FR) method. A total of 20 landslides were inventoried across four wards, revealing a range of failure mechanisms, including planar, wedge, toppling, rotational, and creep failures, with many occurring in weathered phyllitic materials of the Kuncha Formation. Seven conditioning factors slope angle, aspect, curvature, geology, distance from streams, distance from roads, and distance from faults were used to develop the quantitative susceptibility model. Land use/land cover (LULC) was mapped

separately and used as supporting information for interpretation rather than as a quantitative model factor. The principal findings are as follows:

- All mapped landslides in the present inventory occur within the Kuncha Formation; however, because the formation covers approximately 93% of the study area, this association should not be interpreted as independent evidence of dominant lithological control. The results instead indicate a strong spatial association between mapped landslides and the Kuncha Formation, consistent with the susceptibility of weathered phyllitic materials to instability.
- Fault proximity emerged as a strong statistical control, with landslide density concentrated within 200 m of mapped faults. Field observations independently identified unsupported road cuts, irrigation seepage, and paddy cultivation on steep terrain as site-specific anthropogenic factors that amplify natural susceptibility, although the road-distance FR layer itself exhibits a different, area-driven statistical pattern (Section 5.1).
- Model validation yielded a training-based success-rate AUC of 0.734, indicating fair-to-good model fit comparable to that reported for FR applications in similar Lesser Himalayan settings. Because the test subset was too small to support a stable independent prediction-rate curve, this AUC should be interpreted as indicative rather than as evidence of confirmed independent predictive skill.
- The geotechnical results indicate low cohesion (2.4–6.1 kPa) and moderate friction angles (20°–28°), reflecting limited shear resistance of the slope materials. Combined with steep terrain, unfavorable geological conditions, monsoon wetting, and anthropogenic disturbances such as unplanned roads, irrigation, and intensive agriculture, these factors collectively increase landslide susceptibility. Although the 11-year rainfall record cannot establish a long-term climate trend, potential future changes in rainfall characteristics may further influence rainfall-triggered slope instability.
- Rainfall at Okhaldhunga station during 2014–2024 was strongly concentrated in the monsoon season, with 80.3% of the annual total occurring between June and September. Rainfall was also intense when it occurred, as indicated by an SDII of approximately 10.8 mm per wet day and an R95p contribution of 30.6% of total rainfall. The record further shows a statistically non-significant positive tendency of approximately +26.8 mm/year over the 2014–2024 period. Comparison with the Caine (1980) global rainfall intensity–duration threshold shows that short-duration extreme rainfall events at the station meet or exceed the minimum conditions historically associated with shallow landslide triggering, although no single day in the record reached the 144 mm/day regional threshold reported by Dahal and Hasegawa (2008) for the wider Nepal Himalaya. Incorporating this rainfall characterization strengthens the hydroclimatic context of the landslide susceptibility assessment in Chishankhugadhi Rural Municipality and provides a quantitative basis for future rainfall threshold-based early-warning applications in the area.
- The generated susceptibility map provides a quantitative, spatially explicit basis for regional scale screening, preliminary land-use planning, drainage and infrastructure routing considerations, and prioritization of sites for detailed geotechnical investigation within Chishankhugadhi Rural Municipality wards 1, 4, 5 and 7; given its current resolution and limited spatial discrimination, it is not a substitute for site-specific slope design, which requires dedicated engineering-geological investigation at the site scale.

AUTHOR CONTRIBUTION

Bijay Baral (first and corresponding author) conceived and designed the study, conducted the literature review, carried out field investigations, performed data processing and analysis, interpreted the results, prepared the figures and tables, wrote the original draft and revised the manuscript. **Ashwin Duwadi**, assisted in field investigations, field sampling, laboratory testing and ground truth verification.

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DATA AVAILABILITY

The raw data supporting the conclusions of this article are available from the corresponding author upon reasonable request.

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