

Article

Landslide Risk Associated with Glacier Tourism in the Mt. Everest Region (Sagarmatha National Park), High-Mountain Nepal

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Abstract

Assessment of landslide risk is crucial given the substantial related economic losses and infrastructure damage in mountain areas every year. Particularly, the Sagarmatha National Park (SNP), a key destination for Himalayan glacier tourism, remains relatively understudied in this context. Existing studies primarily focus on regional inventories or simply inventory landslides and lack tourism-specific hazard assessment. This study evaluates landslide distribution, its controlling factors, and the exposure of infrastructure to varying degrees of landslide susceptibility in SNP. A blind inventory of 680 landslides and twelve conditioning factors, including six topographic and six non-topographic variables, were analyzed using Frequency Ratio (FR), Logistic Regression (LR), and Random Forest (RF) models. In addition, spatial overlay analysis was employed to assess the degree of infrastructure exposure. Results indicate that Land Surface Temperature (LST) is the most dominant factor influencing landslides occurrence, followed by rainfall, elevation, and slope, along with specific aspects like south and west and, land cover class like Barren land and Alpine meadows. Random Forest achieved the highest predictive accuracy (91%), outperforming both Logistic Regression (87%) and Frequency Ratio (84%). Exposure assessment of key tourism infrastructure indicates that trekking routes, helipads, buildings, campsites, and bridges are subject to varying levels of landslide risk. Although only 2.73 km (0.52%) of trekking routes intersect active landslide scars, 147 km (28%) lie within high-exposure zones. Consequently, both typical and paraglacial landslides threaten access to glacier tourism destinations, highlighting significant implications for Nepal's tourism.



Academic Editor: Dmitry A. Ruban

Received: 20 January 2026

Revised: 23 February 2026

Accepted: 24 February 2026

Published: 6 March 2026

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Keywords: landslide susceptibility; paraglacial landslides; Himalaya; glacier tourism; Sagarmatha National Park

1. Introduction

Landslides are among the most destructive and catastrophic natural hazards worldwide, responsible for significant loss of life and property each year [1,2], with an increased frequency and intensity in recent years, especially in mountainous regions. The Himalayas

are widely recognized as one of the world's most unstable regions [3,4]. This vulnerability is primarily due to steep slopes and significant local relief spanning kilometers from river valleys to adjacent peaks [5]. Simultaneously, mountain systems worldwide, and most notably the Himalayas, are undergoing rapid changes resulting from climate change and human activities [6–9]. One significant consequence of these changes is the dramatic decrease in the extent and volume of high-mountain glaciers as well as the degradation of permafrost [6–10], adding to the increased risk of landslide hazards in these high mountains [11–13]. In addition, the Himalayas are characterized by a persistent seismic activity, and an increasing frequency of extreme precipitation events, further amplifying the landslide hazard and susceptibility [14–18]. Together, these factors pose increasing risks to human settlements, infrastructure, and economic activity including mountain tourism [19–23].

Nepal, located in the heart of the Himalayan Mountain system, cannot be immune to these threats [3,5,24]. The interplay of these natural drivers with growing human disturbances such as haphazard growth of infrastructure, deforestation, and land-use changes has further amplified the risk and frequency of landslide events [24–26]. Moreover, remote and previously uninhabited high-mountain areas are increasingly being utilized for recreational and tourism purposes, bringing more people and infrastructure presence into hazardous terrains, thus escalating the human exposure to landslide risk [4].

Within this broader context, the Everest region represents highly sensitive high-mountain environment in terms of landslide occurrence. The region is characterized by continuous permafrost degradation [27], rapid glacier retreat [28,29], and growing human tourism activity [30,31]. The presence of a diverse range of landslide scarps and deposits across the major valleys [9,32], already stands as compelling evidence of past landslides. Notable examples include the Namche Bazaar, situated in the region's soul and crucial gateway, which is built within a distinctive bowl-shaped old landslide scarp [9,32,33]. Another example includes a large landslide that occurred during the 1974 monsoon at Tongmat in Gokyo valley [33]. While landslides at such high elevation may occur less frequently compared to lower elevations [34,35], their impact are often severe due to limited road access, time consuming and high reconstruction costs [36], and the potential for debris to travel over several kilometers [37,38]. Therefore, landslides in the Everest region have significant implications for local communities and tourism.

On the other hand, the Nepalese Himalayas, home to the world's highest mountain range, have long been a primary destination for trekkers and mountaineers [36]. This influx of tourism is a crucial pillar of Nepal's economy, contributing significantly to exports earnings, foreign currency reserves, and employment [39,40]. Among the most prominent destinations is the Sagarmatha National Park (SNP), a globally recognized high altitude hub for adventure, cultural, and ecological tourism (ACE). The park's unique landscape featuring extensive glaciers, glacial lakes, globally renowned icy peaks, snow-covered landscapes and high-altitude trekking that also traverse glaciers, serve as the foundation and primary driver of tourism. In 2023 alone, 52,499 foreign tourists visited the park, accounting for 18% of the total foreign visitors across 20 national parks and conservation areas in Nepal [39]. At the same time, the growing number of tourists and tourism activities increase the human exposure to landslide hazard. As trekking trails, settlements, and tourism infrastructures are often situated near steep or potentially unstable slopes, landslide pose a direct threat to tourism activities and infrastructures in SNP.

Over the past decades, advances in remote sensing (RS), Geographic Information Systems (GIS), and data-driven modeling have greatly improved landslide detection, susceptibility assessment, and the assessment of their controlling factors [41–44]. Landslide susceptibility, a key concept in landslide studies, has evolved from heuristic and statisti-

cal approaches to probabilistic and machine learning models including Frequency Ratio, Logistic Regression and Random Forest [2,45,46]. While emerging technologies like UAV surveys and high-resolution imagery offer emerging potential enabling the more accurate hazard detection [46–48], their application in high-mountain environment is often limited by high operational costs and logistical challenges. In this context, Google Earth offers a practical and widely adopted alternative for landslide inventory development in remote mountainous region [49–52].

Despite Everest region's global prominence as a premier destination for glacier tourism and its importance to Nepal's economy, most existing landslide studies [34,53], and datasets [35,54–56] focus on regional scale assessment or simply inventory landslides. Although these studies highlight a growing trend in landslides occurrence, they do not explicitly evaluate park specific landslide risk. Early efforts such as prototype hazard map [57], provided valuable baseline information; however, the specific risk of landslide to the Everest region particularly for trekking routes and tourism infrastructure within the park, remain overlooked. To address this gap, this study aims to 1. Assess landslide susceptibility using R, LR and RF models; 2. Identify the dominant factor influencing landslide occurrences; and 3. Evaluate the elements at risk for this iconic glacier tourism destination by analyzing the exposure of trekking routes and key tourism infrastructure.

2. Data and Methods

2.1. Study Area

SNP, located in the Solukhumbu district of Nepal, is a UNESCO World Heritage Site renowned for its striking natural features, including Mt. Everest (Also known as Sagarmatha in Nepal and Qomolangma in China), the highest peak on Earth. The park spans between $86^{\circ}31' - 86^{\circ}58' \text{ E}$ and $27^{\circ}47' - 28^{\circ}71' \text{ N}$, covering 1148 km^2 (Figure 1). It is home to numerous glaciers, including the vast Ngozumpa, which covers 98.8 km^2 . The region's landscape is dominated by rugged terrain, alpine meadows, and deep glacial valleys, with elevations ranging from 2845 m to the towering summit of Sagarmatha at 8848 m. Surrounding peaks, such as Lhotse, Cho-Oyu, Amadablam, and many more (25 peaks above 6000 m), further enhance the region's dramatic alpine environment, which is continually shaped by the movement and retreat of glaciers [58]. The glacial and icy landscapes in the park are among their most defining characteristics, featuring numerous icy peaks, glacial lakes of various sizes, and 29 glaciers that feed the region's rivers. These glaciers have been shrinking over the decades due to rising temperatures. This icy wilderness, along with the dramatic landforms carved by glaciers, makes the park a globally significant geological area, while also presenting challenges due to the hazards of glacier retreat and increased landslides [29,59].

Tourism is the primary source of income and livelihood for the approximately 3000 Sherpas residing in the region [60,61]. It not only benefits local communities but also generates substantial revenue for the country and directly supports the significant number of people from far downstream areas through business, services or employment. In the fiscal year 2023/24, the park recorded 48,804 foreign tourists, contributing Rs. 15,47,60,566 NPR to the park's annual revenue [62]. Trekking tourism is the dominant form of tourism in the region, driven by the absence of roads and other transport facilities. The Everest region's appeal lies in its vast opportunities for hiking, trekking, and mountaineering expeditions [58]. The main trekking route begins at Lukla, with several settlements along the way, including Ghat, Phakding, Namche, including Dingboche and Gokyo in the north eastern part and Thame in the western part, catering to varying levels of skill and attracting adventurers from around the globe [58,63]. Overall, SNP is a unique blend of nature, culture, and adventure, with its dramatic glacial landscapes and tower-

ing peaks serving as the primary drivers, making it a globally significant high-altitude tourist destination.

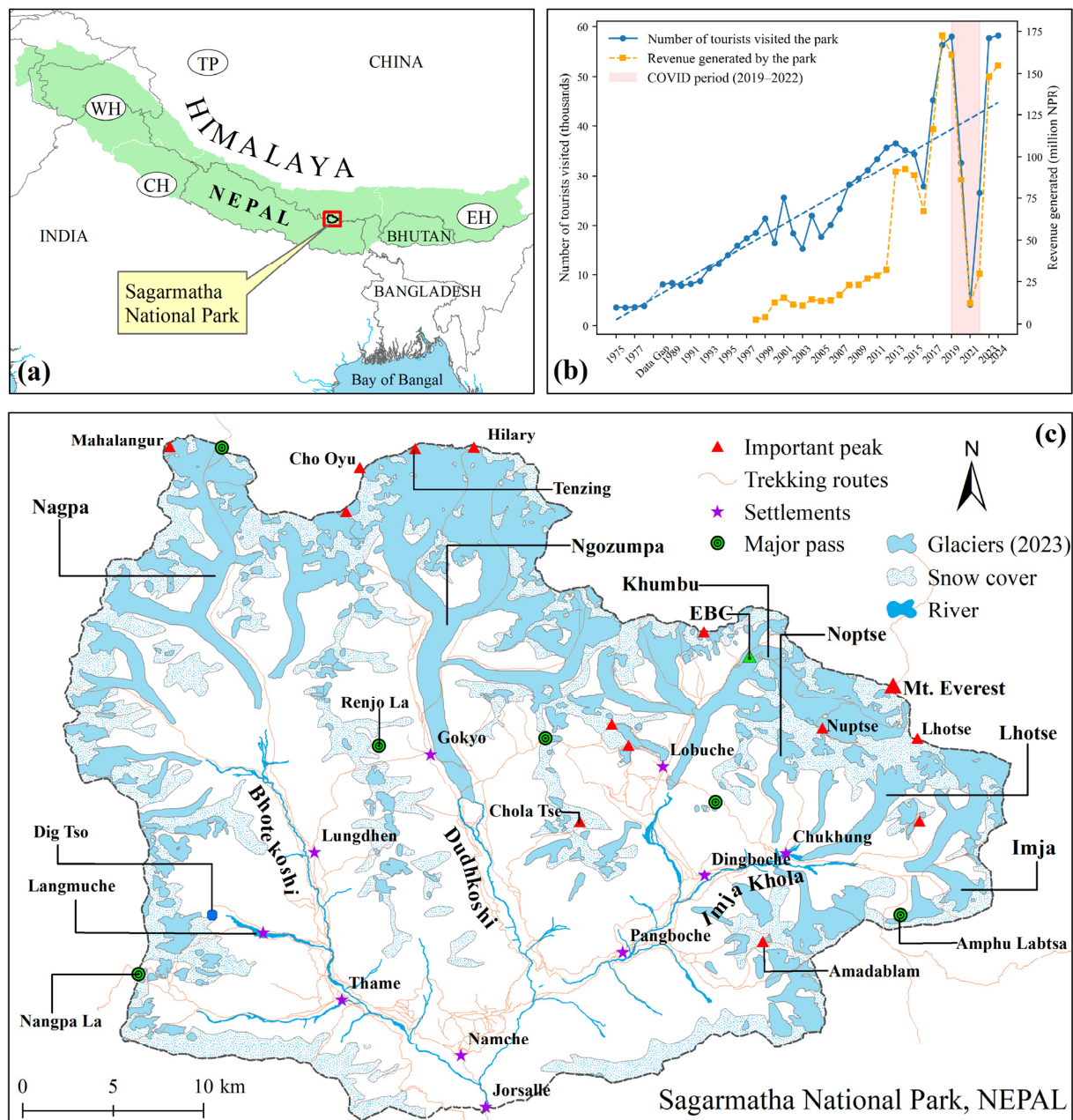


Figure 1. Overview of the study area. (a) Location of the Sagarmatha National Park in Central Himalayas in high-mountain Nepal; (b) yearly flow of recorded tourist in the park since 1975 and corresponding revenue generation; (c) SNP and its highlights.

The study area focuses on regions free from perennial snow and glacier cover (Figure 1), as this study evaluates landslide susceptibility associated with soil and rock slope failure, primarily occur in non-glacierized terrain. In permanently snow- and glacier-covered areas, slope instability is governed by cryospheric processes (e.g., ice flow and ice avalanches) [64], and conventional landslide conditioning factors (e.g., land use, soil properties, and vegetation cover) are either absent or poorly defined, potentially introducing significant uncertainty into susceptibility modeling. Snow- and glacier-free areas were delineated using Sentinel-2 imagery (10 m) from the COPERNICUS/S2-SR-HARMONIZED dataset, with cloud-free (<5%) images from minimal snow cover periods (March–May and September–

November) between 2015 and 2024. The Randolph Glacier Inventory (RGI) 7.0 [65], was used to delineate and mask the glacier covered area and to correct overlap and errors, enabling accurate identification of perennial snow and glacier zones. After excluding persistent snow (218.33 km²) and glaciers (271.12 km²) covered terrain, the resulting study area covers 658.57 km². This area encompasses the majority of settlements, trekking routes, and historically reported landslide locations, making it representative of the zones where landslide processes pose the greatest practical risk within SNP.

2.2. Spatial Database Design and Construction

2.2.1. Infrastructure Database

The Mt. Everest region, with its significant potential for glacier tourism, relies heavily on infrastructure such as trekking routes, bridges, buildings (hotels and lodges), and settlements (service facilities) to support and enhance visitor experiences. The infrastructure data was collected using various methods. ArcGIS 10.8.2 (at a scale of 1:2500 for accuracy and consistency) and Google Earth Pro were the primary tools used to create trekking routes with high-resolution attributes, supplemented by relevant trekking maps (Nepal Himal Peak Profile (NHPP) at <https://nepalhimalpeakprofile.org> (accessed on 21 October 2024), and 'KHUMBU HIMAL' trekking map [66]. Trekking routes are well-marked with clear footprints, while routes without clear footprints were digitized by evaluating topographic conditions and consulting the sources mentioned. An inventory of bridges and infrastructures was created using data from OpenStreetMap (OSM), ICIMOD's Regional Database System (RDS), and Google Earth.

2.2.2. Landslide Inventory Database

It is assumed that landslides occur in similar conditions to those in the past [67]. The initial step in landslide studies involves generating a landslide inventory and identifying the locations of existing landslide scars. In areas with diverse terrain, including tree lines, glaciers, and snow-fed regions, it is very challenging to differentiate the spectral and visual properties that indicate whether an area is affected by landslides. The complexity arises due to similar surface characteristics, such as a barren land or snow fed area, which can obscure the distinct signs of landslide activity, making accurate detection and analysis more difficult. This ambiguity increases the likelihood of mispredictions if some automatic image classification methods are used. Open-source datasets (Sentinel-2/LANDSAT ETM) have less spatial resolution, where the small landslides are not visible or distinguishable. On the other hand, visual assessment of landslides can be more effective when conducted with high spatial resolution and human judgment, considering specific features and properties (Figure 2). Some previous studies [49–52,68], already practiced Google Earth to study landslides along with criteria and visual interpretation to identify landslides. We also employed Google Earth for landslide identification and mapping, utilizing QGIS spatial overlay tool, with one single expert interpreter. To minimize subjectivity, the mapping followed predefined criteria (Appendix B) and was re-examined across multiple temporal sequence of images to ensure internal consistency. The identification was based on seven key components: elevation, slope angle, pattern, association, depth, chronology, and material involved. Each was evaluated individually and in combinations until a confident classification was achieved. For example, a scar located below the tree line and on a steep slope was more likely classified as a landslide, whereas similar features at higher elevations could correspond to a snow- or ice-eroded area or a result of natural surface erosion. (Detailed in Appendix B). Nevertheless, some uncertainty may remain, particularly in high-altitude, snow-affected or periglacial areas.

S. N.	Component	Elements	Landslide ? Yes / NO	
①	Elevation	Below/near tree line	☒	☒
		Above tree line	☐	☐
②	Slope angle	Steep	☒	☒
		Flat	☐	☐
③	Pattern	Top narrow, bottom flat	☐	☐
		Top flat, bottom narrow	☒	☒
		Fan shape in the bottom	☒	☐
④	Association	River	☒	☒
		Steep cliffs	☒	☒
		Previous landslide scars	☒	☒
		Moraines (Glacier or GL)	☒	☐
⑤	Depth	Surficial	☐	☒
		Deep	☒	☐
⑥	Chronology	Historical footprints	☐	☒
		New	☒	☐
⑦	Material	Material deposition	☒	☒
		No Deposits	☐	☐

Figure 2. Reference decision rule matrix for identification/confirmation of landslides. Abbreviation: GL—glacial lake.

2.2.3. Landslide Influencing Factors Database

The careful selection of input parameters is a fundamental step in landslide studies to ensure the model accurately reflects the key factors driving slope failure. The number and types of parameters may vary across studies, depending on the research focus and the data availability [69]. The choice of parameters for the current study is based on data availability and insights from previous studies in similar mountainous topographies. Twelve influencing factors of landslide initiation: six topographic (Figure 3) and six non-topographic (Figure 4) were chosen which include elevation, slope, aspect, curvature, relative relief, Topographic Wetness Index (TWI) [69–73], Normalized Difference Vegetation Index (NDVI) [71,73,74], rainfall, proximity to the river [70,74], land cover and drainage density [43]. LST was included as a novel parameter.

a. Topographic Factors:

Elevation is crucial in landslide studies as it affects soil, vegetation, rainfall, and human activities, influencing slope stability [43,75]. Additionally, elevation maps are essential for deriving key topographic factors like slope, curvature, relative relief, and aspect. The present research used the 30 m NASADEM [76]. Slope angles and aspects are key in landslide research, as slope angles affect steepness and gravitational forces, while slope aspect influences moisture, vegetation, and rainfall patterns. Together, they provide a complete understanding of terrain stability [72,75,77]. Curvature indicates the morphology of topography, with negative values (concave surfaces) linked to higher landslide probability [78]. Relative relief represents local elevation variations, with higher relief increasing the potential for landslides. It is calculated as the maximum height dispersion normalized by length or area [43,73,79].

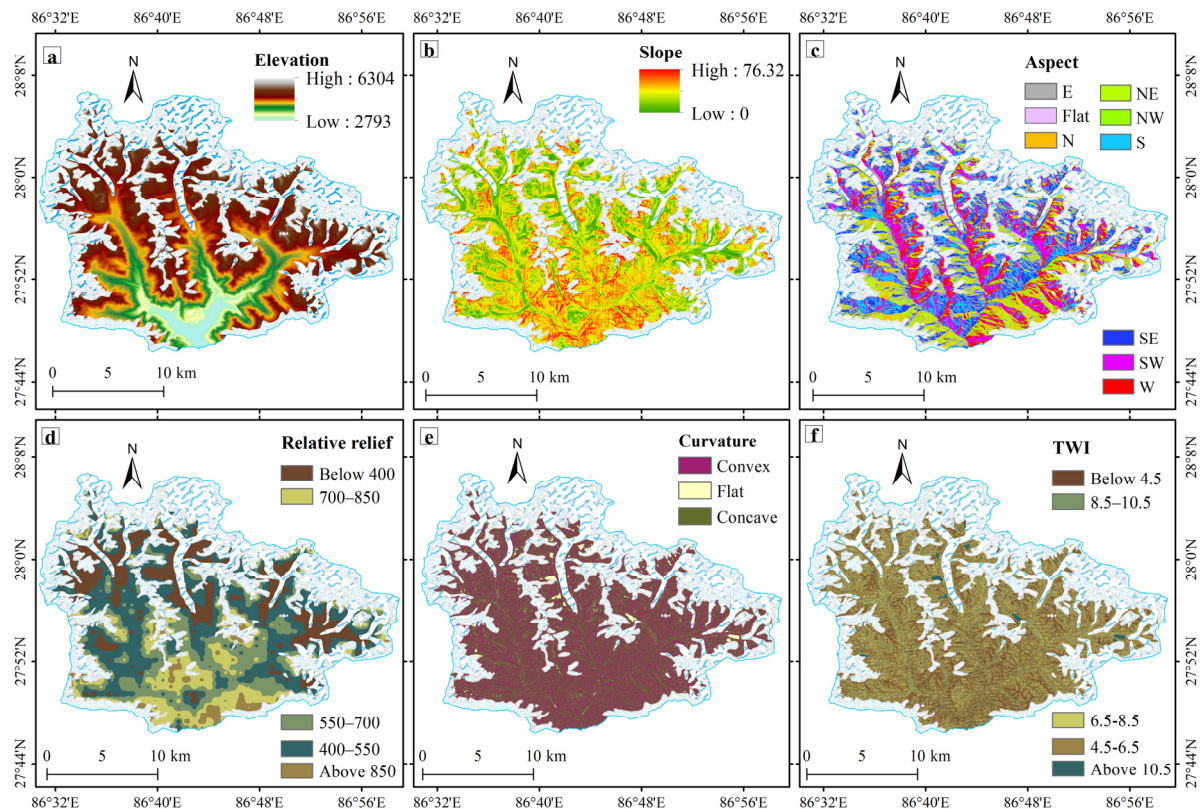


Figure 3. Thematic map of topographic factors. (a) Elevation; (b) Slope; (c) Aspect; (d) Relative relief; (e) Curvature; (f) TWI.

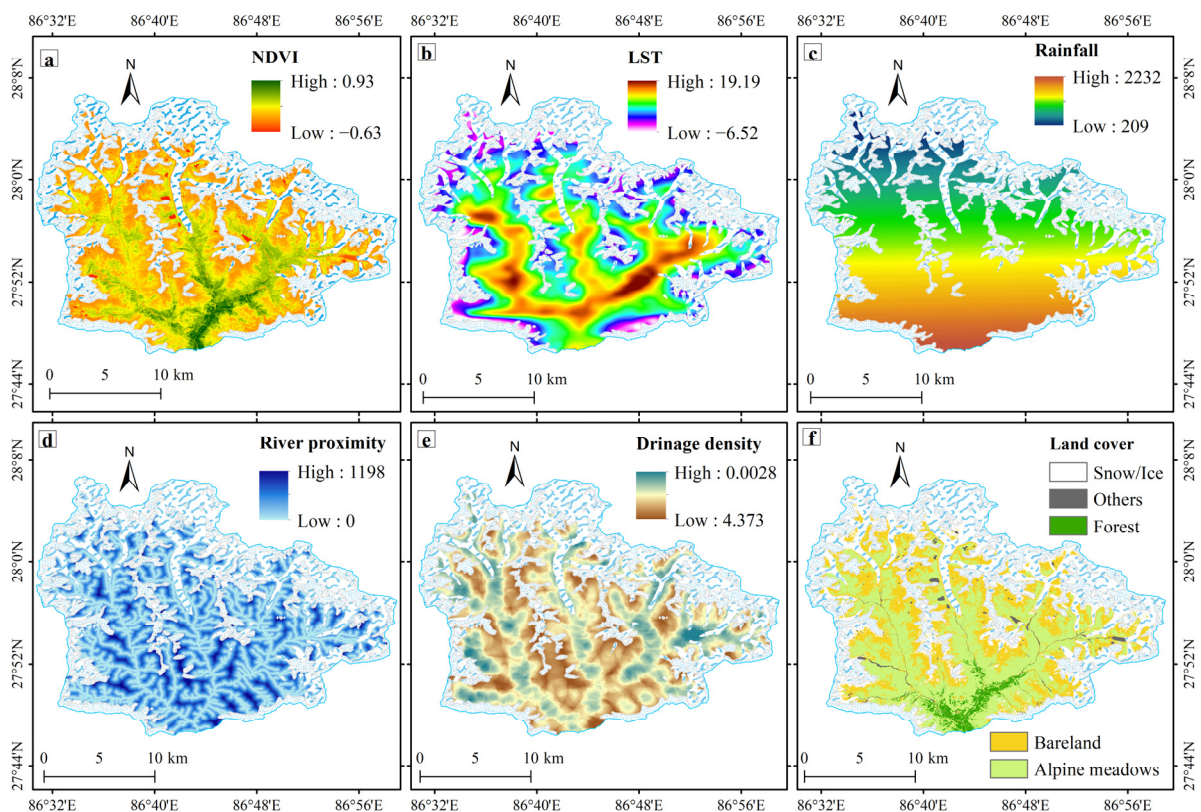


Figure 4. Thematic map of non-topographic factors. (a) Normalized Difference Vegetation (NDVI); (b) Land Surface Temperature (LST); (c) Rainfall; (d) Proximity to river; (e) Drainage density; (f) Land cover.

TWI refers to the location and size of the saturated area subject to overflow, runoff generation, and long-term moisture availability in the landscape [80]. It is commonly used to quantify the topographic control on hydrological processes, helping to understand how terrain influences moisture distribution and landslide susceptibility [81]. *TWI* was examined using the 30 m NASADEM within a GIS environment employing the following formula:

$$TWI = \ln\left(\frac{A}{\tan(s)}\right) \quad (1)$$

where *A* represents the flow accumulation (the upstream contributing area for each cell), and *S* is the slope (elevation change per unit of horizontal distance).

b. Non-Topographic Factors:

NDVI is vital in landslide studies as it measures surface vegetation density, which influences landslide initiation on steep slopes [73]. Vegetation enhances slope stability by modifying soil cohesion, internal friction, soil weight, and pore-water pressure through root reinforcement and increased soil suction [82]. *NDVI* indicates vegetation density: Low *NDVI* corresponds to sparse vegetation and increased landslide risk, while high *NDVI* suggests denser vegetation and strengthened stability. *NDVI* was derived from Sentinel-2 (20 m) using GEE referring to the formula expressed as

$$NDVI = \frac{Band\ 8\ (NIR) - Band\ 4\ (Red)}{Band\ 8\ (NIR) + Band\ 4\ (Red)} \quad (2)$$

Land surface temperature (LST) is critical in high-mountain environments like SNP, where temperature fluctuations can affect slope stability through melting of glaciers, thawing permafrost, and freeze–thaw activity [83–85]. Thus, LST is a crucial factor influencing landslide risk in mountainous regions. Average mean LST was derived from MODIS data (MOD11A1 product) for the years 2001–2024, considering <5% cloud cover, focusing on daytime measurements (LST_Day_1 km) using GEE.

Considering land cover is vital in landslide studies as vegetation-like forests stabilize slopes and reduce landslide risk, while past human activities, such as farming, increase susceptibility [86]. We used the European Space Agency (ESA) WorldCover 10 m land cover map (2021), derived from Sentinel-1 and Sentinel-2 data products, as the base land cover dataset. To improve its relevance and accuracy for the study area, several modifications were applied, including merging attribute fields and intersecting manually digitized water bodies to ensure better thematic consistency and spatial representation. Other important parameters to consider include hydrological factors. The intensity and spatial distribution of rainfall is a critical factor influencing landslide susceptibility, particularly in mountainous and hilly regions. This study considered a 30-year ERA5 monthly average dataset (1993–2023), derived using GEE, to analyze precipitation patterns. The dataset was resampled to the study grid using cubic convolution, and any missing or invalid values were imputed using the monthly mean of the available data. Proximity to rivers and drainage density are both crucial factors to consider, as streams can destabilize slopes through toe undercutting or by saturating materials within the water level of the stream [77,87].

2.3. Assessment of Landslide Susceptibility

This study assesses spatial landslide susceptibility using Frequency Ratio, Logistic Regression, and Random Forest models, incorporating 12 influencing factors (six topographic and six non-topographic) and a blind inventory of 680 landslides. The dataset was split into 70% for training and 30% for testing. All continuous variables were normalized prior to model training to ensure comparability using mean-max scaling (0–1), except for the

Frequency Ratio (FR), which is inherently ratio based. In addition, multicollinearity among parameters was tested using Tolerance (TOL) and Variance Inflation Factor (VIF), a widely used approach [41,88]. No significant multicollinearity was detected among the chosen variables (Figure A1, Table A1). Each model was applied independently to the training dataset to predict landslide susceptibility and the final landslide susceptibility classes were derived from the 0–1 susceptibility index using the natural breaks (Jenks) method. This data-driven approach minimizes variance within classes while maximizing differences between them [89,90], making it well-suited for skewed susceptibility distributions and enabling consistent comparison of spatial patterns across different models. The resulting classes are categorized as very low, low, moderate, high, and very high, demonstrating relative probability of landslide occurrence.

2.3.1. Frequency Ratio (FR)

The Frequency Ratio (FR) method is a straightforward and accurate bivariate statistical technique used in landslide susceptibility mapping [91]. To develop a probability model for landslide hazard using the FR method, it is assumed that specific factors influence landslide occurrences and that future events will occur under similar conditions as past ones [92]. Widely applied in landslide studies [5,74,93–97], the FR method evaluates the relationship between landslides and conditioning factors by calculating the ratio of landslide affected areas to the total area for each factor. The frequency ratio for each class of a conditioning factor is expressed as

$$FR = \frac{\frac{N_{pix}(\text{Landslide in class } i)}{N_{pix}(\text{Total Landslide})}}{\frac{N_{pix}(\text{Class } i)}{N_{pix}(\text{Total Area})}} \quad (3)$$

where $N_{pix}(\text{Landslide in class } i)$ is the number of landslide pixels within class i , $N_{pix}(\text{Total Landslide})$ is the total number of landslide pixels, $N_{pix}(\text{Class } i)$ is the total number of pixels in class i , and $N_{pix}(\text{Total Area})$ is the total number of pixels in the study area.

The Landslide Hazard Index (LHSI) is derived by summing the FR values for each factor:

$$LHSI = FR_1 + FR_2 + FR_3 + \dots + FR_n \quad (4)$$

Here, LHSI indicates the overall hazard level (Landslide Hazard Susceptibility Index), with higher values reflecting greater risk. These values are used to create landslide hazard maps [98,99].

2.3.2. Logistic Regression (LR)

Logistic regression is an extensively used method for landslide susceptibility [42,73,100,101]. It allows the formation of a multivariate regression relationship between a binary dependent variable (indicating landslide presence or absence) and multiple independent variables, such as Elevation, Slope, . . . , and TWI. The logistic regression model is expressed as

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_n x_n \quad (5)$$

where Y is the dependent variable indicating the absence (0) or presence (1) of landslides, $x_1, x_2, x_3, \dots, x_n$, are independent variables that contribute to the occurrence of landslide, β_0 is the constant, $\beta_1, \beta_2, \beta_3, \dots, \beta_n$ are coefficients quantifying the influence of each factor on the likelihood of landslide occurrence. The probability of landslide occurrence $P(Y = 1)$ is calculated using the logistic function:

$$P(Y = 1) = \frac{1}{1 + e^{-y}} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_n X_n)}} \quad (6)$$

The natural logarithm of the odds of landslide occurrence (*logit*) is

$$\text{logit}(P) = \ln\left(\frac{P}{1-P}\right) \quad (7)$$

where P represents the estimated conditional probability of landslide occurrences (i.e., $Y = 1$), e is the base of the natural logarithm, and $\ln\left(\frac{P}{1-P}\right)$, is the odds of a landslide occurring, which is linearly related to the independent variables [73,102].

In this study, Logistic Regression was implemented using the Logistic Regression algorithm from the scikit-learn library (Python 3.13.5), employing L2 regularization with the default inverse regularization strength ($C = 1.0$) to control overfitting [103,104]. This method's flexibility allows it to handle both continuous and categorical variables, without requiring a normal distribution [41]. Accordingly, Aspect and Land Cover were treated as categorical variables, while Elevation, Slope, . . . , and TWI were considered continuous variables.

2.3.3. Random Forest (RF)

Random Forest (RF) is a supervised ensemble algorithm that enhances prediction accuracy by combining multiple decision trees (DTs), each built on a bootstrapped subset of the data [105,106]. In our study, the RF model was implemented using the RandomForest Classifier from the scikit-learn library (Python). RF uses Out-Of-Bag (OOB) samples to estimate model accuracy and variable importance, providing an unbiased error rate by evaluating predictions on data not included in individual tree training [107]. RF can effectively handle both categorical and continuous variables and is less sensitive to overfitting compared to other machine learning techniques like artificial neural networks and support vector machines [108]. The key hyperparameters in RF include the number of trees, maximum tree depth, and the maximum number of features considered at each split [107,109]. In our study, model hyperparameters were optimized using grid search with five-fold stratified cross-validation. The parameter grid included the number of trees ($n\text{-estimators} = 100, 200, 300$), maximum tree depth ($\text{max depth} = \text{None}, 10, 20, 30$), minimum number of samples required to split an internal node ($\text{min samples split} = 2, 5, 10$), minimum number of samples required at a leaf node ($\text{min samples leaf} = 1, 2, 4$), and the number of features considered at each split ($\text{max features} = \text{'sqrt'}, \text{'log2'}$). The optimal parameter combination ($n\text{-estimators} = 200$, $\text{max depth} = \text{None}$, $\text{min samples leaf} = 2$, $\text{min samples split} = 5$, $\text{max features} = \text{'sqrt'}$) achieved the highest mean cross-validation score (0.839) and was therefore selected for final model training. The dataset was divided into 70% training and 30% testing samples using stratified random sampling. The robustness and high classification accuracy of RF in landslide susceptibility assessment have been widely demonstrated in previous studies [110–115].

2.4. Comparison and Validation

Receiver Operating Characteristic (ROC) curve analysis and relative landslide density index ($R\text{-Index}$) method (Equation (9)) was utilized to evaluate the performance of models in landslide susceptibility zoning and validate the accuracy of the susceptibility map generated. To construct an ROC plot, *sensitivity* (true positive rate) and *specificity* (true negative rate) are key parameters. *Sensitivity* is calculated as the ratio of true positives to the sum of true positives and false negatives, while *specificity* is calculated as the ratio of true negatives to the sum of true negatives and false positives (8) [116].

$$\text{Sensitivity} = \frac{TP}{TP + FN}, \quad \text{Specivity} = \frac{TN}{TN + FP} \quad (8)$$

Here, *TP* is the True Positive, *FN* is the False Negative, *TN* is the True Negative, and *FP* is the False Positive. The same dataset of 680 landslides used for model training (70%) and testing (30%) was subsequently used to assess the model's performance and prediction ability.

2.5. Quantification of Exposure and Elements at Risk

To quantify the exposure level within each landslide susceptibility class, the relative landslide density (*R-Index*) method was applied [73,117,118], expressed as

$$R\text{-Index} = \frac{n_i / N_i}{\sum (n_i / N_i)} \times 100 \quad (9)$$

where n_i = Number of observed landslides within susceptibility class i , N_i = Total area of susceptibility class i , and The summation $\sum \frac{n_i}{N_i}$, refers to the sum of the landslide densities calculated as $(\frac{n_i}{N_i})$ across all susceptibility classes of the respective model.

The *R-Index* values were interpreted to define three exposure levels:

- Low exposure (*R-Index* < 10): Indicates a low likelihood of landslide occurrence, typically corresponding to very low, low, and moderate susceptibility zones.
- Moderate exposure (*R-Index* $\approx$ 20): Represents areas with moderate vulnerability, generally observed in high susceptibility zones.
- High exposure (*R-Index* $\approx$ 60 or above): Corresponds to very high susceptibility zones, indicating high vulnerability and areas where elements are considered at significant risk.

The *R-Index* thresholds were defined based on outputs from all three models, each of which exhibited three distinct and consistent patterns across the data. The output from the Random Forest (RF) model was used as a base map for quantifying exposure, as it achieved the highest predictive accuracy among the models.

To provide additional insight, a buffer-based proximity analysis was conducted for the trekking routes, creating buffer zones at 0 m (intersecting), 0–50 m, 51–75 m, and 76–100 m. As the trekking routes represent most critical elements of driving tourism in the park, landslides within these zones were identified to assess both direct and near field threats. This approach enabled a more detailed evaluation of route segments at risk of disruption, damage, or potential closure.

3. Results

3.1. Infrastructure Assessment

In the context of landslide susceptibility and associated risk study in the region, assessing infrastructure is of paramount importance due to its significant implications for tourism. The web of trekking routes in the SNP region spans a total of 678.88 km (Figure 1), including 88.38 km routes spanning within glaciers, and 85.01 km within 100 m of glaciated zone. Other key infrastructure includes 15 bridges, 10 helipads (essential for tourism and services), and 42,396 m² of buildings across 81 settlements, including hotels, schools, and health posts including 28 camping sites, two museums, 16 religious sites, and nine public service centers (Figure A2).

3.2. Landslide Inventory

A total of 680 landslides has been identified, covering 3.55 km², which accounts for 0.55% of the total area. The sizes of these landslides vary significantly, ranging from up to 0.19 km². The average size of the landslides is 5169.26 m². The landslides are distributed throughout the region, with a marked concentration near the river. Although there are a few relatively small landslides, proximity to sensitive areas lacking alternative routes

can have significant impacts (Figure 11a). Consequently, the size of the landslides varies considerably across different locations. The landslide size distribution was analyzed using the global landslide size classification proposed by McColl and Cook (2024) [119], which identified classes ranging from small to medium-sized landslides. The results show an inverse relationship between landslide size and frequency, where smaller landslide occur more frequently, whereas larger landslides are less common but affect a proportionally greater area (Table 1). For instance, five large landslides cover 14% of the total affected area, while 68 landslides cover 52%, and 608 smaller landslides account for just 34%.

Table 1. Classification of landslide size according to [119].

S.N.	Descriptor	Minimum Area	Number of Landslides		Area Range	Total Area	Total Area (%)	
0	Small	≥10	15	278	30–100	1145.96	0.03	3.7
1		≥100	148		100–500	46,141.22	1.31	
2		≥500	115		500–1000	82,796.88	2.36	
3	Medium	≥1000	330	402	1000–10,000	1,083,770.7	30.83	96.3
4		≥10,000	68		10,000–1,000,000	1,812,807.2	51.57	
5		≥100,000	4		1,000,000–197,662	488,438.82	13.9	
Total			680	680	30–197,662	3,515,100.8	100	

3.3. Landslide Susceptibility Analysis

The susceptibility analysis reveals variations across models, reflecting their strengths and limitations. The final maps categorize the area into very low to very high susceptibility, with most regions falling under low (very low and low) to moderate risk zones (Figure 5). Although only a small portion of the area lies within the high susceptibility zone, this zone encompasses a significant proportion of the total landslides.

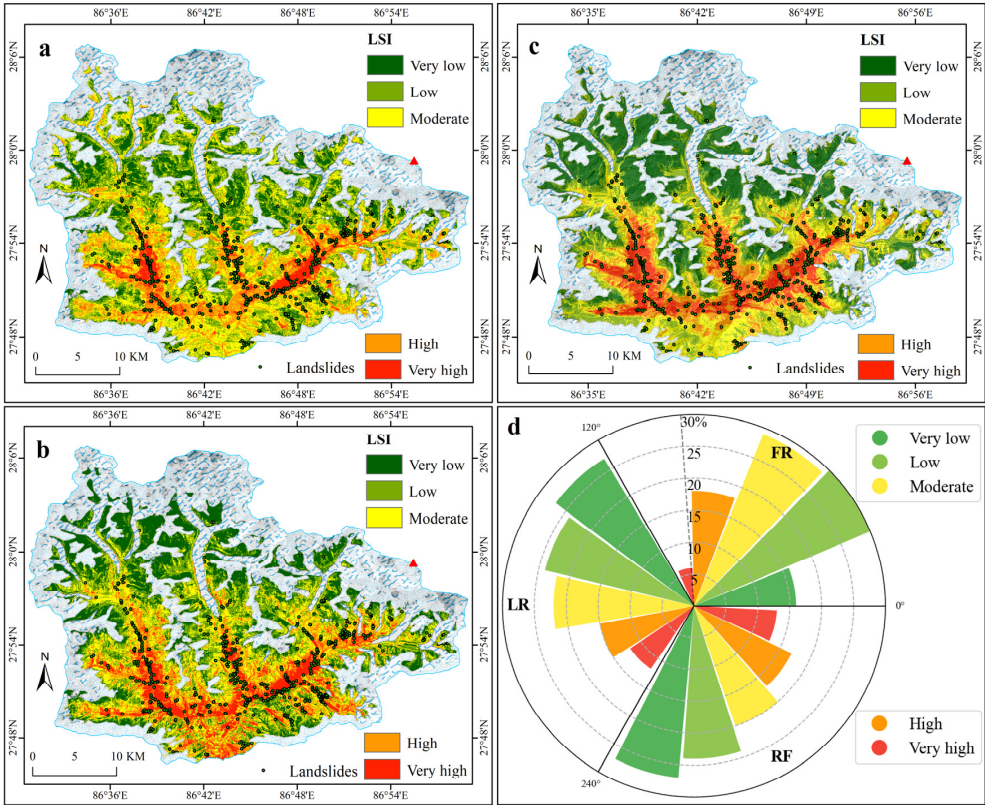


Figure 5. Landslide susceptibility maps. (a) FR; (b) LR; (c) RF; (d) Percentage area representing landslide sensitivity by respective methods. Abbreviation: LSI—Landslide Susceptibility Index.

3.3.1. Frequency Ratio (FR)

The results from the *FR* model include a susceptibility map and the *FR* values or Landslide Susceptibility Weight (LSW) for all 12 factors (Table 2). Each factor's LSW value reflects the correlation between that factor's class and its influence on landslide occurrence: values near zero indicate an average influence, positive values show a stronger influence, and negative values suggest a weaker influence.

Table 2. Calculated *FR* weights of each class of the influencing factors.

Factors	Class	Landslide Pixels in Domain	% of Land-slide Pixels	FR	LSW	Factors	Class	Landslide Pixels in Domain	% of Land-slide Pixels	FR	LSW
Elevation [m]	Below 3850	382	14.42	2.16	0.34	Drainage density [10^{-3} m/km ²]	0.044–0.826	278	10.49	0.50	−0.30
	3850–4450	967	36.50	2.28	0.36		0.826–1.3	642	24.24	0.81	−0.09
	4450–4850	448	16.91	0.79	−0.10		1.3–1.763	1030	38.88	1.23	0.09
	4850–5250	576	21.74	0.62	−0.21		1.763–2.854	699	26.39	1.53	0.18
	Above 5250	276	10.42	0.50	−0.30						
Slope°	Below 15	217	8.19	0.37	−0.43	Land cover	Forest	9	0.34	0.09	−1.05
	15–30	990	37.37	1.00	0.00		Barren land	1850	69.89	1.93	0.29
	30–45	1191	44.96	1.45	0.16		Alpine meadows	526	19.87	0.43	−0.37
	45–55	218	8.23	1.16	0.06		Snow/Ice	190	7.18	0.63	−0.20
	Above 55	33	1.25	0.46	−0.34		Others	72	2.72	1.40	0.15
Aspect	Flat	1	0.04	0.04	−1.40	LST (°C)	Negative (<0)	12	0.45	0.24	−0.63
	N	101	3.81	0.56	−0.25		0–4.5	274	10.34	0.84	−0.08
	NE	153	5.78	0.57	−0.25		4.5–7.5	241	9.10	0.43	−0.37
	E	292	11.02	0.76	−0.12		7.5–10	516	19.48	0.74	−0.13
	SE	358	13.51	0.91	−0.04		10–13	575	21.71	0.97	−0.01
	S	449	16.95	1.08	0.03		13–16	843	31.82	2.30	0.36
	SW	594	22.42	1.34	0.13	Rainfall	Above 16	188	7.10	3.46	0.54
	W	568	21.44	1.70	0.23		Below 750	183	6.91	0.82	−0.09
Curvature	NW	133	5.02	0.66	−0.18		750–1050	121	4.57	0.30	−0.52
	Concave	943	35.60	0.89	−0.05		1050–1350	254	9.59	0.45	−0.34
	Flat	226	8.53	0.63	−0.20		1350–1600	946	35.71	1.67	0.22
	Convex	1480	55.87	1.21	0.08		1600–1850	596	22.50	1.29	0.11
Distance from the river	Below 75	908	34.28	1.91	0.28	Relative relief	Above 1850	549	20.72	1.26	0.10
	75–150	493	18.61	1.08	0.03		Below 400	374	14.12	0.67	−0.17
	150–225	355	13.40	1.11	0.05		400–550	1051	39.68	1.12	0.05
	225–300	287	10.83	0.87	−0.06		550–700	812	30.65	1.26	0.10
	Above 300	606	22.88	0.57	−0.25		700–850	328	12.38	0.82	−0.08
NDVI	Negative	186	7.02	0.91	−0.04	TWI	Above 850	84	3.17	0.72	−0.14
	0.000–0.113	1133	42.77	1.26	0.10		Below 4.5	638	24.08	1.03	0.01
	0.113–0.285	875	33.03	1.15	0.06		4.5–6.5	1308	49.38	1.00	0.00
	0.285–0.494	397	14.99	0.64	−0.20		6.5–8.5	424	16.01	0.93	−0.03
	0.494–0.936	58	2.19	0.35	−0.46		8.5–10.5	149	5.62	1.05	0.02
							Above 10.5	130	4.91	1.06	0.03

Note: The LSW column uses a continuous color gradient to indicate the influence of each factor and respective classes on landslide occurrence, ranging from green (weakest influence) through yellow (moderate) to red (strongest influence).

The highest LSW in elevation of 0.36 occurs between 3850 and 4450 m, followed by below 3850 m (0.34). As elevation increases, LSW decreases, with LSWs of -0.10 (4450–4850 m), -0.21 (4850–5250 m), and -0.43 (above 5250 m). Susceptibility increases with slope angles greater than 15° . The most influential range is between 15 and 45° , with positive LSW afterward declines for steeper angles. The aspect reveals that the West (0.23), Southwest (0.13), and South (0.03) aspects have positive LSW, indicating a higher contribution to landslide occurrence, others have negative weights. The west aspect shows the highest LSW and the flat aspect shows the lowest. Convex curvature shows a positive influence (LSW of 0.08), while flat (-0.20) and concave (-0.05) curvatures demonstrate negative weights. Proximity to rivers and drainage density both show a positive relationship with landslide occurrence, with increasing proximity and density corresponding to higher LSWs. Positive *NDVI* values indicate a good influence up to 0.285 but weak above this threshold. Negative *NDVI* values show a negative influence (-0.04). Barren land (0.29) shows a strong influence, while forest cover (-1.05) has the weakest influence among the land cover classes as well as all other variables. LST shows a strong positive correlation with as increasing LST values correspond to a rise in LSW. The ranges 13 – 16°C (0.36) and above 16°C (0.54) exhibit the highest LSWs among all factors and the respective classes. Rainfall also shows a positive correlation mirroring LST. Relative relief demonstrates a distinct pattern, with very low (<400 m) and very high (>700 m) relative relief showing negative weights, while moderate relief (400 – 700 m) shows a positive weight. Additionally, higher *TWI* values (above 10.5) are positively correlated with landslide susceptibility, reflected by a positive LSW of 0.02 and 0.03.

The derived *FR* susceptibility map shows that 13% of the area is classified as very low, 30% as low, and 29% as moderate. High susceptibility covers 18%, while very high accounts for only 6% (Figure 5d).

3.3.2. Logistic Regression (LR)

The LR coefficients represent the impact of each factor on the likelihood of landslide occurrence (Table 3). Positive coefficients suggest a higher probability, whereas negative coefficients indicate a lower probability. The magnitude of the coefficient indicates the strength of the relationship. Slope, rainfall, and drainage density are the most influential factors, with high positive coefficients (2.68, 2.88, and 1.62, respectively), indicating that steeper slopes, increased rainfall, and higher drainage density significantly increase landslide susceptibility. In contrast, elevation (-1.86) and *NDVI* (-1.05) are negatively influential, as their negative coefficients suggest that higher elevations and areas with greater vegetation cover are less likely to experience landslides. Additionally, land cover types such as Barren land (2.02) and Alpine Meadows (1.46), as well as specific aspect orientations like SW and W (with coefficients of 0.90 and 0.79), strongly contribute to landslide occurrence. The susceptibility map from LR designates most of the area (51%) in the very low (27%) and low (24%), followed by moderate (22%) susceptibility category. A smaller proportion of the area is classified as high (15%) and very high (12%) but covers 76% of total landslide area (Table 4), indicating that landslides are more likely to occur in areas with very high to high susceptibility class, even if the class covers less area.

Table 3. Regression coefficients of independent variables.

S.N.	Factors	Coefficient	S.N.	Factors	Class	Coefficient
1	Elevation [m]	−1.86	11	Aspect	Flat	0
2	Slope°	2.68			N	−1.28
3	Curvature	0.41			NE	−0.15
4	River proximity	−0.93			E	0.58
5	Drainage density	1.62			SE	0.53
6	NDVI	−1.05			S	0.16
7	LST (°C)	3.5			SW	0.9
8	Rainfall	2.88			W	0.79
9	Relative relief	−0.47			NW	−0.35
10	TWI	0.33			Others	0.72
Constant		−5.26	12	Land Cover	Forest	0
					Alpine Meadows	1.46
					Barren land	2.02
					Snow/Ice	0.7

Table 4. Relative Landslide Density (*R*-Index) reflecting the accuracy of landslide susceptibility models and illustrating exposure level.

Models	Hazard Class	Susceptibility		Total Landslides			<i>R</i> -Index	Exposure
		Area (km ² - <i>N_i</i>)	%	Count (<i>n_i</i>)	Area (km ²)	%		
Frequency ratio	Very low	106.41	16.41	15	0.06	1.84	1.5	Low
	Low	194.75	30.03	64	0.21	6.02	3.5	
	Moderate	187.92	28.97	151	0.60	17.09	8.5	
	High	119.06	18.36	180	0.85	24.21	16.0	Moderate
	Very high	40.43	6.23	270	1.79	50.85	70.6	High
	Total	648.57	100	680	3.52	100	-	-
Logistic Regression	Very low	172.32	26.57	11	0.14	3.86	0.9	Low
	Low	153.91	23.73	31	0.23	6.46	2.8	
	Moderate	144.38	22.26	95	0.51	14.37	9.0	
	High	100.03	15.42	206	0.68	19.45	28.2	Moderate
	Very high	77.94	12.02	337	1.97	55.87	59.2	High
	Total	648.57	100	680	3.52	100	-	-
Random Forest	Very low	172.39	26.58	2	0.12	3.36	0.2	Low
	Low	153.57	23.68	20	0.36	10.26	1.8	
	Moderate	130.18	20.07	53	0.28	7.980	5.5	
	High	108.84	16.78	148	0.58	16.50	18.4	Moderate
	Very high	83.59	12.89	457	2.18	61.90	74.1	High
	Total	648.57	100	680	3.52	100	-	-

3.3.3. Random Forest (RF)

The results of the landslide susceptibility assessment using the RF model reveal the relative importance of various factors (feature importance) influencing landslide occurrence (Figure 6).

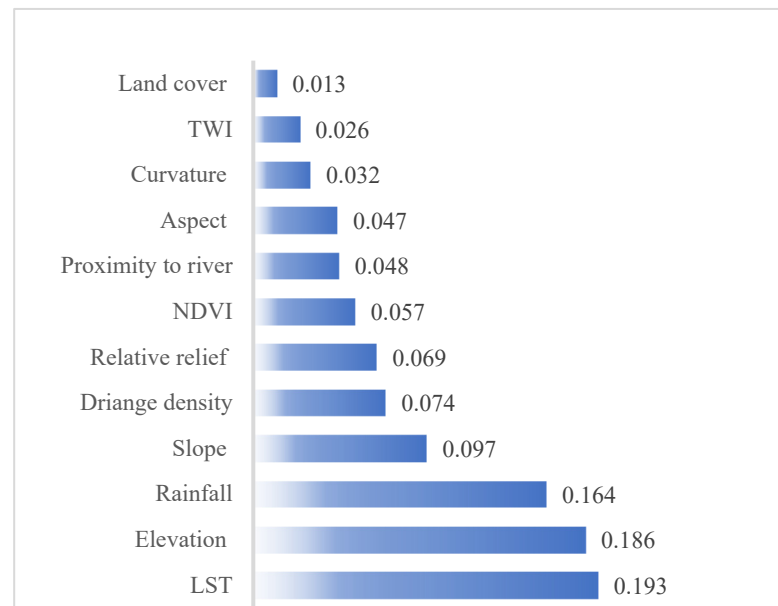


Figure 6. Feature importance of Random Forest model.

LST was the most influential factor, contributing to 19%, followed by elevation 18% and rainfall of 16%, highlighting the significant role of climate and topography in landslide risk. Slope (10%) and drainage density (7%) also played important roles, indicating the relevance of terrain features in susceptibility. Relative relief (7%) and NDVI (6%) provided additional insights, though with lower impact. Factors such as proximity to river (5%) and aspect (5%) were moderately important, while curvature (3%), TWI (3%), and land cover (1%) had a minimal influence on the model. Utilizing the RF model, nearly 50% of the area is classified into very low (27%) and the low (24%) class while 20% in moderate. The remaining 28.76% are divided into high (17%) and very high (13%) which covers 78% of landslide area (Table 4).

3.4. Comparison and Validation

There is an inverse relationship between landslide coverage and susceptibility classes across all models. In low-susceptibility areas (very low and low), the total area is extensive, but landslide coverage is minimal. As susceptibility increases, the total area decreases while landslide coverage rises relative to the hazard class (Table 4).

The FR model classifies 25% of the area as high (18%) and very high (6%) hazard zones, which together account for 75% of the landslides in the region. Notably, 51% of the landslides are concentrated in just 6% of the area classified as a very high hazard zone. In contrast, the LR model classifies 27% of the area as high (15%) and very high (12%) hazard, with 75% of the landslide area concentrated in these zones. This performance is nearly identical to that of the frequency ratio model. Meanwhile, the RF classifies 30% of the area as high (17%) and very high (13%) hazard, with 78% of the landslide area concentrated in these zones. Particularly impressive is that only 13% of the area, classified as very high hazard, accounts for 62% of the landslides, demonstrating the significant accuracy of the model's output. On the other hand, the FR model designates 46% of the total area as very

low (16%), low (30%) and hazard zones, which collectively account for only 8% of the total landslide-affected areas. Similarly, the LR model classifies 50% of the area as low (24%) and very low (27%) hazard, with these zones covering just 10% of the landslide-prone regions. Meanwhile, the RF model also designates 50% of the area as low (24%) and very low (27%) hazard, collectively covering 13% of the landslide-affected area.

Among the models, the RF model demonstrates the highest predictive accuracy, achieving 91% prediction accuracy and 94% performance accuracy, indicating superior classification capability (Figure 7).

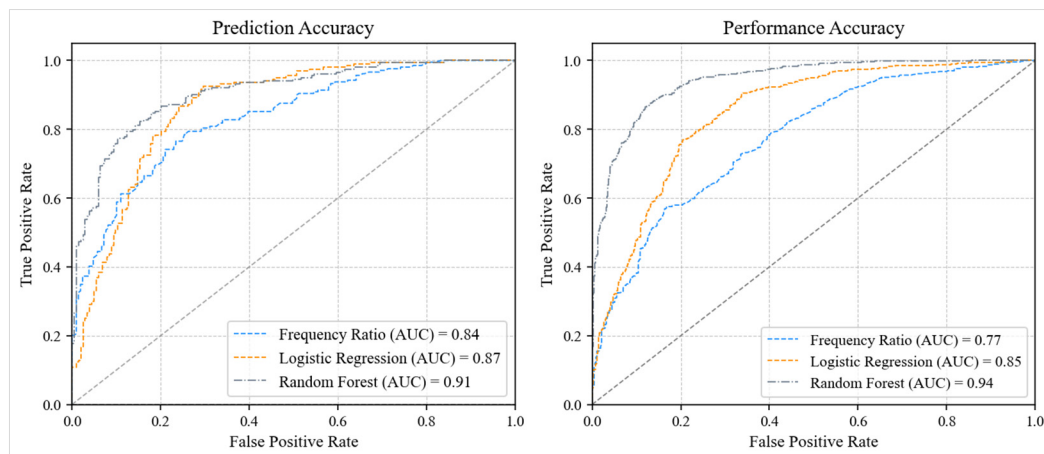


Figure 7. The ROC curve showing the area under the curve (AUC) of the applied models.

The LR model follows with 87% prediction accuracy and 85% performance accuracy, while the *FR* model exhibits the lowest success rates, with 84% prediction accuracy and 77% performance accuracy. Despite variations in performance, all three models exhibit good accuracy in identifying landslide-prone areas, with the Random Forest model outperforming the others in both predictive capability and overall performance.

3.5. Exposure and Elements at Risk

The analysis of infrastructure exposure to landslide hazards reveals significant variations across different elements. The majority (56%) of structures are in moderately vulnerable zones, while 26% fall in high, indicating substantial risk (Table 5).

Most of the buildings are in moderate (58%) and high exposure zones (25%), making them particularly vulnerable. Remaining few (17%) buildings are in low vulnerable areas. Similarly, 67% of bridges and 50% of religious sites are in high-hazard areas, emphasizing the susceptibility of critical infrastructure. Settlements show a notable presence in high (40%) and moderate (37%) zones, raising concerns about population safety. Helipads and public service centers are mostly within moderate zones, while museums remain in low-risk areas. Camping sites exhibit an even distribution, with 50% in low-, 25% in moderate-, and 25% in high exposure, reflecting variable vulnerability. Our analysis reveals that 641 buildings (25% of the total in the region) and 32 settlements, including major ones like Pangboche, Thame, and Thore, fall within this risk. Seven camping sites (25%), one helipad, eight religious sites, one public service center, and 10 bridges are the other elements at this risk.

The total length of trekking routes within the study area is 521.34 km, of which 2.73 km (0.52%) is immediately threatened by landslides, as these segments are located within active landslide scars. Analysis of trekking route exposure to landslide susceptibility zones reveals that 44% of the routes fall within low-exposure zones, while 27% (142.49 km) are situated in moderate-exposure zones, and 28% (147.19 km) lie within high-exposure zones, indicating

a significant level of vulnerability. A representative case of such high-vulnerability areas is illustrated in Figure 8, the second most popular trekking route in the region. The route takes hikers to many glaciers such as Ngozumpa and Gunar, as well as glacier lakes like Gokyo, Tobuche (second lake), and Thonka (fourth lake), which are popularly known and promoted destinations in the Khumbu valley of SNP for glacier tourism. Additionally, the route offers stunning views of prominent peaks like Mahalangur, Gyachungkhang, and Cho Oyu. These areas are susceptible to various landslides, and even the newly developed alternative route also intersects landslides, hindering the primary access to glacier tourism in the region. This is the same place as Zimmermann highlighted in 1986 considering a special case and stated that, the both sides of the valley of Gokyo between Phortse up to 400–800 m above the river bed are marked by instability manifesting itself in high landslide activity [57]. Our findings aligns with [57], as most of this section falls under high exposure to landslides.

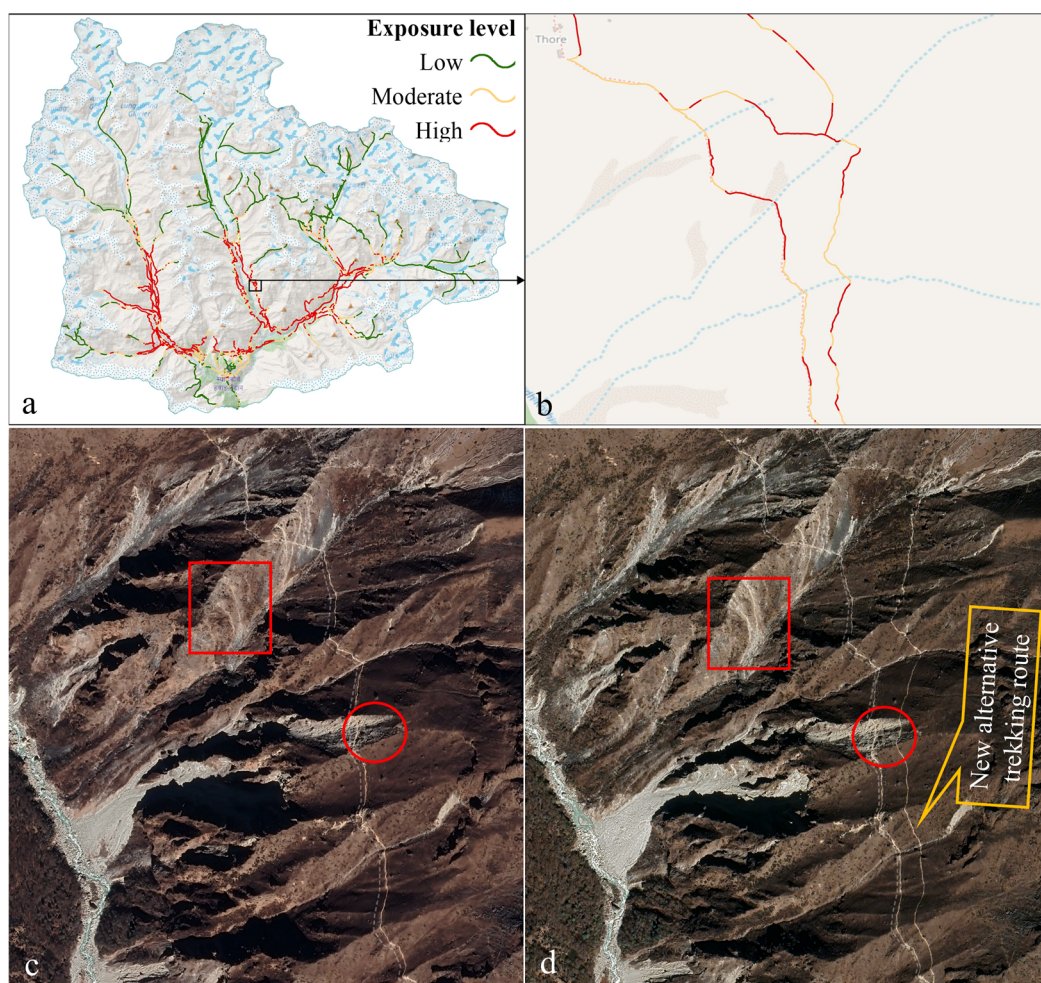


Figure 8. Exposure level of trekking routes to landslide. (a) The degree of exposure of trekking routes to landslide susceptibility; (b) inset map of the selected area in a; (c) Google Earth images of high exposure area in 2014; (d) 2021. Red circles and red squares in the images indicate the same locations shown in different time periods. Source: Google Earth.

Table 5. Statistics of exposed elements at a high degree of landslide exposure.

S.N.	Elements	High		Moderate		Low		Total	
		Number	%	Number	%	Number	%	Number	%
1	Buildings	641	25	1465	58	437	17	2543	100
2	Camping site	7	25	7	25	14	50	28	100
3	Helipads	1	11	4	44	5	50	10	100
4	Museum	-	-	-	-	2	100	2	100
5	Religious sites	8	50	6	38	2	13	16	100
6	Public service center	1	11	5	56	3	33	9	100
7	Bridges	10	67	4	27	1	7	15	100
8	Settlements	32	40	30	37	19	23	81	100
Total		700	26	1521	56	482	18	2703	100

4. Discussion

4.1. Landslide Distribution and Influencing Factors

Analysis of all 680 observed landslides indicates that both topographic and non-topographic factors play a decisive role in shaping landslide distribution patterns. Being the most influential topographic factor (Table 2), landslides predominantly occur on slopes between 15° and 55° (90%), with peaking at 30–45° (44%) and decreasing afterward (Figure 9a). This pattern is consistent with established research trends in similar mountainous topographies [20,72,73,75,120,121]. The highest frequency of landslides (96%) is observed on slopes with south and western aspects (SW, S, W, SE), in line with [121], and further supported by [34], due to variations in insolation, weather, land cover, and soil conditions; in the Himalayas, the abundance of these slopes combined with intensified monsoon and westerly precipitation amplifies this effect (Figure 9c).

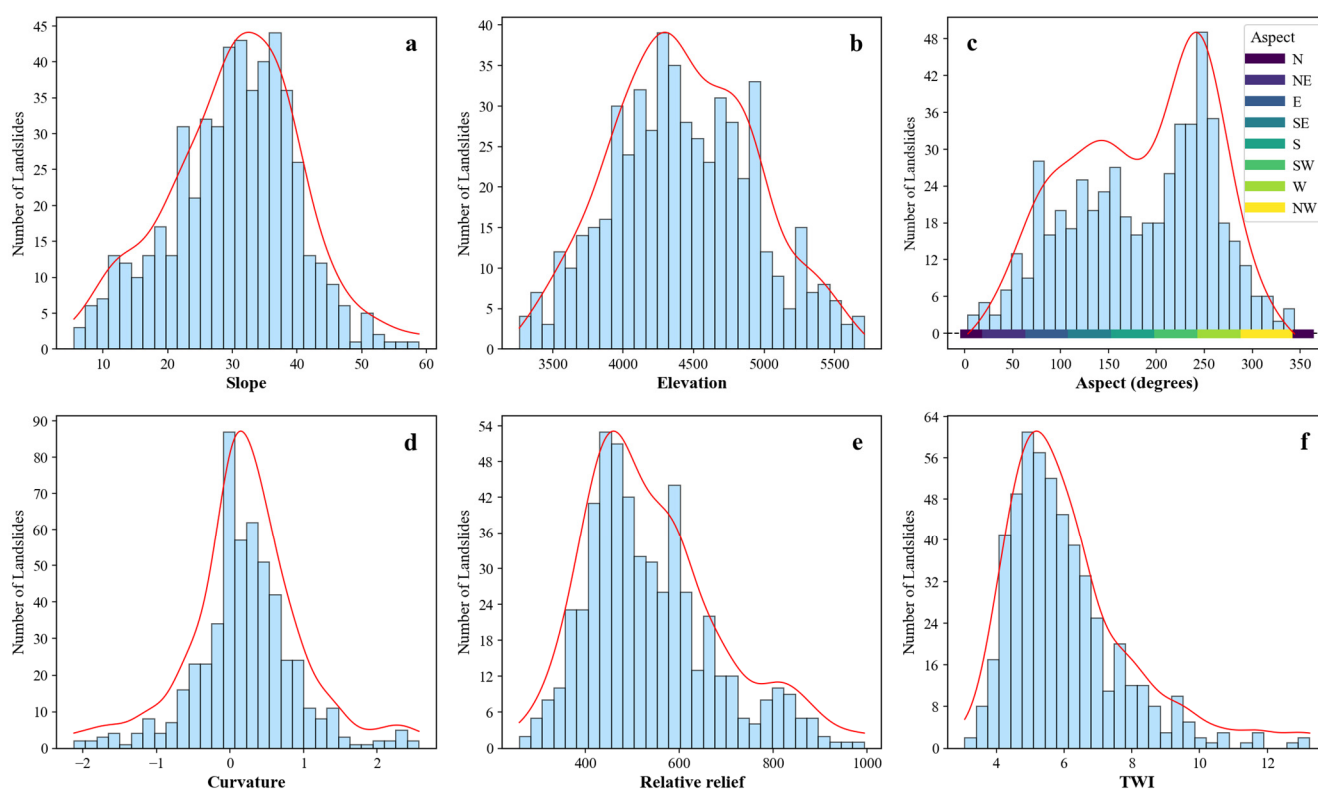


Figure 9. Landslide distribution with topographic factors. (a) Slope; (b) elevation; (c) aspect; (d) curvature; (e) relative relief; (f) TWI.

While previous studies [34,54–56,72,122] report peak landslide activity in the Nepal Himalayas below 3000 m a.s.l., whereas our findings show a peak near 4450 m (Figure 9b). This discrepancy is likely due to the distribution of the significant portion of the study area at higher elevation, which is characterized by sparse vegetation and more barren conditions, suitable for reducing slope stability compared to the denser vegetation found at lower elevations [73,82]. Because the vegetation enhances slope stability by modifying soil cohesion, internal friction, soil weight, and pore-water pressure through root reinforcement and increased soil suction [82]. This is further supported by non-topographic indicators such as *NDVI* and land cover (Figure 10a,f).

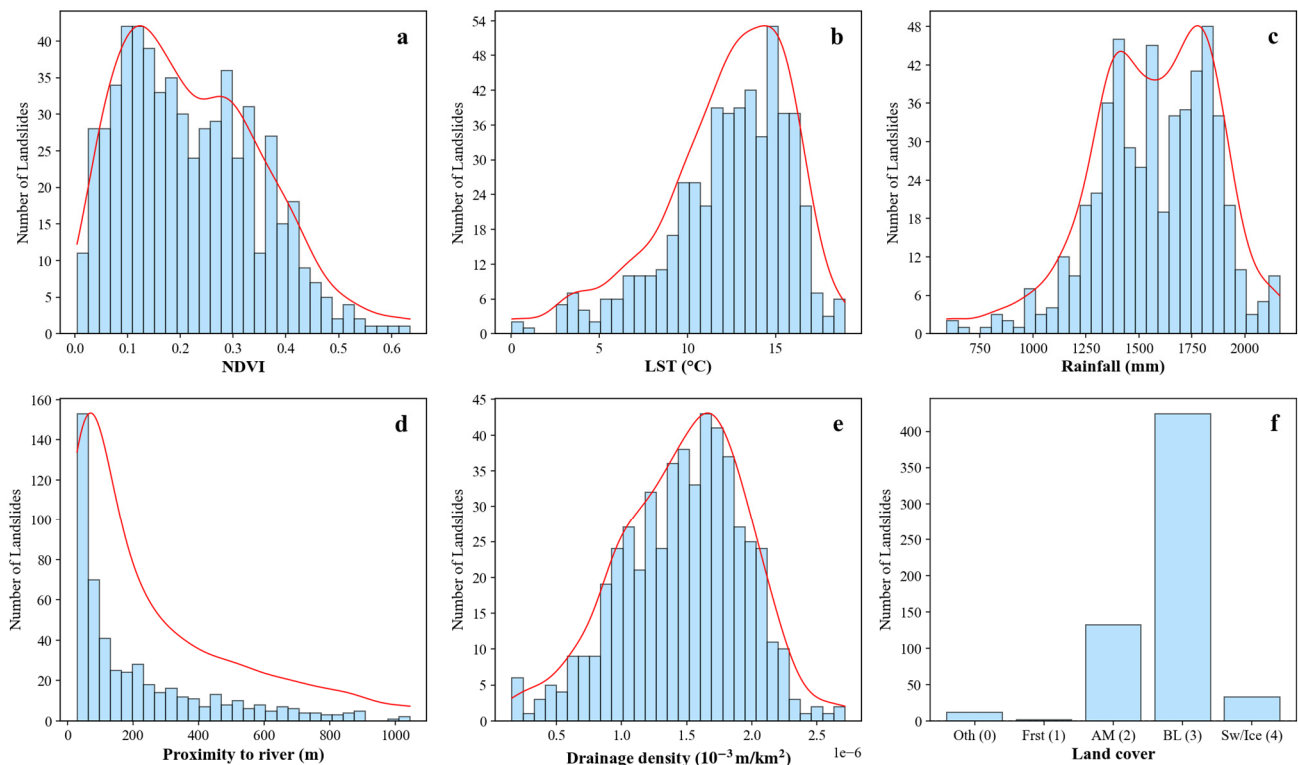


Figure 10. Landslide distribution with non-topographic factors. (a) *NDVI*; (b) *LST*; (c) rainfall; (d) proximity to river; (e) drainage density; (f) land cover.

A significant portion (92%) of the landslides occur within the *NDVI* range of 0.00–0.49, with the highest concentration (46%) in the 0.00 to 0.11 range, which corresponds to areas with sparse vegetation or barren land. Overall, 67% of landslides are concentrated in barren land and 24% in Alpine meadows. The positive correlation between relative relief and landslide occurrence has been documented in previous studies. This relationship may be explained by the increase in potential energy, which enhances erosion and mass movement as local elevation rises [73,123]. Regions with negative curvature (convexity) exhibit a stronger correlation with landslide occurrence compared to those with positive curvature (concavity). This contrasts with most studies [70,72,81,99], which report higher landslide concentrations on concave slopes. However, a few studies align with our findings [73,124]. This may result from regional topographic variations, as the curvature influences acceleration, deceleration, convergence, and divergence of flow [124]. The relationship pattern between *TWI* and landslides mirrors findings from previous studies conducted in Nepal [5,81,125].

Land Surface Temperature (*LST*) is the most influencing factor driving landslides susceptibility in the region and shows a strong positive correlation with landslide distribution (Figure 10b). Landslide frequency increases with *LST* values from -7°C to 19°C . Only 0.43% occurs below 0°C , but warmer intervals show higher occurrences: $0\text{--}4.5^{\circ}\text{C}$ (7%),

4.5–7.5 °C (11%), 7.5–10 °C (18%), and 10–13 °C (22%). The peak concentration is in the 13–16 °C range (36%). LST values above 16 °C account for only 2% of the area but contribute to 6% of landslides. This pattern may be influenced by elevation and aspect, as both factors affect solar radiation and surface heating. However, this strong positive correlation suggests that increasing temperatures, likely driven by permafrost degradation and slope melting, could lead to an increase in landslide occurrences, particularly in the context of climate change. The literature support that the climate change-driven temperature rise directly influence slope stability by reducing the structural support once provided by ice, increasing water infiltration, and altering meltwater regimes in high mountains [84,85]. The mechanisms include glacier retreat, debuttressing of valley walls, and permafrost thaw which increases the likelihood of rockfalls, and debris flows with the loss of frozen ground that acts as natural “cement”, and seasonal meltwater peaks including driven by the reduced snow cover and repeated freeze–thaw cycles. Seasonal meltwater peaks elevate pore water pressure in slopes, while reduced snow cover and repeated freeze–thaw cycles weaken rock masses by widening fractures, together increasing the likelihood of slope instability [85,126]. Moreover, rising annual average temperatures in high-altitude and permafrost regions not only deepen the active layer above permafrost but also shift the lower permafrost boundary upward, reducing the mechanical strength of frozen ground and increasing landslide susceptibility [127,128]. These mechanisms are supported by observations as the records demonstrate continuous increase in mean, maximum and minimum temperatures in the study area. While precipitation exhibits an overall declining pattern, winters are warming approximately 2.5 times faster than summer [129]. Reduced precipitation limits snow accumulation and insulation, while accelerated winter warming intensifies mid-winter melt and freeze–thaw activity, together reinforcing thermally driven slope instability in the region.

Hydrological factors, such as proximity to rivers, drainage density, and precipitation, also correlate positively with landslides. These patterns align with previous studies in Nepal [99,102,125,130], and other mountainous regions beyond [74,88,98]. This is because rainfall is a key factor that accelerates slope erosion and significantly impacts landslide stability, particularly in mountainous and hilly regions whereas proximity to rivers and drainage density both can destabilize slopes through toe undercutting or by saturating materials within the water level of the stream.

4.2. Evaluation of Susceptibility Mapping Approaches for High-Mountain Areas of Nepal

The assessment outcomes underscore the crucial roles played by both topographic and non-topographic factors. Interestingly, the non-topographic factors, particularly LST, rainfall, and drainage density, exhibited a more pronounced impact on landslide occurrence compared to the topographic factors such as elevation, slope, and aspect. Among all factors, LST emerged as the most influencing factor followed by rainfall, elevation, and slope. Slope and elevation emerged as the most influential topographic factors in landslide susceptibility, aligning with prior research in Nepal [72,81,102,131,132]. Specific aspects such as south and west, and land cover types like barren land and alpine meadows, have already been discussed in previous sections. On the other hand, aside from LST, the dominant non-topographic influences were hydrological factors (rainfall and drainage density), as previously highlighted [68,73,99,130]. The model performance in high-mountain areas of Nepal showcased consistent trends in both performance and prediction accuracy, similar to other research findings. Random Forest demonstrates the best performance metrics (prediction 91%, performance 94%) among the models employed, surpassing Logistic Regression (prediction 87%, performance 85%) and Frequency Ratio (prediction 83%, performance 82%) [113,133,134].

Comparable studies from other high-mountain regions highlight both shared and distinct patterns of landslide susceptibility. For instance, in the Andes, multi-model approaches integrating Fuzzy Logic, TRIGRS, and Support Vector Machines identified topographic factors (slope), lithology, and rainfall events as key controls in data-scarce terrains [135]. In a basin in the Northern Alps of Italy, Random Forest and Logistic Regression models effectively captured the influence of elevation, slope, and land cover on landslide occurrence, although the study focused primarily on methodological comparisons rather than ranking specific environmental factors [136]. In the Western Carpathians, predictive modeling using Random Forest and Logistic Regression highlighted elevation, groundwater depth, and geological substrate as important predictors, with Random Forest achieving superior predictive performance [137]. Similarly, in the Flysch Carpathians of Poland, machine learning models were successfully applied to assess landslide susceptibility, underlining the utility of such approaches in complex terrain [138]. Collectively, these studies highlight that while modeling approaches and dominant conditioning factors vary across regions, topographic and hydrological parameters consistently show a central influence on high-mountain landslide susceptibility. Controlling factors such as slope, elevation, and rainfall appear to have universal significance, whereas variables like land surface temperature (LST) and vegetation exhibit regional variability. Accordingly, the patterns observed in Sagarmatha National Park reflect both globally consistent drivers of landslide susceptibility and locally specific environmental influences associated with glacier-dominated terrain.

Although traditional landslide investigation methods may overlook the distinctive landslide risks linked to high-altitude regions where landslides are also affected by cryospheric dynamics, the introduction of a novel parameter like LST emerged as the most influential indicator for landslide occurrence across all three models in high-mountain areas of Nepal. While further investigation is necessary to understand the underlying causes and quantify the exact contribution of warming induced cryospheric dynamics on slope instability, this finding underscores the significance of considering Land Surface Temperature (LST) in landslide susceptibility assessments in high-altitude regions.

4.3. Risk of Landslides Associated with Trekking and Glacier Tourism

The identified landslide distribution patterns in this study are consistent with previously reported landslide occurrences in the Everest region [9,32,53,57]. Historical events such as the Namche Bazaar landslide and the Tongmat landslide in the Gokyo Valley demonstrate the long-term geomorphic instability of the region. A very recent example includes the 2025 Namche-Jorsalle landslide demonstrated in Figure A4 [139,140], which occurred following intense rainfall in the Khumbu region, triggering slope failure near the Dudh Koshi River and blocking the main trail between Jorsalle and Namche Bazaar: one of the most important and heavily used trekking routes in the Everest region. The event disrupted trekking activities, resulting in the closure of the trail for more than a week. Although no fatalities were reported along this trail, approximately 1000 trekkers, guides, and residents were temporarily stranded in the Sagarmatha region, with later rescued safely through coordinated efforts. This incident underscores the potential impact on tourism in the region. The present susceptibility and subsequent exposure analysis further confirms that a large portion of trekking routes and many settlements are highly exposed to landslide (Figure 11a), highlighting the continuing hazard potential in the region. The occurrence of landslides along these routes is a common phenomenon. Interestingly, while proximity to rivers generally shows a less significant impact in the LR and FR models, a specific class in FR exhibits a higher influence based on the distance from the river. The distribution pattern of landslides also indicates a notable association with the proximity to rivers. Given that many trekking routes in the region follow the river corridors, this unique risk factor

is not surprising. Moreover, as study area being in the high-mountain region of Nepal, the occurrence of Glacial Lake Outburst Floods (GLOFs) is a familiar occurrence, which can sometimes trigger landslides in the areas associated with river channels [57,141–143], which may disrupt trekking routes that are near the stream channels as already observed in the past [144].

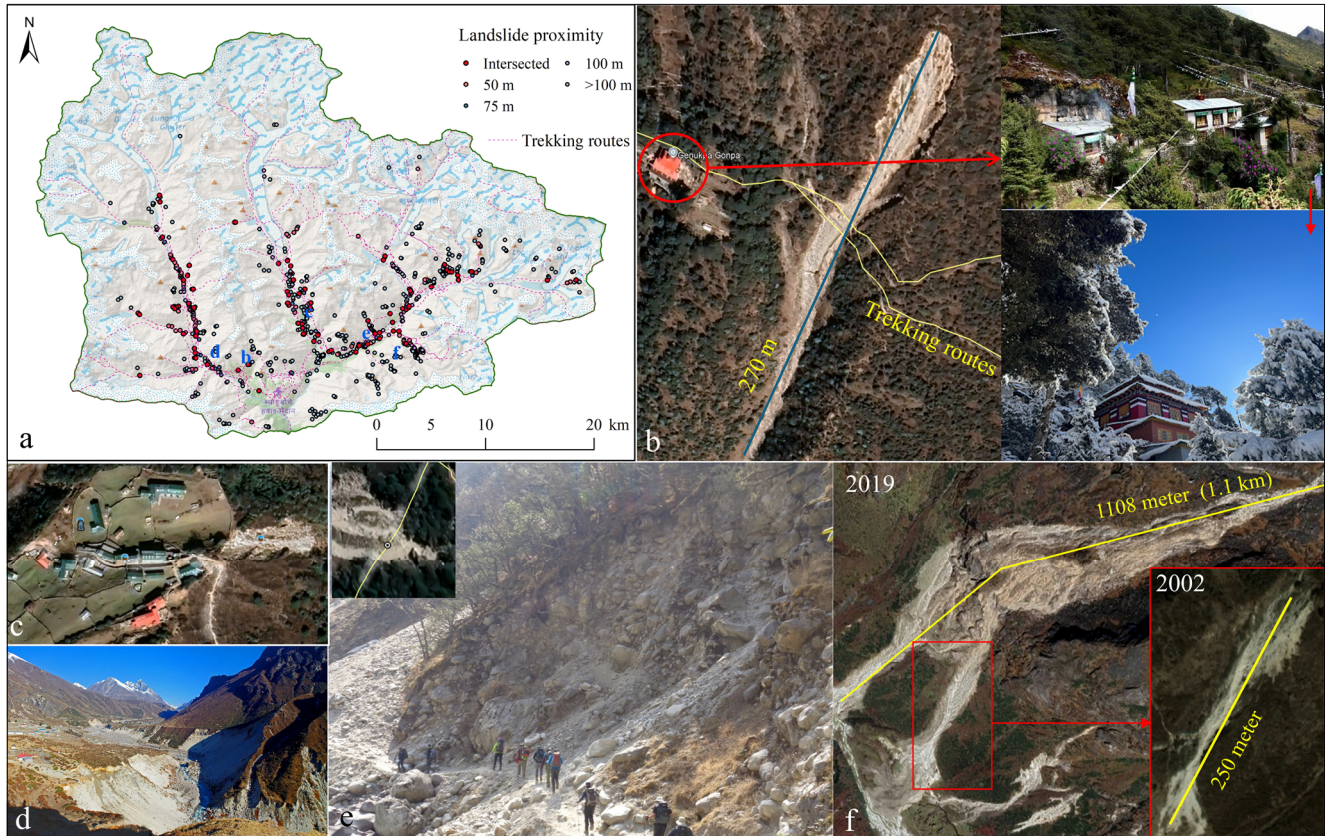


Figure 11. Landslides intersecting trekking routes; (a) proximity of landslides to trekking routes in SNP; (b) Genukpa Gonpa near Mende; (c) Dole (route to Gokyo); (d) Thame; (e) near Imja suspension bridge (route to Everest) [145]; (f) right of Milin. Source: Google Earth.

In support of these findings, several sections of the Everest Base Camp trekking route remain highly exposed to landslide risk, despite mitigation measures such as construction of suspension bridge and localized trail realignments have reduced exposure in some areas. These include the Phakding–Monjo section, where landslide risk persists despite fencing. Another example includes the stretches between Tengboche and Pangboche characterized by loose clay, sand, and large boulders conducive to slope failure. Some of these sections have also been associated with past injuries and fatalities. Additional hazardous zones occur near and immediately before Everest Base Camp, especially across glacial moraine terrain between Lobuche and Gorakshep, where unstable debris slopes and overhanging material increase the risk [145]. These observations strongly support the proximity analysis of landslides along trekking routes in SNP (Figure 11), highlighting that even well-established trekking routes remain highly exposed to landslide hazards. Our investigation identified in 94 landslide locations directly intersecting trekking routes, 168 (94 + 74) landslides within a 50 m range of trekking routes, 209 (168 + 41) within a 75 m range, and 253 (209 + 44) within 100 m range (Figure 11a). These occurrences have the potential to obstruct hikers' access to glacier tourism destinations

or incur significant costs (Figure 11), especially since it is an empirical fact that landslide incidents can potentially recur in areas where they have previously occurred [146].

4.4. Paraglacial Landslide and Associated Risk on Glacier Tourism

The findings regarding paraglacial landslides near glaciers, likely driven by the shrinkage of glaciers and the melting of permafrost [12,84,85], highlight critical patterns and emerging risks in SNP. Notable examples include landslides on the east (Figure 12b), and west slopes of the Lungsumna glacier.

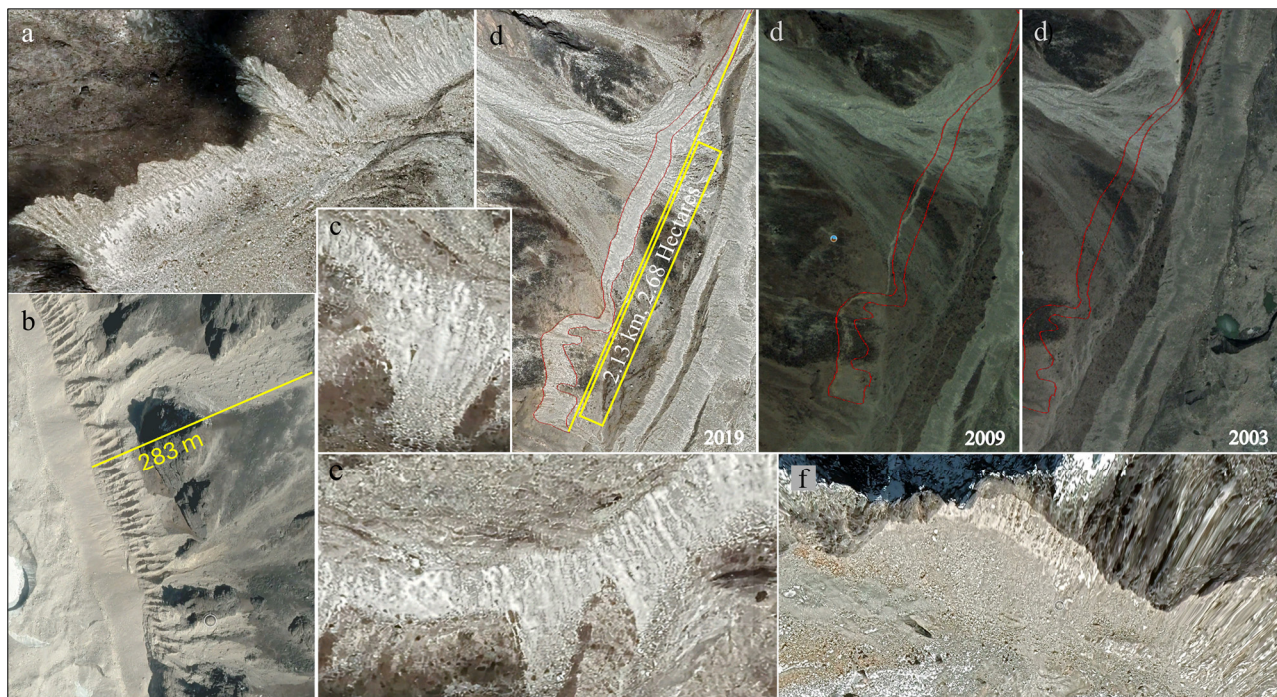


Figure 12. Examples of paraglacial landslides in SNP; (a) northern slope of Cholo glacier; (b) eastern slope of Lungsumna glacier; (c) near the terminus of the Nuptse glacier; (d) western lateral slope of the Imja glacier at different observation years (2003, 2009 and 2019); (e) near the terminus of Khumbu glacier; (f) northern slope of Unnamed glacier. Source: Google Earth.

These slides appear to be primarily caused by the weakening of the upper slope due to failure in lateral moraines (Figure A3). As glaciers shrink, the lateral support they provide diminishes, leading to collapses surrounding terrain. Additional significant examples found on the northern slope of the Cholo glacier (Figure 12a), near the terminus of the Nuptse glacier (Figure 12c), near the terminus of Khumbu glacier (Figure 12e), the northeast of the Nare glacier, and the northern and southwestern slopes (near terminus) of the Lobuche glacier. These examples point to a broader trend that under the condition of continued glacier shrinkage, such landslides in the region are likely to increase in size, frequency, and severity, a trend already observed in high-mountain Asia (HMA) [13,147]. As evidence, a significant landslide is the rockslide near Imja Lake (Figure 12d), which underwent dramatic growth from a narrow fracture in 2009 to a massive rockslide by 2019, expanding to 2.13 km in length and covering approximately 2.68 hectares in just over a decade. An additional example include the northern slope of an unnamed small glacier (Figure 12f), which shrank by 65% from 1980 to 2010 [148,149], and vanished completely by 2021, resulting in a major slope failure.

The destabilization of slopes in regions like SNP poses significant risks not only to the environment but also to human safety and the economy, as these areas rely heavily on glaciers and glacial landscapes as major attractions essential for local livelihoods. Key

trekking routes, such as the path to Everest Base Camp (EBC) via Dingboche and Lobuche, require crossing lateral moraines and areas already affected by existing paraglacial landslides, particularly near the terminus of the Khumbu (Figure 13b) and Lobuche glaciers (Figure 13d–f) as well as before Gorakshep (Figure 13g).

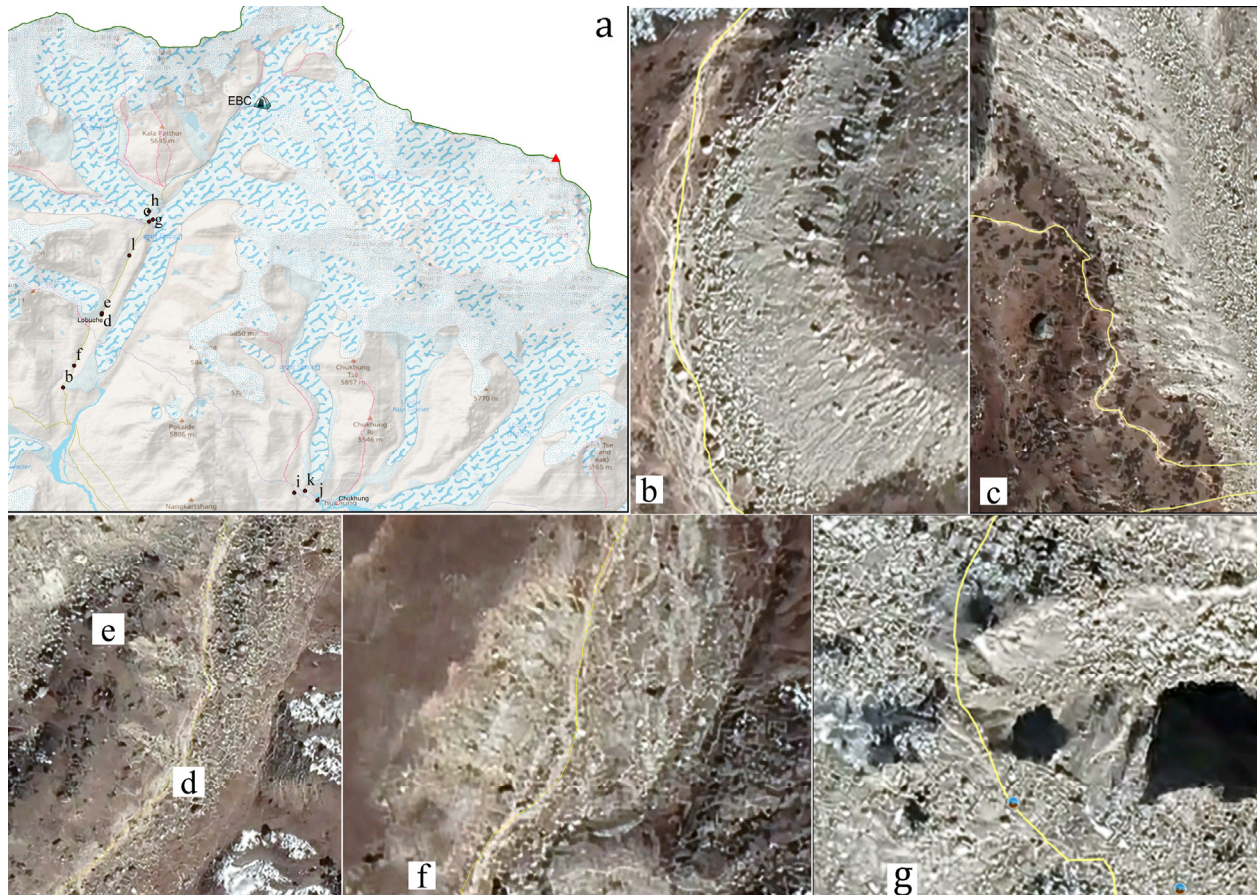


Figure 13. Paraglacial landslides threatening trekking routes in SNP; (a) examples along the route to Everest Base Camp; (b) near the terminus of Khumbu glacier; (c) near Chukhung; (d,e) near terminus of Lobuche glacier; (f) near the terminus of Khumbu glacier; (g) before Gorakshep (Changgrishar glacier). Source: Google Earth.

Additionally, the route near Chukhung traverses several paraglacial landslide zones (Figure 13c). As glaciers continue to shrink, the risk of landslides impacting these trekking routes is expected to rise, similar to the disruption of access routes to high-mountain refuges in the Mer de Glace Basin of the Mont Blanc Massif in France [150]. This becomes more significant when LST has a strong correlation with landslide occurrences in the area. Especially concerning are the recent winter temperature reconstructions at Everest Base Camp, which indicated a unprecedented warming events in January 2021, with winter freezing levels exceeding 6000 m, the highest recorded since 1950, with 13 January, 14 January, and 12 January, being the first, second, and third warmest winter days in the last 72 years [151]. These extreme thermal conditions, combined with ongoing cryospheric shrinkage and accelerated glacial ablation, heighten the likelihood of landslides. The high-mountain regions known for home to permafrost, glaciers, and snow cover landscapes are especially sensitive [84,85,152–154].

5. Conclusions

This study evaluates the landslide risks associated with glacier tourism in the Sagarmatha National Park, with a focus on exposure of infrastructures. Our study found that landslide occurrence is controlled by an interplay of both topographic and non-topographic factors, with Land Surface Temperature (LST) emerging as the dominant driver. This highlights the potential role of cryosphere dynamics, particularly permafrost degradation and glacier retreat driven by rising surface temperature associated with climate warming, as they weaken slope stability in such a high-mountain environment. However, this study does not directly quantify permafrost degradation or long-term climate change impacts, which is a key limitation. Future research should therefore quantify the role of warming-induced cryospheric processes including permafrost thaw, glacier retreat, and moraine instability, in driving slope instability. Other significant factors include slope, rainfall, elevation and drainage density, where landslide activity increases with slope, rainfall, and drainage density, indicating a positive relationship with these factors, while elevation shows a negative relationship. Landslides are predominantly concentrated between elevations of 3850 and 4450 m, with maximum occurrence around 4400 m, slopes ranging from 15° to 45°, south- and west-facing aspects, and largely in barren and alpine areas.

The RF model demonstrated the highest predictive accuracy, emphasizing the need for robust methodologies in assessing landslide hazards in mountainous terrains. However, the multi-model approach is critical for the comprehensive study of landslides. Where Frequency Ratio provides insights into class-wise influences, Logistic Regression examines the magnitude and direction of parameters, and Random Forest offers a comprehensive view of their strength on landslide occurrences.

Importantly, the study highlights that critical tourism infrastructures including trekking routes are substantially exposed to landslide hazards, including the paraglacial landslide associated with cryospheric dynamics. There are 0.73 km (0.52%) trekking routes intersect active landslide scars and 147 km (28%) lie within high-exposure zones. These instabilities disrupt glacier tourism access, threaten local communities and impact the regional economy. Therefore, targeted monitoring, additional detailed investigation, and risk-informed management in high exposure areas are essential to safeguard glacier-based tourism and the regional economy in this iconic high-mountain region.

Although effective for regional mapping, this study is limited by reliance on Google Earth imagery and long-term high-resolution data, which may miss smaller events and reduce temporal monitoring accuracy. Future studies should integrate UAV surveys, field data and long-term observations to improve inventory precision, capture temporal landslide dynamics, and optimize modeling.

Author Contributions: Conceptualization, L.S. and Q.L.; methodology, L.S. and B.G.; formal analysis, L.S., Q.L. and N.R.K.; writing—original draft preparation, L.S. and Q.L.; writing—review and editing, N.R.K. and Y.L.; supervision, Q.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by the National Key Research and Development Program of China (Grant No. 2024YFC3013400), and National Science Foundation of China (Grant No. 42361144874).

Data Availability Statement: Data are contained within the article.

Acknowledgments: The first author is thankful to the Alliance of International Science Organizations (ANSO) for the ANSO Scholarship for Young Talents, which supported this research undertaken at the Institute of Mountain Hazards and Environment, Chinese Academy of Sciences (CAS).

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

SNP	Sagarmatha National Park
NDRRP	National Disaster Risk Reduction Portal
MOCTC	Ministry of Culture, Tourism and Civil Aviation
LST	Land Surface Temperature
TWI	Topographic Wetness Index
NDVI	Normalized Difference Vegetation Index
EBC	Everest Base Camp
LSW	Landslide Susceptibility Weight
LSI	Landslide Susceptibility Index

Appendix A

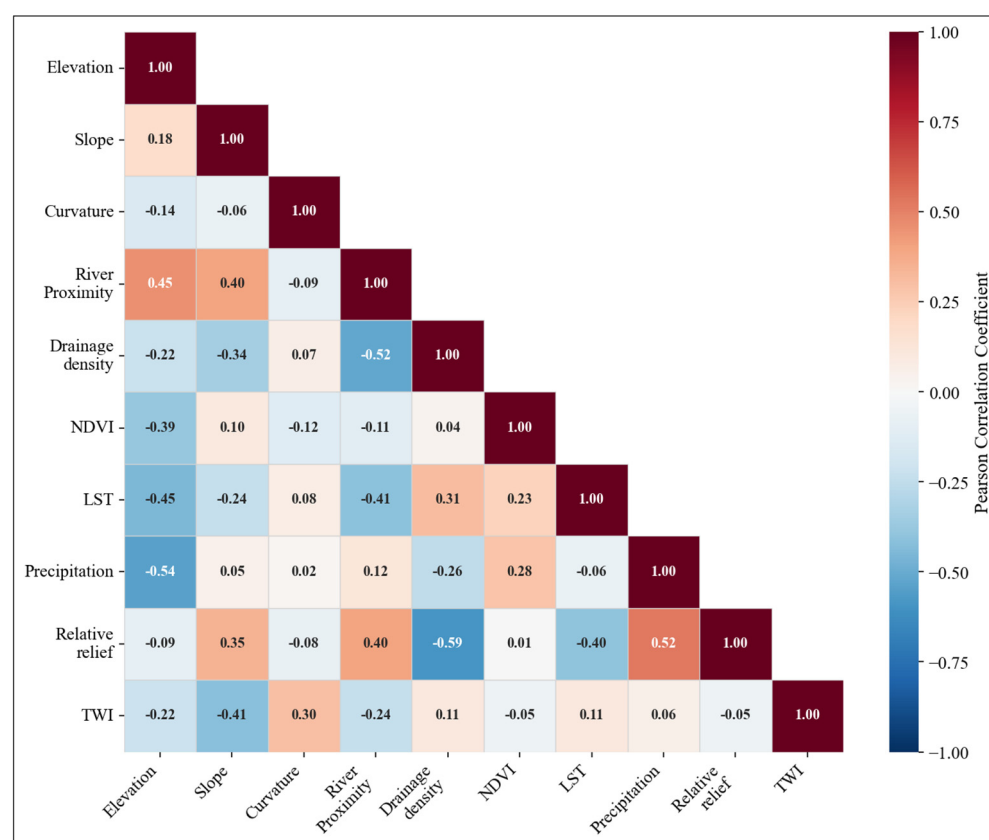


Figure A1. Correlation heatmap of the collinearity test matrix for the continuous variables.

Table A1. Multicollinearity diagnosis indexes for independent variables.

S.N.	Factors	VIF	TOL
1	Elevation	3.397	0.294
2	Slope	1.564	0.639
3	Curvature	1.171	0.854
4	Proximity to river	2.031	0.492
5	Drainage density	1.932	0.518
6	Normalized Difference Vegetations Index (NDVI)	1.330	0.752
7	Land Surface Temperature (LST)	1.772	0.564
8	Rainfall	2.480	0.403
9	Relative relief	2.555	0.391
10	Topographic Wetness Index (TWI)	1.377	0.726

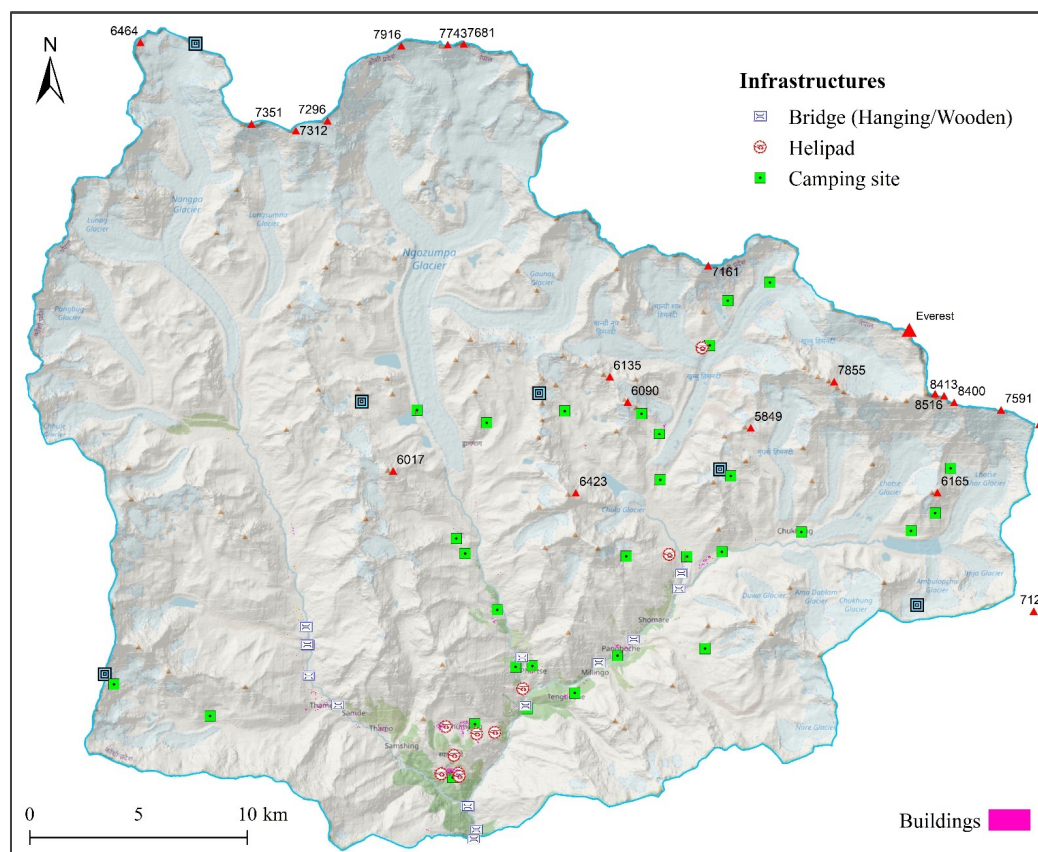


Figure A2. Spatial distribution of key infrastructure except trekking route in SNP.

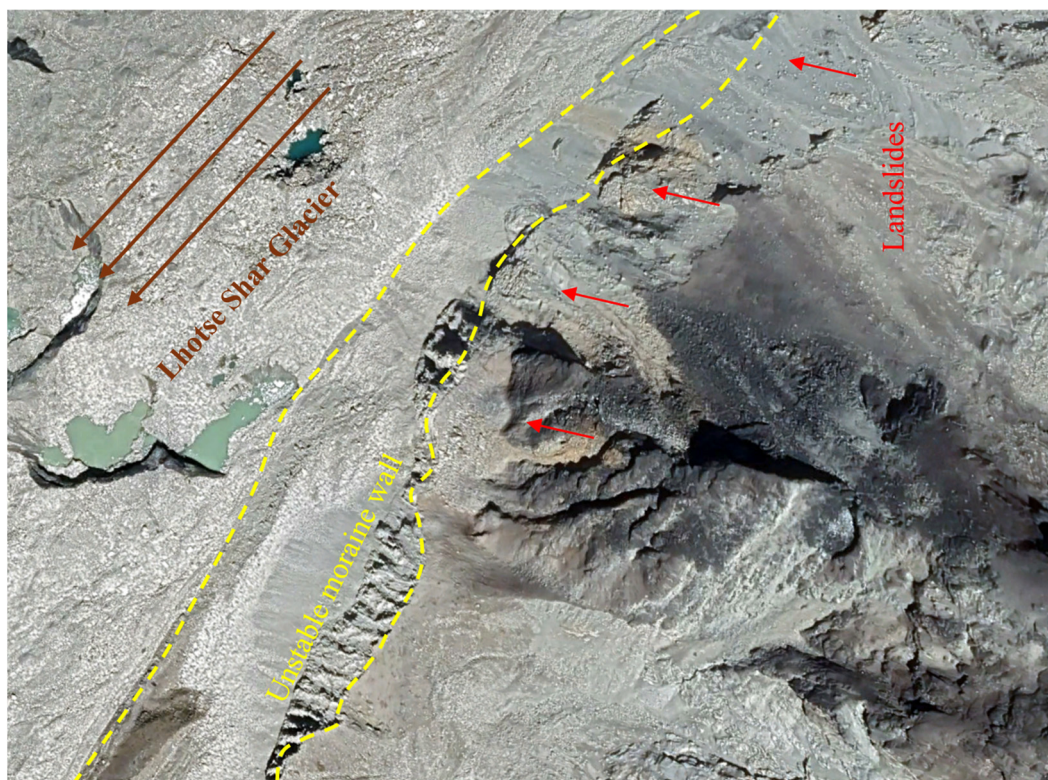


Figure A3. Unstable moraine wall and associated preglacial landslide in Lhotse Shar glacier.



Figure A4. The Namche Jorsalle landslides (5 October 2025). (a) After repair and before repair condition of the trekking route of first landslide; (b) the second landslide; (c,d) after the route was reopened after repair and maintenance (14 October 2025). Source: [139,140], and Adhikari Madhav/Everest Base Camp Trek Information Centre.

Appendix B. Expert-Based Visual Interpretation Criteria for Landslide Identification in Sagarmatha National Park

We employed Google Earth for landslide identification and mapping using expert-based visual interpretation supported by seven key components to enhance accuracy and reliability. These components include elevation, slope angle, surface pattern, geomorphic association, depth, chronology, and material involved. Each component was evaluated individually or in combination, depending on feature clarity, to assess whether a geomorphic scar represented a landslide. The following definitions and expert-based visual interpretation criteria were applied.

1. **Elevation:** When a feature is located around and below the tree line, it is more likely to be a landslide scar. However, in higher elevations, the same feature could potentially be a snow-eroded area or a result of natural surface processes.
2. **Slope:** A scar on a steep slope is more likely to be a landslide, while a scar on a flat slope may not be.
3. **Pattern/shape:** Landslides often exhibit a distinct pattern, with a larger area at the source and narrowing down towards the deposition area. These characteristics help identify the presence of a landslide. If a feature has a fanlike shape in the bottom, it probably could be a landslide.
4. **Depth:** If the scar has greater depth, it is more likely to be associated with a landslide. On the other hand, if the scar appears superficial or shallow, it is more likely to be a result of natural surface erosion or snow erosion.

5. Association: If a feature exhibits spatial associations with other landforms, such as rivers, steep cliffs, or previous landslide scars, this could be a landslide.
6. History: If a certain place has no historical footprints of previous landslides and exhibits a newly formed scar below the snowfall zone, the probability of it being a landslide is higher. The absence of previous landslide footprints combined with a newly formed scar suggests that a landslide event may have occurred recently.
7. Material: If a feature exhibits a deposition at its bottom, it is more likely to be associated with a landslide. The presence of deposited material suggests that a significant mass movement event, such as a landslide, has occurred in the area.

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