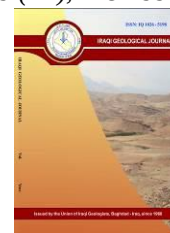




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Geospatial Modeling of Landslide Susceptibility Using Statistical Index and Frequency Ratio Methods in the West Seti Watershed, Nepal

Hemanta Joshi¹, Hira Bahadur Karki¹, Tekendra Bahadur Saud¹, and Bharat Prasad Bhandari^{1,2}

¹ College of Applied Sciences, Tribhuvan University, Kathmandu, Nepal

² Central Department of Environmental Science, Tribhuvan University, Kathmandu, Nepal

* Correspondence: bbhandari@cdes.edu.np

Abstract

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The Hilly and Himalayan region of Nepal is highly sensitive to landslides and debris flows. Many people lose their lives and settlements every year during the rainy season due to landslides in the Nepalese Himalaya. This study aims to assess the landslide susceptibility in the West Seti watershed of Sudurpashchim Province, Nepal. The landslide susceptibility map was prepared by using frequency ratio and statistical index models. The work began with the preparation of a landslide inventory map by using Google Earth and Sentinel-2 imagery. The old landslides were used as training data (70%), and recent landslides that occurred post-2018 were mapped for testing data (30%). A total of 2,029 old and new landslide locations were identified in the study area. The eleven conditioning factors of topographical (slope, elevation, plan curvature, profile curvature, aspect, topographical wetness index), geological (geological map, hydrological (rainfall, distance to drainage, stream power index), and (l) land use/land cover, distance to road) were used for landslide susceptibility analysis after conducting a multicollinearity test. The area under the curve method was used to validate model performance. The landslide susceptibility index was divided into five susceptibility classes, namely very high, high, medium, low, and very low. The very high to very low susceptibility percentages obtained from the model were 9%, 21%, 23%, 27%, and 10%. Similarly, the very high to very low class susceptibility obtained from the SI model were 13%, 24%, 20%, 25%, and 17%. The results indicate that the success and prediction for the FR model were 62.7% and 55.4%, while the success and prediction rate for the SI model were 74.7% and 71.2%. The SI model provided better success and prediction rates in comparison to the FR model. These findings are useful for the local authorities in the study area for disaster risk management planning and safer land-use planning.

Keywords: Landslide susceptibility; landslide inventory; Frequency ratio; Statistical index; West Seti; Nepal

1. Introduction

A landslide can be characterized as a significant displacement of earth, rocks, and gravel from the summit of a slope to its base (Cruden, 1991). Landslides are considered a major natural hazard in hilly and Himalayan regions, resulting in significant loss of life and properties worldwide every year. The landslide occurs when the shear stress exceeds the shear strength of the slope due to any internal or external forces (Kumar et al., 2017). Landslides are anticipated to rise significantly in mountainous regions characterized by extreme climatic conditions, seismic activity, and unregulated human

interventions (Li et al., 2024). The landslide mechanisms cause the formation of new landforms and may create serious threats to human life, the environment, sustainable economic and social development on a global scale (Chen et al., 2018). Consequently, in order to mitigate and diminish the possible detrimental effects of landslides, it is advantageous to delineate and identify areas susceptible to such occurrences (Chen and Li, 2020). Landslides occur due to the interaction of various triggering and conditioning factors. Several methods and techniques in geology and geomorphology are used to assess the landslide susceptibility. The landslide events provide knowledge about the landslide mechanism and development process that supports preparing the landslide mitigation plan.

The hilly and Himalayan regions of Nepal experience frequent mass movements and landslides each year, particularly during the rainy season when heavy, continuous rainfall occurs. The significant altitude variations, combined with monsoon conditions, contribute to the overall fragility of the mountain system (Upreti, 1999). Many settlements in Nepal are located near ancient landslide deposits that periodically become reactivated (Bhandari, 2024). Landslide incidence increases in the Southeast Asian countries during the summer monsoon. Based on the global dataset, India and Nepal contribute 16% and 10 % of all rainfall-triggered landslide events (Froude and Petley, 2018; Nayava et al., 2022). As of July 17, 2024, there have been 38 fatal landslides recorded, resulting in a total of 135 deaths in Nepal. The significant increase in fatalities was due to a landslide on July 12 that swept two buses into the river.

Nepal is highly susceptible to landslides due to complex geology, challenging topography, heavy rain and tectonic activities. The extent of landslide-prone area is increasing due to unplanned development and climate change. Moreover, the landslide events increase during the monsoon period, particularly in the peak rainfall intensity. A total of 337 landslide incidents occurred in 2021 and caused 178 deaths and NPR 34,635,000 in economic loss due to property damage (Saud et al., 2025). A total of 2,458 catastrophic landslides occurred in Nepal between 2011 and 2021 that caused 1,384 deaths and NPR 1,752,650,237 in estimated economic loss. A detailed study of the spatio-temporal landslide distribution is essential for reducing their impacts. Such knowledge provides ability to identify the susceptible area for future landslides. Generally, the landslides are likely to happen in the previously affected areas (Malamud et al., 2004).

Landslide susceptibility mapping is the most effective tool to reduce the effects of future landslides and emergency decision-making (Zhao et al., 2024). Landslide susceptibility indicates the likelihood of a landslide occurring in a certain region based on various causative factors (Hong et al., 2019). There are several methods that have been used for landslide susceptibility analysis. The most widely used techniques for landslide susceptibility mapping (LSM) are heuristic, physically based, and data-driven approaches (Hussin et al., 2016). The analytical hierarchy process and spatial multi-criteria evaluation are widely used heuristic approaches for landslide susceptibility analysis (Yan et al., 2019) however, there are some limitations of knowledge-driven methodologies. Researchers may introduce bias and weaknesses when selecting factors and scores, which can result in outcomes that differ from the actual situation (Pham et al., 2019). The physical-based models for slope stability analysis mainly depend on mathematical representations of slope characteristics, including geological and hydrogeological data (Youssef et al., 2015). Deterministic methods are commonly used at the local level. Due to this limitation, connecting input parameters across large areas is challenging (Jacobs et al., 2020), which renders the deterministic model ineffective for regional landslide susceptibility assessment (Trigila et al., 2015). There are three categories for data-driven models: namely; statistical, machine learning, and deep learning (Wei et al., 2024).

The statistical models are considered the most effective techniques for predicting landslide susceptibility at both national and regional levels (Hong et al., 2020; Pham et al., 2018). Statistical methods correlate landslides with triggering factors to predict the landslide-susceptible zone. The common statistical models are bivariate and multivariate techniques (Pradhan and Lee, 2010). Both

techniques are simple to develop and involve less data. They present better interpretations and more accurate results so that they are widely used for susceptibility mapping (Saud et al., 2025). The widely used bivariate approaches for (LSM) are frequency ratio, statistical index, and weight of evidence (Martinello et al., 2022).

The multivariate statistical techniques are used to study the interrelation between several variables. These techniques utilize mathematical statistical tools without the requirement for complex parameters (Pham et al., 2019). The widely used multivariate models for (LSM) are logistic regression and discriminant analysis (Hong et al., 2020). However, the multivariate analysis cannot distinguish between the internal categories of each conditioning factor (Liao et al., 2019). Due to the limitations of both methods, the combined techniques of various statistical models are used to provide better landslide susceptibility prediction (Woodard et al., 2024).

This paper endeavors to explore a clear, highly precise, interpretable, and dependable models. This study aims to develop landslide susceptibility maps for the West Seti watershed, Sudurpaschim province of Nepal employing two models: Frequency Ratio and Statistical Index. Similarly, the study further aims to compare the success and prediction performance of the landslide susceptibility at the catchment scale. The primary objectives of this study are to ascertain the predictive capability and significance of the factors conditioning landslides, as well as to examine the independence correlations among these factors and to validate and comparing the efficacy of the models through area under curve.

2. Study Area

The study area (Fig. 1) is located in the Far -Western Region of Nepal, primarily focusing on the area around the Seti River watershed of Bajhang District with coordinate (29°26' 44.05"N, 80°54' 40.04"E) and (30° 2' 22.41"N, 81°16' 3.79"E). The West Seti River Basin (WSRB), is a significant Himalayan basin in Nepal, serves as a crucial source of fresh water for the western part of the country (Bhatta et al., 2020). The Seti River is the main watercourse in the area, primarily fed by snow and supplemented by numerous tributaries that are fueled by both snow and rain. The study region falls into a subtropical to temperate climate with annual rainfall of 1825 mm. More than 70% of rainfall occurs in the monsoon period. The monsoon begins in June, ending in September.

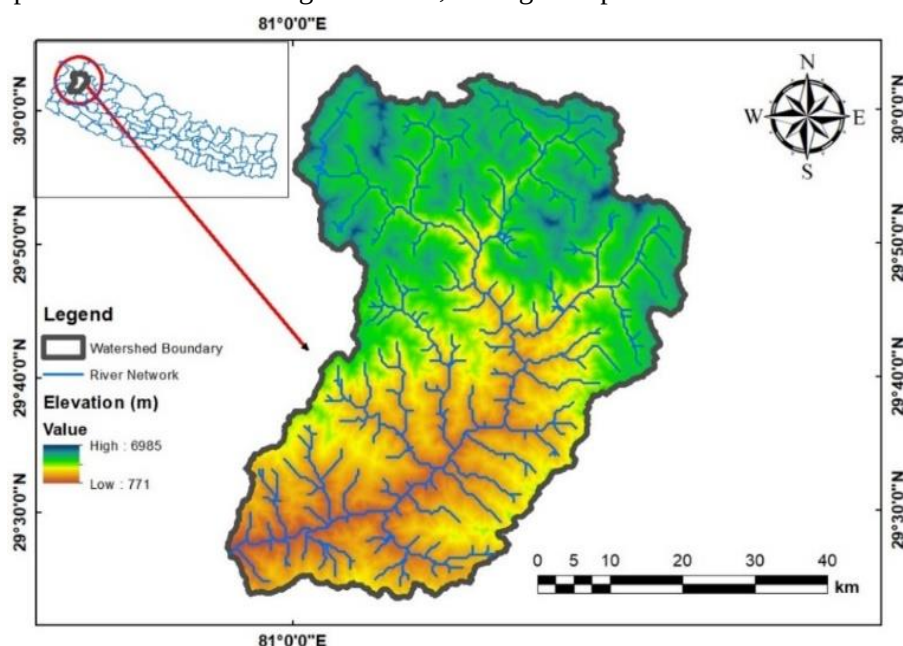


Fig 1. Location map of the West Seti River basin

Steeply sloped topography and heavy rainfall cause several mass movements in the Far Western region (Manchado et al., 2022). Some human settlements have been relocated from vulnerable area to safer locations. The climatic conditions of the Far Western Region of Nepal differ from those of other regions due to unpredictable winter snowfall (Talchabhadel et al., 2018). The precipitation mainly occurs between June and September. The mean annual rainfall documented from 2000 to 2022 AD was 2042 mm.

3. Materials and Methods

3.1. Landslide Inventory Mapping

The perfect landslide inventory map can predict accurate landslide susceptibility conditions of the particular region (Jacobs et al., 2020). The landslide inventory map was prepared using data from Google Earth, Landsat and Sentinel-1 dataset. The old landslides are selected for training data (70%), while the landslides that occurred after 2018 are used for testing data (30%). Due to cloud and shadow effects, some landslides were not visible in the imagery. Consequently, were mapped in the field using GPS.

3.2. Landslide Conditioning Factors

The conditioning factors for landslides need to be selected scientifically; however, it is also important to use ground-based knowledge to assess the role of these factors. The proper conditioning factors significantly influence the final susceptibility map (Wang et al., 2020). Due to the complexity of landslide processes, there is a lack of consensus regarding factor selection in landslide predictive modeling (Wang et al., 2020). Twelve landslide conditioning factors were identified based on the availability of data in the study area. The Digital Elevation Model (DEM) was used to obtain the morphological and hydrological factors. The DEM and various factor maps with their sources are given in Table 1.

Table. 1. Data sources of various factors and their using techniques

S.N.	Factors	Data Used/ Resolution	Technique
1	Slope	ALOSPALSAR DEM (12.5*12.5 m) resolution	By using the DEM, slope was determined using GIS software
2	Aspect	ALOSPALSAR DEM (12.5*12.5 m) resolution	By using the DEM aspect was determined using GIS software
3	Curvature	ALOSPALSAR DEM (12.5*12.5 m) resolution	By using the DEM Curvature was determined using GIS software
4	Topographic Witness Index	ALOSPALSAR DEM (12.5*12.5 m) resolution	$TWI = \ln (A_s / \tan \beta)$
5	Stream Power Index	ALOSPALSAR DEM (12.5*12.5 m) resolution	$SPI = A_s \tan \beta$
6	Distance from Stream	ALOSPALSAR DEM (12.5*12.5 m) resolution	By using the DEM distance from stream was determined using GIS software
7	Distance from road	ESRI SENTINAL 2 (10*10m) resolution	Traced out the road and extracted in GIS
8	Geological map	Department of Mines and Geology, Government of Nepal	Digitized in the GIS and clipped by area boundary
9	Elevation	ALOSPALSAR DEM (12.5*12.5 m) resolution	Developed in the GIS
10	Rainfall	Shaped file of study area and the data from DHM	By using interpolation, IDW in Arc GIS
11	LULC	ESRI SENTINAL 2 (10*10m) resolution	Supervised classification

3.2.1. Slope

The slope plays a significant role in the occurrence of landslides by interacting with various factors, such as geomorphological characteristics and geological composition (Bhandari and Dhakal, 2021; Bhandari and Dhakal, 2020), even land use. The slopes are susceptible to destabilization when subjected to triggering factors, including intense rainfall, earthquake activities, and human activities such as excavation and loading. The slope angle controls the shear force of the surface materials, therefore it is widely used for landslide modeling. The 12.5 m resolution (DEM) was used to develop a slope gradient map. The slope was categorized into five distinct classes (Fig. 2a).

3.2.2. Aspect

The solar radiation varies spatially. The level of sunlight and rainfall change the moisture level in the soil, which ultimately controls the vegetation and slope stability (Bhandari and Dhakal, 2020; Bhandari et al., 2025). South-facing slopes are often drier due to increased sunlight and evaporation. The slope aspect was classified into nine categories: flat, north, northeast, east, southeast, south, southwest, west, and northwest (Fig. 2b). The landslide inventory shows that the south-facing slope has the highest concentration of landslide deposits.

3.2.3. Plan curvature

The planar curvature affects the water's convergence or divergence in the downward flow (Yilmaz et al., 2012). Plan curvature, which describes the horizontal shape of a slope, plays a significant role in landslide occurrence. Specifically, concave areas are more prone to landslides than convex or planar areas, due to water accumulation and convergence. the curvature map was classified into three categories: concave (-123.233 to -2.696), planar (-2.696 to 0.151), and convex (0.151 to 119.739), (Fig. 2c).

3.2.4. Profile curvature

The profile curvature represents the slope's rate of change. As a result, it affects the speed at which water drains the surface, causing erosion and the subsequent transport of debris downslope (Yilmaz et al., 2012). The profile curvature plays a significant role in landslide occurrence by altering water flow and accumulation on a slope, thereby increasing soil stability (Meten et al., 2015). Concave slopes, marked by negative profile curvature, accumulate water, hence heightening the risk of landslides due to elevated pore-water pressure and diminished soil strength. In contrast, convex slopes with positive profile curvature are more likely to drain water, thereby potentially diminishing the risk of landslides (Meten et al., 2015). The profile curvature was classified into three classes as (-247.469-, -3.778, -3.778-3.148 and 3.148-246.211), (Fig. 2d).

3.2.5. Stream power index (SPI)

The (SPI) measures the erosive capacity of water. The SPI is a major topographical factor which leads to landslide occurrence (Conforti et al., 2011). The level of erosion increases with increasing SPI value. Similarly, increasing SPI increases the susceptibility of landslides (Timalsina and Bhandari, 2024). The (SPI), however, depends on the drainage density of the particular region therefore it plays an important role in landslide occurrence. The (SPI) of the study area is classified into six classes as shown in (Fig. 3a) as given below.

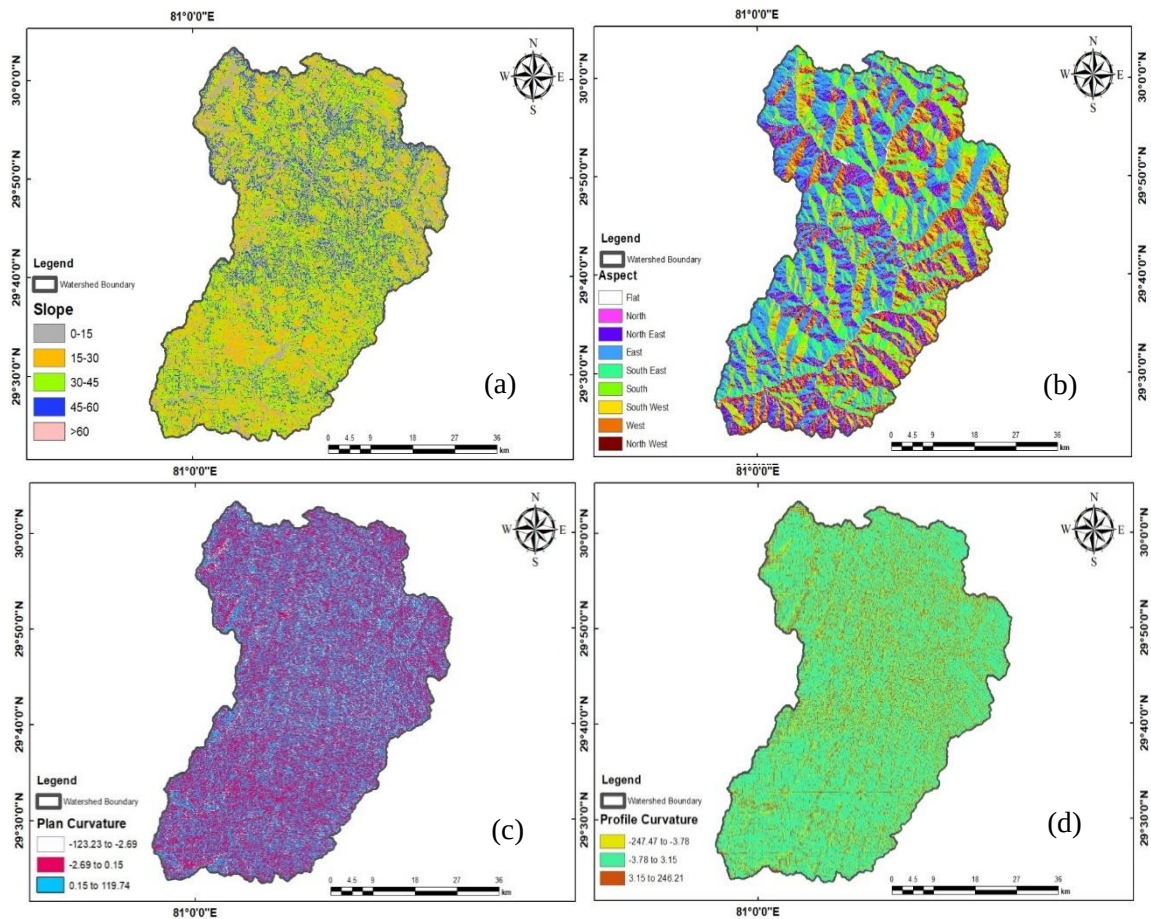


Fig. 2. Landslide triggering factors map: (a) slope; (b) Aspect; (c) Plan curvature; (d) Profile curvature of the West Seti watershed

3.2.6. Topographic wetness index (TWI)

The TWI is a function of surface slope and the upstream area per unit width perpendicular to the flow direction. Because of the accumulation of water in the valleys and concave slopes, the TWI value is significantly higher in those areas. As a result, the pore water pressure increases and shear strength decreases so that the area becomes susceptible to landslide. Continuous and intense rainfall increases soil saturation in locations with high topographic wetness indexes and exceed their slope stability threshold, resulting in landslides (Nakileza and Nedala, 2020). The TWI is classified into six classes as shown in (Fig. 3b) as given below.

3.2.7. Land use or land cover (LULC)

The LULC may change the drainage pattern and the soil characteristics of the particular area. These actions ultimately lead to unstable soil conditions (Murgia et al., 2024). Sentinel-2 imagery with 10 m resolution was used to prepare the LULC map. A supervised classification technique was used to identify the land cover features. In the present study, the LULC areas were classified into eight different classes, as shown in Fig. 3c as given below.

3.2.8. Rainfall

Heavy and continuous rainfall in the monsoon period plays a significant role to cause landslides in Nepal Himalaya. As the level of saturation increases, the shear strength decreases and pore water pressure increases, so that the failure possibility increases on the slope (Dahal and Hasegawa, 2008).

The possibility of a surface disintegration is increased when heavy rainfall hits the surface; the surface runoff causes the soil erosion on the surface having loose soil. The increasing rate of erosion causes erosion-induced landslides (Guzzetti et al., 2022). The rainfall map was developed in ArcGIS, based on the rainfall data which provided by the Department of Hydrology and Meteorology (DHM), Nepal. The entire map was divided into five classes as shown in (Fig. 3d) as given below.

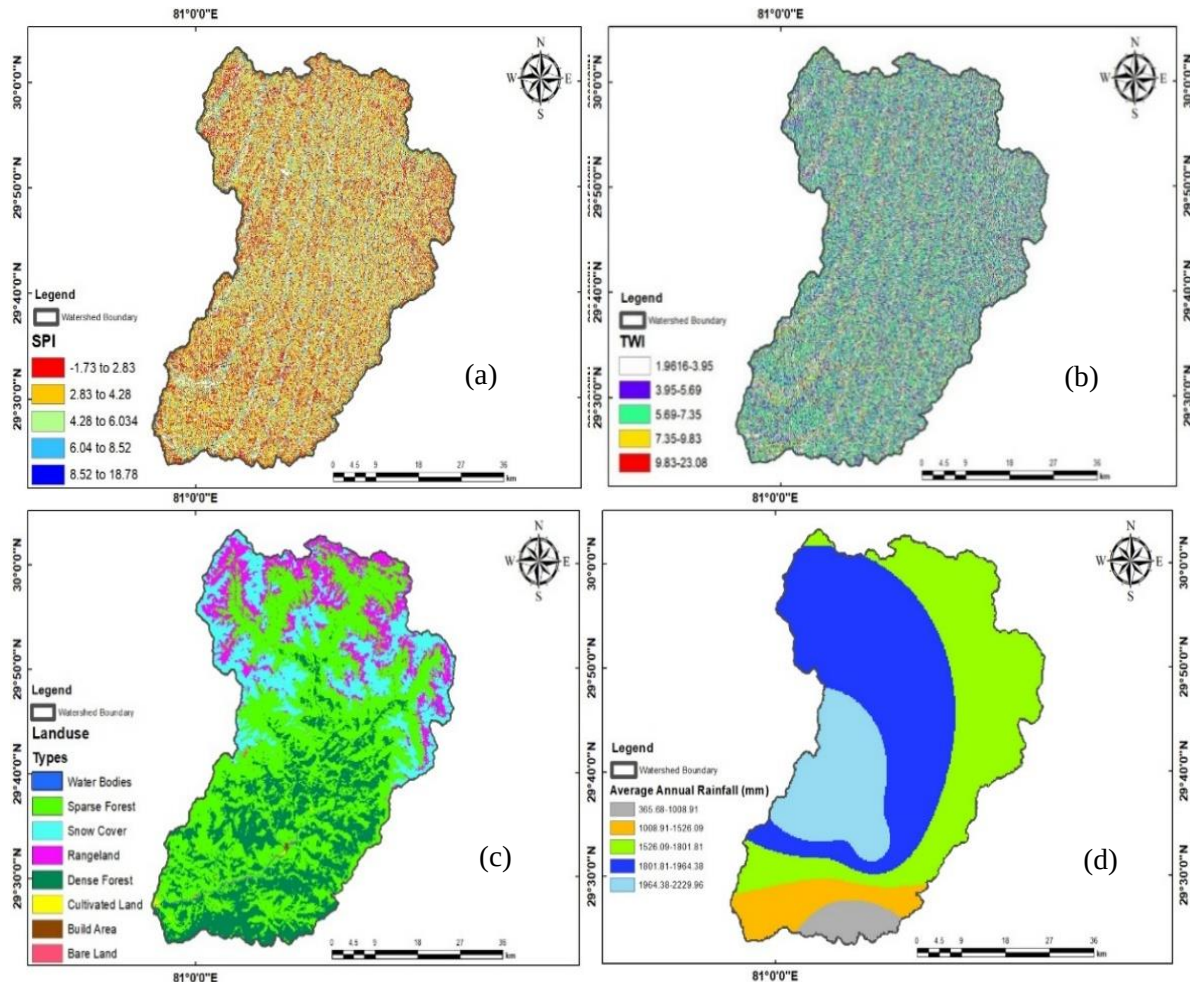


Fig. 3. The landslide causative factors map: (a) Stream power index; (b) Topographical wetness index; (c) Land use; (d) Rainfall map of the West Seti watershed

3.2.9. Distance to river

In mountainous regions, rivers induce surface and bank erosion, resulting in elevating the likelihood of landslides (Park et al., 2013). Slope stability can be controlled by hydrologic factors, one of which is the distance to the river. The soil moisture increases near the river. The distance to the river map was produced and was categorized into five groups: 0-50 m, 50-100 m, 100-150 m, 150-200 m and >200 m (Fig.4a) as given below.

3.2.10. Distance to road

A major anthropogenic variable to cause landslides is the distance to a road. Road development and other human activities disturb the slope stability due to unmanaged cut slopes. The road construction and the configuration of the road network can profoundly affect the occurrence of landslides (Yao et al., 2023). The destabilization of slopes is primarily influenced by practices such as undercutting, modification of natural drainage patterns, and the additional weight imposed by spoil disposal

associated with road construction (McAdoo et al., 2018). The distance to the road was classified into five classes as shown in (Fig. 4b) as given below.

3.2.11. Elevation

Elevation does not directly control landslide occurrence but influences it in combination with other factors (Saud et al., 2025). Elevation affects slope angles, erosion rates, and climatic conditions in the region. Higher elevations are often associated with steeper slopes, which then can impact landslide phenomena (Umar et al., 2014). Furthermore, the elevation may influence rainfall patterns, vegetation types, and soil moisture, which ultimately affect the slope stability. The elevation was classified into five classes as shown in (Fig. 4c) given below.

3.2.12. Geological map

The geology of the specific area significantly influences landslide occurrence (Bhandari and Dhakal, 2021). The geological information was obtained from the regional map that developed by the Department of Mines and Geology (DHM), Government of Nepal (Fig.4d). The regional map was obtained from the (DHM) and processed using ArcGIS.

The designated area was delineated using the clipping tool, and the remaining map within the study area's boundaries was clipped. The geological formation of the study area is categorized into ten distinct groups: Snow Area, Kushma Formation, Suntar Formation, Ulleri Formation, Ranimatta Formation, Himal Group, Galyang Formation, Lakharpata Formation and Basic Rocks (Fig.4d).

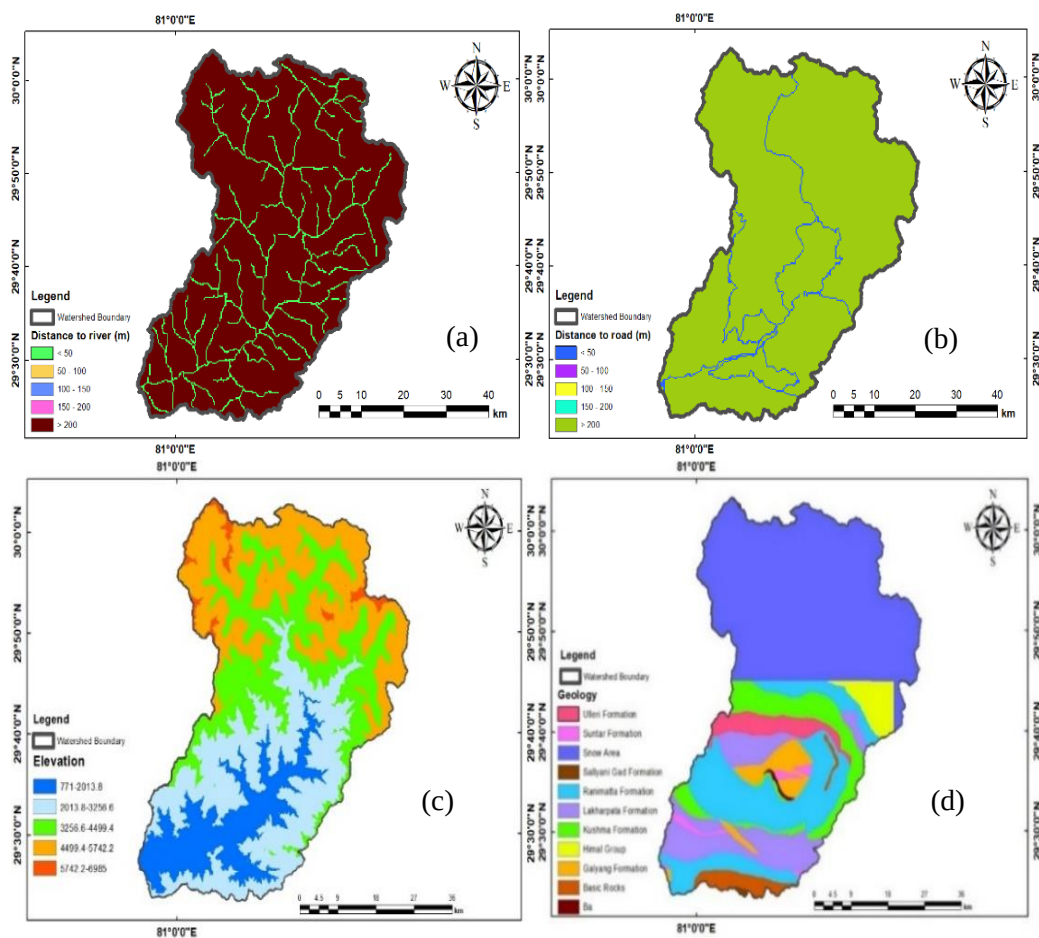


Fig. 4. The landslide causative factors: (a) Distance to river; (b) Distance to road; (c) Elevation; (d) Geology

3.3. Multicollinearity Analysis

Multicollinearity arises when specific conditioning factors exhibit a strong correlation with other variables, potentially leading to disturbances that can affect the accuracy and quality of the model (Hong et al., 2020). The multicollinearity analysis was conducted to select the factors without having multiple correlation. For multicollinearity analysis, Pearson's correlation, tolerance value, and variance inflation factor (VIF) were used (Lee et al., 2020). Pearson's correlation coefficient measures the linear relationship between pairs of landslide conditioning factors (Wang et al., 2020). This metric is articulated as the covariance between variables, normalized by their respective standard deviations. The Pearson's correlation equation was adopted for multicollinearity analysis as presented below.

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2 \sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (1)$$

Where (X and Y) are the landslide conditioning factors, ($\bar{X}$ and $\bar{Y}$) are the means of (X and Y) and (n) is the number of samples. The coefficient ranges from (-1 to +1), indicating negative to positive linear correlation. Specifically, according to Dou et al. (2019), Hong et al. (2020), and Wang et al. (2020), a high correlation between the (X and Y) components is indicated by (r) value as more than 0.7, and one of the variables should be eliminated from the model.

Two common indicators of multicollinearity are used in landslide studies, the (VIF) and tolerance. (VIF) is the reciprocal of tolerance, which shows that lower tolerance indicates higher multicollinearity (Lee et al., 2020; Wang et al., 2020). (VIF) is used to evaluate the inflation of variance among the components that influence landslides.

$$VIF = \frac{1}{tolerance} = \frac{1}{(1 - R_j^2)} \quad (2)$$

Where, R_j^2 is the coefficient of determination for the regression of the independent variable (j) on all of the other variables. In particular, if the value of (R_j^2) is relatively close to (1), the variance inflation factor (VIF) becomes very large, and tolerance is close to (zero), this indicates a significant correlation between the components. Previous studies suggest that the relevant factors are considered to have significant multicollinearity and should be eliminated from the landslide evaluation if the (VIF) value is greater than (10) or the tolerance value is less than (0.1) (Wang et al., 2020).

3.3.1. Landslide susceptibility models

The very popular and widely used Frequency Ratio and Statistical Index models were used to obtain the landslide susceptibility map.

3.3.2. Frequency ratio model

The frequency ratio is the ratio between landslide occurrence probability and non-occurrence (Thapa and Bhandari, 2019). The frequency ratio (FR) for each class of factors was calculated through a three-step process. First, the ratio of the landslide pixels which occurred to the total landslide pixel within each factor class was determined. Next, the proportion of each class of the factor to the total area of that factor was also calculated. According to (Lee and Pradhan, 2007), the Frequency Ratio (FR) for a specific class of factors is given as:

$$FR = (A/B)/(C/D), \quad (3)$$

Where, 'A' is the landslide pixels for each factor, 'B' is a total landslide pixels within the total area, 'C' is the number of pixels of the class and 'D' is a total pixels in the study area. The equation provided by Lee and Pradhan, (2007) was used to develop the final susceptibility map as shown in (Eq 4).

$$LSI = \sum Fr, \quad (4)$$

A higher landslide susceptibility index (LSI) value indicates higher susceptibility to landslides and vice versa. Different techniques such as equal intervals, natural breaks, and standard deviations are commonly used for landslide susceptibility index classification. The landslide susceptibility indices are classified into five classes namely; very high, high, moderate, low and very low.

3.3.3 Statistical index method (SIM)

The statistical index (SI) model has been widely applied to assess landslide susceptibility (Cheng et al., 2022). This is a bivariate statistical method used for assessing landslide susceptibility (van Westen, 1997). The (SI) method gives a weighted value to a parameter class by computing the natural logarithm of the landslide density. The calculation of (SIM) is based on the equation presented by (Pradhan et al., 2012).

$$W_{ij} = \ln\left(\frac{f_{ab}}{f}\right) = \ln\left(\frac{\frac{Lab}{Aab}}{\frac{L^*}{A^*}}\right), \quad (5)$$

Where, (W_{ij}) is the weight category (b of factor a), (f_{ab}) is the landslide density within class (b of factor a). The variable f represents the overall landslide density across the entire study area. (Lab) is the number of landslide units in the class (b of factor a), while (Aab) is the number of units in class (b of factor a). (L^*) is the total number of landslide units within the study area, and (A^*) is the total units in the study area.

3.3.4. Validation of landslide susceptibility map

Validation is an important part of the landslide susceptibility because it provides the confident and validity of the model (Cao et al., 2019). The area under the curve (AUC) and receiver operating characteristics (ROC) methods are very popular and mostly used for validating the accuracy of the model (Hong et al., 2019). The (ROC) curve plots the false-positive rate and the true-positive rate for each potential binary classification of a dataset (Hong et al., 2019). In the perfect prediction accuracy, the maximum (ROC) curve reaches the point (0, 1) with an (AUC) of (1). An $AUC > 0.5$ indicates acceptable predictive performance (Huang and Zhao, 2018; Zhu et al., 2018).

4. Results

4.1. Multicollinearity Diagnostics

The correlation coefficients among the eleven conditioning factors are shown in (Table. 2). A strong correlation was observed between elevation and slope (0.81) and elevation and stream power index. The correlation coefficients exceeded (0.7) means the multicollinearity is present. Consequently, conditioning factor (elevation) has been excluded from this study to reduce multicollinearity. The subsequent phase in the selection of landslide conditioning factors within the context of multicollinearity analysis involves Variance Inflation Factor (VIF) and tolerance, as presented in (Table. 3). The maximum value of the (VIF) is (4.34) which is below the threshold value of (10).

The (VIF) values show that there is no multicollinearity between eleven factors that were selected from the Pearson's correlation. Only eleven factors were selected for the landslide conditioning factors.

Table 2. Pearson's coefficient between the landslide triggering factors

	1	2	3	4	5	6	7	8	9	10	11	12
1	1											
2	0.03	1										
3	0.06	0.01	1									
4	0.023	0.00	-0.61	1								
5	-0.23	0.12	0.18	0.32	1							
6	0.027	0.14	0.04	0.08	-0.33	1						
7	0.11	0.02	0.06	0.02	0.43	-0.56	1					
8	-0.19	-0.24	0.12	0.09	-0.14	0.02	0.00	1				
9	0.02	-0.18	-0.01	-0.34	0.24	-0.51	0.32	0.001	1			
10	0.12	0.04	-0.34	0.17	0.47	-0.39	0.44	0.51	-0.28	1		
11	0.81	0.03	0.00	0.00	0.78	0.23	-0.24	0.00	0.00	-0.69	1	
12	-0.03	0.00	0.021	-0.32	0.013	-0.12	0.12	0.016	0.18	0.512	0.5	1

1.Slope 2. Aspect 3. Plane curvature 4. Profile curvature 5. Stream power index 6. Topographical wetness index 7. Distance to river 8. Distance to road 9. Geological units 10. Rainfall 11. Elevation 12. Land use

Table 3. Multicollinearity test result for landslide conditioning factors

SN	Landslide-conditioning factors	VIF	Tolerance
1	Slope	1.92	0.52
2	Aspect	1.31	0.76
3	Plane curvature	1.22	0.82
4	Profile curvature	1.20	0.83
5	Stream power index	1.31	0.76
6	Topographical wetness index	1.38	0.72
7	Distance to river	1.72	0.58
8	Distance to road	4.34	0.23
9	Geological units	2.04	0.49
10	Rainfall	1.51	0.66
11	Land use	1.72	0.58

4.2. Landslide Inventory Map

A total of (2029) landslides were recognized within the study area as shown in (Fig. 5). The training and testing data consisted of (1353 and 676) landslides respectively. The distribution of landslides is clustered towards the south whereas scattered towards the north.

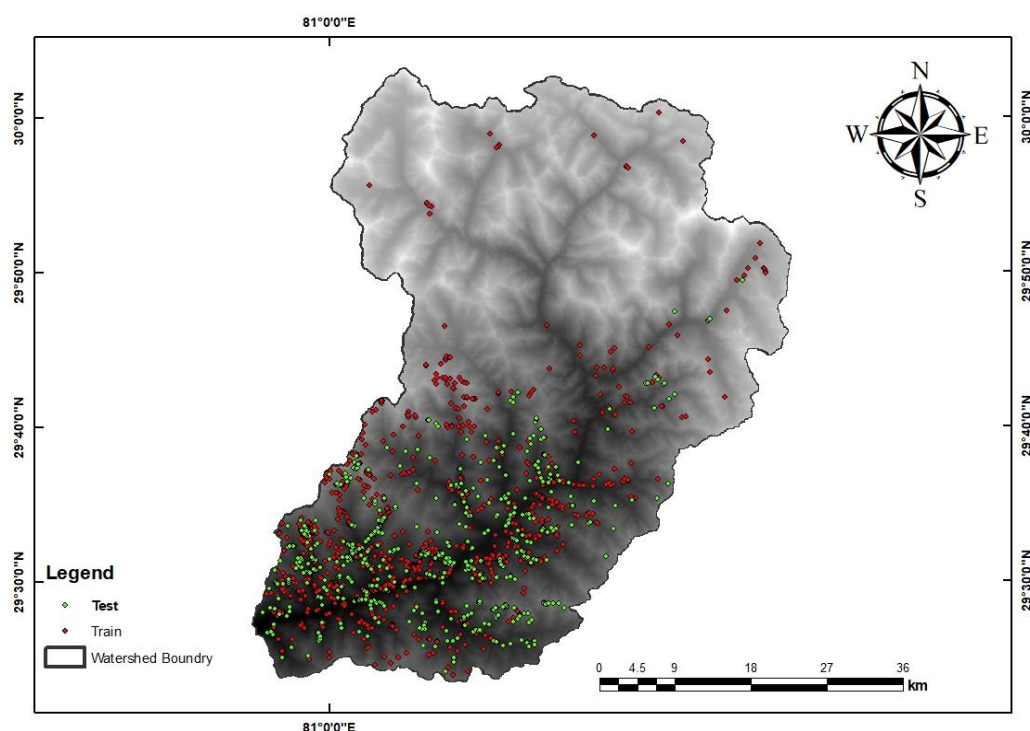


Fig. 5. Landslide inventory map of West Seti River Watershed

4.3. Relation between Landslide and Causative Factors from FR Model

After running the model, the Frequency Ratio (FR) and Statistical Index (SI) values were acquired. A value close to (1) indicates a strong association between the landslide and the class, while values near (zero) indicate a weak correlation. The (FR) for the slope class is categorized into five divisions according to the steepness degree. Slopes between (0-15) degrees have a lower (FR), but slopes between (45-60) degrees demonstrate a higher (FR) value of (1.346). The results indicate that the (FR) value increased with increasing slope angle. The (FR) value is maximum (1.041) in the distance class (0.50)m. The (FR) value decreased as the distance from the river increased. The (FR) value is minimum at a distance above (200) meters. The (FR) values for the distance to road are divided into five classes. The distance class ranges from (0-50) meters have a (FR) value (1.306). Distances above (250) m has a (FR) value less than (1). The (FR) value less than (1) indicates weak correlation between landslide and the class. The (TWI) between 1.96 to 3.94 has a (FR) value (1.31) whereas the (TWI) class from 9.829 to 23.081 has (FR) value (0.81). The result shows that the (FR) value decreased with increasing (TWI). The stream power index ranges from (-1.733 to 2.834), has a (FR) value (0.707), while (SPI) class between 8.523 to 18.779, has a (FR) value (1.081). Correspondingly, the (FR) value for the lowest (SPI) class is (-1.733 to 2.834 is -0.150). The (SPI) between (8.523 and 18.779) has an (SI) of (0.034). The findings indicate that both the (FR) and (SI) values increase as the stream power index increases.

The northern direction exhibits the lowest (FR) value, while the southern, southwestern, and southeastern directions display the greatest (FR) values. Correspondingly, the (SI) value is positive in the southern orientation and negative in the northern orientation. The results indicate that the southern aspect is more prone to landslides.

In terms of land use and land cover, water bodies, built-up areas, and bare ground are more prone to landslides. Uncultivated soil has the greatest values of (FR) and (SI). Likewise, a water body with a (FR) value above (4) and (SI) value approaching (1) has a stronger link with landslides. The (FR) and (SI) value increased with increasing rainfall class. The (FR) and (SI) values are maximal in the greatest rainfall category and minimal in the lowest rainfall category. The minimal rainfall class, ranging from

365.681 to 1008.911 mm per annum, has a (FR) of (0.444) and a statistical index (SI) of (-0.352). The greatest rainfall category (ranging from 1964.382 to 2229.958 mm per annum) exhibits a (FR) of (3.631) and a (SI) of (0.560).

The (FR) values for profile curvature are (1.198) for concave, (0.948) for flat, and (1.089) for convex curvature. Similarly, the (SI) values for concave, flat, and convex in profile curvature are (0.079, -0.023, and 0.037), respectively. The (FR) values for plan curvature are (1.270) for concave, (1.029) for flat, and (0.929) for convex. The (SI) values for concave, flat, and convex in plan curvature are (0.104, 0.013, and -0.034), respectively. The Kushma and Ulleri formations have the highest (FR) and (SI) values, whereas the Himal group exhibits the lowest (FR) and (SI) values.

4.4. Landslide Susceptibility Map Using the FR Method

The landslide susceptibility map (Fig. 6) for the Seti River watershed was developed using the FR model. The map categorizes the area into five susceptibility levels: Very low, low, moderate, high, and very high. It also includes training and test landslide points. The map illustrates that the Seti River watershed has varying degrees of landslide susceptibility, with very high susceptibility zones primarily located in the central parts of the watershed.

The area covered by each susceptibility class was displayed in (Table. 4), stated as a percentage of the entire area and pixel count of each susceptibility class's covered area. The Medium class covers the greatest area, making up (33%) of the total area. It is followed by the High class (27%), Low class (21%), Very High (10%), and Very Low class (9%).

Table 4. Area covered by each class based on FR

Class	Pixel	Km ²	%
Very Low	1558991	29.31	9
Low	3843727	72.27	21
Medium	5976249	112.37	33
High	4771907	89.72	27
Very High	17848997	33.56	10

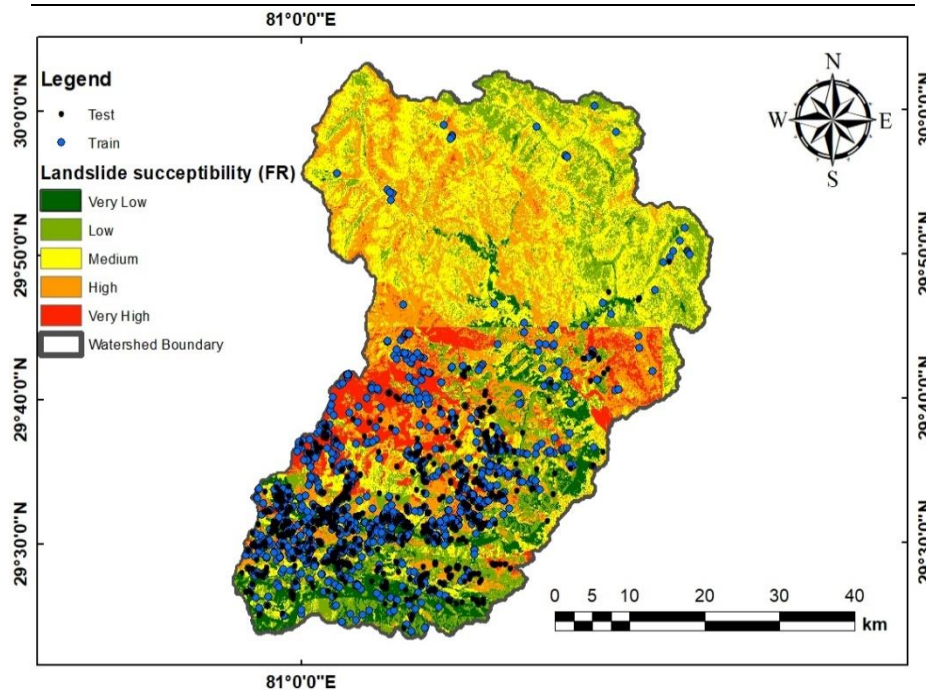


Fig. 6. Landslide susceptibility map of Seti River watershed acquired from FR model

4.5. Application of SI Model

The landslide susceptibility map for the Seti River watershed was obtained using the (SI) model (Fig. 7). It features five distinct susceptibility categories: very low, low, moderate, high, and very high. The map effectively illustrates the landslide susceptibility distribution throughout the watershed. Additionally, black dots on the map denote Test points, while blue dots represent Training points.

Based on the (SI) model, the area covered by each class was shown in (Fig. 7) and (Table. 5). There are (2382415) pixels in the very low susceptibility class, which make up (45) km² or (13%) of the entire region. There are (4287102) pixels in the low susceptibility class, covering (81) km² (24%) of the total area. The region covered by the (3601862) pixels in the moderate susceptibility class is (68) km², or (20%) of the total area. The (4570590) pixels that make up the high susceptibility class (86) km², or (25%) of the total area. Finally, the very high susceptibility class has (3093802) pixels, or (17%) of the overall area, covered (58) km².

Table 5. Area covered by each class based on SI model

Class	Pixel	Km ²	%
Very Low	2382415	44.79	13
Low	4287102	80.61	24
Medium	3601862	67.72	20
High	4570590	85.94	25
Very High	3093802	58.17	17

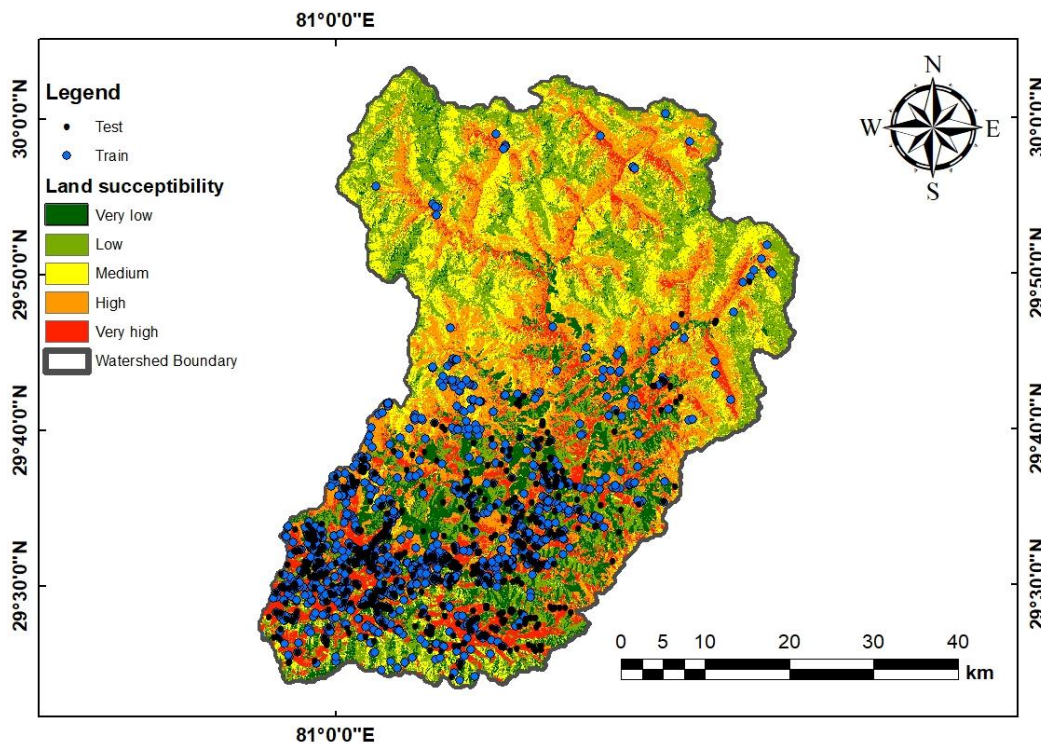


Fig. 7. Landslide susceptibility map of Seti River watershed acquired from SI model

4.6. Model Validation and Comparison

The success and prediction rates indicate the accuracy of identifying existing landslides and forecasting the future landslide potential area in the given map. The (ROC) curves show the success rate of landslide susceptibility maps developed by the (FR) and (SI) models. The area under the curve value

of (SI) and (FR) models is (0.747 and 0.627), respectively. Comparatively, the success rate of the (FR) model is less than the (SI) model.

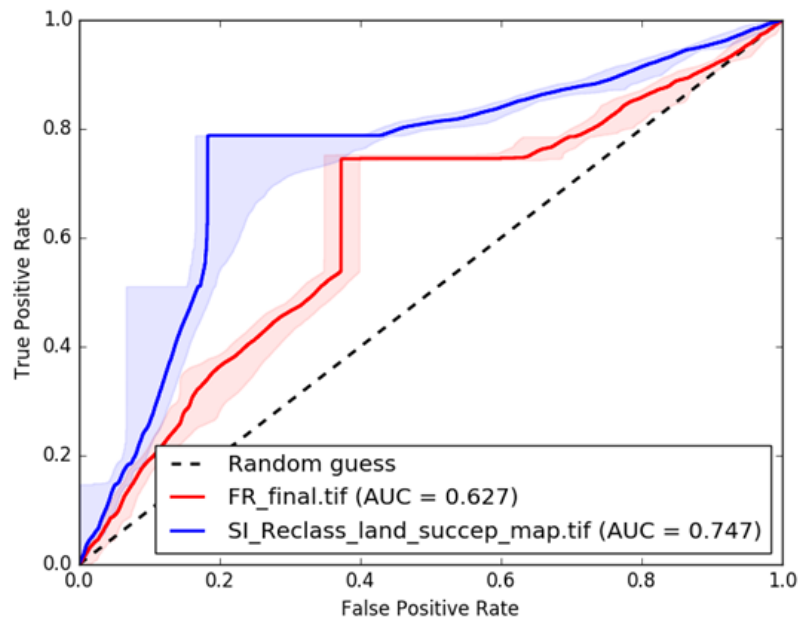


Fig. 8. Success rate of the both FR and SI models

The prediction rate of both models are shown in (Fig. 9). The prediction rates of (SI) and (FR) models are (0.712 and 0.554), respectively. The prediction rate of the (SI) model is significantly higher than that of the (FR) model. The results show that both success and prediction rate of (SI) model is greater than the (FR) model.

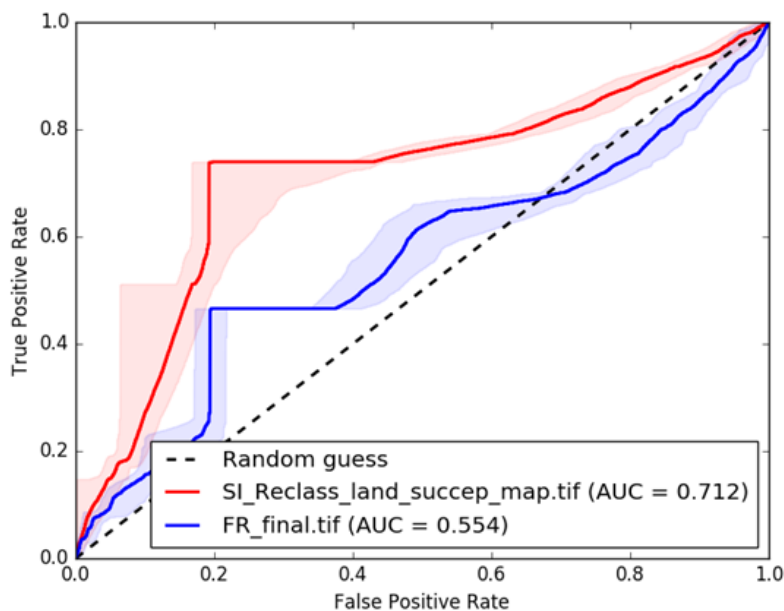


Fig. 9. Prediction rate of the both SI and FR models

5. Discussion

Creating a detailed database of past landslides is essential for predicting the future landslide potential zone. The detailed landslide inventory map provides insightful information for obtaining the landslide susceptibility (Yadav et al., 2023). Various techniques and steps are required to prepare

landslide inventory map. The inventory process begins with identification of landslide. The field survey, aerial photo, satellite imagery and historical records are needed for landslide identification and recording process.

A total of (2030) landslides polygons of new and old landslides were drawn. The study effectively developed and validated a landslide susceptibility model. This method ensures the reliability of landslide prediction (Duman et al., 2005). The inventory map indicates an increasing frequency of landslide occurrences in the study area. This trend highlights the need for effective mitigation strategies based on the research's detailed spatial and size-class distribution data. In short, making detailed maps and classifying landslides improves understanding of landslide dynamics and helps us make targeted efforts to lessen their bad effects on infrastructure, communities and the environment in the watershed.

The proportional significance and influence of elements on the features of the area can be understood from the (FR) value for each class as well as their total (FR) value. Maps depicting an area's propensity to experience landslides are useful for predicting spatial occurrence. This is defined by the interplay between the preexisting landslide, the local environment, and the factors that contributed to it. The expected distribution and locations of landslides are also depicted on these maps. However, the maps cannot predict the timing or volume of landslide events. Nevertheless, local land use planning may get benefit from predictive models in order to decrease and limit landslide dangers (Silalahi et al., 2019; Dhakal and Tamang, 2025). Based on the (SI) model, the area which covered by each class was shown and given in (Table. 5). There are (2382415) pixels in the very low susceptibility class, which make up (45) km² or (13%) of the entire region. There are (4287102) pixels in the low susceptibility class, or (81) km², or (24%) of the total area. The region covered by the (3601862) pixels in the moderate susceptibility class is (68) km², or (20%) of the total area. The (4570590) pixels that make up the high susceptibility class total (86) km², or (25%) of the total area. Finally, the very high susceptibility class has (3093802) pixels, or (17%) of the overall area, spread throughout (58) km².

The ground is covered in very loose paleo landslides and debris layers. The surface having the slope greater than (30) degrees are highly susceptible to landslide. High or extremely high susceptibility is found on surfaces with steep slopes, near streams, water bodies, bare land, and concave surfaces. The results show that the first two classes of slopes, (0–15°) and (15–30°), have (FR) and (SI) values below (one), suggesting that the likelihood of a landslide is low because of the weak stream power index and reduced gravitational pull force. As the slope decreases, the erosive power of the water decreases as well. There is a larger association between the occurrence of landslides and slope (g) greater than (30°. This result agrees with the previous research (Silalahi et al., 2019), found that materials move downslope with high speed when the gradient of the slope increases. Anthropogenic activities, such as the expansion of road networks, changes to surface morphology, and other geometries, have considerably disrupted the buildup area. The accumulation area became more vulnerable to landslides as a result of these human actions. Physical deterioration and water erosion can also affect the bare land. Landslides caused by erosion can happen in hilly and Himalayan regions, especially on steep slopes when bare soil is present.

Landslide occurrence is more likely in the rainfall classes with (1964-2229 mm) compared to the other classes with lower probabilities. Landslides are more likely to occur in areas with positive (FR) and (SI) values greater than (one) (Dhakal and Tamang, 2025). Landslides are less likely to occur in areas that are farther from rivers, according to the correlation between the two variables. A modest association is observed at distances greater than (250) meters from a river, whereas (FR) values greater than (one) and (SI) values at (50) meters or less indicate a strong correlation with landslide occurrence. There is a weak correlation between landslide susceptibility and the comparatively lower (FR) and (SI) values found in the other Formations of the same lithology class, whereas the highest (FR) and (SI) values in the Kushma and Ulleri formations suggest a strong correlation between these two. A landslide in the Himalayas can have its roots in the region's geology (Bhandari and Dhakal, 2021). The aspect that

faces south, southeast, or southwest had the greatest (FR) and (SI) values, suggesting a high probability of landslides, but the aspect that faces any other direction had lower values, suggesting a weak link. Previous research in the Nepal Himalaya has shown comparable results (Saud et al., 2025). Planar surfaces and concave slopes have greater (SI) and (FR) values in the case of plan curvature, whereas convex and concave slopes have higher (SI) and (FR) values in the case of profile curvature. This indicates that the two types of curvature play distinct roles in the occurrence of landslides. Landslide-affected pixels are inversely related to (TWI) values. The (FR) and (SI) values are higher in the lowest (TWI) class.

The validation results indicate that both models perform at excellent to very good levels. Furthermore, there is a larger disparity in the proportion of landslides in the extremely high susceptibility groups for (FR) (32% vs. 17%). This is due to the fact that issues were identified in (FR) when evaluating the weight of each factor class. The reliability of the model as a whole is affected by this. Research conducted in the Rangun Khola watershed in far western Nepal by (Pathak and Devkota, 2022) identified zones of moderate, low, very low, and very high vulnerability, respectively, covering (19.74%, 18.29%, 18.68%, and 15.31%) of the region, according to the (FR) method. In Sunsari District, Province No. 1, 17.3% and 3.68% of Barahakshetra Municipality were deemed high landslide risk zones (Thapa and Bhandari, 2019). However, the Frequency Ratio was compared with Weight of Evidence models for landslide susceptibility in Purchaudi Municipality of Farwestern Nepal. Since the (FR) model achieved a success and prediction rate of more than (75%), one can be reasoned that there must be little difference between these two models.

To determine how well the landslide susceptibility maps categorise areas with active landslides, the success rate method can be useful. (Pourghasemi et al., 2012). The success rate of landslide forecasting using the model and predictor variable is shown by the prediction rate. This approach is being used frequently to assess a predictive rule's performance (Mohammady et al., 2012; Ozdemir and Altural, 2013). The frequency ratio model shows a success rate of (62.7%) and a prediction rate of (55.4%), as shown by the area under the curve. The (SI) model shows a comparable success rate of 74.7% and a prediction rate of 71.2%. The two models differ significantly in their success rate and prediction rate curves. The models demonstrated high accuracy in forecasting the landslides. Different methodologies exhibit differing levels of success regarding predictive ability and simplicity of use. Logistic Regression (LR) has shown prediction rates over 82% in the study of Kathmandu, Mugling, and Gorkha Districts of Nepal Himalaya (Dahal, 2014). (Gautam et al., 2021) enhanced the prediction accuracy to 86.9% in the highly mountainous Sindhupalchowk district using an Artificial Neural Network (ANN) approach. The Weight of Evidence (WoE) and Frequency Ratio (FR) models produced comparable outcomes and predictive accuracy. The results from the (FR) and (WoE) models were analogous to those reported by (Regmi et al., 2014). Applying the analytical hierarchy process (AHP), Kayastha et al. (2012) attained a success rate of 77.54% in the Tinau watershed and the Kaligandaki hydrocatchment. Numerous researchers in the Nepal Himalaya, including (Regmi et al., 2014; Kayastha et al., 2012; Thapa and Bhandari, 2019; Ayer and Bhandari, 2025), used (AUC-ROC) curves to validate models and assess landslide susceptibility outcomes.

Several studies used the success rate curve and predictive rate curve to back up the (FR) model's findings. (Regmi et al., 2014) compared landslide susceptibility mapping in the Central Nepal Himalaya using frequency ratio, weights of evidence, and statistical index models. The (FR) model outperformed the others, with a success rate of (76.8%) and a predicted accuracy of (75.4%). In a section of the Himalayas in Uttarakhand, India, the (FR) model scored (75%) for success and (70%) for forecasting landslide risk (Pham et al., 2018). For landslide susceptibility mapping in the Bhalubang-Shivapur area of Mid-Western Nepal, Regmi et al. (2014) used the (FR) model and achieved an accuracy of (83.31%) for success and (78.58%) for prediction. Both investigations found similar findings, with area under the curve showing percentage success rates of 72.55% and prediction rates of 71.73% (Thapa & Bhandari,

2019) obtained more than (70%) success and prediction rate by using (FR) model in the Barhabise Municipality of Sindhupalchok district. The research model shows impressive accuracy in predicting the area's susceptibility to landslides. In this study, the result found that the (SI) model is a good fit for mapping the risk of landslides in the area under consideration and the current results are very similar to those of the previous research.

6. Conclusions

This study compared the prediction accuracy of two bivariate models. The success and prediction rate as well as the susceptibility class percentage are compared manually. A comprehensive inventory of (2030) landslides using Google Earth imagery was developed. It also considered (11) critical Landslide Causative Factors (LCFs) in the analysis. 30% of the data was reserved for validation and 70% for training. The resulting landslide susceptibility map, generated using GIS software, categorized the areas into five susceptibility levels: very low, low, moderate, high, and very high. Under the accounts for 9% of the region, low susceptibility for (21%), moderate susceptibility for 23%, high susceptibility for 27%, and very high susceptibility for 10% of the area. Similarly, the class distribution from the (SI) model is very low susceptibility (13%), low susceptibility (24%), moderate susceptibility (20%), high susceptibility (25%), and very high susceptibility (17%). The prediction and success rates of the statistical index model are (71.2%) and (74.7%), respectively. Similarly, the success and prediction rate of the (FR) model are (55.4% and 62.7%), respectively. This indicates that the (SI) model performed better in terms of prediction accuracy and success rate than the (FR) model. This study provided the effectiveness of two bivariate statistical models for landslide susceptibility in the catchment scale. This study is useful for preparing landslide management, mitigation, and landuse planning for the local government of the West Seti watershed of Nepal. This study also supports disaster risk reduction planning.

Author's Contribution

Hemanta Joci and Hira Karki collected the data and prepared the factor maps. Tekendra Saud and Hemanta Joci analyzed the data and obtained the final result. Hemanta Joci and Hira Karki prepared the draft of the manuscript. Bharat Prasad Bhandari guided the study and prepared the final manuscript.

Declaration of Competing Interest

The authors declare that they have no competing financial interests or personal relationships that could influence the work reported in this study.

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Data Availability

Data will be made available on request

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