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Research Article

LANDSLIDE SUSCEPTIBILITY MAPPING USING REMOTE SENSING AND BIVARIATE FREQUENCY RATIO METHOD IN BAHRABISE MUNICIPALITY OF SINDHUPALCHOK DISTRICT, NEPAL

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ABSTRACT

Sindhupalchok district, located in the northeastern region of Bagmati Province, Nepal, is highly susceptible to landslides. Every year during the monsoon season, many people lose their lives and properties due to landslides. Bahrabise municipality, in particular, has experienced repeated landslide events in recent years, yet remains under-researched in terms of localized susceptibility mapping. The area's steep terrain, fragile geology, and proximity to settlements make it a critical zone for detailed landslide risk assessment. The present study focuses on mapping areas susceptible to landslides in Bahrabise Municipality, which lies in the Sindhupalchok district of Nepal. An integrated methodology was adopted in this study, incorporating Geographic Information System (GIS), Remote Sensing (RS), and the Frequency Ratio (FR) model. To prepare the landslide susceptibility map for the area, various spatial and environmental datasets were utilized, including precipitation, slope gradient, elevation, proximity to drainage networks, topographic wetness index, geological features, distance from roads, land use and land cover (LULC), terrain curvature, and slope orientation. These factors and thematic layers were derived from both remotely sensed data and ground – based information such as GPS field surveys, visual inspections, and household interviews, and analyzed using ArcGIS software. The Frequency Ratio (FR) model was applied to assign weights to each thematic layer, representing their influence on landslide occurrence. These weighted factors were then combined within the ArcGIS environment to generate the final landslide susceptibility map for the study area. The resulting landslide susceptibility map classified the study area into four zones, with 47.9% falling under high and very high susceptibility. The model achieved a prediction accuracy of 81.3%, indicating strong reliability in identifying landslide-prone areas. The study examines the feasibility of employing more comprehensive methodologies to identify the landslide susceptibility in the region.

Keywords: Bahrabise, extrinsic factors, frequency ratio, landslide susceptibility, Sindhupalchok

INTRODUCTION

Nepal is a mountainous country where landslides often occur, especially during monsoon seasons. A range of factors contribute to landslide occurrences, such as geological and geomorphological dynamics, alterations in vegetation, patterns of land use, and variations in hydrological conditions(Ercanoglu *et al*., 2008; Dahal *et al*., 2008; Bhandari and Dhakal, 2018; Bhandari and Dhakal, 2021). According to Pradhan (2007), landslides, debris flows, and floods are common in Nepal due to the country's geographical diversity, geological features, and heavy rainfall during the monsoon season. From 2019-2021, altogether 2,251 landslide events occurred near the settlement area in Nepal which killed 567 people and 106 are missing (MoHA, 2022). Landslides have been the source of catastrophic geomorphic disasters in Nepal, claiming many lives and causing massive property damage. Landslides cause floods at the downstream, adding to the river's enormous sediment burden.

Mapping landslide susceptibility serves as an essential initial step in identifying potential triggering factors and reducing the associated risks and damages (Regmi *et al*., 2014). According to Funes *et al.* (2021), assessing landslide risk by integrating susceptibility and vulnerability maps has lately become a method of analyzing and controlling landslide-prone areas. In many developing countries prone to landslides, there is a need for risk assessment tools that support disaster management, starting with prevention, using open geographical data and appropriate models (Funes *et al*., 2021). Communities living in landslide-prone mountainous regions are frequently exposed to risk due to inadequate development planning and lack of scientific assessment. Therefore, proper scientific research is essential to understand slope dynamics, which is a crucial first step in addressing such hazards effectively (Adhikari *et al*., 2015). Geographic Information Systems (GIS) functionalities have provided a reliable platform to ease the slope stability problem through various geotechnical analysis tools. Extracting relevant spatial information related to landslide occurrence is integral to hazard assessment. Statistical methods combined with GIS are practical tools for generating and processing spatial data. The advancement in Earth Observation (EO) techniques facilitates effective landslide detection, mapping, monitoring, and hazard analysis (Tofani *et al*., 2013). Most methods currently used in assessing and mapping landslide susceptibility are based on accurately evaluating the spatial distribution of the "causal factors" and the landslides that occurred. Such a process involves handling, interpreting, and graphically representing extensive territorial data (Magliulo *et al*., 2009).

In recent years, geospatial technologies have become very important in landslide investigation. Geographic Information Systems (GIS) have significantly streamlined disaster assessment owing to their remarkable geographic data processing capabilities. The GIS facilitates data capture, input, manipulation, transformation, visualization, integration, querying, analysis, modeling, and output (Carrara *et al*., 1999). It is possible to use susceptibility assessments to predict the spatial trends of future landslides. This stems from the uniformitarianism principle, which holds that the same factors that caused landslides in the past are likely to cause them in the future (Guzzetti *et al*., 2005).

Landslide susceptibility assessment methods are generally divided into quantitative and qualitative approaches (Yalcin *et al*., 2011). Quantitative methods mainly evaluate the probability of landslides by analyzing the relationship between causative factors and the landslide inventory (Erener *et al*., 2016). Quantitative techniques are widely used for landslide susceptibility analysis which encompass various models, including the logistic regression model (Chauhan *et al*., 2010), weight of evidence model (Pokhrel and Bhandari, 2019), frequency ratio (Wu *et al*., 2016; (Thapa & Bhandari, 2019a); Bhandari *et al*., 2024), index of entropy model (Devkota *et al*., 2013), fuzzy logic (Rostami *et al*., 2016), and the support vector machine (Tien Bui *et al*., 2016). Qualitative techniques are inherently subjective and typically rely on the landslide inventory to identify areas with comparable topographical, geological, and geomorphological features that are prone to sliding (Yalcin, 2008). Certain qualitative techniques, like the analytic hierarchy process (AHP), incorporate the concepts of ranking and weighting, which may categorize them as semi-quantitative in nature (Yalcin, 2008; Hung and Lo, 2015). AHP relies on heuristic methods that primarily take into account the insights of experts in a given field (Kayastha *et al*., 2013; Mansouri and Reza, 2014).

In addition to rainfall-induced landslides, Nepal is also highly prone to earthquake-triggered slope failures due to its active tectonic setting. Numerous researchers have explored landslides triggered by earthquakes in Nepal through the use of spatial analysis and statistical modeling techniques. For example, Pyakurel *et al.* (2024) implemented machine learning algorithms to assess co-seismic landslide susceptibility in several districts, including Bahrabise. In another study, Gautam *et al.* (2021) employed logistic regression within a GIS framework to analyze landslides caused by seismic activity in the Upper Indrawati Watershed.

Landslide susceptibility maps play a crucial role in both disaster management and the strategic planning of developmental initiatives in countries with mountainous terrain, such as Nepal (Devkota *et al*., 2013; Bhandari *et al*., 2024). The Himalayas are geologically very young and tectonically the most unstable mountain landscape in the world (Searle *et al*., 1987). In Bahrabise Municipality, landslides are a serious concern due to its steep hills, varied soil types, and fluctuating elevations, which increase the likelihood of slope failure, particularly during intense rainfall. Thus, it is essential to identify areas most at risk and understand the socio-environmental impacts of landslides in this specific locality. Although Sindhupalchok District has been the subject of numerous studies on landslide susceptibility, research specifically focused on Bahrabise Municipality remains limited. Most existing studies address broader regional patterns and tend to overlook the unique topographic and settlement characteristics of Bahrabise. This study aims to fill that gap by analyzing landslide risk at the municipal level and exploring the interaction between human activity and natural hazards. According to the Sindhupalchok District Police Office, landslides on September 13, 2020, in Bahrabise-7—particularly in Bhirkharka, Nagpuje, and BK Tole—resulted in 15 deaths and 16 individuals reported missing. By identifying landslide-prone zones and vulnerable areas, the findings of this research can support local stakeholders involved in disaster risk reduction and land use planning.

MATERIALS AND METHODS

Study Area

Bahrabise Municipality is located in Sindhupalchowk District in the Bagmati Province of Nepal, in the country's central part **(Fig. 1).** It shares its eastern border with Dolakha District and its western border with Balephi and Jugal Rural Municipalities. It has a total area of 134.8 sq. km. Additionally, its northern and southern borders are connected to Bhotekoshi Rural Municipality and Tripura Sundari Rural Municipality, respectively. It is located between latitudes 27°47'30.2"N and longitudes 85°54'20.2"E. It is situated at 500 meters to 4000 meters elevation above sea level; this city is characterized by numerous "thali," "thumka," hills, and peaks. The annual rainfall is about 3,200 mm and temperatures vary from 7.5 ºC to 32 ºC.

Methods of data collection

In order to achieve the main goal of producing a landslide susceptibility map, the process began with the collection of spatial data and extraction of relevant factors. These factors were analyzed for their correlation with landslide occurrences and subsequently validated. Both primary and secondary data were utilized to develop a spatial inventory and generate the susceptibility map, using aerial image interpretation via Google Earth, remote sensing, and GIS-based methods. Additionally, multiple thematic data layers were generated to represent the landslide conditioning factors required to generate the final susceptibility map.

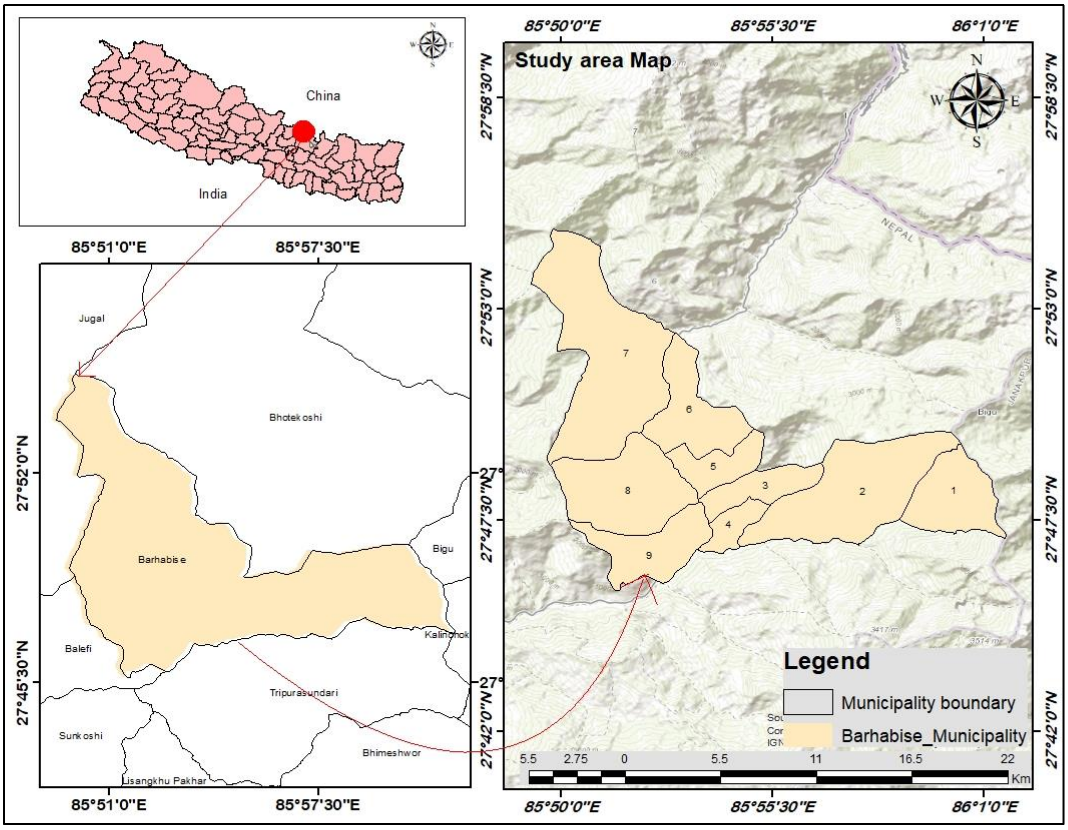


Figure 1. Location map of the study area

Primary Data Collection

The primary data was collected through field observations using tools such as GPS devices and a prepared checklist. The initial field visit focused on surface mapping of the study area, which contributed to the development of the landslide inventory map. A subsequent field survey was conducted to assess land use/land cover (LULC) conditions, previous disaster history, and visible slope instability. GPS coordinates and photographs were collected to support visual interpretation and spatial analysis. Household interviews were carried out in four landslide-affected wards: Bahrabise-4, Bahrabise-5, Bahrabise-7, and Bahrabise-9. Households were selected based on their proximity to recent landslide sites and visible damages or risk exposure, using purposive sampling. These interviews aimed to understand community perceptions regarding the environmental consequences of landslides. Over 70% of mapped landslides were verified in the field through visual inspection. Some of the major observed landslides are shown in Figures 2 a, b, c, & d.

Secondary Data Collection

The landslide susceptibility assessment of Bahrabise Municipality was conducted using multiple tools and data sources, each selected based on data availability and suitability for specific thematic layers. Google Earth and Sentinel imageries were used to visually identify and digitize historical and recent landslide scars. OpenStreetMap (OSM) provided basic road network data, while USGS was the source for satellite imagery and digital elevation models (DEMs). Meteorological data (such as rainfall records) were obtained from the Department of Hydrology and Meteorology, and geological data were sourced from the Department of Mines and Geology (DMG), Nepal. ArcGIS software was used to process, analyze, and integrate all these spatial datasets. Field verification was conducted to validate the landslide inventory, cross-checking mapped features against ground conditions observed during site visits.

Remote sensing data

The Digital Elevation Model (DEM) used to compute the slope and aspect of the terrain was obtained from the Advanced Land Observing Satellite (ALOS), with a spatial resolution of 12.5 meters. The landslide inventory and land cover map were generated using imagery obtained from Landsat and Sentinel. The landslide inventory for the study area was created through visual image classification using Google Earth and Sentinel imagery. The mapped landslides were subsequently validated through field verification, which led to necessary adjustments in the delineated landslide boundaries.

Figure 2. a) Landslide observed at Lisankhu, Pakhar-5 b) Nagpuje landslide observed from the base c) Jure landslide d) Cropland distracted by landslide at Gathi area.

Preparation of landslide conditioning factor maps

Several terms are used in the literature to describe the factors contributing to landslide events, including "causative factors," "preparatory conditions," "intrinsic elements," "conditioning variables," and other similar classifications(Zhu *et al*., 2014). Understanding and analyzing these factors is essential for identifying landslide-prone areas. Recognizing landslide-prone areas and producing susceptibility maps play a vital role in disaster risk reduction and preparedness planning, offering significant assistance to planners, local authorities, and policymakers (Kavzoglu *et al*., 2014). This study considered eleven landslide-contributing factors, chosen through literature review and supported by field-based observations. The selected elements were chosen for their observable effects and their capacity to induce landslides, rendering them appropriate for the creation of susceptibility maps.

Slope

The slope plays a crucial role in the occurrence of landslides and other forms of mass movement. The distribution and intensity of landslides are closely related to terrain steepness (Bhandari *et al*., 2024), with mass wasting events more frequent on steeper slopes. In this study, slope data was derived from the Advanced Land Observing Satellite (ALOS) Digital Elevation Model (DEM), which has a spatial resolution of 12.5 meters. The slope map was generated in ArcGIS using the Raster Surface tool, and slope angles ranged from 0° to 78°, categorized into five susceptibility classes: <18°, 18–27°, 27–36°, 36–47°, and >47° (Fig. 3a). These slope angle ranges were selected based on commonly used classifications in landslide susceptibility studies, where steeper slopes are generally more prone to instability, and the categorization helps in identifying terrain vulnerability with increasing gradient. The choice of 12.5 m resolution was made to achieve higher spatial detail compared to coarser datasets such as ASTER (30 m), improving the accuracy of terrain-related analysis in steep mountainous regions.

Aspect

Aspect significantly influences landslide occurrence by affecting soil moisture conditions. The direction a slope faces can impact various environmental processes, including sunlight exposure, rainfall distribution, evapotranspiration, and wind flow (Hamza and Raghuvanshi, 2017). In this study, an Aspect map was generated using Geographic Information System (GIS) tools from a 12.5-meter resolution Digital Elevation Model (DEM) obtained from the Advanced Land Observing Satellite (ALOS). The higher spatial resolution of this dataset was selected to capture finer terrain variations that influence slope orientation in the mountainous study area. Aspect values ranged from -1 to 359.8 degrees and were categorized into eight directional classes: north, northeast, east, southeast, south, southwest, west, and northwest (Fig. 2b).

Elevation

While elevation does not directly influence landslide occurrence, it indirectly affects other contributing factors such as rainfall and tectonic activity. Elevation plays a role in landslide susceptibility, as higher elevations tend to have a greater likelihood of landslides. In this research, elevation values were obtained from a Digital Elevation Model (DEM) and categorized into five separate classes, as shown in Figure 3c.

Topographical Wetness Index

Many researchers have used topographic indicators to explain how soil moisture is distributed in different landscapes (Burt and Butcher, 1986; Moore *et al.*, 1991). The Topographic Wetness Index (TWI), introduced by Beven and Kirkby (1979) as part of the TOPMODEL runoff framework, is widely used to assess how topography influences hydrological processes by integrating the local upslope contributing area with the slope gradient. The mathematical expression is given by:

$$\mathrm{TWI} = \ln\left(\frac{a}{tan\beta}\right)$$

In this context, "a" represents the upslope contributing area per unit contour length flowing through a given point, while "tan β" refers to the slope angle at that location. TWI was included as an additional influencing factor in this study, as illustrated in Fig. 3d.

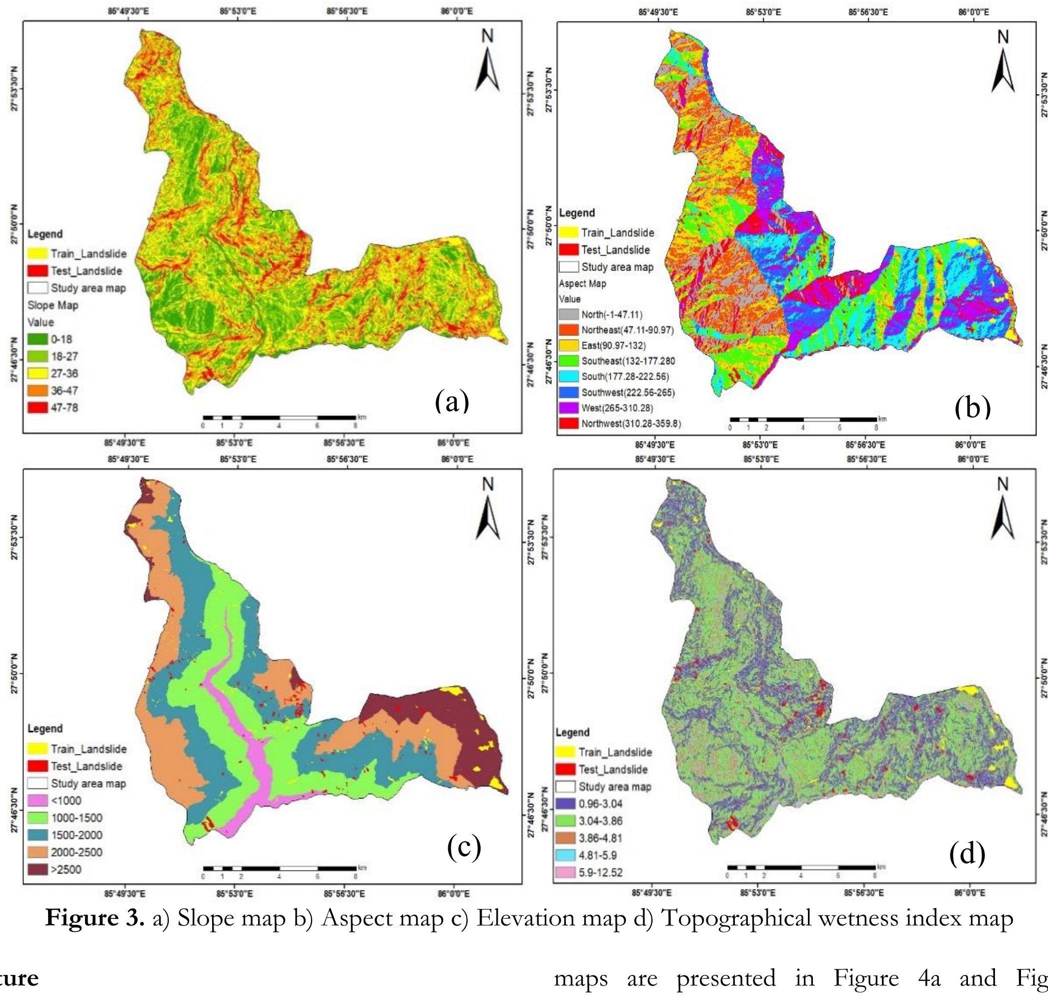


Figure 3. a) Slope map b) Aspect map c) Elevation map d) Topographical wetness index map

Curvature

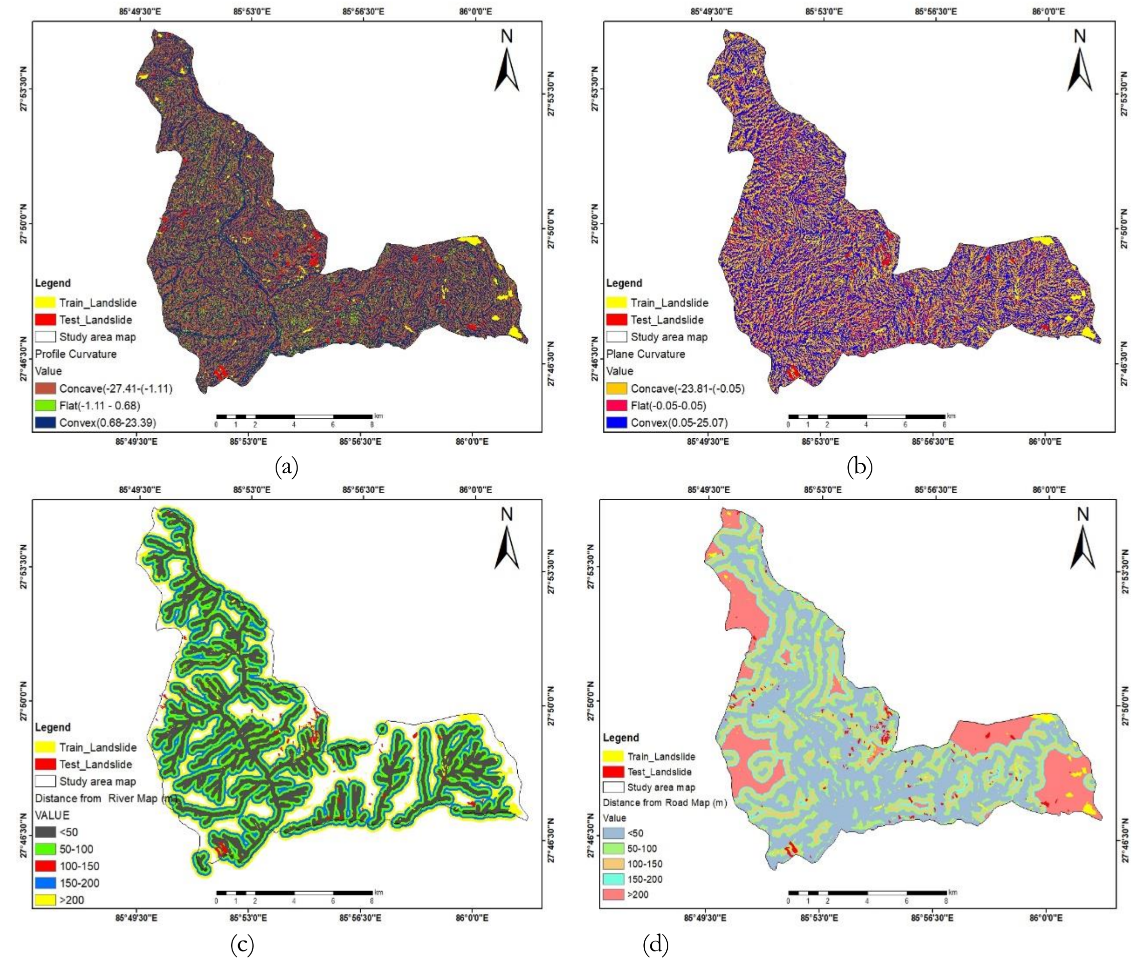
Curvature is an important factor in landslide occurrence. In geoscience, curvature describes the curved shapes found in landscapes. It is typically classified into three categories: concave, planar, and convex. In this study, a curvature map was generated using a 12.5 × 12.5 meter resolution DEM within ArcGIS. These values represent the landform shape and surface characteristics (Lee and Min, 2001). The resulting profile and plane curvature maps are presented in Figure 4a and Figure 4b, respectively.

Distance from stream

In regions with soft rock formations, such as mountainous areas, river activity can trigger landslides by undercutting slope bases and increasing moisture levels. To incorporate this factor into the analysis, river buffer zones were established using mapped river locations derived from topographic maps, followed by the application of the Euclidean distance tool. In the study area, the proximity to rivers varied between 0 and 200 meters. These distances were categorized into five groups: 0-50, 50-100, 100-150,150-200,>200 meters, as shown in Fig. 4c.

Distance from road

Field-based studies have indicated that inadequately planned road construction, often ignoring geological and geotechnical factors, can lead to shallow landslides. In this study, road proximity was analyzed using the Euclidean distance tool, based on a newly digitized road network created from topographic maps and Google Earth Pro imagery (2021). Road distances within the study area ranged from 0 to 200 meters and were categorized into the following intervals: 0–50, 50–100, 100–150, 150–200, and >200 meters, as shown in Fig. 4d.



(a) (b) (c) (d)

Figure 4. a) Plane curvature Map b) Profile curvature Map c) Distance to stream Map d) Distance from road

Land Cover

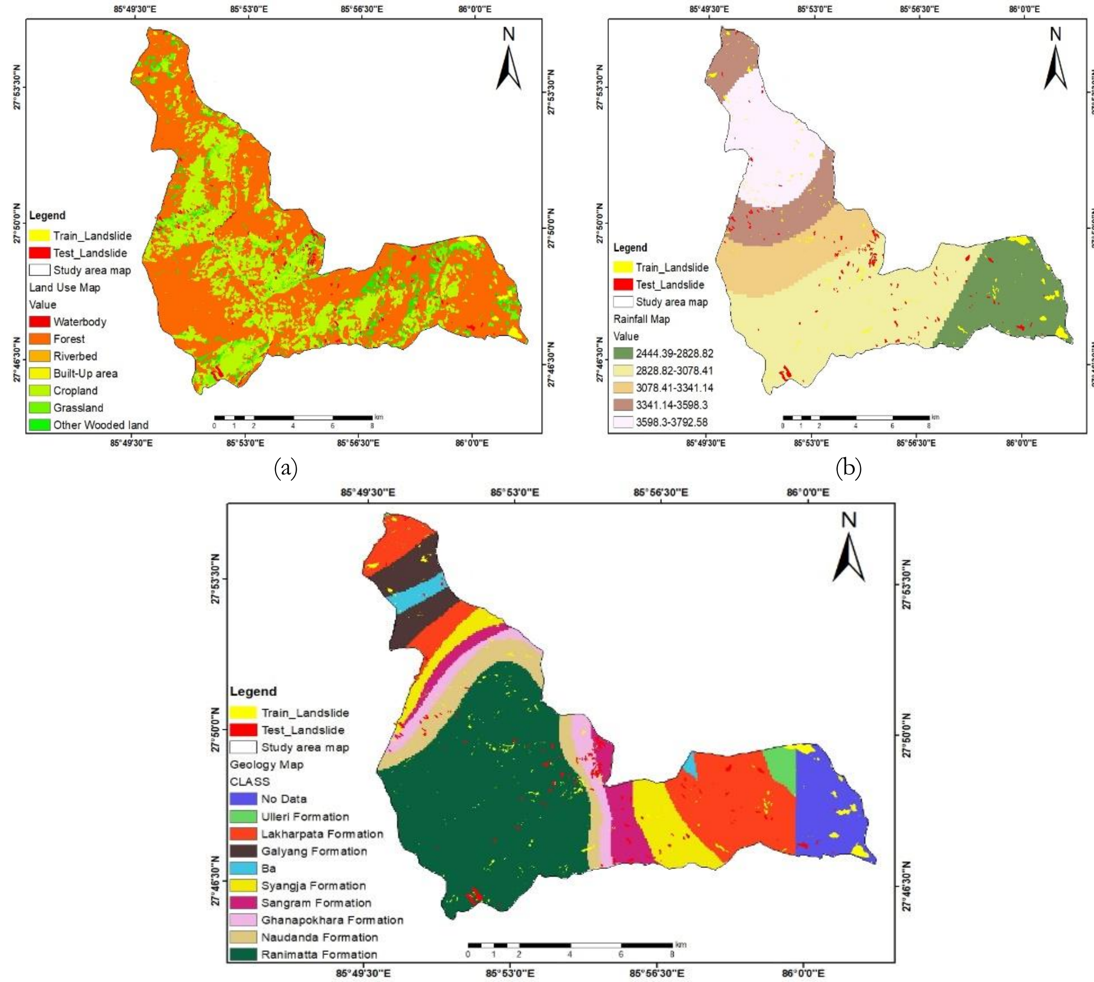
Land cover describes the physical and biological characteristics present on the Earth's surface. Alterations in land cover can influence landslide susceptibility, either increasing or decreasing the level of risk in a given area. Geological structures, rock formations, and land cover can undergo rapid changes as a result of natural phenomena or human interventions (Reichenbach *et al.*, 2018).To understand how land cover affects landslides, it's important to study the link between different land cover types and landslide events. This connection is key because land cover can change rapidly over short periods. Examining the relationship between land cover and landslides allows researchers to assess the effects of land cover changes and gain deeper insights into their contribution to landslide susceptibility (Pisano *et al.*, 2017). The land use and land cover distribution for the study area is shown in Fig5a.

Rainfall

More rainfall increases soil moisture on slopes, reducing their stability. Rainfall data measures the amount of water falling on the Earth's surface over a specific period, recorded in millimetres (mm) (Fell *et al.*, 2008). In this study 20 years of rainfall data (2001-2021) from seven monitoring stations (Chautara, Gumthang, Bahrabise, Thokarpa, Dhap, Nagdaha, Charikot, and Tarke Ghyang) were used to categorize rainfall amounts in the area. The rainfall map is shown in Fig5 b.

Geology

Geology is a crucial factor in landslide susceptibility analysis, as it helps determine how various rock types react to ongoing geomorphological processes (Pradhan *et al.*, 2002). In this study, the geological map was obtained from the Department of Mines and Geology (DMG), Government of Nepal, and later digitized using ArcGIS. The geological units identified by DMG were utilized to explore the relationship between landslide occurrences and underlying geology. The geological map of the study area comprises six formations: Lakharpata, Galyang, Ranimatta, Sallyani Gad, Ba, and Syangja. (Fig. 5c).



(a) (b)

(c)

Figure 5. a) Landuse Map b) Rainfall Map c) Geological Map

Landslide Inventory Mapping

The landslide inventory map for the study area was developed by digitizing landslide features visible in satellite imagery sourced from Google Earth. Landslides were categorized into training and testing datasets, where each landslide was delineated as a polygon and imported into ArcGIS for further analysis. These polygons were converted into raster format and projected using the WGS 1984 UTM Zone 44N coordinate system for spatial consistency. Mapping was conducted at a scale of 1:25,000, which offers a practical balance between spatial detail and interpretability for municipal-level hazard analysis in mountainous terrain. Field surveys were used to support and validate mapped landslides. The training dataset included 77% of historical landslides, while the testing dataset represented 23% of recent active landslides. Each causative factor map was reclassified, and the pixel area for each class was manually recorded. These were then cross-tabulated with the landslide inventory to calculate the landslide pixel area. The resulting values were used to apply the Frequency Ratio (FR) model for susceptibility analysis.

Landslide Susceptibility Mapping

In landslide susceptibility mapping, it is important to recognize that the occurrence and spatial distribution of landslides are determined by various causative factors. It is also assumed that future landslides will occur under similar conditions as past landslides (Lee & Ja, 2005). This study employed the Frequency Ratio (FR) method for mapping landslide susceptibility. Evaluating the likelihood of landslides requires a comprehensive understanding of the specific physical conditions and triggering processes within the Area of interest. In this study, the Frequency Ratio (FR) technique, supported by GIS techniques and spatial data, was employed to assess landslide susceptibility quantitatively (Lee *et al.*, 2010; Chen *et al.*, 2016). The FR technique is widely recognized and effectively utilized for landslide susceptibility mapping (Chen *et al.*, 2016). This approach depends on quantifying the relationship between the landslide inventory and its triggering factors (Reis *et al.*, 2012). The frequency ratio (FR) for each category of causative factors is calculated by integrating the landslide inventory map with the respective factor map, as shown in Equation (1) (Mondal & Maiti, 2013).

$$\text{FR} = \frac{Npix\,(1)\,/\,Npix\,(2)}{\Sigma Npix\,(3)\,/\,\Sigma\,Npix\,(4)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Where,
Npix (1) = the number of pixels containing a Landslide in a class
Npix (2) = total number of pixels of each class in the whole Area
Σ Npix(3) = total number of pixels containing Landslide
Σ Npix(4) = total number of pixels in the study area
Thus, the obtained frequency ratio is summed to develop a landslide susceptibility Index (LSI) map using (Equation 2) by (Lee & Talib, 2005).

$$\text{LSI}=Fr1 + Fr2 + Fr3 + Fr4 + \cdots \ldots\ldots\ldots\ldots\ldots\ldots + Frn \ldots\ldots\ldots\ldots\ldots\ldots.(2)$$

Where Fr is the frequency ratio, n is the number of selected causative factors.

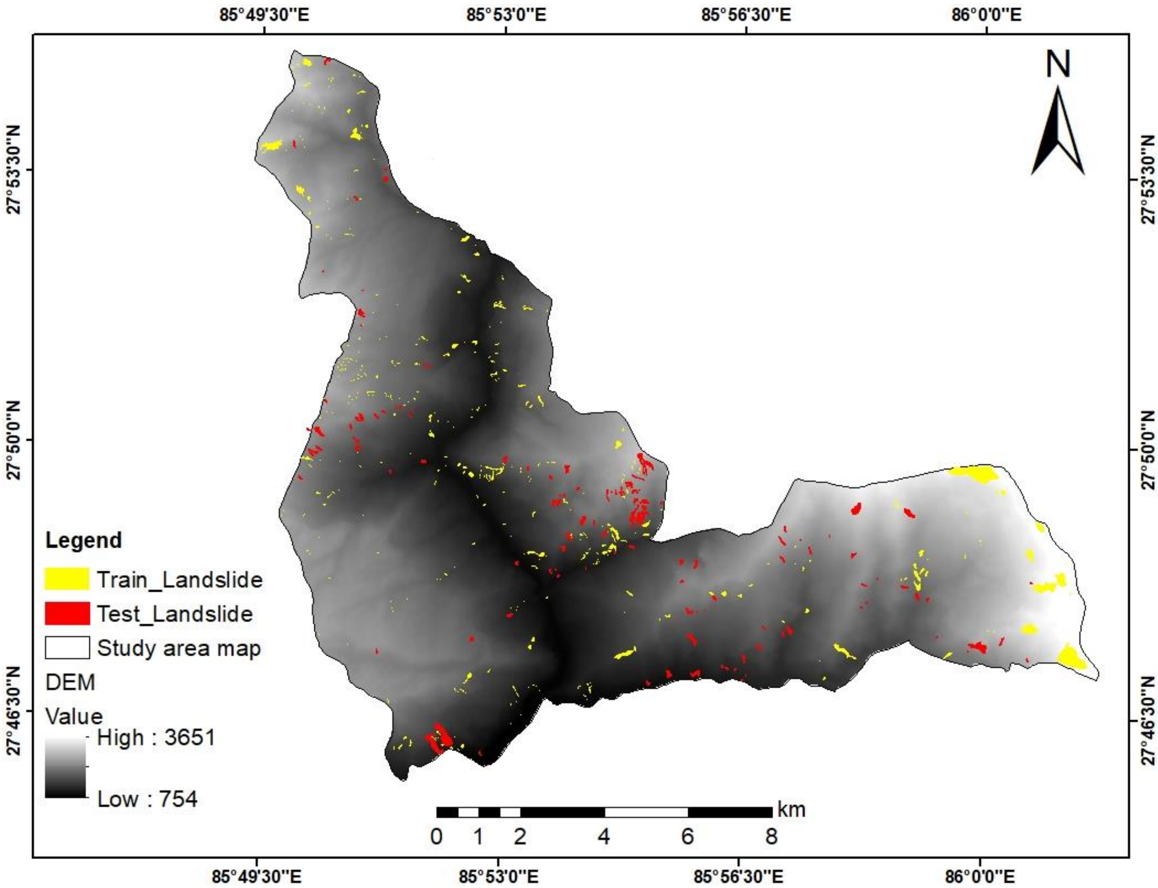


Figure 6. Landslide Inventory Map of the study area.

Depending upon the technique, the ratio is calculated by comparing the Area of landslide occurrence to the total Area, with a value of 1 indicating an average correlation. Values greater than 1 signify a higher percentage of landslides compared to the Area, indicating a stronger correlation, while values below 1 suggest a lower degree of correlation (Akgun *et al.*, 2007). The Landslide Susceptibility Index (LSI) map is subsequently reclassified to produce the final landslide susceptibility map.

Model validation

After developing the models, a validation process was conducted to assess and analyze the efficacy and predictive capabilities. The purpose of validation is to verify the models' accuracy and ability to forecast future landslides. The accuracy was evaluated by comparing the existing dataset on landslides with the results of landslide susceptibility, considering rate curves and the areas under these curves (Chung & Fabri, 1999). The success rate curve was produced by plotting the cumulative percentage of training landslide occurrences against the cumulative percentage area of the susceptibility map. The prediction rate curve was generated by plotting the cumulative percentage of test landslide locations against the cumulative percentage area of the susceptibility map. To create the success rate curve for each LSI map, pixel values were first sorted in descending order and then divided into 100 equal intervals, each representing a 1% cumulative range. These categorized maps were overlaid with the landslide inventory map, and the success rate curve was derived based on the resulting cross-tabulated values. A similar procedure was followed to obtain the prediction rate curve. The effectiveness of the frequency ratio model was evaluated using the Area Under the Curve (AUC) approach (Kayastha *et al.*, 2013). The Area under the curve was calculated through SDM Arctool.

RESULTS AND DISCUSSION

Landslide Inventory Map

The landslide inventory map was created using high-resolution imagery from Google Earth. A total of 776 landslides were identified in the study area between 2000 and 2021. Of these, 595 (77%) older landslides were used as training data, while the remaining 181 (23%) recent active landslides were used as testing data for validation. The landslides are unevenly distributed throughout the study area. A comparison of the training and testing datasets revealed significant spatial overlap, indicating that many active landslides have occurred in areas previously affected by landslides (Figure 6). A higher concentration of landslides was observed near stream channels and on the upper slopes of hills.

Landslide susceptibility

Landslide susceptibility in the study area was assessed using the Frequency Ratio (FR) model. Each conditioning factor map was reclassified and overlaid with the training landslide data to compute the FR values. In the Frequency ratio model, the final landslide susceptibility map was obtained by calculating all factors. At first, the inserted FR ratio value was used to reclassify the factor map by adding a new attribute column. This process was followed for each factor map respectively. Then from the raster calculator, all the factor maps were calculated, and the final susceptibility map was obtained as shown in Figure 7.

The frequency ratio increased as the slope gradient grew steeper. For slope gradients between 0^0 and 78^0, the frequency ratio was highest in the class 0^0 - 18^0 followed by 47^0-$78^{0,}$ and lowest in the 18^0 - 27^0. The FR value > 1 was found in the South-East, South-west, and South aspects. The correlation between elevation and landslide occurrence indicated a higher likelihood of landslides at elevations above 2500 meters, however when elevation decreases below 2500m, FR values and landslide occurrence decrease. In terms of profile curvature, convex slopes have the highest FR (1.08), followed by concave slopes (0.96), while flat slopes have the lowest FR value (0.81). Similarly, in terms of plane curvature, concave slopes have the highest FR (1.03), followed by convex slopes (0.99), while flat slopes have the lowest FR (0.93**)**. The relation between topographic wetness index (TWI) and landslide shows a positive correlation for the distance of 0.96-3.04m and 4.81-5.9m (FR>1). About the distance from the river, the distance >400 shows the highest correlation with the landslides. All other land use classes exhibited a negative correlation with landslide occurrence. Distance from Roads shows that landslide frequency increases as the distance from roads increases. The Frequency Ratio (FR) values for several factors reveal their correlation with landslide occurrence. Distances greater than 150 m from drainage lines showed FR values above 1, indicating a stronger relationship with landslide distribution, while areas closer than 150 m had lower FR values (<1), suggesting a weaker association. In terms of precipitation, the FR value was greater than 1 for rainfall ranges between 3598.3 mm and 3792.58 mm, showing a positive correlation with landslide events. However, no specific geological formation demonstrated a significant positive correlation (FR > 1) with landslide susceptibility in the study area.

Based on the combined influence of all causative factors, a landslide susceptibility map was developed and categorized into four zones: low (16.76%), moderate (35.34%), high (36.61%), and very high (11.29%) susceptibility (Fig. 8). Higher LSI values indicate greater landslide susceptibility.

Validation Using AUC

The model's performance was validated using the Area Under the Curve (AUC) derived from the Receiver Operating Characteristic (ROC) analysis. The AUC was generated by using both training and testing landslide datasets with the susceptibility map in ArcSDM software. The success rate curve yielded an AUC of 81.3%, while the prediction rate was 79.9% (Fig. 9). Since both values fall between 0.7 and 0.8, the FR model is considered to have good predictive capability for landslide susceptibility in the study area.

In the study carried out by Pathak and Devkota (2022) in the Rangun Khola watershed of far western Nepal, the susceptible zones cover areas of 19.74%, 18.29%, 18.68%, and 15.31%, corresponding to moderate, low, very low, and very high susceptibility classes using FR method. Similarly, Thapa and Bhandari (2019) reported that 17.3% and 3.68% of Barahakshetra Municipality in Sunsari District, Province No. 1, were classified as high and very high landslide susceptibility zones, respectively. Similarly, (Bhandari *et al.*, 2024) compared the four bivariate models for landslide susceptibility in the Siwalik hills of Nepal and found no significant difference between the models where the frequency ratio provided more than 70% success and prediction rate. (Ayer & Bhandari, 2024) conducted a comparative study of the Weight of Evidence and Frequency Ratio models for landslide susceptibility in Purchaudi, Farwestern Nepal and suggested that there is no significant difference between both the models where FR model showed greater than 75% success and prediction rate.

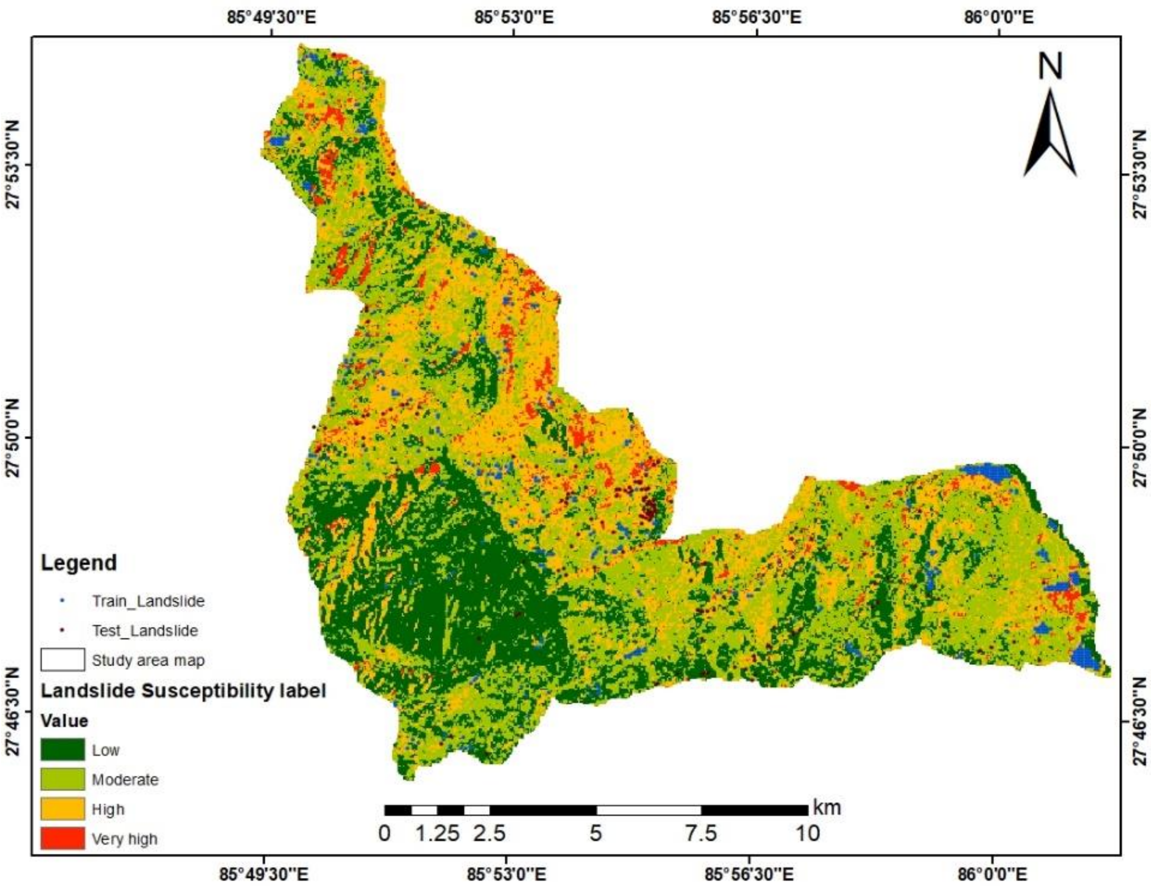


Figure 7. Landslide Susceptibility Map by using Frequency Ratio Model.

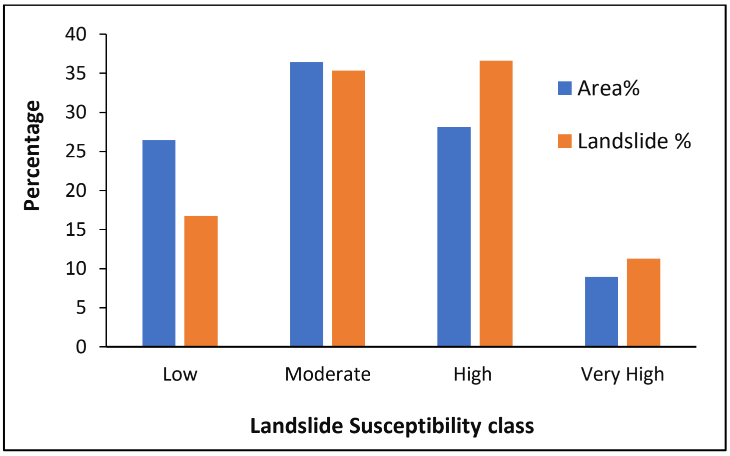


Figure 8. Landslide susceptibility class and landslide occurrence division in the study area.

The statement provided indicates that 79.9% of the region lies beneath the success rate curve. This signifies that the model effectively predicted susceptibility of 79.9% of the study area. The region under the curve denotes true positive predictions, highlighting areas correctly identified as prone to landslides. This underscores the model's high accuracy in assessing landslide susceptibility within the study area. The Area Under the Curve (AUC) value serves as a measure of the model's ability to differentiate between susceptible and non-susceptible regions. A higher AUC value signifies enhanced performance in this distinction. For the prediction rate in this case, the AUC value was determined to be 81.3%. This value underscores the model's proficiency in predicting landslide susceptibility effectively.

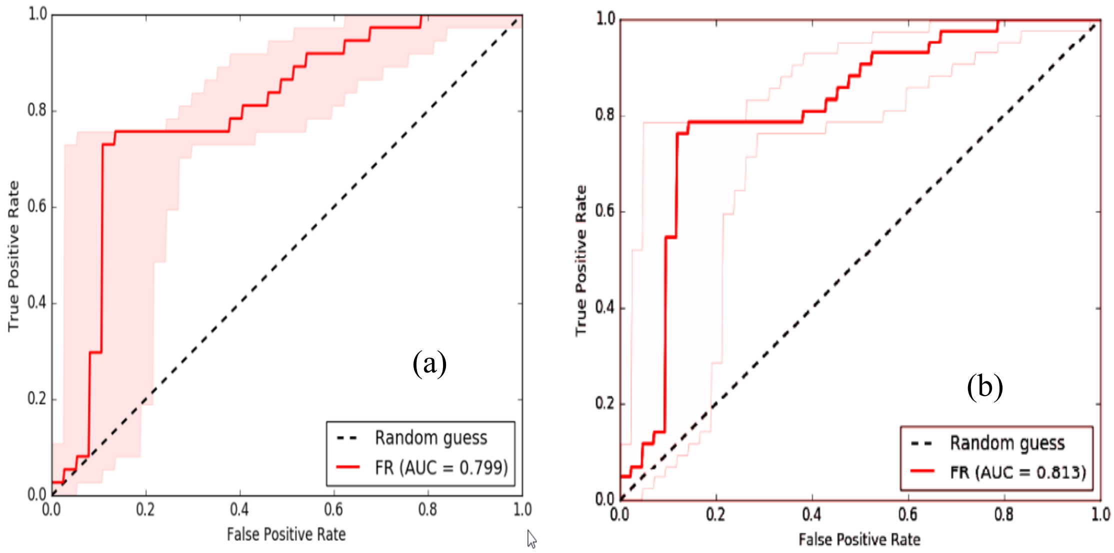


Figure 9. The validation curves show a) prediction rate and b) success rate of landslide susceptibility.

The AUC values for the success rate of the FR model for both test and train landslide scenarios are 81.3% and 79.9% respectively. These values suggest that the models are dependable tools for forecasting and delineating areas prone to landslides in the research area. The AUC value of the curve surpassing 70% indicates the frequency ratio model's notable accuracy, making it suitable for application in the study region. Consequently, in the study area, the FR model is deemed appropriate for mapping landslide susceptibility.

A similar study undertaken by (Pathak & Devkota, 2022) in the Rangun Khola watershed of Far-Western Nepal employed the FR method for landslide susceptibility mapping. The FR model demonstrated a success rate of 76.4% and a prediction rate of 75.1% for the entire dataset. Likewise, (Poudel & Regmi, 2016) achieved a success accuracy of 85.18% and a prediction accuracy of 78.76% when applying the Frequency Ratio method for landslide susceptibility mapping along the Tulsipur – Kaporkot Road Section of the Rapti zone in Nepal. Validation results from the study on potential landslide - prone areas in the Siwalik zone of the Chatara-Barahakshetra section, Nepal, demonstrated that the Frequency Ratio (FR) model performed better than other approaches. It attained a success rate of 72.55% and a predictive accuracy of 71.73% (Thapa & Bhandari, 2019).

CONCLUSIONS

This study demonstrated the effectiveness of the Frequency Ratio (FR) model in generating a reliable landslide susceptibility map for Bahrabise Municipality, where 47.9% of the area was classified under high and very high susceptibility zones. The model achieved a prediction accuracy of 81.3%, highlighting its potential as a cost-effective and efficient tool for landslide hazard assessment in mountainous regions. The integration of eleven causative factors, combined with field verification, ensured the spatial accuracy and contextual relevance of the results. These findings can support local governments, planners, and disaster management authorities in identifying high-risk zones, prioritizing land-use planning, and implementing early warning and preventive measures. Furthermore, the methodology adopted in this study can be replicated in similar geologically fragile regions to assess landslide risk and enhance resilience at the community level.

The prepared landslide susceptibility maps have practical utility for various stakeholders in terms of land use planning and developing mitigation strategies to address the increasing landslide occurrences in the Bahrabise Municipality. Even with currently available local data, valid and practical susceptibility maps for landslide occurrences can be generated. In conclusion, the landslides in Bahrabise Municipality have had significant socio-environmental impacts, resulting in loss of life, destruction of houses, and risks to livelihoods. Adequate compensation, relocation measures, and infrastructure development are necessary to mitigate future landslides and protect the well-being of the affected population.

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AUTHOR CONTRIBUTIONS STATEMENT

Bharat Prasad Bhandari conceived of the presented idea, analysed the data and conducted supervision. Pratikshya Bista and Anamol Nagarkoti collected the data and prepared the causative factors map. Prakash Ayer and Pratikshya Bista prepared the draft manuscript. All authors discussed the results and contributed to the final manuscript.

CONFLICT OF INTEREST

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

DATA AVAILABILITY STATEMENT

Upon reasonable request, the corresponding authors will provide the data supporting the study's conclusions.

REFERENCES

Adhikari, N., Acharya, S., Dhungana, J., Shrestha, S., & Bhuju, D.R. (2015). *Climate Change Vulnerability Mapping for Central Development Region of Nepal.* Proceedings of IOE Graduate Conference, 2015.

Akgun, A., Dag, S., & Bulut, F. (2007). Landslide susceptibility mapping for a landslide-prone area (Findikli, NE of Turkey) by likelihood-frequency ratio and weighted linear combination models. *Engineering Geology*, *54*, 1127–1143.

Arrogante-Funes, P., Bruzón, A.G., Arrogante-Funes, F., Ramos-Bernal, R.N., & Vázquez-Jiménez, R. (2021). Integration of Vulnerability and Hazard Factors for Landslide Risk Assessment. *International Journal of Environmental Research and Public Health*, *18*(22), 11987. https://doi.org/10.3390/ijerph182211987.

Ayer, P.B., & Bhandari, B.P. (2024). Landslide Susceptibility Mapping Using Frequency Ratio and Weight of Evidence Models in Purchaudi Municipality, Baitadi District, Nepal. *Nepal Journal of Environmental Science*, *12*(2), 59–72. https://doi.org/10.3126/njes.v12i2.73671.

Beven, K.J., & Kirkby, M.J. (1979). A physically based, variable contributing area model of basin hydrology / Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin versant. *Hydrological Sciences Bulletin*, *24*(1), 43–69. https://doi.org/10.1080/02626667909491834.

Bhandari, B.P., & Dhakal, S. (2021). Decadal Evolution of Landslides in the Siwalik Zone: A Case Study of Babai Watershed, Nepal. *Journal of Institute of Science and Technology*, *26*(1), 57–62. https://doi.org/10.3126/jist.v26i1.37864.

Bhandari, B.P., Dhakal, S., & Tsou, C.-Y. (2024). Assessing the Prediction Accuracy of Frequency Ratio, Weight of Evidence, Shannon Entropy, and Information Value Methods for Landslide Susceptibility in the Siwalik Hills of Nepal. *Sustainability*, *16*(5), 2092. https://doi.org/10.3390/su16052092.

Bhandari, B.P & Dhakal, S. (2018). Lithological Control on Landslide in the Babai Khola Watershed, Siwaliks Zone of Nepal. *American Journal of Earth Sciences*, *5*, 54–64.

Burt, T., & Butcher, D. (1986). Stimulation from simulation? A teaching model of hillslope hydrology for use on microcomputers. *Journal of Geography in Higher Education*, *10*(1), 23–39. https://doi.org/10.1080/03098268608708953.

Carrara, A., Guzzetti, F., Cardinali, M., & Reichenbach, P. (1999). Use of GIS Technology in the Prediction and Monitoring of Landslide Hazard. *Natural Hazards*, *20*(2/3), 117–135. https://doi.org/10.1023/A:1008097111310.

Chauhan, S., Sharma, M., & Arora, M.K. (2010). Landslide susceptibility zonation of the Chamoli region, Garhwal Himalayas, using logistic regression model. *Landslides*, *7*(4), 411–423. https://doi.org/10.1007/s10346-010-0202-3.

Chen, W., Wang, J., Xie, X., Hong, N., Trung, V. N., Bui, D. T., Wang, G., & Li, X. (2016). Spatial prediction of landslide susceptibility using integrated frequency ratio with entropy and support vector machines by different kernel functions. *Environmental Earth Sciences*, *75(20)*, 1344.

Chung, C.-J., & Fabri, A. (1999). Probabilistic prediction models for landslide hazard mapping. *Photogrammetric Engineering and Remote Sensing*, *65(12)*, 1389–1399.

Dahal, R.K., Hasegawa, S., Nonomura, A., Yamanaka, M., Dhakal, S., & Paudyal, P. (2008). Predictive modelling of rainfall-induced landslide hazard in the Lesser Himalaya of Nepal based on weights-of-evidence. *Geomorphology*, *102*(3–4), 496–510. https://doi.org/10.1016/j.geomorph.2008.05.041.

Devkota, K.C., Regmi, A.D., Pourghasemi, H.R., Yoshida, K., Pradhan, B., Ryu, I.C., Dhital, M.R., & Althuwaynee, O.F. (2013). Landslide susceptibility mapping using certainty factor, index of entropy and logistic regression models in GIS and their comparison at Mugling–Narayanghat road section in Nepal Himalaya. *Natural Hazards*, *65*(1), 135–165. https://doi.org/10.1007/s11069-012-0347-6

Ercanoglu, M., Kasmer, O., & Temiz, N. (2008). Adaptation and comparison of expert opinion to analytical hierarchy process for landslide susceptibility mapping. *Bulletin of Engineering Geology and the Environment*, *67*(4), 565–578. https://doi.org/10.1007/s10064-008-0170-1.

Erener, A., Mutlu, A., & Sebnem Düzgün, H. (2016). A comparative study for landslide susceptibility mapping using GIS-based multi-criteria decision analysis (MCDA), logistic regression (LR) and association rule mining (ARM). *Engineering Geology*, *203*, 45–55. https://doi.org/10.1016/j.enggeo.2015.09.007.

Fell, R., Corominas, J., Bonnard, C., Cascini, L., Leroi, E., & Savage, W.Z. (2008). Guidelines for landslide susceptibility, hazard and risk zoning for land use planning. *Engineering Geology*, *102*(3–4), 85–98. https://doi.org/10.1016/j.enggeo.2008.03.022.

Gautam, P., Kubota, T., & Aditian, A. (2021). Evaluating underlying causative factors for earthquake-induced landslides and landslide susceptibility mapping in Upper Indrawati Watershed, Nepal. *Geoenvironmental Disasters*, *8*(1), 30. https://doi.org/10.1186/s40677-021-00200-3.

Guzzetti, F., Reichenbach, P., Cardinali, M., Galli, M., & Ardizzone, F. (2005). Probabilistic landslide hazard assessment at the basin scale. *Geomorphology*, *72*(1–4), 272–299.

Hamza, T., & Raghuvanshi, T.K. (2017). GIS based landslide hazard evaluation and zonation – A case from Jeldu District, Central Ethiopia. *Journal of King Saud University - Science*, *29*(2), 151–165. https://doi.org/10.1016/j.jksus.2016.05.002.

Hung, C.-H., & Lo, K.-C. (2015). Relationships between Ambient Ozone Concentration Changes in Southwestern Taiwan and Invasion Tracks of Tropical Typhoons. *Advances in Meteorology*, *2015*, 1–17. https://doi.org/10.1155/2015/402976.

Kavzoglu, T., Sahin, E.K., & Colkesen, I. (2014). Landslide susceptibility mapping using GIS-based multi-criteria decision analysis, support vector machines, and logistic regression. *Landslides*, *11*(3), 425–439. https://doi.org/10.1007/s10346-013-0391-7.

Kayastha, P., Dhital, M.R., & De Smedt, F. (2013). Application of the analytical hierarchy process (AHP) for landslide susceptibility mapping: A case study from the Tinau watershed, west Nepal. *Computers & Geosciences*, *52*, 398–408. https://doi.org/10.1016/j.cageo.2012.11.003.

Lee, S., & Min, K. (2001). Statistical analysis of landslide susceptibility at Yongin, Korea. *Environmental Geology*, *40*(9), 1095–1113. https://doi.org/10.1007/s002540100310.

Lee, S., Pradhan, B., & Lee, M.J. (2010). Landslide susceptibility mapping using GIS-based weighted linear combination, and frequency ratio models in the Gangjeong-Goryeong area, Korea. Journal. *Journal of Earth Science*, *119*(6), 681–694. https://doi.org/DOI: 10.1007/s12040-010-0068-6.

Lee, S., & Talib, J. A. (2005). Probabilistic landslide susceptibility and factor effect analysis. *Environmental Geology*, *47*(7), 982–990. https://doi.org/10.1007/s00254-005-1228-z.

Magliulo, P., Di Lisio, A., & Russo, F. (2009). Comparison of GIS-based methodologies for the landslide susceptibility assessment. *GeoInformatica*, *13*(3), 253–265. https://doi.org/10.1007/s10707-008-0063-2.

Mansouri Daneshvar, M.R. (2014). Landslide susceptibility zonation using analytical hierarchy process and GIS for the Bojnurd region, northeast of Iran. *Landslides*, *11*(6), 1079–1091. https://doi.org/10.1007/s10346-013-0458-5.

MoHA. (2022). *Nepal Disaster Report 2022*. Government of Nepal, Ministry of Home Affairs.

Mondal, S., & Maiti, R. (2013). Integrating the analytical hierarchy process (AHP) and the frequency ratio (FR) model in landslide susceptibility mapping of Shiv-khola watershed. *International Journal of Disaster Risk Science*, *4(4)*, 200–212.

Moore, I.D., Grayson, R.B., & Ladson, A.R. (1991). Digital terrain modelling: A review of hydrological, geomorphological, and biological applications. *Hydrological Processes*, *5*(1), 3–30. https://doi.org/10.1002/hyp.3360050103.

Pathak, L., & Devkota, K.C. (2022). Landslide susceptibility assessment in the Rangun Khola watershed of far western Nepal. *Journal of Nepal Geological Society*, 33–44. https://doi.org/10.3126/jngs.v63i01.50827.

Pisano, L., Zumpano, V., Malek, Ž., Rosskopf, C.M., & Parise, M. (2017). Variations in the susceptibility to landslides, as a consequence of land cover changes: A look to the past, and another towards the future. *Science of The Total Environment*, *601–602*, 1147–1159. https://doi.org/10.1016/j.scitotenv.2017.05.231.

Pokhrel, K., & Bhandari, B.P. (2019). Identification of Potential Landslide Susceptible Area in the Lesser Himalayan Terrain of Nepal. *Journal of Geoscience and Environment Protection*, *07*(11), 24–38. https://doi.org/10.4236/gep.2019.711003.

Poudel, K., & Regmi, A.D. (2016). Landslide susceptibility mapping along Tulsipur-Kapurkot road section and its surrounding region using bivariate statistical model. *Journal of Nepal Geological Society, 50*, 83–93.

Pradhan, B.K. (2007). *Disaster preparedness for natural hazards: Current status in Nepal*. International Centre for Integrated Mountain Development (ICIMOD).

Pradhan, U., Shrestha, R., KC, S., & Sharma, S. (2002). *Geological map of petroleum exploration block—7, Malangawa, Central Nepal (Scale: 1: 250,000).* Petroleum Exploration Promotion Project, Department of Mines and Geology, Kathmandu.

Pyakurel, A., K.C., D., & Dahal, B.K. (2024). Enhancing co-seismic landslide susceptibility, building exposure, and risk analysis through machine learning. *Scientific Reports*, *14*(1), 5902. https://doi.org/10.1038/s41598-024-54898-w.

Regmi, A.D., Yoshida, K., Pourghasemi, H.R., DhitaL, M.R., & Pradhan, B. (2014). Landslide susceptibility mapping along Bhalubang—Shiwapur area of mid-Western Nepal using frequency ratio and conditional probability models. *Journal of Mountain Science*, *11*(5), 1266–1285. https://doi.org/10.1007/s11629-013-2847-6.

Reichenbach, P., Rossi, M., Malamud, B.D., Mihir, M., & Guzzetti, F. (2018). A review of statistically-based landslide susceptibility models. *Earth-Science Reviews*, *180*, 60–91. https://doi.org/10.1016/j.earscirev.2018.03.001.

Reis, S., Yalcin, A., Atasoy, M., Nisanci, R., Bayrak, T., Erduran, M., Sancar, C., & Ekercin, S. (2012). Remote sensing and GIS-based landslide susceptibility mapping using frequency ratio and analytical hierarchy methods in Rize province (NE Turkey). *Environmental Earth Science*, *66(7)*, 2063–2073.

Rostami, Z.A., Al-modaresi, S.A., Fathizad, H., & Faramarzi, M. (2016). Landslide susceptibility mapping by using fuzzy logic: A case study of Cham-gardalan catchment, Ilam, Iran. *Arabian Journal of Geosciences*, *9*(17), 685. https://doi.org/10.1007/s12517-016-2720-3.

Searle, M.P., Windley, B.F., Coward, M.P., Cooper, D.J. W., Rex, A.J., Rex, D., Tingdong, L., Xuchang, X., Jan, M.Q., Thakur, V.C., & Kumar, S. (1987). The closing of Tethys and the tectonics of the Himalaya. *Geological Society of America Bulletin*, *98*(6), 678. https://doi.org/10.1130/0016-7606(1987)98<678:TCOTAT>2.0.CO;2.

Thapa, D., & Bhandari, B.P. (2019a). GIS-Based frequency ratio method for identification of potential landslide susceptible area in the Siwalik Zone of Chatara-Barahakshetra section, Nepal. *Open Journal of Geology*, *09*(12), 873–896. https://doi.org/10.4236/ojg.2019.912096.

Tien Bui, D., Tuan, T.A., Klempe, H., Pradhan, B., & Revhaug, I. (2016). Spatial prediction models for shallow landslide hazards: A comparative assessment of the efficacy of support vector machines, artificial neural networks, kernel logistic regression, and logistic model tree. *Landslides*, *13*(2), 361–378. https://doi.org/10.1007/s10346-015-0557-6.

Tofani, V., Segoni, S., Agostini, A., Catani, F., & Casagli, N. (2013). Technical Note: Use of remote sensing for landslide studies in Europe. *Natural Hazards and Earth System Sciences*, *13*(2), 299–309. https://doi.org/10.5194/nhess-13-299-2013.

Wu, Y., Li, W., Wang, Q., Liu, Q., Yang, D., Xing, M., Pei, Y., & Yan, S. (2016). Landslide susceptibility assessment using frequency ratio, statistical index and certainty factor models for the Gangu County, China. *Arabian Journal of Geosciences*, *9*(2), 84. https://doi.org/10.1007/s12517-015-2112-0.

Yalcin, A. (2008). GIS-based landslide susceptibility mapping using analytical hierarchy process and bivariate statistics in Ardesen (Turkey): Comparisons of results and confirmations. *CATENA*, *72*(1), 1–12. https://doi.org/10.1016/j.catena.2007.01.003.

Yalcin, A., Reis, S., Aydinoglu, A.C., & Yomralioglu, T. (2011). A GIS-based comparative study of frequency ratio, analytical hierarchy process, bivariate statistics and logistics regression methods for landslide susceptibility mapping in Trabzon, NE Turkey. *CATENA*, *85*(3), 274–287. https://doi.org/10.1016/j.catena.2011.01.014.

Zhu, A.-X., Wang, R., Qiao, J., Qin, C.-Z., Chen, Y., Liu, J., Du, F., Lin, Y., & Zhu, T. (2014). An expert knowledge-based approach to landslide susceptibility mapping using GIS and fuzzy logic. *Geomorphology*, *214*, 128–138. https://doi.org/10.1016/j.geomorph.2014.02.003.