Journal of Engineering Issues and Solutions

Landslide susceptibility mapping using GIS-based statistical models and remote sensing in the Kathmandu valley, Nepal

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Received: June 11, 2024; Revised: July 5, 2024; Accepted: July 6, 2024

doi: https://doi.org/10.3126/joeis.v3i1.66773

Abstract

Landslides are geological hazards that typically occur in different settings on both temporal and spatial scales, causing significant loss of life and property. The landslides in Nepal have increased in recent years, claiming loss of lives and properties. The coupling effect of Asian monsoon, seismo-tectonic activities, and anthropogenic activities are the major cause of landslide generation in the Nepal Himalaya. Systematic landslide research is essential to prevent or control the issues generated by landslides, including widespread damage of buildings and structures, property, cultivated areas, and loss of life. This study aims to perform a GIS-based landslide susceptibility mapping of the Kathmandu valley using bivariate statistical approaches (Frequency Ratio and Information Value) and a heuristic approach. The landslide inventory database was prepared from 2010 to 2021 using Google Earth Pro, where 105 landslides were identified. Predisposing factors were categorized into different classes (aspect, slope, geology, curvature, land use, distance to road, distance to drainage, rainfall, NDVI, and relative relief) for the suitability mapping. The landslide susceptibility classes for all three methods were divided into low, medium, and high classes. Furthermore, the frequency ratio (FR) and information value (IV) methods were validated through the area under curve approach. Results indicate that the FR and IV approaches have predictive rates of 70.16% and 81.43%, respectively. This study is helpful for geohazard assessment for infrastructure planning and land use zoning.

Keywords: *Bivariate; heuristic; Kathmandu; landslide; susceptibility*

1. Introduction

Nepal is considered one of the world's most disaster-prone countries because of its geomorphic and ecological diversity (DRR Portal, n.d.). Several areas in Nepal are susceptible to hazards such as landslides, debris flow, floods, and earthquakes due to their weak geology, steep slopes, and climatic conditions (Budha et al., 2016; Regmi et al., 2014). Landslides occur yearly in various areas of Nepal, resulting in numerous individual and property losses. Most of the landslides in Nepal are caused by earthquakes and excessive monsoon precipitation events, while human activities including improper land use, encroachment into susceptible land slopes, and unmanaged developmental projects and construction without appropriate protections in the vulnerable areas, worsen the risk (Acharya et al., 2017).

Landslides are geological hazards that typically occur in different settings on both temporal and spatial scales, causing significant loss of life and property (McKean & Roering, 2004). A landslide is the downward and outward flow of slope-forming material over the separating surfaces (Varnes, 1958). It occurs when the driving force outweighs the resisting force (Gariano & Guzzetti, 2016; Gill et al., 2014; Pardeshi et al., 2013). Consequently, triggers for landslides include those responsible for amplifying the impacts of downslope forces and those that contribute to poor or decreased strength of the material. Landslides are of concern that can result in economic losses, casualties, and environmental issues (Acharya et al., 2017).

In the last decade alone, there have been over 2600 recorded incidents of significant landslides in Nepal, resulting in the death of more than 1300 people and an estimated loss of 2 billion Nepalese Rupees (DRR Portal, n.d.). Furthermore, the landslide events have destroyed over 3000 infrastructures. The 2015 Mw 7.8 Gorkha Earthquake in Nepal has caused over 20,000 small and large-scale landslides in 14 districts across Central and Western Nepal (Rosser et al., 2021). Insufficient early warning systems (EWS) and emergency preparedness with mitigation strategies have aggravated the situation (Thapa & Adhikari, 2019). Kathmandu Valley is a densely populated and significant area from an economic standpoint, with rapidly growing settlements (Mesta et al., 2022). According to a study conducted by Kincey et al. (2024), Kathmandu, Bhaktapur, and Lalitpur rank 55th, 48th, and 60th in district-wise mean landslide susceptibility, indicating low landslide susceptibility of the valley. However, Kathmandu ranks 20th in population exposure and 3rd in building exposure, which has the potential to cause severe damage to the residing population, infrastructure, and economy. Therefore, a systematic landslide study is essential to prevent or control the loss and damages caused by landslides, including widespread damage to buildings and structures, property, cultivated areas, and loss of life (Pardeshi et al., 2013). This can be done with the help of landslide risk assessment, where susceptibility and vulnerability provide the sectoral information. Landslide susceptibility can be defined as the probability of a landslide taking place at a specific location based on local topographical characteristics, which assesses the extent to which future slope movement may affect the ground (Rahman et al., 2022). The susceptibility models predict where landslides are likely to occur. Landslide inventory and susceptibility mapping are critical steps in hazard and disaster risk management practices associated with landslides, particularly in the Himalayan region, where many people have been affected, and the property has been destroyed (Acharya et al., 2017; Regmi et al., 2014).

Landslide hazard assessment and risk mitigation can be performed by providing professionals with conveniently available, comprehensive, and reliable information regarding the incidence of landslides. As a result, reliable susceptibility mapping information is essential for a broader range of stakeholders. Recent and developing tools such as high-resolution Landsat images, Digital Elevation Model (DEM), and Geographic Information System (GIS) are very useful in generating the landslide susceptibility map, hazard analysis, and risk evaluation (Basharat et al., 2016). The first step in landslide management and mitigation is to prepare and develop a landslide inventory.

The landslide inventory provides systematic data on the locations, types, dynamics, and prevalence of landslides in the area. High-resolution sentinel images and DEM are used to create landslide inventory maps (Basharat et al., 2016). Moreover, geospatial tools are essential in generating a digital database and monitoring landslide data. Following the development of the landslide inventory, the second phase is creating a landslide susceptibility map containing pre-disposing factors (Basharat et al., 2016).

Several qualitative and quantitative methodologies exist to build the thematic layers for the landslide susceptibility map preparation. Previously, researchers created susceptibility maps by qualitatively superimposing topographical and geological attributes onto landslide data. Nowadays, researchers have been using advanced approaches for susceptibility mapping, such as bivariate and multivariate statistical models, logistic regression analysis, artificial neural network (ANN), and Analytic Hierarchy Process (AHP) (Basharat et al., 2016; Kamiński, 2019; Shahabi & Hashim, 2015). GIS-based statistical models such as the Frequency Ratio (FR), Weight of Evidence (WoE), Logistic Regression (LR), and Information Value (IV) models have been used by researchers in Nepal (Acharya et al., 2017; Pathak & Devkota, 2022; Regmi et al., 2014; Thapa & Adhikari, 2019), and around the world (Addis, 2023; Mersha & Meten, 2020; Sarkar et al., 2013; Wubalem, 2021; Wubalem & Meten, 2020).

Among various methods of statistical analysis, the logistic regression approach is among the most reliable for determining landslide susceptibility (El-Fengour et al., 2021; Lee & Pradhan, 2007; Sajadi et al., 2022; Wubalem & Meten, 2020). However, the technique requires a large dataset and more computational resources than FR and IV and is less suitable in data-scare areas with limited inventory. FR and IV models have the advantage over LR of being simple and free of complex mathematical analysis (Sarkar et al., 2013). Mersha & Meten (2020) used the WoE and FR approach to conduct landslide susceptibility assessment and found that the results from FR were more accurate than the WoE approach. Furthermore, Gholami et al. (2019) conducted the assessment using the Frequency Ratio, Fuzzy Gamma, and Landslide Index Method, where the result from the FR technique was the most accurate.

The study aims to fit different susceptibility models in order to determine the landslide susceptibility of the Kathmandu valley, and compare the results of other models. The comparative analysis of models and model validation helps to select the best model based on the local characteristics of the region.

2. Study Area

Kathmandu valley is the capital city of Nepal located in the central Nepal. It is an intermontane basin within the Mahabharat Lekh. The Bagmati River drains all the water in the valley. Steep mountainous regions of over 2,000 meter elevations surround the area, and it is made up of very gentle and flat terrain at elevations of around 1,300 meters (Figure 1). The Kathmandu Valley is situated within 85° 11' 30.7" - 85° 31' 38.47" due East and 27° 32' 13.16" - 27° 49' 4.19" due North, covering an area of 652 square kilometers. Geologically, the valley is bounded by Gneiss, Schist, and Granite of Shivapuri Gneiss to the north and sedimentary rocks of Phulchauki Group to the south (Acharya & Paudyal, 2019). The valley sediment comprises lacustrine deposits such as sand, silt, and mud lignite, particularly along the Bagmati river banks of Lukundol, Naikhandi, and upstream of Nakhu river. Black and grey silt and mud can be found in the Kalimati formation along the center of the Kathmandu basin, extending thinly towards the south (Paudel & Sakai, 2008).

The average annual rainfall of the Kathmandu basin is around 1755 mm, depending on the altitude (Devkota, 2005). Rainfall often increases in steep and hilly areas, and it is heavier on slopes with a southern aspect than the north-facing slope. The rainy season (June to September) receives about 80% of the yearly precipitation (Devkota, 2005; Pokharel & Hallett, 2015). The valley is surrounded by forests from all sides: Shivapuri forest in the northern part, Nagarjun forests in the north-west, Chandragiri in the south-west, and Godawari in the south and south-eastern regions. The central part of the basin is a core residential area, with agricultural and croplands distributed further away from the center. The residential or built-up areas of Kathmandu have significantly increased from 41 km^2 in 1975 to 177 km^2 in 2018 (Mesta et al., 2022). Furthermore, Mesta et al. (2022) anticipate the built-up areas to double by 2050 and reach 352 km^2, which covers roughly half of the Kathmandu valley's total area.

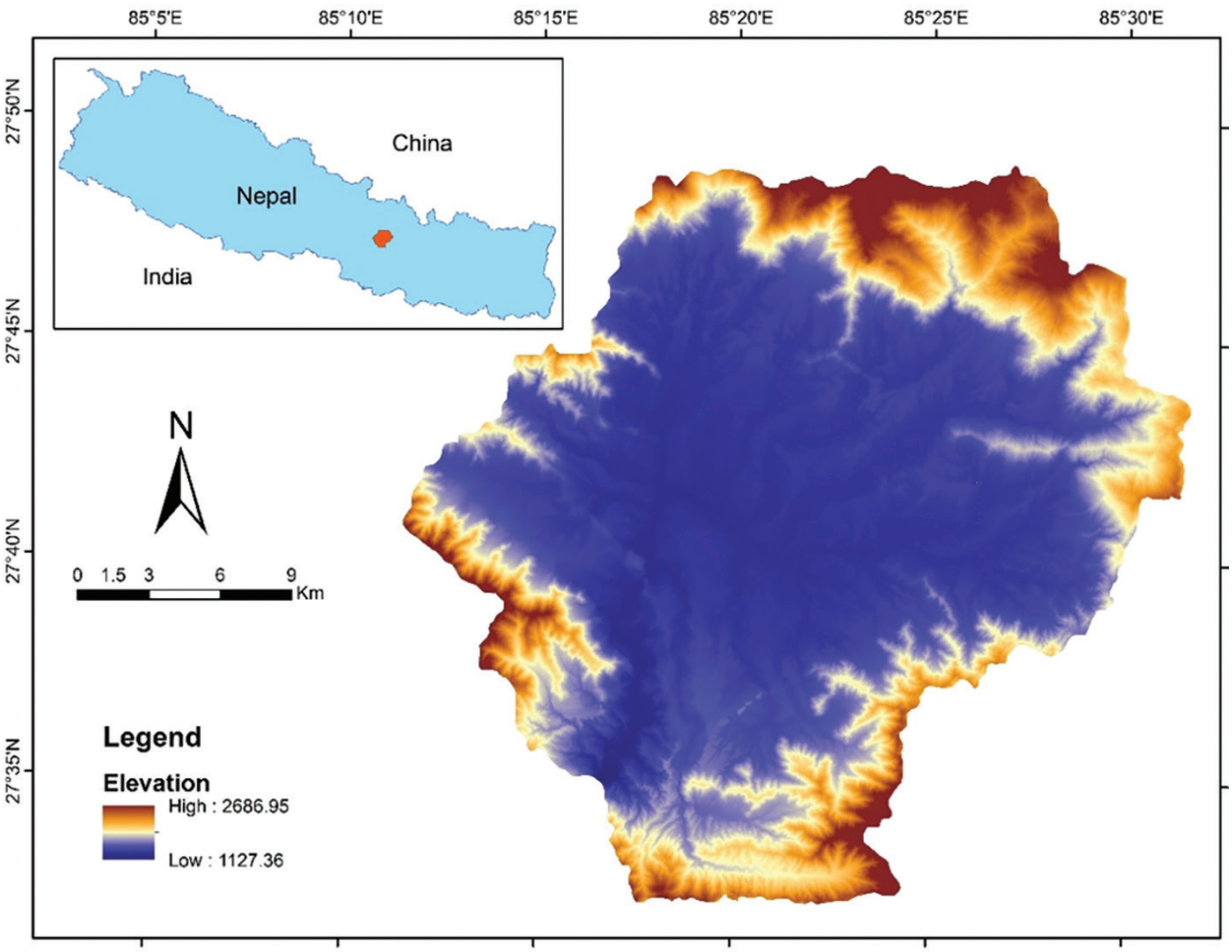


Figure 1: Study area

3. Materials and Methods

The study has adopted several bivariate statistical models, such as Information Value, Frequency Ratio, and Heuristic method for the landslide susceptibility mapping of the Kathmandu valley. These analyses were performed using different topographical and hydro-meteorological data. The obtained susceptibility models were validated statistically using the AUC method (Figure 2).

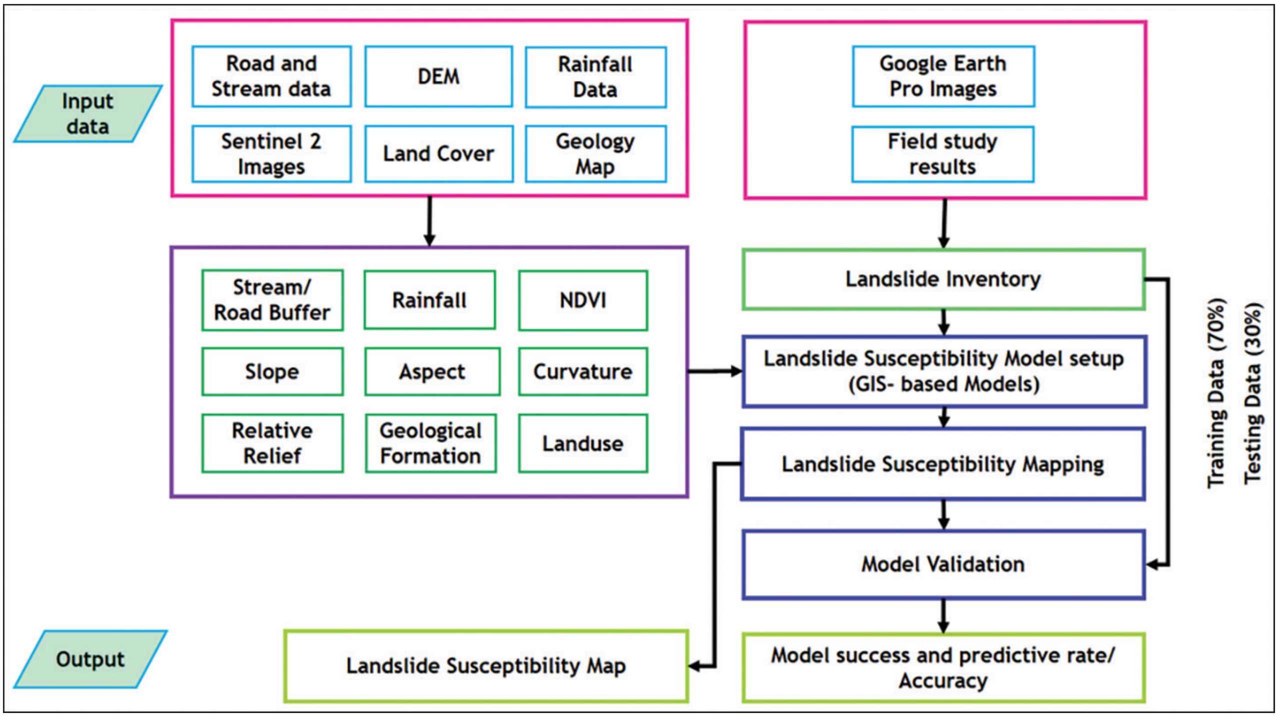


Figure 2: Methodological framework

3.1 Landslide inventory

Landslide inventory provides systematic data on the locations, types, dynamics, and prevalence of landslides in the area. The landslide inventory was generated through Google Earth Pro, by identifying landslide areas from 2010 to 2021. A total of 105 landslides were identified in the Kathmandu valley. The landslides were prominent at the outskirts of Kathmandu valley, primarily at higher slope and elevation areas, as seen in Figure 3 (a). 70% of the total inventory (74 landslides) was used as training data, and the remaining 30% was used as testing data for the validation of susceptibility models using Area Under Curve (AUC) method.

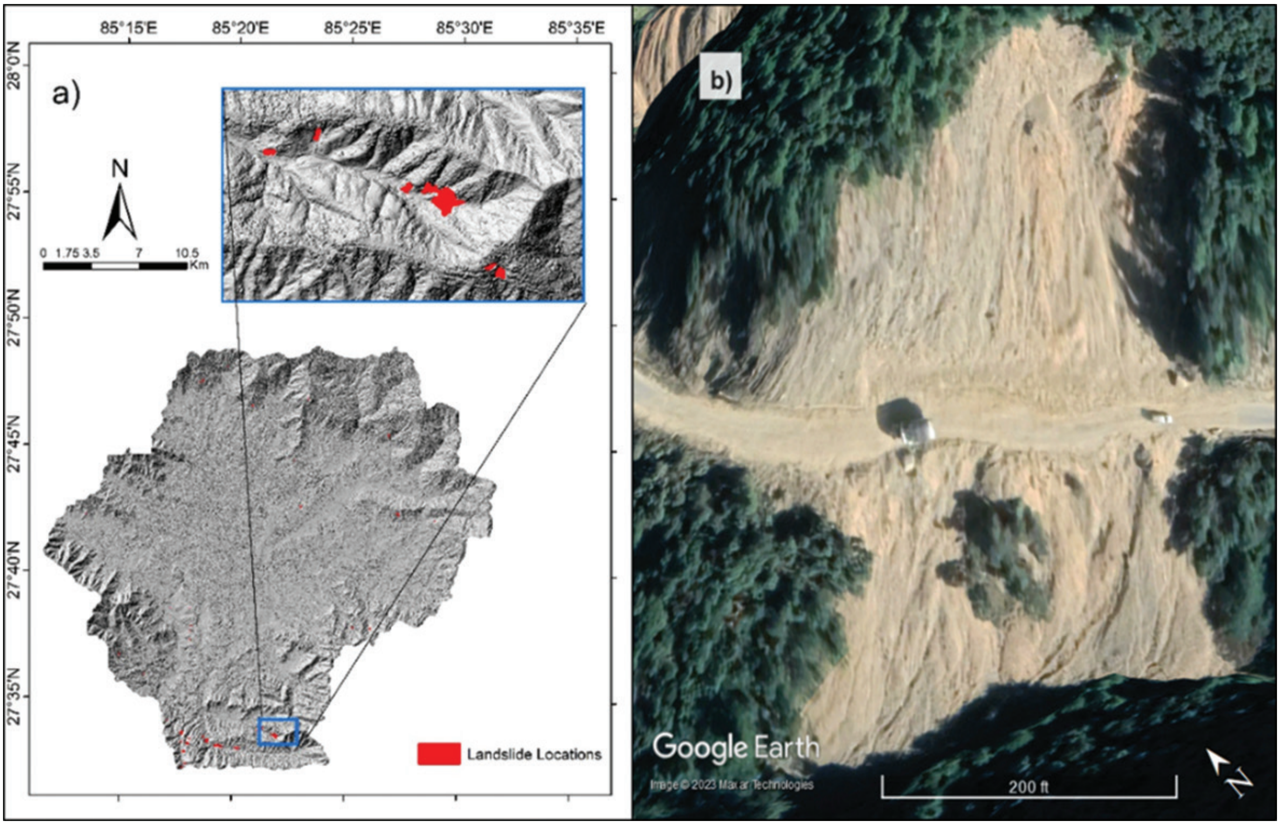


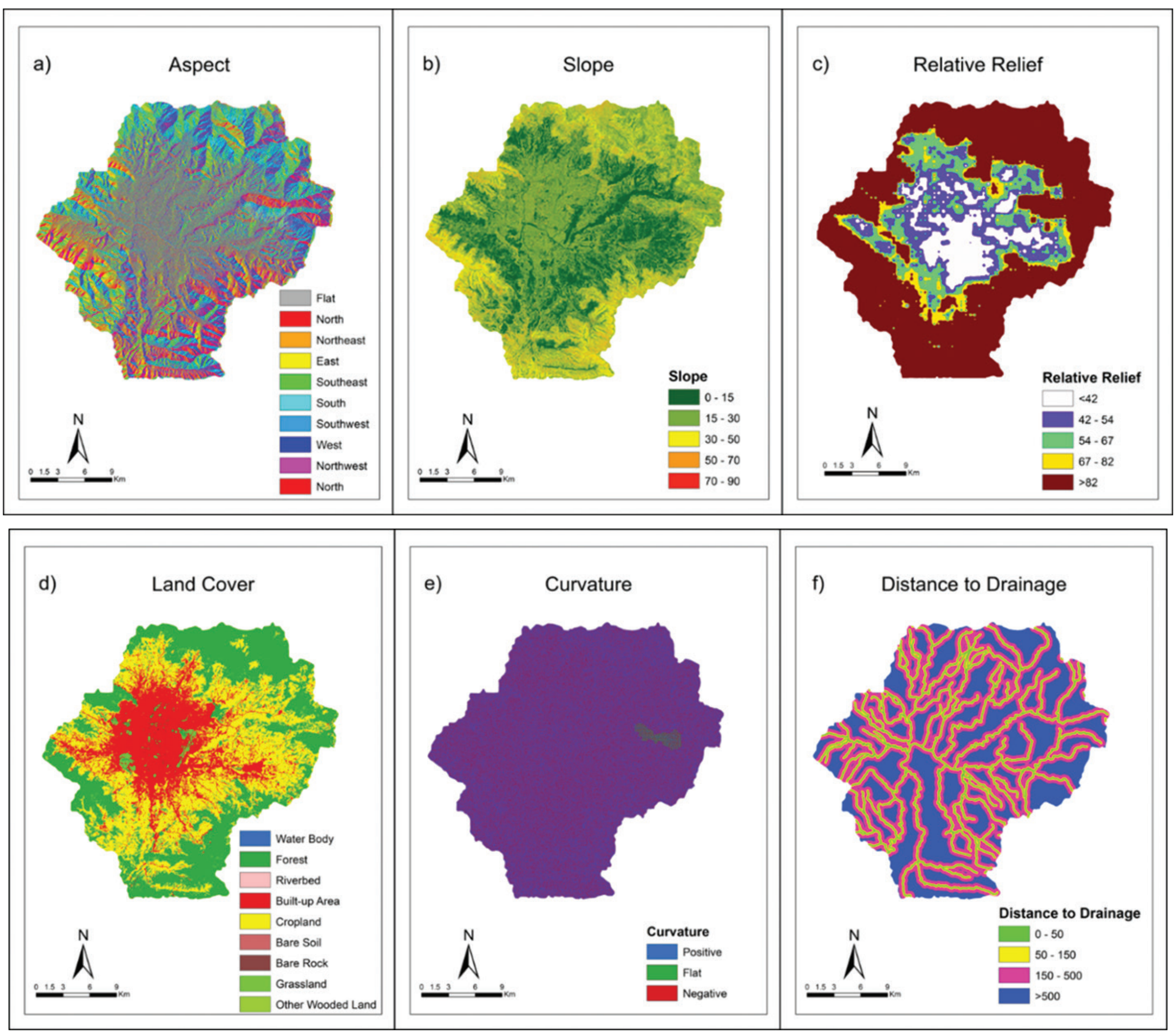
Figure 3: (a) Landslide inventory; (b) Landslide identified on Google Earth

3.2 Data collection and preparation

The generation of a landslide susceptibility map is dependent on various landslide hazard elements and the strong interaction between landslides and earth's surface data (Wubalem, 2021). The study considered a total of 10 predisposing factors: aspect, slope, geology, curvature, land-use, distance to road, distance to drainage, rainfall, NDVI, and relative relief. The DEM (2*2 m) was used to generate slope, aspect, relative relief, and curvature of the study area, as provided in Table 1. The land cover dataset of Nepal, 2019 was developed through the National Land Cover Monitoring System (NLCMS) (ICIMOD, 2019). The Normalized Difference Vegetation Index (NDVI) was generated using the Sentinel-2 images of 10m resolution (European Space Agency, 2022). Furthermore, the drainage and road data were obtained from National Geoportal of Nepal (Survey Department, 2022). Rainfall data from 1990 to 2016 was used to generate isohyet for the further analysis. The thematic layers were prepared using various spatial analyst tools in ArcGIS v10.4.1 and resampled into 2*2m resolution for further modeling. Each factor was divided into different classes based on their characteristics.

Table 1: Input parameters used for the study

Input Parameters	Source	Purpose
DEM	ALOS Palsar	Slope, aspect, relative relief, curvature
Road and stream data	Government website	Stream/ Road buffer
Rainfall data	Dept. of Hydrology and Meteorology	Rainfall/ Theissen polygon
Sentinel 2 Images	EarthData website	Vegetation index/ NDVI
Land Cover	National Land Cover Monitoring System	Landuse
Geology Map	Department of Mines and Geology	Geological formation



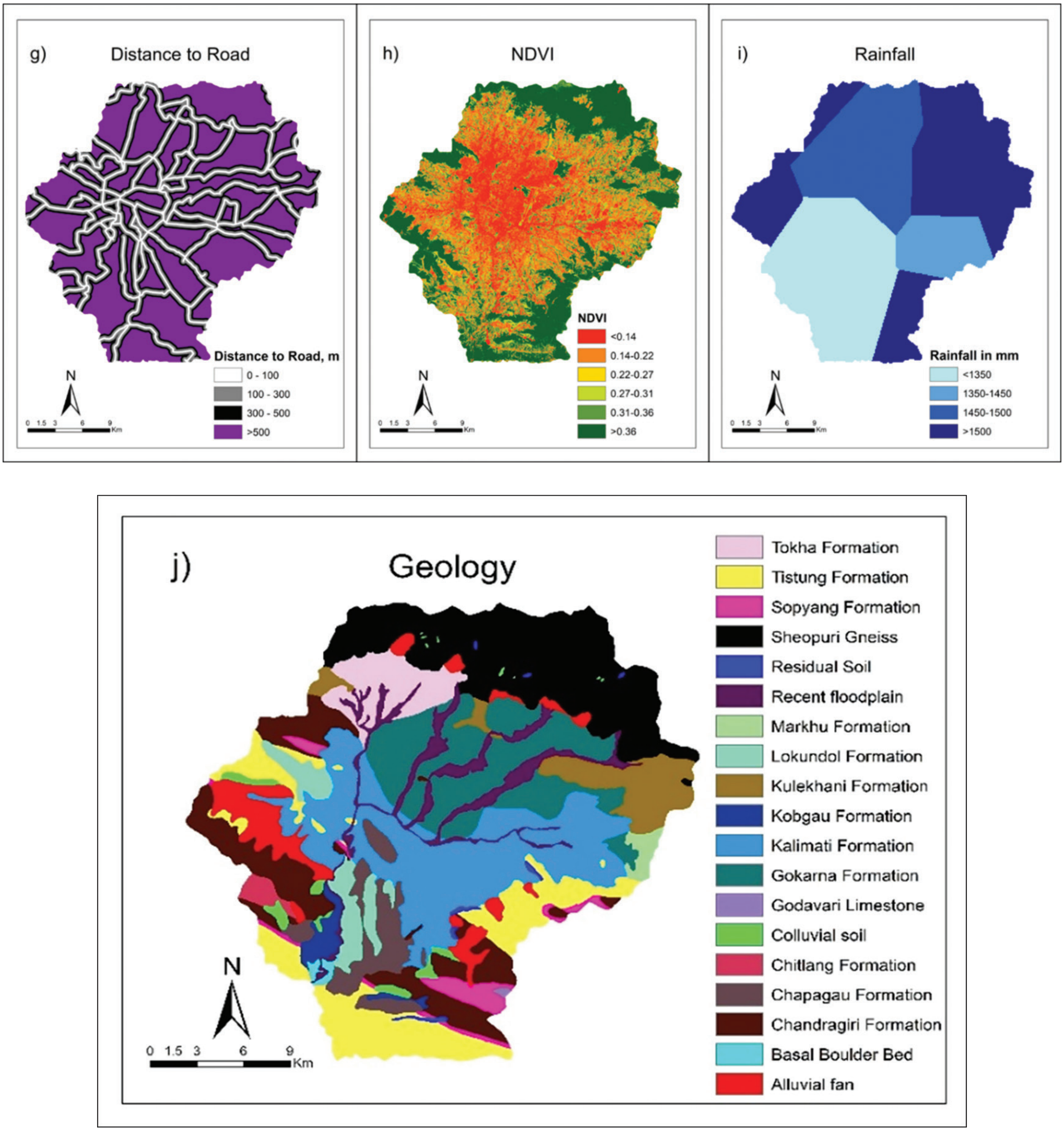


Figure 4: Predisposing factor maps, (a) aspect; (b) slope; (c) relative relief; (d) land cover; (e) curvature; (f) distance to drainage; (g) distance to road; (h) NDVI; (i) Rainfall; (j) Geology.

3.3 Landslide susceptibility model setup

Once the datasets were generated for the study, a Landslide Susceptibility Model was set up. The study adopted three different models for developing the LSM— the Frequency Ratio Model, Information Value Model, and Heuristic Model. The key distinction between these approaches is the numerical weightage assigned to the landslide contributing elements (Mersha & Meten, 2020). The preparation of a landslide susceptibility map indicates the landslide prone area in which a landslide might take place in the future (Lee & Pradhan, 2007).

3.3.1 Frequency ratio model

The frequency ratio (FR) technique is founded on a quantitative relationship between the landslide inventories and the landslide predisposing elements (Kamiński, 2019). A table was prepared to determine the frequency ratio of each class of the predisposing factors, as well as the final weightage (influence) of the factors. Using the equation as presented below, a composite of the landslide inventory map and thematic factor map was built to determine the frequency ratio (FR) for each category of the predisposing factors (Mersha & Meten, 2020).

$$FR = \frac{\mathrm{Np}(1)/\mathrm{Np}(2)}{\sum \mathrm{Np}(3)/\sum \mathrm{Np}(4)} \quad \text{.......(1)}$$ where,

Np(1) = The number of pixels containing landslide in a class

∑Np(2) = Total number of pixels containing landslide

Np(3) = Total number of pixels of each class in the whole area

∑Np(4) = Total number of pixels in the study area

The derived frequency ratio is summed to develop a Landslide Susceptibility Map using Eq. (2)

$LSI = Fr_1 + Fr_2 + Fr_3 + \ldots + Fr_n$ ....(2)

where Fr is the frequency ratio, and n is the number of selected predisposing factors.

The estimated FR value shows how closely a given class of the predisposing factor and a given landslide are related. Based on the approach, frequency ratio is the area in which the landslides occur to the entire area, with a value of 1 representing an average value. If the number is larger than one, the percentage of the landslide is higher than the area, indicating a higher relationship, whilst values less than one imply a lesser correlation (Khan et al., 2019; Mersha & Meten, 2020).

3.3.2 Heuristic model

The heuristic model is built based on the expert knowledge and experience. The premise of the Heuristic model is to provide a certain weightage to the predisposing factor maps for the landslides based on the judgment and experience of experts (Barredo et al., 2000; Leoni et al., 2015). The predisposing factors were divided into different classes and assigned an individual rank; the total ranks of each factor were combined to generate the final susceptibility map (Figure 5). The final map was divided into classes, and expert judgment was used to map the hazardous locations.

3.3.3 Information value model

Information value method is a probabilistic approach and a bivariate statistical method used to predict the relationship between landslides and landslide predisposing factors (Wubalem, 2021). Information value numbers are crucial in defining the part that each causative factor plays in the various classes of landslide occurrence (Wubalem & Meten, 2020). Depending on the historical location of landslides, the information values for each class of the predisposing factor were generated by using the equation below, and tabulated. The total ranks were also calculated.

$$\text{Information Value} = \ln(\frac{\text{Conditional probability (CP)}}{\text{Prior probability (PP)}} \quad \text{.......(3)}$$ where,

Conditional probability (Np(1)/ Np(2)) is the ratio of the landslide pixels within a class of a certain factor to the total pixels of the class.

Prior probability (∑Np(3)/∑Np(4)) is the ratio of the number of landslide pixels of the study area to the number of total pixels in the area.

An information value of more than 0.1 indicates a high correlation of landslide occurrence and predisposing factor classes, thus high susceptibility. Furthermore, an information value of less than 0.1 or 0 indicates a low correlation of landslide occurrence and predisposing factor classes, thus low susceptibility (Wubalem & Meten, 2020). In this study, information value for each class was determined using Microsoft Excel and ArcGIS. The landslide susceptibility index (LSI) for the area was then generated, and lookup tool was used to rasterize each factor.

LSI = IV ∗ Slope + IV ∗ Aspect + IV ∗ Curvature+ IV ∗ Geology+ IV ∗ Landuse + IV ∗ Distance to stream + IV ∗ Distance to road + IV ∗ Relative relief + IV ∗ NDVI + IV ∗ Rainfall.

After calculating the landslide susceptibility index, the values were categorized using natural break method in ArcGIS into three classes— low, medium, and high, to indicate the level of susceptibility in the area.

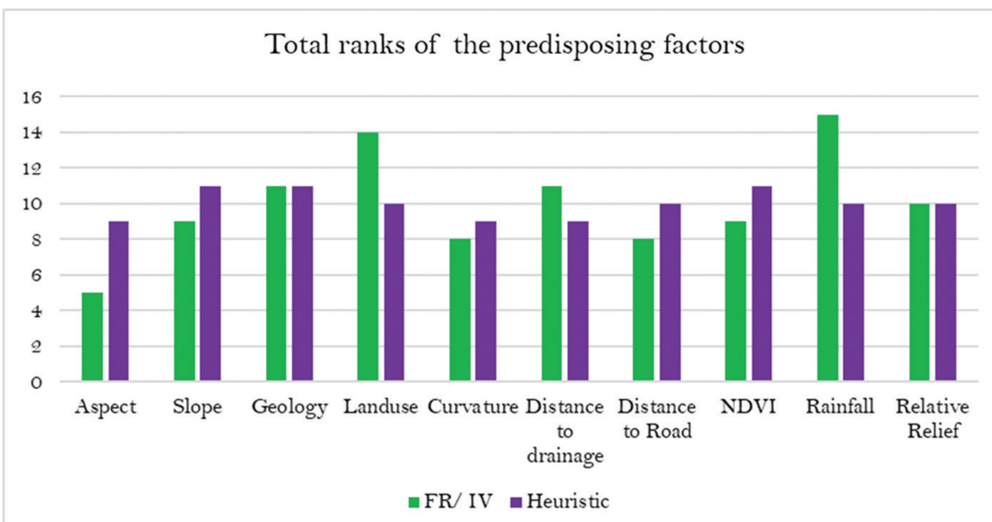


Figure 5: Total ranks of the predisposing factors using different approaches

3.4 Model validation

After the susceptibility map for Kathmandu Basin was developed, the landslide polygons were separated into training and testing datasets for the validation of landslide susceptibility mapping (Figure 5). Taking into account their distribution pattern, the landslide polygons were randomly divided into two groups using the subset tool in ArcGIS, with 70% used for training and 30% used for testing. Model validation was carried out using Area Under Curve (AUC) approach.

The success rate and prediction rate curves were created using the AUC approach. The comparison between the predicted model and the training dataset gives the success rate curve, which provides the ability to accurately characterize the incidence of existing landslides (Mersha & Meten, 2020; Shahabi & Hashim, 2015; Wubalem, 2021). Furthermore, predictive rate curve is determined by comparing the predicted model and testing dataset, and helps demonstrate how well the landslide model can forecast landslide susceptibility (Wubalem & Meten, 2020). The model is considered to be most accurate when the AUC value is between 90% and 100%, and it performs very well when it is between 80% and 90%. Moreover, AUC values between 70% and 80% indicate that the model is performing well. The model performance is acceptable if the AUC value is between 60% and 70%, and poor if the AUC values are between 50% and 60% and equal to 50% or less (Wubalem & Meten, 2020).

In this study, the Landslide Susceptibility Index was reclassified into 100 classes and AUC was determined by combining it with the landslide inventory. The success rate and predictive rate curve were determined for Frequency Ratio and Information Value approach.

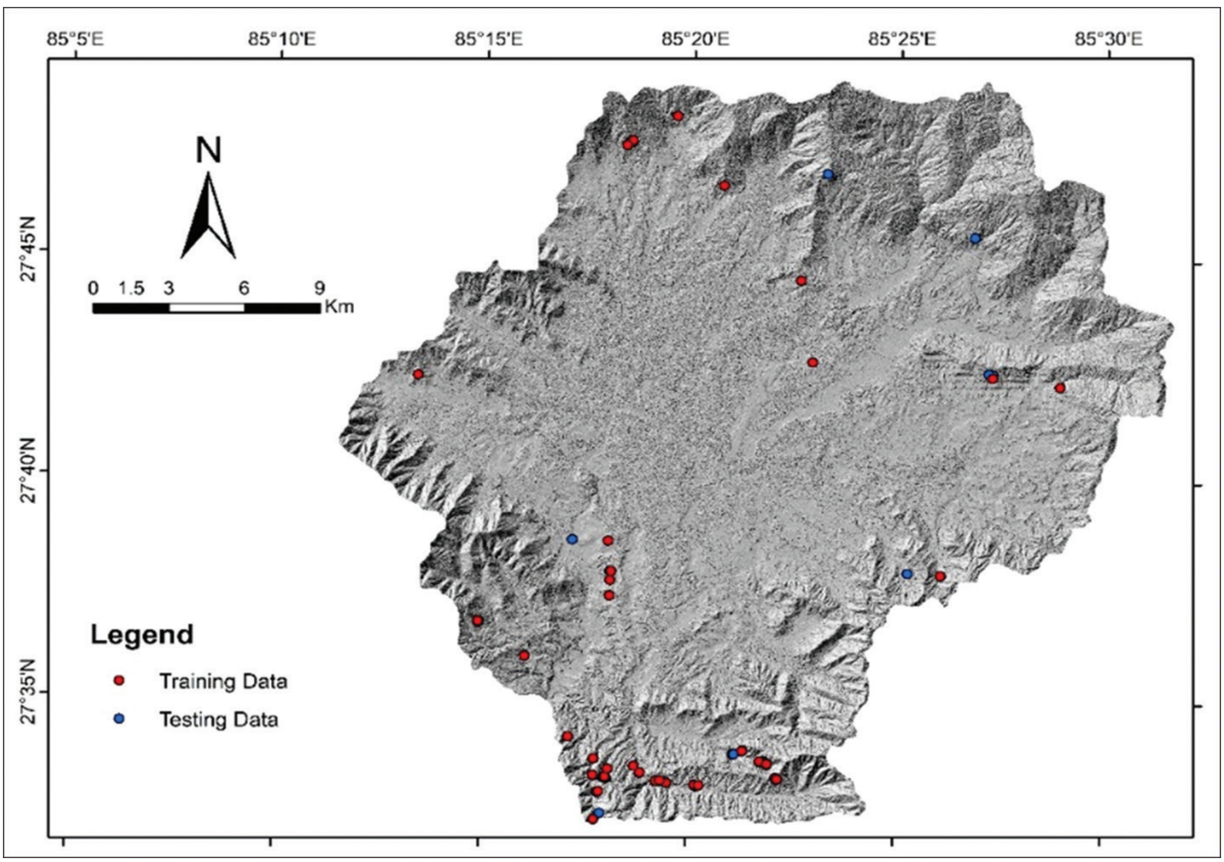


Figure 6: Training and Testing data for Model Validation

4. Results

The results derived from landslide susceptibility mapping of Kathmandu basin show that the regions in south, south-east, and south-west are highly susceptible to landslides as compared to others. Furthermore, the central region with low elevation and slope is less susceptible to landslides.

4.1 Landslide susceptibility mapping and distribution

After calculating the weightage of the individual classes and total rank of the predisposing factors, Landslide Susceptibility Index was calculated for the three models, by multiplying each thematic map with their weightage and adding them in raster calculator. The reclassification of resulting Landslide Susceptibility Indices were carried out using natural breaks method to create a map for landslide susceptibility (Figure 6).

In case of FR method, 49.15% of the total area fall under low susceptibility (316.00 km^2), followed by 37.96% (244.07 km^2) in medium susceptibility, and 12.89% (82.89 km^2) in high susceptibility. Furthermore, the susceptibility in information value method determined that 27.71% of the area had low susceptibility (178.15 km^2), followed by 44.55% (286.46 km^2) in medium susceptibility, and 27.74% (178.35 km^2) in high susceptibility. The results of Heuristic method were found to be closer to the IV method, with 25.48% of the total area under low susceptibility (163.85 km^2), 46.17% (296.84 km^2) in medium susceptibility, and 28.35% (182.27 km^2) in high susceptibility (Figure 7).

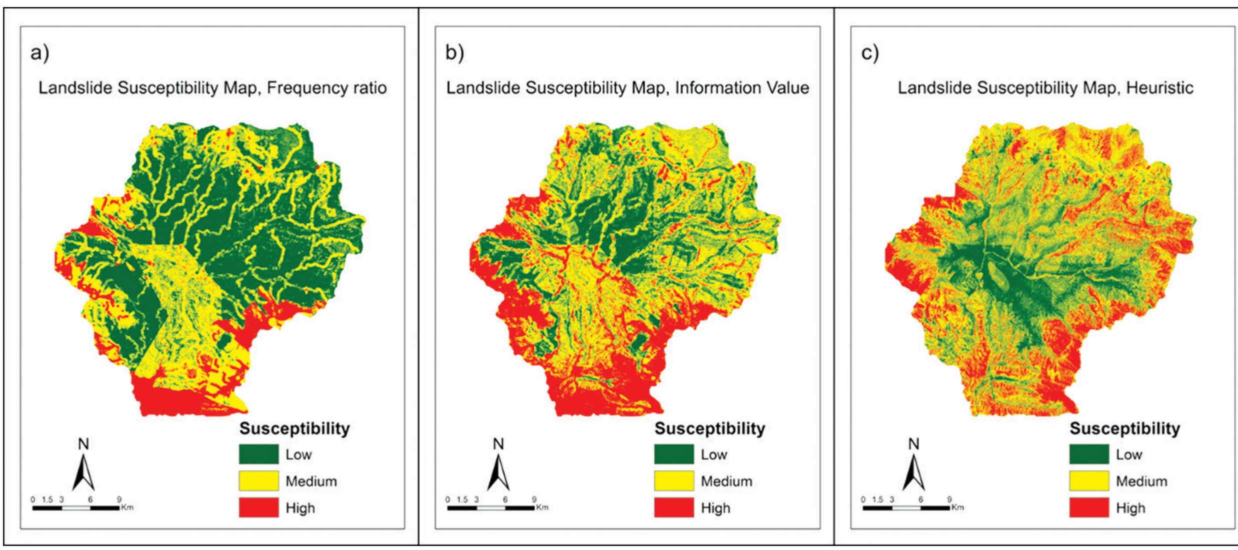


Figure 7: Landslide susceptibility map using (a) frequency ratio method; (b) information value method; (c) Heuristic method

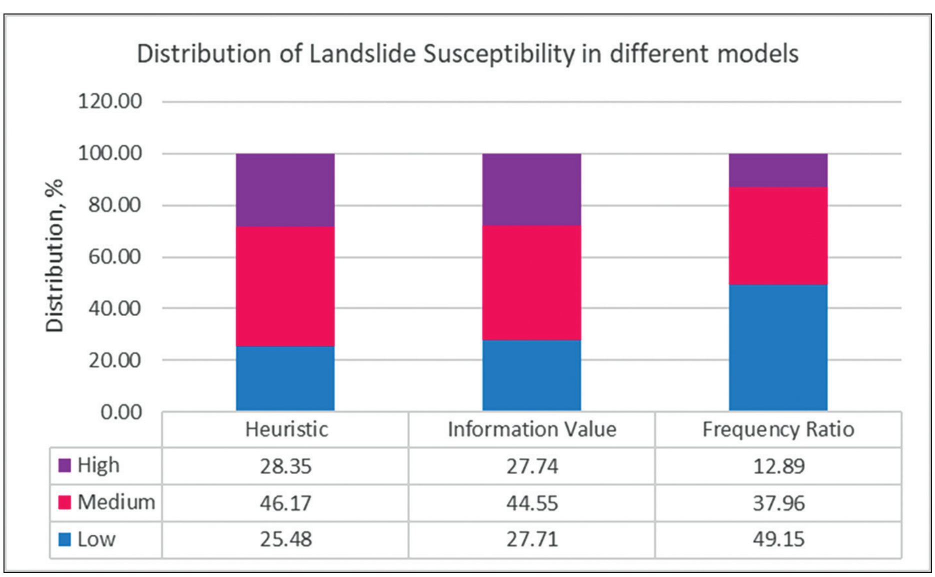


Figure 8: Distribution of landslide susceptibility in different models

4.2 Comparison and validation of susceptibility models

Comparing the results, it is seen that the susceptibility map produced by Heuristic method is closer to that by information value than frequency ratio method, which can be seen in Figure 7. The area lying in low susceptible zone are 25.48 and 27.71 percent in heuristic method and IV method respectively, which are close values as compared to 49.15 percent of FR method. The FR and IV approaches indicated that rainfall had highest influence or weightage in the area while aspect had the lowest. In case of Heuristic, the slope, geology, and vegetation index had a high influence, while aspect, curvature, and distance to drainage had a low influence.

Furthermore, the AUC values under success rate curve and predictive rate curve for Information value method were obtained as 81.43% and 78.37% respectively. Similarly, the AUC values under success rate curve and predictive rate curve for Frequency ratio model were obtained as 70.16% and 61.9% respectively as shown in Figure 8. While the values for both methods are within the acceptable range, it is seen than information value method has provided a higher value in both success and predictive rate. Therefore, it gives a more accurate and reliable result than frequency ratio method.

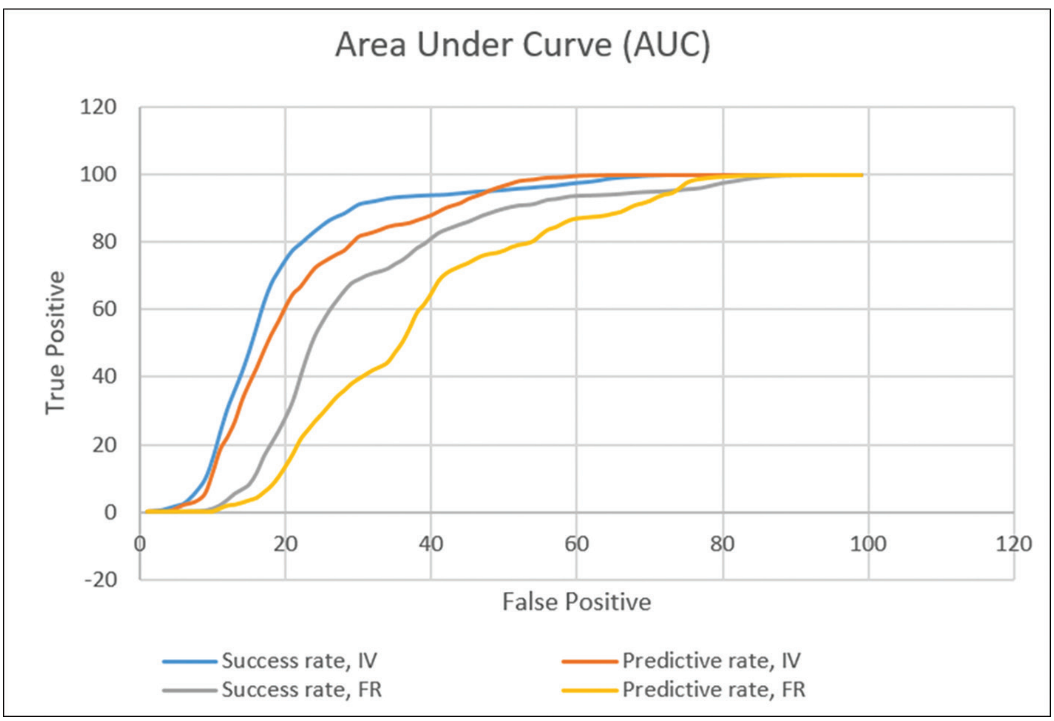


Figure 9: Success and Predictive rate curves for IV and FR methods

5. Discussion

Based on the susceptibility results, the majority of the area lies in medium and high susceptibility zones (74.52% in Heuristic, 72.59% in IV, and 50.85% in FR). The values of Heuristic and IV are considerably higher as compared to previous study conducted by Khatakho et al. (2021), where the medium, high, and very high areas cover 60% of the valley. In order to generate a more accurate representation of the susceptibility zones, the hill slopes can be solely considered in the study. Since the landslides primarily occur on such areas, disregarding the flat lands in the central part of the valley can help reduce discrepancies in the results.

The high susceptible areas are concentrated in the southern and south-eastern region of the basin, while the low susceptible areas are spread in the northern and north-west region around Baneshwor, Thimi, and Patan areas where the elevation is relatively lower. The distribution of susceptibility can be attributed to several reasons and predisposing characteristics of the area. Since the south-facing slopes in the area are typically steep, rain-bearing wind, exposure with sun rays, the majority of the landslides are located on the south-east, south, and south-west.

The south and SE slopes have a gentle steep topography, and usually lie on the windward side. Similarly, the areas with slope from 50 to 70 degrees have been observed to be more susceptible to landslides, closely followed by the slopes with 30 to 50 degrees. The shear stress increases in soil or other unconsolidated elements as slope increases, and the downhill component of force is greater on steeper slopes (Cellek, 2022). However, as the slope approaches 90 degrees and becomes nearly vertical, the gravitational forces that act on the soil are almost perpendicular to the slope surface, which increases slope stability. The regions with geological formations of the Phulchoki group (Tistung formation, Sopyang formation, Chandragiri formation, and Chitlang formation) are moderate to highly susceptible areas, which can be attributed to their weakly metamorphosed composition (Acharya & Paudyal, 2019). The forest areas and cropland have high number of landslide occurrences, which is evident from the lack of vegetation increasing the susceptibility to the landslides.

The areas with negative or concave curvature appear to have a higher susceptibility than the positive curvature areas, although the difference is small. This result is comparable to the study conducted by Ohlmacher (2007) in northeastern Kansas, where the hillsides concave areas had a marginally higher probability of landslide than the convex areas. The study further discusses that water flow is directed to the hollows where curvature is concave, increasing the soil's moisture content as well as the time the soil is saturated. This results in a decreased soil stability and an increased soil erosion. In relation to the distance the drainage, landslide appearances are increasing as the distance from stream is increased the landslide occurrence is highest as the distance is more than 500 meters. The distance to rivers is a risk factor for landslides, and influential in landslide susceptibility mapping as saturation degrees of the components strongly influence slope stability (Thapa & Adhikari, 2019). A similar case is found in case of the distance to road, in which the frequency of landslides occurring is highest where the distance is more than 500 meters. Relative relief is also an essential factor in determining whether the study area is susceptible to landslides or not. Landslides are more common at higher elevations because higher elevations have heavier rainfall and a faster rate of weathering, both of which generate unstable surfaces.

The success rate of FR and IV models is in the acceptable range; however, it is lower compared to other studies that have employed these models (Addis, 2023; Sarkar et al., 2013; Wubalem, 2021). This is partly due to the insufficient landslide inventory for the Kathmandu valley. The susceptibility models were chosen based on the data limitations, to provide the most reliable analysis feasible with the available data. In order to obtain more accurate results, the inventory data can be enhanced using high-resolution satellite images such as Landsat and Sentinel-2. Moreover, Heuristic approach is suitable in data-scarce regions. The key benefit of the Heuristic assessment approach is its relative simplicity, where the weightage is not based on historical data, but rather on the influence of each variable class (Shano et al., 2020).

Statistical techniques for LSA are critical for defining the geographical distribution of landslides and how they relate to various landslide influencing factors. With their simplicity and less demand for primary data, they have an advantage over numerical and physical-based models. While they are appropriate in large areas with low availability of geotechnical data, they provide limited to no information regarding the safety factor and ultimately quantitative details on the instability of slopes (Wubalem & Meten, 2020). These bivariate statistical approaches may not be sufficiently reliable or accurate to fulfill the practical requirements. This is because of their inability to assess the complex non-linear interdependence of the elements (Tien Bui et al., 2017). Due to their capacity to handle complicated interactions within datasets, machine learning techniques can be used for determining landslide susceptibility (Sajadi et al., 2022).

6. Conclusions

This study has aimed to perform landslide susceptibility mapping of Kathmandu valley using Frequency Ratio (FR), Information Value (IV), and Heuristic approaches. The areas facing south-east and south directions are more susceptible to landslide. The final susceptibility maps obtained from the three methods were reclassified into three levels; low, medium, and high based on natural break method of classification. The results were obtained as: low (49.15%), medium (37.96%), and high (12.89%) for FR; low (27.71%), medium (44.55%), and high (27.74) for IV; low (25.48%) medium (46.17%), and high (28.35%) in Heuristic. The maps were validated using Area Under Curve (AUC) approach, which revealed that the models are fairly reliable; however, leaving room for improvement. Results from IV method were found to be closer to Heuristic method. The susceptibility maps may be utilized by urban planners, policymakers, and geologists for urban land use planning of Kathmandu valley and implementation of landslide mitigating strategies. Furthermore, vulnerability and factors can be applied to the map to assess the landslide risk of the area.

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