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Landslide susceptibility mapping of a hilly region through a semi-quantitative technique

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ABSTRACT

Characterization of landslide susceptibility carries great importance in hilly regions as it is one of the frequently occurring natural hazards which comes with huge destruction of life as well as property. Identification of such landslide susceptible zones is usually decided based on the necessity and available resources. It is considered a valuable input for planning developmental activities by policymakers. The current study focuses on Pabbar Catchment, located in the state of Himachal Pradesh in India and prepares a Landslide Susceptibility Map (LSM) at a catchment scale using Analytical Hierarchy Approach (AHP). Eleven geo-morphological attributes of the catchment called causative factors were used in thematic form while creating the LSM. Being a semi-quantitative method, AHP performed satisfactorily to produce a realistic distribution of landslide susceptibility with a prediction accuracy of 0.768 under the Area Under Curve (AUC) technique. Approximately 72% of the geographical area from the catchment falls under the 'high' landslide susceptible zone. Unavailability of LSM at this scale is addressed through this study that may be useful to regional planners for future land use planning.

KEYWORDS

Landslides; AHP; LSM; causative factors; AUC; semi-quantitative

Introduction

Landslides are one of the destructive natural hazards that occurs in mountainous regions very often causing huge damage to property as well as life (Panchal and Shrivastava 2022). The occurrence of landslides can be attributed to several natural as well as anthropogenic activities (Sonker et al. 2021). The natural sources include numerous causative factors like slope, geology, Land use land cover pattern, etc., and a few triggering factors like rainfall and earthquake. The other category includes activities like road construction, deforestation, change in land use and land cover.

The demand from the ever-increasing population leads to an increase in settlements (El Jazouli et al. 2019). Hence, the identification of landslide-prone areas carries importance, specifically in hilly regions (Fan et al. 2019; Roy and Saha 2019). Landslide Susceptibility Map is one of the efficient ways to recognize the spatial distribution of these locations (Wang and Li 2017).

There are several techniques available to prepare a landslide susceptibility map which is positioned under three primary categories i.e. qualitative, quantitative and semi-quantitative approaches, well-summarized in literature (Panchal and Shrivastava 2022). The qualitative approach is subjective as it weighs on expert opinion and subsequent weightage assignment (Sila-lahi et al. 2019). However, the quantitative approach relies on a mathematical relationship between the causative factors and the occurrence of landslides (Budimir et al. 2015). The semi-quantitative

approach that includes techniques like Analytical Hierarchy Process (AHP), Analytic Network Process (ANP) is a combination of the above-mentioned two approaches and performs well as reported in earlier studies (Kayastha et al. 2013; Wang and Li 2017; Singh and Kumar 2018; Leonardi et al. 2022). The use of Geographical Information System (GIS) in an efficient manner, due to the availability of high-resolution spatial and temporal data has certainly added advantage to the prediction accuracy (El Jazouli et al. 2019).

Frequency Ratio (FR) is one of the very widely used techniques to prepare landslide susceptibility maps. Mersha and Meten (2020) used the FR technique and the Weights of Evidence (WoE) method to prepare Landslide Susceptibility Maps (LSM) for the Simada area in North-western Ethiopia. The prediction accuracy was found to be 88.2% and 84.8% for FR and WoE approaches respectively. Silalahi et al. (2019) used the FR method to create a susceptibility map of Bogor, Indonesia area with a prediction accuracy of 87.30%. Kannan et al. (2015) used the Bureau of Indian Standard (BIS), multi-criteria analysis (MCA), and frequency ratio model for preparing the landslide zonation map of Bodi-Bodimettu Ghat section, Theni District of Tamilnadu state and found the low hazard and moderate hazard zones seem to merge to indicate one single zone. Shano et al. (2021) prepared a landslide susceptibility map of Gamo highland, South Ethiopia using the Frequency Ratio method and achieved 82% accuracy. A few other examples of the FR technique are (Pradhan 2010; Park et al. 2013; Regmi et al. 2014).

Logistic Regression (Polykretis and Chalkias 2018), Bivariate models (Shahabi et al. 2013; Kavzoglu et al. 2015; Ram et al. 2020), Multivariate models (Sarkar et al. 2013; Akgun and Erkan 2016) are reported with satisfactory results. The accuracy of the quantitative approaches is higher in comparison to the qualitative approaches. However, it depends on the availability of verified landslide inventory. The semi-quantitative approach like AHP, which is a combination of both qualitative and quantitative approaches is an ideal technique to prepare reliable landslide susceptible maps. A few of the successful attempts made by researchers are appended below.

Panchal and Shrivastava (2022) prepared the landslide hazard map using AHP for a section of National Highway 5 in Himachal Pradesh. The prediction rate was found to be 0.825 with 79% of the landslides falling in the high and very high landslide hazard zones. The performance of the model may be considered as good. The accuracy assessment of the AHP model came out as 73% when Sonker et al. (2021) used this in integration with GIS to identify the landslide-prone zones in Sikkim, India. The landslide vulnerability map of the Oum Er Rabia high basin created using the AHP method by El Jazouli et al. (2019) produced satisfactory results with 76.7% accuracy. Kayastha et al. (2013) used the AHP method for the Tinau watershed, Nepal for landslide susceptibility map preparation and found agreement with past landslide occurrences. Leonardi et al. (2022) use the AHP technique to prepare a landslide susceptibility map for the Reggio Calabria metropolitan city, South of Italy and obtained satisfactory results. Kumar and Anbalagan (2016) used the AHP method for the rim region of the Tehri reservoir to prepare a susceptibility map with 78.7% validation accuracy. In another study, the AHP, the statistical index (W_i), and weighting factor (W_f) methods were used to produce and later compare three susceptibility maps where the AHP method produced a realistic landslide susceptibility map (Yalcin 2008). Intarawichian and Dasananda (2010) used AHP and WLC approach to prepare a landslide vulnerability map of the Mae Chaem Watershed in the north of Thailand and achieved 64.9% accuracy for the AHP method. Roy and Saha (2019) used Fuzzy – Landslide Numerical Risk Factor (LNRF) and AHP to create a landslide susceptibility map of Darjeeling District, West Bengal, India. The Fuzzy-LNRF model produced better results (91%) than AHP (90%) for the study.

A few other techniques reported in the literature are discussed below. Huang and Zhao (2018) used Support Vector Mechanism (SVM) and compared the results with AHP, Logistic Regression, ANN and Random Forest methods while creating the landslide susceptibility map for Sichuan Province in China. Lin et al. (2017) created a landslide casualties threshold value curve using the landslides that occurred during the years of 2003–2014 in China, which matched the real estimates. The weighted Linear combination (WLC) method was applied to create the landslide vulnerability map

of the Simbu Province, Papua New Guinea which produced satisfactory results. Anbalagan et al. (2015) applied the fuzzy logic relationship and fuzzy operation to prepare the landslide hazard zonation map of the Sikkim area that yield encouraging results. Nayak (2010) used the landslide inventory map and its magnitude to do a landslide hazard assessment and probability assessment for NH-108 in Uttarakhand State in India. Budimir et al. (2015) summarized the studies conducted to estimate the probability of landslide occurrence using logistic regression on a global scale by establishing the 'slope' as the most important parameter for it.

The literature indicates that the AHP is a competent method that produces satisfactory results when used for mapping the landslide susceptibility zones irrespective of the location. The current study presents the application of the Analytical Hierarchy Process (AHP) to prepare a Landslide Susceptible Map for the identified study area which was less documented. Preparation of the landslide susceptibility map provides first-hand information of the study area which can be used as an effective tool by regional planners as it demonstrates the degree of susceptibility of the area at a micro scale concerning landslide occurrence. As the method used in this study is independent of the study area, it can be used as a fundamental tool for landslide hazard assessment and mitigation strategy.

Study area and data

The identified area for the current study is the Pabbar catchment (Figure 1) in Himachal Pradesh, India. The geographical spread of this area is 77°77'98.73"E to 77°77'89.60"E longitudes and 31°20'86.37"N to 31°20'85.26"N latitudes. The study area falls in the Survey of India (1:50,000) toposheets numbers 53E/15, 53E/16, parts of 53E/14 and 53F/13. The geographical area of the catchment is 1234 km². The average annual precipitation in and around the catchment is approximately 1500 mm. The topography of the region is rugged and has a steep slope. The elevation varies from 1300 m to 4638 m. The minimum temperature is observed during January and it goes as low as 2° centigrade. The maximum temperature is observed during June and it is approximately 25° centigrade. The water holding capacity of soil is poor as the maximum soil is of argillaceous origin. Demographically, Rohru, Hatkoti, Chirgaon and Jubbal are a few of the major towns in the catchment. Rohru is one of the Municipal committees of the Shimla District in Himachal Pradesh. As per Census 2011, Rohru has a population of approximately 50,000 and the majority of them live in the rural area. Rohru has a population density of 213 inhabitants per square kilometer.

Bhukosh of Geological Survey of India (GSI), satellite Imagery and field surveys are the sources from where the required data were collected. The prepared landslide inventory presents the spatial distribution of all the landslides occurred in the region between 2013–2020. The attributes of the landslides derived from the inventory are used in the study while preparing the landslide susceptibility map. The dimension of the landslides was found to be varying between 30m² to 39000m². With Majority of the landslides are shallow translational in nature consisting of debris flow with rapid movement. The second most type of landslides observed is rock fall. The primary reason for most of the landslides may be attributed to the oversaturation of the formation during the monsoon season triggering the slide. In most of the cases, quartzite is the geological formation. The Digital Elevation Model (DEM) was obtained from ALOS PALSAR dataset with 12.5 m spatial resolution which is further used to create maps of slope, curvature, aspect and relief. The data of geology, land use and land cover (LULC), soil and lithology were collected from GSI, SOI and FAO which were finally converted into thematic layers. A few glimpses of landslide occurrences in the study area are shown in Figure 2.

Methodology

Causative factors

A landslide is a multifaceted phenomenon that involves a lot of geomorphological features. These attributes may be placed under the following categories like DEM derived attributes, drainage and

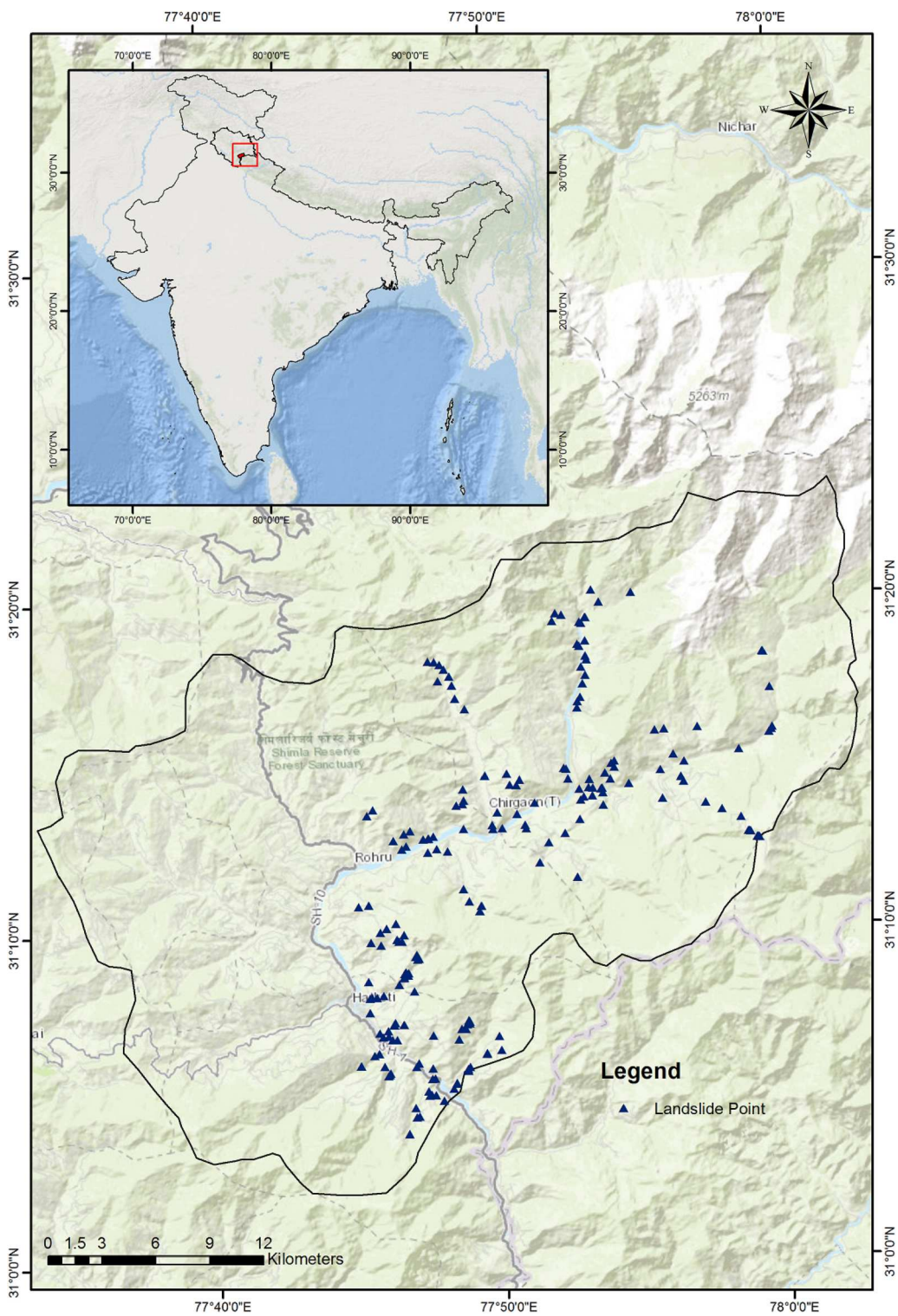


Figure 1. Location of the study area along with Landslide Inventory.



Figure 2. Instances of landslides in the study area.

lineament attributes and geological attributes (Panchal and Shrivastava 2022). There are eleven such attributes identified and pertaining data was collected based on availability at the required scale. The details of these factors are mentioned below.

Slope

The degree of slope is one of the vital factors that cause landslides. The steepness of the slope is directly proportional to the probability of landslide occurrence (Lee and Min 2001). The nature of the soil, LULC and steepness influence the instability of soil mass. A steep slope is observed in the study area. The thematic map is shown in Figure 3 (a).

Distance to faults

The faults present in the study area are primarily due to the formation of Himalayan Mountain ranges. The relatively young age of the geomorphology of the Himalayan region aids the occurrence of landslides. A buffer zone was created and shown in the form of a layer in Figure 3 (b).

Distance to road

Construction of roads involves cutting of natural slopes and installation of heavy structures which affects the slope stability. The distance to roads is estimated using Euclidean distance in a GIS setup. A buffer layer was created while estimating the distance [Figure 3 (c)]

Land use land cover (LULC)

The study area is divided into 5 classes of LULC namely forest (241), agricultural lands (65), water bodies (21), Settlement (46) and barren lands (78) considering the above-mentioned sample sizes. The forest forms 50% of the catchment followed by barren land. Landsat 8 images are used for creating the thematic map [Figure 3 (d)]. The overall accuracy of the dataset was found out to be 79.06%. 70% of the samples were used for training purpose while rest 30% were used for testing (Shetty et al. 2021).

Aspect

Aspect represents the direction of the slope. It affects the exposure of the sun, the nature of erosion and the flow of water (Singh and Kumar 2018). Aspects are grouped into 9 classes such as flat (-1°), north ($337.5^\circ - 360^\circ$, $0^\circ - 22.5^\circ$), northeast ($22.5^\circ - 67.5^\circ$), east ($67.5^\circ - 112.5^\circ$), southeast ($112.5^\circ - 157.5^\circ$), south ($157.5^\circ - 202.5^\circ$), southwest ($202.5^\circ - 247.5^\circ$), west ($247.5^\circ - 292.5^\circ$), and northwest ($292.5^\circ - 337.5^\circ$). The thematic layer of it is shown in Figure 3 (e).

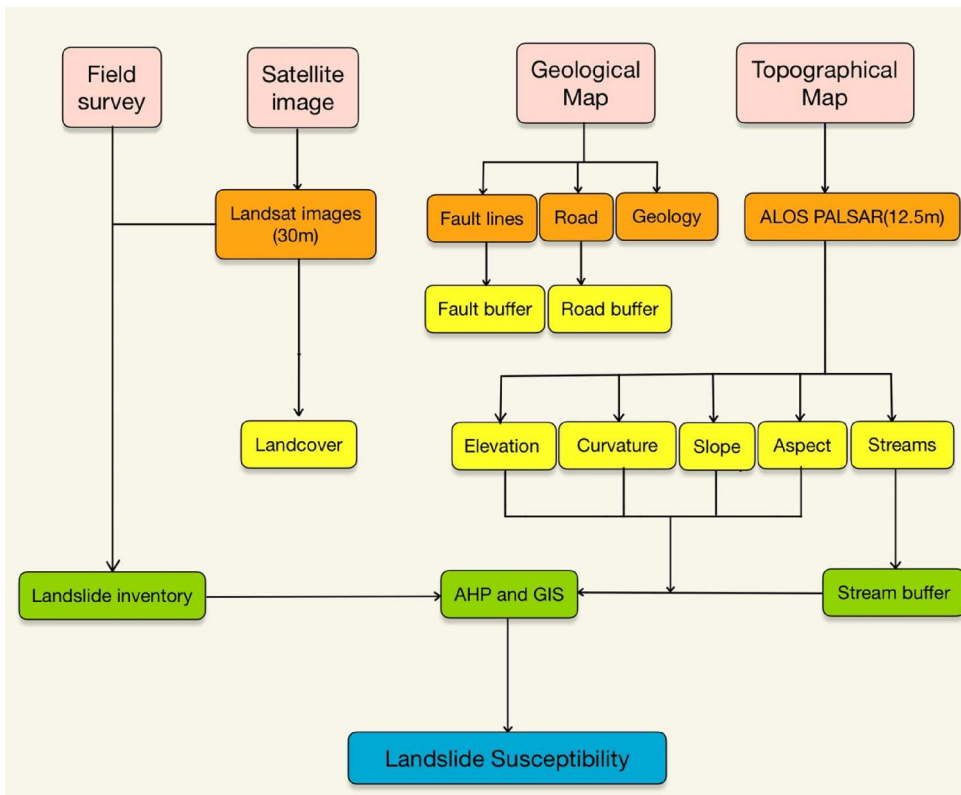


Figure 3. Flow chart of the AHP method.

Distance to rivers

The main stream present in the study area is the Pabbar River. It starts from Dhauladhar Range and falls into River Yamuna. The length of the river in the catchment is 62 km. The distance to the rivers and other small streams is presented in the form of a thematic map [Figure 3 \(f\)](#)

Elevation

The elevation of the catchment varies between 1300 m to 4638 m. The DEM was used to estimate the magnitudes and presented in form of a thematic layer in [Figure 3 \(g\)](#).

Plan curvature

The intersection of a random plane with the surface of the earth is called curvature (Ohlmacher 2007). Curvature is the rate of change of slope or slope of slope i.e. a second derivative of the surface. A negative and positive value represent concave and convex surfaces respectively. It will be a plane surface if the value is zero. The flow action of water is indirectly represented by curvature, specifically in landslide-prone regions. The thematic map is shown in [Figure 3 \(h\)](#).

Lithology

Lithology [[Figure 3 \(i\)](#)] in and around the study area is divided into 32 classes by GSI, which is obtained from Bhukosh. Lithology consists of Sillimanite – kyanite bearing schist, quartzite, leucocratic granite, aplite, quartz veins Bed rock classification which is most affected due to landslides.

Topographic wetness index (TWI)

TWI is an indicator of the moisture content of the soil. It gives a measure of water holding capacity (Mattivi et al. 2019). Mathematically TWI can be expressed as.

$$TWI = \ln \left(\frac{SCA}{\tan \varphi} \right) \quad (1)$$

Where SCS is the specific catchment area and φ is the slope angle. Flow accumulation area per unit width of the contour is SCS. Keeping the properties of soil, SCS explains the tendency to hold water, while, the slope angle suggests draining. The thematic layer is presented in Figure 3 (j).

Normalized difference vegetation index (NDVI)

NDVI is a very widely used indicator that represents the health of the vegetation. A higher NDVI value suggests healthy vegetation cover which offers better slope stability (Nohani et al. 2019). NDVI is calculated using the Near Infrared (NIR) and Red (RED) band using the following equation.

$$NDVI = \left(\frac{NIR - RED}{NIR + RED} \right) \quad (2)$$

A thematic map [Figure 3 (k)] is prepared and categorized into 5 classes.

Analytical hierarchy process (AHP)

Among the many Multi-Criteria Decision Analysis (MCDA) methods, Analytical Hierarchy Process (AHP) is the one used for the present study taking into account its success in estimating the landslide-susceptible areas reported in the literature. It is a tool that uses simple criteria to take decisions related to complex problems. The three primary steps followed by AHP include the disintegration of the problem, comparative assessment and analyze the importance of factors through ranking (Saaty 1980; Panchal and Shrivastava 2020). AHP breaks multifaceted decision-making scenario into a hierarchy of factors and alternatives. Weights are assigned to these factors and alternatives on a nine-point ordinal scale (Table 1) by virtue of a pair-wise comparison between them. Factors or their classes are organized in the form of matrix which contains same number of rows and columns, where scores are logged on one side of the diagonal, while values of 1 are placed in the diagonal of the matrix (Saaty 1980; Gorsevski et al. 2006; Kumar and Anbalagan 2016). Professional knowledge inspires pair-wise comparison and judgement score. Relative value of each pair of the factors was assigned on the basis of expert knowledge of the region and presence of landslide in those classes. The value varies between 1 and 9 when the parameter mentioned in the vertical axis is more important than the horizontal axis. The value varies between $\frac{1}{2}$ and $\frac{1}{9}$ when the scenario is inverted (Yalcin 2008).

Table 1. Scale for Pair-wise matrix in AHP.

Scales	Degree of preference	Explanation
1	Equally	Two activities contribute equally to the objective
3	Moderately	Experience and judgment slightly to moderately favor one activity over another
5	Strongly	Experience and judgment strongly or essentially favor one activity over another
7	Very Strongly	An activity is strongly favored over another and its dominance is showed in practice
9	Extremely	The evidence of favoring one activity over another is of the highest degree possible of an affirmation
2,4,6,8	Intermediate values	Used to represent compromises between the preferences in weights 1, 3, 5, 7, and 9
Reciprocals	Opposites	Used for inverse comparisons

The ranking of the selected criteria is estimated through the Eigenvector technique and estimation of maximum eigen value is also a part of AHP. This is further validated using the Consistency Ratio (CR) Indicator (Saaty 1980). The CR is estimated as follows:

$$\text{Consistency Ratio (CR)} = \frac{\text{Consistency Index (CI)}}{\text{Randomness Index (RI)}} \tag{3}$$

$$\text{Where Consistency Index (CI)} = \frac{\lambda_{max} - n}{n - 1} \tag{4}$$

λ_{max} is the major eigenvalue and n is the order of the matrix. The values of RI are suggested by (Saaty 1980) which depends on n presented in Table 2. The comparison is deemed consistent if the CR value is less than 10%. Otherwise, the weights need to be reallocated. The value of 0 indicates perfectly consistent comparison. One of the major drawbacks of subjective decision-making process is that the relative score given by a person may not get the acceptance by others. Nonetheless, pair-wise comparison delivers a simple and satisfactory decision rule. In studies like landslide susceptibility, some factors have a certain degree of reliance on influencing landslides. However, AHP considers all factors present in hierarchy as an independent unit. For instance, a relatively moderate slope can fail due to rise in the moisture content of soil but then again in AHP system, moderate slope will be given smaller weightage compared to high slope class. However, the flexibility AHP provides in making a simple decision makes it one of the widely used technique for landslide susceptibility analysis. It can also seamlessly get integrated to GIS setup. The weightage assigned to the responsible factors is mentioned in Table 3. A flowchart of the AHP is depicted in Figure 4.

The Landslide Hazard Index (LHI) is computed using the following equation.

$$\begin{aligned} LSI_{AHP} = &[(\text{Slope} \times W_{AHP}) + (\text{Distance to Faults} \times W_{AHP}) + (\text{Distance to Road} \times W_{AHP}) + \\ &(\text{LULC} \times W_{AHP}) + (\text{Aspect} \times W_{AHP}) + (\text{Distance to River} \times W_{AHP}) + (\text{Elevation} \times W_{AHP}) + \\ &(\text{Plan Curvature} \times W_{AHP}) + (\text{Lithology} \times W_{AHP}) + (\text{TWI} \times W_{AHP})] + (\text{NDVI} \times W_{AHP}) \end{aligned} \tag{5}$$

Results and discussion

To prepare the landslide Susceptibility Map of the study area, Analytical Hierarchy Process (AHP) was used. The landslide inventory map along with the thematic maps of the causative factors (Figure 4) was prepared using the data collected from GSI Bhukosh and field visits.

A total of 198 landslides were spotted during the process, of which 70% was used for training and the rest 30% was used for validation purposes during the simulation. The impact of identified causative factors was analysed using the AHP technique and its consistency was checked at the end. The consistency ratio which was obtained by the highest Eigenvalue and randomness index is kept below 10%. The details of the pair-wise comparison matrix are mentioned in Table 3. The weightage assigned to each causative factor along with the CR is presented in Table 4.

Among all the causative factors considered for this study ‘distance from roads’ had the uppermost influence on the occurrence of the landslides with a weightage of 0.648 followed by ‘distance from rivers and the ‘Lithology’ factor with a weightage of 0.418 and 0.263 respectively.

Slope, being one of the major causative factors on which the occurrence of landslide depends, was analyzed through the prepared thematic map. Approximately 85% of the study area falls

Table 2. Randomness Index (RI).

Number of Criteria	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.0	0.0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.58

Table 3. Pair-wise comparison Matrix of the identified causative factors.

	Slope	Distance to Faults	Distance to Road	LULC	Aspect	River	Elevation	Plan Curvature	Lithology	TWI	NDVI	Priorities
Slope	1											0.023
Distance to Faults	3	1										0.086
Distance to Roads	5	4	1									0.233
LULC	2	3	0.33	1								0.074
Aspect	2	0.25	0.2	0.5	1							0.039
Distance to Rivers	3	0.5	0.25	3	4	1						0.090
Elevation	2	0.33	0.2	0.33	2	0.25	1					0.045
Plan Curvature	3	0.25	0.17	0.5	0.5	0.33	0.33	1				0.035
Lithology	5	2	0.5	4	5	5	7	7	1			0.194
TWI	2	0.33	0.14	0.33	0.33	0.25	0.33	0.33	0.2	1		0.024
NDVI	3	0.5	0.2	0.5	0.5	0.33	0.5	0.5	0.25	2	1	0.036

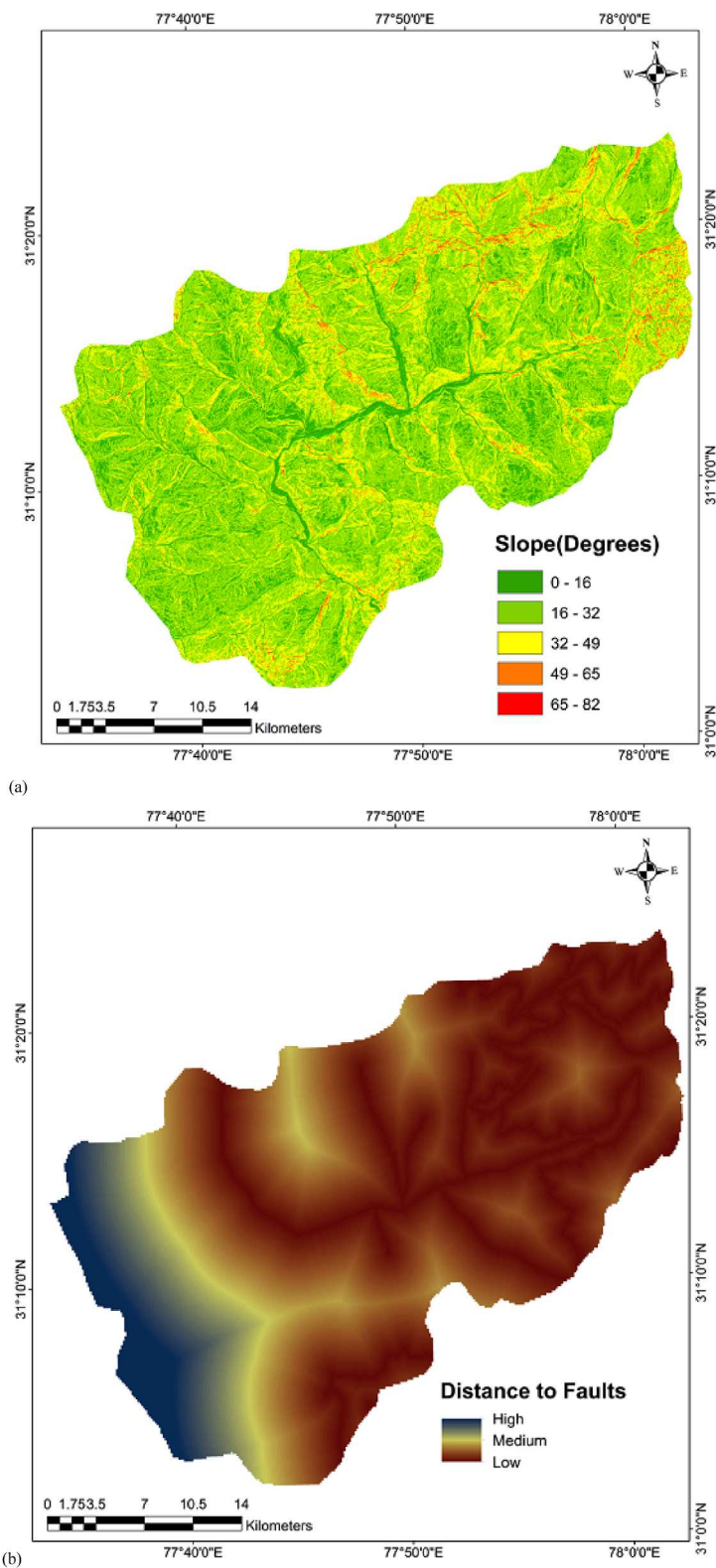


Figure 4. Thematic layers of the causative factors a) slope, (b) geology (c) distance to faults (d) distance to roads (e) LULC (f) aspect (g) distance to river (h) plan curvature (i) lithology (j) TWI and (k) NDVI.

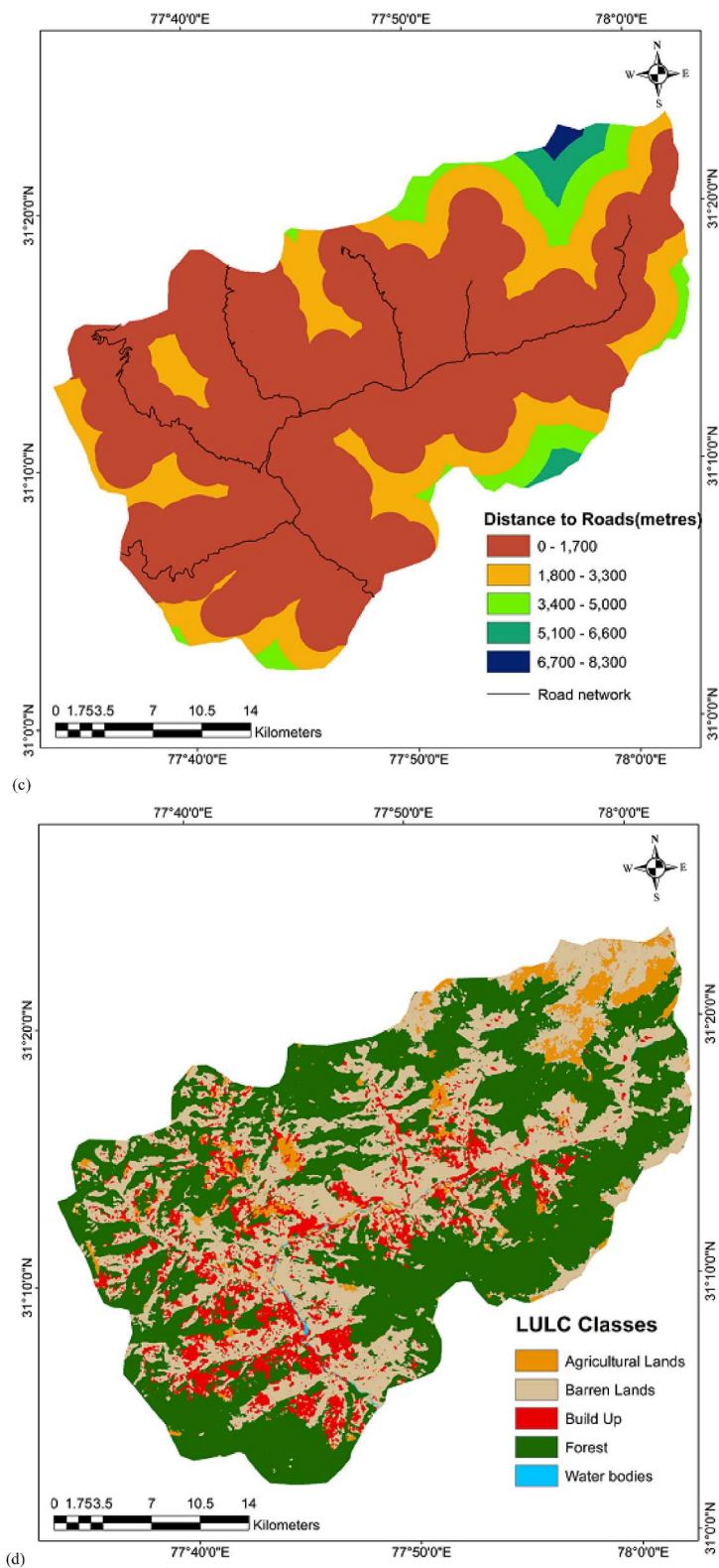


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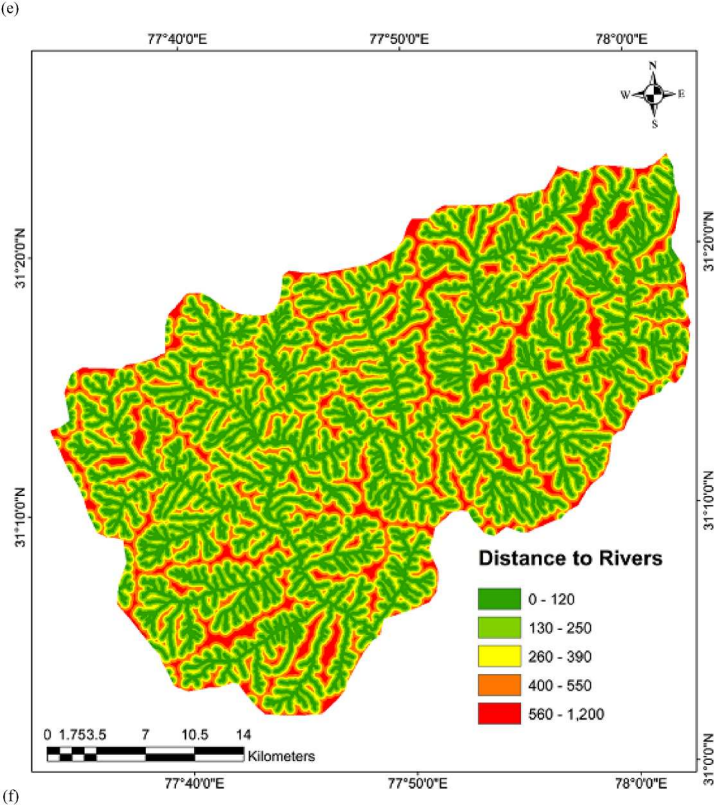
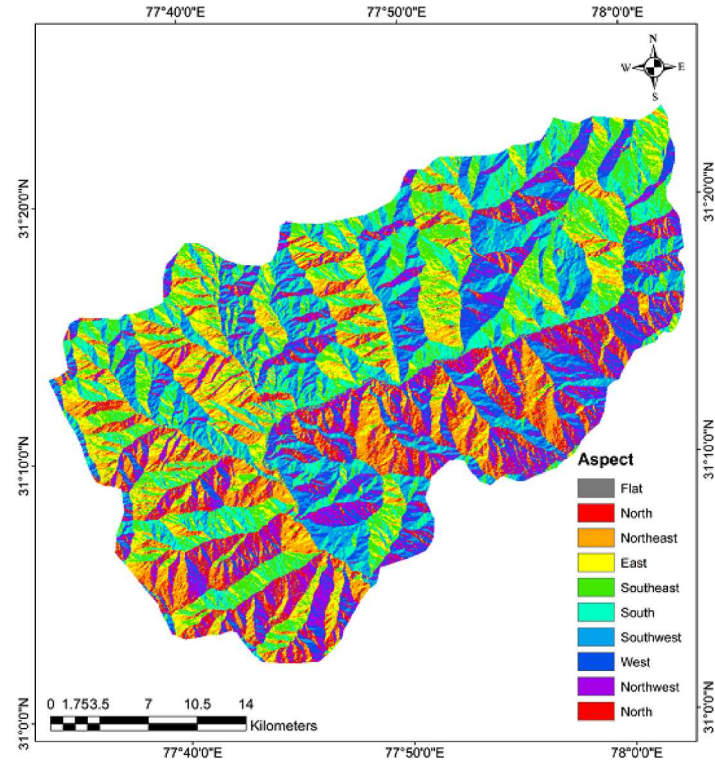


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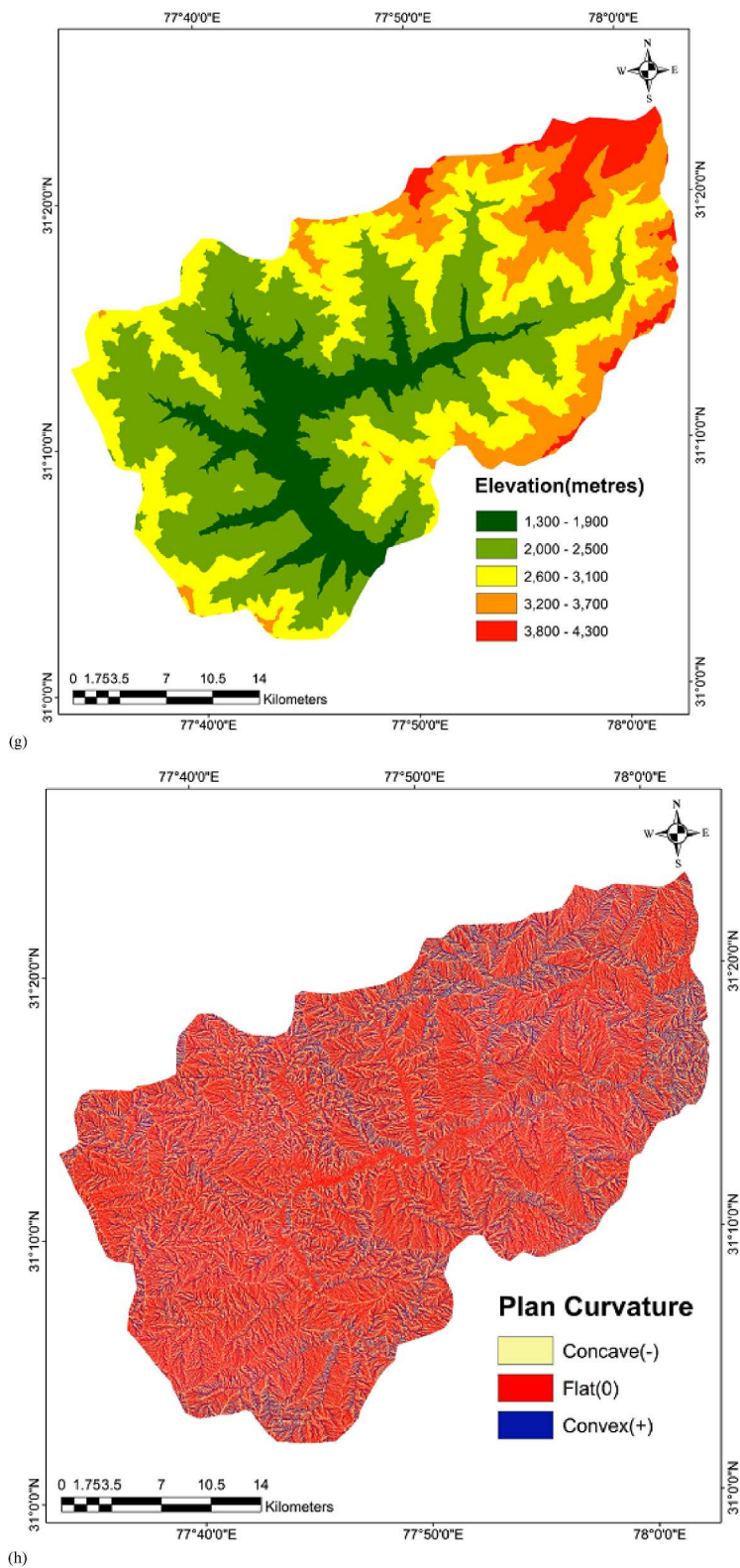


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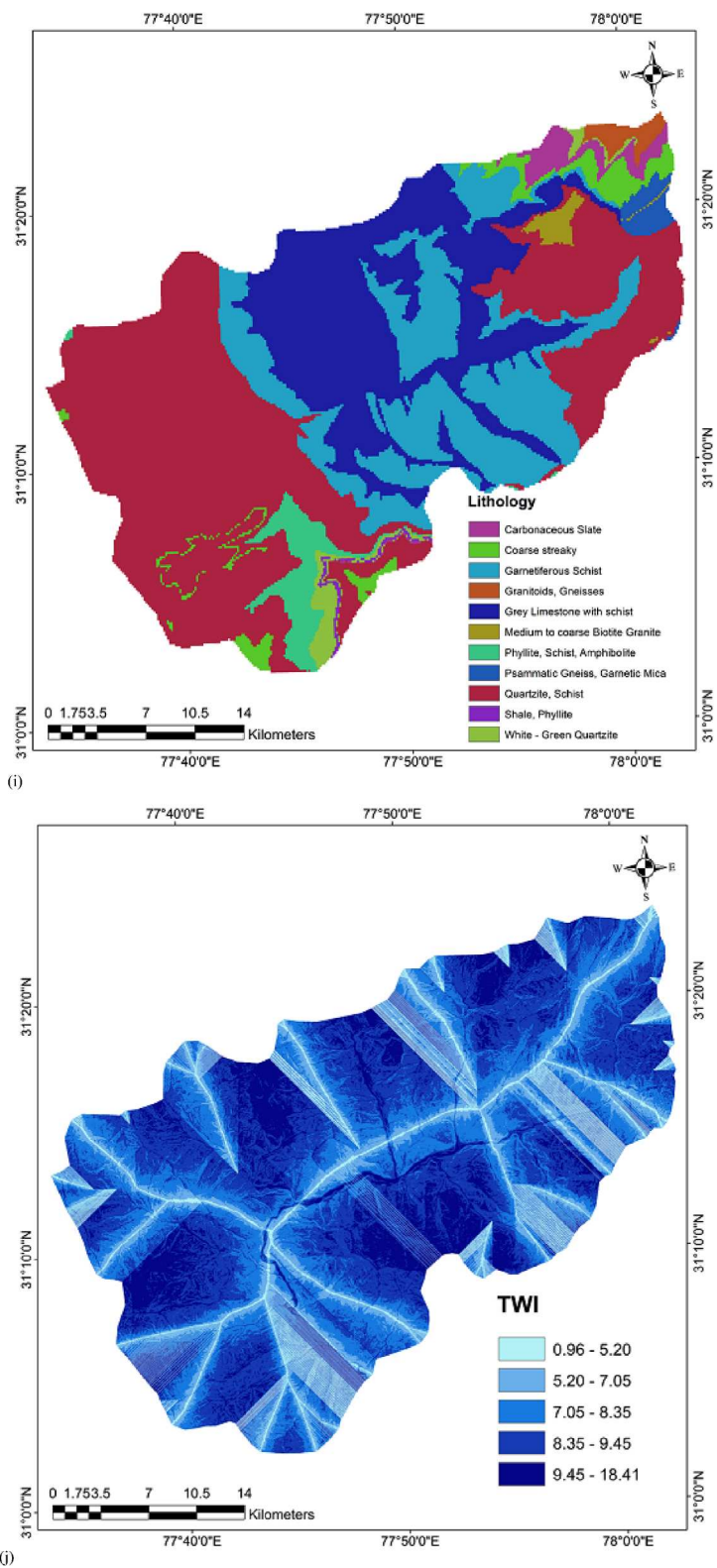


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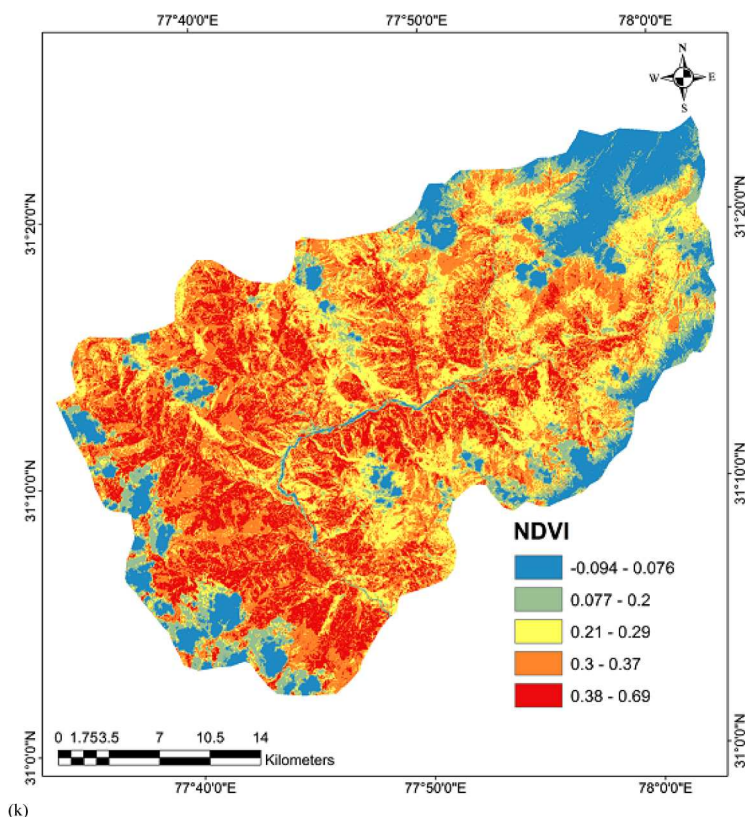


Figure 4. Continued.

under 31° to 65° class and 55.26% of the total landslide events occurred in these regions. This may be manifested to the fact that the weight of the likely transferable material under gravity will be higher in contrast to modest slope angles. Primarily the North-East region of the study area where a majority of these events were reported. 11% of the study area falls under 65° to 80° class and experiences 15.05% of the total landslide events. No landslide was reported or observed in areas having a slope less than 20°.

North, Southwest and West aspect experienced a majority of the landslides that are reported. The probable reason for this may be due to the activities related to road construction and erosion, resulting from rainfall. Approximately 27.2% of the landslides occurred in the Southwest aspect. The north and west aspects have 19.3% and 16% of the total landslides respectively.

The impact of water will be evident on concave surfaces due to erosion (Panchal and Shrivastava 2022). Approximately 34.31% of the total landslides occurred on concave surfaces while the rest 57.5% occurred on a convex surface. The flat surface had no evidence of landslide occurrence. However, some debris flow and erosion observed in flat curvature are due to the flow of water in close proximity with the river.

The elevation of the study area lies between 1300 meters to 4700 meters approximately. 60.51% of all landslides were observed in the 1900m – 3100 m class. Road construction activities are prevalent in this area. 29.16% of the total landslides occurred in class 3100m-3700 m and higher due to rocky soil mass, erosion and steepness of the feature.

Approximately 42% of the total landslides fall in the built-up area in LULC class. It may be due to the cutting of natural slopes for road widening and construction activities. Areas that are in close proximity to water bodies experienced 26.17% of the total landslides. Soil erosion, loose soil mass and low shear strength of the soil might be the probable causes for it. Forest, barren lands and

Table 4. AHP weightage for causative factors.

Causative Factors/Sub-factors		Classes		AHP Weightage	
Slope	0–15	1			0.043
	16–30	7			0.256
	31–50	7	1		0.365
	51–65	3	0.5	1	0.186
	65–80	2	0.333	0.25	0.089
	>80	2	0.2	0.333	0.061
CR		0.047		1	
Aspect	Flat	1			0.024
	North	3			0.048
	Northeast	5	2		0.106
	East	7	3	1	0.160
	Southeast	7	4	3	0.272
	South	5	3	3	0.193
	Southwest	4	2	0.5	0.079
	West	2	2	0.333	0.062
	Northwest	3	3	0.25	0.057
		0.072		0.333	1
	Concave (-)	1			0.343
	Flat (0)	0.2	1		0.082
Plan Curvature	Convex (+)	2	6	1	0.575
CR		0.025			
Elevation	1300–1900	1			0.103
	1900–2500	5	1		0.339
	2500 - 3100	3	0.5	1	0.266
	3100–3700	2	0.333	0.5	0.147
	3700–4300	0.5	0.2	0.333	0.093
	4300<	0.333	0.25	0.5	0.052
CR		0.078		1	
Land Use and Land Cover	Build Up	1			0.422
	Forest	0.2	1		0.054
	Barren Lands	0.25	2	1	0.092
	Agricultural Lands	0.5	4	2	0.172
	Water Bodies	0.25	5	3	0.262
CR		0.077		1	
Distance to roads	Buffer(600 m)	1			0.648
	Buffer(1200 m)	0.333	1		0.230
	>Buffer(1800 m)	0.2	0.5	1	0.122
CR		0.003			

(Continued)

Table 4. Continued.

Causative Factors/Sub-factors		Classes		AHP Weightage	
Distance to rivers	Buffer(100 m)	1			0.418
	Buffer(200 m)	0.5	1		0.250
	Buffer(300 m)	0.333	0.5	1	0.192
	Buffer(400 m)	0.2	0.333	1	0.084
	>Buffer(400 m)	0.2	0.25	0.5	0.056
CR		0.036			
	Low	1			0.096
	Moderate	4	1		0.284
Distance to Faults	High	5	3	1	0.619
		0.075			
CR Lithology	Carbonaceous Slate	1			0.048
	Coarse Streaky	2	1		0.039
	Garnetiferous Schist	5	5		0.263
	Granitoids, Gneisses	2	0.5		0.035
	Grey Limestone with schist	5	5		0.170
	Medium to Coarse Biotite Granite	0.5	2	0.2	0.051
	Phyllite, Schist, Amphibolite	0.5	2	0.2	0.055
	Psammitic Gneiss, Garnetic Mica	0.33	2	0.14	0.030
	Quartzite, Schist	5	4	0.5	0.165
	Shale, Phyllite	2	2	0.25	0.056
	White – Green Quartzite	2	2	0.33	0.087
		0.079			
	0.96 - 5.20	1			0.250
	5.20 - 7.05	2	1		0.368
	7.05 - 8.35	0.5	0.5	1	0.188
CR TWI	8.35 - 9.45	0.33	0.33	0.5	0.113
	9.45 - 18.41	0.5	0.25	0.33	0.081
		0.036			
CR NDVI	-0.094-0.076	1			0.488
	0.077-0.2	0.33	1		0.246
	0.21-0.29	0.2	0.33	1	0.124
	0.3-0.37	0.2	0.25	0.5	0.081
CR	0.38-0.69	0.2	0.33	0.5	0.062
		0.054			

agricultural lands account for 5.37%, 9.15% and 17.16% of the total landslides respectively. The five classes of NDVI suggest a significant portion of the study area lacks healthy vegetation leading to a higher probability of landslides.

Pabbar watershed falls under two eras of geological time scale: – Proterozoic era which spans from 2500 to 538.8 million years and Palaeoproterozoic era which spans from 2500 to 1600 million years. Similar observations were made regarding fault density where more than 62% of the total landslides occurred in low fault-density zones. Moderate fault density zones experienced a handful of landslides.

The slopes beside the roads considered in this study are steep and there is little vegetation cover. The vegetation present is also sparse and offer very little stabilization to the soil mass. Most of the debris flow and landslides were triggered by rainfall. Due to disturbances in natural slopes for road widening activities going on in the Pabbar watershed area, increases slope instability along the roads. 72% of the study area makes up a buffer zone of 600 meters of distance from roads and 64.79% of the landslides occur in this area. 20% of the study area makes up a buffer area of 1200 m buffer zone and accounts for 23% of all the landslides. The remaining 12.22% of the landslide occur in a buffer zone of 1800 m and above which makes up 8% of the study area.

A linear pattern can be observed while analyzing the impact of 'distance from rivers' towards landslide susceptibility. As the buffer zone decreases, the landslide event increases. This means the area where the stream density is high, there is a higher chance of landslide occurrence. 58% of the total area comes under a buffer zone of 100 meters and contributes 41.82% of the landslide events. Buffer zones of 200 , 300 , and 400 m and above contribute 25%, 19.18%, 8.4% and 5.6% of the landslide events respectively.

The landslide hazard index (LHI) is calculated using the following equation with weights assigned to them earlier:

$$\begin{aligned} \text{Landslide Hazard Index (LHI)} = & 0.023 * [\text{Slope}] + 0.086 * [\text{Distance to Faults}] + \\ & 0.223 * [\text{Distance to Road}] + 0.074 * [\text{LULC}] + 0.039 * [\text{Aspect}] + 0.090 * \\ & [\text{Distance to River}] + 0.045 * [\text{Elevation}] + 0.035 * [\text{Plan Curvature}] + 0.194 * \\ & [\text{Lithology}] + 0.024 * [\text{TWI}] + 0.036 * [\text{NDVI}] \end{aligned} \quad (6)$$

The landslide susceptibility map is categorized into five categories using natural breaks i.e. very low, low, moderate, high and very high. It is found that 6% of the total area lies under a very high landslide hazard zone which faced approximately 7% of the total landslides. 72% of the total region lies under the high landslide hazard zone which faced 76% of the total landslide events. 19% of the total study area lies under the moderate landslide hazard zone while it faced only 12% of total landslide events. 2% of the region lies under the low landslide hazard zone and only 4% of the landslides occurred in this region. 2% of the region lies under the very low landslide hazard zone and it accounts for only 1% of the total landslides that occurred in this region. The Landslide Susceptibility Map is shown in Figure 5.

The following phase is to validate the landslide susceptibility regions through the determination of success and prediction rates. The success rate shows how well the model results match past landslide events (Chung and Fabbri 2003; Silalahi et al. 2019). To plot the success rate curve, the index values of all cells of the study area were arranged in descending order and were divided into 256 equal classes ranging from very highly susceptible classes to very low susceptible classes. Ultimately, the success rate curve is a plot between the susceptible classes beginning with the highest values to the lowest values on the X-axis and the cumulative percentage of landslides occurrence on the Y-axis (Silalahi et al. 2019). On the other hand, the prediction rate shows how well the model can detect unknown upcoming landslide events. This curve was prepared using the same procedure as that of the success rate with only one exception where the validation landslide group was used in the calculation instead of the calibration group.

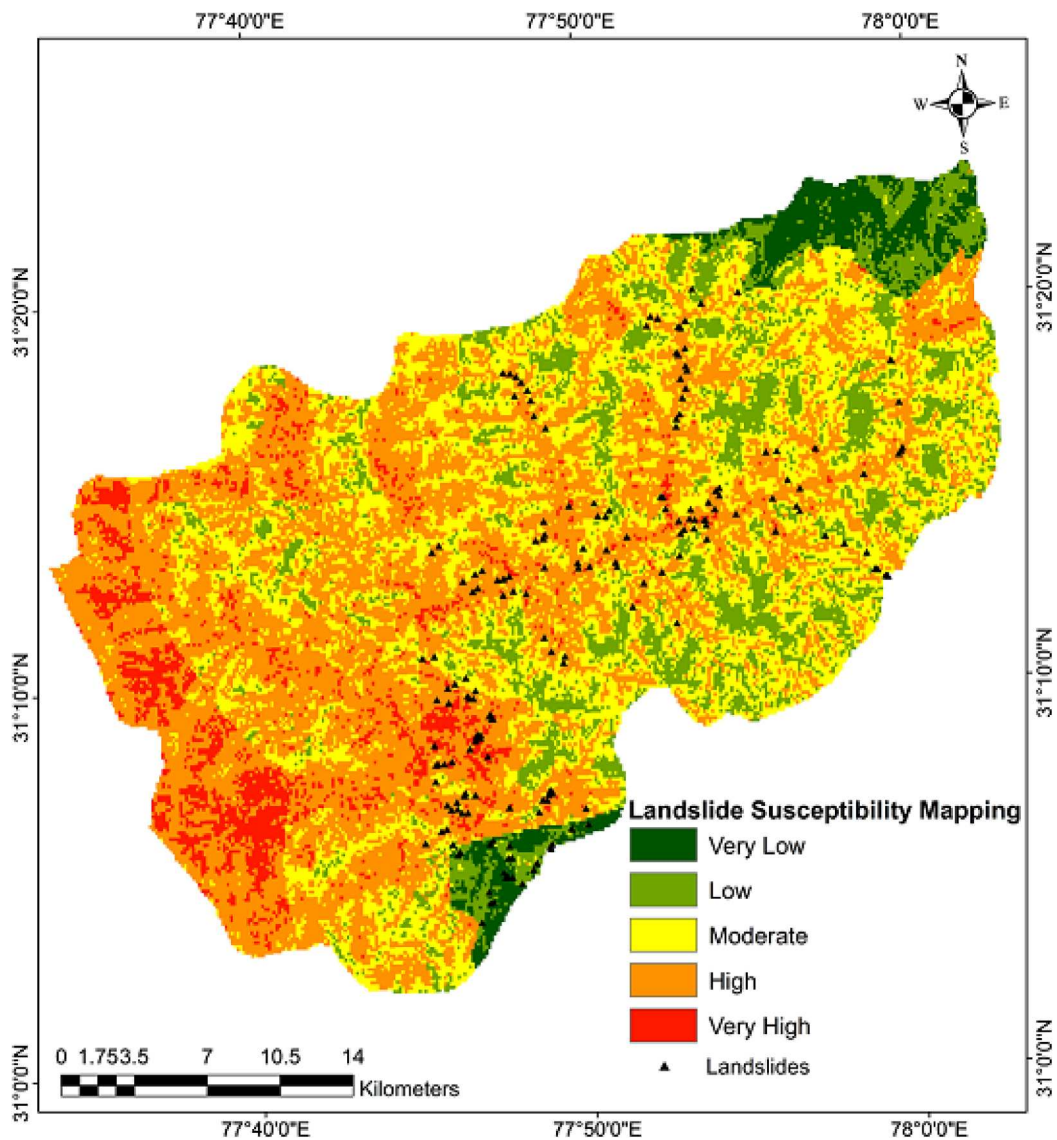


Figure 5. Landslide Susceptibility Map of the study area.

In the ROC curve (Figure 6a and b), the sensitivity of the model (the share of unstable pixels rightly predicted by the model) is mapped against 1-specificity (the share of predicted unstable pixels over the total). These values imply the capability of the model to rightly distinguish between positive and negative interpretations in the validation sample. High sensitivity suggests a high number of correct predictions (true positives) while high specificity (low 1-specificity difference) reveals a low number of false positives. The AUC value for the success rate was found to be 0.783 and for the prediction rate, it was 0.768.

Use of a multi-criteria method like AHP is a competent method to produce satisfactory results of landslide susceptibility as demonstrated in the current study. This can be further studied using deterministic approach considering a few more geotechnical parameters to understand the slope changes, changes in discontinuity orientation. One of the limitations of the AHP approach can be that it needs correct field conditions with precisely determined characteristics by a subject expert. The popularity of Machine learning techniques is growing swiftly. However, these techniques use data without

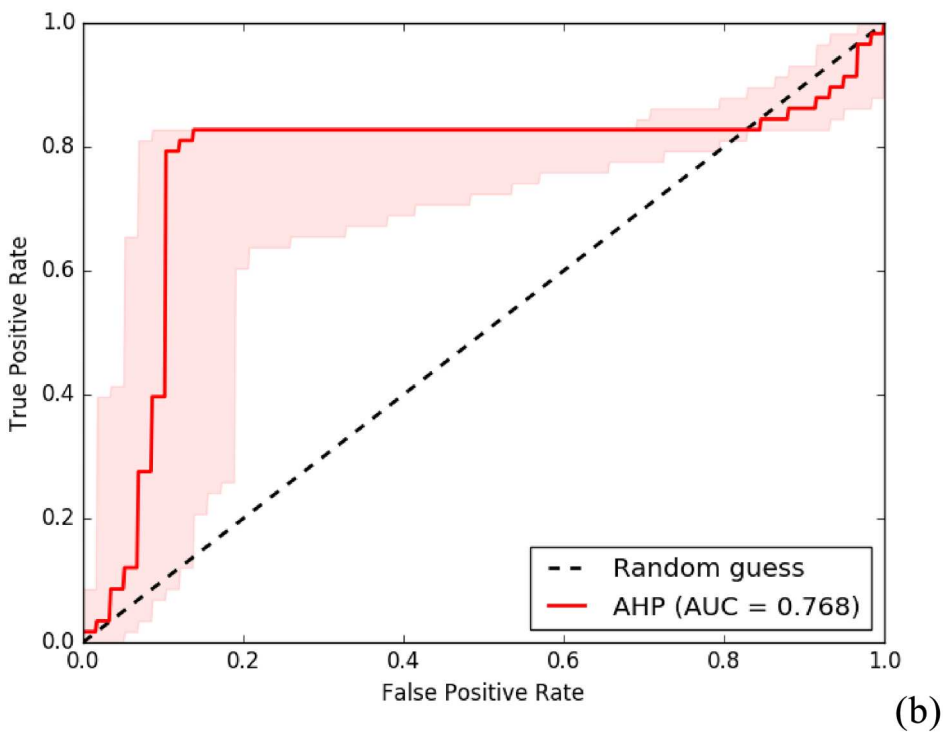
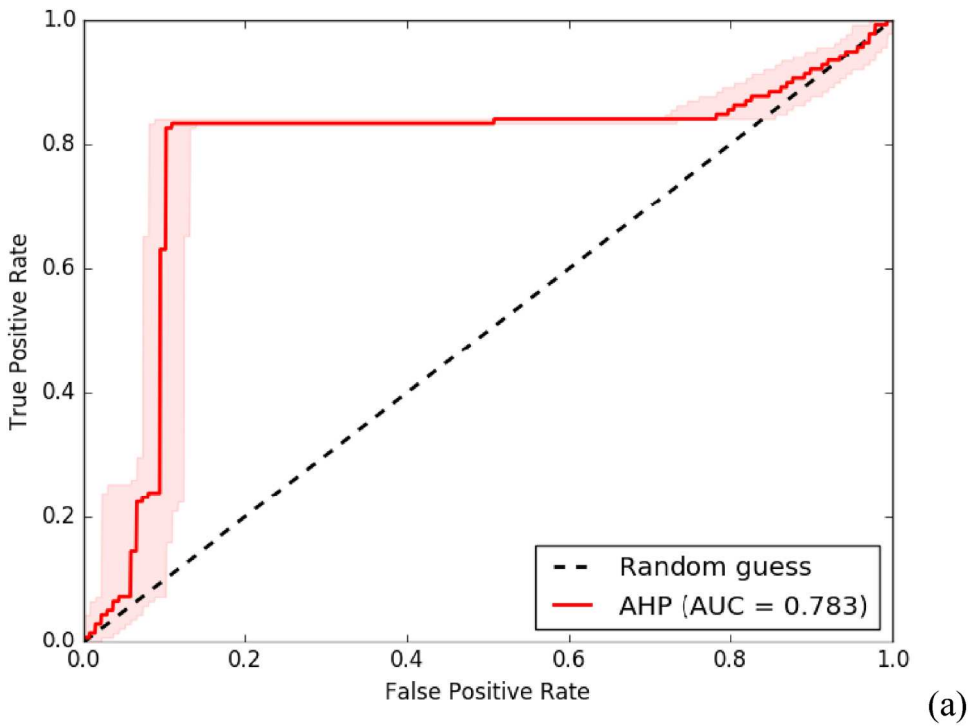


Figure 6. ROC Curve (a) success rate (b) prediction rate of LSM prepared from the AHP.

considering the rule-based functions, whereas quantitative techniques reorganize the relationship between the variables in the data using mathematical equations (Merghadi et al. 2020). The introduction of ML in Landslide Susceptibility Mapping means there are few informative resources for improved understanding meant for those who are not connoisseurs in ML, and so it is crucial and appropriate to formulate a synopsis of the different ML algorithms accessible and deliver a comparison between the available learning algorithms for Landslide Susceptibility Mapping.

Conclusions

Landslide Susceptibility Assessment of any hilly area carries utmost importance as the devastating effect of it can be felt for a considerable period due to loss of life as well as property. LSM identifies and presents the susceptible zones in a spatial form. AHP is one of the popular techniques to identify susceptible zones and was used in the current study after identifying eleven causative factors manipulating the landslides. 'Distance to Roads' and 'Distance to rivers' turned out to be the major influencing factors causing the landslides. The prediction accuracy came out to be 76.8% in the ROC method. The results can be termed satisfactory (Sonker et al. 2021). The results can be used by the planners and policymakers for appropriate usage of the geographical area in the current study area as well as similar areas.

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Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article.

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