



# Landslide Susceptibility Mapping and Comparison Using Frequency Ratio and Analytical Hierarchy Process in Part of NH-58, Uttarakhand, India

Ramesh Veerappan, Ankur Negi, and Anbazhagan Siddan

## Abstract

In Himalayas, National Highway 58 (NH-58) is one of the important and the major lifelines, which is very badly affected by frequent landslide occurrences particularly during the monsoons and cause recurring problems to pilgrims and local people. In the present research, the 52 km stretch ghat road in part of NH-58 was chosen for the landslide susceptibility zonation (LSZ) mapping using frequency ratio (FR) and analytical hierarchy process (AHP) models and through integrated remote sensing and geographical information systems (GIS) techniques. The landslide inventory details were mapped out using high resolution satellite image, the data collected from secondary sources and field investigation. There are 11 landslide influencing parameters were considered for the analyses. LSZ maps were generated by calculating relationship between the landslide influencing factors with training landslide data in the case of FR model but for AHP model pair-wise comparison were made to derive the weights and final score. The LSZ map prepared using FR and AHP models and classified into five different susceptibility zones. The LSZ maps were compared and validated with validation landslide dataset using Area Under Curve (AUC) method. The AUC value of FR model is 0.8157 showing better prediction accuracy than the AHP model (AUC value is 0.6780).

## Keywords

Landslide susceptibility zonation (LSZ) • Frequency ratio (FR) • Analytical hierarchy process (AHP) • NH-58 • Uttarakhand • India

V. Ramesh (✉) · N. Ankur

Centre for Geoinformatics, Jamsetji Tata School of Disaster Studies (JTSDS), Tata Institute of Social Sciences (TISS), Maiti and Jal A.D. Nairoji Campus (Annex), Deonar Farm Road, Post Box No. 8313Deonar, Mumbai, 400088, Maharashtra, India  
e-mail: rameshremote@gmail.com

N. Ankur

e-mail: negi.ankur72@gmail.com

S. Anbazhagan

Centre for Geoinformatics and Planetary Studies (CGIPS), Periyar University, Periyar Palkalai Nagar, Salem, 636011, Tamil Nadu, India

e-mail: anbu02@gmail.com

## Introduction

Landslide is one of the important natural hazards, which commonly and frequently occurring phenomena along ghat roads in mountainous region and causes heavy loss to human life, property, damages to infrastructure in every year (Aleotti and Chowdhury 1999). The delineation of zones which are prone to landslides is essential for future planning and growth in a region (Anbazhagan and Ramesh 2014). LSZ mapping illustrates the spatial distribution of different zones of probable landslide occurrence (Corominas and

Moya 2008) and explains the type, intensity, spatial area of past and present landslides in a region but it lacks the frequency (AGS 2007).

The different landslide susceptibility/hazard mapping methods given by Aleotti and Chowdhury (1999) and Kanungo et al. (2009) includes two broad categories qualitative and quantitative methods. The qualitative approach is based on subjective knowledge and includes distribution analysis (Wieczorek 1984), geomorphic analysis (Hearn 1995), and map combination (Champati Ray 2005). The quantitative approach is based on the relationship between past landslide distribution and causative factors (Guzzetti et al. 1999). The quantitative analysis further classified into statistical analysis (Nandi and Shakoor 2010; Ramesh and Anbazhagan 2015), probabilistic approaches (Chung and Fabri 1999), and distribution free methods such as fuzzy (Ramesh et al. 2016) and artificial neural network (Choi et al. 2012). The deterministic approach involves site specific analysis of safety factor of a slope (Ahmed et al. 2015).

In the present research work, LSZ mapping in part of National Highway 58 (NH-58) ghat road section situated in the Uttarakhand Himalayas, India, was carried out using statistical method frequency ratio (FR) and multi-criteria evaluation technique analytical hierarchy process (AHP). The importance of the present study is to prepare the LSZ map and further compare and validate the LSZ maps prepared through complete statistical method and subjective knowledge based method. Hence, the study could explain the effect and applicability and impact of weightage deriving process in both the model over the final LSZ map.

## Study Area

In Uttarakhand state, NH-58 is one of the important and the major lifelines, which connects the state with rest of the country and linked with its socioeconomic progress. The stretch of NH-58 cuts across through three districts of Uttarakhand namely Tehri Garhwal, Rudraprayag and Chamoli. This highway is very badly affected by number of landslides (Sarkar et al. 2013). This NH-58 is used by thousands of tourists and pilgrims to reach the holy shrine of Badrinath. The 52 km stretch of road, where the study has been conducted, is located between 30° 03'07"N and 30° 16' 08"N latitude and 78° 30'58"E and 78° 44'03"E longitude (Fig. 1).

## Geospatial Database Generation

The past landslide distribution and various causative factors that directly or indirectly influences landslide should be collected, constructed and used to apply the various models

for the purpose of LSZ mapping (Dietrich et al. 1995). There is no worldwide common practice for selecting the influencing parameters for LSZ mapping (Ayalew et al. 2005). The parameters can be selected based on the literatures, domain knowledge, data availability and different derivative maps using software (Hasekiogullari and Ercaoglu 2012). The geospatial database of all the causative factors and landslide distribution map were constructed using high resolution satellite image (Resourcesat2 LISS IV MX with 5.8 m resolution, dated on 1st Feb, 2016), Cartosat1 Digital Elevation Model (DEM) with resolution of 1 arc s × 1 arc s, landslide inventory data collected from Government and NGO offices and field investigation.

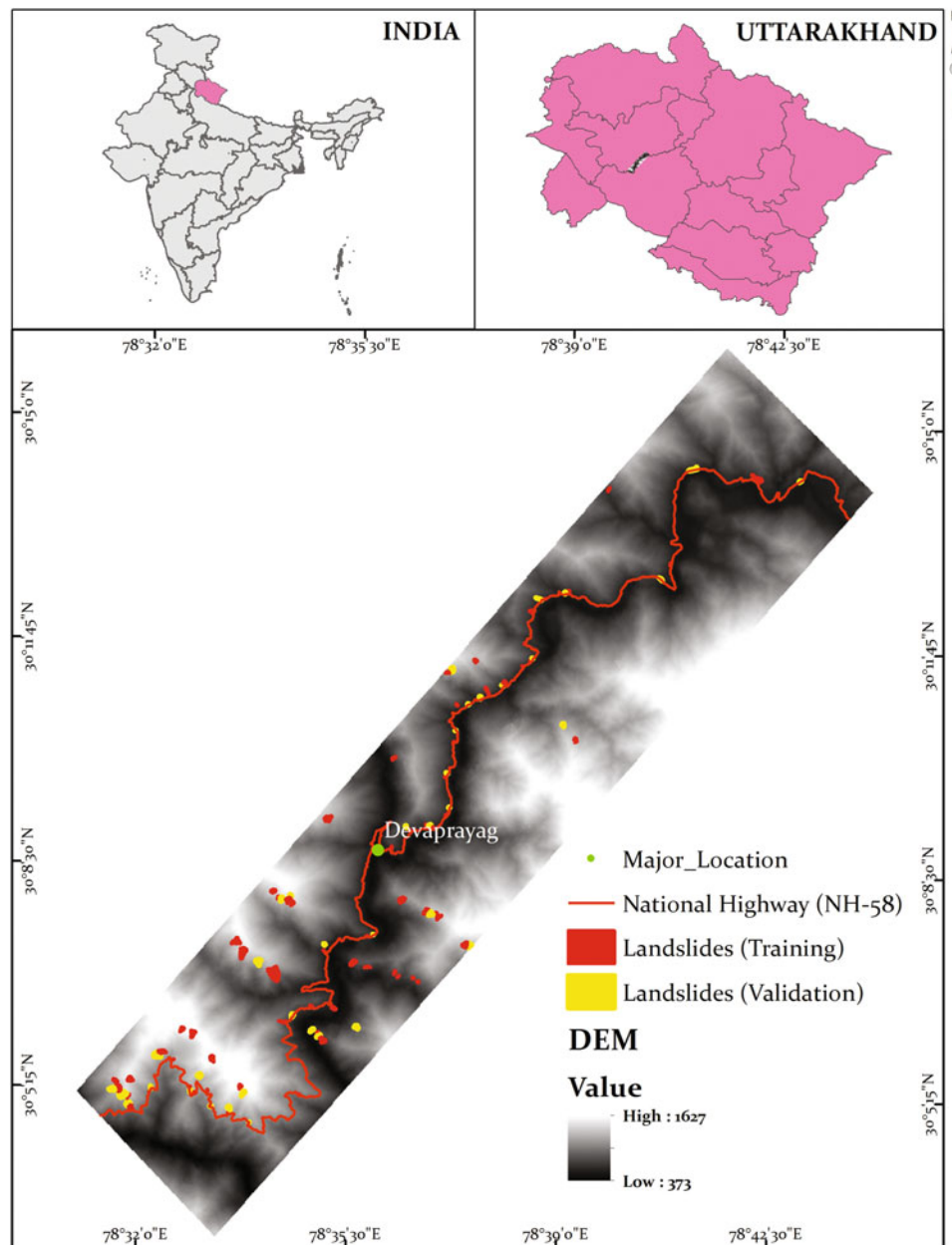
## Landslide Distribution

The mapping of details and distribution of past landslides is useful to determine the causes and parameters influenced the landslides in a region (Guzzetti et al. 1999) as well as to validate the final LSZ map. In the present research work, preliminarily the data related to past landslide occurrences were collected from the Disaster Mitigation and Management Centre (DMMC). The landslide locations were superimposed over the high resolution satellite image of Resourcesat2 LISS IV MX with 5.8 m resolution and digitized the area of the landslide. There were 121 landslides have demarcated covering the area of 493558.87 m<sup>2</sup>. All the landslides in the study area were divided into two datasets as training dataset which covers 70% slides and the remaining 30% of slides classified as validation datasets (Fig. 1).

## Landslide Influencing Factors

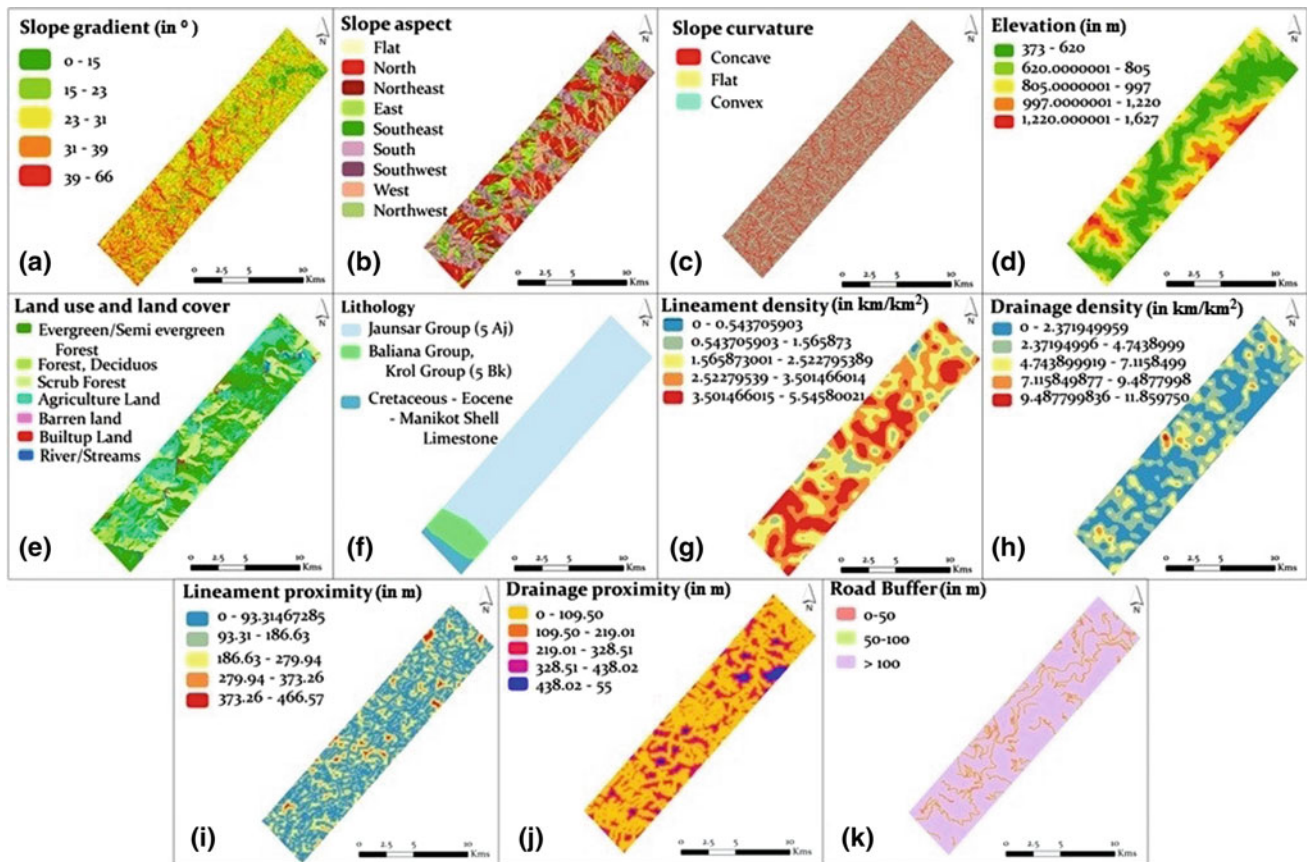
The topographical factors such as slope gradient, slope aspect, slope curvature and elevation were derived from Cartosat1 DEM data downloaded from Bhuvan, National Remote Sensing centre (NRSC) using the Spatial Analyst tool in ArcMap 10@ESRI. The slope gradient map with slope ranging from 0° to 66° was reclassified into five classes (Fig. 2a), adopting the Jenks natural breaks classification method (Jenks 1967). The slope aspect map which represent the direction of slope was reclassified into eight directional classes and one Flat (-1 value) class (Fig. 2b). The combo curvature (combination of both plane and profile curvature) map were prepared and classified the negative values as concave, the positive values were classified as convex, and the values fall in zero class classified as flat (Fig. 2c). In this study region, the elevation varies from 373 to 1627 m was reclassified into five classes following Jenks natural breaks classification (Fig. 2d).

**Fig. 1** The map illustrates the location of the study area and digital elevation model along with distribution of past landslide areas



The land use and land cover features Evergreen/Semi-evergreen forest, deciduous forest, scrub forest, barren land, builtup land, agriculture land, rivers/streams were visually interpreted using high resolution satellite image (Fig. 2e). The lithological units of the study area includes Jaunsar group, Baliana and Krol group, Cretaceous-Eocene-Manikot shell limestone was prepared from geological map published by GSI (2002) (Fig. 2f). The drainage

and lineament were mapped out from the high resolution satellite image. Then, the kernel density of lineaments and drainages was calculated as density per sq.km. using density tool in ArcGIS 10@ESRI version. The lineament density (Fig. 2g) and drainage density (Fig. 2h) maps were reclassified into five classes. The proximity to lineament (Fig. 2i) and proximity to drainage (Fig. 2j) was calculated using Euclidean distance method in ArcGIS 10@ESRI and



**Fig. 2** Landslide causative factors: **a** Slope gradient, **b** Slope aspect, **c** Slope curvature, **d** Elevation, **e** Land use and land cover, **f** Lithology, **g** Lineament density, **h** Drainage density, **i** Lineament proximity, **j** Drainage proximity, **k** Road buffer

reclassified into five classes based on Jenks natural breaks classification. The road influence (i.e.) road buffer was created for 0–50, 50–100, >100 m (Fig. 2k).

## Methods Adopted

### Frequency Ratio (FR) Method

The FR method provides the correlation between the landslide distribution and each landslide inducing factors in the study area. The ratio is that of the area where landslides occurred to the total area, so that a value of 1 is an average value in the relationship analysis. If the FR value is greater than 1, the correlation between the landslides and the factors will be high, whereas value lower than 1 indicates lower correlation. The FR values of each class in a thematic layer were calculated using Eq. 1. The frequency ratios of each thematic layer were then summed to estimate the landslide susceptibility index (LSI) (Eq. 2) (Ramesh and Anbazhagan 2015; Balamurugan et al. 2016). The LSI value is

corresponds to the relative susceptibility to landslide occurrence. Hence, the greater FR value indicates the higher susceptibility to landslide occurrence.

$$FR = \frac{\text{Slide Ratio}}{\text{Class Ratio}} \quad (1)$$

(where, slide ratio is number of landslide grids in a class to total number of landslide grids; class ratio is number of grids in individual class to total number of grids in whole class).

$$LSI = \sum FR \quad (2)$$

(Where, LSI landslide susceptibility index; FR frequency ratios of each causative factor).

### Analytical Hierarchy Process (AHP) Method

In the present study, a multi-objective, a multi-criteria decision making approach AHP which was developed by Saaty (1977) were used to evaluate the weights of the factors

**Table 1** Scale of preference between two factors in AHP (after Saaty 2008)

Scales	Remarks
1	Equal importance
3	Moderate dominance of one over another
5	Strong or essential dominance
7	Very strong or show dominance
9	Extremely high dominance
2, 4, 6, 8	Intermediate values
Reciprocals	For opposite comparison
1.1–1.9	If the dominance is very close

**Table 2** RI values for the pairwise comparisons in AHP analysis (after Saaty 1980)

N	1	2	3	4	5	6	7	8	9	10	11
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51

and ratings of the classes in the each factor. In decision making process, the AHP method allows to consider the subjective as well as objective factors (Yalcin 2008). Each factor/classes is rated against other factor/classes in the pair-wise comparison matrix by assigning a relative dominant value between the ranges from 1 to 9 (equal preference to extremely high preference) to the intersecting cell (Table 1) (Park et al. 2013). The value varies between 1 and 9 when the factor on the vertical axis is more important than the factor on the horizontal axis and in opposition the value varies between the reciprocals 1/2 and 1/9 (Saaty 1980). If the activities are very close the values of 1.1 to 1.9 could be assigned (Saaty 2008). These values are very difficult to assign and smaller in nature but it still reflects the relative important between the factors. In AHP method, the judgment of score can be assigned based on the professional knowledge i.e. subjective, objective, and combination of both (Yalcin 2008). In this study relative value of each pair of the factors/classes were assigned based on subjective as well as objective approach i.e. on the basis of presence of landslide in those classes.

In AHP method, the inconsistency caused through subjectivity (Feizizadeh and Blaschke 2013) can be determined by calculation of consistency index (CI) using Eq. 3 and consistency ratio (CR) using Eq. 4 (Saaty 1980). CR can be calculated by ratio CI/RI, where RI stands for random index, which was compiled by Saaty (1980) on the basis of a number of random samples (Table 2).

$$CI = \frac{(\lambda_{max} - n)}{(n - 1)} \quad (3)$$

$$CR = \frac{CI}{RI} \quad (4)$$

(Where,  $\lambda_{max}$  is the maximum eigen value and  $n$  is the number of causative factors present in the row/column of the matrix).

CR value of 0.1 is the maximum threshold of consistency of the matrix. If  $CR < 0.1$  is reflecting consistency wherever  $CR > 0.1$  indicates inconsistency among the parameters in the pair-wise comparison and needs to be revised (Wu et al. 2016). The landslide susceptibility index (LSI) using Eq. 5 (Thanh and De Smedt 2012).

$$LSI = \sum_{j=1}^n (W_j w_{ij}) \quad (5)$$

(Where, LSI is the landslide susceptibility index,  $W_j$  is the weight value of causative factor  $j$ ,  $w_{ij}$  is the weight value of class  $i$  in causative factor  $j$ , and  $n$  is the number of causative factors).

## Results and Discussion

The AHP model was carried out through pair-wise comparison of causative factors and classes within the causative factors were made and normalized to get criteria weight. The weight value of causative factor, the rating values of each class in a causative factor, and the CI values are given in the (Table 3). The FR was calculated using Eq. 1 and the results presented in Table 4.



**Table 3** Pair-wise comparison matrix between causative factors

Causative factors	1	2	3	4	5	6	7	8	9	10	11	Normalized weights
Drainage density (1)	1											0.017
Drainage proximity (2)	1	1										0.017
Elevation (3)	2	2	1									0.023
Slope curvature (4)	3	3	2	1								0.033
Slope aspect (5)	4	4	3	2	1							0.047
Lithology (6)	5	5	4	3	2	1						0.065
Road buffer (7)	6	6	5	4	3	2	1					0.091
Lineament density (8)	6	6	6	5	4	3	2	1				0.114
Lineament proximity (9)	7	7	6	5	4	3	2	2	1			0.136
Land use and land cover (10)	8	8	7	6	5	4	3	3	2	1		0.192
Slope gradient (11)	9	9	8	7	6	5	4	4	3	2	1	0.265
Consistency ratio = 0.059												

**Table 4** Weights and rating values of causative factors and each class in a causative factor

Causative factors	Class ratio	Slide ratio	FR	AHP		
				$w_{ij}$	$W_j$	$W_j w_{ij}$
Slope gradient (in °)				CR = 0.097547062		
0–15.09085681	10.02	0.53	0.05	0.03	0.27	0.009
15.09085682–23.41684678	22.42	5.40	0.24	0.07		0.018
23.41684679–30.702088	30.41	13.50	0.44	0.13		0.035
30.70208801–38.50770359	25.74	33.53	1.30	0.27		0.073
38.5077036–66.34773254	11.41	47.04	4.12	0.49		0.131
Slope aspect (in °)				CR = 0.060111399		
Flat (–1)	0.00	0.00	0.00	0.03	0.05	0.001
North (337.5°–22.5°)	16.54	0.05	0.00	0.03		0.001
Northeast (22.5°–67.5°)	14.23	1.41	0.10	0.04		0.002
East (67.5°–112.5°)	11.62	4.70	0.40	0.08		0.004
Southeast (112.5°–157.5°)	10.13	20.16	1.99	0.15		0.007
South (157.5°–202.5°)	14.02	38.96	2.78	0.34		0.016
Southwest (202.5°–247.5°)	12.21	32.13	2.63	0.25		0.012
West (247.5°–292.5°)	10.24	2.59	0.25	0.06		0.003
Northwest (292.5°–337.5°)	11.02	0.00	0.00	0.03		0.001
Curvature (Unit less)				CR = 0.047725425		
Concave (–)	47.89	52.19	1.09	0.63	0.03	0.021
Flat (0)	2.77	1.99	0.72	0.11		0.004
Convex (+)	49.34	45.82	0.93	0.26		0.009
Elevation (in m)				CR = 0.028798975		
373–620	31.30	31.65	1.01	0.14	0.02	0.003
620.0000001–805	30.86	17.17	0.56	0.07		0.002
805.0000001–997	22.95	35.04	1.53	0.49		0.011
997.0000001–1220	12.25	15.03	1.23	0.27		0.006
1220.000001–1627	2.64	1.11	0.42	0.04		0.001
Land use and land cover				CR = 0.061076882		
Evergreen/Semi-evergreen forest	40.79	8.72	0.21	0.04	0.19	0.007
Deciduous forest	7.38	12.39	1.68	0.16		0.030
Scrub forest	20.25	58.70	2.90	0.24		0.047
Agriculture land	26.65	17.12	0.64	0.06		0.012
Barren land	0.08	0.38	4.56	0.38		0.072
Builtup land	2.77	2.69	0.97	0.10		0.019
River/streams	2.08	0.00	0.00	0.03		0.005
Lithology				CR = 0.087253944		
Jaunsar Group	86.33	89.39	1.04	0.61	0.07	0.040
Cretaceous–Eocene–Manikot shell limestone	4.08	0.73	0.18	0.12		0.008
Baliana Group, Krol Group	9.59	9.88	1.03	0.27		0.018
Drainage density (in km/km <sup>2</sup> )				CR = 0.011418371		
0–2.371949959	44.11	35.97	0.82	0.04	0.02	0.001
2.37194996–4.743899918	40.23	37.25	0.93	0.08		0.001
4.743899919–7.115849876	13.92	23.43	1.68	0.27		0.004
7.115849877–9.487799835	1.60	2.16	1.35	0.14		0.002
9.487799836–11.85974979	0.14	1.18	8.31	0.47		0.008

(continued)

**Table 4** (continued)

Causative factors Classes	Class ratio	Slide ratio	FR	AHP		
				$w_{ij}$	$W_j$	$W_j w_{ij}$
Lineament density (in km/km <sup>2</sup> )				CR = 0.089013104		
0–0.543705903	0.24	0.00	0.00	0.04	0.11	0.005
0.543705903–1.565873	7.42	12.39	1.67	0.47		0.053
1.565873001–2.522795389	30.08	37.71	1.25	0.26		0.029
2.52279539–3.501466014	37.20	35.65	0.96	0.15		0.017
3.501466015–5.545800209	25.06	14.25	0.57	0.08		0.010
Drainage proximity (in m)				CR = 0.083469987		
0–109.5047485	59.74	62.32	1.04	0.50	0.02	0.008
109.5047486–219.0094971	23.67	18.50	0.78	0.26		0.004
219.0094972–328.5142456	8.75	13.37	1.53	0.13		0.002
328.5142457–438.0189941	5.68	5.81	1.02	0.07		0.001
438.0189942–547.5237427	2.16	0.00	0.00	0.03		0.001
Lineament proximity (in m)				CR = 0.088868802		
0–93.31467285	40.75	35.14	0.86	0.50	0.14	0.068
93.31467286–186.6293457	43.72	45.95	1.05	0.26		0.035
186.6293458–279.9440186	11.24	17.25	1.53	0.14		0.019
279.9440187–373.2586914	3.37	1.66	0.49	0.07		0.010
373.2586915–466.5733643	0.92	0.00	0.00	0.04		0.005
Road buffer (in m)				CR = 0.047725425		
0–50	13.60	43.82	3.22	0.63	0.09	0.058
50–100	11.35	15.03	1.32	0.26		0.024
>100	75.05	41.15	0.55	0.11		0.010

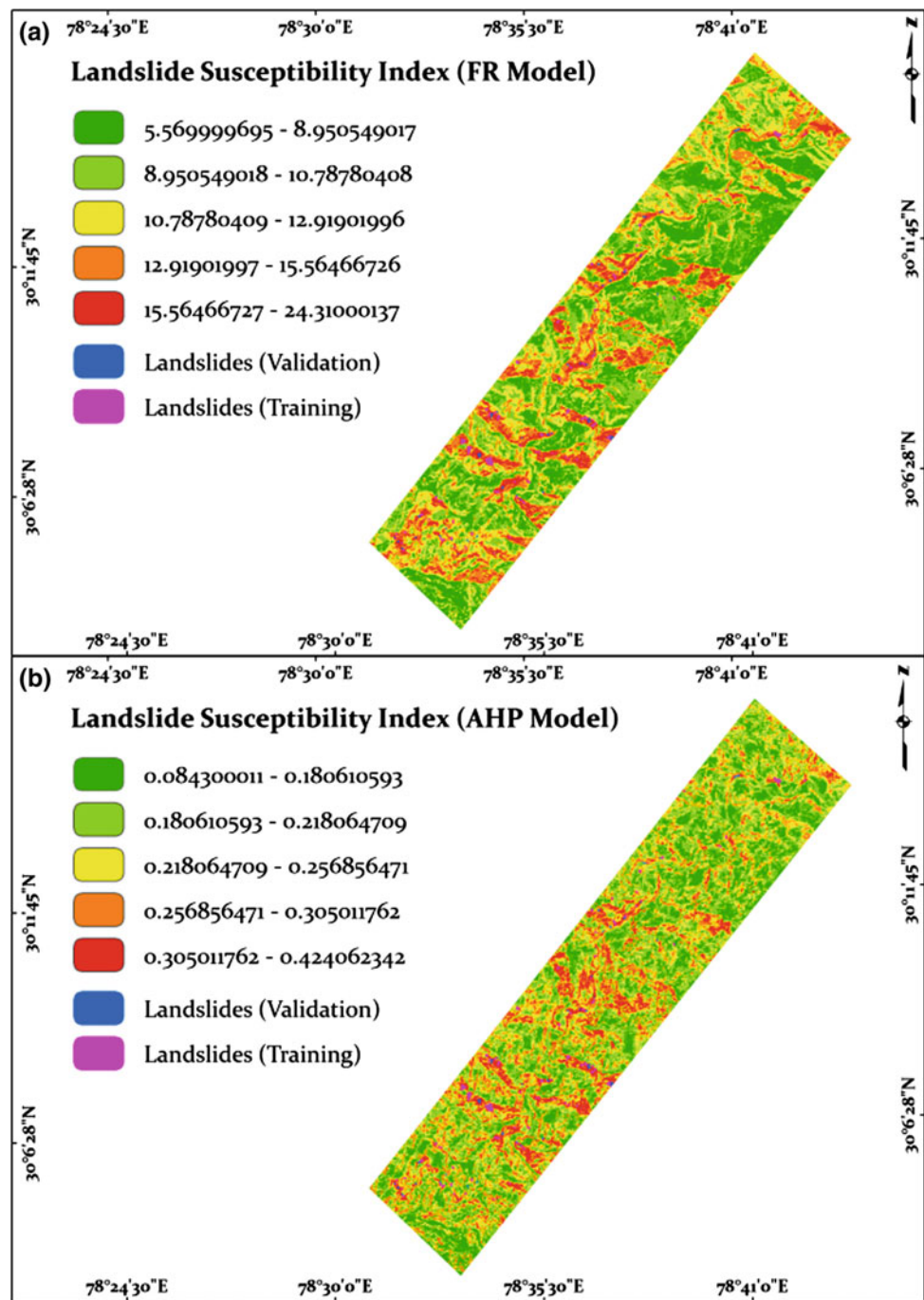
### Landslide Susceptibility Zonation (LSZ) Mapping

For the purpose of preparation of LSZ map, all the 11 causative factors were converted into a raster format using the grid size of  $10 \times 10$  m. The total grid present in the study area is 1,439,982, and the total number of landslide grids in the study area was 4929. The FR and Score values of all the classes were added to the each class and converted to the raster dataset and integrated using the raster calculator tool in ArcGIS 10@ESRI. The landslide susceptibility index

was calculated using the Eqs. 2 and 5. The LSI results produced by using the FR model given the minimum, mean, maximum and standard deviation of LSI are 5.569999695, 10.96282259, 24.31000137, and 2.69695544, respectively. In the case of AHP model, LSI values had a minimum value of 0.084300011, mean value of 0.220502825 and a maximum value of 0.424062342, with a standard deviation of 0.04978307. The LSZ maps prepared using FR and AHP methods were classified into five susceptibility classes viz., very low, low, moderate, high and very high based on Jenks



**Fig. 3** LSZ maps; **a** frequency ratio (FR) model, **b** Analytical Hierarchy Process (AHP)

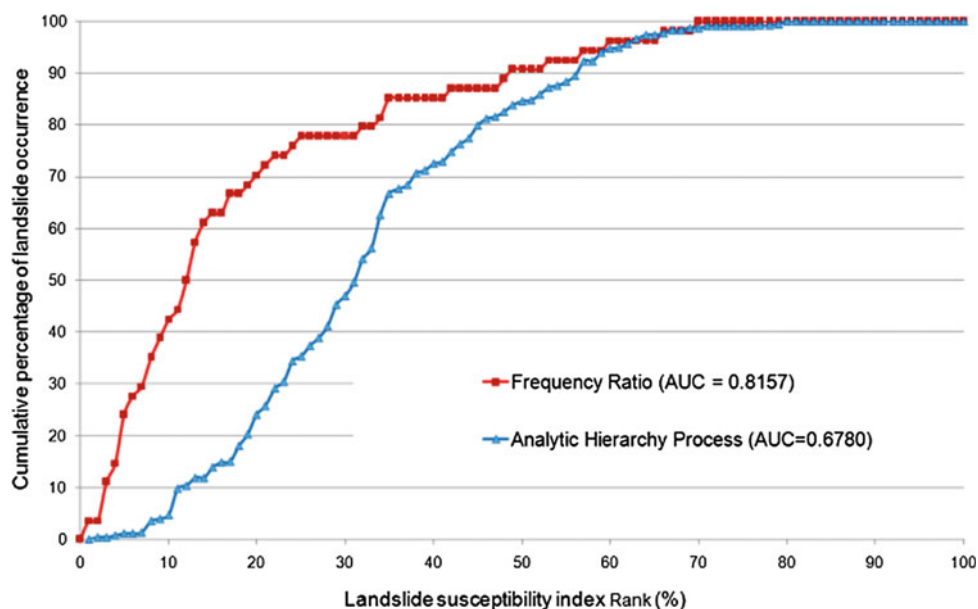


natural breaks classification method (Fig. 3a, b). In FR model 92.38% of the training landslide areas were identified in high and very high susceptibility classes, whereas in AHP model 83.13% of the training landslide areas identified in the high and very high susceptibility classes.

### Comparison and Validation of the Models

In the present study, the most common validation method Area Under Curve (AUC) were adopted to determine the prediction accuracy (prediction rate) of the each model

**Fig. 4** Prediction rate curve of FR and AHP models



(Begueria 2006). The AUC value was determined through integrating the validation landslide dataset with the LSZ maps. If the AUC value close to 1.0 indicates the model is ideal, whereas an AUC value close to 0.5 reflects the inaccuracy in the model (Fawcett 2006). The AUC value of prediction rate curve (Fig. 4) for FR and AHP models was found to be 0.8157 and 0.6780 respectively.

## Conclusions

In the present study, frequency ratio and analytical hierarchy process models were adopted for the landslide susceptibility zonation mapping in part of NH-58, Uttarakhand, India. The results depicts that occurrence of landslides is so high along  $>30^\circ$  slope, south, southeast, southwest, convex, 805–1220 m elevation, barren land, scrub forest, road buffer within the distance of 0–50 m classes. The prediction accuracy result show that the FR model has best prediction accuracy (AUC value = 0.8157) than the AHP model (AUC value = 0.6780). The present research work and its results could help for policy and decision makers to proceed with developmental activities like land use planning in this region.

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