Landslide susceptibility mapping using knowledge driven statistical models in Darjeeling District, West Bengal, India

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Abstract

Landslide is an important geological hazard in the large extent of geo-environment, damaging the human lives and properties. The present work, intends to identify the landslide susceptibility zones for Darjeeling, India, using the ensembles of important knowledge driven statistical technique i.e. fuzzy logic with Landslide Numerical Risk Factor (LNRF) and Analytical Hierarchical Process (AHP). In the study area, 326 landslides have been identified and a landslide inventory map has been prepared based on these landslides. The landslide inventory map has considered as the dependent factor and the geo-environmental factors like rainfall, slope, aspect, altitude, geology, soil texture, distance from river, lineament and road, land use/ land cover, NDVI and TWI have been considered as independent factors. Landslide susceptibility maps were prepared based on the Fuzzy- Landslide Numerical Risk Factor (LNRF) and Fuzzy- analytic hierarchy process (AHP) methods in a GIS environment. According to the results of LNRF and AHP based fuzzy logic 34 and 22% areas are highly susceptible to landslide in this district. The landslide maps of both models have been validated through ROC curve and RMSE. The areas under curves are 91% (for Fuzzy-LNRF) and 90% (for Fuzzy-AHP) and RMSE values of these models are 0.18 and 0.14 which are indicating the good accuracy of both models in the identification of landslide susceptibility zones. Moreover, the Fuzzy-LNRF model is promising and sufficient to be advised as a method to prepare landslide susceptibility map at regional scale.

Keywords: Landslide numerical risk factor (LNRF), Fuzzy-AHP, Fuzzy logic (FL), Landslide susceptibility, GIS

Introduction

The mountainous areas of the world are frequently affected by the occurrences of the landslide because of high energy with variability and instability of masses (Gerrard 1994). From the environmental point of view, different kind of problems such as loss of soil fertility, acceleration of deforestation rate etc. may be caused by the landslides (Van Eynde et al. 2017). Most of the mountainous regions of India are characterized by the landslide disaster. A number of avalanche zones in the Indian Himalayan region are prominent, e.g. Jammu Kashmir, Himachal Pradesh, Kumayun, Darjeeling and Sikkim and North-eastern hilly states (Bhandari 2004). Landslide causes loss of property far greater than the any natural disaster (Turner and Schuster 1996; Garcia-

Rodriguez et al. 2008). Probably this rate of property damage will become more faster in the upcoming time in parity with the gradual development of urban centers, economic and rising regional rainfall due to climatic change in the landslide prone areas (Turner and Schuster 1996). Landslide occurrence is a significant barrier to the development in Darjeeling district. In Darjeeling district, landslides mainly take place due to heavy Monsoonal rainfalls and seismicity (Panikkar and Subramanyan 1996). The Darjeeling district had been experienced major landslides in July–August, 1993, May 2009 and September 2011 (Sarkar 1999). Massive rain caused landslides at Darjeeling town, Mirik, Kurseong and Kalimpong during June–July, 2015 and induced the loss of properties and lives. Reduction of effect of landslide can be possible only with a comprehensive knowledge about the probability of occurrence, character and magnitude of landslide in an area. Therefore, delineation of landslide vulnerable regions is indispensable for

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carrying out safer alleviation programs, and future planning of the area (Fan et al. 2019). In the present paper the main thrust has been given to delineate the landslide susceptible zones and chalk out suitable method.

Landslide is the major hazardous phenomenon which sometimes causes loss of human lives and properties. Therefore, any environmental factor may cause landslide when soil resistance power is lower than the shear force (Refahi 2000; Bouma and Imeson 2000). For landslide hazard evaluation several qualitative and quantitative methods have been used (Aleotti and Chowdhury 1999; Reichenbach et al. 2018). According to the qualitative method, the expert can evaluate the landslide susceptibility zones in his own opinion. The expert also can assess the vulnerable areas on the basis of similar geological and geomorphological character using the landslide inventory maps or existing landslide areas (Ayalew and Yamagishi 2005). The multi-criteria decision approach (MCDA) is an important way for indentifying the potential landslide areas using proper database. GIS based MCDA has been considered as the powerful techniques and procedures for evaluating, designing and accuracy judgments' of the results (Feizizadeh and Blaschke 2011, 2013). The present study has followed the GIS based MCDA techniques like Fuzzy-Landslide Numerical Risk Factor (LNRF) and Fuzzy-AHP for the landslide susceptibility mapping. Several other researchers applied Fuzzy-AHP and LNRF. Torkashvand et al. (2014) applied the Landslide Numerical Risk Factor (LNRF) model using GIS in East of the Sabalan volcanic mass region in Iran. Mokarram and Zarei (2018), Feizizadeh et al. (2014), Mosavi et al. (2017), Hejazi (2015), Mirnazari et al. (2015) and Hembram and Saha (2018) used Fuzzy-AHP model for their work and they got fruitful result for susceptibility mapping. Various statistical methods have been used by the researchers for analyzing the spatial pattern of landslides and preparing the landslide susceptible map such as logistic regression (Zêzere et al. 2017; Budimir et al. 2015), hierarchical approach (Youssef et al. 2014), statistical index (Dou et al., 2015), conditional analysis (Pourghasemi et al. 2012), weight of evidence Pradhan and Lee (2010). In the recent years, different machine learning techniques have also been used by some scholars for mapping the landslide disaster like decision tree (Pradhan 2013), random forest (Dou et al. 2019), artificial neural network Pradhan and Lee (2010), support vector machine (Tien Bui et al. 2012) etc. For identifying the landslide susceptibility zones, they used some important factors such as the elevation, lithology, slope, land use, river, topographical wetness index, aspect, road, fault, and precipitation maps. The rationale of this work is to identify the landslide susceptible areas using the ensemble models that are fuzzy- LRNF and Fuzzy-AHP of Darjeeling district

and compare with them which have not been used in this district previously. The main advantage of ensemble of fuzzy logic and LRNF is that we can use both expert knowledge as well as statistical method for predicting landslide susceptibility using various causative factors.

In this study, remote sensing data along with meta data have been used to outline the landslide susceptibility areas for the Darjeeling District. Geo-environmental factors such as rainfall, slope, aspect, altitude, geology, soil texture, distance from river, distance from lineament, distance from road, land use/ land cover, normalized difference vegetation index (NDVI) and topographical wetness index (TWI) have been taken out to facilitate the quantification of landslide. Fuzzy-LRNF and Fuzzy-AHP have been applied considering the extracted database. Using the LRNF models, the fuzzy membership value has been calculated and thereafter, using the fuzzy gamma operator the membership values of parameters have been assembled for producing the landslides susceptible map of Darjeeling district. Similarly using the Fuzzy-AHP method, another map has also been produced. Finally, the maps have been verified and compared using known landslide locations based on ROC and RMSE quantitative validation methods. The main novelty is that the first time knowledge driven technique (Fuzzy logic) has been assembled with LRNF in this work to delineate the landslide susceptible zone of Darjeeling district and compared with the Fuzzy-AHP method. Moreover, according to the previous literatures so many researchers used LRNF and AHP method for mapping the landslide susceptibility but not a single researcher has used ensemble of fuzzy logic and LRNF model for predicting the spatial landslide probability and compared this ensemble method with fuzzy-AHP.

Study area

The Darjeeling district is located in the northernmost part of the West Bengal in India. It is an important mountainous part of the eastern Himalaya. Geographically the study area is extended between the latitudes 26°27″ to 27°13″N and longitudes 87°59″E–88°53″E. The study area is covered with an area of 3149 sq.km (Fig. 1). According to the census of 2011, the total population of the district is 18, 46,823 with 9, 37,259 males and 9, 09,564 females. The population density of the district is 586 person/ km² (District Statistical Handbook 2013). The number of rural households and the urban households of Darjeeling district was 212000 and 89584 in 2001, but these have increased to 236000 and 154540 in 2011 respectively (District Statistical Handbook 2011). The total length of national highway, state highway, major district road and other ordinary district road were 100, 80, 37 and 516 km respectively (District Gazetteer of Darjeeling District 1980). But the length of national
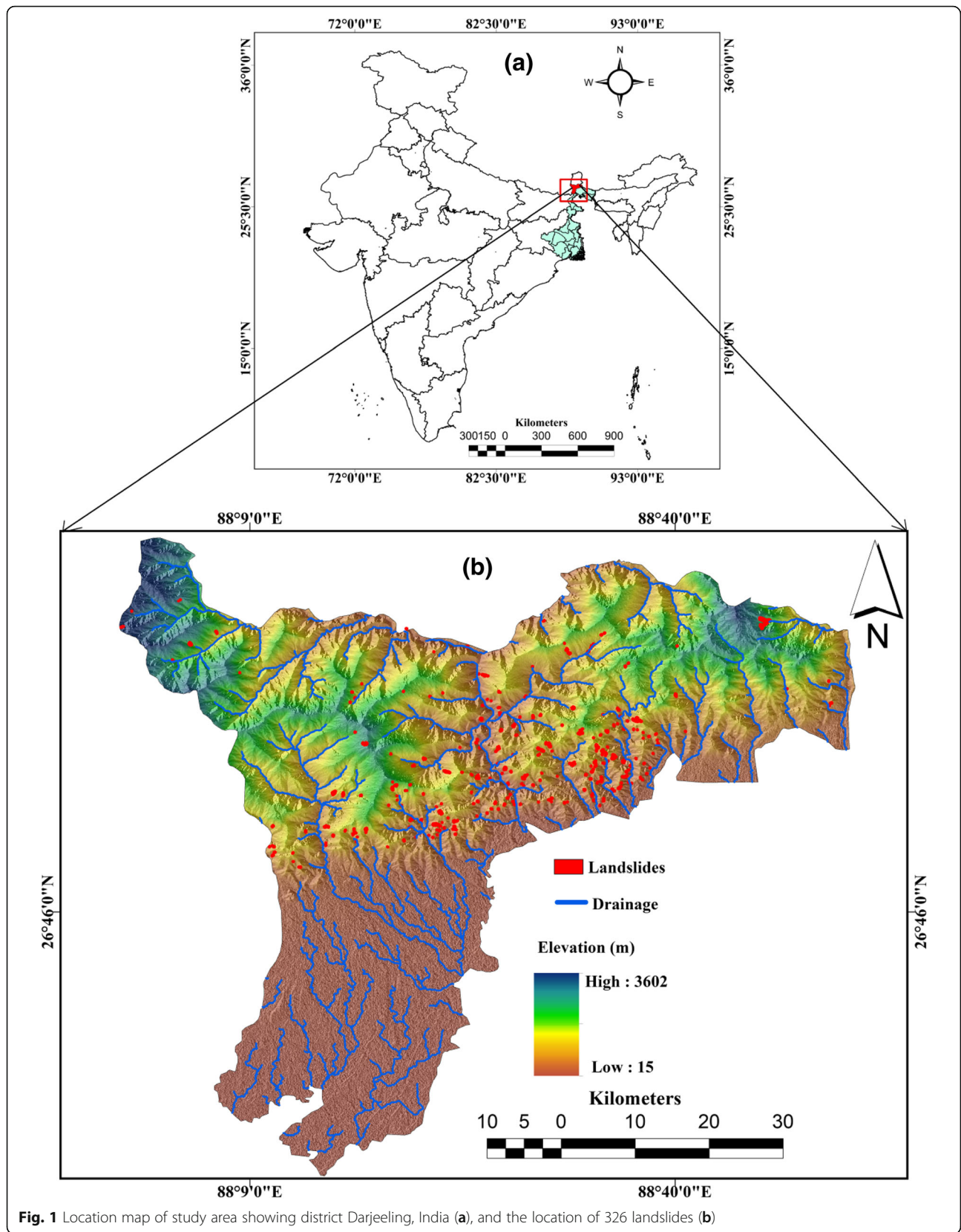
Fig. 1 Location map of study area showing district Darjeeling, India (**a**), and the location of 326 landslides (**b**)

highway, state highway and main district highway have increased to 111, 191 and 79 km respectively in 2011. The total length of surfaced and unsurfaced roads are 3696.54 km and 1652.51 km approximately in 2013–14. The characteristics of both plain and mountainous topographies exit in this study area. The altitude of the study area ranges from 15 m to 3602 m from mean sea level and the slope from 0° to 80° approximately. The major portion of the study area is covered with Triassic rocks. The soil character of the study area is varied from one region to another region. The study area receives huge amount of rainfall in the monsoon season. The average annual rainfall of the study area is about 3051 mm. The major rivers of the study area are Mahananda, Tista, Mechi, Balason, Jaldhaka, Rammam and Rangit, which are flowing from northern part. The district has some reputed eco-tourism sites and pilgrimage sites namely like Tiger Hill, Rock Garden, Mahakal Temple, Dhirdham Temple, Batasia Loop, Ghoom Monastery and Happy Valley Tea Garden, etc. Historically, Tea Plantation and Cinchona are the main sources of livelihood in the Darjeeling district. The community of the study area depends on the horticulture, tourism, and forestry. Siliguri is the major town of the study area which is familiar with 'gate way' of eastern India.

Materials and methodology
Data sources
For the fulfillment of the present work, various important data have been collected from different sources e.g. rainfall and temperature data from Indian Meteorological Department, population data from District Statistical Handbook, Census of India 2011, drainage and road networks from Open series Topographical Sheets (2015), images and ASTER DEM from USGS Earth Explorer, Soil map from National Bureau of Soil Survey & Land use Planning and Geological map from Geological Survey of India. The summery of the procedues followed is depicted in the flowchart (Fig. 2).

Software used
To predict the landslide potential areas, the thematic layers of selected geo-environmental parameters namely rainfall, slope, elevation, aspect, geology, soil texture, distance from lineament, distance from river, distance from road, natural differential vegetation index (NDVI) and TWI have been prepared with the help of ArcGIS 10.3.1, ENVI 4.7, GEOMATICA and the mathematical calculations have been done with the help of SPSS softwares.

Preparation of landslide inventory map
The landslide inventory map is the vital part for analyzing the landslide susceptibility, hazard and risk (Guzzetti et al. 2006). Pradhan and Lee (2009) and Pourghasemi et al. (2012) prepared the landslide inventory map for identifying the landslide hazards zones. Van Westen et al. (2000) remarked that the different data such as field investigations, historical landslide events and satellite image analysis can be used to prepare the landslide inventory map (Fig. 1b). In the present study, 326 landslides have been identified from Google earth imagery and multiple field visits. The landslide inventory map has been prepared in the GIS environment for
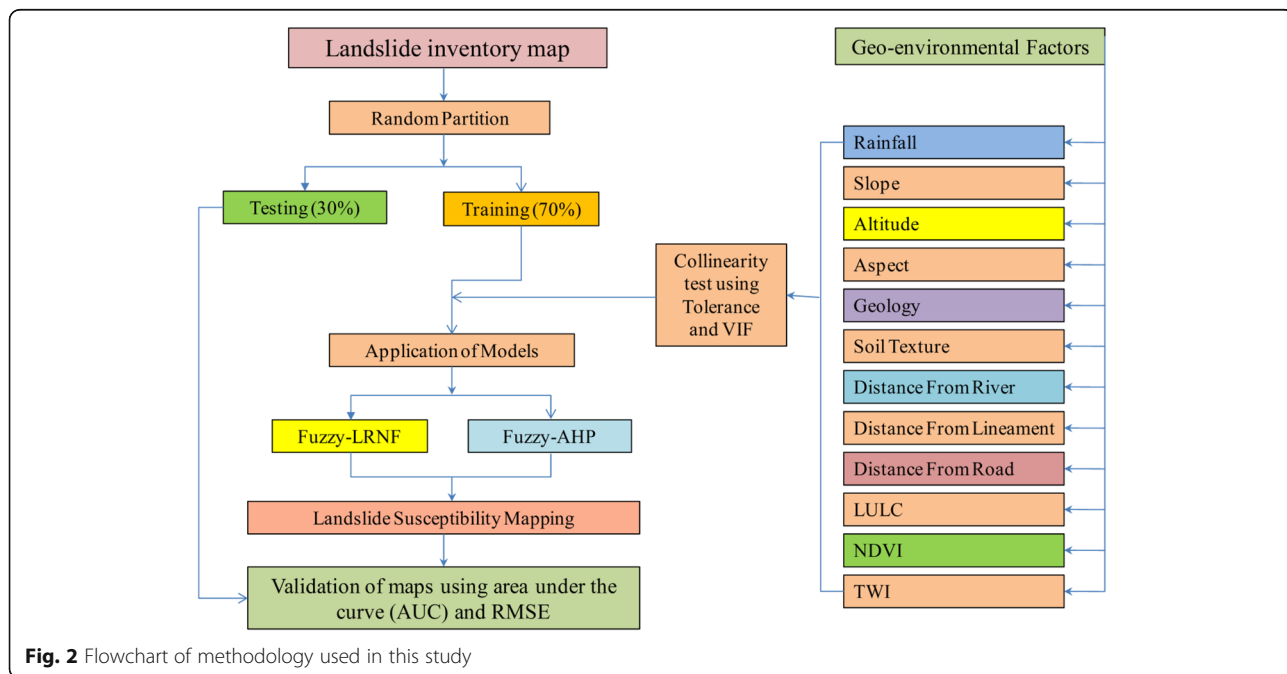

Fig. 2 Flowchart of methodology used in this study

calculating the LNRF to predict the potentials landslide susceptibility areas in this district.

Selection and Muliti-collinearity analysis of landslide causative factors

There is a variety of geo-environmental parameters that have been used by the various researchers for producing the landslide susceptibility map. Still there is no standard guideline for selecting the landslide predictors. In this research 12 landslide causative factors i.e. rainfall, slope, aspect, altitude, geology, soil texture, distance from river, distance from lineament, distance from road, land use/ land cover, NDVI and TWI have been selected based on the multi-collinearity analysis for mapping the landslide susceptibility. In the landslide susceptibility analysis aforementioned causative factors are widely used (Dou et al. 2019; Arnone et al. 2016; Tien Bui et al. 2012).

Multi-collinearity analysis is an important way to verify the effectiveness of the landslide conditioning factors (Saha 2017). For the present study, the collinearity test of landslide determining factors has been done in the SPSS software. A tolerance of less than 0.10 and and variance inflation factors (VIF) 10 or above indicates multicollinearity problems (Dormann et al. 2012; Wang et al. 2008). In the present study, the values of tolerances and VIF of all the selected parameters are less than 10% (Table 1). So, there is no collinearity problem among the selected landslide determining factors.

Preparation of thematic layers of selected parameters

The average annual rainfall data of last 5 years, since 2012 to 2017 have been collected from Indian Meteorological Department. The thematic layer of rainfall has been prepared with the help of the interpolation method of IDW in GIS environment based on the average

Table 1 Collinearity statistics of landslide determining factors

Sl. No	Parameters	Collinearity statistics	
		Tolerance	VIF
1	Rainfall	0.494	2.024
2	Elevation	0.638	1.566
3	Slope	0.894	1.118
4	Aspect	0.742	1.348
5	Geology	0.743	1.346
6	Soil	0.858	1.166
7	Distance from River	0.635	1.575
8	Distance from Lineament	0.818	1.223
9	Distance from Road	0.527	1.898
10	LULC	0.833	1.201
11	NDVI	0.804	1.243
12	TWI	0.884	1.132

annual rainfall data of last 5 years (Fig. 3a). The slope map of the study area has been prepared from ASTER DEM with the help of 3D analyst tool of ArcGIS 10.3.1 software (Fig. 3b). In case of elevation and aspect, these data layers have been prepared from ASTER DEM with the help of 3D analyst tool of surface in GIS environment (Fig. 3c, d).

The geology map has been prepared with the help of digitations process from referenced geological map which has been collected from Geological Survey of India (Fig. 3e).

The thematic layer of soil texture has been generated with the help of the digitations process form referenced soil map which has been collected from National Bureau of Soil Survey and Land Use Department (Fig. 3f). The distance from river and distance from road maps have been prepared with the help of Euclidian distance buffering tool in GIS environment (Fig. 3g, h). The lineament of the study area has been extracted from Landsat 8 OLI (Optical land Imager) image with the help of the ENVI 4.7 and GEOMATICA softwares. The distance from lineament map has been prepared with the help of Euclidian distance buffering tool of ArcGIS software 10.3.1 (Fig. 3i). The land use/ land cover (LULC) map has been prepared from Landsat 8 OLI imagery with the help of maximum likelihood classification method (Fig. 3j). The normalized differential vegetation index (NDVI) has been calculated from Landsat 8OLI image with the help of image analysis tool in ArcGIS 10.3.1 software (Fig. 3k). The thematic layer of TWI has been prepared from ASTER DEM imagery in GIS environment using Eq. 1 (Fig. 3l) which was suggested by Moore et al. (1991).

$$TWI = In\left(\frac{\alpha}{\tan\beta}\right) \quad (1)$$

Where, TWI = topographic wetness index, α is cumulative upslope area draining through a point (per unit contour length), β is the slope gradient (in degree). The minimum, maximum, categorical classification and methods of the selected geo-environmental conditional factors have been done in GIS environment and mentioned in the following Table 2.

Fuzzy method

For the present study, the Fuzzy method has been assembled with AHP and LNRF methods. The fuzzy maps of selected parameters have been prepared with the help of membership function (MF) tool in GIS environment. The membership function (MF) values range between 0 and 1 (Zadeh 1965). The value 0 means that x is not a member of the fuzzy set, while the value 1 means that x is a full member of the fuzzy set. A sample of fuzzy set
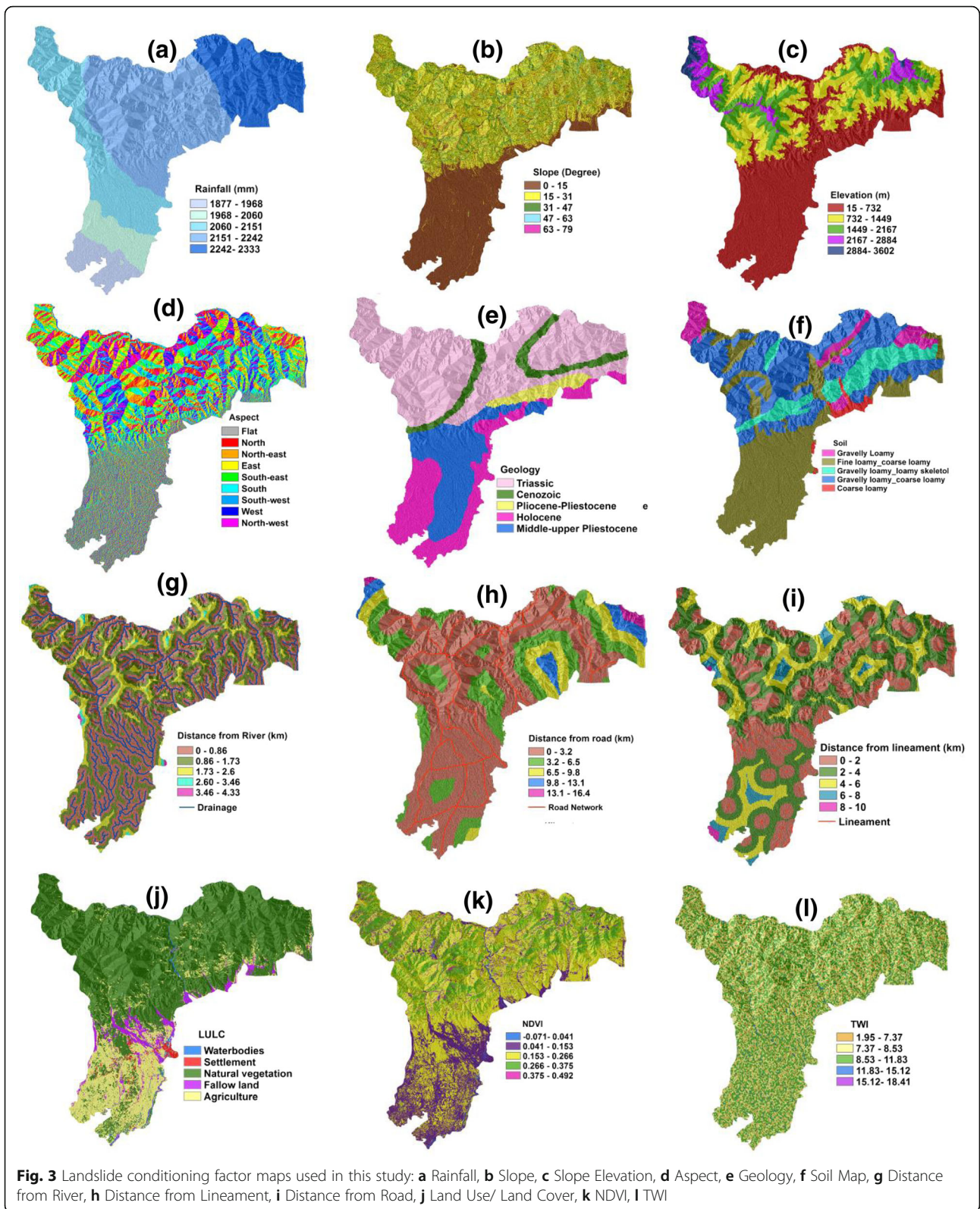
Fig. 3 Landslide conditioning factor maps used in this study: **a** Rainfall, **b** Slope, **c** Slope Elevation, **d** Aspect, **e** Geology, **f** Soil Map, **g** Distance from River, **h** Distance from Lineament, **i** Distance from Road, **j** Land Use/ Land Cover, **k** NDVI, **l** TWI

Table 2 Overview of selected parameters used for landslide susceptibility mapping

Parameters	Ranges		Classes	Methods
	Min	Max		
Rainfall (mm)	1877	2334	1. 1877.38–1991.9	Natural Break
			2. 1991.97–2090.54	
			3. 2090.45–2167.44	
			4. 2167.44–2239.06	
			5. 2239.06–2333.96	
Slope (Degree)	0	79.2	1. 0–9.32	Natural Break
			2. 9.32–18.64	
			3. 18.44–27.34	
			4. 27.34–36.66	
			5. 5. 36.66–79.23	
Altitude (m)	15	3602	1. 15–422.93	Natural Break
			2. 422.93–985.6	
			3. 985.6–1576.4	
			4. 1576.4–2279.73	
			5. 5. 2279.73–3602	
Aspect	–	–	1. Flat (–1)	Equal interval
			2. North (0–22.5)	
			3. Northeast (22.5–67.5)	
			4. East (67.5–112.5)	
			5. Southeast (112.5–157.5)	
			6. South (157.5–202.5)	
			7. Southwest (202.5–247.5)	
			8. West (247.5–292.5)	
			9. Northwest (292.5–337.5)	
			10. north(337.5–360)	
Geology	–	–	1. Triassic	lithological units
			2. Cenozoic	
			3. Pliocene-Pleistocene,	
			4. Holocene	
			5. Middle-upper Pleistocene	
Soil texture	–	–	1. Gravelly loamy,	soil texture classes
			2. Fine loamy - Coarse Loamy	
			3. Gravelly loamy Skeletol	
			4. Gravelly Loam - Coarse Loamy	
			5. Coarse Loamy	
Distance from River (km)	0	4.33	1. 0–0.42	Natural Break
			2. 0.42–1.10	
			3. 1.10–1.66	
			4. 1.66–2.26	
			5. 2.26–4.33	
Distance from Lineament (km)	0	10.1	1. 0–1.54	Natural Break
			2. 1.54–2.85	
			3. 2.85–4.20, 4	
			4. 4.20–5.75	
			5. 5.75–10.12	
Distance from Road (km)	0	16.5	1. 0–1.74	Natural Break
			2. 1.74–3.94	

Table 2 Overview of selected parameters used for landslide susceptibility mapping *(Continued)*

Parameters	Ranges		Classes	Methods
	Min	Max		
			3. 3.94–6.72	
			4. 6.72–10.22	
			5. 10.22–16.49	
Land use/Land cover	–	–	1. Water bodies	supervised classification
			2. Vegetation	
			3. Fallow land	
			4. Agricultural land	
			5. Settlement	
NDVI	−0.07	0.49	1. −0.07-0.12	Natural Break
			2. 0.12–0.17	
			3. 0.17–0.23	
			4. 0.23–0.29	
			5. 0.29–0.49	
TWI	1.95	18.9	1. 1.95–7.37	Natural Break
			2. 7.37–8.53	
			3. 8.53–9.76	
			4. 9.76–11.70	
			5. 11.70–18.91	

is shown in the following equation (Mcbratney and Odeh 1997).

$$A = \{x, \mu_A(x)\} \text{ for each } x\varepsilon X \tag{2}$$

Where, μ_A is the MF (membership of x in fuzzy set A) so that:

If x does not belong to A then μ_A = 0.
If x belongs completely to A then μ_A = 1.
If x x belongs in a certain degree to A then

$$0 < \mu_A(x) < 1$$

According to Eq. 3 MF was used for rainfall, elevation, aspect, slope, NDVI, TWI [8].

$$\mu_A(x) = f(x) = \begin{cases} 0 & x \leq a \\ x & \text{-a/b-a} \quad a > x < b \\ 1 & x \geq b \end{cases} \tag{3}$$

Where x is the input data and a, b are the limit values.
For geology, soil texture, distance from river, distance from lineament, LULC and distance from road the following MF has been used [4].

$$\mu_A(x) = f(x) = \begin{cases} 0 & x \leq a \\ b & \text{-x/b-a} \quad a > x < b \\ 1 & x \geq b \end{cases} \tag{4}$$

Fuzzy gamma operators

Several fuzzy operators exist for combining membership functions such as AND, OR, SUM, PRODUCT and GAMMA. In the present study, gamma operator has been used for combining membership functions.

Fuzzy gamma operation has been calculated using eqs. (5).

$$\mu_\gamma = (\mu_{sum})k^\gamma \cdot \left(\mu_{product}\right)^{1-\gamma} \tag{5}$$

The exponent γ, which is a number from < 0, 1 > interval, allows optimization of the membership combination. Setting it to the extremes of the interval give either fuzzy algebraic sum (γ = 1) or fuzzy algebraic product (γ = 0). To perform fuzzy gamma operation, several gamma operator (k) values, i.e. 0.50, 0.70, 0.80, 0.90, 0.95, and 0.975 are there. In the present study, fuzzy gamma operator (k) value of 0.975 has been applied for producing the landslide susceptibility map.

Landslide numerical risk factor (LNRF) model

Landslide Numerical Risk Factor (LNRF) model is an important method for identifying the landslide hazard zones especially in the mountain region (Gupta and Joshi 1990). According to this model, the LNRF > 1 value indicates that the geo-environmental factors have high responsibility for the occurrences of landslide. The LNRF < 1 values represent that the geo-environmental factors are more stable and have less effect in landslides occurrences (Gupta and Joshi 1990). The LNRF has been calculated through Eq. (6):

Table 3 Computation of LNRF model on landslide determining Factors

Parameters	Area		Landslides Area		LNRF	Fuzzy membership values using LNRF model
	In Hectare	In Percentage	In Hectare	In Percentage		
Rainfall (mm)						
Very Low (1877.38–1991.97)	27659.36	8.78	0	0	0	0
Low (1991.97–2090.54)	24856.96	7.89	0	0	0	0
Moderate (2090.45–2167.44)	80967.44	25.71	31.56	7.32	0.37	0.11
High (2167.44–2239.06)	114335.78	36.31	294.58	68.29	3.41	1.00
Very High (2239.06–2333.96)	67080.46	21.3	105.21	24.39	1.22	0.36
Slope (Degree)						
Very Low (0–9.32)	101505.25	32.23	14.5	3.36	0.17	0.11
Low (9.32–18.64)	58545.55	18.59	52.56	12.18	0.61	0.39
Medium (18.44–27.34)	70795.02	22.48	103.31	23.95	1.2	0.76
High (27.34–36.66)	57571.95	18.28	135.93	31.51	1.58	1.00
Very High (36.66–79.23)	26482.23	8.41	125.06	28.99	1.45	0.92
Altitude (m)						
Very Low (15–422.93)	115880.61	36.8	35.17	8.15	0.41	0.16
Low (422.93–985.6)	71784.89	22.8	224.01	51.93	2.6	1.00
Medium (985.6–1576.4)	63320.09	20.11	81.46	18.88	0.94	0.36
High (1576.4–2279.73)	44471.47	14.12	72.2	16.74	0.84	0.32
Very High(2279.73–3602)	19442.94	6.17	18.51	4.29	0.21	0.08
Aspect						
Flat (−1)	163.37	0.05	0	0	0	0
North (0–22.5)	20317.92	6.45	7.41	1.72	0.09	0.07
North-East (22.5–67.5)	39614.59	12.58	25.92	6.01	0.3	0.22
East (67.5–112.5)	39009.88	12.39	59.24	13.73	0.69	0.51
South-East (112.5–157.5)	44774.25	14.22	87.01	20.17	1.01	0.75
South (157.5–202.5)	45083.47	14.32	116.63	27.04	1.35	1.00
South-West (202.5–247.5)	39204.16	12.45	70.35	16.31	0.82	0.61
West (247.5–292.5)	32441.32	10.3	49.98	11.59	0.58	0.43
North-West (292.5–337.5)	35974.84	11.42	12.96	3	0.15	0.11
North (337.5–360)	18316.21	5.82	1.85	0.43	0.02	0.01
Geology						
Triassic	166113.98	52.75	302.86	70.21	3.51	1
Cenozoic	23200.35	7.37	82.6	19.15	0.96	0.27
Pliocene-Pleistocene	11258.98	3.58	45.89	10.64	0.53	0.15
Holocene	58152.53	18.47	0	0	0	0
Middle-upper Pleistocene	56174.15	17.84	0	0	0	0
Soil texture						
Gravelly loamy	23549.04	7.48	68.11	15.79	0.79	0.46
Fine loamy Coarse Loamy	126713.02	40.24	113.51	26.32	1.32	0.77
Gravelly loamy, Loamy Skeletal	38586.66	12.25	147.57	34.21	1.71	1
Gravelly Loamy Coarse Loamy	120449.25	38.25	90.81	21.05	1.05	0.61
Coarse Loamy	5602.03	1.78	11.35	2.63	0.13	0.08
Distance from River (km)						
0–0.42 km	99542.45	31.61	73.65	17.07	0.85	0.37
0.42–1.10 km	110752.04	35.17	199.89	46.34	2.32	1
1.10–1.66 km	64340.57	20.43	115.73	26.83	1.34	0.58
1.66–2.26 km	32920.37	10.45	42.08	9.76	0.49	0.21

Table 3 Computation of LNRF model on landslide determining Factors *(Continued)*

Parameters	Area		Landslides Area		LNRF	Fuzzy membership values using LNRF model
	In Hectare	In Percentage	In Hectare	In Percentage		
2.26–4.33 km	7344.58	2.33	0	0	0	0
Distance from Lineament (km)						
0–1.54 km	81563.6	25.9	110.6	25.64	1.28	0.77
1.54–2.85 km	95262.67	30.25	44.24	10.26	0.51	0.31
2.85–4.20 km	77028.98	24.46	143.78	33.33	1.67	1.00
4.20–5.75 km	44870.1	14.25	99.54	23.08	1.15	0.69
5.75–10.12 km	16174.66	5.14	33.18	7.69	0.38	0.23
Distance from Road (km)						
0–1.74 km	140275.58	44.55	88.48	20.51	1.03	0.67
1.74–3.94 km	84741.4	26.91	44.24	10.26	0.51	0.33
3.94–6.72 km	50166.43	15.93	66.36	15.38	0.77	0.50
6.72–10.22 km	27267.21	8.66	132.72	30.77	1.54	1.00
10.22–16.49	12449.37	3.95	99.54	23.08	1.15	0.75
Land use/Land cover						
Water bodies	3466.31	1.1	39.87	9.24	0.46	0.16
Vegetation	227240.32	72.16	255.55	59.24	2.96	1.00
Fallow land	14437.29	4.58	29	6.72	0.34	0.11
Agricultural Land	65442.75	20.78	106.93	24.79	1.24	0.42
Settlement	4313.33	1.37	0	0	0	0.00
NDVI						
Very Low (−0.07–0.12)	37936.34	12.05	114.18	26.47	1.32	0.91
Low (0.12–0.17)	83384.9	26.48	125.06	28.99	1.45	1.00
Medium (0.17–0.23)	85506.39	27.15	96.06	22.27	1.11	0.77
High (0.23–0.29)	70015.86	22.23	65.25	15.13	0.76	0.52
Very High (0.29–0.49)	38056.51	12.09	30.81	7.14	0.36	0.25
TWI						
Very Low (1.95–7.37)	49986.44	15.87	63.12	14.63	0.73	0.35
Low (7.37–8.53)	113766.56	36.13	178.85	41.46	2.07	1.00
Medium (8.53–9.76)	93346.92	29.64	115.73	26.83	1.34	0.65
High (9.76–11.70)	46923.5	14.9	73.65	17.07	0.85	0.41
Very High (11.70–18.91)	10876.58	3.45	0	0	0	0

$$LNRF = \frac{A}{E} \qquad (6)$$

Where A: landslide area in every unit, E: mean area of landslide in the whole unit.

The sub-parameters wise LNRF values have been calculated (Table 3). In the present study, fuzzy membership values have been allotted based on LNRF. To transform the LNRF values to Fuzzy membership values each sub-class has been divided by the maximum value of LNRF of individual parameter. The membership value ranges from 0 to 1. The fuzzy membership values using LNRF model have been converted into a single layer to chalk out the landslide susceptibility zone using Fuzzy Gamma operators (k) values of 0.975 in GIS environment.

Analytic hierarchy process (AHP)

Analytic hierarchy process is an important multi-criteria decision analysis (MCDA) method which can be applied for assigning the weights to the individual parameter (Saaty and Vargas 1998). AHP method is a pair wise comparison matrix. When the matrix is formed, the consistency ratio (CR) value ranges from 0 to 1 (Saaty 1980, 1990, 1994). To identify the potentiality index, general linear combination method can be performed with the help of AHP method (Malczewski 1999). The pair wise matrix has been formed with the help of the Saaty's (1980) fundamental scale (Table 4). In the present

Table 4 Fundamental scale of Saaty's (1980)

Scale	Description
1	Equal Importance
3	Moderate Importance
5	Strong Importance
7	Very Strong Importance
9	Absolute Strong Importance
2,4,6,8	Intermediate values between the two adjacent judgments

case, the weight of parameters calculated based on AHP method has been combined with fuzzy logic to prepare landslide susceptibility map of the study area.

Results

Application of fuzzy-LNRF model

The spatial distribution of average annual rainfall of the study area ranges from 1877.38 mm to 2333.96 mm (Fig. 3a) respectively. The rainfall map has been categorized into five classes such as very low (1877 mm–1991 mm), low (1991 mm–2090 mm), moderate (2090 mm–2167 mm), high (2167 mm–2239 mm) and very high (2239 mm–2333 mm) respectively. The high sub-class of rainfall with 36.31% area is covered the 68.29% landslides of the study area (Table 3). The LNRF values have been calculated and converted into fuzzy membership (FM) value. Here, high rainfall sub-class has attained the highest FM value i.e. 1, indicating the high risk of landslide than other sub-class of rainfall (Table 3). The spatially the slope of the study area ranges from 0 to 79.23° (Fig. 3b). It has been classified into five categories such as very low (0°-9.32°), low (9.32°-18.64°), medium (18.44° -27.34°), high (27.34° – 36.66°) and very high (36.66°-79.23°) classes based natural break classification method in GIS environment. The high and very high slope classes are covered with 31% and 28% landslides area. The fuzzy membership values of these sub-classes are nearer to 1, representing as high landslides risk areas. The altitude of the study area ranges from 15 m to 3602 m (Fig. 3c) respectively. The altitudinal map has been categorized into five classes such as very low (15 m to 422.93 m), low (422.93 m to 985.6 m), medium (985.6 m to 1576.4 m), high (1576.4 m to 2279.73 m) and very high (2279 m–3602 m). The low elevation class is covered with 51.93% landslide area (Table 3). The fuzzy membership value of 422.93 m–985.6 m elevation range is 1, representing higher landslide susceptibility than other sub-layers. Aspect of the study area has been classified into several categories such as flat, north, northeast, east, southeast, south, southwest, west and northwest. South sub-layer with 14.32% area is covered 27.04% landslide area. Geologically, the study area is composed of five geological segments namely Triassic, Cenozoic, Pliocene-Pleistocene, Holocene and Middle-

upper Pleistocene (Fig. 3e). Triassic geological segment with 52.75% area is encompassed with 70.21% landslide area. According to the LNRF model using fuzzy logic, the Triassic geological segment has attained the maximum LNRF and fuzzy membership value. The other sub-layers of geological segment are indicating the less probability of landslide occurrence. Pedagogically, the region is composed with several soil textural classes namely Gravelly loamy, Fine Loamy to Coarse Loamy, Gravelly Loamy to Loamy Skeletal, Gravelly Loamy to Coarse Loamy and Coarse Loamy (Fig. 3f). The 34.21% landslide areas are concentrated in Gravelly Loamy to Loamy skeletal soil texture class (Table 3) and the LNRF and fuzzy membership values are 1.71 and 1, which are representing high risk of landslides. The distance from river map (Fig. 3g) has been classified into five classes such as 0–0.42 km, 0.42 km – 1.10 km, 1.10 km – 1.66 km, 1.66 km – 2.26 km and 2.26 km to 4.33 km. The classes 0.42 km – 1.10 km and 1.10 km – 1.66 km of river buffering are covered with 46.34% and 26.83% landslide area (Table 3). The LNRF values of 0.42 km – 1.10 km and 1.10 km – 1.66 km sub-layers are 2.32 and 1.34 as well as fuzzy membership values of the same layers are 1 and 0.58 which are indicating high landslide susceptibility. The lineament distance map (Fig. 3h) has been classified into five buffer zones such as 0–1.54 km, 1.54 km – 2.85 km, 2.85 km – 4.20 km, 4.20 km – 5.75 km and 5.75 km – 10.12 km. The 2.85–4.20 km buffer zone has higher LNRF value (Table 3) than the other buffer zones. Road building activity in mountain areas is regarded as an infrastructure improvement, which may ground detrimental effects on slope steadiness; therefore, it can be helpful for delineating the prone areas to landslide occurrence. The buffer layer 6.72 km to 10.22 km. distance area from road is covered 30.77% landslide area (Table 3). This road buffer class has attained the fuzzy membership value 1. Other sub-layers of distance from road are showing the low to medium landslide susceptibility. The five type of land use classes have been identified in this study area namely water bodies, natural vegetation, sand, agricultural land and settlement with the help maximum likelihood classification method in GIS environment (Fig. 3j). The 72.16% area is covered with natural vegetation area in this district. The agricultural land and settlement areas are indicating less probability for the occurrence of landslide. Natural differential vegetation index (NDVI) is one of the important factors of environment. The value of the NDVI of the study area ranges from – 0.07 to 0.49 (Fig. 3k) respectively. The NDVI map of the study area has been classified into five classes such as very low (– 0.07–0.12), low (0.12–0.17), medium (0.17–0.23), high (0.23–0.29) and very high (0.29–0.49). According to LNRF model, the low sub-class of NDVI is attained the highest LNRF and fuzzy membership values i.e. 1.45 and 1 which are also
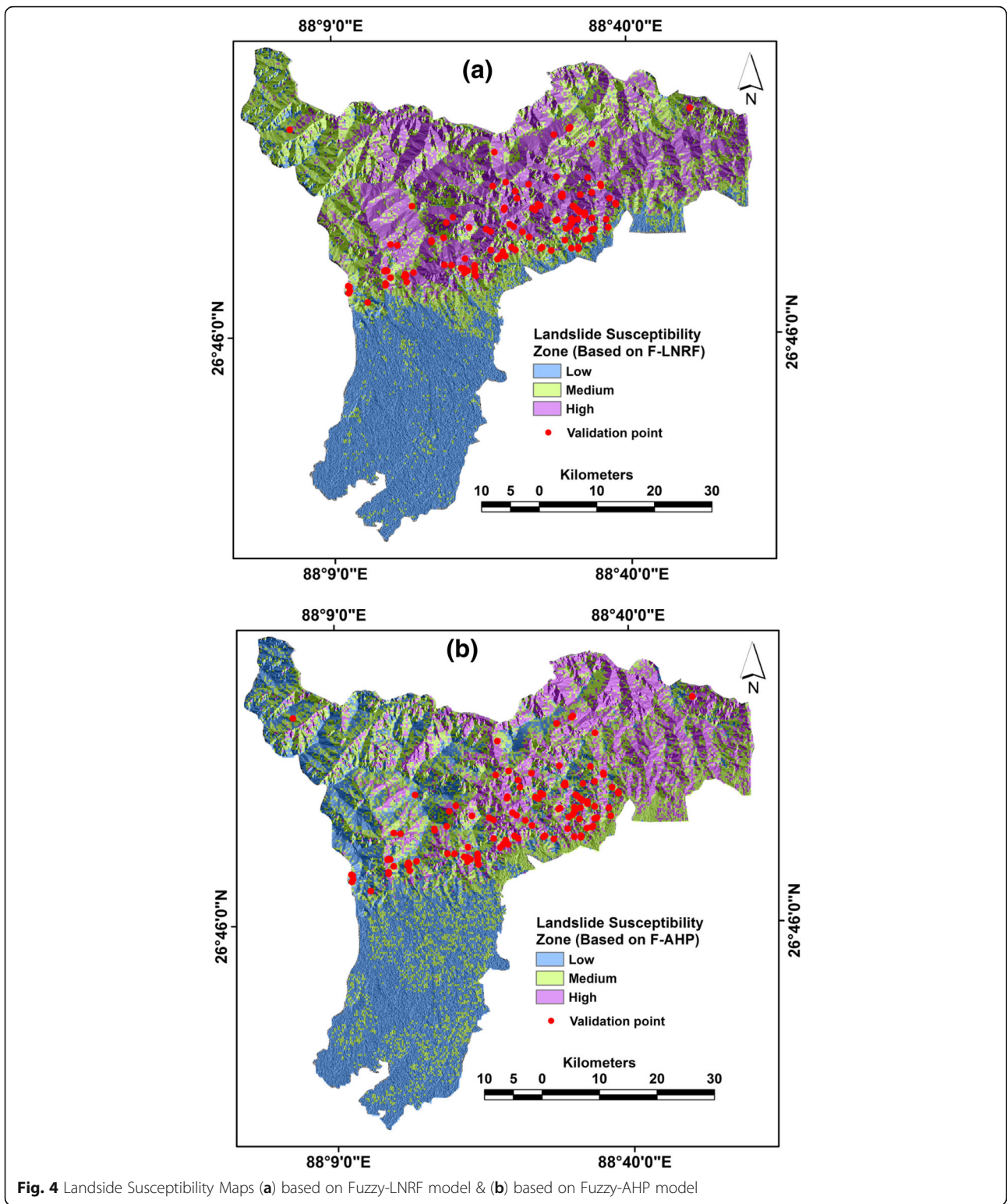
Fig. 4 Landside Susceptibility Maps (**a**) based on Fuzzy-LNRF model & (**b**) based on Fuzzy-AHP model

indicating the high landslide susceptibility. The spatial distribution of TWI of the study area ranges from 1.95 to 18.91(Fig. 3l) respectively. TWI map of the study area has been classified into five classes namely very low (1.95 to 7.37), low (7.37–8.53), medium (8.53–9.76), high (9.76–11.70) and very high (11.70–18.91) (Table 4). The low and medium TWI classes area representing the high risk for landslide than other sub-layers.

The landslide susceptibility map (LSM) based on fuzzy membership values has been prepared with the help of fuzzy gamma operators (k) value of 0.975 and shown in Fig. 4a. It has been classified into three classes namely low, medium and high landslide susceptibility zones. Out of the total district 34% area is highly susceptible to landslide (Table 6).

Application of fuzzy-AHP model

In the present work the Fuzzy set theory with AHP is considered as the multi-criteria decision approach for identifying the landslide susceptibility zones. The integration of fuzzy set theory and AHP can be provided a good and reliable technique for zoning landslide susceptibility. AHP is a single process which helps to determine the weight of different factors based on the expert's opinion and knowledge. For the present work, weights have been assigned to landslide determining factors (Table 5) with the help of AHP method. The highest weight has been assigned to rainfall (0.180) and followed by slope (0.162), distance from the river (0.108), soil texture (0.095) and elevation (0.086) for mapping the landslide probability. Thereafter, the linear membership function (MF) has been used to prepare the fuzzy map of the selected parameters for landslide susceptibility mapping. The value of fuzzy membership ranges from 0 to 1. Therefore, values of prepared fuzzy maps of all selected parameters must be ranged from 0 to 1. The weights of parameters, calculated by AHP method, have been integrated with fuzzy maps of selected parameters to generate a single layer of landslide susceptibility with the help of

raster calculator of spatial analyst tool in Arc-GIS10.3.1 software. The landslide susceptibility map (Fig. 4b) has been classified into three categories like low, medium and high landslide susceptibility zones covering an area of 37.88%, 39.29% and 22.83% respectively (Table 6).

Some landslides identifed from google earth imagery and directly from the field are mentioned below- (Fig. 5)

Validation

The landslide susceptibility maps of Darjeeling district, prepared by Fuzzy-LNRF and Fuzzy-AHP models have been validated through the ROC curve and RMSE. Model based work may be possible to evaluate and justify easily with the help of ROC curve (Chung and Fabbri 2003). The ROC curve is drawn by X and Y axis. The X axis represents the false positive rate (1-specificity) and the Y axis represents the true positive rate (sensitivity) (Negnevitsky 2002). Mallick et al. (2018) and Feizizadeh et al. (2014) have applied the ROC curve for the validation of the landslide susceptibility zone. In the present study, 98 landslide patches have been selected among the 326 landslide patches for validating the landslide susceptibility maps. The area under curve (AUC) can be drawn for the landslide susceptibility zones with the help of the Table 7. According to the results of ROC curve, the area under curve (AUC) values of landslide susceptibility maps, prepared by the Fuzzy-LNRF and Fuzzy-AHP models are 91% and 90% which are indicating the excellent potentiality of these models for landslide susceptibility mapping (Fig. 6a, b). The LSM of both models have also been

Table 5 Parameters wise weights, matrix and consistency ratio using AHP

Parameters	Rainfall	Slope	Elevation	Aspect	Geology	Soil Texture	Distance from River	Distance from lineament	Distance from Road	LULC	NDVI	TWI	Weights
Rainfall	1												0.180
Slope	0.5	1											0.162
Elevation	0.33	0.2	1										0.086
Aspect	0.2	0.5	1	1									0.084
Geology	0.5	0.5	0.5	2	1								0.080
Soil Texture	0.5	0.2	2	1	0.5	1							0.095
Distance from River	0.2	0.2	0.5	0.5	0.2	0.5	1						0.108
Distance from lineament	0.2	0.2	0.5	0.5	0.5	0.2	0.5	1					0.046
Distance from Road	0.5	0.2	0.5	1	0.5	0.5	2	2	1				0.062
LULC	0.17	0.2	0.5	0.2	0.5	0.5	0.5	0.5	0.5	1			0.051
NDVI	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	2	1		0.025
TWI	0.14	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.5	2	1	1	0.021

Consistency Ratio = 0.078

Table 6 Areal distributions of LSM based on LNRF and Fuzzy-AHP models

Landslide susceptibility zones	LNRF model		Fuzzy-AHP model	
	Area in sq. km	% of Area	Area in sq.km	% of Area
Low	950.15	30.17	1192.97	37.88
Medium	1114.40	35.39	1237.17	39.29
High	1084.46	34.44	718.86	22.83

validated through RMSE method. The RMSE is calculated using the Eq.7.

$$RMSE = \sqrt{\dfrac{\sum_{i=1}^{N} (P\text{-}A)^2}{N}} \tag{7}$$

Where, N is the numbers of samples, A is the observed values and P is the predicted values. Can et al. (2005) has considered the RMSE value of 0.5, as the cut-off value. The values of RMSE > 0.5 and < 0.5, indicate the bad predictive and good predictive model. In the

Fig. 5 Picture showing the landslide sites – from the google earth image. **a** Lish catchment (26°57′N, 88°30′17″E), **b** Nimbong Khasmahal (26°58′04″N, 88°34′16″E), **c** Sittong (26°52′N, 88°22′30″E) and from the field, **d** Near Kurseong town (26°55′46.32″N, 88°19′50.38″E), **e** Near Darjeeling town (26°53′13.37″N, 88°17′46.45″E), **f** Nathula road (26°54′43.14″N, 88°18′21.10″E)
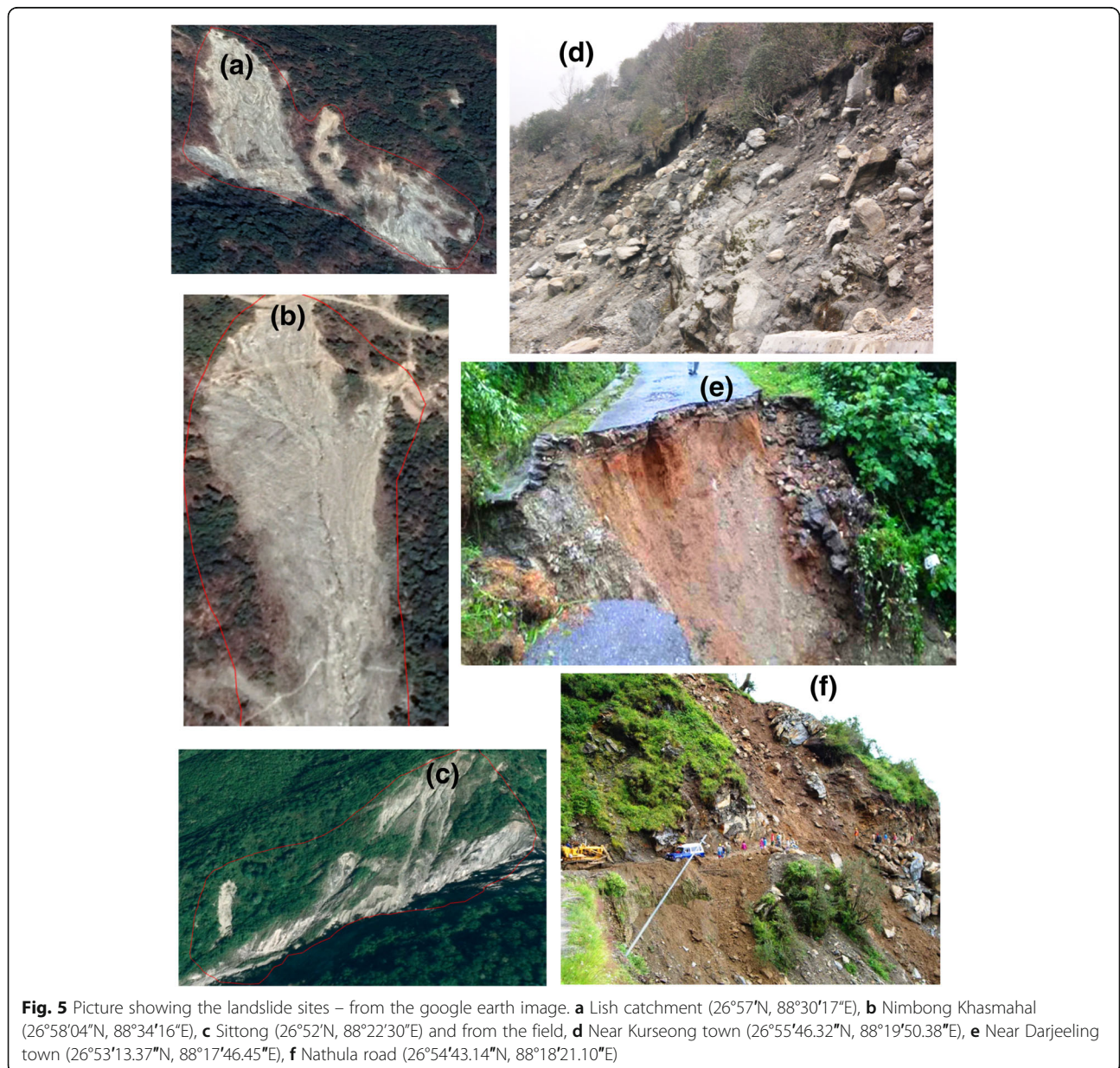
Table 7 Characteristics of AUC of ROC curve (Yesilnacar 2005)

AUC Values	Characters
0.6–0.5	Average
0.7–0.6	Good
0.8–0.9	Very Good
1–0.9	Excellent

present study, the results of RMSE are justified Fuzzy-LNRF (RMSE = 0.14) and Fuzzy-AHP (RMSE = 0.18) models as good predicative models for landslides susceptibility mapping.

Discussions

In the landslide prone areas appropriate methods of landslide susceptibility mapping play significant task in providing a proper approach to authorities and decision makers. Very fundamental information regarding the landslide conditioning factors can be acquired from the landslide susceptibility mapping (LSM) and it can be an essential way in hazard mitigation measures and management. There is a large number of weight combining methods for preparing the landslide susceptibility map. The results of some multi-criteria decision analysis such as AHP, LNRF, Fuzzy logic, Artificial Neural Network Support Vector Machine, Logistic Regression and Frequency Ratio are a little bit varied from region to region. Some researchers such as, Malik et al. (2016), Mohammadi et al. (2014), Shadfar et al. (2011) and Gupta and Joshi (1990) pointed out that LNRF method is suitable method in landslide susceptibility mapping. On the other hand, Abedini and Tulabi (2018) was indicated that LNRF is not suitable method like frequency ratio and AHP.

In this work, Fuzzy-AHP and Fuzzy-LNRF, the two efficient and easily operate ensemble models have been used for delineating landslide susceptibility and compared with them. In these two ensemble models Fuzzy-AHP and Fuzzy-LNRF, input process, calculations and output process are very simple and can be readily understood. The geo-environmental factors like slope, aspect, altitude, geology, soil texture, distance from river, distance from lineament, distance from road, rainfall, land use/ land cover, NDVI and TWI have been considered for the determination of the landslide susceptible area of the Darjeeling district. According to the Fuzzy-LNRE and Fuzzy-AHP maps 34.44% and 22.83% areas (Fig. 7a and b) of the district fall under the high susceptibility of landslide. Based on these findings, it can be acknowledged that the high susceptibility zone delineated by the Fuzzy-LNRF method is forecasting greater percentage of the landslide area. Additionally, the reliability of the results of two susceptibility maps has been validated based on the known landslide dataset by employing the area under the curve (AUC) of the receiver operating characteristics (ROC) and RMSE. A landslide inventory map has been prepared considering the multiple field works and Google Earth Images. Out of the 326 landslides 246 (70%) locations have been used for training data and remaining 80 (30%) have been used as testing data. Respective AUC values of 91% and 90% for fuzzy-LRNF and fuzzy-AHP proved that the map produced by the fuzzy-LRNF model looks like having a better accuracy than the fuzzy-AHP model. This finding is helpful for emergency situation because time is very significant in hazard studies. It could be assessed that the models applied have relatively similar accuracies. Methods such as LNRF (Gupta and Joshi 1990 & Abedini and Tulabi 2018) and fuzzy-AHP (Roodposhti et al. 2014) were used
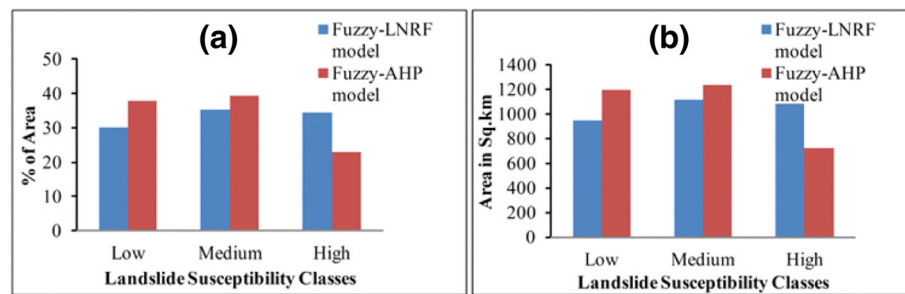

Fig. 6 Validation of LSMs by ROC curve **a** for Fuzzy-LNRF model **b** for Fuzzy-AHP model
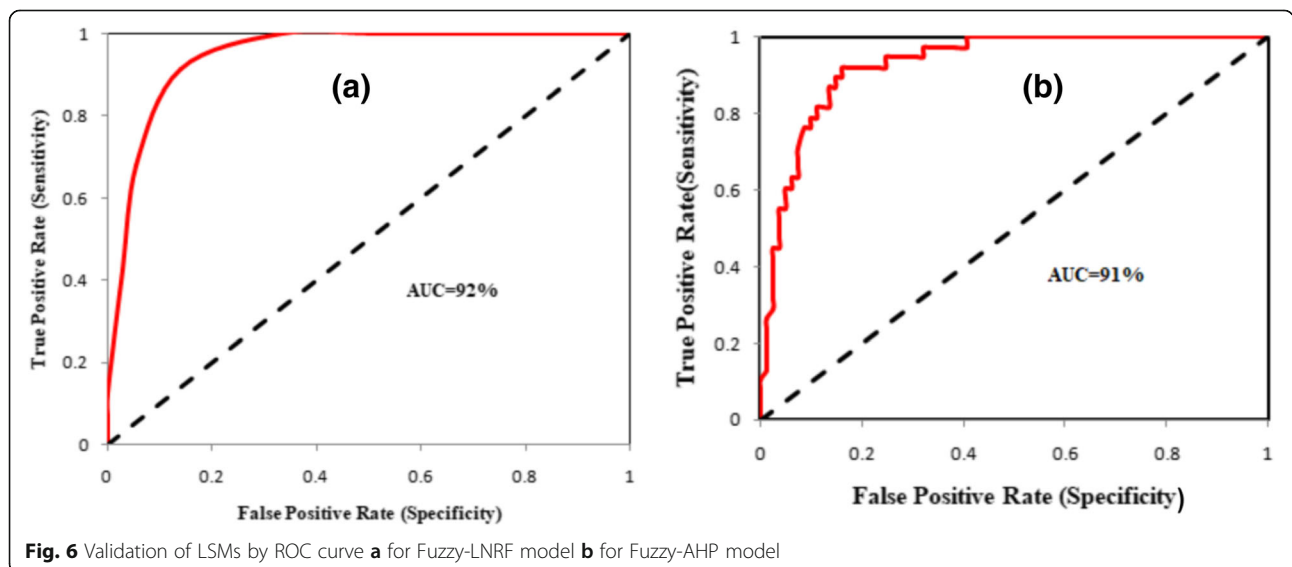
Fig. 7 Graph showing the distribution of area under different susceptibility classes **a** Percentage of area and **b** Area in sq.km

in mapping the landslide susceptibility. Compared to these previous studies the used methods i.e. fuzzy-LNRF and Fuzzy-AHP in this study are showing better performance in preparing the LSM. Taking into account the performances, we suggest that both Fuzzy-LNRF and Fuzzy-AHP models can be used in landslide studies, as they are capable of producing flawless and stable landslide susceptible maps for mitigating the risk and management planning. There are little differences in result between the Fuzzy-LNRF and Fuzzy-AHP derived susceptibility maps. Moreover, the Fuzzy-LNRF model is promising and sufficient to be advised as a method to prepare landslide susceptibility map at regional scale.

Conclusions

For the prevention of human lives and property, a short and long-term solution is necessary for mitigating the landslide risk in this region. At present day, landslide is to be considered the most serious natural hazards in the Darjeeling district. The study has been adopted the suitable multi-criteria decision making approaches like Fuzzy-AHP and Fuzzy-LNRF to outline the landslide susceptibility zones. The landslide susceptibility maps of both models have been categorized into three classes such as low, moderate and high landslide susceptibility zones. The high landslide susceptibility zone has been found in the middle and northern portions of the study area because of the presence of fragile soil, high concentration of drainage, frequent heavy rainfall and sloppy land. Among these two ensemble models, Fuzzy-LNRF is showing better acceptability than the other model. So, the study has been done by these two ensemble models help to understand the landslide hazards problem of an area. The study also provides the essential information to the planner, government, local people and researchers to take suitable steps for the reduction and the mitigation of the landslides problems in the Darjeeling district.

Abbreviations

AHP: Analytical hierarchical process; ASTER: Advanced space borne thermal emission and reflection radiometer; DEM: Digital elevation map; GIS: Geographical information system; LNRF: Landslide Numerical Risk Factor; LSM: Landslide susceptible map; LULC: Land use/Land cover; MCDA: Multi-criteria decision approach; MF: Membership function; NDVI: Normalized differential vegetation index; OLI: Operational land imager; RMSE: Root mean square error; ROC: Receiver operating characteristic; TM: Thematic mapper; TWI: Topographical wetness index; VIF: Variance inflation factors

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