Geo-spatial approach-based landslide susceptibility mapping using analytical hierarchical process, frequency ratio, logistic regression and their ensemble methods

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Abstract

Kurseong municipality and its surrounding hill slope are famous high altitudinal residential areas in the Darjeeling Himalayan region of India. In Darjeeling Himalayas, huge landslides occur in the rainy season every year. This paper was aimed to delineate landslide susceptibility zone (LSZ) in Kurseong and its surrounding hill slope in Darjeeling Himalayas. Nine landslide inducing parameters (i.e., slope, altitude, rainfall, geological structure, distance from river channels, distance from lineament, soil type or characteristics, land-use/land-cover and aspect) were used for mapping LSZ applying analytic hierarchy process (AHP), frequency ratio (FR), binary logistic regression (BLR) models and their ensemble (AHP–FR; AHP–BLR; and FR–BLR) with the aid of ArcGIS, SPSS and ERDAS software. The landslide susceptible maps produced in GIS environment by the AHP, FR, BLR and their ensemble models were classified into five susceptibility classes such as very low, low, moderate, high and very high. The area under curve (AUC) of receiver operating characteristics (ROC) and kappa statistics were used to analyze the accuracy of the LSZ maps. The AUC values of prepared maps were 78.86% (AHP), 80.22% (FR), 80.67% (BLR), 83.44% (AHP–FR), 84.39% (AHP–BLR) and 84.73% (FR–BLR). Overall kappa statistics were 0.789 (AHP), 0.812 (FR), 0.799 (BLR), 0.837 (AHP–FR), 0.856 (AHP–BLR) and 0.868 (FR–BLR), indicating the good accuracy of the models. The mapping of LSZ will be useful for land-use planning and future landslide hazard mitigation strategies.

Keywords Analytic hierarchy process · Frequency ratio · Binary logistic regression · Ensemble modeling · Landslide susceptibility mapping · Kurseong region

1 Introduction

The most distressing environmental hazards in the Himalayan mountainous and adjacent foot-hill area are landslide. The landslide (LS) causes damage to human life, assets and infrastructure in the Himalayan mountain region [1, 2]. Landslide is a complex process, which is caused due to some internal and external factors. The inherent factors consist of the stability situation of the slope, geological factors, soil category, groundwater condition, geometry of slope (slope inclination, aspect, elevation and curvature)

and land-use/land-cover changes [3–6]. Several researchers developed specific models or approaches to map the landslide susceptibility zone (LSZ) in numerous mountains areas around the world. Analysis of LSZ includes consideration of the physical factors that cause slope instability in an area, assessment of their contribution and appraisal of their aggregate influence. This is carried out using a variety of methodologies that can be widely categorized as qualitative and quantitative analyzes, considering the physical factors identified as variables causing landslides. Basharat and Saha offered a detailed description of the analysis

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of those techniques [4, 5]. The qualitative methodology uses specific parameters focused on subjective judgment rules taken by the geoscientist on the landslide-influencing physical factors [4, 7]. In addition to the recently introduced approaches, such as the fuzzy technique, they include statistical and geotechnical methods [7, 8].

The probability of LS was investigated in the mountainous area of several countries, like Japan, Korean, Bhutan, Malaysia, India, etc. [5, 9, 10]. Sakkas applied a generalized model of the linear combination process for analyzing LS susceptibility in Greece [11]. The slope failure probability models and logistic regression models were applied for LS risk assessment [12]. Raghuvanshi [13] described that the internal parameters handle the stable status of the shield, such as geological factors (lithological structure, soil type and underground conditions), shield geometry (shield aspect, curvature or height) and also land-use/land-cover. The machine language-based artificial neural network model for LSZ analysis was applied in the Cameroon, Malaysia [14]. Saaty [15] initiated the analytical hierarchy process (AHP), the semiquantitative method based on comparative judgment. AHP method was subsequently applied in Taiwan and Nepal for LSZ mapping [16, 17]. Soil characteristics were used for slope mass rating and modeling the landslide susceptibility in Himalayan mountainous area [18]. The LSZ mapping was done in Inje area basin of Korea using logistic regression [19]. Saha et al. analysis [5] and Shit et al. analysis [20] applied the probabilistic approaches for the LSZ risk and hazard analysis. Ensemble model for LSZ mapping using RS and GIS was applied by Basharat et al. [4], Park et al. [19] and Nithya et al. [21]. The risk of LS and its vulnerability in the European mountainous region were deliberated using various models used in different researcher's work [9, 10]. Some notable LS modeling works have been done using the hybrid methods [22], explicit deep learning neural network model [23], artificial neural network model [24, 25], adaptive neuro-fuzzy inference system (ANFIS) multiple meta-heuristic model [27].

Sarkar et al. [27] in their work assigned numeric weight to the landslide-conditioning factors on the basis of occurrence of landslide in the study area. In the AHP model, weights are allocated to landslide-conditioning factors for predicting the landslide probability. Recently, some researches were done to prepare the LSZ map using AHP method in the Himalayan region [4, 5, 20]. A large number of researchers produced LSZ maps using frequency ratio (FR) and binary logistic regression (BLR) models [5, 28–30]. The relationship between LS site and landslide-conditioning factors can be analyzed through the BLR model [30–32].

The Kurseong and its surrounding area are regularly hit by the landslides and trigger tremendous losses of life and property. Mapping the landslide susceptibility zones is

important for handling landslide problems in this area. The main objective of this paper is to prepare the LSZ maps of Kurseong municipal and its surrounding in Darjeeling Himalaya using individual AHP, FR, BLR methods and their ensemble models. The comparison of the efficiency of novel ensemble AHP–FR, AHP–BLR and FR–BLR methods with performance of individual AHP, FR and BLR models in landslide susceptibility assessment is the main novelty of this work. The ensemble technique of AHP–FR, AHP–BLR and FR–BLR methods is yet not implemented in landslide susceptibility studies in Darjeeling Himalayan, India. The key advantage of the study is that an accurate landslide susceptibility map (LSM) was being developed, which is a crucial asset for land and town planners in the mountainous area. These maps will assist the planner to adopt the mitigation strategies and to allocate suitable areas especially for the development of infrastructure activities.

2 Materials and methods

2.1 Study area

Kurseong municipality along with its neighboring downhill slope of Darjeeling Himalaya is extended between 26°46'30" and 26°57'47" North latitudes and 88°08'25" to 88°27'54" longitudes comprising an area of 380.33 km² in the district of Darjeeling, WB, India (Fig. 1). Municipality of Kurseong is a subdivisional town and a hill station. The name 'Kurseong' is come from the word 'Kharsang,' originally a local word 'Lepcha,' connoting 'the land of white orchids' [33].

It is one of the most ancient urban centers. Kurseong Town was founded back in 1835 when the British Government of India brought this region out of the kingship of Sikkim. The tiny hamlet eventually became a popular spot for the colonial government in 1880 and became a favored location for sanatoriums where the ill would heal. It has a nice year-round climate, and winters are not as extreme as they were in Darjeeling. The region's climate is aligned with climate-type CWA (subtropical humid) by Koppen. The average annual temperature is 23.69 °C, and the average annual rainfall is about 325 cm (weather record for the municipalities from 1991 to 2016). During the north-east monsoon, the marked rainy seasons are observed in the first week of June to the last week of September [5]. Through the northeast monsoon, it receives rainfall during both northeast monsoons. Every year, Monsoon (June–September) rainfall induces a number of landslides and destroys property and farmland. It is observed that the spatial distribution of landslides in the region is influenced by both morphological and hydrological characteristics of the

Fig. 1 Location map of the study area: **a** India, **b** Northern part of West Bengal, **c** Kurseong and its surrounding area with landslide points

slopes. The region portrays a heavily sculpted degraded environment in its youthful stage of turbulence cutting down by tumultuous streams and rivers coupled with

preexisting geological deformities with rocks of Darjeeling gneiss and Daling sequence of Archaeans, Permian

Gondwana rocks, Siwalik rocks and Pleistocene elevated terrace (Geological Survey of India) [34].

2.2 Database

The Landsat 8 OLI satellite imageries (30-m resolution) of 2018 were used to derive land-use data and Google Earth imageries were utilized to identify landslides in Kurseong and its surroundings. Nine contributing factors such as (a) altitude, (b) slope, (c) aspect, (d) rainfall map, (e) drainage system, (f) lithology, (g) land-use/land-cover (LULC), (h) lineament and (i) geology related to the occurrence of landslides were considered to prepare LSZ map in Kurseong and its nearby region of Darjeeling Himalaya. The aspect, slope and altitude map were derived from the Shuttle Radar Topography Mission (SRTM)-based DEM (created by NASA), using ArcGIS 10.3 platform (Table 1). In addition, these maps were classified using the quintile method [35, 36]. Geological map was derived from GSI, soil zonation map from NBSS and LUP Regional Centre, lineaments driven from bhuvan.nrsc.gov.in website and drainage system driven from Toposheet (Table 1). The LULC was generated from Landsat 8 OLI (Bands 2, 3 and 4; resolution 30 m) data using supervised classification technique and maximum likelihood algorithm through ERDAS 14.0 software. Field visits were carried out to realize the ground truth of landslide inventory. The process of preparing landslide susceptibility maps followed a number steps which are explained one by one (Fig. 2).

2.3 Landslide inventory mapping:

According to Balzano et al. [2], Roy et al. [28], Zhao et al. [31], the first and foremost move for the assessing of an area's landslide susceptibility is to examine, locate and map the landslides. This may be achieved by field surveys or via high-resolution aerial imagery. The LS occurrences were identified and mapped by field inspection and with the help of high-resolution imagery from Google Earth for the current study. The LS occurrences were identified and mapped by

field inspection and with the help of high-resolution imagery from Google Earth for the current study. In general, spatial mapping of landslides is required to assess the relationship between distributions of LS with the predisposing factors of the LS. At first, LS locations were recognized using the GPS coordination system, and later, the location of LS was drawn as a polygon using Google Earth images (Fig. 3). A total of 221 LSs locations are identified in this study area. Within 221 cases, 70% are being applied as training data to accumulate LSI, and the remaining 30% is applied to authenticate those models [37–39]. Hence, it was found out that LSs are most common in the middle and steep slope base upper altitude of this study area. In the lower part of the study area, the landslides were found along riverside, and they occur almost every year. Many landslides in the upper catchment are mainly restricted to under-gravity scrambling of rocks and rubble. The landslides are mostly debris, topsoil and mud flow in the middle catchment area, but in the western part of the middle catchment, rock falls sometimes happen as well.

2.4 Susceptibility modeling techniques

2.4.1 Analytic hierarchy process (AHP) analysis

AHP is an important multi-criteria decision approach (MCDA) which is used for assigning the weights. The AHP is a technique which calculates throughout pairwise comparisons of dissimilar factors. Based on expert decisions, the priority scales put on [39]. According to Saaty, the comparison can be done using a nine-point scale or real data [39]. The 9-point weight extent includes: [9, 8, 7, 6, 5, ... 1/5, 1/6, 1/7, 1/8, 1/9], where 9 means extreme preference, 7 means very active preference, 5 means strong preference, and so on, low to 1, which means no preference (Table 2) [40, 41]. The procedure is to assign priority weights for every factor through computation of normalized eigenvector (EV) which is very popular method of measuring the preferences from inconsistent pairwise comparison matrices [40]. The weights were derived by summing up the values in each column of pairwise comparison matrix,

Table 1 Various data layer with source used in the study

Major data	Sources	Scale or resolution
Topographical map and Google Earth (2018)	Survey of India (SOI), Kolkata. Map no. 78B/5 and Google earth	1:50,000
Geological map	Geological Survey of India (GSI), Kolkata	1:250,000
Lineament	bhuvan.nrsc.gov.in	1:50,000
Landsat 8 (OLI) (Path 139; Row 41)	Earthexplore.usgs.gov (date-29/02/2018)	30 m × 30 m
SRTM DEM	Earthexplorer.usgs.gov (date-23/09/2014)	30 × 30 m
Soil map	NBSS and LUP Regional Centre, Kolkata	1:250,000
World climate data	https://www.worldweatheronline.com/lang/en-in-west-bengal.aspx	3 os (~ 1 km ²)

Fig. 2 Flowchart of methodology

and each cell value is divided by the summed values of the same factors column. The average value of each row is the primary eigenvector of the matrix. As this matrix was randomly prepared, for this reason, some degrees of inconsistency may occur [17, 41]. The calculation table arranges in the tabular format according to Saner technique [42].

pixels in the subclass of landslide-conditioning factor; and 'tx' is the total pixels [43, 45, 46].

The FR value is indicating the association of landslide occurrence and landslide-conditioning variable. The landslide susceptibility index (LSI) was calculated by summing up of Fr values of every factor using the ArcGIS raster calculator in Eq. 2.

$$LSI = \left(\begin{array}{l} \text{slope classes fr} + \text{Altitude fr} + \text{Geological structure fr} + \text{Distance} \\ \text{from lineament fr} + \text{Distance from river fr} + \text{Soil fr} + \text{LULC fr} + \text{Aspect fr} \end{array} \right) \quad (2)$$

2.4.2 Frequency ratio (FR) model

FR defines the proportion of landslide pixels for each input layer in the specific category [43–45]. FR assumes that future landslides will occur in conditions similar to the past. It may be defined as the ratio of landslide pixels in a category (a class of factor) to the relative frequency of all landslide pixels in an area. FR values for subclass of every factor were calculated using Eq. (1).

$$FR = \frac{f/tf}{x/tx} \quad (1)$$

where 'f' is landslide pixels in the subclass of landslide conditioning; 'tf' is the total landslide pixels; 'x' is the total

(LSI: landslide susceptibility index; fr: the rating of each factor's class). The landslide susceptibility map was prepared using the LSI values and is shown in Fig. 5b.

2.4.3 Binary logistic regression (BLR) model

Logistic regression (LR) is a statistical model that allows for the evaluation of multivariable regression between a dependent and a group of independent variables [9, 29, 31]. The major benefit of logistic regression is that it can perform with the help of an appropriate link function to the ordinary linear regression. In this case, if the data are either continuous or categorical, or both, there is no problem and the regression does not require the normal distribution of data. For this analysis, the binary number '0' denotes non-landslide points and the binary number '1' denotes landslide point. The logistic regression method

Fig. 3 Some landslide Google images collected through Google earth pro **a** 26°55′01″N; 88°19′28″E; **b** 26°52′23″N; 88°21′01″E; **c** 26°52′37″N; 88°2′26″E; **d** 26°55′42″N; 88°26′31″E; and **e** 26°53′09″N; 88°27′07″E in this study area

means optimum likelihood calculation after the translation of the dependent variable into the logit component. Thus, logistic regression measures the probability of an event.

In this BLR model, the calculation was done applying Eqs. 3 and 4 and more detail can be found in some recently published articles [29, 30]. BLR model can be carried out using Eq. 3

$$LS^p = \frac{1}{(1 + Af^{-z})} \quad (3)$$

where 'LS^p' denotes the landslide probability. 'Af' denotes the affecting factors selected in this work. 'LSI' denotes the liner model combination, and it ranges between $-\omega$ and $+\omega$ (Eq. 4).

$$LS = (a_0 + a_1xv_1 + a_2xv_2 \dots a_nxv_n) \quad (4)$$

where 'a₀' signifies models intercept. The 'a₁, a₂...a_n' signify the slope of coefficient. And the xv₁, xv₂, ..., xv_n denotes the independence factor number.

$$\text{LSI} = \text{Intercept} - (\text{Slope} * B) + (\text{Altitude} * B) + (\text{Rainfall} * B) + (\text{Distance from lineament}) \\ + (\text{Distance from Drainage} * B) + \text{Geology}B + \text{Soiltype}B + \text{Land} - \text{cover}B + \text{Aspect}B \quad (5)$$

where B is the logistic regression coefficient value, while land-use/land-use B , geology B , soil type B and aspect B are the logistic regression coefficient values.

Based on independent variables, the BLR model forecasts the existence or absence of LS. On the basis of pre-failure conditions (independent variables), the linear LR represents the existing conditions (presence or absence of landslide). For the landslide susceptibility mapping by the BLR first, all the pixels of map were converted into points and then used these as input data layers in the SPSS software to calculate logistic regression values [47]. The logistic regression model is considered as quantitative method that finds out the effects of individual independent variable with the help of the coefficients and antilogarithm of the coefficients [9, 30]. Finally, the BLR model-based LSZ map was prepared using Eq. 5 [29, 30, 47, 48].

2.5 Process of models' ensemble

The ensemble modeling is a technique of joining the effects of different models into an incorporated embedded model to develop predictive capability [35, 48–50]. This technique has risen in recent last few years of reducing gully erosion [35]; modeling flood probability [49]; landslides susceptibility [50]; and different purposes. In this work, the ensemble models can be generated using the weighted combination of an individual model. The ensemble technique of AHP–FR, AHP–BLR and FR–BLR has been

followed by sequentially khosravi [49], althuwaynee [50] and Shafapour Tehrani [51] articles.

2.6 Landslide-influencing factors:

Major nine LS-influencing factors, those are the altitude, slope, rainfall map, slope aspect, soil map, geomorphology, distance from lineaments, distance from rivers and LU/LC map, were prepared to generate LSZ map. The landslide-conditioning factors are selected based on the literature survey and multi-collinearity test.

2.6.1 Slope

Slope having great role in making the area susceptible to landslide is frequently used in preparing LSZ maps [32, 38, 52, 53]. For this research, the slope map was prepared from DEM and classified into six groups (Fig. 4a).

2.6.2 Altitude

Altitude is a frequently used parameter for landslide susceptibility assessment [30, 48, 52]. In the study, the elevation ranges between 120 and 2440 m and is classified into 5 categories (Fig. 4b). To prepare this LSZ map, the elevation was divided into 5 groups and their weights were estimated according to matrix and consistency ratio for each class.

Table 2 The comparison scale in AHP (Saaty 1990)

Important concentration	Classification	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Weak importance of one over another	Experience and judgment slightly favor one activity over another
5	Necessary or strong importance	Experience and judgment strongly favor one activity over another
7	Demonstrated importance	An activity is strongly favored, and its dominance is demonstrated in practice
9	Supreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgments	When compromise is needed
Reciprocals of more than nonzero	If activity i have one of the above nonzero numbers assigned to it when compared with activity j , then j has the reciprocal value when compared with i	

Fig. 4 Landslide-conditioning factors: **a** slope, **b** altitude, **c** rainfall, **d** geological structure, **e** distance from lineament, **f** distance from river, **g** soil map, **h** land-use/land-cover map and **i** aspect map

Fig. 4 (continued)

2.6.3 Rainfall

The role of antecedent rainfall in causing landslides is also investigated by considering daily rainfall during failure and the cumulative rainfall to discover at what point

antecedent rainfall plays an important role in Himalayan landslide processes [43, 44]. Rainfall is an essential triggering factor in landslide occurrences [17]. In the Himalayan region, mean precipitation is very high compared to another part of India. The average is 525.5 cm in June,

July, August and September month of the monsoon season (<https://www.worldweatheronline.com/lang/en-in/west-bengal.aspx>). In the study, the average monsoon rainfall map was generated and divided into three classes, i.e., 400 cm, 400–500 cm and more than 500 cm per monsoon season (Fig. 4c).

2.6.4 Geological

The geomorphological element is the most notable phenomenon which plays an important role in landslides [55]. The high peak in the study area appears in the north-western part. This Himalayan part is regarded as the structural mountains, denudation plain and floodplain. Geological map of the study area was collected from the Geological Survey of India (GSI). The boundaries of geological segment and names of the geological unit were used in previous studies [34, 43, 55, 56]. This region is dissected into numerous small ridges, spurs, deep 'V'-shaped valleys and other erosional features. The geological map was digitized using ArcGIS v10.3 software and was converted into a grid map with 30 m × 30 m resolution. Alluvium and limestone deposits have a high capability for water adsorption and influence the landslide occurrences. Gneiss and States-Schist are semipermeable and have a limited water adsorption potential, and this geological unit is moderately susceptible to the landslide.

2.6.5 Lineament

Faults form a weak line or zone well marked by broken rocks [28, 31, 34, 43]. The lineament map was derived from bhuvan.nrsc.gov.in with a 1:50,000 scale. The distance from lineaments was calculated by Euclidean distance buffer tool in GIS environment and classified into 5 categories considering an interval of 300 m (Fig. 4e).

2.6.6 Distance from the river

Another important, promising and functional variable is the distance from the river for landslide occurrences [43, 45, 47]. Howard (1997) notified that isolation is a limited model, which influences the dominant hills-shield transportation process in relation to distance from the river and mean decay rates, through a threshold presence or absence for landslides and climate corrosion [55, 56]. The distance from the river was divided into 5 categories where an interval of 500 m was taken into account [36, 55–60] (Fig. 4f).

2.6.7 Soil type

The soil of Eastern-Himalayan hill and foot-hill area depends upon the fundamental geological structure [14, 34]. But, in general, the soil has been formed in cooperation fluvial action with lithological disintegration (Fig. 4g). The soils formed in the Kurseong area are predominantly reddish in color. Occasional dark soil is found due to the extensive existence of Phyletic and schist. Soils in the highland stretching from the west to east of the district along most of the inter-fluvial areas are mainly a mixture of sandy loam and loamy, and southern slopes of Kurseong are mainly composed of clayey loam and reddish in color. The basic soil types of the study area are yellow soils, red-brown soils and forest soils. Main soil types of the study area are WOO2 (Course Loamy, Typic Udorthents, Loamy-skeletal, Typic Dystrochrepts), WOO4 (Loamy-skeletal, Typic Udorthents, Loamy-skeletal, Typic Haplumbbrepts), WOO6 (Course loamy, Umbric Dystrochrepts) and WOO9 (Fine Loamy, Umbric Dystrochrepts, Course Loamy, Typic Udorthents). In the Kurseong, due to the presence of gneiss rock the red-brown soil and red soils are developed. In some parts of the study area, dark clayey soils are also present.

2.6.8 Land-use and land-cover

Rapid settlement expansion (building) takes place on mountain slopes where large landslides occurred historically that are not realistically sustainable in this area [34, 46, 60, 61]. This could result in major loss of property and human life at the time of future high magnitude landslide. In Kurseong hilly regions, land-use patterns are an important influencing factor for landslide occurrence [5]. Some restrictions should be imposed on building constructions for sustainable environmental management in Kurseong and its surrounding Darjeeling Himalaya [33, 34]. The forest and pasture areas should not be used for various purposes, which is announced by the Darjeeling hills area development program under the 8th 5-year plan. The major land-use is tea gardens where landslides are being observed noticeably. In addition, deep forest, plantation and riverside lands are also susceptible to landslides where the expansion of human settlement happened. The Sentinel-2 data were derived from glovis.usgs.gov satellite at 10 m scale (using band 2; band 3; and band 4). The West Bengal government blockwise LULC map, the topographical map from SOI no. 78B/5 and field verifications were incorporated and processed through ArcGIS v10.3 and

Table 3 Classification accuracies of LULC

Class name	LULC from Landsat 8 OLI satellite data			
	Reference	Classified	Correct	Conditional kappa
Settlement	40	40	36	0.895
Plantation	30	25	23	0.914
Social forestry	24	21	21	1.000
Open forest	29	24	22	0.910
Deep Forest	33	32	27	0.831
crops zone	56	50	44	0.872
Sand Deposition	16	19	16	0.844
Water Body	20	20	18	0.895
Total	248	231	207	
Kappa statistic 0.872				

ERDAS v14 software (Table 1) for preparing the LULC map of the study area. Thereafter, this LULC map was converted into a grid map with a resolution of 30×30 m (Fig. 4h). The accuracy of the LULC map was assessed by applying kappa statistics. Overall classification kappa statistics is 0.8727, which is desirable (Table 3).

Table 4 Result of multi-collinearity diagnosis of landslide conditioning factors

Independent variables	TOL	VIF
Slope	0.596	1.945
Altitude	0.745	1.308
Rainfall	0.445	2.648
Geological structure	0.529	1.854
Distance from lineament	0.584	1.873
Distance from river	0.737	1.269
Soil types	0.784	1.284
Land-use/Land-cover	0.774	1.257
Aspect	0.791	1.146

Table 5 Pairwise comparisons, factors priority and consistency ratio by AHP

Factors	Slope	Altitude	Rainfall	Geology	DL	DR	Soil type	LU LC	Aspect	Weight (W_i)
Slope	1	2	3	3	4	5	6	8	9	0.129
Altitude	1/2	1	2	2	3	4	5	8	9	0.113
Rainfall	1/3	1/2	1	2	2	3	4	5	7	0.087
Geology	1/3	1/2	1/2	1	2	3	4	5	5	0.075
DL	1/4	1/3	1/2	1/2	1	2	2	3	5	0.059
DR	1/5	1/5	1/4	1/3	1/2	1	2	2	3	0.051
Soil type	1/7	1/5	1/5	1/3	1/3	1/2	1	2	3	0.045
LULC	1/8	1/7	1/5	1/5	1/3	1/3	1/2	1	2	0.038
Aspect	1/9	1/7	1/7	1/5	1/5	1/3	1/3	1/2	1	0.033

2.6.9 Aspect

The slope aspect was recognized as a driving factor for a landslide [17, 34, 59]. The aspect map was derived from the digital elevation model (Fig. 4i). Due to an increase in moisture during the rainy season (July–September), some parts in the south-east and the south-western part of this Himalayan range become much more vulnerable to landslide occurrences.

3 Results

3.1 Multi collinearity test

Before preparing the landslide susceptibility models by the AHP, FR and BLR testing of multi-collinearity among the independent variables is essential [36, 56, 60, 61]. A tolerance of less than 0.10 and/or a VIF of 5 and above indicates a multi-collinearity problem [62–64]. In this study, both indices were calculated (Table 4). The values of tolerances and VIF of all the selected parameters are more than 0.2 and $< 10\%$ [62, 64]. So, there is no collinearity problem among the selected landslide determining factors. Among these selected factors rainfall factor has the highest VIF (2.648) and the slope aspect has the lowest VIF value (1.146).

3.2 Landslide susceptibility maps

In the calculation of AHP highest consistency ratio (CR) is achieved by slope (0.137) and lowest by aspect (0.033). Rainfall (0.092), altitude (0.112), distance from river (0.059) and geological structure (0.076) are also have high CR value (Table 5). In FR model the weight of soil type w-004 (16.22) is the highest and 83% of landslides are found in this soil segment. FR model also depicting that soil type w-006 (3.57) settlement (1.25) and fellow land (0.95) are highly influencing factors for LS and the opposite situation found in slope 0 to 5° (0.19), dense forest (0.63); open

Table 6 Pairwise comparison matrix for consistency ratio; weights of each sub layer by AHP method and frequency ratio (FR) values of the landslide-conditioning factors

Main factor (layer sequence no.)	Subclass	AHP method		FR values of the landslide conditioning		
		Consistency Ratio (CR)	Priority (R_i)	Number of pixel in sub-class	Number of pixel under landslide	Frequency ratio
1. Slope (°)	0–5	0.127	0.022	152,237	1922	0.19
	5–10		0.027	105,763	1308	0.81
	10–15		0.036	118,334	2111	0.56
	15–20		0.037	59,348	1524	0.40
	20–25		0.055	21,954	1045	0.21
	25 <		0.112	8539	678	0.12
2. Altitude (m)	2000 <	0.109	0.182	32,632	1631	0.25
	1500–2000		0.091	51,279	3006	2.17
	1000–1500		0.045	88,573	3349	1.26
	500–1000		0.023	181,809	1249	1.35
	500 >		0.015	163,161	686	1.67
3. Rainfall (cm)	500 <	0.092	0.219	181,709	4559	0.39
	500–400		0.147	46,616	691	0.67
	400 >		0.074	237,849	3326	0.69
4. Geological structure	Alluvial	0.076	0.021	111,882	1975	0.57
	Gneiss		0.032	125,867	2490	0.51
	States-schist		0.129	97,896	1892	0.51
	Limestone		0.146	107,220	1803	0.59
	Damuda		0.193	23,310	428	0.54
5. Distance from lineament (meter)	> 300	0.059	0.193	152,220	4711	0.32
	300–600		0.114	134,775	4031	0.33
	600–900		0.047	82,631	141	0.17
	900–1200		0.024	38,470	80	0.21
	1200 <		0.016	58,079	105	0.18
6. Distance from River (m)	2000	0.051	0.012	62,935	163	0.25
	1500–2000		0.038	83,911	773	1.07
	1000–1500		0.076	104,889	2404	0.43
	500–1000		0.114	92,302	1116	0.82
	500		0.152	75,520	6130	1.18
7. Soil type	w-002	0.043	0.188	118,850	731	0.61
	w-004		0.031	8141	1321	16.22
	w-006		0.015	99,212	3548	3.57
	w-009		0.125	193,354	2988	1.54
8. Land-use and land-cover	River	0.039	0.197	24,480	195	1.25
	Fellow land		0.172	48,895	1370	0.95
	Sandbank		0.147	120,714	1905	0.63
	Settlement		0.133	113,042	1140	0.79
	Cultivation land		0.073	57,301	855	0.67
	Plantation agriculture		0.049	33,535	660	0.51
	Open forest		0.024	23,405	1265	0.18
	Dense forest		0.012	18,535	723	0.26

Table 6 (continued)

Main factor (layer sequence no.)	Subclass	AHP method		FR values of the landslide conditioning		
		Consistency Ratio (CR)	Priority (R_i)	Number of pixel in subclass	Number of pixel under landslide	Frequency ratio
9. Aspect	Flat	0.033	0.002	147	18	0.08
	North		0.028	25,022	50	0.20
	North-east		0.002	58,824	395	0.67
	East		0.003	59,310	657	0.14
	South-east		0.041	68,039	599	1.10
	South		0.060	70,466	1348	1.91
	South-west		0.041	64,586	1454	2.25
	West		0.006	49,014	1449	2.95
	North-west		0.003	49,285	758	1.53

forest (0.79); soil w-002 (0.061); sandbank (0.18); distance from lineament subclass 600–900 m (0.17); 900–1200 m (0.21); and more than 1200 m (0.18) (Table 6). BLR model shows that the all the factors have not equal role in making the area susceptible to landslide in Kurseong and its surrounding. Slope (0.028); altitude (0.338); rainfall (1.476); geological structure (0.119); settlement; fellow land; and cultivation land in LULC have a positive role in causing the LS as the coefficient value which has found in the BLRM is positive. On the other hand, FCFs like distance from the river (−0.005) and w-006 (soil type) distance from the lineaments have a negative relationship with the LS. According to the BLR, rainfall (4.37) is the most important determining factor for the landslide in this region (Table 7).

Applying the AHP method (Table 5), LSZ map was obtained. The higher value of the LSI indicates the higher probability of landslide and vice versa. The LSI has a minimum value of 1.08 and the highest value of 2.85. The Kurseong range and its surrounding areas were divided into major 5 susceptibility regions according to the quintile method [57]: very low 16.63% of total area 63.25 km², low 21.43% of total area 81.19 km², moderate 88.65 km², high 20.88% of total area 99.91 km² and very high 17.75% of total area 71.08 km² (Fig. 5a; Table 8).

Applying the FR model, an LSZ map was obtained. If the LSI value is very higher, it means a high probability of landslide; lower value means lower probability to the landslide. The LSI has a minimum value of 10.48, and the highest value of 42.85 came in probability assessment. The Kurseong range and its surrounding were divided into major 5 susceptibility regions according to the quintile method [57]: very low, low, moderate, high and very high susceptibility classes cover 24.63% (93.63 km²); 17.72% (71.19 km²); (33.09 km²), 11.70% (44.50 km²); 26.27% (99.91 km²) and

19.69% (71.08 km²) areas of the study area, respectively (Fig. 5b; Table 8). Another single model BLR (Fig. 5c) was very high 13.23% (50.23 km²); low 20.67% (78.61 km²); and very low 30.48% (113.58 km²) LS suspect region.

In ensemble AHP–FR, AHP–BLR and FR–BLR models, very low, high and very high susceptibility classes cover 18.92% (71.59 km²), 20.68% (78.63 km²) and 18.64% (71.31 km²); 23.22% (88.31 km²), 16.36% (62.21 km²) and 17.43% (66.29 km²); and 22.72% (86.40 km²), 21.47% (81.64 km²) and 18.29% (69.56 km²) of the study area, respectively (Fig. 5d–f).

3.3 Models validation and comparison

For measuring the prediction accuracy of landslide susceptibility maps induced by different methods, application of suitable methods is necessary. Among the different validation approaches, area under curve (AUC) of receiver operating characteristic (ROC) curve has been widely used in geographical community [28, 47]. The ROC has been prepared by plotting the true positive (TP) against the false positive (FP) values at different threshold settings. ROC represents the true positive rate (TPR) and the false positive rate (FPR). The true positive rate (TPR) is called as the sensitivity, and false positive rate (FPR) is termed as specificity. The higher TPR denotes more accuracy, and higher FPR reflects error prediction of the models. ROC curves were used to decide the threshold value for the LSZ map [17, 19, 56]. The area under the curve (AUC) reflects the accuracy of the model [19, 46, 59, 66]. The area under curve (AUC) values can be classified into five categories such as poor (0.5–0.6), average (0.6–0.7), good (0.7–0.8), very good (0.8–0.9) and excellent (0.9–1) [2, 64, 65]. The

Table 7 Coefficient of logistic regression model of landslide conditioning factors

Independence variable	B	SE	WaldChi	dfr	Sig	Exp(B)	95% CI for Exp(B)	
							Upper	Lower
Slope	0.028	0.003	13.401	1	0.002	1.028	1.980	0.970
Altitude	0.334	0.167	0.398	1	0.039	1.397	1.477	1.131
Rainfall	1.476	0.108	93.714	1	0.000	4.375	9.881	2.251
Distance from lineament	0.001	0.007	5.013	1	0.023	1.001	1.02	0.98
Distance from river	−0.005	0.003	33.58	1	0.000	0.995	0.992	0.998
Geology								
Alluvial*	1.194	0.334	11.224	1	0.005	3.300	3.141	2.981
Gneiss*	1.445	0.530	7.842	1	0.006	4.242	4.328	3.924
States-schist*	0.119	0.051	4.642	1	0.000	1.126	1.129	1.121
Limestone*	1.114	0.402	6.987	1	0.005	3.047	3.659	2.489
Damuda*	1.102	0.384	4.487	1	0.005	3.010	3.257	1.884
Distance from lineament	0.001	0.007	5.013	1	0.023	1.001	1.02	0.98
Distance from river	−0.005	0.003	33.58	1	0.000	0.995	0.992	0.998
Soil type								
w-002	0.084	0.012	14.068	1	0.082	1.088	1.224	0.768
w-004	0.091	0.013	25.625	1	0.002	1.095	1.909	0.0941
w-006	0.078	0.012	43.609	1	0.000	1.081	1.671	0.932
w-009	0.048	0.007	6.289	1	0.000	1.049	1.835	0.914
LULC								
Settlement*	0.122	0.061	6.152	1	0.000	1.130	2.195	1.113
Fellow land*	2.478	0.065	7.125	1	0.000	11.917	12.651	4.766
Open forest*	3.412	0.039	7.048	1	0.000	30.326	31.102	5.292
Dense forest*	−1.744	0.105	2.781	1	0.732	2.175	2.845	1.332
Cultivation land*	1.062	0.435	18.306	1	0.000	2.892	2.985	2.735
Aspect								
North*	−0.179	0.025	50.35	1	0.010	0.836	0.849	0.821
North-east*	0.348	0.004	70.49	1	0.000	1.416	1.728	1.684
East*	−0.447	0.007	14.31	1	0.000	0.640	0.704	0.614
South-east*	0.531	0.003	29.64	1	0.010	1.701	2.571	1.561
South*	−0.632	0.031	11.94	1	0.000	0.532	0.603	0.503
South-west*	−1.185	0.013	48.17	1	0.000	0.306	0.564	0.298
West*	−1.32	0.037	14.45	1	0.000	0.267	0.327	0.101
North-west*	−2.199	0.031	49.45	1	0.030	0.111	0.343	0.049
Intercept	0.221	0.045	22.709	1	0.019	1.247		

B=Calculated coefficient value; SE=standard error of estimate; WaldChi=Wald Chi-square values; dfr=degree of freedom; Sig.=significance. *Categorical data

intensity of the accuracy of the model has been categorized after Pradhan et al. [14].

The perfect model demonstrates a curve that has the largest area under curve (AUC). A perfect model concludes an AUC value nearest to 1.0, whereas a value close to 0.5 indicates the erroneous nature of the model [13, 45, 65, 66]. In the study, the ROC curve was produced by imprint y-axis TPR against FPR at the x-axis with a fixed threshold or cut-off value (Fig. 6). The constructed LSZ map was matched up to recognize landslide locations through ROC curve. To verify the accuracy rate of LSZ maps, 66 of the 221 landslide points were used (Table 8). The diagram (Fig. 6) is

showing the AUC values are 78.86% in AHP, 80.22% in FR, 80.67% in BLRM, 83.44% in AHP–FR, 84.39% in AHP–BLR and 84.73% in FR–BLR models. All the models revealed a very good accuracy in mapping the landslide susceptibility (Fig. 6). Another accuracy process, kappa statistics, showed that overall accuracy is 0.789 in AHP, 0.842 in FR, 0.799 in the BLR, AHP–FR 0.837, AHP–BLR 0.856 and 0.868 in FR–BLR models for the final output maps (Table 9). The ROC and kappa statistics both results were showed FR–BLR ensemble model giving better output and AHP model giving comparatively low accuracy in mapping the susceptibility to landslide in Kurseong of Darjeeling Himalaya.

Fig. 5 Landslide susceptibility maps prepared by **a** AHP method and statistical prediction techniques, **b** FR model, **c** BLR model, **d** AHP–FR model, **e** AHP–BLR model and **f** FR–BLR model

Table 8 Area under the landslide susceptibility classes

Landslide susceptibility class	AHP		FR		BLRM		AHP-FR		AHP-BLR		FR-BLR	
	Area under class (km ²)	Area in percentage	Area under class (km ²)	Area in percentage	Area under class (km ²)	Area in percentage	Area under class (km ²)	Area in percentage	Area under class (km ²)	Area in percentage	Area under class (km ²)	Area in percentage
Very low	63.25	16.63	93.63	24.62	113.52	30.48	71.95	18.92	88.31	23.22	94.01	24.72
Low	81.50	21.43	71.19	17.72	78.61	20.67	73.55	19.34	78.12	20.54	64.01	16.83
Moderate	88.65	23.31	44.50	11.7	86.67	22.16	85.30	22.43	85.38	22.45	71.08	19.69
High	79.41	20.88	99.91	26.27	51.19	13.46	78.65	20.68	62.22	15.36	81.65	20.47
Very high	67.51	17.75	71.08	19.69	50.32	13.23	70.89	18.64	66.29	17.43	69.56	17.29

Fig. 6 ROC curve for the assessment of susceptibility maps prepared for **a** AHP (83.58%), FR (86.82%), BLRM (85.17%); **b** AHP-FR (85.34%), AHP-BLR (87.32%) and FR-BLR (88.73%) models

4 Discussion

Landslide is a complex phenomenon on account of multiple variables influence in its occurrence. Improving the performance of models of LS susceptibility has still drawn enormous attention from the research community for proper mapping. The application of remote sensing and GIS can be useful in the study of hazard management due to their high accuracy and speed where accuracy and time are two vital aspects of landslide modeling [1, 34, 67, 68]. Factor selection is also a significant concern for making the model more effective and precise. Different causes lead to the occurrence of landslides where some are significant and others are minor contributory factors [34, 61].

Different methodologies were examined from the viewpoints of effectiveness and reliability to prepare LS susceptibility maps. This present study attempted to assess the proficiency of various methods such as knowledge-driven AHP, probabilistic FR and BLR models and ensemble models AHP-FR, AHP-BLR and FR-BLR to assess the LS susceptibility of Kurseong region of the Himalaya, India. The employ of ensemble methods to generate high accuracy mapping [68, 69] is considered an important step in this

Table 9 Applied kappa statistics for accuracy assessment of landslide susceptibility maps with field data

Single models	Class name	Classified total	No. of observed	Producers accuracy	User's accuracy (%)	Ensemble models	Class name	Classified total	No of observed	Producers accuracy	User's accuracy (%)
AHP	Very low	7	10	6	85.71	AHP-FR	Very low	8	9	6	87.5
	Low	14	12	11	78.57		Low	18	15	14	77.78
	Moderate	48	53	41	83.33		Moderate	38	47	32	84.21
	High	110	104	98	89.70		High	106	106	98	92.45
	Very high	39	42	30	76.92		Very high	52	47	45	86.53
	Overall classification accuracy = 81.37						Overall classification accuracy = 85.73				
FR	Very low	6	11	5	82.71	AHP-BLR	Very low	8	9	7	87.50
	Low	15	15	13	85.48		Low	15	12	13	86.66
	Moderate	41	48	33	80.19		Moderate	43	53	37	86.05
	High	111	102	100	89.09		High	106	104	96	90.56
	Very high	48	45	44	91.66		Very high	41	42	33	84.61
	Overall classification accuracy = 84.95						Overall classification accuracy = 87.38				
BLRM	Very low	7	9	6	85.71	FR-BLR	Very low	6	8	5	83.33
	Low	18	15	13	72.72		Low	15	15	13	86.67
	Moderate	37	47	31	83.78		Moderate	41	48	33	80.48
	High	107	106	98	91.58		High	110	101	100	90.90
	Very high	52	47	45	86.53		Very high	48	45	45	93.75
	Over all classification accuracy = 82.45						Overall classification accuracy = 88.42				

Overall landslide susceptibility maps kappa statistics in AHP = 0.789; FR = 0.842; BLR = 0.799; AHP–FR = 0.837; AHP–BLR = 0.856 and FR–BLR = 0.868

regard. This Kurseong is chosen as a case study because of the high frequency of LS in eastern Himalaya and high sensitivity of this area in terms of population, concentration, tea garden and agricultural land.

At the first and second steps, LS inventory map (221 LS locations) was made and randomly divided into two subsets for testing and training (70:30), respectively, and after that, LS-conditioning factors were prepared after multi-collinearity test. Afterward, these factors were used to correlate LS with the each class of conditioning factors and then evaluated the susceptibility to LS by AHP, FR, BLR, AHP–FR, AHP–BLR and FR–BLR models. The LSMs were constructed and classified into five categories in order to produce the susceptibility map. The success rate and prediction rate curves were used to determine efficiencies and compare the results of LSMs. The landslide susceptible maps both single model and ensemble model have provided better result than the previous works done by the different researchers in the Himalayan region [5, 8, 17, 27, 29, 33, 46]. In addition, validation results indicated the better performance of FR–BLR ensemble model with a prediction rate of 84.76% compared with AHP, FR, BLR, the ensemble of AHP–FR and AHP–BLR models having the AUC values of 78.86%, 80.67%, 83.44% and 84.39% respectively. A different accuracy process, kappa statistics, confirmed that overall accuracy is 0.789 in AHP, 0.842 in FR, 0.799 in the BLR, AHP–FR 0.837, AHP–BLR 0.856 and 0.868 in FR–BLR models for the final output maps.

It is shown in Tables 5 and 8 that the Damuda, limestone geological structure with slope above 15° and altitude above 1500 m are extremely vulnerable to landslides. Areas closer to the lineament and river are highly susceptible to landslides. Soil type w-004 (Loamy-skeletal, Typic Udorthents and Loamy-skeletal, Typical Haplumbrepts) also plays a crucial role in triggering landslides. Sandy clay with the largest frequency ratio was identified as the most susceptible type. Intense commercial agriculture is done in this particular soil type by small terraces. Most of the settlements are located in the moderately susceptible areas. Site-specific slope control is necessary to check and mitigate landslide phenomena in the Kurseong range and its surrounding region. The LS maintenance could involve armoring the drain along the junction between the road and the hill slope, building a retaining wall, wall and trap water drain, controlling subsurface water, installation of fern vegetation, strict and constant surveillance along NH 55 and road diversion to prevent high landslide occurrence. The failure of unstable slopes in hazardous areas, in addition to fatalities and economic damage, has devastating social and environmental effects. Identification of vulnerable landslide areas is an important source for local authorities and decision makers.

5 Conclusion

The LSZ maps of Kurseong subdivision of Himalaya were produced using one knowledge-driven method, i.e., AHP method, two probabilistic methods, i.e., FR and BLR and their ensemble, i.e., AHP–FR, AHP–BLR and FR–BLR. Major 9 landslide-conditioning factors have been considered for the generation of landslide susceptibility maps using GIS. The numerical weights have been assigned by AHP, FR and BLR to each subclass of every factor, after ensemble approach applied for AHP–FR, AHP–BLR and FR–BLR modeling landslide susceptibility. LSZ maps study areas have been classified into five zones, such as very high, high, medium, low and very low. The AHP-based LSZ map shows that large portion of the study area (38.63%) falls in high and very high LS susceptibility due to the prevalence of very steep slopes, high altitude, rainfall and distance from the river. On the other hand, FR model-based map showed 45.96% and BLRM showed 26.69% of the total areas fall in high and very high LSZ. But their ensembles AHP–FR map showed 39.32%, AHP–BLR map showed 32.79%, and FR–BLR showed 37.76% of total area under very high and high LSZ. The low LSZ is safe for construction and needs some geotechnical investigation before any construction. The outcome of the LSZ mapping was verified applying the ROC curve and kappa statistics. The ROC curves are showing 78.86% (AHP), 80.22% (FR), 80.67% (BLR), 83.44% (AHP–FR), 84.39% (AHP–BLR) and 84.76% (FR–BLR) accuracy of models, respectively. Similarly, kappa coefficient values also show the accurateness of the produced landslide susceptible maps. Therefore, the LSZ maps can be used for LULC planning and future construction in this mountain region. The LSZ map can be efficiently used for ensuring further developmental activities. In addition, the probability map of the region will provide enough information about current and future possibility of landslides to common people, engineers and planners.

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