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Landslide susceptibility mapping using certainty factor, index of entropy and logistic regression models in GIS and their comparison at Mugling–Narayanghat road section in Nepal Himalaya

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Abstract Landslide susceptibility maps are vital for disaster management and for planning development activities in the mountainous country like Nepal. In the present study, landslide susceptibility assessment of Mugling–Narayanghat road and its surrounding area is made using bivariate (certainty factor and index of entropy) and multivariate (logistic regression) models. At first, a landslide inventory map was prepared using earlier reports and aerial photographs as well as by carrying out field survey. As a result, 321 landslides were mapped and out of which 241 (75 %) were randomly selected for building landslide susceptibility models, while the remaining 80 (25 %) were used for validating the models. The effectiveness of landslide susceptibility assessment using GIS and statistics is based on appropriate selection of the factors which play a dominant role in slope stability. In this case study, the following landslide conditioning factors were evaluated: slope gradient; slope aspect; altitude; plan curvature; lithology; land use; distance from faults, rivers and roads; topographic wetness index; stream power index; and sediment transport index.

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These factors were prepared from topographic map, drainage map, road map, and the geological map. Finally, the validation of landslide susceptibility map was carried out using receiver operating characteristic (ROC) curves. The ROC plot estimation results showed that the susceptibility map using index of entropy model with AUC value of 0.9016 has highest prediction accuracy of 90.16 %. Similarly, the susceptibility maps produced using logistic regression model and certainty factor model showed 86.29 and 83.57 % of prediction accuracy, respectively. Furthermore, the ROC plot showed that the success rate of all the three models performed more than 80 % accuracy (i.e. 89.15 % for IOE model, 89.10 % for LR model and 87.21 % for CF model). Hence, it is concluded that all the models employed in this study showed reasonably good accuracy in predicting the landslide susceptibility of Mugling–Narayanghat road section. These landslide susceptibility maps can be used for preliminary land use planning and hazard mitigation purpose.

Keywords Landslides · Susceptibility · Index of entropy · Certainty factor · Logistic regression · Geographic information systems (GIS) · Remote sensing · Nepal

1 Introduction

Nepal lies at the center of 2,400-km-long Himalayan mountain range, which is one of the tectonically most active zones on earth. Among the various land degradation process prevalent in the Himalaya, landslides are one of the most significant phenomena (Ahmad and Joshi 2010) as this region is tectonically very unstable with rugged topography, unstable geological structures, soft and fragile rocks, common earthquakes, along with heavy and prolonged rainfalls during monsoon periods (Deoja et al. 1991; Dhital 2000; DPTC 1996). The study of landslides has drawn worldwide attention mainly due to increasing awareness of its socio-economic impact as well as the increasing pressure of urbanization on the mountain environment (Aleotti and Chowdhury 1999). In Nepal, a significant number of landslides occur each year (as many as 12,000). The impact of artificial structures and human interventions on mountain slopes followed by expansion of agricultural land and watershed management and overgrazing has compounded the landslide disaster problem in the country (Rajbhandari et al. 2002).

The Mugling–Narayanghat road is one of the vital links of the strategic road network in Nepal. About two-thirds of the highway runs through the right bank of the Trishuli River, and hence, it is vulnerable both to toe cutting by the river and debris deposition by cross drains (Adhikari 2009). This road corridor was severely affected by an extreme rainfall of July 29–30, 2003. The 24-h accumulated rainfall recorded at Bharatpur and Devghat stations was 364 mm and 446 mm, respectively (Adhikari 2009). The incessant and intense rainfall was the causative factor to trigger numerous slides and slope failures along the road section and its surrounding areas. This situation was further worsened during the monsoon of 2006, blocking the traffic for several weeks (DWIDP 2009). To minimize the losses of human life and economic value, potential landslide-prone areas should, therefore, be identified. In this respect, landslide susceptibility assessment can provide valuable information essential for hazard mitigation through proper project planning and implementation.

Landslide susceptibility is the likelihood of a landslide occurrence in an area on the basis of local terrain conditions (Brabb 1984). It is the degree to which a terrain can be affected by slope movements, that is, an estimate of “where” landslides are likely to occur. The advent of remote sensing and GIS has made the landslide susceptibility mapping easier these days (Jia et al. 2010; Karimi Nasab et al. 2010; Bednarik et al. 2012; Wang et al. 2011; Pradhan et al.

2011). Different methods to prepare landslide susceptibility and hazard maps using statistical methods and GIS tools were developed in the last decade (Van Westen et al. 2003; Guzzetti et al. 2005). The most common approaches proposed in the literature are bivariate (Chung and Fabbri 1999; Saha et al. 2005; Pradhan et al. 2006; Magliulo et al. 2008; Pareek et al. 2010; Pradhan and Youssef 2010; Bednarik et al. 2010) and multivariate (Akgün et al. 2011; Ayalew and Yamagishi 2005; Can et al. 2005; Lee et al. 2007; Gorum et al. 2008; Nefeslioglu et al. 2008; Pradhan 2010a; Pradhan et al. 2008; Tunusluoglu et al. 2008; Pradhan and Lee 2010c; Oh et al. 2011; Choi et al. 2012), statistical techniques such as the logistic regression (LR). Other different methods have been proposed by several investigators, including weights-of-evidence methods (Bonham-Carter 1991; Neuhäuser and Terhorst 2007; Pradhan et al. 2010d; Regmi et al. 2010a; Pourghasemi et al. 2012a, b), modified Bayesian estimation (Chung and Fabbri 1999), weighting factors, weighted linear combinations of instability factors (Ayalew et al. 2004), landside nominal risk factors (Saha et al. 2005), probabilistic-based frequency ratio model (Chung and Fabbri 2003, 2005; Lee and Pradhan 2006, 2007; Akgün et al. 2008; Pradhan et al. 2010c 2011, 2012), certainty factors (Pourghasemi et al. 2012a), information values (Saha et al. 2005), modified Bayesian estimation (Chung and Fabbri 1999). Among recent models for landslide susceptibility mapping, soft computing techniques such as neuro-fuzzy (Sezer et al. 2011; Vahidnia et al. 2010; Oh and Pradhan 2011), artificial neural networks (Bui et al. 2012a; Lee et al. 2007; Pradhan and Lee 2009, 2010a, b; Pradhan et al. 2010a, b, d; Pradhan and Buchroithner 2010; Pradhan and Pirasteh 2010; Pradhan 2011a; Poudyal et al. 2010; Yilmaz 2009a, b, 2010a, b; Choi et al. 2012; Zarea et al. 2012), fuzzy-logic (Akgün et al. 2012; Bui et al. 2012b; Ercanoglu and Gokceoglu 2002; Kanungo et al. 2008; Pradhan 2010b, 2010c, 2011b; Pradhan et al. 2009; Pourghasemi et al. 2012c) can be seen in the literature. Additionally, there exists some other data mining techniques such as support vector machine (SVM) (Bui et al. 2012c; Brenning 2005; Yilmaz 2010a), decision tree methods (Saito et al. 2009; Nefeslioglu et al. 2010), spatial decision support system (SDSS) (Wan 2009), spatial multi-criteria evaluation (SMCE) (Pourghasemi et al. 2012d), index of entropy (Bednarik et al. 2010; Constantin et al. 2011; Pourghasemi et al. 2012e), evidential belief function (EBF) (Althuwaynee et al. 2012), etc. to evaluate the landslide susceptibility, to overcome shortcomings in the above-mentioned methods.

The aim of this paper is to produce landslide susceptibility map of Mugling–Narayanghat road corridor using two bivariate statistical models [certainty factor (CF), index of entropy (IOE)] and one multivariate statistical model [logistic regression (LR)]. These models exploit information obtained from the inventory map to predict where landslides may occur in future. These models are tested, and the results are discussed. In literature, various bivariate and multivariate approaches for landslide susceptibility exist. However, a comparison of these approaches is not commonly encountered. This contribution provides originality to this study.

2 The study area

The 36-km-long Mugling–Narayanghat road is located in a mountainous terrain of Central Nepal, in the Chitwan District of the Narayani Zone. The study area (longitude 84°26'00" E to 84°34'30" E and latitude 27°51'30" N to 27°45'30" N) falls within the topographical map 2784-03C (Mugling) and 2784-02D (Jugedi Bajar) and covers an area of about 65 km² (Fig. 1). The minimum and maximum altitudes of the area vary from 200 m at Jugedi Bajar and 1,380 m in the vicinity of Mulethumki and Chaur.

Brunsdon et al. (1975) were one of the first to develop a geomorphological map of a road corridor in Nepal. Kojan (1978) studied the landslide problems along the

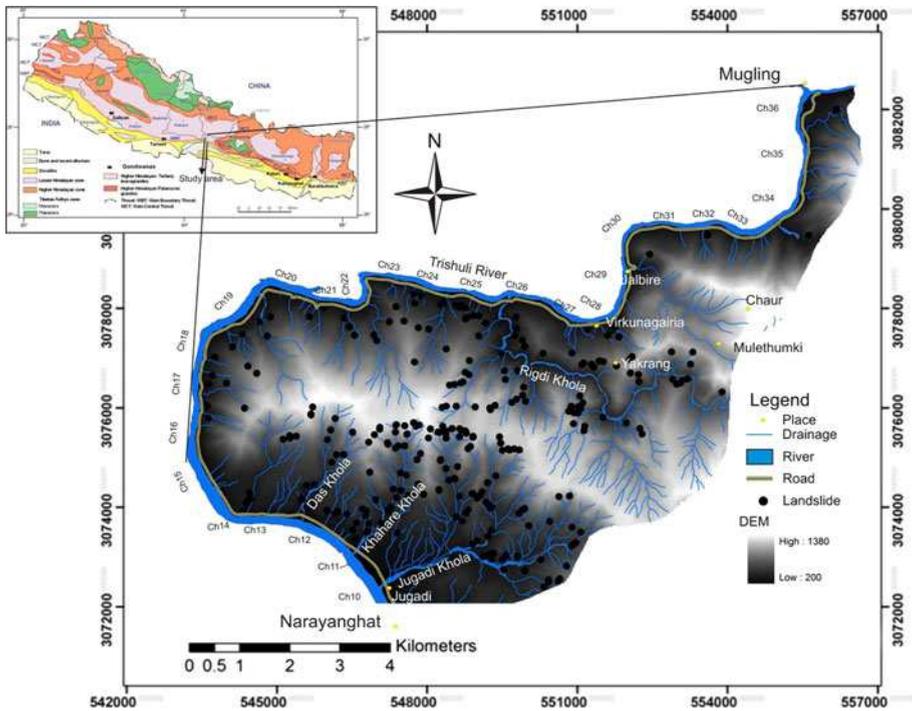


Fig. 1 Study area with the distribution of landslides

Godavari–Dandeldhura road. He identified the main hazardous areas along the road section and recommended various methods of slope stabilization. Wagner (1981) was the first to prepare a landslide and gully erosion hazard map based on field observation in Nepal. Many researchers tried to establish linkage between landslides and human activities (Gerrard 1994). In Himalayas, this link forms a major component of what is known as Himalayan Environmental Degradation Theory (Ives and Messerli 1981). From the airborne survey of Nepal, Laban (1979) concluded that geological structure and lithology accounted for more than 70 % of landslides occurrences in this region. Deoja et al. (1991) further developed this method and proposed various ratings for attributes such as rock type, soil type, slope angle, relative relief, groundwater, surface hydrology, folds, and faults. The first detailed landslide hazard mapping was carried out along the Tulsipur–Sallyan, Ghorahi–Piuthan, and Piuthan–Libang roads of mid-west Nepal (DoR/USAID 1986). These maps were derived from engineering geological maps of the road alignment on a scale of 1:5,000, aerial photo interpretation, and kinematic analysis of joints. Feasibility- and detailed-stage landslide hazard mappings were carried out along the Baitadi–Darchula road alignment in far west Nepal (Dhital et al. 1991). According to Shroder and Bishop (1998), landslides in the Himalaya are scale-dependent and range from massive extent of a whole mountain range (gravity tectonics) through the failure of single peaks to very minor slope failures. Gerrard and Gardner (2000a, b) suggested that there is a clear anthropogenic influence in the occurrence of landslides in the mountainous areas of Nepal. Recently, many researchers have applied various GIS-based statistical techniques in the landslide susceptibility mapping in various parts of Nepal Himalaya (Dhital et al. 2006; Dahal et al. 2008, 2012; Poudyal et al. 2010; Regmi et al. 2010b; Dhakal et al. 2000). Some work has been done on the role of rock

weathering and clay minerals in landslide formation in Nepal Himalaya (Regmi et al. 2012 and Hasegawa et al. 2009). Rainfall threshold for landslides in certain part of Nepal was calculated by Dahal and Hasegawa (2008). Petley et al. (2006) analyzed a database of landslide fatalities in Nepal from 1978 to 2005 and found that there is a high level of variability in the occurrence of landslides from year to year, but its overall trend is increasing.

3 Geological and morphological settings

The Mugling–Narayanghat road passes through the Precambrian Lesser Himalayan rocks of the Nawakot Complex (Stöcklin and Bhattarai 1978; Stöcklin 1980), the Miocene Siwaliks and Holocene alluvial deposits (Fig. 2). The Nawakot Complex is divided into the Lower Nawakot Group and Upper Nawakot Group, and along this road section, the rocks from both the groups are observed. The main rock types are mudstones, sandstones, limestones, dolomites, slates, phyllites, quartzites, and amphibolites. A majority of instabilities were observed within the Nourpul Formation. The Kuncha Formation, Fagfog Quartzite, Dandagaun Phyllite, Nourpul Formation, and Dhading Dolomite are from the Lower Nawakot Group, while Benighat Slates represents the Upper Nawakot Group. The Purebesi Quartzite Member is a distinct quartzite zone, overlying the phyllites of the Dandagaun Formation, and forms the basal part of the Nourpul Formation. Apart from this, some amphibolite bands are also observed within the Nourpul Formation. The Siwalik

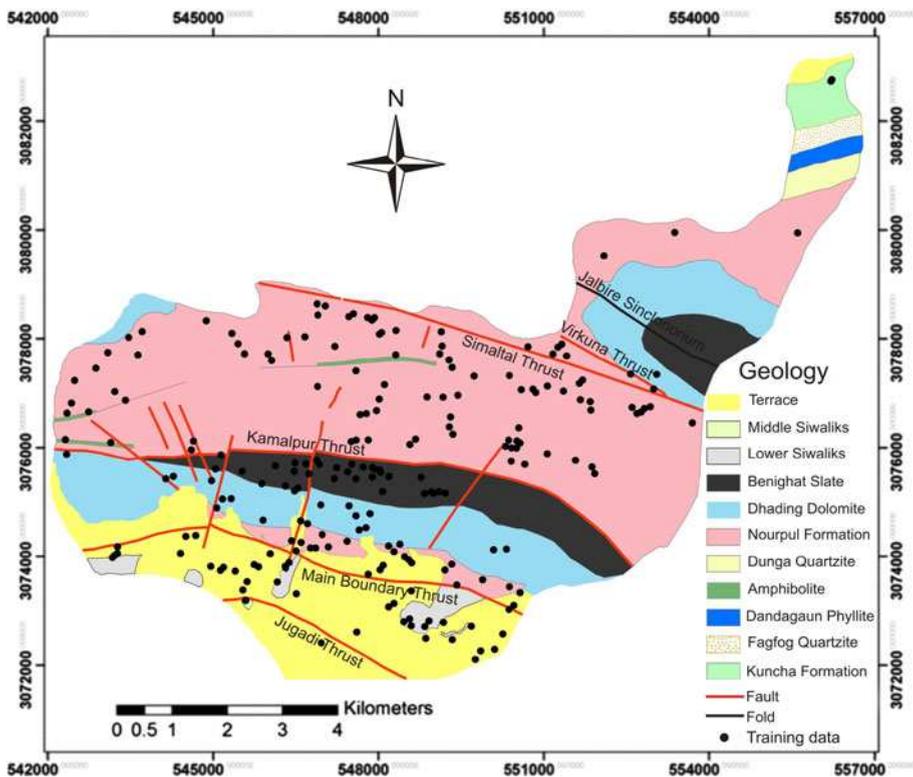


Fig. 2 Geological map of the study area

Group in the study area consists of the Lower Siwaliks and Middle Siwaliks (Ganser 1964). The Holocene deposits consist of river terraces of different ages. The main rock types are mudstones, sandstones, limestones, dolomites, slates, phyllites, quartzites, and amphibolites. Majority of instabilities were observed within Nourpul Formation rocks. The main geological structures that demarcate the study area are the Main Boundary Thrust (MBT), Jugadi Thrust (JT), Kamalpur Thrust (KT), Simaltal Thrust (ST), and Virkuna Thrust (VT). All the thrusts are trending in east–west direction. The MBT is a major fault separating the Lesser Himalaya to the north from the Siwaliks to the South (Fig. 2).

The highway between km 23 and km 28 lies within this thrust zone, where thick colluviums and plenty of seepage are observed. Geomorphologically, Nepal is divided into the following eight units running east–west: the Terai, Churia Range, Dun Valley, Mahabharat Range, Midland, Fore Himalaya, Higher Himalaya, Inner and Trans Himalaya (Hagen 1969) and the Mugling–Narayanghat road lies within the Mahabharat Range, Churia Range, and Dun Valley. The southernmost tableland belongs to the Dun Valley and is covered by various alluvial deposits. Here, the slope is gentle and the elevation is subdued. As the alluvium covers most of the Siwaliks composing the Churia Range, they are exposed only on the riverbanks, where the stream erosion is intense. Most of the study area belongs to the Mahabharat Range, which lies to the north of the Churia Range and consists of higher mountains with steeper slopes.

4 Landslide inventory map

Understanding the role of individual factors controlling landslide location, geographical pattern, and spatial density is important to predict where landslides can occur in the future, that is, to ascertain landslide susceptibility (Varnes 1984; Soeters and Van Westen 1996; Guzzetti et al. 1999, 2005). A landslide inventory map is one that identifies the definite location of the existing landslides along with its type and the time of occurrence (Wieczorek 1984; Einstein 1988; Soeters and van Westen 1996). The first step in landslide susceptibility assessments is to acquire information about the landslides that have occurred in the past. This stage is considered as the fundamental part of the landslide hazard studies (Guzzetti et al. 1999; Ercanoglu and Gokceoglu 2004). Since landslide occurrences in the past and present are keys to spatial prediction in future (Guzzetti et al. 1999), a landslide inventory map is a prerequisite for such a study. A landslide inventory map provides the basic information for evaluating landslide hazards or risk. Accurate detection of the location of landslides is very important for probabilistic landslide susceptibility analysis. The landslides on the Mugling–Narayanghat road were identified from the interpretation of aerial photographs (taken after the monsoon of 2003), satellite images and were verified in the field. In total, 321 landslides were mapped (Fig. 1) and subsequently digitized for further analysis. The mapped landslides cover an area of 2.05 km², which constitutes 3.15 % of the entire study area, where the dominant failure is of rotational type (Fig. 3). Rock falls, debris flow, and topples are also observed along the highway (Fig. 3). From these landslides, 241 (75 %) randomly selected instabilities were taken for making landslide susceptibility models and 80 (25 %) were used for validating the models.

5 Landslide conditioning factors

The factors controlling instabilities considered in the present study are slope gradient, slope aspect, plan curvature, altitude, stream power index (SPI), topographic wetness index



Fig. 3 Figure showing different types of landslides observed in the study area. **a** Thick debris deposit which buried the bridge over the road section, at 21 + 500 km; **b** debris slide observed at 20 + 800 km of the road section (L2); **c** Landslide at 23 + 760 km of the road section; **d** rock topple observed at the upstream of Keraghari Khola, at 21 + 560 km; **e** slope failure observed at 30 + 500 km

(TWI), stream sediment transport index (STI), geology, land use, distance from faults, distance from rivers, and distance from roads. A short description of each thematic map is given below. The geomorphic factors like slope gradient, slope aspect, plan curvature, altitude, SPI, TWI, and SPI were obtained from the DEM produced by the topographic map of 1:25,000 scale provided by the Department of Survey, Nepal. The land use map was also

provided by the Department of Survey, Nepal. Geological map was prepared in the field based on the geological map of Central Nepal (Stöcklin and Bhattarai 1978; Stöcklin 1980). The geological maps were also useful for the delineation of major faults in the study area. The distance from rivers and the distance from roads maps were produced, respectively, from the drainage map and the topographic map using ArcGIS 9.3. Brief description of each thematic map used in the present study is given below.

5.1 Slope gradient

The slope gradient is one of the most important factors that influence slope stability (Bednarik et al. 2009). In general, stability of slope is the interplay of slope angle with material properties such as friction angle, permeability, and cohesion. Slope gradient map was derived from DEM of 20×20 (m) grid size. The original slope angle values vary between 0° and 79.54° , and the values were reclassified into 5 categories (Fig. 4a) which are most widely used subdivisions in Nepal and other southeast Asian countries (Pradhan and Lee 2010a; Dhital et al. 2006; Saha et al. 2005).

5.2 Slope aspect

The slope aspect or the direction of maximum slope of the terrain surface is divided into nine classes (Fig. 4b). Although the relation between the aspect and the mass movement has been investigated for a long time, no general decision could have been given regarding the aspect–landslide relationship (Ercanoglu et al. 2004). However, it is emphasized that the aspect is one of the significant factors producing the landslide susceptibility maps (Lee et al. 2004). Physically, the aspect is related to the parameters such as the orientation of discontinuities controlling landslides, precipitation, wind impact, and exposition to sunlight (Ercanoglu et al. 2004).

5.3 Plan curvature

The curvature values represent the morphology of the topography (Lee and Min 2001; Lee et al. 2004; Ercanoglu and Düzgün 2010). The curvature maps (Fig. 4c) were obtained from the second derivative of the surface.

5.4 Altitude

Altitude is another frequently used parameter for landslide susceptibility studies. It is stated that the landslides have more tendency to occur at higher elevations (Ercanoglu et al. 2004). In the study area, the elevation ranges between 200 and 1,380 m. The elevation values were divided into eight categories with an interval of 150 m. (Fig. 4d).

5.5 Stream power index (SPI)

SPI measures the erosion power of the stream and is also considered as a factor contributing toward stability within the study area. The SPI can be defined as (Moore and Grayson 1991):

$$\text{SPI} = A_s \tan \beta \quad (1)$$

where A_s is the specific catchment area and β is the local slope gradient measured in degrees. In the present study, SPI is divided into 4 classes (Fig. 4e).

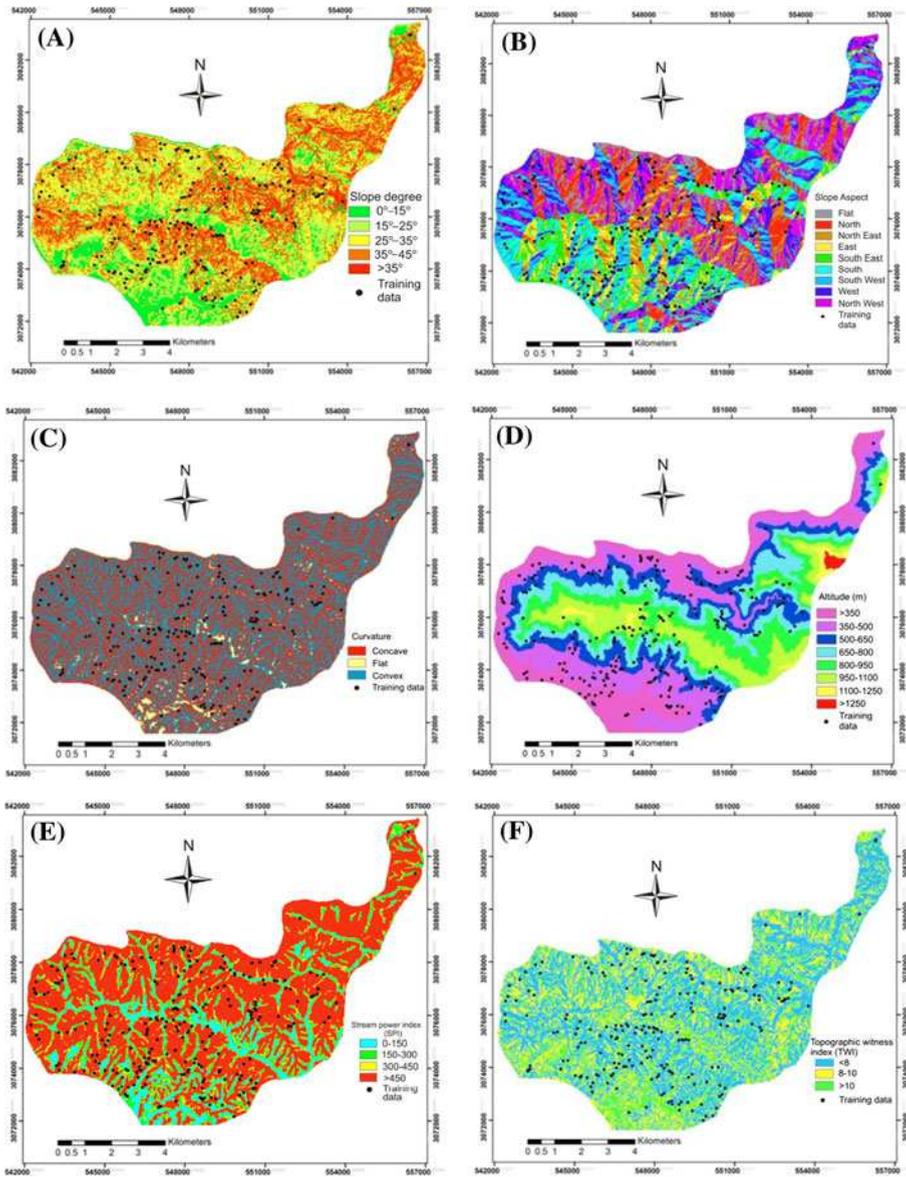


Fig. 4 Thematic maps used in this study. **a** Slope map (in degree); **b** Aspect map; **c** Curvature map; **d** Elevation map (in m); **e** Stream power Index map; **f** Topographic wetness index map; **g** Sediment transport index map; **h** Distance to drainage map; **i** Distance to road map; **j** Distance to fault map; **k** Land use map

5.6 Topographic wetness index (TWI)

The topographic wetness index (TWI), which combines local upslope contributing area and the entire slope, is commonly used to quantify topographic control on hydrological processes. It is expressed as:

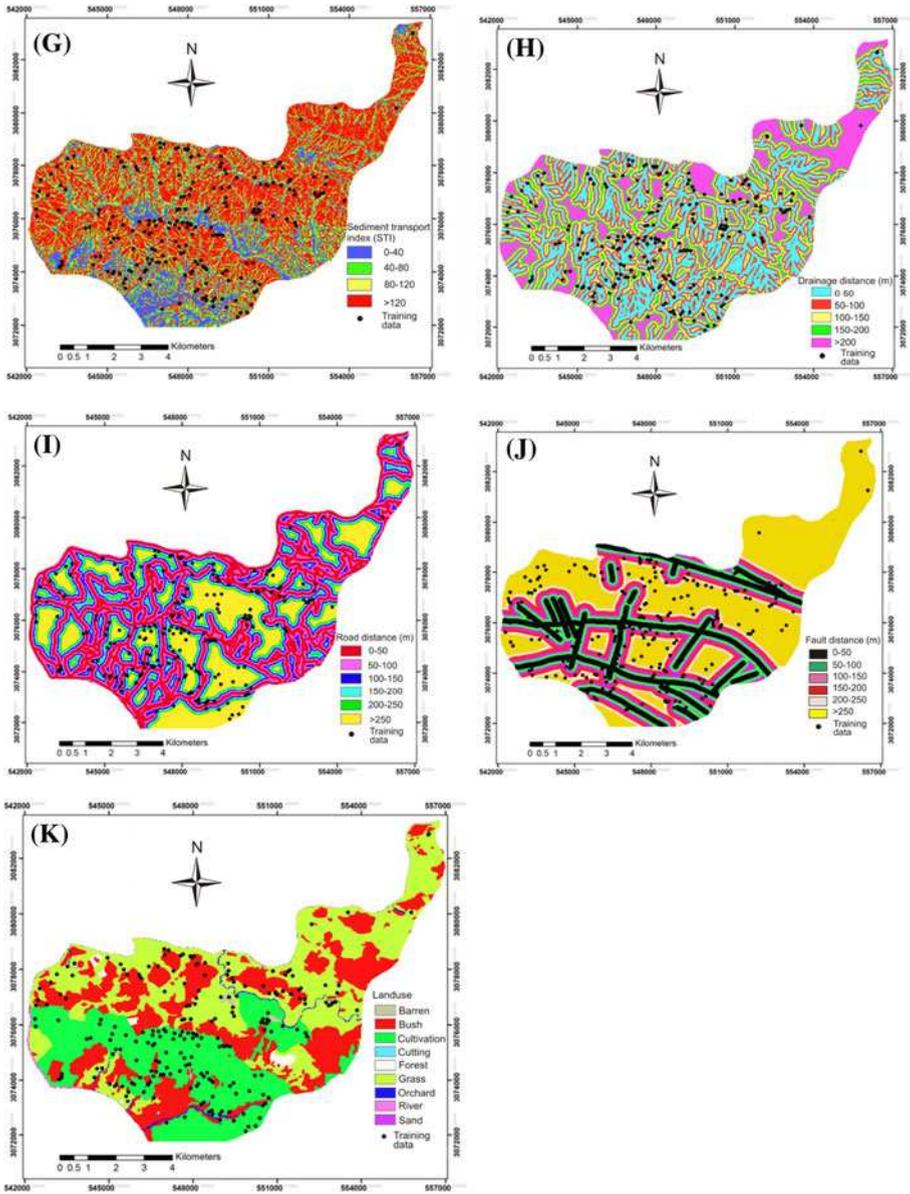


Fig. 4 continued

$$TWI = \ln\left(\frac{\alpha}{\tan \beta}\right) \tag{2}$$

where α is the cumulative upslope area draining through a point (per unit contour length) and $\tan \beta$ is the slope angle at the point. It affects the spatial distribution of soil moisture, and the groundwater flow often follows surface topography. In this study, TWI was considered as another contributing factor (Fig. 4f).

5.7 Sediment transport index (STI)

The sediment transport index (STI) characterizes the process of erosion and deposition. In the present study, STI is divided into 4 classes (Fig. 4g).

5.8 Land use map

Land use also plays a significant role in the stability of slope. The land covered by forest regulates continuous water flow and water infiltrates regularly, whereas the cultivated land affects the slope stability due to saturation of covered soil. Based on field observations and mapping, the following nine classes are considered: cutting, cultivation, forest, orchard, grass, bush, sand barren, and river (Fig. 4k). Bush (37 %) covers the highest amount of area followed by cutting (31 %) and cultivation lands (29 %).

5.9 Lithology

Lithology plays an important role in landslide susceptibility studies because different geological units have different susceptibilities to active geomorphic processes of the Himalaya (Pradhan et al. 2006). The sediments and rocks in this watershed belong to Holocene alluvial deposits, Miocene Siwaliks, and Precambrian Lesser Himalaya and consist of sandstone, siltstone, mudstone, conglomerate, limestone, dolomite, slate, phyllite, quartzite, and amphibolites (Fig. 2).

5.10 Distance from faults

Faults are the tectonic breaks that usually decrease the rock strength. These dislocations are responsible for triggering a large number of landslides on the Mugling–Narayanghat road. Fault lines were derived from the geological map of the region. In the present study, the distance from fault map was reclassified into 6 divisions (Fig. 4j).

5.11 Distance from rivers

Runoff plays an important role as a triggering factor for landslides. On the basis of rivers and streams, a map of proximity to drainage was generated using Arc GIS 9.3. In the present study, the distance from river map is divided into 5 categories (4 h).

5.12 Distance from roads

The roads built on the slopes cause the loss of toe support. The change of the topography and the loss of support lead to the increase of strain behind the slope and the development of cracks. Instabilities occur in the slope because of the negative effects such as water infiltration afterward. Also, a given road segment may act as a barrier, a net source, a net sink or a corridor for water flow, and depending on its location in the area, it usually serves as a source of landslides (Pradhan et al. 2010a). The detail road network map provided by the Department of Survey, Nepal, was used to generate the distance from roads map (Fig. 4i).

6 Modeling approach

6.1 Certainty factor model

Certainty Factor (CF) is a model that has been applied by different researchers in landslide susceptibility mapping (Kanungo et al. 2011; Gökçeolu et al. 2005). The CF approach is one of the possible proposed favorability functions to handle the problem of combining different data layers and the heterogeneity and uncertainty of the input data. The certainty factors (CF) are given by the following equation:

$$CF_{ij} = \begin{cases} \frac{f_{ij}-f}{f_{ij}(1-f)} & \text{if } f_{ij} \geq f \\ \frac{f_{ij}-f}{f(1-f_{ij})} & \text{if } f_{ij} \leq f \end{cases} \quad (3)$$

where CF_{ij} is the certainty factor given to a certain class i of parameter j . f_{ij} is the conditional probability having a number of landslide event occurring in class i of parameter j and f is the prior probability having total number of landslide event occurring in the study area.

The value of the certainty factor ranges between -1 and $+1$. The minimum -1 means definitely false and $+1$ means definitely true. A positive value means an increasing certainty in landslide occurrence, while a negative value corresponds to a decreasing certainty in landslide occurrence. A value close to 0 means that the prior probability is very similar to the conditional one; hence, it is difficult to give any indication about the certainty of the landslide occurrence (Pourghasemi et al. 2012e).

The CF values for all the condition factors were calculated by overlying landslides with the parameter class, that is, by calculating the landslide density and the CF values of all the layers using Eq. 3. Next, the CF values of the landslide conditioning factors were used for creating various CF layers (Table 1). Then, the calculated CF layers were combined pairwise. The combination of two CF values, X and Y , due to two different layers of information, is expressed as Z in Eq. 4, given below:

$$Z = \begin{cases} X + Y - XY & X, Y \geq 0 \\ \frac{X+Y}{1-\min(|X|,|Y|)} & X, Y \text{ Opposite sign} \\ X + Y + XY & X, Y < 0 \end{cases} \quad (4)$$

The pairwise combination is performed repeatedly until all the CF layers are added to obtain the landslide susceptibility index (LSI). To make the results easier to interpret, the LSI values are grouped into susceptibility classes to create landslide susceptibility zonation map for the study area. Several authors have applied various methods for dividing the LSI map. In this study, natural break classification method (Constantin et al. 2011; Xu et al. 2012) was used to divide the interval into four classes and a susceptibility map was prepared. Subsequently, the same classification approach was used for index of entropy and logistic regression models.

6.2 Index of entropy model

The second model used for evaluating the landslide susceptibility in the present study is the bivariate index of entropy model (Van Westen 2004). The method is based on the principle of bivariate analysis, where the density of landslides within a certain parameter is determined. This approach allows calculation of the weight for each input variable. In the

Table 1 Spatial relationship between each landslide conditioning factor and landslide by frequency ratio and certainty factor

Factor	Class	No. of pixels in domain	Percentage of domain (a)	No. of landslide	Percentage of landslides (b)	Certainty factor
Slope gradient (°)	0–15	22,111	13.76	6	2.49	−0.82
	15–25	30,542	19.01	45	18.67	−0.02
	25–35	42,515	26.47	86	35.68	0.26
	35–45	40,693	25.33	88	36.51	0.31
	>45	24,776	15.42	16	6.64	−0.57
Slope aspect	Flat	1,201	0.75	0	0	−1
	North	29,104	18.12	31	12.86	−0.29
	Northeast	18,906	11.77	20	8.3	−0.3
	East	12,363	7.7	25	10.37	0.26
	Southeast	11,936	7.43	31	12.86	0.42
	South	18,154	11.3	43	17.84	0.37
	Southwest	21,037	13.1	36	14.94	0.12
	West	23,680	14.74	29	12.03	−0.18
	Northwest	24,125	15.02	26	10.79	−0.28
Plan curvature	Concave	73,478	45.74	114	47.3	0.03
	Flat	2,127	1.32	0	0	−1
	Convex	84,894	52.85	127	52.7	−0.003
Altitude (m)	<350	25,421	15.83	43	17.84	0.11
	350–501	34,691	21.6	73	30.29	0.29
	501–650	27,266	16.97	47	19.5	0.13
	651–800	25,533	15.89	39	16.18	0.02
	800–950	24,907	15.51	19	7.88	−0.49
	951–1,100	19,790	12.32	20	8.3	−0.33
	1,101–1,250	2,357	1.47	0	0	−1
>1,250	6,72	0.42	0	0	−1	
SPI	0–150	14,196	8.84	8	3.32	−0.62
	150–300	19,750	12.29	39	16.18	0.24
	300–450	14,807	9.22	21	8.72	−0.06
	>450	111,884	69.65	173	71.78	0.03
TWI	<8	86,989	54.15	148	61.41	0.12
	10	51,763	32.22	73	30.29	−0.06
	>10	21,885	13.62	20	8.3	−0.39
STI	0–40	22,258	13.86	17	7.05	−0.49
	40–80	30,532	19.01	55	22.82	0.17
	80–120	25,488	15.87	51	21.16	0.25
	>120	82,359	51.27	118	48.96	−0.05
Land use	Barren	220	0.14	0	0	−1
	Bush	38,983	24.27	40	16.6	−0.32
	Cultivation	49,758	30.98	117	48.55	0.36
	Cutting	128	0.08	0	0	−1
	Forest	994	0.62	0	0	−1

Table 1 continued

Factor	Class	No. of pixels in domain	Percentage of domain (a)	No. of landslide	Percentage of landslides (b)	Certainty factor
Lithology	Grass	68,712	42.77	82	34.02	-0.2
	Orchard	1,451	0.9	2	0.83	-0.08
	River	255	0.16	0	0	-1
	Sand	5	0.003	0	0	-1
	Amphibolite	617	0.38	1	0.415	0.07
	Benighat Slates	16,221	10.1	24	9.96	-0.01
	Dandagaun Formation	849	0.53	0	0	-1
	Dhading Dolomite	26,709	16.63	26	10.79	-0.35
	Purebesi Quartzite	961	0.6	2	0.83	0.28
	Kuncha Formation	1,988	1.24	1	0.41	-0.66
	Lower Siwaliks	2,488	1.55	10	4.15	0.63
	Middle Siwaliks	65	0.04	1	0.41	0.9
	Nourpul Formation	82,099	51.11	122	50.62	-0.01
	Fagfog Quartzite	1,303	0.81	1	0.41	-0.49
	Terrace Deposits	27,206	16.94	55	22.82	0.26
Distance from faults (m)	0–100	25,436	15.83	33	13.69	-0.14
	100–200	22,302	13.88	42	17.43	0.2
	200–300	20,801	12.95	34	14.11	0.08
	300–400	17,733	11.04	30	12.45	0.11
	400–500	15,127	9.42	29	12.03	0.22
	>500	59,107	36.8	73	30.29	-0.18
Distance from rivers (m)	0–50	54,983	34.23	100	41.49	0.17
	50–100	38,565	24.01	58	24.07	0.002
	100–150	26,264	16.35	39	16.18	-0.01
	150–200	17,252	10.74	23	9.54	-0.11
	>200	23,442	14.59	21	8.71	-0.4
Distance from roads (m)	0–50	45,379	28.25	56	23.24	-0.18
	50–100	30,591	19.04	50	20.75	0.08
	100–150	22,536	14.03	33	13.69	-0.02
	150–200	17,410	10.84	34	14.11	0.23
	200–250	12,412	7.73	28	11.62	0.33
	250–300	9,539	5.94	8	3.32	-0.44
	>300	22,639	14.09	32	13.28	-0.06

present model, the weighting process is based on the methodology proposed by Vlcko et al. (1980). The weight value for each parameter taken separately is expressed as an entropy index.

The weight parameter was obtained from the defined level of entropy representing the approximation to normal distribution of the probability. The entropy index indicates the extent of disorder in the environment. It also expresses which parameters in a natural environment are most relevant for the development of mass movements (Bednarik et al. 2010). The equations used to calculate the information coefficient W_j representing the weight value for the parameter as a whole are:

$$P_{ij} = \frac{A_{sd}}{A_t} \tag{5}$$

$$(P_{.j}) = \frac{P_{ij}}{\sum_{j=1}^{S_j} P_{ij}} \tag{6}$$

Here, H_j and H_{jmax} are the entropy values (Eqs. 7, 8) and they are written as;

$$H_j = \sum_{i=1}^{S_j} (P_{ij}) \log_2(P_{ij}), \quad j = 1, \dots, n \tag{7}$$

$$H_{jmax} = \log_2 S_j, \quad S_j \text{ is the number of classes} \tag{8}$$

I_j is the information coefficient (Eq. 9) and W_j represents the resultant weight value for the parameter as a whole (Eq. 10).

$$I_j = \frac{H_{jmax} - H_j}{H_{jmax}} \tag{9}$$

$$W_j = I_j \times P_j \tag{10}$$

The result varies from 0 to 1. The closer the value is to the number 1, the greater the instability is. Here, P_j is the slope failure probability for ($j = 1, \dots, n$). The complete calculation of weight determination for individual parameters is presented in Table 2. The final susceptibility value is expressed by the sum of all parameter classes, ranked according to the calculated landslide density for each class. It is expressed as;

$$y = \sum_{i=1}^n \frac{z}{m_i} \times C \times W_j \tag{11}$$

where y is the sum of all the classes; i is the number of particular parametric map ($1, 2, \dots, n$); z is the number of classes within parametric map with the greatest number of classes; m_i is the number of classes within particular parametric map; C is the value of the class after secondary classification and W_j is the weight of a parameter.

6.3 Logistic regression model

Logistic regression allows forming a multivariate regression relation between a dependent variable and several independent variables. The dependent variable is dichotomous, while the independent variable can be interval, dichotomous, or categorical (Atkinson and Massari 1998). In the present situation, the dependent variable is a binary variable

Table 2 Spatial relationship between each landslide conditioning factor and landslide by index of entropy Model

Factor	Class	Percentage of domain	Percentage of landslide	P_{ij}	(P_{ij})	H_j	H_{jmax}	I_j	W_j
Slope gradient (°)	0–15	13.76	2.49	0.18	0.04	2.05	2.32	0.12	0.101
	15–25	19.01	18.67	0.98	0.22				
	25–35	26.47	35.68	1.35	0.31				
	35–45	25.33	36.51	1.44	0.33				
	>45	15.42	6.64	0.43	0.1				
Slope aspect	Flat	0.75	0	0	0	2.23	3.17	0.3	0.287
	North	18.12	12.86	0.71	0.08				
	North East	11.77	8.3	0.71	0.08				
	East	7.7	10.37	1.35	0.15				
	South East	7.43	12.86	1.73	0.2				
	South	11.3	17.84	1.58	0.18				
	South West	13.1	14.94	1.14	0.13				
	West	14.74	12.03	0.82	0.09				
	North West	15.02	10.79	0.72	0.08				
Plan curvature	Concave	45.74	47.3	1.03	0.51	1	1.58	0.37	0.249
	Flat	1.32	0	0	0				
	Convex	52.85	52.7	1	0.49				
Altitude (m)	<300	15.83	17.84	1.13	0.19	1.59	3	0.47	0.344
	300–500	21.6	30.29	1.4	0.24				
	500–650	16.97	19.5	1.15	0.2				
	650–800	15.89	16.18	1.02	0.17				
	800–950	15.51	7.88	0.51	0.09				
	950–1,100	12.32	8.3	0.67	0.11				
	1,100–1,250	1.47	0	0	0				
>1,250	0.42	0	0	0					
SPI	0–150	8.84	3.32	0.38	0.1	1.89	2	0.06	0.052
	150–300	12.29	16.18	1.32	0.36				
	300–450	9.22	8.72	0.95	0.26				
	>450	69.65	71.78	1.03	0.28				
TWI	<8	54.15	61.41	1.13	0.42	1.54	1.58	0.03	0.025
	10	32.22	30.29	0.94	0.35				
	>10	13.62	8.3	0.61	0.23				
STI	0–40	13.86	7.05	0.51	0.13	1.92	2	0.04	0.039
	40–80	19.01	22.82	1.2	0.3				
	80–120	15.87	21.16	1.33	0.33				
	>120	51.27	48.96	0.95	0.24				
Land use	Barren	0.14	0	0	0	1.92	3.17	0.39	0.174
	Bush	24.27	16.6	0.68	0.17				
	Cultivation	30.98	48.55	1.57	0.39				
	Cutting	0.08	0	0	0				
	Forest	0.62	0	0	0				

Table 2 continued

Factor	Class	Percentage of domain	Percentage of landslide	P_{ij}	(P_{ij})	H_j	H_{jmax}	I_j	W_j
Lithology	Grass	42.77	34.02	0.8	0.2				
	Orchard	0.9	0.83	0.92	0.23				
	River	0.16	0	0	0				
	Sand	0.003	0	0	0				
	Amphibolite	0.38	0.415	1.09	0.05	2.45	3.46	0.29	0.536
	Benighat Slates	10.1	9.96	0.99	0.05				
	Dandagaun Formation	0.53	0	0	0				
	Dhading Dolomite	16.63	10.79	0.65	0.03				
	Purebesi Quartzite	0.6	0.83	1.38	0.07				
	Kuncha Formation	1.24	0.41	0.33	0.02				
	Lower Siwaliks	1.55	4.15	2.68	0.13				
	Middle Siwaliks	0.04	0.41	10.3	0.51				
	Nourpul Formation	51.11	50.62	0.99	0.05				
	Fagfog Quartzite	0.81	0.41	0.51	0.03				
Terrace Deposits	16.94	22.82	1.35	0.07					
Distance from faults (m)	0–100	15.83	13.69	0.86	0.13	2.57	2.58	0.01	0.008
	100–200	13.88	17.43	1.26	0.2				
	200–300	12.95	14.11	1.09	0.17				
	300–400	11.04	12.45	1.13	0.18				
	400–500	9.42	12.03	1.28	0.2				
	>500	36.8	30.29	0.82	0.13				
Distance from rivers (m)	0–50	34.23	41.49	1.21	0.26	2.29	2.32	0.01	0.014
	50–100	24.01	24.07	1	0.21				
	100–150	16.35	16.18	0.99	0.21				
	150–200	10.74	9.54	0.89	0.19				
	>200	14.59	8.71	0.6	0.13				
Distance from roads (m)	0–50	28.25	23.24	0.82	0.11	2.75	2.81	0.02	0.021
	50–100	19.04	20.75	1.09	0.15				
	100–150	14.03	13.69	0.98	0.14				
	150–200	10.84	14.11	1.3	0.18				
	200–250	7.73	11.62	1.5	0.21				
	250–300	5.94	3.32	0.56	0.08				
>300	14.09	13.28	0.94	0.13					

representing the presence or absence of landslides. The logistic model can be expressed in its simplest form as:

$$p = \frac{\exp(z)}{1 + \exp(z)} \quad (12)$$

where p is the probability of an event (landslide) occurrence, which varies from 0 to 1 on an s-shaped curve; z is defined as the following equation (linear logistic model), and its value varies from $-\infty$ to $+\infty$:

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n \quad (13)$$

where 0 represents the intercept of model, 1, 2, ..., n the partial regression coefficients, X_1, X_2, \dots, X_n represent the independent variables. The logistic regression model involves fitting of Eq. 13 to the data and then expressing the probability of the presence/absence of landslides in each mapping unit. The relative contribution of each mapping unit to the logistic function can be obtained by looking at the significance of each regression parameter. The logistic regression analysis was performed using the SPSS statistical software. Firstly, all the conditioning factors and landslides were converted into grid format, and then, these grid maps are converted into ACSII data format (Acronym for the American Standard Code for Information Interchange). The ASCII data of each map was exported to SPSS, and then the logistic regression model was run to obtain the coefficients of the landslide conditioning factors.

7 Results and discussion

7.1 Certainty factor (CF) model

The correlation between the location of landslides and the landslide conditioning factors was performed. The final landslide susceptibility map obtained by CF model is shown in Fig. 5. The CF values were reckoned for all conditioning factors by overlaying and calculating the landslide frequency (Table 1). Then, the CF values of twelve landslide conditioning factors were determined using Eq. 3. The results of spatial relationship between landslide and conditioning factors using CF model are given in Table 1.

The slope class 35° – 45° has the highest value of CF(0.31) followed by 25° – 35° class (0.26). The lowest value of CF(−0.82) is for slope class 0° – 15° . From this, it is clear that the landslide occurrence increases by the increase in slope gradient up to a certain extent, and then, it decreases. Few landslides occur on a very gentle slope and the landslide occurrence decreases as the slope becomes higher than 45° . In the case of slope aspect, the CF value is positive for east to southwest-facing slope facing, with the maximum value (0.42) at southeast-facing slope followed by south-facing (0.37) slope. The north-facing slopes are less prone to landslides as they have negative CF value. The CF values of altitude show that they are positive for the ranges of <350, 350–500, 500–650, 650–800, with the highest value (0.29) for the altitude ranging between 350 and 500 m. The CF value decreases with both the increase and decrease in altitude. It becomes negative after 800 m. This shows that the probability of landslide occurrence decreases as the altitude becomes higher than 800 m. In the case of curvature, the CF value is positive (0.03) only on concave slopes. The convex and flat slopes are not responsible for landslide hazard in this area. For the geology, it can be seen that the Middle Siwaliks (CF = 0.9), Lower

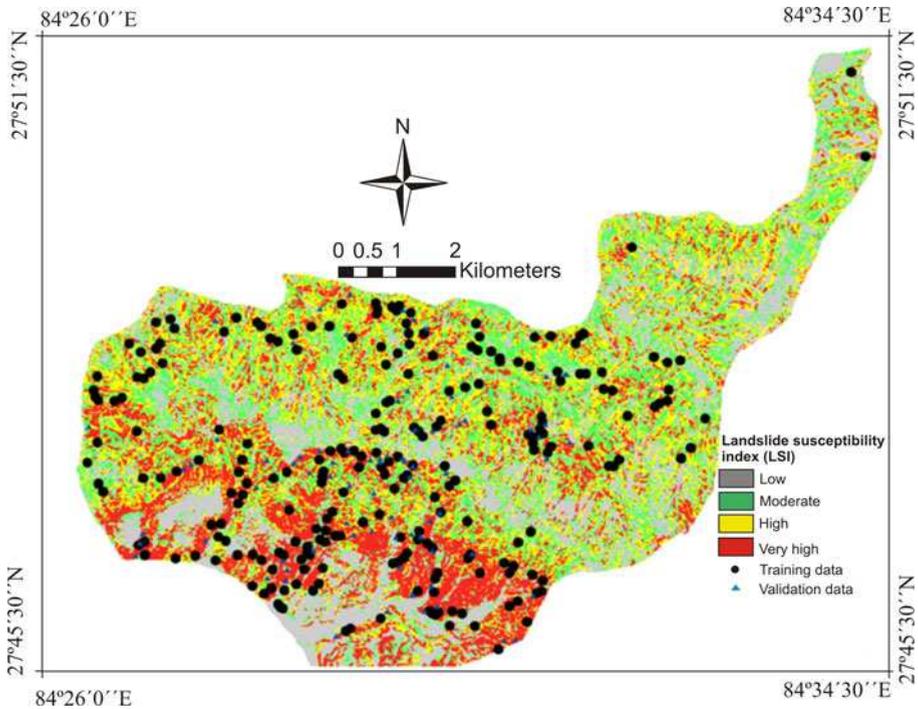


Fig. 5 Landslide susceptibility map based on certainty factor (CF) model

Siwaliks (CF = 0.63), Purebesi Quartzite (CF = 0.28), alluvial deposits (CF = 0.26), and amphibolites (CF = 0.07) are found to be more susceptible to sliding (Table 1). In the case of land use, positive value of CF is seen only on cultivation land. This may be due to the unplanned excavation of slope during agricultural activities, as well as due to the increase in moisture content during the irrigation process. In the case of distance from faults, the intervals 100–200, 200–300, 300–400, and 400–500 m have weights (CF) of 0.2, 0.08, 0.11 and 0.654, respectively. The influence of drainage system upon the landslide susceptibility was also analyzed by identifying the drainage river line by buffering. The distance range of 0–50 m (0.17) has the highest CF value, followed by 0–100 m (0.002). This indicates that the landslide occurrence decreases with the increase in distance from the river. In the case of distance from roads, the intervals 150–200 (0.23) and 200–250 (0.33) have higher CF values, that is, the landslide susceptibility is higher in these ranges. The relation between TWI landslide probabilities showed that 0–8 class has the highest value of CF (0.12), and for SPI, the class of 150–300 shows a high CF value (0.24). Similarly, for sediment transport index, the highest CF value was obtained for the interval of 40–120 m.

7.2 Index of entropy (IOE) model

The procedure for calculating the final weight W_j of the conditioning factors is explained in the earlier section, and the result is presented in Table 2. The final landslide susceptibility map was prepared by summing of weighted multiplications of the secondarily reclassified conditioning factors maps as given by Eq. 14 (Fig. 6)

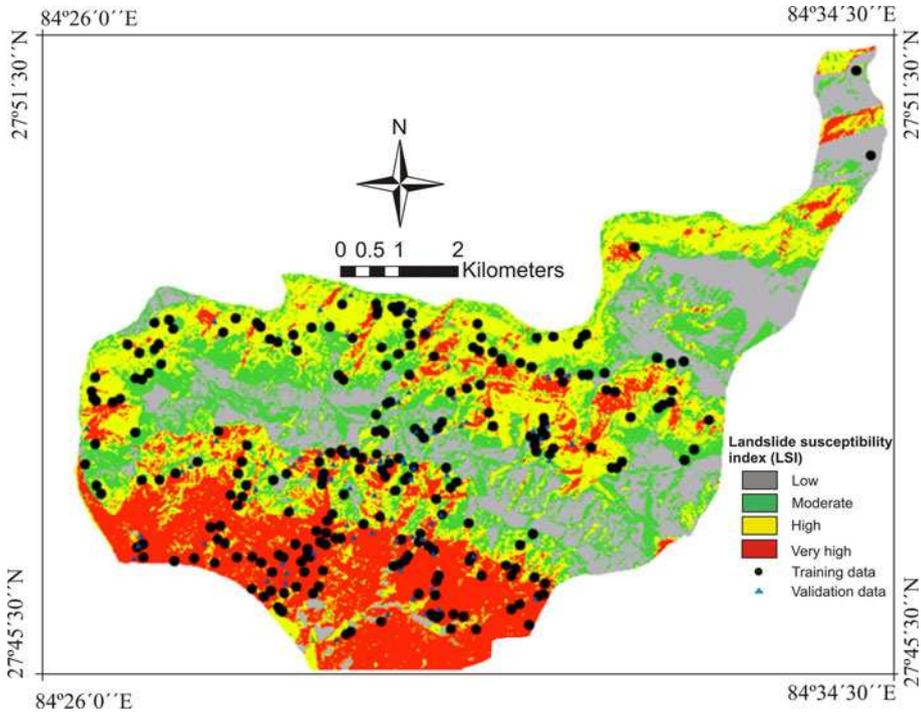


Fig. 6 Landslide susceptibility map derived from the index of entropy (IOE) model

$$\begin{aligned}
 y = & \text{Slope}_{\text{reclass}} \times 0.101 + \text{Aspect}_{\text{reclass}} \times 0.287 + \text{Altitude}_{\text{reclass}} \times 0.344 \\
 & + \text{Plan curvature}_{\text{reclass}} \times 0.249 + \text{Geolog}_{\text{reclass}} \times 0.536 \\
 & + \text{Distance from faults}_{\text{reclass}} \times 0.008 + \text{Distance from rivers}_{\text{reclass}} \\
 & \times 0.014 + \text{Distance from roads}_{\text{reclass}} \times 0.021 + \text{TWI}_{\text{reclass}} \times 0.025 \\
 & + \text{SPI}_{\text{reclass}} \times 0.052 + \text{STI}_{\text{reclass}} \times 0.039 + \text{Land use}_{\text{reclass}} \times 0.174
 \end{aligned}
 \tag{14}$$

From the result (P_{ij}), it is seen that slope interval of 35° – 45° is highly prone to landslide followed by the slope class 25° – 35° . In the case of aspect, southeast-facing slopes followed by south-facing, east-facing, and southwest-facing slopes are susceptible to landsliding. From the W_j value, it is seen that the lithology has the highest impact in the landslide susceptibility, followed by altitude, aspect, slope, and land use, while others are less significant in the landslide susceptibility of the region. It is seen that slope in the case of curvature, the concave slope is most susceptible to landslides, followed by convex slope. The slopes ranging in altitude between 350 and 500 m have the highest (P_{ij}) value of 1.4, followed by 500–650 m (1.15), 200–350 m (1.13), and 650–800 m (1.02) intervals. It is seen that the landslide density increases from 200 to 500 m, and it gradually decreases from 500 m upward. From the analysis of (P_{ij}) value of geology, it is seen that the Middle Siwaliks, Lower Siwaliks, alluvial deposits, Purebesi Quartzite followed by amphibolites are more susceptible to landslides. In the case of distance from faults, 400–500 m range has the highest P_{ij} value (1.28) followed by 100–200 m (1.26), 300–400 m (1.13), and

Table 3 Coefficients of each thematic map used in logistic regression modeling

Factor	Class	β
Slope	Flat	0.0214
	North	-13.2269
Aspect	Northeast	-0.106
	East	0.1073
	Southeast	0.8568
	South	0.3029
	Southwest	0.5532
	West	0.1169
	Northwest	-0.1373
Curvature		0
Altitude		0.0221
SPI		0.08
TWI		0.038
STI		-0.2813
Lithology		-0.002
	Terrace Deposits	0.606
	Middle Siwaliks	2.369
	Lower Siwaliks	0.591
	Benighat Slates	0.369
	Dhading Dolomite	-0.598
	Nourpul Formation	0.294
	Purebesi Quartzite	-0.341
	Amphibolites	0.127
	Dandagaun Formation	-14.34
	Fagfog Quartzite	-14.511
Land use	Kuncha Formation	0
	Barren	14.447
	Bush	12.814
	Cultivation	13.445
	Cutting	-1.555
	Forest	-1.508
	Grass	12.954
	Orchard	13.108
	River	-1.264
Sand	0	
Distance form faults		-0.000041
Distance form roads		-0.00038
Distance form rivers		-0.0004

Constant is -18.991

200–300 m (1.09). The distance from rivers shows that the P_{ij} value decreases as the distance from river increases. From this, it is clear that the bank erosion is one of the main triggering factors. Most of the landslides are located at a distance of 200–250 m from the road section as the values of (P_{ij}) is highest (0.2) here. It decreases with both the increase

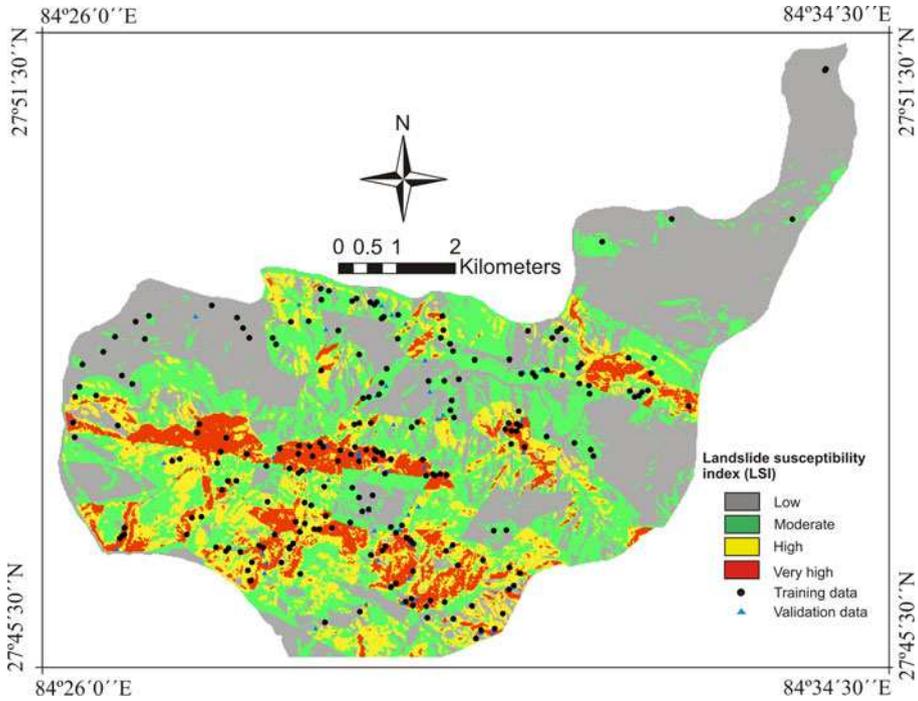


Fig. 7 Landslide susceptibility map derived from the logistic regression (LR) model

and decrease of distance from the road. In the case of TWI (P_{ij}), the value decreases with increasing TWI, it is highest (0.42) for class 0–8. This shows that TWI strongly affects the landslide occurrence. In the case of SPI, class 150–300 has the highest (P_{ij}) value, while for STI, the range between 80 and 120 has the highest (P_{ij}) value, indicating that this range is most susceptible to landsliding. The cultivation land has the highest (P_{ij}) value of 1.57 and is the main land use type that is most susceptible for landsliding.

7.3 Logistic regression model

The resultant beta (β) coefficients for each independent variable in the logistic regression equation are given in Table 3. Based on the obtained result, Eq. 15 can be rewritten as

$$\begin{aligned}
 z = & (0.0214 \times \text{Slope}) + \text{Aspect} + (0.08 \times \text{Altitude}) + (0.0221 \times \text{Plan curvature}) \\
 & + (0.038 \times \text{SPI}) + (-0.2831 \times \text{TWI}) + (-0.002 \times \text{STI}) + \text{Lithology} \\
 & + \text{Land use} + (-0.000041 \times \text{Distance from faults}) \\
 & + (-0.00038 \times \text{Distance from roads}) \\
 & + (-0.0004 \times \text{Distance from rivers}) - 18.991
 \end{aligned}
 \tag{15}$$

Finally, landslide susceptibility index (LSI) map is obtained by using the raster calculator in ArcGIS 9.3 (Fig. 7).

From the analysis of logistic regression coefficients, it is seen that slope angle, curvature, and SPI have prominent role in the landslide susceptibility of the area, as they all have positive β value. Also, it is seen that SPI has highest β coefficient (0.038), followed

by curvature (0.0221) and slope (0.0214). Distance from fault, road, river, and TWI has negative effect in landslide formation as they all have negative β coefficient and hence are considered to be less significant in landslide formation on the road section. In the case of aspect, the slope trending toward east ($\beta = 0.8658$), south ($\beta = 0.5532$), southeast ($\beta = 0.3029$), and west ($\beta = 0.1169$) has high probability of landslide susceptibility as they have positive β coefficient. As far as the geology is concerned, the Middle Siwaliks ($\beta = 2.369$) are most susceptible to sliding. Alluvial deposits ($\beta = 0.606$), consisting of loose sediments, also show a higher susceptibility. The Lower Siwaliks ($\beta = 0.591$) are also highly prone to landsliding; the Benighat Slates ($\beta = 0.369$), Nourpul Formation ($\beta = 0.294$), and Amphibolites ($\beta = 0.127$) all have positive β coefficient and hence are more susceptible to landsliding than the rest. In the case of land use, barren land ($\beta = 14.447$), cultivated land ($\beta = 13.445$), orchard ($\beta = 13.108$), followed by bush ($\beta = 12.814$), and grassland ($\beta = 12.954$) have the susceptibility levels in decreasing order, while the remaining land use types does not have any role in landslide susceptibility of the region.

7.4 Validation of the landslide susceptibility maps

The landslide susceptibility maps derived by three models were tested using the landslide data sets that were used for model building process as well as from those that were not used in model building process. For this, the total landslides observed in the study area were split into 2 parts, 241 (75 %) was randomly selected from the total 321 landslides as the training data and the remaining 80 (25 %) landslides are kept for validation propose. Spatial effectiveness of these susceptibility maps was checked by receiver operating characteristics (ROC).

The ROC curve is a useful method for representing the quality of deterministic and probabilistic detection and forecast systems (Swets 1988). The ROC can be represented equivalently by plotting the fraction of true positives out of the positives versus the fraction of false positives out of the negatives, for a binary classifier system as its discrimination threshold is varied (Table 4). By tradition, the plot shows the false-positive rate (1 specificity) on the x -axis (Eq. 16) and the true-positive rate (the sensitivity or 1—the false-negative rate) on the y -axis (Eq. 17).

$$X = 1 - \text{specificity} = 1 - \left[\frac{\text{TN}}{(\text{TN} + \text{FP})} \right] \tag{16}$$

$$Y = \text{sensitivity} \left[\frac{\text{TN}}{(\text{Tp} + \text{FN})} \right] \tag{17}$$

The area under the ROC curve (AUC) characterizes the quality of a forecast system by describing the system’s ability to predict correctly the occurrence or non-occurrence of predefined ‘events’. The model with higher AUC is considered to be the best. If the area under the ROC curve (AUC) is close to 1, the result of the test is excellent. On the other

Table 4 Parameters for the calculation of ROC curve (modified from Swets 1988)

	Landslide bodies	Landslide free areas
Landslide occurrence based on calculated function	True positive (TP)	False positive (FP)
Safe areas based on calculated function	False negative (FN)	True negative (TN)

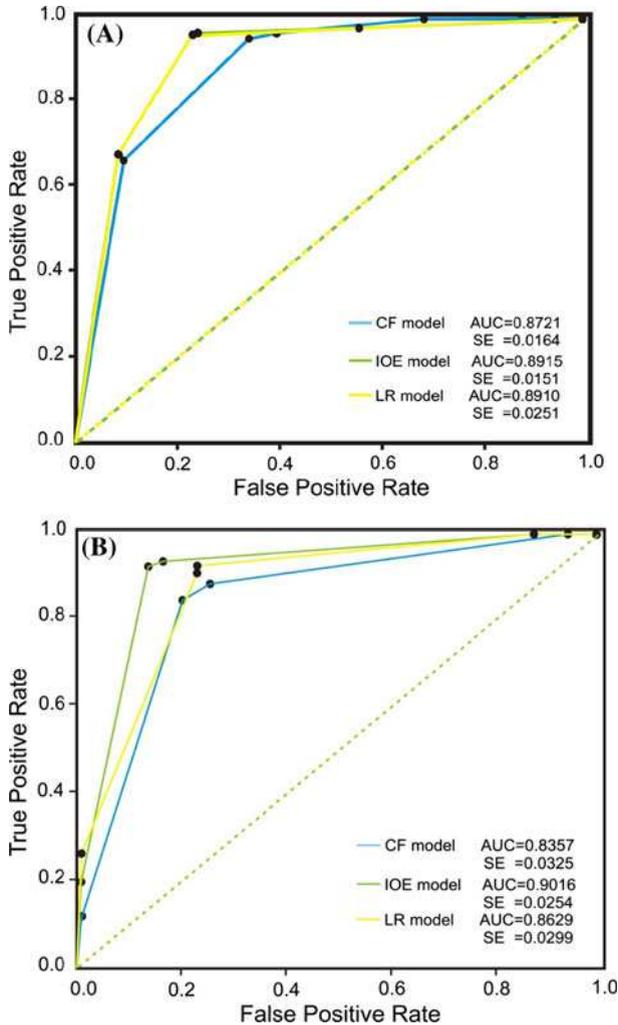


Fig. 8 Area under the curve (AUC) for the landslide susceptibility maps produced by three models. **a** Success rate graph, and **b** prediction rate graphs

hand, if the model does not predict well, then this value will be close to 0.5. Both the success rate and prediction rate of the models were used for assessing the prediction capability of the models.

The success rate results were obtained by comparing the landslide training data with the susceptibility maps (Fig. 8a). From the figure, it is seen that the index of entropy model (IOE) has the highest area under the curve (AUC) value (0.8915), followed by logistic regression model (0.8910) and certainty factor model (0.8721). Since the success rate method used the training landslide data that have already been used for building the landslide models, the success rate is not a suitable method for assessing the prediction capability of the models (Bui et al. 2011). However, this method is useful to know the performance of the models. Thus, the validations of the models were done by using the prediction rate curve. The prediction rate explains how well the model and predictor

variable predicts the landslide (Lee 2007). Also, the prediction rate curve shows that the index of entropy has the highest area under curve (AUC) value (0.9016), while logistic regression model and certainty factor model have (0.8629) and (0.8357) value of (AUC), respectively. From this, it is seen that both the success rate and prediction rate curve show almost similar result, and the all the models employed in this study showed reasonably good accuracy in predicting the landslide susceptibility of the road section.

8 Conclusions

Since landslides pose a serious threat to the life and property, their susceptibility mapping can be one of the preliminary steps toward minimizing the damages incurred by them. A landslide susceptibility map divides an area into various categories that range from stable to unstable ones. In this research, two bivariate models (i.e., certainty factor and index of entropy models) and one multivariate model (i.e., logistic regression) were used for identifying the areas susceptible to landsliding at Mugling–Narayanghat road and its surrounding areas.

For this purpose, twelve landslide conditioning factors (i.e., slope gradient; slope aspect; altitude; plan curvature; lithology; land use; distance from faults, rivers and roads; topographic wetness index (TWI); stream power index (SPI); and sediment transport index (STI)) were used. A landslide inventory map was prepared using aerial photographs, satellite images, and extensive field survey. In this process, a total of 321 landslides were identified and mapped. Out of which, 241 (75 %) were randomly selected for generating a model and the remaining 80 (25 %) were used for validation proposes. The ROC plots showed that the susceptibility map produced using the index of entropy model has the highest perdition accuracy (90.16 %), followed by the logistic regression model (86.29 %) and the certainty factor model (83.57 %). Success rate curve also gives similar result, with index of entropy model (IOE) the highest (AUC) value (0.8915), followed by logistic regression model (0.8910) and certainty factor model (0.8721). This shows that all the models employed in this study showed reasonably good accuracy in predicting the landslide susceptibility of Mugling–Narayanghat road section. The increasing population pressure has forced people to concentrate their activities on steep mountain slopes. Thus, to safeguard the life and property from landslides, the susceptibility maps can be used as basic tools in land management and planning future construction projects in this area. While the low susceptibility zones are relatively safe for the development of infrastructures, the high and very high susceptibility zones require further engineering geological and geotechnical considerations.

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