A replication of landslide hazard mapping in catchment scale

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Abstract

Landslide hazard assessment is a primary tool to understand the basic characteristics of the slopes that are prone to landslides especially during extreme rainfall. In this study, weights-of-evidence modelling with respect to bivariate statistical method and logistic regression model, multivariate statistical method, were used for landslide hazard mapping in two catchments of Siwaliks. Two typical catchments viz. Charnath and Jalad of Siwaliks in eastern Nepal were selected for the landslide hazard mapping. Both modelling was applied by considering 10 intrinsic and 1 extrinsic factors. Mainly DEM-based causative factors and field data were used to prepare data layers of landslide causative factors. In many approaches of modelling of landslide hazard in GIS, model validation process is always dependent and landslide data, which is used to calculate Landslide Hazard Index (LHI), is applied for verification. But in this study, Landslide

Hazard Index was calculated in one catchment (Jalad) and same index for different class of causative factors was applied for another catchment (Charnath) and LHI was verified. Verification results were very promising with about 75% independent prediction rate. This validates weights-of-evidence and logistic regression models for landslide hazard assessment in the Siwalik Range of Nepal.

1 Introduction

Landslides are amongst the most disastrous natural hazards in tropical, subtropical and temperate climatic zones of the world. Potential sites that are particularly prone to landslides should therefore be identified in advance so as to reduce damages from potential landslide disasters. Landslide hazard or susceptibility assessment is a primary tool to understand the basic characteristics of the slopes that are prone to failure especially during extreme rainfall.

In general, landslide hazard can be depicted as the physical potential of the process to produce damage. The damage is merely depends on particular impact characteristics of landslides as well as the magnitude and frequency with which it occurs or is encountered. Fundamentally, landslide hazard can be characterised by statements of ‘what’, ‘where’, ‘when’, ‘how strong’ and ‘how often’ (Crozier and Glade, 2005). Unfortunately, the ability to prediction of landslide hazard with precision is always limited and consequently landslide hazard predictions are generally described in terms of likelihoods and probabilities. In many landslide hazard mapping techniques, probabilities of failure are usually categorised and landslide hazard zonation maps are prepared. Landslide hazard zonation is defined as the mapping of areas with an equal probability of occurrence of landslides within a specified period of time (Varnes, 1984). Landslide hazard zonation demonstrates spatial and temporal occurrence of future landslides in terms of probability.

The majority of the published literatures on landslide hazard mapping mainly address to landslide susceptibility mapping. There are numerous studies involving landslide hazard evaluation, and particularly, Guzzetti (2005) has explored many cases of landslide hazard studies. Landslide hazard levels can be addressed qualitatively or quantitatively as well as either directly or indirectly (Guzzetti *et al*. 1999). Qualitative methods always describe landslide hazard in descriptive terms whereas quantitative methods use probabilities values to predict landslide hazard in the study area. Direct methods consist of the geomorphological mapping of landslide hazard where as indirect methods usually deal with identification and mapping of group of physical factors which are directly or indirectly associated with the landslides. Such physical factors are called as intrinsic and extrinsic factors. In many cases, intrinsic (bedrock geology, geomorphology, soil depth, soil type, slope gradient, slope aspect, slope curvature, elevation, land use pattern, drainage pattern and so on) and extrinsic (rainfall, earthquakes, and volcanoes) factors are used to determine landslide hazard in an area (Siddle *et al*. 1991; Dai *et al*. 2001; Çevik and Topal 2003; Dahal *et al*. 2008a). The extrinsic factors are site specific and possess temporal distribution. Moreover, they are difficult to be estimated because of lack of information about the spatial distribution. Hence, in landslide hazard assessment practice, the term “landslide susceptibility mapping” is addressed without considering the extrinsic factors in determining the probability of occurrence of a landslide event (Dai *et al*. 2001, Dahal *et al*. 2008a). A region is considered to be susceptible to landslides when the terrain conditions at that site are similar to those in the region where a slide has occurred (van Westen, 2000). The integrated analysis of all intrinsic variables in relation to the spatial distribution of landslides has gained enormous success by the introduction of Geographic Information Systems (GIS), the ideal tool for the analysis of parameters with a high degree of spatial variability. For a landslide hazard assessment, the assumption is made that conditions, which led in the past to landslides, will also result in potential unstable conditions in present and future. Thus, a landslide inventory map, differentiating the type, activity, dimensions of mappable landslides, is a primary data for landslide hazard or susceptibility zonation. The inventory map also need to cover information of time span based landslide distribution as far as possible. When mapping of intrinsic factors, emphasis should be given to the most relevant terrain parameters related to the occurrence of landslides. Generally, it is true that the selection of intrinsic parameters takes the nature of the study area and the data availability into account. But in a GIS-based technique, it is also necessary to be sure that any selected factor is functional (has a certain degree of affinity with previous occurrences of landslides), complete (is reasonably represented all over the study area), non-uniform (remarkable spatial variation), measurable (can be expressed by nominal, ordinal, interval, ratio scales), and non-redundant, i.e., outcome of selected factors should not account for double effects in the final result (van Westen, 2000; Yalcin, 2008).

Landslide hazard and susceptibility mapping are assessed through heuristic, statistical, and deterministic approaches (Okimura and Kawatani 1987; Yin and Yan 1988; Soeters and van Westen 1996; van Westen and Terlien 1996; Gökceoglu and Aksoy, 1996; Pachauri *et al*. 1998; van Westen 2000; Dai *et al*. 2001; Zêzere *et al*. 2004; Süzen and Doyuran 2004; van Westen *et al*. 2003; Saha *et al*. 2005; Dahal *et al*. 2008b, Prahdan *et al*. 2009; Pradhan and Lee 2010; Poudyal *et al*. 2010; Regmi *et al*., 2010; Chauhan *et al*. 2010; Odzemir 2011).

Heuristic approach is a direct or semi direct mapping methodology in which a direct relationship is established between the occurrence of landslides and the causative terrain parameters during the landslide inventory. Therefore, in this approach, the opinions of the experts are very important to estimate the potential of landslides based on the intrinsic factors of landslides included in the analysis.. Similarly, assigning weight values and ratings to the variables is very subjective and the results are not reproducible. Deterministic approaches, however, are based on slope stability analyses, and are only applicable when the ground conditions are relatively homogeneous across the study area and the landslide types are known. Mainly, the infinite slope stability model has been widely used to assess landslide susceptibility in deterministic approaches (Wu and Sidle 1995; Terlien 1996; Gökceoglu and Aksoy 1996; Dahal *et al*. 2008c), and such stability model needs high degree of simplification of the intrinsic variables. Statistical approach, on the other hand, is an indirect susceptibility mapping methodology which involves statistical determination of the combinations of variables that have led to landslide occurrence in the past. All possible intrinsic variables are entered into a GIS and crossed for their analysis with a landslide inventory map. Both bivariate and multivariate statistical approaches have been used for mapping landslide hazards (Siddle *et al*. 1991; Atkinson and Massari 1998; Guzzetti 1999).

In the most of the cases of statistical approach of landslide hazard mapping, either bivariate or multivariate, the replication of hazard indexes of causative parameters is always a problem. It is really hard to find same intrinsic parameters in two different regions. To avoid these limitations, in this study, two catchments are evaluated for replication of landslide hazard mapping. In this study, the landslide hazard is evaluated in GIS platform using the weight-of-evidence modelling and the logistic regression modelling. Two catchments (Jalad and Charnath catchments) of Sub

Himalayan Zone (Siwalik Group) of the Nepal Himalaya are selected as the ideal sites of the study because both catchments have serious rainfall-induced landslides and slope degradation problems . They have typical geological and geomorphological settings of the region.

2 The study area

The study area is located in the south-eastern hills of the Nepal Himalaya and belongs to the Sub Himalaya Zone or Siwaliks (Fig 1) of the Himalaya.

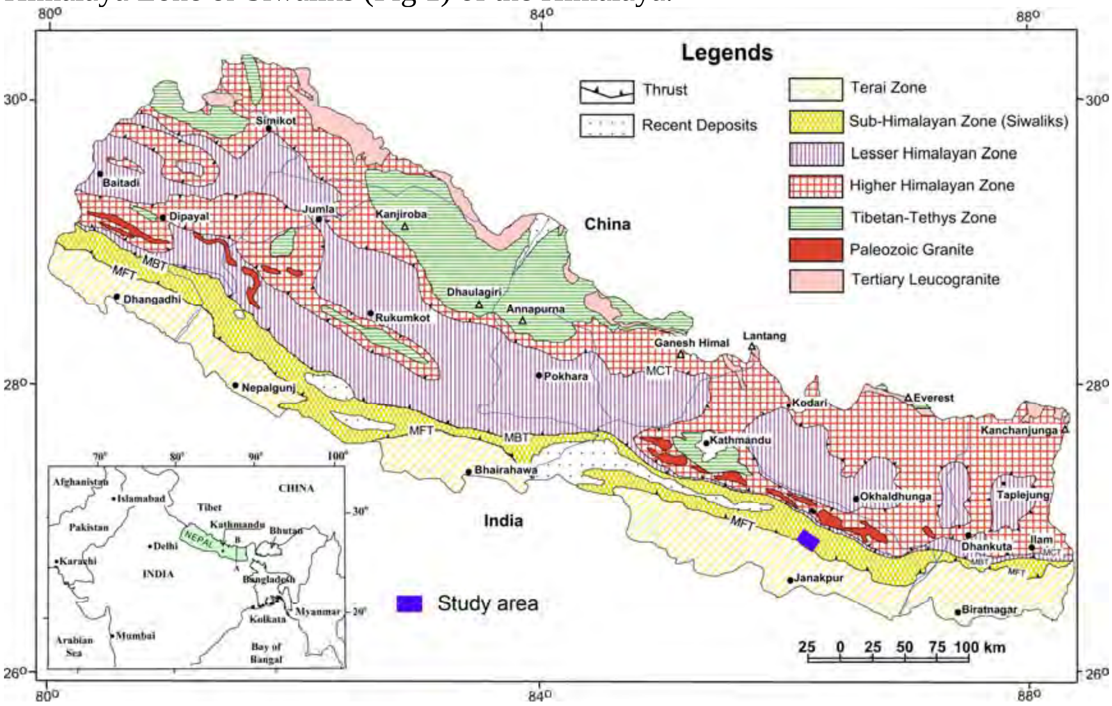

Fig. 1, Location of the study area and general geological map of Nepal (modified after Dahal and Hasegawa, 2008)

Siwaliks, also called as Churia in Nepal, is the youngest low-altitude mountain in the Himalayan chain. Siwaliks consists of relatively unconsolidated soft rock namely, mudstone, sandstone and loose conglomerate and it comprises many vertical slopes and rugged terrain. The average slope and relief of terrain are high in the western regions compared to other regions of Nepal. Many parts of the Siwaliks are inhabited by relatively large human population with agriculture and livestock as the mainstays of livelihood. River valleys, comprised of narrow tracts of flatland, are extensively used for cultivation and settlement.. The population and livelihood activities are highly vulnerable to floods, debris torrents, debris slides and debris flows from hill-slopes. Obviously, the pressure of the population and fast growing development and economic activities on forest and cultivation is high in the entire Siwaliks. Land use and land cover distribution pattern shows the predominance of forest in the hill slopes and cultivated land in the plain area. Considerable patches of cultivated areas also lie on areas of steep topography, flood and slope failure-prone areas. Over the last four decades there has been a tremendous change in land use and land cover, but this change has been less in the last decade (Ghimire *et al.* 2008) because of the conversion of forest areas into cultivated lands. The change was more pronounced in slopes of Siwaliks and inner river valleys. A significant expansion of cultivated land in steep slopes and in flood prone areas clearly indicates environmental degradation and livelihood vulnerability in the Siwaliks (Ghimire *et al*. 2008).

Two typical catchments viz. Charnath and Jalad (Fig 2) are selected for the study. Both catchments are located in the northern part of Dhanusa district of Nepal (Fig 2).The Jalad and Charnath are two major river systems originating from the Siwaliks and they are highly disastrous rivers. These catchments have very fragile lithology and steep topography, predisposing the landscape to have significant problems of geology and geomorphology related slope failures. The Charnath River is about 8 km east from the outlets of the Jalad River in Terai. Jalad catchment in Churia is north-south elongated where as Charnath is northwest-southeast elongated.

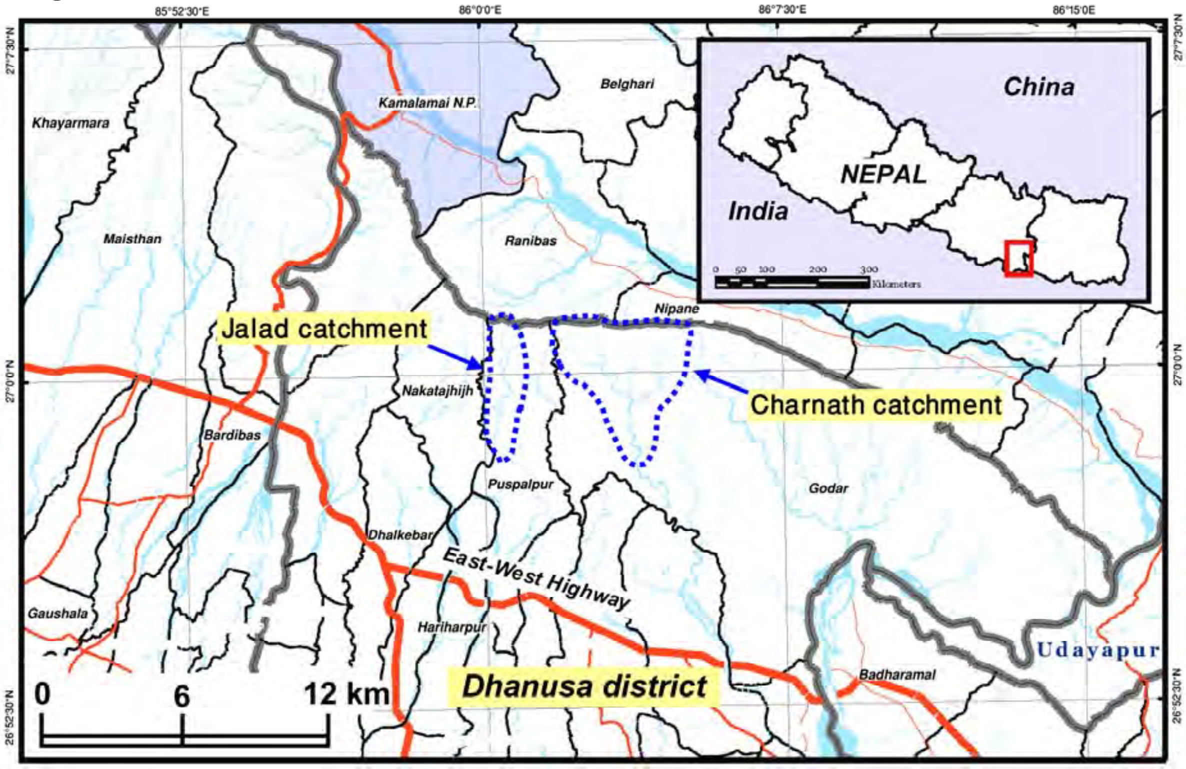

Fig 2, Location map of Jalad and Charnath catchments in Siwaliks of Dhanusa district, Nepal (map modified after UNDP Nepal 2010)

2.1 Geological and geomorphological settings of selected catchments

Geology of the Nepal Himalaya has been divided into east-west trending five major tectonic units (Fig 1). From south to north, these units are Terai Zone, Sub-Himalayan Zone (Siwaliks), Lesser Himalayan Zone, Higher Himalayan Zone, and

Tibetan-Tethys Zone. As mentioned in earlier sections, the study area belongs to the Siwaliks Zones. The Siwaliks is made up of geologically very young sedimentary rocks such as mudstones, shale, sandstones, siltstones and conglomerates. These rocks are soft, unconsolidated and easily disintegrable. According to three fold classifications of Siwaliks, it can be divided into three geological units (Burbank *et al.*, 1996, Ulak and Nakayama, 1999), Lower Siwaliks, Middle Siwaliks and Upper Siwaliks as per the occurrence of rock types. Lower Siwaliks usually has thin to thickly bedded green to grey coloured mudstone and siltstone, whereas Middle Siwaliks has thick to very thickly bedded sandstone. The Upper Siwaliks contains thick beds of loose and fragile conglomerates.

Factors such as the excessive rainfall and human intervention are the main triggering agents of landslides in Siwaliks. The factors like, groundwater condition, river under cuttings and deforestation on slopes are also facilitating slope failures. Similarly, Lower Siwaliks and Middle Siwaliks have problem from alternating beds of mudstones and sandstone. In such alternating bands, mudstone can flow when saturated with water, which results overhanging sandstone beds. Such overhang jointed sandstone beds are easily disintegrated into blocks. Similarly, throughout Nepal, the rainfall within the Siwaliks is normally in the range of 2000 to 2500 mm per year (Ghimire *et al*. 2008). As a result, geological conditions and the climate render the Siwaliks highly susceptible for landslides.

In the both Jalad and Charnath catchments, the Siwaliks can be divided into two units: Middle Siwaliks and Upper Siwaliks on the basis of lithological composition (Fig 3). Middle Siwaliks consists of alternation of thickly bedded light yellow to light grey coloured mudstone and light grey coloured sandstone with subordinate pebbles. The proportion of sandstone and mudstone is equal on the southern part, while the proportion of sandstone increases towards upstream of both catchment.

Fig 3, Thickly bedded alternating bands of coarse and fine grained sandstonesin the Middle Siwalik (left) and loose conglomerate in the Upper Siwalik as seen in the upstream of the Jalad River (right).

Land degradation is a common problem in fragile and steep hill slopes of both catchments, where pressure from human intervention and grazing animal are extensively high. All transport routes are terribly used only for smuggling wood from forest. As a result, vicinity of the routes are exceedingly deforested. Debris slides and debris flows are the major land degradation processes in the both catchments. Charnath catchment is relatively densely populated than the Jalad catchment. In Nepal, landless population is high in the northern Lesser Himalyan Zone and migration to the southern Siwalik Range is a common problem. Both catchments have same problem of migration and improper agricultural practices make both catchments highly vulnerable to landslides.

The stream channels are narrowed and meandered showing cliffs formed by bank cuttings on their concave banks. The river width is relatively higher in upstream than downstream. The sediment thickness of channel lag on the riverbed is not more than 10 m, while in some places, the river flows over the bedrock. Main geological difference in Jalad and Charnath is on the coverage of Upper Siwalik (loose conglomerate). The nearly half portion of Jalad catchment has Upper Siwalik where as Charnath has Upper Siwalik only in upper reaches. As a result, there are fewer amounts of gravels in Charnath river bed in comparison to the Jalad river bed.

3 Goals and Objectives of the Study

The main goal of this study is to prepare landslide hazard maps of the selected catchment by replicating landslide hazard index of one catchment into another catchment. The specific objectives achieved to accomplish this study are as follow:

- To conduct field work to gather the relevant data and information regarding shallow landslides;
- To identify similar causative intrinsic and extrinsic factors of landslides in both catchments;
- To analyze the geological and geomorphological data and information for landslide hazard mapping;
- To prepare weights-of-evidence and logistic regression models and apply them in the Jalad catchment for assessment of landslide hazard index (LHI);
- To apply same LHI of each causative factors obtained from Jalad catchment in similar causative factors of Charnath catchment and validate the models;
- To evaluate replication procedure of landslide hazard mapping in catchment scale.
- To prepare landslide hazard zonation map (scale 1:10,000) of both catchments based on the validation and comparative results of weights-of-evidence and logistic regression models.

4 Methodology and Materials

Although there are various methods in statistical approach of landslide hazard study, in this study, weights-of-evidence modelling and logistic regression modelling was used for the hazard analysis in the two selected catchments. First, Jalad catchment was analysed with weights-of-evidence and logistic regression models, and then results were applied in the Charnath catchment. Details of methods and data used in the analysis were described in the following paragraphs.

4.1 Weights-of evidence model

In this study, both bivariate and multivariate approaches were selected to assess landslide hazard indexes. In bivariate statistical approach, the weights-of-evidence model was used to assess the landslide hazard index. The method uses the Bayesian probability model, and was originally developed for mineral potential assessment (Bonham-Carter *et al*. 1988, 1989; Agterberg 1992; Agterberg *et al*. 1993; Bonham-Carter 2002). Several authors have applied the method to mineral potential mapping using GIS (Emmanuel *et al*., 2000; Harris *et al*., 2000; Tangestani and Moore, 2001; Carranza and Hale, 2002). Cheng (2004) used the method to predict the location of flowing wells and Daneshfar and Benn (2002) used weights-of-evidence to analyse spatial associations between faults and seismicity whereas Zahiri *et al*. (2006) applied weights-of-evidence model for mapping cliff instabilities associated with mine subsidence. The method has also been applied to landslide susceptibility and hazard mapping (Lee *et al*. 2002; VanWesten *et al*. 2003, Lee and Choi 2004; Lee and Sambath 2006; Sharma and Kumar 2008; Neuhäuser and Terhorst, 2007; Dahal *et al*. 2008a, 2008b, Regmi *et al*. 2010).

A detailed description of the mathematical formulation of the method is available in Bonham-Carter (2002) and mathematical relationships for landslide hazard mapping is available in Dahal *et al*. (2008b). For landslide hazard modelling, the method calculates the weight for each landslide causative factor based on the presence or absence of the landslides within the area. Therefore, historical landslide data are essential for weighting factors. The modelling procedure also relies on the fundamental assumption that future landslides will occur under conditions similar to those contributing to past landslides. It also assumes that causative factors for the mapped landslides remain constant over time.. The method calculates the weight for each landslide predictive factor (F) based on the presence or absence of the landslides (L) within the area, as indicated in Bonham-Carter (2002) and modified by Dahal *et al*. (2008a) for landslide hazard assessment as follows:

$$W_{\mathrm{i}}^{+} = \log_{\mathrm{e}} \frac{P\left\{F \mid L\right\}}{P\left\{F \mid \bar{L}\right\}} \qquad (1)$$

$$W_{\mathrm{i}}^{-} = \log_{\mathrm{e}} \frac{P\left\{\bar{F} \mid L\right\}}{P\left\{\bar{F} \mid \bar{L}\right\}} \qquad (2)$$

A positive weight (W_{i}^{+}) indicates that the causative factor is present at the landslide location and there is a positive correlation between presence of the causative factor and landslides. A negative weight (W_{i}^{-}) indicates an absence of the causative factor and shows the level of negative correlation. The difference between the two weights is known as the weight contrast, W_{f} ($= W_{\mathrm{i}}^{+} - W_{\mathrm{i}}^{-}$), and the magnitude of contrast reflects the overall spatial association between the causative factor and landslides. In weights-of-evidence model, the combination of causative factors assumes that the factors are conditionally independent of one another with respect to the landslides (Bonham-Carter 2002; Lee and Choi 2004). In this research also, the assumption is made that all landslides in the selected catchment area occur under the same combination of parameters, and that all sets of parameters are conditionally independent.

4.2 Logistic regression model

In this study, logistic regression model was used to assess landslide hazard indexes. Logistic regression can be used to determine the relation of landslide occurrence and the related factors (Guzzetti *et al*. 1999; Dai and Lee 2002; Ohlmacher and Davis 2003; Lee 2005; Ayalew and Yamagishi, 2005; Zhu and Huang 2006; Chen and Wang 2007; Akgün and Bulut 2007; Chauhan *et al*. 2010). It is useful when the outcome variable or dependent variable is binary or dichotomous. The dependent variable for this analysis is the absence or presence of a landslide.

Considering n independent variables x_1, x_2, x_3, …… , x_n, affecting landslide occurrences, the vector $X = (x_1, x_2, x_3, \ldots\ldots, x_n)$ has been defined. In logistic regression analysis, the logit y is assumed as a linear combination of independent variables and is given as follow.

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + \ldots\ldots. + b_n x_n \qquad (3)$$

Where, b_0 is the constant of the equation, and b_1, b_2, … , b_{n} are the coefficients of independent variables, x_1, x_2, x_3, …… , x_n. For landslide hazard assessment, the dependent variable is a binary variable, with values of 1 or 0, representing the presence or absence of landslides. Quantitatively, the relationship between the occurrence and its dependency on several variables can be expressed as follow (Hosmer and Lemeshow 2000).

$$P = 1 \Big/ 1 + e^{-y} \quad (4)$$

Where, P is the estimated conditional probability of landslide occurrence and e is the constant 2.718. From equation 3 and equation 4, a relationship can be obtained in which the natural logarithm of the odds, $\log(P/1-P)$, is linearly related with the independent variables as follow.

$$\log\left(P \big/ 1-P\right) = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + ... + b_n x_n \quad (5)$$

The goodness of fit of the model was tested with the Wald statics and Hosmer-Lemeshow test (Hosmer and Lemeshow 2000). By examining the sign of a dependent variable's coefficient estimate, the effect of that variable on the probability of landslide occurrence can be determined. These values were utilized to decide final landslide hazard index (LHI) of the Jalad catchment of the study area.

4.3 Data preparation

The main steps for landslide hazard mapping are data collection and the construction of a spatial database, from which relevant causative factors were extracted. This is followed by assessment of the landslide hazard using the relationship between landslides and causative factors, and the subsequent validation of results. A key feature of this method is that the probability of landslide occurrence will be comparable with observed landslides.

For the modelling in weights-of-evidence and logistic regression, a number of thematic data of causative factors have been identified, including 1) slope, 2) slope aspect, 3) distance to drainage, 4) wetness index, 5) sediment transport index, 6) relief, 7) distance to transportation route, 8) curvature, 9) geology, 10) land cover, and 11) mean annual rainfall. Topographic maps and aerial photographs provided by the Department of Survey, Government of Nepal were considered as basic data sources for generating these layers. Field surveys were carried out for data collection and to prepare data layers of various factors. Landslide distribution maps of both catchments were also prepared in the field. These data sources were used to generate various thematic layers using the GIS software ILWIS 3.7. Brief descriptions of the preparation procedure of each data layer are provided here.

4.3.1 Landslide characteristics and inventory maps

A landslide inventory map is the simplest output of direct landslide mapping. It shows the location of discernible failures. Two landslide inventory maps for Jalad and Charnath catchment were prepared. However, a detailed landslide map was prepared for the Jalad catchment and only recent locations of landslides were mapped in the Charnath catchment. Only scars (main failure portion) were used to delineate the landslides. With the use of field data and satellite image, 426 landslide scars were delineated in the Jalad catchment. Satellite image PRISM (Panchromatic Remote-sensing Instrument for Stereo Mapping) has 2.5 m resolution and very useful to recognise landslide image even from visual interpretation. The landslide scars mapped in field were again revised with PRISM data and final Landslide inventory maps were prepared for both catchments. All landslides were used to assess landslide hazard index from both logistic regression and weights-of-evidence modelling. Finally, to check the predictive power of model in all possible aspects of both models, the LHI of each class of causative factors estimated from the Jalad catchment was used for same class of causative factors in Charnath catchment. Moreover, prediction rates of the both model were evaluated from landslide inventory of Charnath catchment. The inventory maps of both catchments are given in Fig 4 and Fig 5.

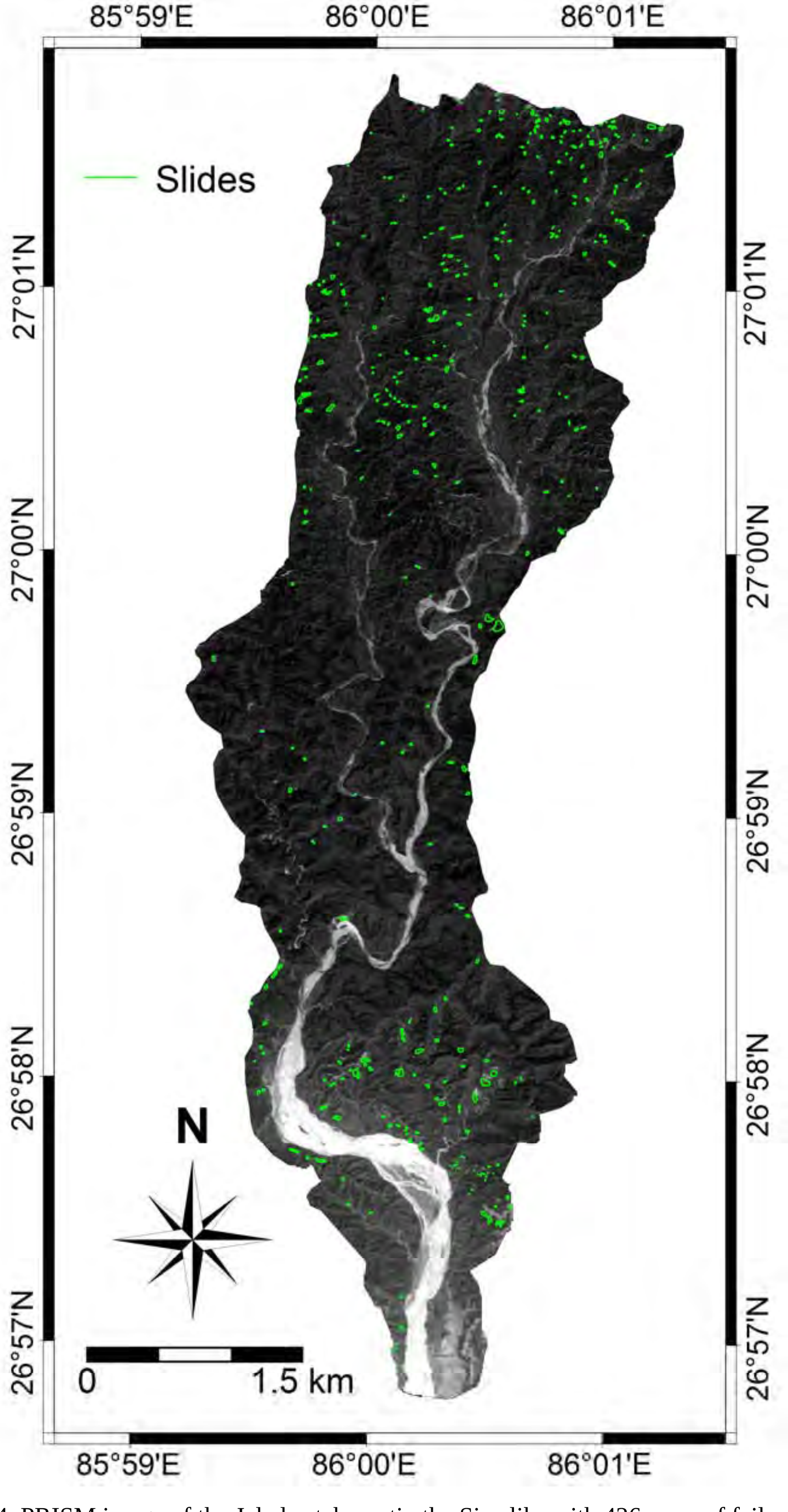

Fig 4, PRISM image of the Jalad catchmentin the Siwaliks with 426 scars of failures

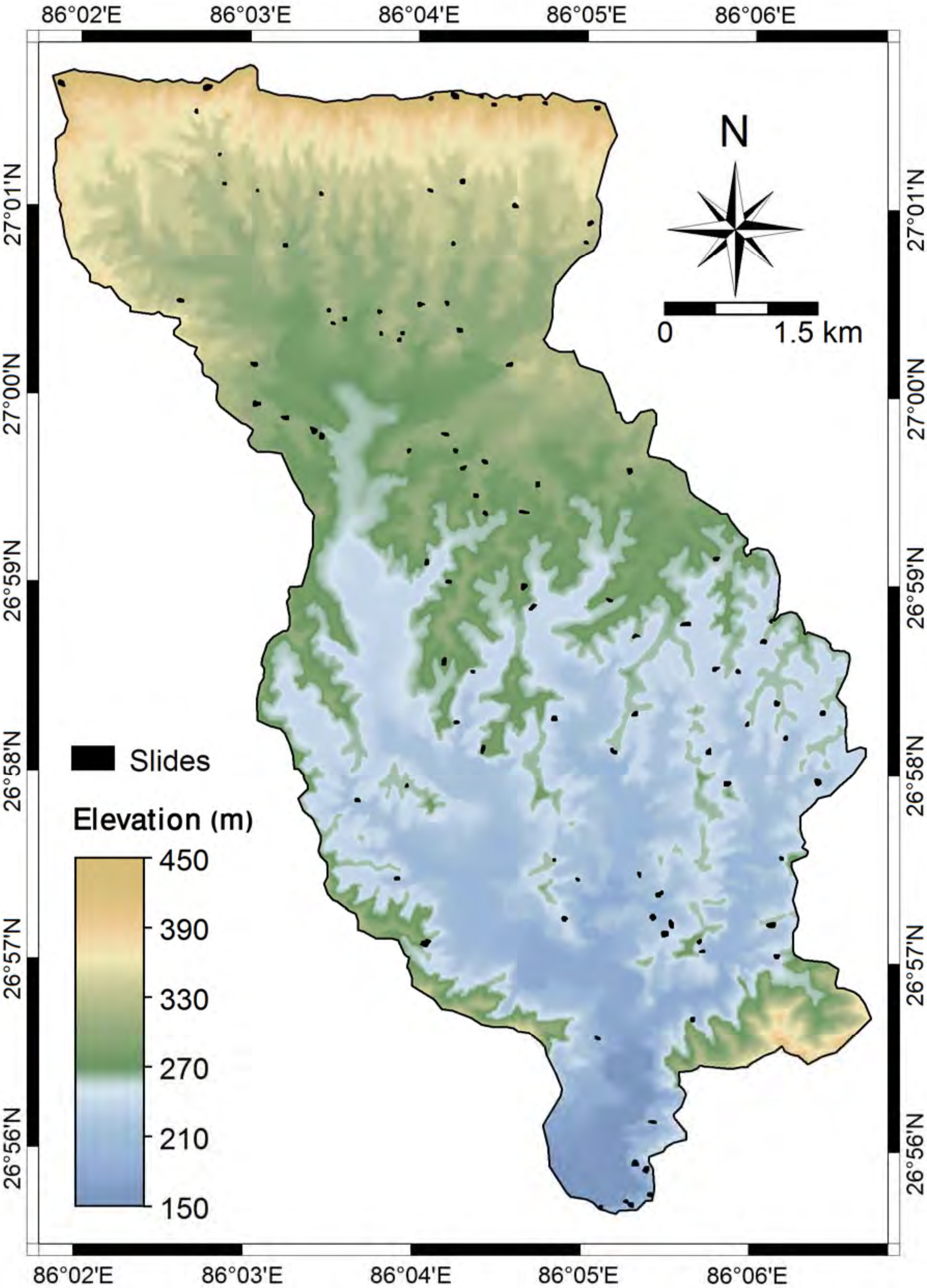

Fig 5, DEM of Charnath catchment in the Siwaliks with 101 scars of recent landslides.

4.3.2 Geological map

Geology plays an important role in landslide susceptibility and hazard studies because different geological units have different susceptibilities to active geomorphological processes of the Himalaya (Pradhan *et al*. 2006). Sandstone, mudstone, siltstone and gravel conglomerate are main rocks of the selected catchments and they belongs to the Lower and Upper Siwalik groups. For the geological map preparation, previous studies (DMG, 2004; Ghimire *et al.* 2008) were consulted and geological boundaries of formations were checked in field visit and modified as per the field observations.

4.3.3 Geomorphology related causative factors

A Digital Elevation Model (DEM) representing the terrain is a key to generate various geomorphological parameters, which influence the landslide activity in an area. Hence, DEM was prepared with digital contour data (1:25,000 scale) obtained from the Department of Survey, Government of Nepal. The DEM of study area was prepared in 10 m × 10 m pixel size. From this DEM, geomorphological thematic data layers like slope, aspect, relative relief, distance to drainage, sediment transport index and wetness index were prepared.

4.3.3.1 Slope and Aspect

Slope data layer, an important parameter in slope stability considerations, comprises of eight classes. This classification was based on the slope angles of more than 70 landslides measured in the field. Field measurement signified that most of the landslides occur at slope angle between 15^o and 30^o. Thus, total seven classes, $<5^o$, 5^o to 10^o, 10^o to 15^o, 15^o to 20^o, 20^o to 25^o, 25^o to 30^o, $>30^o$ were used to prepare slope map. Aspect is referred to as the direction of maximum slope of the terrain surface. For the study area, it was divided into nine classes, namely, N, NE, E, SE, S, SW, W, NW and Flat. Both slope and aspect maps were prepared in ILWIS 3.7 from DEM.

4.3.3.2 Relief

Relative relief is another DEM-based derivative and is defined as the maximum height dispersion of a terrain normalized by its length or area. In this study, relative relief is computed as the difference between the maximum and minimum elevations within the given class of elevation. The relief was sliced into six classes at 50 m elevation difference.

4.3.3.3 Distance to drainage

In the study area, appearance of landslide was frequent along the stream. Thus, location of the landslide from stream was considered as another geomorphology related causative factor. Subsequently, a distance to drainage map was generated as per the field identification that slope failure may be more frequent along stream, due to groundwater movement towards stream and toe undercutting. In order to produce the map showing distance to drainage, the drainage segment map was rasterised and the distance to the drainage was calculated in meters. The resultant map was then sliced into 6 classes. The six classes were 0 m to 20 m, 20 m to 40 m, 40 m to 60 m, 60 m to 80 m, 80 m to 100 m, >100 m.

4.3.3.4 Curvature, Sediment transport index and Wetness index

Following rainfall events, water flows from areas of convex curvature and accumulates in areas of concave curvature. This process is known as flow accumulation and is a measure of the land area that contributes surface water to an area where water can accumulate. This parameter was considered as relevant to this study because it defines the locations of water concentration after rainfall and those locations are likely to have a high slope failure incidence.

Other three slope morphology related parameters namely: sediment transport index, wetness index and curvature were considered for slope morphology related parameter study. Sediment transporting process is enhancing slope failure mechanism extensively in Siwaliks. Sediment transport index accounts for the effect of topography on erosion. The planimetric catchment area is used to calculate this index. The wetness index sets catchment area in relation to the slope gradient. An idea of the spatial distribution of zones of saturation can be obtained from wetness index (Moore *et al*. 1991). As per the value of wetness index and sediment transport index as well as histogram information and equal area distribution of cumulative curves, the values were classified into different categories and analysed with landslide inventory map.

4.3.4 Distance to transport route

One of the controlling factors for the stability of slopes is road construction activity. However, in study area, road access was prime factor of forest degradation. As a result, many landslides are prominent in the degraded forest area. Everyday, wood smuggling is increasing (Fig 6) and along the transport route, forest is also declining. Thus, distance to road map was generated as per the hypothesis that slope failure may be more frequent along roads and trails, owing to excessive forest declination along the roads and trails. In order to produce the map showing distance to transport route, the road and foot-trail segment map was rasterised and the distance to the transport routes calculated in meters. The resultant map was then categorised into six classes as <200 m, 200 m to 400 m, 400 m to 600 m, 600 m to 800 m, 800 m to 1000 m, >1000 m.


Fig. 6, Photographic evidences of smuggling of tree logs and fire woods from the selected catchments

4.3.5 Land cover map

More than 90% the study area is covered by forest. To interpret land cover of the area, Normalized Difference Vegetation Index (NDVI) was considered and the NDVI map was obtained from Landsat TM satellite image acquired on 1 November 2005. The NDVI value was calculated using the NDVI = (IR − R)/(IR + R) formula, where IR is near-infrared band image and R is red band image of Landsat TM. The NDVI value denotes areas of vegetation in an image. The presence of dense green vegetation implies high NDVI values, due to high concentration of chlorophyll resulting in a low reflectance in the red band as well as due to the high stacking of leaves. Sparse vegetation, on the other hand, implies low NDVI values. Likewise, water, and clouds have larger visible reflectance than near-infrared reflectance. Thus, these features yield negative index values. Rock and bare soil areas have similar reflectance in the two bands and result in vegetation indices near zero.

To prepare categorical thematic layers of NDVI for Jalad and Charnath catchments, the cumulative frequency curve of NDVI values has been segmented into five classes representing equal distribution to yield five NDVI classes 0%-20%, 20%-40%, 40%-60%, 60%-80%, and 80%-100%.

4.3.6 Rainfall map

Rainfall is an extrinsic variable in hazard analysis, and the spatial distribution of mean annual rainfall is commonly used in this statistical hazard analysis (Dahal 2008a; Regmi *et al*. 2010b). Rainfall stations around the study area were used to prepare mean annual rainfall map. The spatial distribution of rainfall was calculated through the application of the inverse distance squared method in ILWIS 3.7. The resulting map was sliced to give a raster map with four classes having a <1500 mm, 1500 mm-1550 mm, 1500 mm-1600 mm, and >1600 mm for the Jalad catchment and <1450 mm, 1450 mm-1500 mm, 1500 mm-1550 mm, and >1550 mm for Charnath catchment.

All the data layers such as slope, slope aspect, distance to drainage, wetness index, sediment transport index, relief, distance to transportation route, curvature, geology, NDVI, and mean annual rainfall of both catchments are given in Fig 7 and Fig 8.

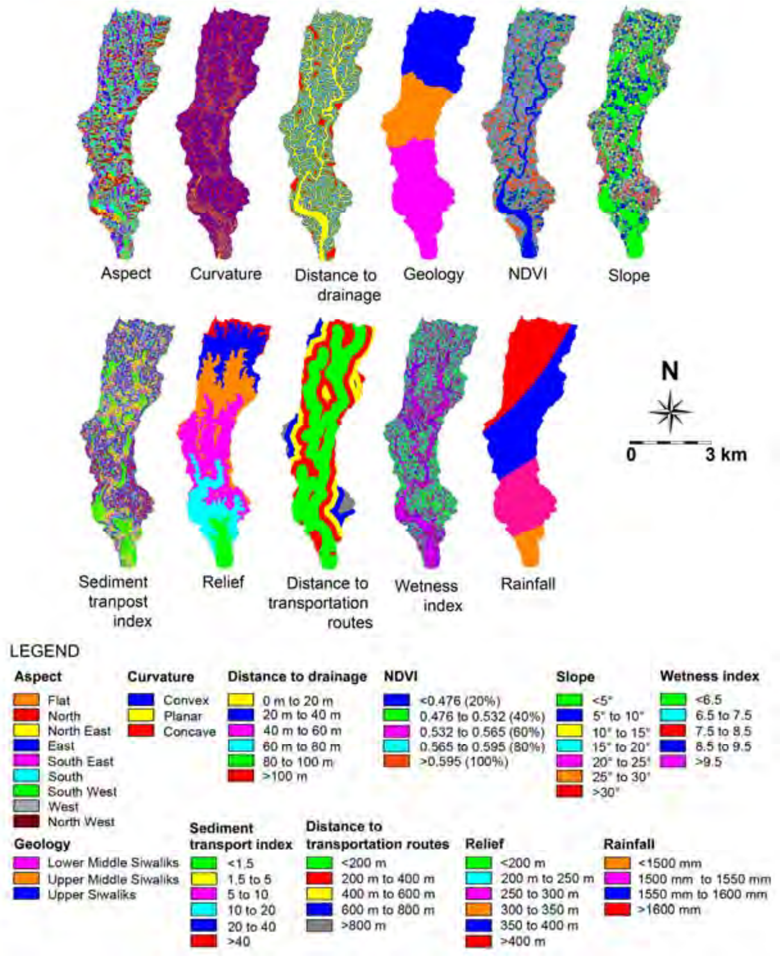

Fig 7, Various data layers used in landslide hazard analysis in the Jalad catchment

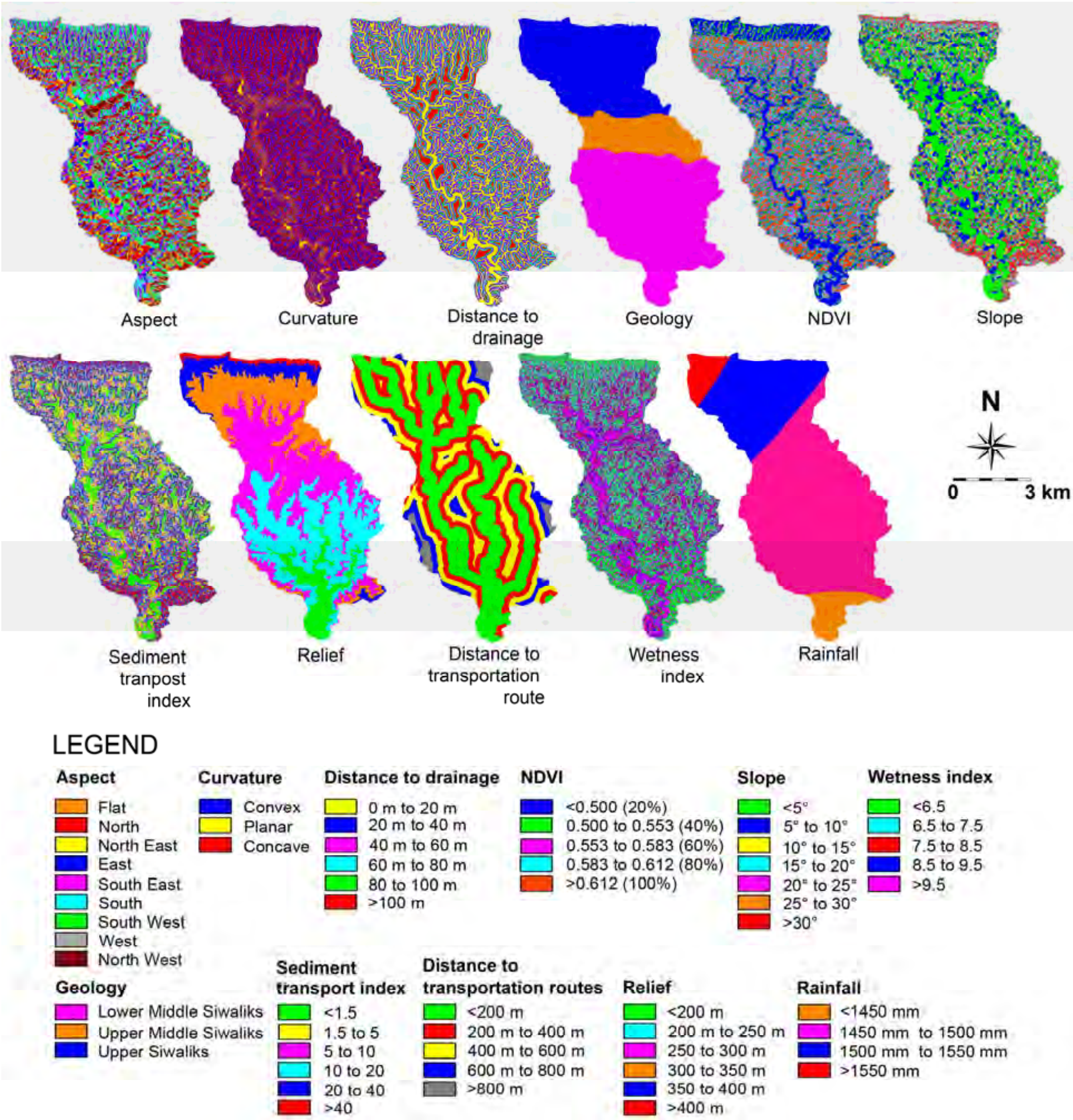

Fig 8, Various data layers used in landslide hazard analysis in the Charnath catchment

5 Analysis and results

5.1 Weights-of-evidence

To evaluate the contribution of each factor towards landslide hazard, landslide distribution data layer of Jalad catchment has been compared with various thematic data layers. For this purpose, equations (1) and (2) were converted to equations (6) and (7) to use in GIS platform.

$$W_i^+ = \mathrm{Log}_e \frac{\dfrac{Npix_1}{Npix_1+Npix_2}}{\dfrac{Npix_3}{Npix_3+Npix_4}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (6)$$

$$W_i^- = \mathrm{Log}_e \frac{\dfrac{Npix_2}{Npix_1+Npix_2}}{\dfrac{Npix_4}{Npix_3+Npix_4}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (7)$$

Where,

$Npix_1$ is number of pixels representing presence of both potential landslide causative factor and landslides

$Npix_2$ is number of pixels representing presence of landslides and absence of potential landslide causative factor

$Npix_3$ is number of pixels representing presence of potential landslide causative factor and absence of landslides

$Npix_4$ is number of pixels representing absence of both potential landslide causative factor and landslides

All thematic maps of causative factors were stored in raster format with a pixel size of 10 m × 10 m and they were combined with landslide inventory map for the calculation of the positive and negative weights. The calculation procedure was written in the form of a script file in ILWIS 3.7, consisting of a series of GIS command to support equations (6) and (7). Consequently, weight of each class of causative factors were calculated (Table 1). Only Jalad catchment was used in the calculation. The weight factors are either positive value or negative value. If the weight is positive, the factor is favourable for the occurrence of landslides, and if it is negative, the factor is not favourable for the occurrence of landslides. The weights were assigned to the classes of each thematic layer, and the resultant weighted thematic maps were overlaid and numerically added to produce a Landslide Hazard Index (LHI) map. The weight integration approach used for the Jalad watershed is as follow::

LHI = W_fSlope + W_fAspect + W_fCurvature + W_fRelief + W_fDistance to Drainage + W_fNDVI+ W_fDistance to Transportation Route + W_fGeology + W_fWetness Index + W_fSediment Transport Index+ W_f Rainfall (8)

In many cases of landslide hazard mapping, old landslide data is used to assess landslide hazard indexes and new landslide data are used in validation of the model approach (van Westen 2003; Lee *et al*. 2007; Dahal *et al*. 2008a). But in the case of landslide hazard index map of Jalad catchment, accuracy of map was not known because all mappable landslides in the catchment were used to assess landslide hazard index. To overcome this issue, in present study, a different attempt has been made to validate the model. First of all, the weights of each class of causative factors obtained based on weights-of-evidence modelling of Jalad catchment were replicated for the factors of Charnath catchment. For this purpose, the class domain of thematic maps of all causative factors in Charnath catchment were converted to value domain with respect to weight value of each class obtained after weights-of-evidence modelling of Jalad catchment (Table 1).

After the replication of weights of each class, weighted thematic maps of the Charnath catchment were prepared which were overlaid and numerically added to produce a landslide hazard index map of the Charnath catchment (Fig 10). During replication, special consideration was made for NDVI and rainfall causative parameters. For NDVI, equal distribution class (0%-20%, 20%-40%, 40%-60%, 60%-80%, and 80%-100%) of Jalad catchment were considered as same class of NDVI causative parameter in Charnath catchment. For the rainfall, hazard indexes of <1500 mm, 1500 mm-1550 mm, 1500 mm-1600 mm, and >1600 mm estimated from the Jalad catchment were replicated for classes <1450 mm, 1450 mm-1500 mm, 1500 mm-1550 mm, and >1550 mm of Charnath catchment. This assumption was made as per the fact that consequences of higher range of rainfall for landsliding are same in both catchments.

5.2 Logistic regression

When using logistic regression model, number of samples to create dependent variables is always an issue. The current literatures have been establishing mainly three kinds of practices (Zhu and Huang 2006). First one is using data from all over the study area, which leads to unequal proportions of landslide and non-landslide pixels (Guzzetti *et al*. 1999; Ohlmacher and Davis 2003). Usually, large volume of data is taken in this method. Second practice is using all the landslide pixels and equal non-landslide pixels, which leads to decrease in data number. The third practice is using all landslide pixels and equal number of randomly selected pixels from areas free of landslides (Yesilnacar and Topal, 2005). In this study, the first category as defined by Guzzetti *et al*. (1999) was used for logistic regression modelling. As the dependent variable is dichotomous and the relationship between the dependent variable and independent variables is nonlinear, logistic regression model was used on the causative factors. In this study the causative parameters were categorised into various classes and each parameter was nominal variable. So these variables were converted to a nominal to a numeric by coding. For this purpose, the landslide density (Carrara, 1983) was used to transform nominal variable to numeric variable.

The landslide density is used to transform nominal variable to numeric variable. It avoids the creation of an excessively high number of dummy variables. Following formula was used to calculate the densities of landslide in each class of causative factors.

$$LD = \frac{l_i / c_i}{\sum_{i=1}^{n} l_i / c_i} \qquad (9)$$

Where, LD is landslide density, c_i is the area of ith class of a factor (such as slope class 10^o to 15^o), l_i is landslide area within ith class of a factor (such as slope 10^o to 15^o), n is the total number of a certain factor. Then the parameter maps were overlaid with the landslide inventory map to calculate landslide densities based on equation (9). All the classes of causative factors were converted to numerical variable landslide density as shown in Table 2. The domain of landslide inventory map was changed from landslide present and landslide absent to numerical variables 1 (for landslide present) and 0 (for landslide absent). All spatial databases of causative parameters and landslide inventory were exported to statistical package (SPSS) and logistic regression analysis was performed for the Jalad catchment. In addition, logistic regression formulae were created as shown in equations (10).

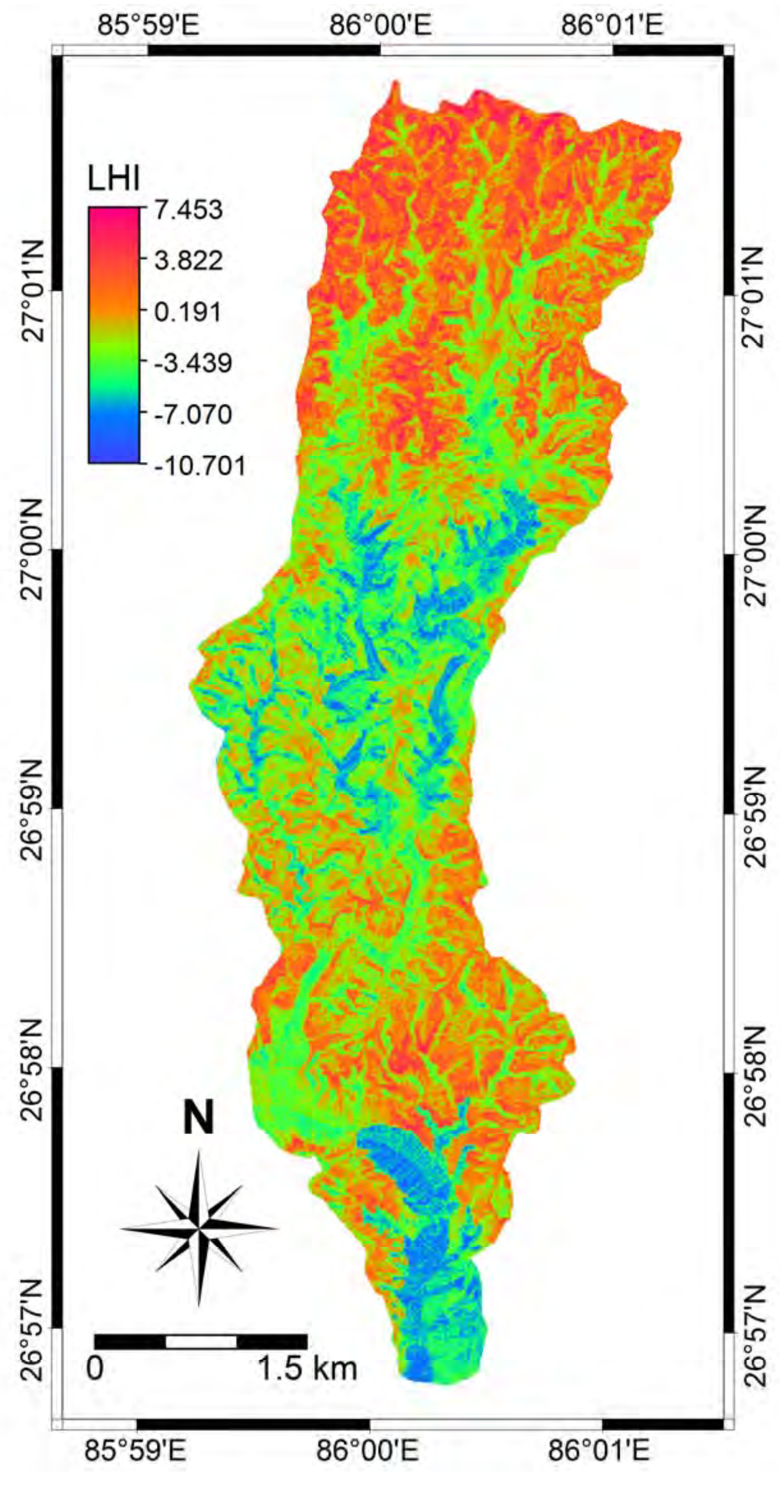

Fig 9, Landslide hazard index map of the Jalad catchment after weights-of evidence modelling

All data are used in the logistic regression modelling and the overall model statistics of the regression conducted in this study is given in Table 3. Hosmer-Lemeshow test showed that the goodness of fit of the equation can be accepted because the significance of chi-square is 0.122. In Hosmer-Lemeshow test, if significance of chi-square value is less than 0.05, the logistic regression model could not be accepted (Zhu and Huang 2006; Chen and Wang 2007). The value of Cox and Snell R^2 and Nagelkerke R^2 showed that the independent variables can explain the dependent variable in an acceptable way. Similarly, ROC (Receiver Operating Characteristics) value of the model is 0.795. For the valid regression model, ROC value should be greater than 0.5 (Hosmer and Lemeshow, 2000). Significance of the Wald statistic for all causative factors is less than 0.05 and it confirms that independent variables have significantly predicted the outcome.

From the logistic regression modelling of Jalad catchment, following logistic regression equations was obtained.

$$\log(P/1-P) = -11.860 + (4.736 \times \text{Slope}) + (8.059 \times \text{Aspect}) + (0.696 \times \text{Curvature}) + (2.499 \times \text{Relief}) + (8.485 \times \text{Distance to Drainage}) + (7.630 \times \text{NDVI}) + (3.656 \times \text{Transportation Route}) - (0.39 \times \text{Geology}) + (2.107 \times \text{Wetness Index}) - (2.696 \times \text{Sediment Transport Index}) + (2.576 \times \text{Rainfall}) \quad (10)$$

The factors given in the equation (10) represent the landslide density values.

For application of model in the Charnath catchment, value of landslide density of each class of all causative factors calculated from the Jalad catchment were replicated in the Charnath catchment as shown in Table 2 and equation (10) was applied to estimate hazard probability of the Charnath catchment after logistic regression modelling. Here also, special consideration was made for NDVI and rainfall parameters. For NDVI, equal distribution class (0%-20%, 20%-40%, 40%-60%, 60%-80%, and 80%-100%) of Jalad catchment were considered as same class of NDVI parameter in Charnath catchment. For the rainfall, landslide density of <1500 mm, 1500 mm-1550 mm, 1500 mm-1600 mm, and >1600 mm estimated from the Jalad catchment were replicated for classes <1450 mm, 1450 mm-1500 mm, 1500 mm-1550 mm, and >1550 mm of Charnath catchment. Here also, this assumption was made as per the fact that consequences of higher range of rainfall for landsliding are same in both catchments. Moreover, slight difference of rainfall value range (50 mm) in the rainfall classes certainly will not introduce a huge uncertainty in the result.

The distribution of landslide hazard probability of the Charnath catchment is given in Fig 11.

5.3 Validation

The landslide hazard index maps of Charnath catchment presented in Fig 10 (after weights-of-evidence modelling) and in Fig 11 (after logistic regression modelling) were prepared without any consideration of previous landslides occurrences in Charnath catchment. To understand its accuracy and to validate weights-of-evidence model and logistic regression modelling, these maps were used to estimate prediction rates. In the science of landslide hazard and susceptibility analysis, success rate and prediction rate are used to validate hazard or susceptibility indexes (Chung and Fabbri 1999; van Westen *et al*., 2003; Lee *et al*., 2007, Lee, 2004, Dahal 2008a, Dahal 2008b, Regmi *et al*., 2010, von Ruette *et al*. 2011). The success rate indicates what percentage of all landslides occurs in the classes with the highest value of hazard. When old landslides are used for LHI calculation and new landslides are used for prediction, the calculated accuracy rate is called prediction rate. In this study, instead of using new landslides of same area (Jalad catchment), landslides from a different area (Charnath catchment) was selected for estimation of prediction rate.

A ROC curve approach is used to analyze the prediction accuracy of the proposed models. The ROC value is measure of success rate and prediction rate usually obtained from ROC curve.

These ROC curves give area under the curve and it is a measure of goodness of fit. The ROC curves of Jalad catchment account the success rate of the models (Fig 12), where as ROC curves of the Charnath catchment (Fig 13) depict prediction rate of the models. From the ROC curve, the success rate and prediction rate of weights-of-evidence model were 0.780 and 0.743, respectively. Similarly, the success rate and prediction rate of logistic regression model were 0.795 and 0.749, respectively.

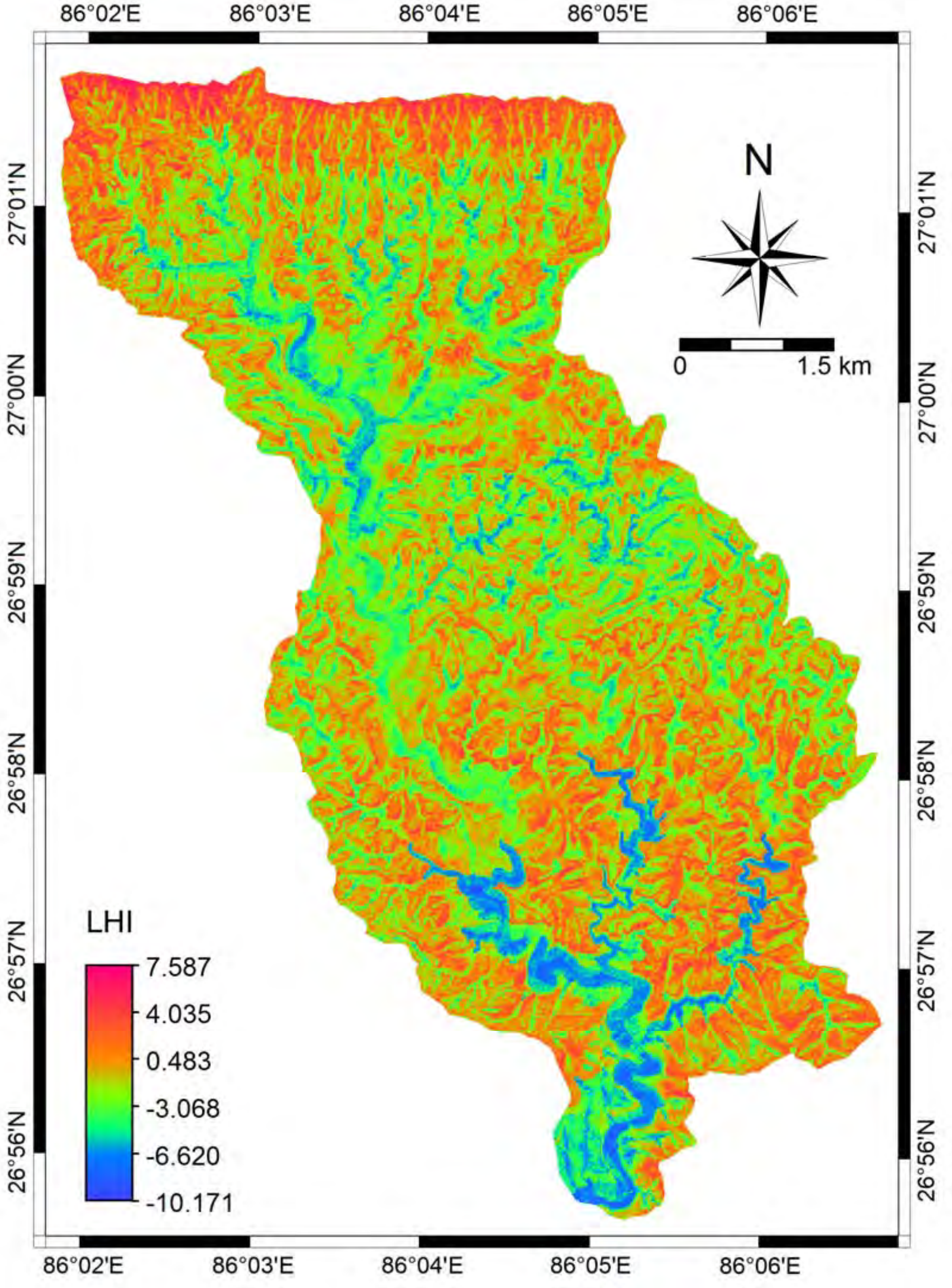

Fig 10, Landslide hazard index map of the Charnath catchment after replication of weights of each class of causative factors from Jalad catchment

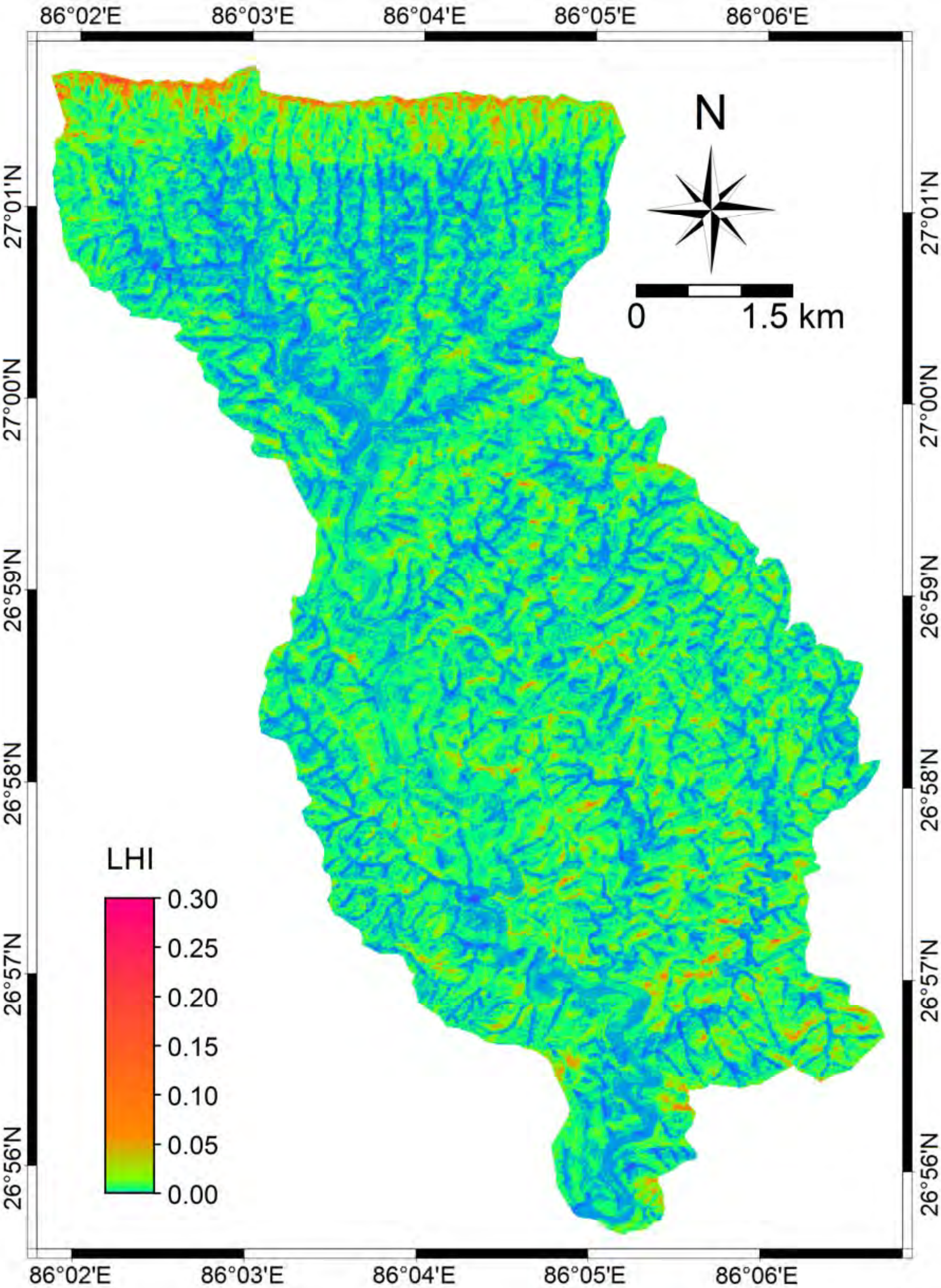

Fig 11, Landslide hazard index map of the Charnath catchment after replication of logistic regression model from Jalad catchment

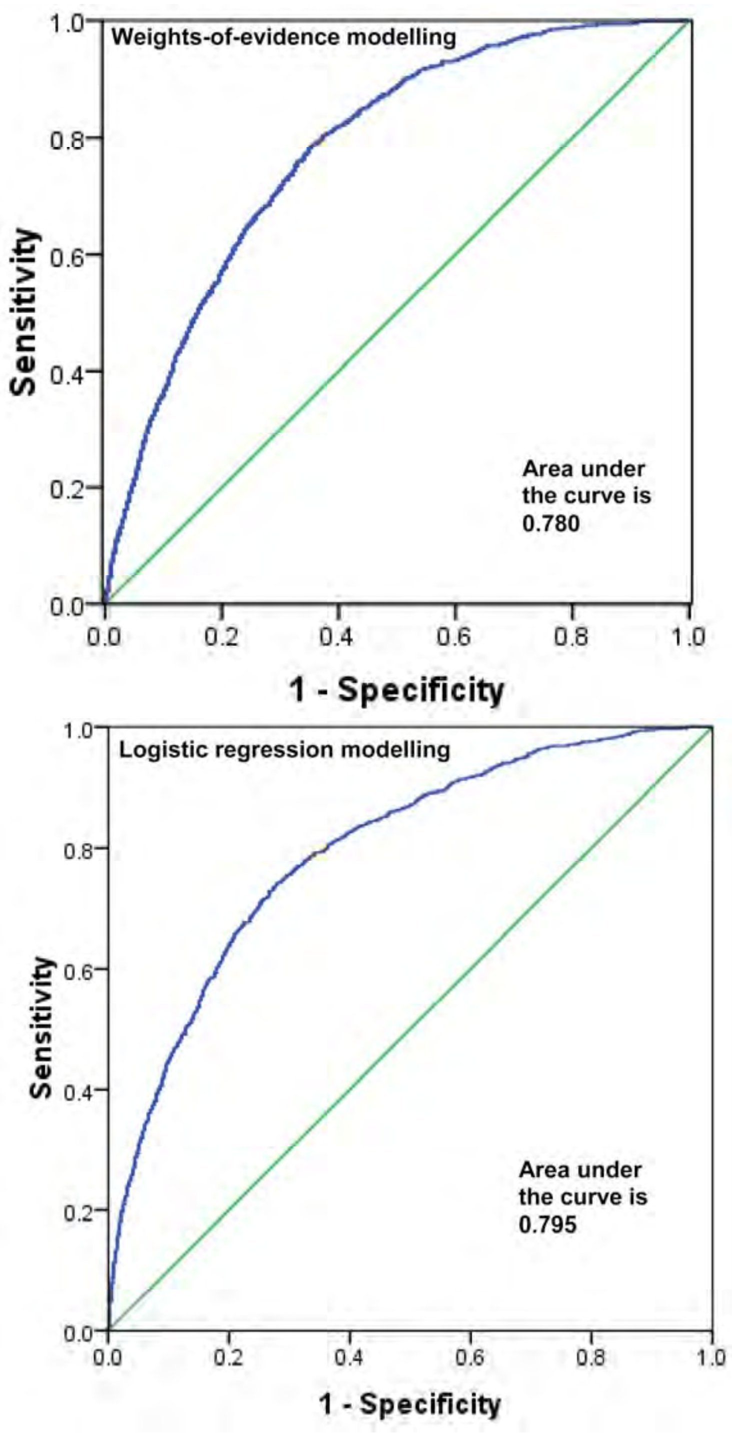

Fig 12, ROC curve (area under the curve) of landslide hazard index estimated from Jalad catchment after weights-of-evidence and logistic regression modelling

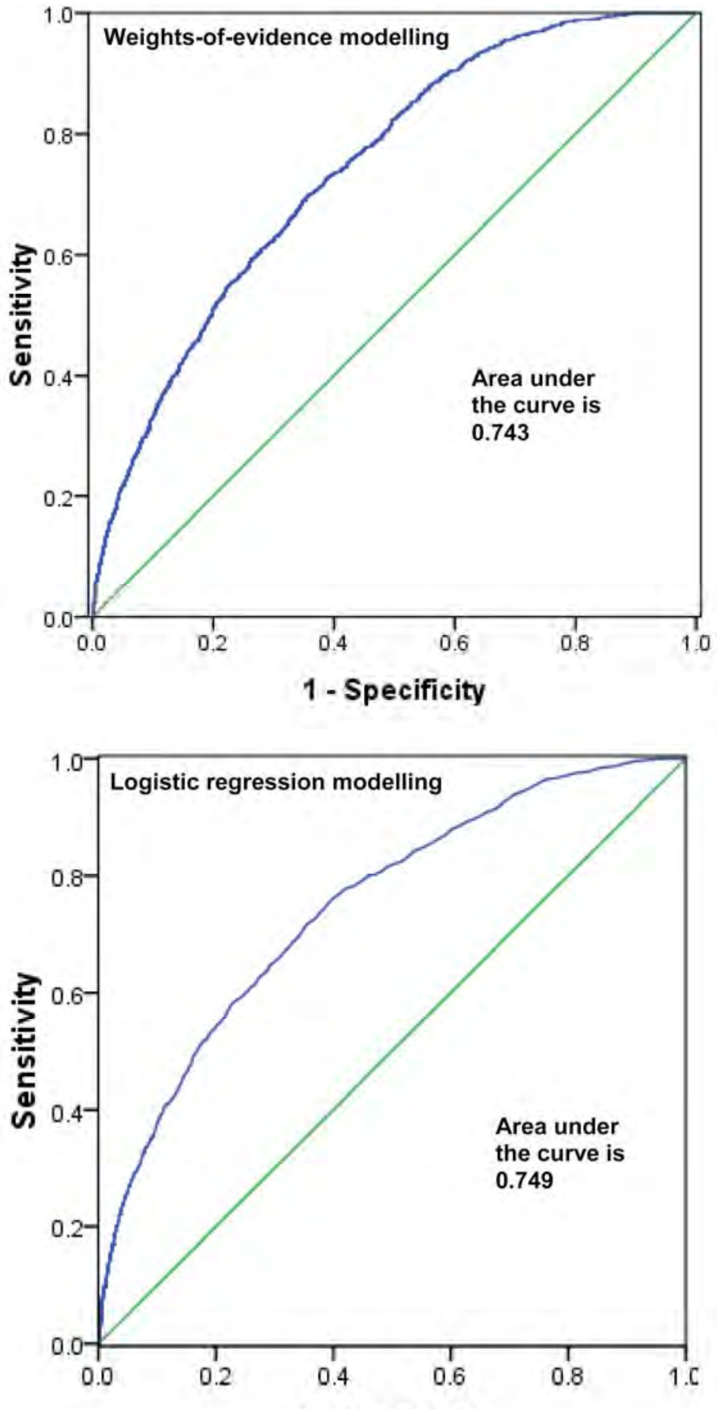

Fig 13, ROC curve (area under the curve) estimated from Charnath catchment after replication of weights-of-evidence and logistic regression models

5.4 Landslide hazard zonation maps

From the independent evaluation of accuracy of the weights-of-evidence and logistic regression models in the Siwaliks for landslide hazard assessment, it was found that logistic regression model had slightly better accuracy than weights-of-evidence model. Therefore, landslide hazard indexes calculated from logistic regression model were considered as suitable model to prepare landslide hazard zonation maps of the selected catchments. Considering the prediction rate of logistic regression from ROC curve, five landslide hazard classes were defined: very low (< 30% class of low to high LHI value), low (30% - 50% class of low to high LHI value), moderate (50% - 70% class of low to high LHI value), high (70% - 90% class of low to high LHI value), and very high (> 90% class of low to high LHI value, i.e., most higher LHI values). Then, landslide hazard zonation maps after logistic regression modelling of both catchments were prepared (Fig 14).

The resulting hazard zonation maps were again compared with the existing landslides of both catchments and results are given in Fig 15. The results show that higher hazard classes correspond to 87% of the landslides in the Jalad catchment and more than 82% of landslides in Charnath catchment.

6 Conclusions

In this study, weights-of-evidence modelling and logistic regression modelling was used for landslide hazard mapping. Models were applied by considering 10 intrinsic factors. The thematic layers of all causative factors and existing slope failures were prepared in GIS (ILWIS 3.7). Mainly DEM-based data and field data were used to prepare data layers of causative factors. The conclusions of this study can be explicitly summarized as follows:

- In many approaches of modelling of landslide hazard assessment in GIS, model validation process is always dependent and same landslide data, which is used for analysis, is considered in verification. But in this study, model was verified independently from landslides which were not used in hazard analysis and results were promising with independent prediction rate of about 0.75. This validates weights-of-evidence modelling and logistic regression models for landslides hazard assessment in the slopes of Siwaliks of the Nepal Himalaya.
- The evaluation of predictive factors used in this modelling suggests that the role of slope morphology, geology and human interventions (such as transportation routes) related factors is found to be significant for landslide processes in the Siwaliks range of Nepal. Specially, Upper Siwalik Group is very susceptible for landslides and transportation route to the forest area is enhancing forest degradation which finally contributes landslide disaster in the study area.
- In the science of landslide hazard mapping, replication of hazard index or methodology is always a problem. In this study landslide hazard index estimated in one catchment was replicated to the other catchment and prediction rate of models were estimated. This study confirms that replication of landslide hazard analysis procedure is possible if the causative factors used in the models are similar in nature and origin.

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