Landslide Susceptibility Zonation (LSZ) Mapping - A Review

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Abstract

Landslides happen to be the most common natural hazards in the mountain regions and can result in enormous damage to both property and life every year. Hence, identification of landslide-prone areas is essential for safer strategic planning of future developmental activities. Therefore, Landslide Susceptibility Zonation (LSZ) becomes important. The relative importance of factors (weights) and their categories (ratings) plays a vital role in LSZ studies. These weights and ratings can be determined by implementing different approaches, which at times are very subjective in nature. Therefore, developing a suitable approach for determination of weights and ratings objectively and their implementation in a Geographic Information System (GIS) environment for LSZ mapping to spatially predict the actual ground scenario is highly important and is an active research area even today. This article reviews advances in mapping landslide susceptibility zoning and discusses the applicability of a variety of approaches to assess landslide hazards.

Keywords: Natural hazards, Landslides, Susceptibility Zonation Mapping, Strategic Planning.

Introduction

Landslides are one of the most widespread and damaging natural hazards in hilly regions. The study of landslides has drawn global attention mainly due to increasing awareness of its socio-economic impacts as well as increasing pressure of urbanization on mountain environment (Aleotti and Chowdhury, 1999; Champati Ray and Lakhera, 2004). Landslides constituted 4.89% of the natural disasters that occurred worldwide during the years 1990 to 2005 (www.em-dat.net). According to Schuster (1996), this trend is expected to continue in future also due to increased unplanned urbanisation and development, continued deforestation and increased regional precipitation as a result of changing climatic conditions in landslide prone areas. Landslides causes loss of life and property, and damage to natural resources, developmental projects and essential commodities, etc. It has been estimated that, on an average, the damage caused by landslides in the Himalayas costs more than US$ one billion, besides causing about 200 deaths every year, which amounts to 30% of such losses occurring world-wide (Naithani, 1999). In 1998, due to massive landslides in Ukhimath area, Garhwal Himalayas, 109 people were dead and several families were affected. Also, Malpa landslide wiped out the whole Malpa village in Uttaranchal during 1998 and at least 210 people were dead (Juyal, 2002). Other major landslides namely Phata landslide of 2001, Budhakedar landslide of 2002 and Uttarkashi landslide of 2003 are burning examples in Himalayas that have caused large-scale human tragedies, resources damage and associated environmental-social hazards. Hence, landslide susceptibility studies are essential for safer strategic planning of future developmental activities in the Himalayan region.

This article provides a detailed review on approaches for landslide susceptibility zonation (LSZ) that are in vogue around the world.

Landslide Susceptibility Zonation (LSZ) Mapping

Spatial prediction of landslide is termed as landslide susceptibility, which is a function of landslide and landslide related internal factors. The aim is to identify places of landslide occurrence over a region on the basis of a set of internal causative factors. This is specifically known as landslide susceptibility zonation (LSZ), which can formally be defined as the division of land surface into near-homogeneous zones and then ranking these according to the degrees of actual or potential hazard due to landslides.

Basic Assumptions

All the available approaches for LSZ mapping are based upon some widely accepted assumptions which can be stated as:

(i) The past and present are keys to the future. This implies that landslides in future are more likely to occur under similar geological, geomorphological, hydrogeologic and climatic conditions, which were and are responsible for the occurrence of past and present landslides. Hence, experiences on existing landslides will be more helpful for landslide susceptibility assessment. However, external causative factors are aggressive and unpredictable with past events due to climatic change and unexpected pressure on land.

(ii) Landslides with distinct geomorphological features can be identified, classified and mapped both through field surveys and remote sensing image interpretations (Rib and Liang, 1978; Varnes, 1978; Hutchinson, 1988; Dikau et al., 1996).

(iii) Landslides are controlled by identifiable internal factors (i.e., inherent attributes of the ground) known as causative factors, which can also be mapped from field surveys and remote sensing image interpretations (Dietrich et al., 1995).

Nevertheless, a number of obstacles may be faced while producing LSZ maps (Aleotti and Chowdhury, 1999). For example,

(i) The discontinuous nature of landslides in space.
(ii) The difficulty in identifying the causative factors, which often are subjective.
(iii) Lack of complete historical data related to landslide occurrences.

Mapping Scale

The scale of LSZ mapping depends on three basic factors (Aleotti et al., 1996a):

(i) The purpose of the study
(ii) The extent of the study area
(iii) Data availability

The choice of the mapping scale affects the selection of the approach (Aleotti and Chowdhury, 1999). Thus, for example, geotechnical investigation based approach may be suitable for studies concerning individual slopes or small areas, whereas, LSZ approach may be suitable for a regional scale study. Further, the mapping scale for a landslide susceptibility zonation study will control the selection of different causative factors and also the level of detailed mapping. A scale of 1:25,000 to 1:50,000 are generally used for delineation of landslide susceptibility zones in hilly regions.

Mapping Unit

A mapping unit is a land surface that is homogeneous in it and show heterogeneity with adjacent units. LSZ requires the selection of a suitable mapping unit, which depends on a number of factors. These include type and degree of details of landslides to be studied; the scale of study; the quality, resolution, scale and type of input data; and the availability of analysis tools such as GIS and remote sensing. For example, in raster-based GIS approach for LSZ, mapping is applied whereby, the study area is divided into regular grids of pre-defined size depending on the data availability. These grid-cells or pixels serve as the mapping units of reference. In this approach, each pixel in the study area is assigned a value of importance or weight corresponding to each causative factor and the weights are integrated in GIS environment to generate a raster output layer.

Causative Factors For Landslide Occurrence

A landslide is seldom attributed to a single causative factor. It is of fundamental importance to identify the causative factors for landslide occurrences in a region, which often is difficult. It is also usually hard to establish the relationships between various causative factors. Nevertheless, it may be possible to demarcate landslide susceptible areas by identifying and analyzing the factors that have caused landslides in the past (Aleotti and Chowdhury, 1999).

There are two types of causative factors responsible for landslide occurrences; one relates to internal or preparatory and the other to external or triggering (Crozier, 1986; Siddle et al., 1991). Internal factors assume a state which will allow the normal fluctuation of external factors to be sufficient to trigger a landslide. Although, internal factors may change over a long period of time to reduce the resistance/shear stress ratio. There is always an external factor which triggers the movement. The internal factors represents the inherent attributes of the ground which makes the slopes susceptible to landslides. The internal factors, even though they are the same, their geometry & their ability to stand up are changing. Hence, the interplay of various factors lead to the occurrence of landslides and therefore, the ultimate failure is indicative of prevailing conditions of the ground rather than effect of some of the internal factors individually.

Various researchers have considered a number of causative factors that may be responsible for landslide occurrences in a region. These include (Dikau et al., 1996; Naithani, 1999):

(a) Internal or preparatory factors:
- i. Lithology of slope material
- ii. Structural features
- iii. Geomorphology
- iv. Vegetation
- v. Hydrogeologic conditions

(b) External or triggering factors:
- i. Seismicity
- ii. Climate
- iii. Undercutting by river
- iv. Anthropogenic factors:
  - (a) Land use change
  - (b) Unplanned construction

Lithology

Lithology basically involves the composition, texture, degree of weathering, as well as other details that influence the physico-chemical and engineering behaviours such as permeability, shear strength, etc. of the rocks and soils. These characteristics in turn affect the slope stability.

Structural Features

In relation to landslides, the structural features include mainly the geological discontinuities such as bedding, joints, faults, folds and shear zones in the slopes. The inter-relationship between the slope and the discontinuities plays an important role particularly in rock slopes to understand the mechanism of failure. Further, the proximity of a slope to a tectonically active zone such as major faults or thrusts or lineaments influences the landslide activity to a great extent.

Geomorphology

An important geomorphologic characteristic of slope instability is to identify the nature and type of pre-existing landslides, as this governs the behavior of the terrain. The geomorphology also includes slope morphology of the area i.e. slope angle and aspect and their physical features involving scarps, concavity/convexity, bulging toes, etc. The slope angle has a direct bearing on instability as the gravitational forces are accentuated with increasing slope angle. Aspect, which represents the direction of slope face, may have a local effect on slope stability.

Vegetation

Vegetation is an important factor in reducing the erosional activities on the slopes. A thickly vegetated slope reduces the effect of erosion because of natural anchorage provided by the tree roots whereas barren slopes are generally more prone to erosional activity and therefore cause slope instability.

Hydrogeologic Conditions

The water infiltration into the slope increases pore water pressure and decreases the shear strength, thereby causing instability to the slopes. The excessive surface run-off through drainages aggravates the erosional activity on the slopes. Therefore, the hydrogeologic conditions indicating the drainage network and the nature of distribution of surface and sub-surface water are also important for landslide occurrences.

Seismicity
The earthquake shocks may be responsible for triggering new landslides and reactivating old landslides. The vibrations due to earthquake may induce instability, particularly in loose and unconsolidated material on steep slopes.

Climate
The climatic pattern due to change in geographic location may influence landslide activities. High rainfall in tropical and sub-tropical climatic regions may trigger landslides, as in the Himalayas.

Undercutting Action of River
The undercutting action of river removes the toe support to the slope thereby causing slope instability.

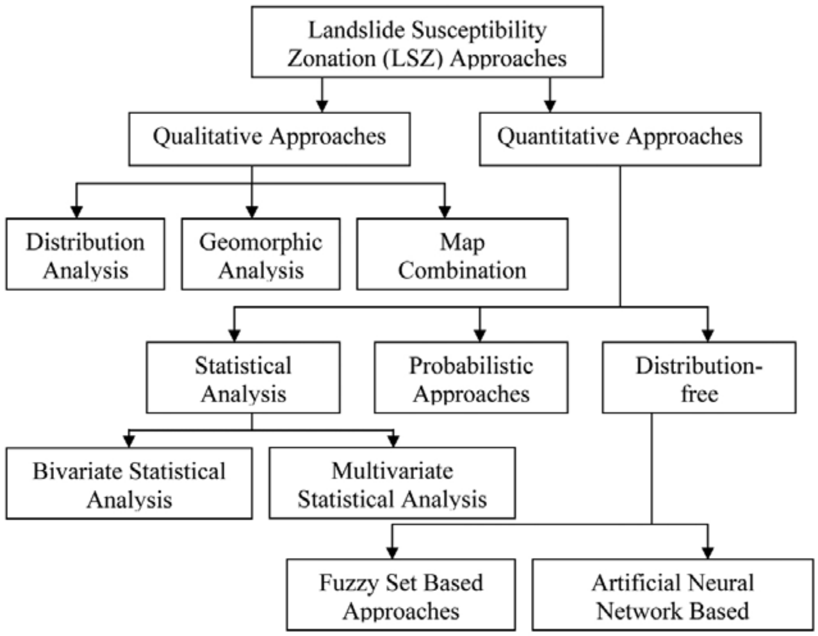
Land use Change
The land use change, such as deforestation, exploitation of natural resources, conversion of vegetated slopes into built up area, etc. may result into landslide occurrences.

Unplanned Construction
The overloading of slopes or removal of lateral support by human interference is a prime concern for slope failures in many areas. The ill-planned construction activities related to hill development programme such as road cutting, housing, quarrying, mining, etc. aggravate the problem of slope instability in hilly regions.

The effective selection of these causative factors is important and will depend on the study area, mapping scale, reliability as well as accuracy of the data (Aleotti and Chowdhury, 1999).

Landslide Susceptibility Zonation (LSZ) Approaches - A Review
The landslide susceptibility zonation is a complex task (Brabb, 1991). Several approaches for LSZ mapping have been proposed. These approaches can be grouped into two broad categories; qualitative and quantitative respectively. The taxonomy of different approaches for LSZ mapping is given in Fig 1.

Figure 1: Flow chart showing taxonomy of LSZ approaches



Qualitative Approaches

In qualitative methods, a lot of subjectivity is introduced in preparation of various thematic data layers contributing for landslide occurrences, which are integrated to the generation of LSZ map of the area.

Distribution Analysis

Distribution analysis is a straightforward approach for landslide susceptibility zonation, which otherwise is known as landslide inventory. This approach shows the distribution of existing landslides mapped from aerial photographs, field surveys and/or historical data of landslide occurrences. These landslide inventory maps, in most of the cases, provide a basis for other landslide susceptibility zonation approaches. The landslide inventory provides a spatial distribution of existing landslides represented on a map either as the affected areas (polygons) or as point events (Wieczorek, 1984). In another alternative, the landslide distribution was represented as a density map (Wright and Nilsen, 1974). Landslide isopleths were drawn by interpolating these density values. This method did not reflect the relationship between the landslides and their causative factors, but it was useful in presenting landslide densities quantitatively (Espizua and Bengochea (2002) prepared susceptibility and risk zonation maps based on an inventory of landslides generated through field work and interpretation of aerial photographs. The purpose was to provide a practical basis for rational land use planning. Landslide susceptibility and risk zones were mapped, in view of the natural hazards and the degree of loss to elements at risk along roads and routes because of a given magnitude of landslide.

The landslide inventory maps do not provide information on the temporal changes in landslide distribution. Therefore, a modification in the inventory maps was done in the form of landslide activity maps, which were based on multi-temporal aerial photo interpretation (Canuti et al., 1979). These activity maps are useful to study the effect of temporal changes in land use on landslide activity.

The distribution analysis approaches are very time consuming, cumbersome and costly, but maps based on these approaches may be useful in providing first hand information on the landslide activities of the area. These maps do not provide information on the degree of susceptibility of future landslide activity.

Geomorphic Analysis

Geomorphological mapping of landslide susceptibility is a direct, qualitative approach that relies on the ability of the investigator or expert to estimate actual and potential slope failures (Guzzetti et al., 1999). In this approach, the LSZ is carried out directly in the field by scientists/geomorphologists based on their experience in the subject, about the area and in other similar situations without describing any rules which have led to this assessment. The LSZ maps are directly evolved from detailed geomorphological maps. One of the most comprehensive projects reported in the literature was the French ZERMOS maps (Humbert, 1977) which involved analysis of active and inactive landslides with respect to the factors responsible for landslide susceptibility and then extrapolation of similar physical conditions for preparation of LSZ maps. These maps generally showed three different classes with varying degrees of susceptibility (i) null or low susceptibility, (ii) potential or uncertain susceptibility, and (iii) ascertained susceptibility. The ZERMOS map of the Moyenne Vesubie in region, France, prepared by Meneroud and Calvino (1976) showed four zones of instability defined on the basis of five factors such as lithology, structures, slope, morphology and hydrology. Another ZERMOS map prepared by Landry (1979) identified seven classes of susceptibility on the basis of the factors like geological nature of the soil and sub-soil, slope angle, drainage and local history of landslides. The LSZ map was used to identify the most favorable sites for construction of power plants. Hearn (1995) developed an LSZ map compiled directly in the field based on geo-morphological features at 1:10,000 scale. This approach allows a rapid assessment of landslide susceptibility in a given area. The main disadvantages of such approaches Leroi, 1996 are: (i) the subjective decision rules that govern the landslide occurrences; this fact makes it difficult to compare the LSZ maps prepared by different experts; (ii) difficult in updating the susceptibility assessment as new data becomes available; (iii) extensive field surveys are required.

Map Combination Approach

The map combination approach for LSZ mapping involves a number of steps (Soeters and van Westen, 1996):

(i) Selection and mapping of the causative factors
(ii) Thematic data layer preparation with relevant categories of the factors
(iii) Assignment of weights and ratings to factors and their categories respectively
(iv) Integration of thematic data layers
(v) Preparation of LSZ map showing different zones

A review of literature reveals that the pre-requisite for LSZ mapping is the preparation of thematic data layers pertaining to different causative factors. Commonly these factors include lithology, lineament, slope, aspect, land use land cover, and drainage etc.

Brabb et al. (1972) first introduced the landslide frequency analysis with respect to litho units (geology) and slope categories by a simple superimposition method and produced an LSZ map. Takei (1982) prepared a debris flow susceptibility map in Japan considering rock types, fracturing, weathering characteristics, springs, vegetation cover, valley slopes and historical records of large landslides as the contributory factors. In New Zealand, Eyles (1983) identified different types of erosion and their severity based on lithology, structure, slope and topography. In the last two decades, LSZ mapping was conventionally carried out based on manual interpretation of a variety of thematic data layers and their superimposition.

In recent times, due to the availability of a wide range of remote sensing data together with data from other sources in digital form and their analysis using GIS, it has now become possible to prepare different thematic data layers corresponding to the causative factors responsible for the occurrence of landslides in a region (Gupta and Joshi, 1990; McKean et al., 1991; Champati Ray, 2005a). The integration of these thematic layers with weights assigned according to their relative importance in a GIS environment leads to the generation of an LSZ map. However, in this approach, the weights were assigned on the basis of the experience of the experts on the subject and about the study area. The weights may vary from expert to expert and also from region to region. The subjectivity in assigning weights to each thematic data layer and to its categories is the major limitation of this approach. Also, there is a difficulty in extrapolating a model developed for a particular area to other areas.

Quantitative Approaches

In order to minimize subjectivity in the weight assignment process, quantitative approaches, objective ways of quantifying the relative importance of various causative factors, can be deployed to produce an LSZ map. A number of approaches have been developed, which are summarized in the following sections:

Statistical Analysis

The statistical approaches have been adopted for LSZ studies to minimise the subjectivity in weight assignment procedure associated with qualitative approaches. The statistical approach compares the spatial distribution of existing landslides in relation to different causative factors (Aleotti and Chowdhury, 1999). GIS tools are quite useful in this analysis. Statistical approaches can broadly be classified into two types: bi-variate and multivariate.

(a) Bi-variate Statistical Analysis

In bi-variate statistical analysis, each individual thematic data layer is compared to the existing landslide distribution layer. The weight value of each category of causative factors is assigned based on landslide density. This involves the overlay of landslide distribution layer on each of the thematic data layers, and calculation of respective landslide density values.

The frequency analysis approach (Pachauri and Pant, 1992, Sarkar et al., 1995; Mehrotra et al., 1996; etc.) involves determination of normalized frequency distribution of landslides per unit area in each category of individual factors. This is achieved by overlaying the landslide layer on each thematic data layer manually or in GIS environment. These frequency values are used as the ratings of the respective categories of causative factors. Constant or arbitrary weights are assigned to the causative factors. These ratings and weights for the factors and their categories are integrated to produce the LSZ map.

The Information Value (InfoVal) approach (Yin and Yan, 1988; Jade and Sarkar, 1993; van Westen, 1997; Lin and Tung, 2003; Saha et al., 2005) for LSZ mapping considers the probability of landslide occurrence within each category of thematic data layer. The rating of a particular category of a thematic data layer is determined as:

(1) $$W_i = \ln\left(\frac{Densclas}{Densmap}\right) = \ln \frac{Npix(S_i)/Npix(N_i)}{\sum_{i=1}^{n} Npix(S_i) \Big/ \sum_{i=1}^{n} Npix(N_i)}$$

where, *Wi* denotes the weight given to the i^{th} category of a particular thematic data layer; Densclas denotes the landslide density within the category; *Densmap* denotes the landslide density within the thematic data layer; $Npix(S_i)$ denotes the number of pixels, which contain landslides, in a category; $Npix(N_i)$ denotes the total number of pixels in a category and n is the number of categories in a thematic data layer. The thematic data layers are overlaid and the ratings (InfoVal) are added to prepare a Landslide Susceptibility Index (LSI) map, which is later categorized into five different landslide susceptibility zones to prepare an LSZ map.

Another approach, known as the Landslide Nominal Risk Factor (LNRF) approach, was developed by Gupta and Joshi (1990), which determines the rating of each category of thematic data layers. The LNRF is determined using the following equation:

(2) $$LNRF_i = \frac{Npix(S_i)}{\left(\sum_{i=1}^{n} Npix(S_i)\right) \Big/ n}$$

where, $Npix(S_i)$ denotes the number of pixels containing landslides in i^{th} category and n is the number of categories present in the particular thematic data layer. A higher value of LNRF (i.e., LNRF >1) implies more susceptibility to landslides than the average; an LNRF value <1 indicates less susceptibility to landslides; whereas, an LNRF value =1 indicates a category with an average landslide susceptibility. The LNRF values were regrouped broadly into three classes for each thematic data layer, and were assigned ratings 0, 1 and 2 for LNRF<0.67 (low susceptibility), 0.67<LNRF<1.33 (medium susceptibility) and LNRF>1.33 (high susceptibility) respectively. The thematic data layers were overlaid and the values were added to prepare an LSI map. The LSI values were classified into three susceptibility zones: low, medium and high. However, it has been observed that regrouping of LNRF values into ordinal numbers (0, 1, 2) leads to coarsening of approach and reduction in the relative importance of various categories. Therefore, Saha et al. (2005) proposed a modified LNRF approach known as modified Landslide Nominal Hazard Factor (m-LNHF), where the computed ratings were directly used without any regrouping.

The bi-variate statistical approaches are based on the observed relationships between each category of factors and the existing landslide distributions in the area. Although, the bi-variate statistical approaches are considered to be a quantitative approach for LSZ mapping, a certain degree of subjectivity exists, particularly in the weight assignment procedures for different causative factors. In all cases, constant weights or arbitrary weights have been assigned to the causative factors for LSZ mapping.

(b) Multivariate Statistical Analysis

Multivariate approaches consider relative contribution of each thematic data layer to the total susceptibility within a defined area. The procedure involves several important steps (Aleotti and Chowdhury, 1999):

(i) Identification of percentage of landslide affected areas in each pixel and their classification into stable and unstable zones,
(ii) Preparation of an absence/presence matrix of a given category of a given thematic layer,
(iii) Multivariate statistical analysis (discriminant and regression), and
(iv) Reclassification of the area based on the results and their classification into susceptibility classes.

These approaches involve analysis of large volume of data and are time consuming. External statistical packages are generally used to support the GIS packages. The statistical analyses most frequently used for LSZ mapping are discriminant analysis and multiple regression analysis (Yin and Yan, 1988; Jade and Sarkar, 1993; Wieczorek et al., 1996; Atkinson and Massari, 1998; Chung and Fabbri, 1999; Clerici et al., 2002).

Carrara (1983) applied multivariate approaches (discriminant analysis and multiple regression analysis) for LSZ mapping in Southern Italy. These approaches proved to be useful in predicting actual and potential landslide susceptibility. In this study, a group of geological-geomorphological attributes, which are directly or indirectly correlated with slope instability, were used in the discriminant functions and in the regression equation. The slope units were discriminated successfully into stable and unstable areas. It was reported that in multiple regression analysis, lithology and its interaction with slope angle contributed significantly in predicting the percentage of unstable areas. However, the result of these statistical approaches underlined the need of other factors capable of improving the efficiency of the approach.

Yin and Yan (1988) analysed 21 categories of different factors based on data collected from field investigation and landslide mapping. Regression analysis approach was used to establish different degrees of instability for the preparation of LSZ map of the area. Clerici et al. (2002) applied the conditional analysis approach for LSZ mapping which simultaneously took into account all the factors contributing to instability. The landslide density of each pixel was computed in correspondence to different combinations of causative factors and an LSZ map was prepared based on the landslide density values. It has been observed that this approach is difficult to implement and requires complex operations. Further, to achieve satisfactory results, the procedure has to be repeated few times changing the combination of factors and their categories.

The limitations of multivariate statistical approach can be listed as follows:

(i) Discriminant and regression analyses require data derived from a normally distributed population that is frequently violated.

(ii) A mixture of continuous (i.e., slope, aspect, etc.) and categorical (i.e., lithology, land use land cover, etc.) factors leads to incorrect solution.

(iii) Some of the factors may bear weak physical relationship with landslide occurrences. Combination of such factors with other factors may generate data which is very difficult to interpret.

Probabilistic Approach

The probabilistic approaches have also been used for LSZ studies to minimise the subjectivity in weight assignment procedure. This approach compares the spatial distribution of landslides in relation to different causative factors within a probabilistic framework. Some of methods based on this approach include conditional probability model, weight of evidence method under Bayesian probability model, certainty factor method under favorability mapping model, etc.

Favourability modeling (FM) approach is a good compromise, offering a valid quantitative method, where subjectivity or expert knowledge can be incorporated in the analysis, particularly when data are not sufficient or reliable. With FM, thematic data can be transformed into continuous data, by considering the degree of relationship between the landslides and the categories of each thematic data layer. Each continuous or non-continuous category can be transformed into a value, called favourability value. The Certainty Factor (CF) approach is one of the possible proposed Favorability Functions (FF) to handle the problem. The CF, defined as a function of probability, originally proposed by Shortliffe and Buchanan (1975) and later modified by Heckerman (1986) can be given as:

$$\text{CF} = \begin{cases} \dfrac{pp_a - pp_s}{pp_a(1 - pp_s)} & if\ pp_a\ ?\ pp_s \\ \dfrac{pp_a - pp_s}{pp_s(1 - pp_a)} & if\ pp_a\ ?\ pp_s \end{cases} \quad (3)$$

where pp_a is the conditional probability of having a number of landslide event occurring in category *a* and pp_s is the prior probability of having the total number of landslide events occurring in the study area. The range of CF values varies from -1 to 1. 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 zero means that the prior probability is very similar to the conditional one. By integrating the CF values of the categories of thematic data layers, an LSZ map can be prepared.

Chung and Fabri (1999) proposed a conditional probability model for LSZ mapping. Five different procedures namely direct estimation, Bayesian estimation under conditional independence, regression model, modified Bayesian model and modified regression model were adopted for estimating conditional probability of landslide susceptibility. GIS-based existing landslide distribution layer and various thematic data layers were used to prepare the LSZ map. The LSZ maps were validated by comparing with the later landslides. It was observed that multivariate regression analysis generated better results than other probability methods.

Lee et al., 2002 applied Bayesian probability model using the weight-of-evidence method of Bonham-Carter (1994) for LSZ mapping. Using the location of landslides and topographic factors, the method was used to calculate the weights (positive and negative) and contrast (difference of positive and negative weights) for each category of different causative factors. The contrast was used as the rating of each category. The contrast is positive for a higher influence on landslide occurrences and negative for a lower influence on landslide occurrences. The ratings of the thematic data layers were summed to calculate the landslide susceptibility index (LSI). The LSI values were categorized into different susceptibility zones to prepare an LSZ map. van Westen et al. (2003) also used the weights of evidence approach to generate statistically derived ratings for all categories of thematic data layers. On the basis of these ratings, a judicious choice of relevant thematic data layers was made for preparation of an LSZ map.

The application of probabilistic prediction model based on likelihood ratio function for LSZ mapping was discussed by Chung and Fabri (1998) and Lee and Min (2001). The existing landslide locations and different thematic data layers were used to implement the model. The probability frequency distribution functions of the landslide affected and non-affected areas should be distinctly different. The likelihood ratio function, which is the ratio of the two frequency distribution functions, can highlight this difference. For each category of thematic data layers, two empirical distribution functions for the landslide affected and non-affected areas were computed and the likelihood ratio for all the categories were determined. The LSZ map was prepared using the likelihood ratio values as the ratings of the categories.

The probabilistic approaches are based on the observed relationships between each category of factors and the existing landslide distributions in the area within a probabilistic framework. The thematic data (continuous and categorical) can be transformed into continuous data by considering the degree of relationship between the landslides and the categories of each thematic data layer. Although, the probabilistic approaches are considered to be a quantitative approach for LSZ mapping, a certain degree of subjectivity in the weight assignment procedures for different causative factors exists.

Distribution-Free Approaches

Generally, qualitative approaches are highly based on experts experience and knowledge and can be considered as subjective (conventional). On the other hand, the quantitative approaches, such as statistical (bi-variate and multivariate) and probabilistic approaches can be considered as more objective due to their data-dependent character. However, success of these approaches is highly affected by the number, quality and reliability of data (Ercanoglu and Gokceoglu, 2004). Therefore, to overcome these limitations, some new approaches such as fuzzy logic, artificial neural networks (ANNs), etc, may be adopted for LSZ mapping on a regional scale. Recently, fuzzy set theory, neural networks and combined neural and fuzzy approaches have been used to generate LSZ maps.

Fuzzy set theory can provide us with a natural method of quantitatively processing multiple datasets. Fuzzy relations play an important role in fuzzy modeling and in the context of LSZ mapping; fuzzy relations can be established based on the philosophy that landslides are related to some extent or unrelated to the causative factors. On the other hand, the most attractive aspect of ANN approaches is the ability to express the nonlinearities in the process to solve the problem similar to the human brain reasoning. Due to uncertainties in the causative factors used in LSZ mapping and the nonlinear character of landslides, utilization of these approaches can be considered as useful alternatives. The fuzzy and ANN approaches are also free from any distributional assumptions or bias of the data and the weights are computed in an objective manner. Chi et al. (2002) discussed the effectiveness of fuzzy set theory for landslide susceptibility mapping. The relationships between input causative factors and past landslides in terms of likelihood ratio functions of each thematic data layer were computed and used as fuzzy membership values. These membership values were able to highlight the difference between areas affected by past landslides and areas not affected by past landslides. Fuzzy inference networks using a variety of different fuzzy operators, especially combination of fuzzy OR and fuzzy gamma operator were used for data integration to prepare the LSZ map. It was observed that fuzzy gamma operator with high gamma value could effectively integrate most datasets for LSZ mapping. Tangestani (2003) also performed LSZ mapping using Land Hazard Evaluation Factor (LHEF) rating scheme of Anbalagan (1992) for determination of fuzzy membership values and fuzzy gamma operator for thematic data layer integration. The LSZ map was validated based on past landslides. It was suggested to evaluate the efficacy of fuzzy gamma operator for data integration in LSZ mapping.

Gorsevski et al. (2003) demonstrated that LSZ mapping can be achieved through an integration of GIS, fuzzy k-means and Bayesian modeling approaches. In the modeling approach, the optimal number of categories was derived by iterative classification for a range of categories or from expert knowledge. The continuous fuzzy k-means classification provided significant amount of information about the character and variability of data and proved to be a useful indicator for landslide susceptibility mapping. The probabilities were revised with Bayes theorem after the categories with similar characteristics were grouped together by fuzzy k-means approach. A broad range of causative factors were integrated through continuous fuzzy k-means classification to prepare an LSZ map. It was observed that the LSZ mapping using the integrated fuzzy/Bayesian approach produced better spatial prediction of existing landslide locations than qualitative models. It was suggested to analyze each individual model in greater detail to improve the understanding between the processes.

Ercanoglu and Gokceoglu (2004) developed a model based on fuzzy relation concept for preparation of LSZ map. The landslide distribution layer was analyzed in relation to the categories of various thematic data layers to compute the fuzzy membership values for each category. By integrating the fuzzy membership values, the LSZ map was prepared. The LSZ map was validated with the existing landslides in the area. The fuzzy relation concept is an objective approach for determination of fuzzy ratings of different categories based on actual landslide data. Hence, this approach introduces relativity concept in rating determination. However, other quantitative approaches such as statistical and probabilistic ones consider the actual landslide data for determination of rating in a crisp manner without employing the relativity.

Arora et al. (2004) proposed an ANN black box approach for LSZ mapping. This approach determines the weights objectively in an iterative process, but the weights in this case remain hidden. The neural network training and testing datasets were prepared using the attributes of various thematic data layers representing the input neurons and the existing LSZ map (Saha et al., 2002) representing the single output neuron. After successful training and testing of different neural network architectures, the best architecture for this specific problem was selected based on the highest training and testing accuracies. The adjusted connection weights of the best network were used to generate the LSZ map of the area. The distribution of landslide susceptibility zones derived from ANN showed similar trends as that observed with the existing landslide locations in the field. A comparison of the results was made with an earlier produced GIS-based LSZ map of the same area and indicated that ANN results were better than the earlier method.

Gomez and Kavzoglu (2005) also used artificial neural networks black box approach for LSZ mapping. In this process, a multilayer perceptron with back propagation learning algorithm was used. This approach used a wide range of causative factors and the existing landslide distribution layer derived from digital elevation model, remote sensing imagery and documentary data for neural network training and testing data preparation. Neural network architecture of 9/28/1 (9 input neurons, 28 hidden neurons and one output neuron) was used for training and testing. After the training and testing process, an LSZ map was generated for the whole area. The existing landslides were considered to validate the LSZ map. It was observed that the predictions were close to reality, indicating a satisfactory performance of the model.

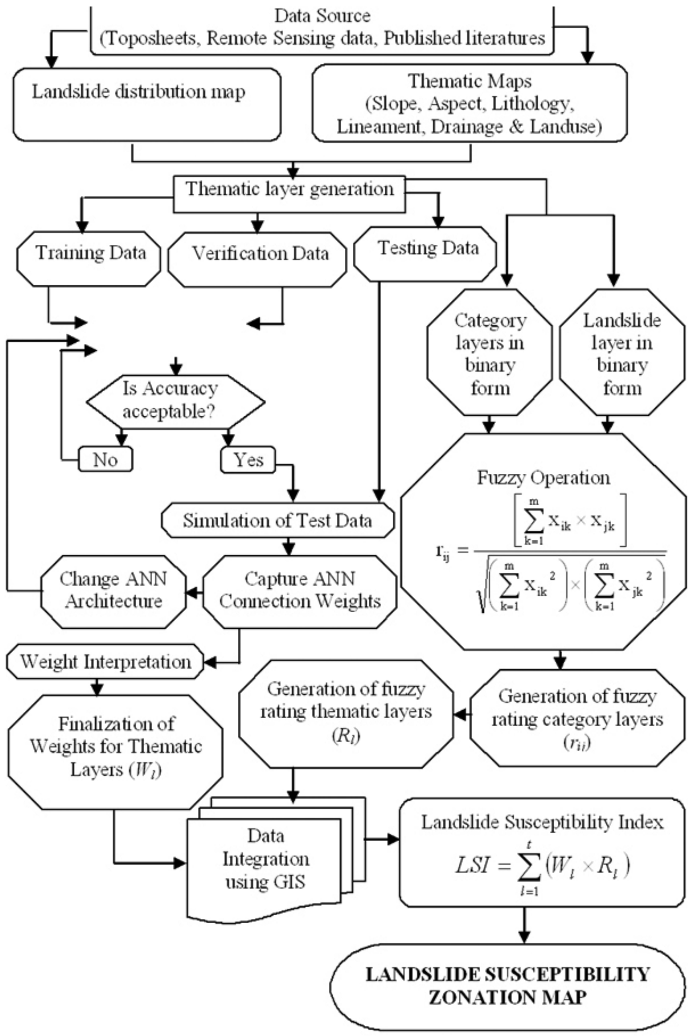
Yesilnacar and Topal (2005) prepared landslide susceptibility maps using both logistic regression analysis and ANN approaches. For this purpose, 19 different thematic data layers were used. In ANN approach, a feed forward back propagation algorithm was adopted. They used single hidden layer neural network architecture. The connection weights of neural networks have been used to determine the weights for the chosen input thematic layers. The landslide susceptibility map produced using the ANN approach predicted higher percentage of landslides, especially in high and very high zones than the logistic regression analysis method.

Elias and Bandis (2000) proposed a neuro-fuzzy approach for LSZ mapping. Fuzzy linguistic rules were used to assign fuzzy membership values to different categories of thematic data layers. The fuzzy membership values were used to provide data to the input neurons for neural network model. A single output neuron with values from 0 to 1 was considered to represent the degree of landslide susceptibility based on actual landslide data. The back error propagation neural network was used for training and an LSZ map was prepared for the area. The trained network was also used for another area to generate the LSZ map. The existing landslides in both the areas were considered to validate the LSZ maps. It was observed that the predictions were close to reality indicating a satisfactory performance of the model.

Lee et al. (2004) attempted the development, application and assessment of probabilistic and artificial neural network approaches for LSZ mapping. Landslide locations and causative factors were used for analyzing landslide susceptibility. A probabilistic method was used for determination of rating of each category and an artificial neural network approach was used for determination of weights of causative factors. The rating of each category was determined using the likelihood ratio function (Lee and Min, 2001). The weight of each factor was determined after artificial neural network training (Hines, 1997). The existing landslide locations and no-landslide areas were used to randomly generate ten sets of training data. The back error propagation neural network was used to train the networks for all the training datasets used. Neural network architecture of 7/15/2 (7 input neurons, 15 hidden neurons and 2 output neurons) was considered for the study. The initial connection weights between the neurons were assigned random values. After successful training of the network, the weights of the factors were determined based on the weight matrices analysis for all the 10 training datasets. The normalized average value of ten different weights for a particular factor was considered as the weight of the corresponding factor. The LSZ maps were prepared by integrating the ratings of the categories only and also by integrating the ratings and the weights together. The two LSZ maps were verified using the existing landslide locations. The verification results were reasonable and acceptable.

Kanungo et al. (2006) developed the combined neural and fuzzy approach (Fig 2) which involved three main steps: (i) weight determination of thematic data layers through ANN connection-weight procedure; (ii) rating determination of categories of thematic layers using cosine amplitude similarity method and (iii) LSZ map preparation by integration of ratings and weights in GIS.

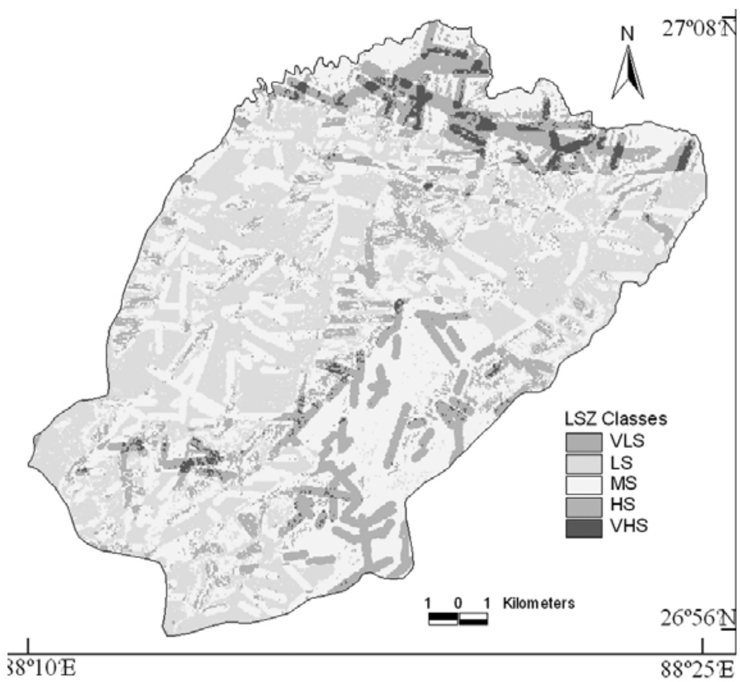
Figure 2 Combined neural and fuzzy approach for LSZ mapping in Darjeeling Himalayas (Kanungo et al., 2006)



A feed forward back-propagation multi-layer ANN with one input layer, two hidden layers and one output layer was considered. Three independent data sets were formed for training, verification and testing. The training dataset was used to train different network architectures, while the verification dataset was used to control the over-training of the networks. The testing dataset was used to evaluate the accuracy of the trained networks.

Levenberg-Marquardt back-propagation algorithm was used. A total of 100 neural network architectures were designed, trained and tested. The adjusted weights of input-hidden, hidden-hidden and hidden-output connections for each network were captured and simple matrix multiplication was performed on these weight matrices to obtain a 6×1 weight matrix for each network, which represented the weights of six causative factors. These causative factors were ranked according to the corresponding absolute weights for each network. The rank of a factor was decided based on the rank observed by the maximum number of networks (majority rule). Subsequently, the normalized average of the weights of these networks at a scale of 0-10 was calculated for a particular factor and assigned as the weight of that factor. The ratings to each category of a thematic data layer corresponding to a causative factor were determined using cosine amplitude similarity method (Ross, 1995; Ercanoglu and Gokceoglu, 2004). The integration of 6 thematic layers representing the ratings for the categories of the layers (obtained from fuzzy set based approach) and weights for the layers (obtained from ANN) was performed using arithmetic overlay operation in GIS and the LSZ map (Fig 3) was produced.

Figure 3 LSZ map using combined neural and fuzzy approach (Kanungo et al., 2006)



It can be observed from the above review that the distribution-free approaches (fuzzy and ANN) are able to determine the weights and ratings of the causative factors and their categories in an objective manner. These approaches also have the ability to handle continuous, categorical and binary data pertaining to various causative factors for LSZ mapping. However, the fuzzy set based approach addresses the determination of ratings of the categories only. Unlike defining crisp ratings to each category, as is done in conventional weighting approach, the fuzzy set theory determines ratings on a 0 to 1 continuous scale thereby providing more realistic values. In most of the ANN approaches for LSZ mapping, single neural network architecture has been attempted. However, an optimal architecture exists for each specific problem of LSZ mapping, as pointed out by Arora et al. (2004). The nature and size of reference data for the output neuron in a neural network influence the training and testing data accuracies (Kanungo et al. 2006). It can also be observed that the weights for the causative factors remain hidden in case of ANN black box approach. This happens to be a key limitation of the ANN black box approach, where the weights and ratings can not be quantified and therefore the contribution of a particular factor is not known. Alternative approach is an ANN connection weight analysis to determine the weights of the factors only. Therefore, a combination of the ANN derived weights and the ratings determined through fuzzy set based approach can identify a real physical situation on the ground.

Summary

The review on LSZ mapping suggests that broadly there are two groups of approaches: qualitative and quantitative approaches for LSZ mapping. The qualitative approaches, such as distribution analysis, geomorphic analysis, map combination methods, etc., were very popular at late 1970s among engineering geologists and geomorphologists. The quantitative approaches became popular in the last decades depending on the advancements in the developments of remote sensing and GIS technologies. Advantages or disadvantages of different LSZ mapping approaches have been commonly discussed by the experts in the field of landslide studies in the literature. The qualitative approaches rely on expert knowledge or experience which dictates the selection, the weighting and the combination function of the factors and therefore, can be considered as conventional or subjective. The quantitative models involve the use of mathematics and statistics to express the relationships between the existing landslide distribution and the categories of factors. Therefore, these can be considered as more objective than conventional approaches due to the fact that data-dependent character and much less experience is needed. However, success of these approaches is highly affected by the quantity, quality and reliability of data. Statistical and probabilistic approaches require the collection of huge amount of data to produce good results. Also, these approaches contribute in determining the ratings of the categories of factors only, but consider constant or arbitrary weights for all the factors to generate the LSZ maps. Therefore, some distribution-free approaches such as fuzzy set based and ANN based approaches have been attempted to evaluate the landslide susceptibility in recent years. The fuzzy set based approach addresses the determination of ratings of the categories only. In most of the ANN black box approaches for LSZ mapping, single neural network architecture has been attempted. However, an optimal architecture exists for each specific problem of LSZ mapping. It can also be observed that the weights for the causative factors remain hidden in case of ANN black box approach. The connection weight analysis seems to be an alternative approach for determination of weights of the causative factors. Moreover, a combination of ratings determined through fuzzy set based approach and weights obtained through ANN connection weight analysis seems to be better for LSZ mapping.

References

Aleotti, P., Baldelli, P. and Polloni, G., (1996a) Landsliding and Flooding Event Triggered by Heavy Rains in the Tanaro Basin (Italy). In: Proceeding International Congress Interpraevent, Garmisch-PartenKirchen, 1, 435-446.

Aleotti, P. and Chowdhury, R., (1999) Landslide Hazard Assessment: Summary, Review and New Perspectives, Bulletin of Engineering Geology & Environment, 58, 21-44.

Anbalagan, R., (1992) Landslide Hazard Evaluation and Zonation Mapping in Mountainous Terrain, Engineering Geology, 32, 269-277.

Arora, M.K., Das Gupta, A.S. and Gupta, R.P., (2004) An Artificial Neural Network Approach for Landslide Hazard Zonation in the Bhagirathi (Ganga) Valley, Himalayas, International Journal of Remote Sensing, 25(3), 559-572.

Atkinson, P.M. and Massari, R., (1998) Generalised Linear Modelling of Susceptibility to Landsliding in the Central Apennines, Italy, Computers & Geosciences, 24(4), 373-385.

Brabb, E. E., (1991) The World Landslide Problem, Episodes, 14(1), 52-61.

Canuti, P., Frascati, F., Garzonio, C. A. and Rodolfi, C., (1979) Dinamica Morfologica di un Ambiente Sogetto a Fenomeni Franosi e ad Intensa Attiva Agricola, Consiglio Nazionale delle Ricerche, Perugia, Italy, 142, 81-102.

Champati Ray, P. K., (2005a) Geoinformatics and its application in Geosciences. Journal of Earth System Science and Environment, 2(1), 4-12.

Champati Ray, P. K., Lakhera, R. C., (2004) Landslide Hazards in India, Proc. Asian Workshop on Regional Capacity Enhancement for Landslide Mitigation (RECLAIM), organized by Asian Disaster Preparedness Centre (ADPC), Bangkok and Norwegian Geo-technical Institute, Oslo, Bangkok, 13-15 Sep. 2004.

Chi, K-H., Park, N-W. and Chung, C-J., (2002) Fuzzy Logic Integration for Landslide Hazard Mapping using Spatial Data from Boeun, Korea. In: Proceedings of Symposium on Geospatial Theory, Processing and Applications, Ottawa.

Chung, C-J. F. and Fabbri, A. G., (1998) Three Bayesian Prediction Models for Landslide Hazard. In: Bucciantti, A. (ed.) Proceeding of International Association for Mathematical Geology Annual Meeting (IAMG'98), Ischia, Italy, 204-211.

Chung, C-J. F. and Fabbri, A. G., (1999) Probabilistic Prediction Models for Landslide Hazard Mapping, Photogrammetric Engineering & Remote Sensing, 65(12), 1389-1399.

Clerici, A., Perego, S., Tellini, C. and Vescovi, P., (2002) A Procedure for Landslide Susceptibility Zonation by the Conditional Analysis Method, Geomorphology, 48, 349-364.

Crozier, M. J., (1986) Landslides: Causes, Consequences and Environment, Croom Helm Australia Private Limited, 252p.

Dikau, R., Brunsden, D., Schrott, L. and Ibsen, M.L. (Eds.), (1996) Landslide Recognition: Identification, Movement and Causes, John Wiley & Sons, Chichester, UK, 251p.

Dietrich, E. W., Reiss, R., Hsu, M. L. and Montgomery, D. R., (1995) A Process-based Model for Colluvial Soil Depth and Shallow Landsliding using Digital Elevation Data, Hydrological Process, 9, 383-400.

Elias, P.B. and Bandis, S.C., (2000) Neurofuzzy Systems in Landslide Hazard Assessment, In: Proceedings of 4th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences, July 2000, 199-202.

Ercanoglu, M. and Gokceoglu, C., (2004) Use of Fuzzy Relations to Produce Landslide Susceptibility Map of a Landslide Pron Area (West Black Sea Region, Turkey), Engineering Geology, 75(3&4), 229-250.

Espizua, L. E. and Bengochea, J. D., (2002) Landslide Hazard and Risk Zonation Mapping in the Rio Grande Basin, Central Andes of Mendoza, Argentina, Mountain Research and Development, 22(2), 177-185.

Eyles, G. O., (1983) The Distribution and Severity of Present Soil Erosion in New Zealand, New Zealand Geographer, 39(1), 12-28.

Gomez, H. and Kavzoglu, T., (2005) Assessment of Shallow Landslide Susceptibility using Artificial Neural Networks in Jabonosa River Basin, Venezuela, Engineering Geology, 78(1-2), 11-27.

Gorsevski, P. V., Gessler, P. E. and Jankowski, P., (2003) Integrating a Fuzzy k-means Classification and a Bayesian Approach for Spatial Prediction of Landslide Hazard, Journal of Geographical Systems, 5, 223-251.

Gupta, R.P. and Joshi, B.C., (1990) Landslide Hazard Zonation using the GIS Approach - A case Study from the Ramganga Catchment, Himalayas, Engineering Geology, 28, 119-131.

Guzzetti, F., Carrara, A., Cardinali, M. and Reichenbach, P., (1999) Landslide Hazard Evaluation: A Review of Current Techniques and their Application in a multi-scale Study, Central Italy, Geomorphology, 31, 181-216.

Hearn, G. J., (1995) Landslide and Erosion Hazard Mapping at Ok Tedi Copper Mine, Papua New Guinea, Quarterly Journal of Engineering Geology, 28, 47-60.

Heckerman, D., (1986) Probabilistic Interpretation of MYCIN's Certainty Factors. In: Kanal, L. N. and Lemmer, J. F. (eds.) Uncertainty in Artificial Intelligence, Elsevier, New York, 298-311.

Hines, J. W., (1997) Fuzzy and Neural Approaches in Engineering. Wiley, New York, 210p.

Humbert, M., (1977) Risk Mapping of areas exposed to Movements of Soil and Sub-soil: French "Zermos" maps, Bulletin of International Association of Engineering Geologists, 16, 80-82.

Hutchinson, J. N., (1988) General Report: Morphological and Geotechnical Parameters of Landslides in relation to Geology and Hydrology. In: Proceeding of Fifth International Symposium on Landslides, Lausanne, 1, 3-35.

Jade, S. and Sarkar, S., (1993) Statistical Models for Slope Instability Classification, Engineering Geology, 36, 91-98.

Juyal, G. P., (2002) Landslides in the Uttaranchal Himalaya and their Rehabilitation by Bio-engineering Measures. In: Nainwal, H. C. and Prasad, C. (eds.) Geodynamics and Environment Management of Himalaya, HNB Garhwal University, Srinagar Garhwal, India, 182-190.

Kanungo, D. P., Arora, M. K., Sarkar, S. and Gupta, R.P. (2006) A comparative study of conventional, ANN black box, fuzzy and combined neural and fuzzy weighting procedures for landslide susceptibility zonation in Darjeeling Himalayas. Engineering Geology, 85 (3&4): 347-366.

Landry, J., (1979) carte ZERMOS. Zones exposes a des risques lies aux mouvements du sol et du sous-sol, region de Lons-le-Saunier a Poligny (Jura), Orleans, Bur. de Rech. Geol. et Miniere, 1 Map, 14.

Lee, S., Choi, J. and Min, K. D., (2002) Landslide Susceptibility Analysis and Verification using the Bayesian Probability Model, Environmental Geology, 43, 120-131.

Lee, S. and Min, K. D., (2001) Statistical Analysis of Landslide Susceptibility at Yongin, Korea, Environmental Geology, 40(9), 1095-1113.

Lee, S., Ryu, J., Won, J. and Park, H., (2004) Determination and application of the weights for landslide susceptibility mapping using an artificial neural network, Engineering Geology, 71, 289-302.

Lin, M-L. and Tung, C-C., (2003) A GIS-based Potential Analysis of the Landslides induced by the Chi-Chi Earthquake, Engineering Geology, 71, 63-77.

McKean, J., Buechel, S. and Gaydos, L., (1991) Remote Sensing and Landslide Hazard Assessment, Photogrammetric Engineering & Remote Sensing, 57(9), 1185-1193.

Mehrotra, G. S., Sarkar, S., Kanungo, D. P., Mahadevaiah, K., (1996) Terrain Analysis and Spatial Assessment of Landslide Hazards in parts of Sikkim Himalaya, Geological Society of India, 47, 491-498.

Meneroud, J. P. and Calvino, A., (1976) carte ZERMOS. Zones exposes a des risques lies aux mouvements du sol et du sous-sol a 1:25000, region de la Moyenne Vesubie (Alps-Matitimes), Orleans, Bur. de Rech. Geol. et Minieres, 1 Map, 11.

Naithani, A. K., (1999) The Himalayan Landslides, Employment News, 23(47), 20-26 February, 1-2.

Pachauri, A. K. and Pant, M., (1992) Landslide Hazard Mapping based on Geological Attributes, Engineering Geology, 32, 81-100.

Rib, H. T. and Liang, T., (1978) Recognition and Identification. In: Schuster, R.L. and Krizek, R. J. (eds.) Landslides Analysis and Control, Washington Transportation Research Board, Special Report, National Academic of Sciences , WA, 176, 34-80.

Ross, T. J., (1995) Fuzzy Logic with Engineering Applications, McGraw-Hill, New York.

Saha, A. K., Gupta, R. P. and Arora, M. K., (2002) GIS-based Landslide Hazard Zonation in a part of the Himalayas. International Journal of Remote Sensing, 23, 357-369.

Saha, A. K., Gupta, R. P., Sarkar, I., Arora, M. K. and Csaplovics, E., (2005) An Approach for GIS-based Statistical Landslide Susceptibility Zonation - with a case Study in the Himalayas, Landslides, 2, 61-69.

Sarkar, S., Kanungo, D. P. and Mehrotra, G. S., (1995) Landslide Hazard Zonation: A case Study in Garhwal Himalaya, India, Mountain Research and Development, 15(4), 301-309.

Schuster, R., (1996) Socioeconomic significance of landslides. In: Turner, A.K., Schuster, R.L. (eds.) Landslides: Investigation and Mitigation, Transportation Research Board, National Research Council, Special Report, National Academic Press, Washington, DC, 247, 12-36.

Shortliffe, E. H. and Buchanan, G. G., (1975) A Model of inexact Reasoning in Medicine, Mathematical Biosciences, 23, 351-379.

Siddle, H. J., Jones, D. B. and Payne, H. R., (1991) Development of a Methodology for Landslip Potential Mapping in the Rhonda Valley. In: Chandler, R. J. (ed.) Slope Stability Engineering, Development and Applications, Thomas Telford, 137-148.

Soeters, R. and van Westen, C. J., (1996) Slope Instability Recognition, Analysis and Zonation. In: Turner, A. K. and Schuster, R. L. (eds.) Landslides, Investigation and Mitigation, Transportation Research Board, National Research Council, Special Report 247, National Academy Press, Washington, DC, U.S.A., 129-177.

Takei, A., (1982) Limitation Methods of Hazard Zones in Japan. In: Takei and Aulitzky (eds.) Report of Japanese-Austrian Joint Research, Forecast of Disaster Zone in Mountainous Regions, 1980-1981, Kyoto University Laboratory of Erosion Control Research Bulletin, 1, 7-25.

Tangestani, M. H., (2003) Landslide Susceptibility Mapping using the Fuzzy Gamma Operation in a GIS, Kakan Catchment Area, Iran. Proceeding of Map India Conference 2003.

van Westen, C. J., (1997) Statistical Landslide Hazard Analysis. In: Application Guide, ILWIS 2.1 for Windows, ITC, Enschede, The Netherlands, 73-84.

van Westen, C. J., Rengers, N. and Soeters, R., (2003) Use of Geomorphological Information in Indirect Landslide Susceptibility Assessment, Natural Hazards, 30, 399-419.

Varnes, D. J., (1978) Slope Movement Types and Processes, Landslides Analysis and Control. Special Report 176, Transportation Research Board, Washington, DC, 11-80.

Wieczorek, G. F., (1984) Preparing a Detailed landslide-Inventory map for Hazard Evaluation and Reduction, Bulletin of International Association of Engineering Geologists, 21, 337-342.

Wieczorek, G. F., Gori, P. L., Jager, S., Kappel, W. M. and Negussey, D., (1996) Assessment and Management of Landslide Hazards near Tully Valley Landslide, Syracuse, New York, USA. In: Proceeding Seventh International Symposium on Landslides, Trondheim, 1, 411-416.

Wright, R. H. and Nilsen, T. H., (1974) Isopleth Map of Landslide Deposits, Southern San Francisco Bay Region, California, US Geological Survey Miscellaneous Field Studies Map, MF-550 (Scale 1:250,000).

Yesilnacar, E. and Topal, T., (2005) Landslide Susceptibility Mapping: A Comparison of Logistic Regression and Neural Networks Methods in a Medium Scale Study, Hendek region (Turkey), Engineering Geology, 79, 251-266.

Yin, K. L. and Yan, T. Z., (1988) Statistical Prediction Model for Slope Instability of Metamorphosed rocks. In: Bonnard, C. (ed.) Proceeding Fifth International Symposium on Landslides, Lausanne, Balkema, Rotterdam, The Netherlands, 2, 1269-1272.