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Landslide risk assessment using concepts of danger pixels and fuzzy set theory in Darjeeling Himalayas

Abstract Landslide risk assessment (LRA) is a key component of landslide studies. The landslide risk can be defined as the potential for adverse consequences or loss to human population and property due to the occurrence of landslides. The LRA can be regional or site-specific in nature and is an important information for planning various developmental activities in the area. LRA is considered as a function of landslide potential (LP) and resource damage potential (RDP). The LP and RDP are typically characterized by the landslide susceptibility zonation map and the resource map (i.e., land use land cover map) of the area, respectively. Development of approaches for LRA has always been a challenge. In the present study, two approaches for LRA, one based on the concept of danger pixels and the other based on fuzzy set theory, have been developed and implemented to generate LRA maps of Darjeeling Himalayas, India. The LRA map based on the first approach indicates that 1,015 pixels of habitation and 921 pixels of road section are under risk due to landslides. The LRA map derived from fuzzy set theory based approach shows that a part of habitat area (2,496 pixels) is under very high risk due to landslides. Also, another part of habitat area and a portion of road network (7,204 pixels) are under high risk due to landslides. Thus, LRA map based on the concept of danger pixels gives the pixels under different resource categories at risk due to landslides whereas the LRA map based on the concept of fuzzy set theory further refines this result by defining the degree of severity of risk to these categories by putting these into high and low risk zones. Hence, the landslide risk assessment study carried out using two approaches in this paper can be considered in cohesion for assessing the risks due to landslides in a region.

Keywords Landslide · Susceptibility · Resource · Risk · Danger pixels · Fuzzy · Linguistic

Introduction

Disasters caused by landslides are common in mountainous regions such as the Himalayas. The landslide incidences in a region are of serious concern to the society due to the loss of life, natural resources, infrastructural facilities, etc. These also pose problems for future development. It has been estimated that, on an average, the damage caused by landslides in the Himalayan region costs more than US$ 1 billion besides causing more than 200 casualties every year (Naithani 1999). The study of landslides has drawn global attention mainly due to increasing awareness of its socio-economic impacts and also increasing pressure of urbanization on the mountain environment. Since geologic, geomorphic, and hydrogeological factors control the overall stability of slopes in an area, evaluation of an area susceptible to landslides and the risk due to landslides to the society at a regional scale is important.

Landslide risk can be defined as the potential for adverse consequences, loss, harm, or detriment to human population and things that human beings value due to landslide occurrences (Lee and Zones 2004). Hence, landslide risk is a combination of the probability of occurrence of landslides and the consequences due to landslides. Development of approaches for landslide risk assessment (LRA) has always been a challenge. The LRA approaches can be applied at different stages in the decision-making process, starting from developmental planning on a regional scale to a particular site evaluation at a local scale. Landslide risk assessment on a regional scale leads to demarcation of areas with different levels of threat to risk elements. This information can be used to establish land use plans, developmental activities, and patterns of building regulations. LRA depends on two factors:

1. the probability of landslide occurrences in a region and
2. the vulnerability of resources at risk.

The probability of landslide occurrences depends both on the inherent factors and the triggering (external) factors. The data pertaining to triggering factors may change over a very short time span and are thus difficult to estimate. In the absence of data belonging to triggering factors, the term "susceptibility" may be used to define the likelihood of occurrence of landslides and has been followed in the present study.

Vulnerability may be defined as the level of potential damage, or degree of loss of resources at risk, subjected to a landslide occurrence of a given intensity (Fell 1994; Leone et al. 1996; Wong et al. 1997). Vulnerability assessment involves the understanding of the interaction between a given landslide and the affected resources. Generally, the vulnerability to landslide may depend on the volume and velocity of sliding, the distance of transported sliding material, the resources at risk, and their nature and proximity to the landslide. The assessment of vulnerability is somewhat subjective and may largely be based on the historical data of the region. The appropriate vulnerability factor may be assessed systematically based on the opinions of experts and can be expressed at a scale of 0 to 1.

In the present context, the probability of landslide occurrences has been considered as landslide susceptibility, and vulnerability of resources at risk has been taken as resource damage potential. Hence, in this case, both landslide susceptibility zonation (LSZ) and LRA are based on data collected in spatial domain and not in the time domain.

The spatial distribution of landslide risk has been obtained by integrating landslide susceptibility and resource damage potential at a spatial level in a geographic information system (GIS) environment. The resulting map has then been categorized into areas of different risk zones. Since the proposed LRA approaches have been developed for regional level risk assessment, the run-out effects due to specific landslides has not been considered, which is pertinent for site-specific landslide risk assessment studies on a local scale.

The literature survey indicates a number of qualitative LRA approaches for regional risk assessment such as risk registers (Lee et al. 1998; Lee 1999; Lee and Clark 2000; Lee and Zones 2004), relative risk scoring (Boggett et al. 2000; McDonnell 2002; Rautela and Lakhera 2000; Chau et al. 2004), risk ranking matrices (Anbalagan and Singh 1996; Van Dine et al. 2002; Cardinali et al. 2002), relative risk rating (Palmer et al. 2002), and failure modes, effects, and criticality analysis (Sandilands et al. 1998; Hughes et al. 2000; Lee 2003).

In this paper, two novel semi-quantitative landslide risk assessment approaches, one based on danger pixel approach and the other based on fuzzy set theory, have been proposed. The two approaches are markedly different from each other and convey varied aspects of risk assessment in the region. The output from these approaches is a risk map depicting the level of risk.

Study area

Darjeeling Himalayas, encompassing a total area of 3,000 km^2 rise abruptly from the alluvial plains of West Bengal and attain a maximum elevation of about 2,600 m. The study area covers Darjeeling hill which lies between latitudes 26°56′ N and 27°8′ N and longitudes 88°10′ E and 88°25′ E and covers an area of about 254 km^2 (Fig. 1). The main habitat areas are Darjeeling, Ghum, Sonada, and Sukhiapokhri. The maximum elevation of 2,584 m occurs at the Tiger hill. The area is dominated by slopes ranging between 15° and 35° while steep slopes (i.e., >35°) occupy a smaller area. The annual rainfall in the region varies from a low of 3,000 mm to a high of 6,000 mm. The major land use practice in the study area is tea plantation and agriculture mostly developed around the habitat areas.

Thematic data layers and LSZ mapping of the area—a brief description

For a study on landslide risk assessment, the pre-requisite is the availability of an LSZ map of the area. Here, LSZ maps of the area were prepared using four different approaches under the domain of remote sensing and GIS. These approaches are:

1. Conventional weighting approach
2. Artificial neural network (ANN) black box approach
3. Fuzzy set based approach
4. Combined neural and fuzzy approach

A detail description of these approaches for LSZ mapping can be found in our peer-reviewed paper (i.e., Kanungo et al. 2006). However, for the sake of completeness of this paper, a brief outline of these approaches for preparation of LSZ maps, which go as input to the landslide risk assessment, has been provided here.

A database of six thematic data layers pertaining to landslide causative factors namely lithology, slope, aspect, lineaments, land use land cover, and drainage was created. As stated earlier, the dynamic factors (i.e., rainfall and earthquakes) were not considered in this study.

Remote sensing images from IRS-1C-LISS-III (acquired on 22nd March, 2000) and 1D-PAN (acquired on 3rd April, 2000) sensors, Survey of India topographic maps at 1:25,000 and 1:50,000 scale, and the geological map at 1:250,000 scale published by Acharya (1989) formed the key data sources to generate the thematic data layers, which were rasterized at 25-m pixel size. Extensive field surveys were conducted during the years 2001 to 2003 to collect information on existing landslide distribution, which assisted in creation of training and testing datasets, finding out fuzzy membership values and for the validation of LSZ maps. A total of 101 landslides of varying dimensions (180 to 27,400 m^2) were mapped from remote sensing images and field surveys. Most of the observed landslides in the region were of rock slides type. However, in some cases, complex types of failure were also observed. The existing landslide distribution map was also

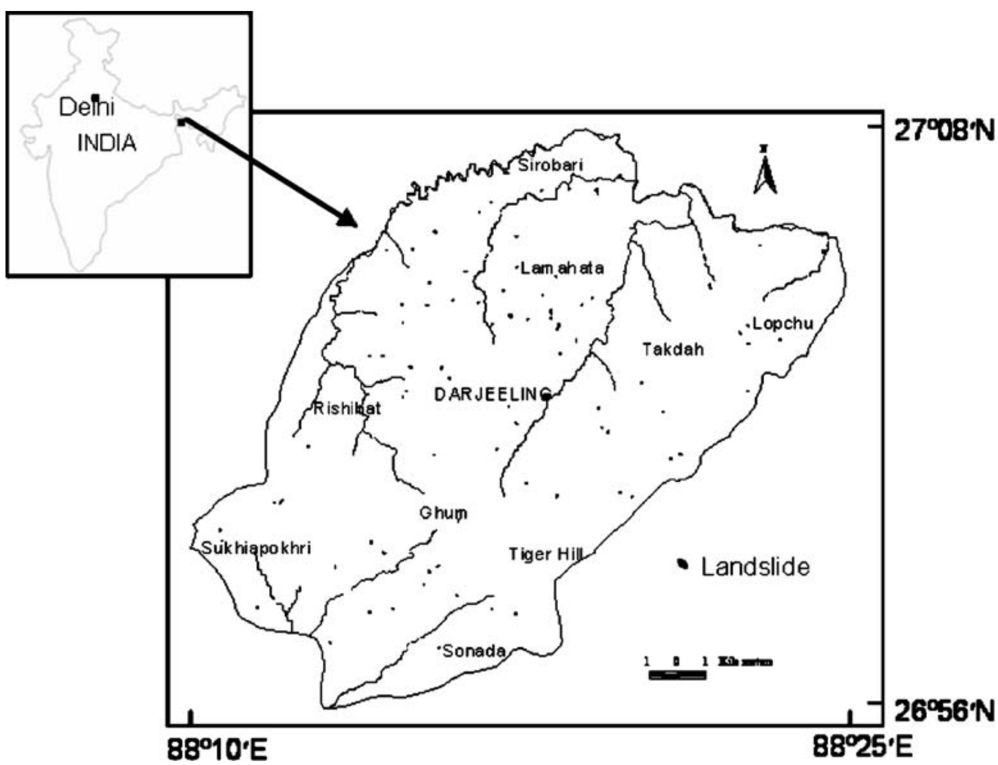


Fig. 1 Study area with landslide distribution in Darjeeling Himalayas

converted to a rasterized thematic data layer at 25-m pixel size, which indicated that there were a total of 339 pixels that belonged to landslides in the region. The thematic database was input to four approaches to generate LSZ maps.

LSZ Map I using conventional weighting approach

The conventional weighting approach involved assigning weights and ratings to the six thematic data layers and their categories, respectively, based on the field knowledge of the area and the (subjective) expert's judgment. The weighted thematic data layers were generated by arithmetically multiplying the weight of the layer with the ratings of the corresponding categories of each layer. These layers were laid over one another and algebraically added to produce the LSZ map (referred to here as Map I, Fig. 2a) representing five landslide susceptibility zones i.e., very high susceptibility (VHS), high susceptibility (HS), moderate susceptibility (MS), low susceptibility (LS), and very low susceptibility (VLS).

LSZ Map II using ANN black box approach

Artificial neural networks are attractive for solving pattern recognition problems such as the preparation of landslide susceptibility zonation map. The traditional ANN black box approach (Arora et al. 2004) was used to generate the LSZ map. Due to non-availability of any up-to-date landslide susceptibility zonation map in the region, the LSZ Map I obtained from conventional weighting approach was used as the reference map. Two independent datasets were formed to train and test the ANN designed for landslide susceptibility zonation. Each dataset consisted of 2,500 mutually exclusive pixels corresponding to 500 pixels per landslide susceptibility zone as defined in the reference map. A total of 39 neural network architectures were designed and trained with Levenberg–Marquardt back-propagation algorithm. The adjusted connection weights obtained from the trained network were subsequently used to process the testing data to assess the generalization capability and the accuracy of the neural network. Finally, the adjusted connection weights obtained from a 6/13/7/1

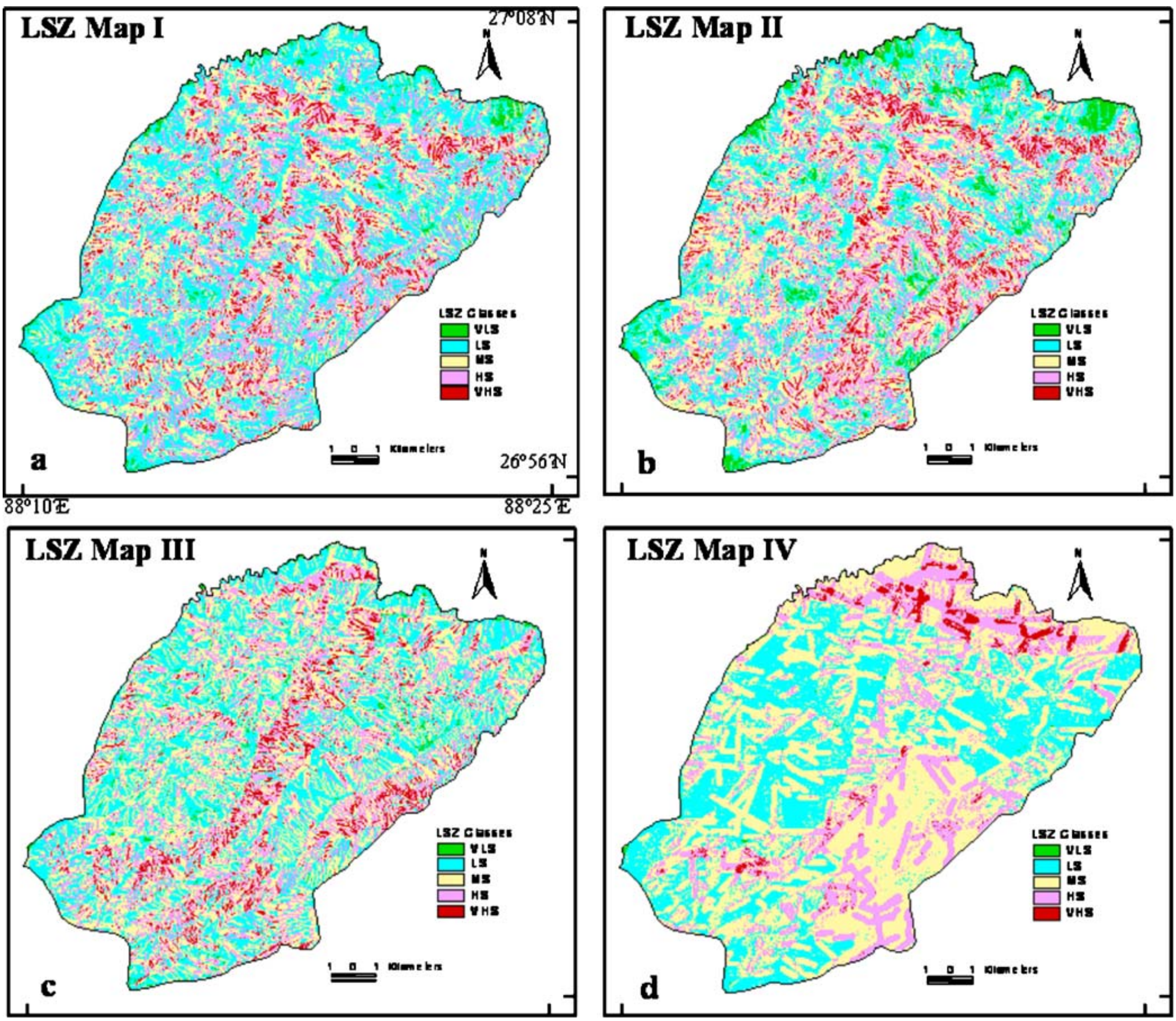


Fig. 2 LSZ maps using four different approaches. (**a**) Conventional weighting approach. (**b**) ANN black box approach. (**c**) Fuzzy set based approach. (**d**) Combined neural and fuzzy approach

(six neurons in input layer, 13 neurons in 1st hidden layer, seven neurons in 2nd hidden layer, and one neuron in output layer) network giving the highest accuracy was subsequently used to determine the network output of all the pixels and the LSZ map (referred to here as Map II, Fig. 2b) was produced.

LSZ Map III using fuzzy set based approach

In the conventional weighting approach, the ratings to the category were given in crisp form (e.g., on an ordinal scale from 0 to 10). In order to bring gradation in ratings, fuzzy set theory is the most appropriate one. In fuzzy set theory, sets of membership values, varying from 0 to 1, are allotted as ratings to a category with 0 indicating no importance and 1 indicating full importance. In the approach used here, 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). These ratings were integrated in GIS to generate the LSZ map (referred to here as Map III, Fig. 2c) by considering the weight of each causative factor as unity.

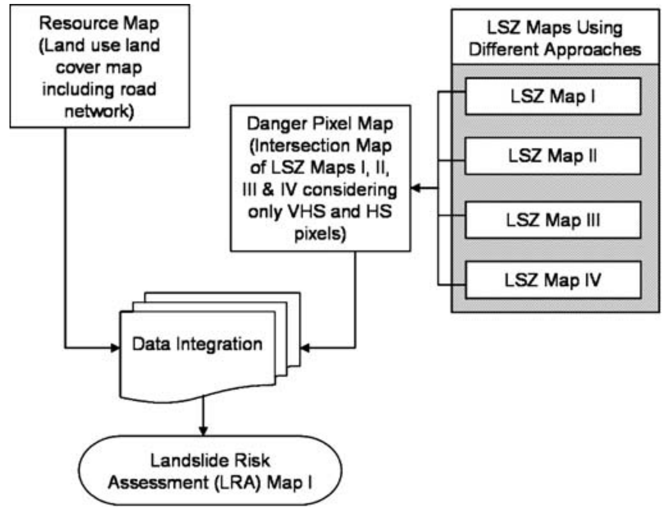


Fig. 3 Steps for landslide risk assessment (LRA) using concept of danger pixels

LSZ Map IV using combined neural and fuzzy approach

In order to further improve the quality of the LSZ map and to bring in more objectivity in the weight rating assignment process, the neural network and fuzzy set based approaches were combined. The combined neural and fuzzy approach involved three main steps:

1. Weight determination of thematic data layers through ANN connection-weight procedure
2. Rating determination of categories of thematic layers using cosine amplitude similarity method and
3. LSZ map preparation by integration of ratings and weights in GIS.

A feed forward back-propagation multi-layer ANN with one input layer, two hidden layers, and one output layer was considered. Three independent datasets 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. Similar to ANN black box approach, 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.

Table 1 Landslide densities in landslide susceptibility zones of LSZ maps derived from conventional, ANN black box, fuzzy, and combined neural and fuzzy approaches

Landslide susceptibility zones	Landslide density (computation based on pixel numbers)			
	LSZ Map I	LSZ Map II	LSZ Map III	LSZ Map IV
VHS	1.63	1.34	6.72	13.09
HS	1.79	1.50	1.11	1.58
MS	0.88	1.02	0.66	0.55
LS	0.41	0.49	0.26	0.40
VLS	0.19	0.12	0	0

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 integration of six 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 (referred to here as Map IV, Fig. 2d) was produced.

Comparative evaluation of LSZ maps

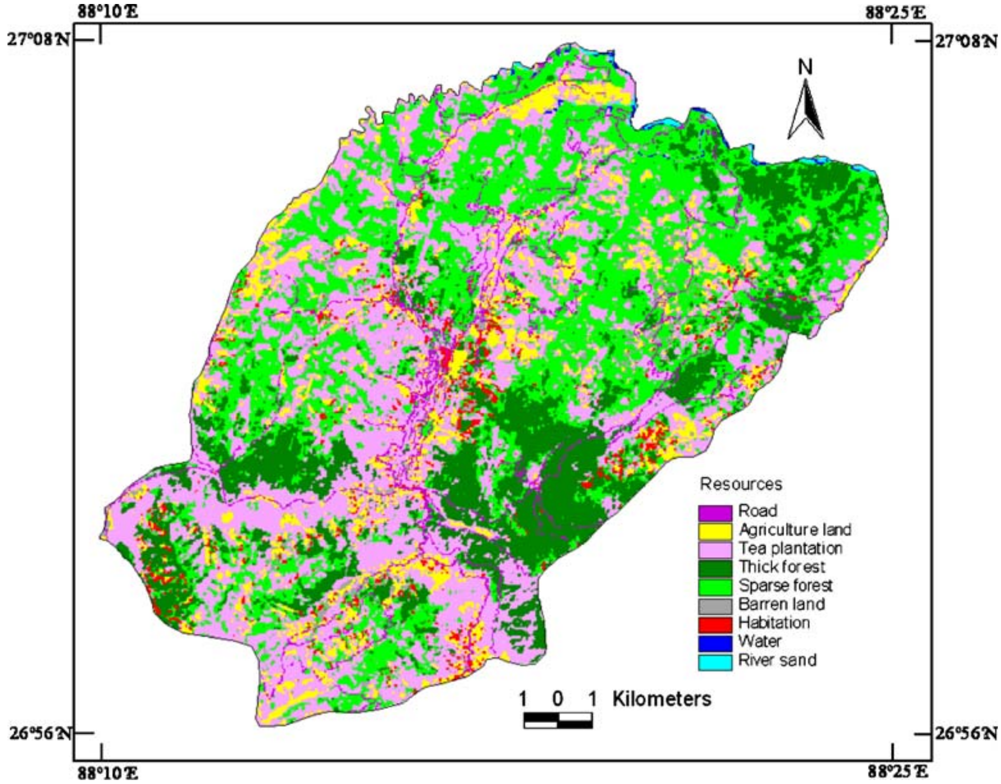
A comparative evaluation of LSZ maps derived from different techniques enables the understanding of the differences in various approaches and the influence of various causative factors on different approaches. The comparative evaluation of the LSZ maps was carried out using visual interpretation and analysis of landslide density.

Visual inspection of LSZ Map I revealed that all the five susceptibility zones were distributed all over the study area. The map thus did not show any well-defined pattern for the distribution of susceptibility zones. It was observed that the VHS and HS zones were represented mostly along 1st and 2nd order drainage buffer areas, which was mainly due to assignment of high weights and ratings subjectively to the categories of this causative factor.

In the ANN black box approach, the weights and ratings remain hidden and are not known. The LSZ Map II produced through this approach showed a lot of similarity with the LSZ Map I, because the latter map was used as the reference map to generate the LSZ Map II. Therefore, the outcome of this map was also biased towards previous approach.

The fuzzy set based approach using cosine amplitude similarity procedure could bring out the relative importance (ratings) of different categories of causative factors in terms of landslide occurrences in an unbiased manner. The LSZ Map III, produced from this approach, depicted an overall NNE–SSW landslide susceptibility zonation trend in the area. It was observed that the southeast and east facing slopes were more susceptible to landslides than other slopes, which showed that there was a topographic control over this LSZ map. Further, a control of drainage lines on landslide incidence and LSZ mapping was also observed. However, the major limitation of this approach was that

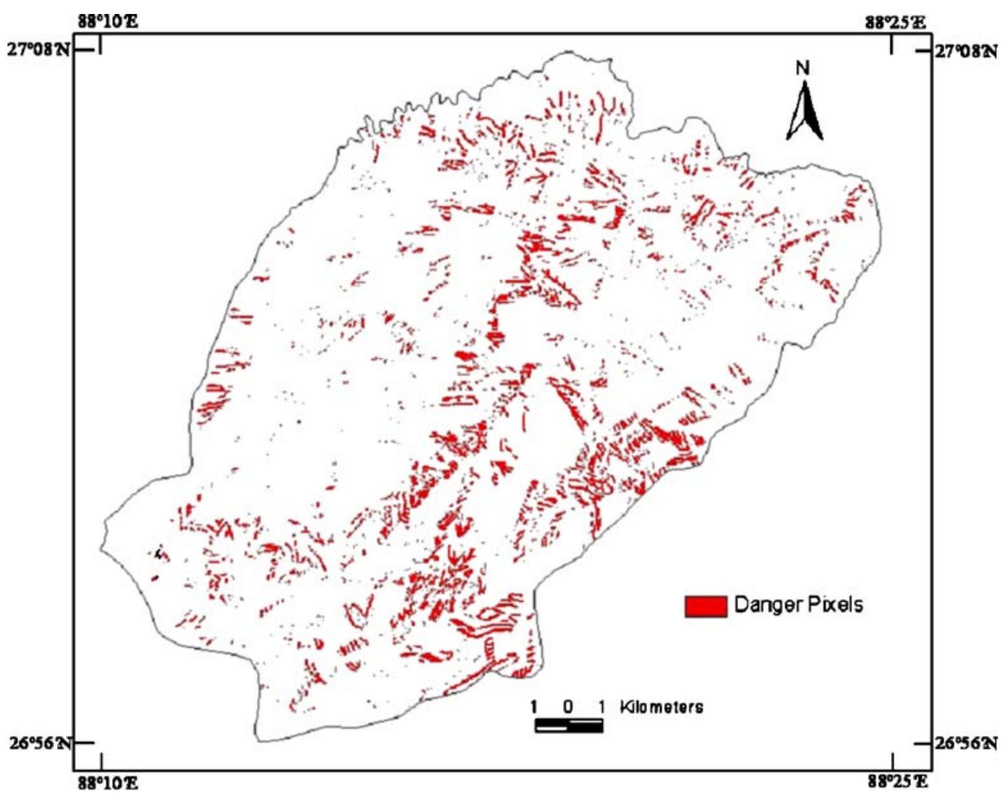
Fig. 4 Resource map of the study area



all the factors were considered equally important as a unit weight was assigned to each factor.

Alternatively, the map (LSZ Map IV) produced from combined neural and fuzzy approach, wherein the weights to factors were assigned via neural network and ratings to categories via fuzzy set theory, revealed that lithology had the most significant effect whereas the drainage buffer had the least significant effect on landslide incidences in the area. The ANN-derived weights also revealed the importance of lineaments. Thus, the LSZ Map IV reflected a preferential distribution of higher landslide susceptibility zones along structural discontinuities (lineaments), which should indeed be the case. Also, the Darjeeling gneiss rock type in

Fig. 5 Danger pixels map of the study area



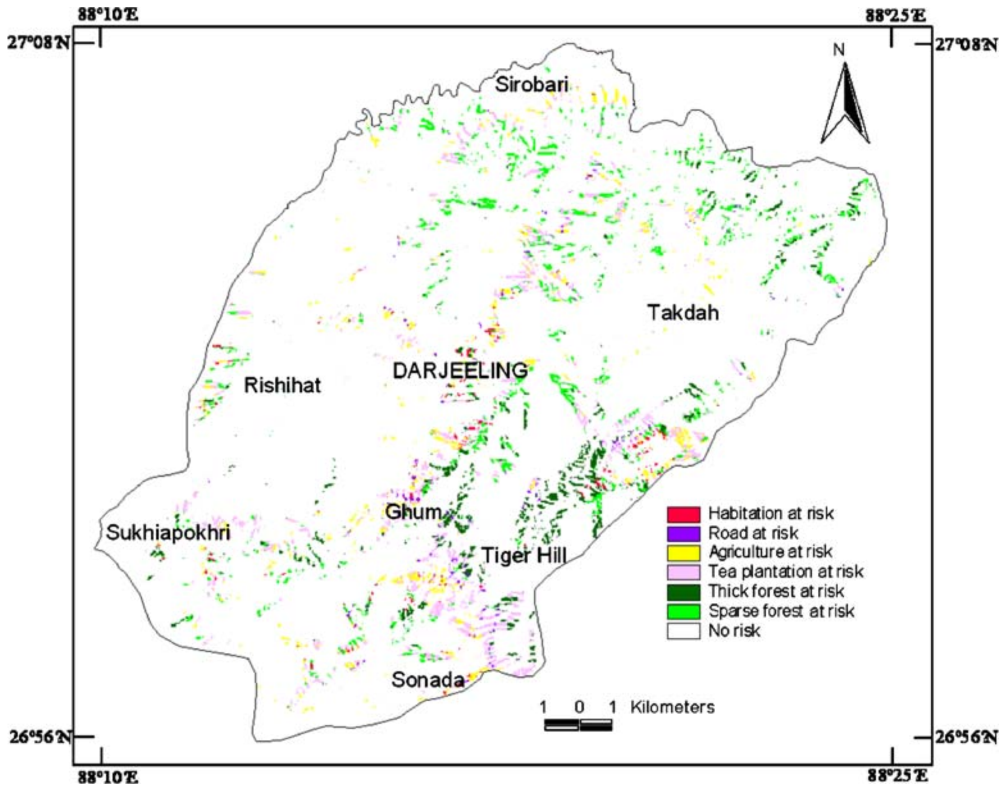


Fig. 6 Landslide risk assessment map (LRA Map I) using concept of danger pixels

the southeastern part, feldspathic greywacke, and Reyang quartzite in the northern part of the study area indicated moderate to very high susceptibility zones.

Landslide density is defined as the ratio of the existing landslide area in percent to the area of each landslide susceptibility zone in percent, and is calculated here on the basis of the number of pixels. Landslide density values for each of the susceptibility zones for different LSZ maps have been calculated separately (Table 1). Usually, an ideal LSZ map should have the highest landslide density for VHS zone, as compared to other zones and there ought to be a decreasing trend of landslide density values successively from VHS to VLS zone.

It can be observed from Table 1 that the landslide densities for VHS zone of LSZ Maps III and IV are much higher as compared to those obtained for other susceptibility zones. There is also a decreasing trend of landslide density values from VHS zone to VLS zone for Maps III and IV.

As far as the landslide density in VHS zone is concerned, it is observed that the LSZ Map IV has a much higher landslide density (>13) for this zone than that observed in other LSZ maps (1.63 for Map I, 1.34 for Map II, and 6.72 for Map III). Further, the Map IV also has a more systematic and reasonable trend of variation in landslide density values from VHS to VLS zones. Thus, based on the landslide density values of different landslide susceptibility zones and their trend from VHS to VLS zones for all the LSZ maps, it was inferred that the LSZ Map IV was the most appropriate to represent landslide occurrences in the study area.

Table 2 Distribution of pixels of various resource categories under risk using danger pixels

Resource categories under risk	Number of pixels
Habitation	1,015
Road	921
Agriculture	4,517
Tea plantation	10,517
Thick forest	5,760
Sparse forest	8,620
Total	31,350

Landslide risk assessment

In the present study, landslide risk is considered as a function of both (a) landslide susceptibility or potential (LP) and (b) the resource damage potential (RDP). Two different approaches for landslide risk assessment have been developed and implemented to prepare the LRA maps of the study area.

1. LRA using concept of danger pixels
2. LRA using concept of fuzzy set theory

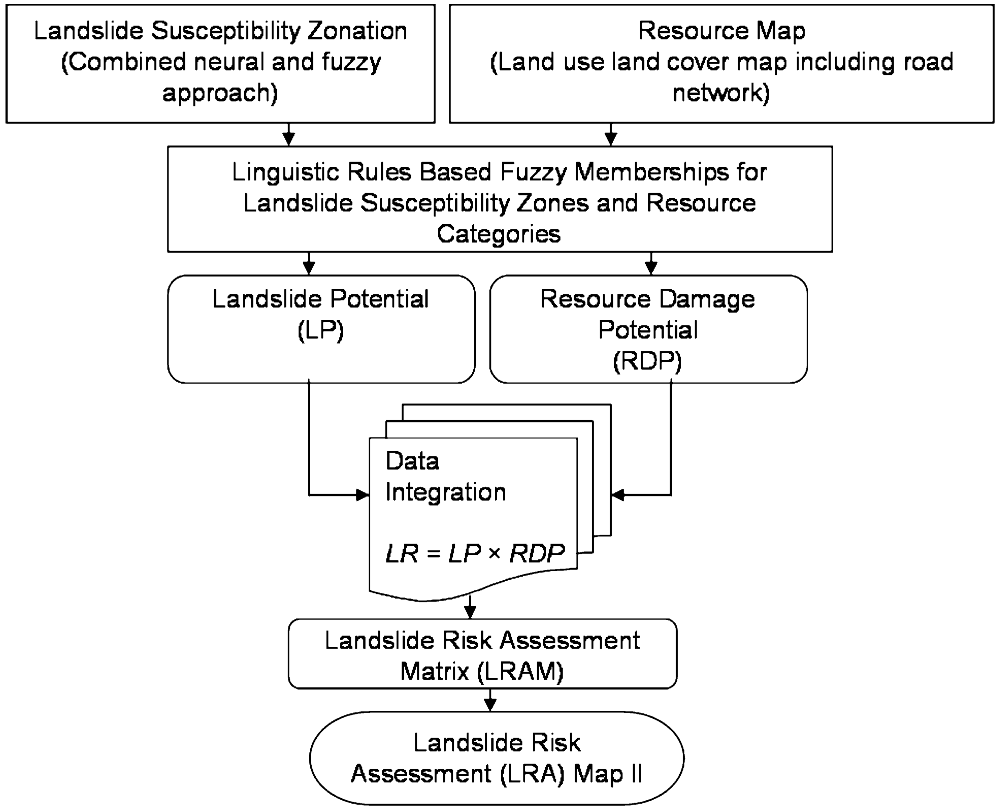
LRA using concept of danger pixels

LRA using danger pixel concept involves a number of steps as given in Fig. 3. The danger pixel map and the resource map of the area are used as two input layers to generate the LRA map.

The resource map (Fig. 4) was produced by integrating the land use land cover map with the road network map of the area. As barren land is usually not an important resource category from a damage point of view, pixels belonging to this category were ignored for landslide risk assessment.

Danger pixels were defined as those pixels (i.e., 25-m size each) which lie in very high and high landslide susceptibility zones (i.e., VHS and HS zones) in all the four LSZ maps together irrespective of the approaches of LSZ map preparation. Thus, for generating a danger pixel map, the VHS and HS zones in each LSZ map were merged together. Pixels belonging to the remaining landslide susceptibility zones (i.e., moderate, low, and very low) were masked out. Hence, the danger pixel map (Fig. 5) is an intersection

Fig. 7 Steps for landslide risk assessment (LRA) using concept of fuzzy set theory



of all the pixels with VHS and HS attributes in the four LSZ maps. It is a binary map in which 1 indicates danger pixel whereas 0 indicates masked pixel.

Finally, the resource map (Fig. 4) and danger pixel map (Fig. 5) were integrated by multiplying the corresponding pixel values in both the maps to produce the LRA map (referred as LRA Map I, Fig. 6) of the study area. The distribution of danger pixels in different resource categories is given in Table 2. The LRA Map I depicts the spatial distribution of different resource categories that appear to be under risk due to landslides. It can be observed from this figure that habitation around Darjeeling and Ghum, a portion of road from Sonada to Ghum, the tea plantation in the southern part, and thick forests in the southeastern part of the study area are under risk due to landslides. Thus, by producing risk assessment maps based on danger pixel concept, category-wise risk can be ascertained and precautionary measures to protect the existing resources in case of landslide disaster can be taken in advance.

Table 3 Linguistic rules for risk scoring of various landslide susceptibility zones

Landslide susceptibility zone	Linguistic rules for risk scoring	Fuzzy membership value for landslide potential
Very high	On-going severe landslides widespread. Landslide almost certain to occur.	1.0
High	On-going landslide activities evident at many places. Most likely occurrence of landslides under adverse conditions.	0.8
Moderate	Landslides have occurred in the past locally. Possible occurrence of landslides under adverse conditions.	0.55
Low	Landslides unlikely to occur. Slopes are generally stable.	0.3
Very low	Very rare or no occurrence of landslides. Inherently stable slopes naturally.	0.1

Table 4 Linguistic rules for risk scoring of various resource categories for damage potential

Resource category	Linguistic rules for risk scoring	Fuzzy membership value for damage potential
Habitation	Direct impact on population and assets such buildings and property etc. Damages in the form of deaths, injuries, and property loss.	1.00
Road	Impact on essential infrastructure/ services (i.e., road network). Damage in the form of lack of connectivity in the area that could also affect the rescue and rehabilitation process during post-disaster management stage.	0.60
Agriculture	Direct impact on economy (earnings) and essential food items for survival.	0.35
Tea plantation	Direct impact on economy (earnings).	0.35
Thick forest	Loss of forest resource of the nation, though no direct impact on individual economy.	0.15
Sparse forest	Loss of some forest resource of the nation, though no direct impact on individual economy.	0.15
Barren land	Little damage	0.05
Water	Little damage	0.05
River sand	Little damage	0.05

However, the landslide risk assessment based only on danger pixel approach may not indicate the degree of severity of risk to different resource categories due to the occurrence of landslides. Therefore, an alternative approach for LRA based on fuzzy set concept has been proposed here. The output from this approach will also be a landslide risk assessment map, which portrays five zones (very high, high, moderate, low, and very low) according to degree of severity of risk to the resource categories.

LRA using concept of fuzzy set theory

A fuzzy set theory based approach focused on the use of fuzzy linguistic rules has been developed and implemented for the generation of LRA map. The proposed approach may be considered as an extension of risk ranking matrices approach suggested by Anbalagan and Singh (1996) for landslide risk assessment. In that study, categories of the landslide potential and the resource damage potential were qualitatively defined as very low, low, moderate, high, and very high. Similarly, the risk ranking matrices were also developed in qualitative terms. However, in the proposed approach, categories of the landslide potential and the resource damage potential have been quantified in terms of fuzzy membership values as per their relative importance to risk assessment. The approach can be regarded as a combination of risk scoring and risk matrix methods.

In the fuzzy set theory, membership values of elements are computed in (0, 1) interval depending upon varying degrees of support or confidence on a phenomenon. There are several ways of computing membership values, which include Cartesian product, closed-form expression, linguistic rules of knowledge, similarity methods in data manipulation, etc. (Ross 1995). Thus, membership values can be assigned to different categories of factors being used as input for landslide risk assessment.

In this study, the most accurate LSZ map (i.e., LSZ Map IV) of the area, prepared using the combined neural and fuzzy approach (Kanungo et al. 2006), was used as an input data layer to quantify landslide potential. Further, the land use land cover map combined with a road network map of the area was treated as resource map to be used as the input layer to quantify the resource damage potential. The fuzzy membership values to various categories of these maps (e.g., landslide susceptibility zones and resource elements) were determined on the basis of a linguistic scale derived from expert knowledge. These two data layers indicating fuzzy membership values were integrated via multiplication in a raster GIS environment to generate an LRA map depicting various risk zones, as defined earlier.

The complete implementation of this approach can be described in following steps (Fig. 7):

(a) Risk scoring of LSZ map to yield LP raster layer
(b) Risk scoring of resource map to yield RDP raster layer
(c) Generation of LRA map

Table 5 LRA matrix for different combinations of landslide potential and resource damage potential

		Landslide Potential (LP)				
		VHS (1.0)	HS (0.8)	MS (0.55)	LS (0.3)	VLS (0.1)
Resource Damage Potential (RDP)	Habitation (1.0)	1.0	0.8	0.55	0.3	0.1
	Road (0.6)	0.6	0.48	0.33	0.18	0.06
	Agriculture (0.35)	0.35	0.28	0.19	0.11	0.04
	Tea Plantation (0.35)	0.35	0.28	0.19	0.11	0.04
	Thick Forest (0.15)	0.15	0.12	0.08	0.05	0.02
	Sparse Forest (0.15)	0.15	0.12	0.08	0.05	0.02
	Barren (0.05)	0.05	0.04	0.03	0.02	0.01
	River Sand (0.05)	0.05	0.04	0.03	0.02	0.01
	Water (0.05)	0.05	0.04	0.03	0.02	0.01

Red—very high risk, *pink*—high risk, *yellow*—moderate risk, *blue*—low risk, *green*—very low risk.

Table 6 Scheme of segmentation of landslide risk values into various landslide risk zones

Landslide risk values	Landslide risk zones
$0.0<LR\leq0.1$	Very low risk zone (VLR)
$0.1<LR\leq0.2$	Low risk zone (LR)
$0.2<LR\leq0.4$	Moderate risk zone (MR)
$0.4<LR\leq0.6$	High risk zone (HR)
$LR>0.6$	Very high risk zone (VHR)

Risk scoring of LSZ map to yield LP raster layer

The LSZ Map IV (Fig. 2d) represents five landslide susceptibility zones namely VHS, HS, MS, LS, and VLS. As per definition, the VHS zone has the highest landslide potential as compared to other susceptibility zones and the VLS zone has the least landslide potential. Accordingly, linguistic rules have been designed to allocate

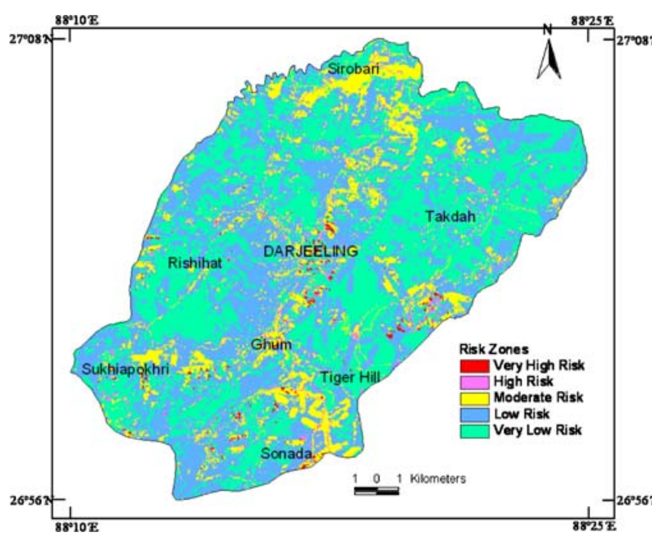


Fig. 8 Landslide risk assessment map (LRA Map II) using concept of fuzzy set theory

Table 7 Spatial distribution of risk zones and resource categories

Risk zones	Number of pixels in different resource categories (% of total area)									Total number of pixels (% of total area)
	Habitation	Road	Agriculture	Tea plantation	Thick forest	Sparse forest	Barren land	Water	River sand	
VHR	2,496 (0.61)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	2,496 (0.61)
HR	4,422 (1.09)	2,782 (0.68)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	7,204 (1.77)
MR	2,820 (0.69)	7,140 (1.75)	13,040 (3.20)	27,415 (6.72)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	50,415 (12.36)
LR	0 (0.00)	4,797 (1.18)	20,246 (4.96)	10,8097 (26.51)	16,246 (3.98)	23,627 (5.80)	0 (0.00)	0 (0.00)	0 (0.00)	173,013 (42.43)
VLR	8 (0.00)	316 (0.08)	121 (0.03)	527 (0.13)	54,570 (13.38)	103,735 (25.44)	13,319 (3.27)	892 (0.22)	935 (0.23)	174,619 (42.83)
Total	9,746 (2.39)	15,035 (3.69)	33,407 (8.19)	136,039 (33.36)	70,816 (17.36)	12,7362 (31.24)	13,319 (3.27)	892 (0.22)	935 (0.23)	407,747 (100)

risk scores to these susceptibility zones. Fuzzy membership values representing the landslide potential (LP) based on these linguistic rules are assigned to each susceptibility zone and are given in Table 3.

Risk scoring of resource map to yield RDP raster layer

The resource map includes all the existing land use land cover categories and the road network of the area. Thus, it represents nine different categories namely habitation, road, thick forest, sparse forest, tea plantation, agricultural land, barren land, water body, and river sand. These resource categories may be subjected to landslides, which result into resource damages. The damage potential ought to be related to the importance of these categories to the society. Keeping this in view, the habitation area (buildings and property etc.) has been assigned the highest damage potential and the categories like barren land, water body, and river sand have been considered as having little landslide damage potential. The linguistic rules in order of their societal importance have been developed to allocate risk scores to these categories. Based on these linguistic rules, fuzzy membership values representing the resource damage potential are assigned to each resource category and are given in Table 4.

LRA mapping

Landslide risk has been considered as a combination of landslide potential and resource damage potential at a particular region. Landslide potential and resource damage potential have been quantified in terms of fuzzy membership values in the form of LP and RDP raster data layers. These layers are integrated using Eq. (1) to determine the risk due to landslides in the region.

$$LR = LP \times RDP \tag{1}$$

where landslide risk, landslide potential and resource damage potential are represented by *LR*, *LP*, and *RDP*, respectively. Thus, landslide risk values for different combinations of landslide potential and resource damage potential can be represented in the form of an LRA matrix, as given in Table 5.

It can be observed from the LRA matrix that the LRA values for each pixel range from 0.01 to 1.00. The value 0.01 indicates very low landslide potential in resource categories such as barren land, water bodies, and river sand whereas the value 1.00 indicates very high landslide potential in habitat areas. The landslide risk values between 0.01 and 1.00 have been sliced into five landslide risk zones as per the scheme given in Table 6, to produce the LRA Map II (Fig. 8) of the area. The boundaries of the risk zones have been defined arbitrarily so that these are consistent with those reported in Anbalagan and Singh (1996).

The LRA map has been superimposed on the resource map to determine the spatial distribution of different risk zones in various resource categories (Table 7). It can be observed from this table that 2,496 pixels (0.61% of total area) are under very high risk (VHR) zone. This may be due to very high fuzzy membership values assigned to habitation and VHS zone. Further, 7,204 pixels (1.77% of total area) are under high risk (HR) zone, which comprises partly habitation (4,422 pixels) and partly road (2,782 pixels). A closer look at the LRA map (Fig. 8) reveals that landslides pose very high risk to the habitation in and around Sonada, Darjeeling, and the northeastern part of Tiger hill and high risk to a section of road from Sonada to Ghum.

Based on this landslide risk assessment map, a risk management action plan (Table 8) can be suggested to minimize the possible risk to the resources available in the area. The high and

Table 8 Risk zones and suggested action plan for risk management

Risk zones	Suggested action plan
VLR	Suitable areas for new developmental activities. Consideration to be given to further studies to investigate slope instability problems during project implementation stage.
LR	Suitable areas for new developmental activities. Landslide stabilization works may possibly be required.
MR	Landslide stabilization works may be required, but further studies required refining the judgments.
HR	Landslide stabilization works through ground investigations likely to be required. Further investigation including a comprehensive assessment of risks will be required. Also, detailed investigation of slope instability problems required to implement proper remedial measures before taking up any new developmental activities in this zone.
VHR	Areas should be avoided to the extent possible for further developmental activities. In case unavoidable, large scale mitigation works will be required. Ground investigations would be required for detailed design of remedial works. Urgent requirement for further investigations including a comprehensive assessment of risks.

very high risk areas should be given top priority for planning and implementation of proper remedial measures to control the landslide activities in these areas.

Thus, LRA Map I based on danger pixels concept indicates that habitations and road sections are under risk due to landslides whereas the LRA Map II further refines this outcome by defining the degree of severity of risk to these categories by putting these into high and low risk zones. Hence, the landslide risk assessment study carried out using two approaches in this paper can be considered in cohesion for assessing the risks due to landslides or any other disaster in a region.

Conclusions

In this paper, two novel semi-quantitative landslide risk assessment methods named as danger pixel approach and fuzzy set theory based approach were proposed.

In danger pixel approach, the risk classes were defined as risk to road, risk to habitation, etc. Danger pixels, as defined earlier, were those pixels which lie in very high and high landslide susceptibility zones in all the LSZ maps together irrespective of the approaches of LSZ map preparation. The danger pixel map and the resource map were integrated to produce the LRA map. This LRA map gives an idea about the risk to the existing resources so that precautionary measures may be taken beforehand in case of landslide disasters. However, in case of fuzzy set theory based approach, the risk classes were defined as very high risk (VHR), high risk (HR), moderate risk (MR), low risk (LR), and very low risk (VLR) according to the degree of risk involved irrespective of resource categories in spatial domain. The landslide risk assessment maps produced from both the approaches can be used in cohesion to reflect the risks to various resources due to occurrence of landslides in the region. For example, LRA map based on danger pixels approach showed that habitation around Darjeeling and Ghum, a portion of road from Sonada to Ghum, the tea plantation in the southern part, and thick forests in the southeastern part of the study area were under risk due to landslides. This observation was further substantiated from the LRA map based on fuzzy set theory based approach that landslides pose very high risk to the habitation in and around Sonada, Darjeeling, and northeastern part of Tiger hill whereas a high risk to the portion of road from Sonada to Ghum. Thus, such maps may be extremely useful to engineers and planners involved in various engineering projects of national importance such as route selection for a highway, general planning, extension of settlement area, implementation of hydropower projects, etc.

References

Acharya SK (1989) The Daling Group, its nomenclature, tectono-stratigraphy and structural grain: with notes on their possible equivalents. Geological Survey of India SPN-22:5–13

Anbalagan R, Singh B (1996) Landslide hazard and risk assessment mapping of mountainous terrains—a case study from Kumaon Himalaya, India. Engineering Geology 43:237–246

Arora MK, Das Gupta AS, Gupta RP (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

Boggett AD, Mapplebeck NJ, Cullen RJ (2000) South Shore Cliffs, Whitehaven—geomorphological survey and emergency cliff stabilisation works. Quaternary Journal of Engineering Geology and Hydrogeology 33:213–226

Cardinali M, Reichenbach P, Guzzetti F, Ardizzone F, Antonini G, Galli M, Cacciano M, Castellani M, Salvati P (2002) A geomorphological approach to the estimation of landslide hazards and risks in Umbria, central Italy. Natural Hazards and Earth System Sciences 2:57–72

Chau KT, Sze YL, Fung MK, Wong WY, Fong EL, Chan LCP (2004) Landslide hazard analysis for Hong Kong using landslide inventory and GIS. Computers and Geosciences 30:429–443

Ercanoglu M, Gokceoglu C (2004) Use of fuzzy relations to produce landslide susceptibility map of a landslide prone area (West Black Sea Region, Turkey). Engineering Geology 75(3&4):229–250

Fell R (1994) Landslide risk assessment and acceptable risk. Canadian Geotechnical Journal 31:261–272

Hughes A, Hewlett H, Samuels PG, Morris M, Sayers P, Moffat I, Harding A, Tedd P (2000) Risk management for UK reservoirs. Construction Industry Research and Information Association (CIRIA) C542, London

Kanungo DP, Arora MK, Sarkar S, Gupta RP (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

Lee EM (1999) Coastal planning and management: the impact of the 1993 Holbeck Hall Landslide, Scarborough, East Midlands. Geographer 21:78–91

Lee EM (2003) Coastal change and cliff instability: development of a framework for risk assessment and management. Unpublished PhD thesis, University of Newcastle upon Tyne

Lee EM, Clark AR (2000) The use of archive records in landslide risk assessment: historical landslide events on the Scarborough Coast, UK. In: Bromhead EN, Dixon N, Ibsen ML (eds) Landslides: in research, theory and practice. Thomas Telford, London, pp 904–910

Lee EM, Zones DKC (2004) Landslide Risk Assessment. Thomas Telford, London

Lee EM, Clark AR, Guest S (1998) An assessment of coastal landslide risk, Scarborough, UK. In: Moore D, Hungr O (eds) Engineering geology: the view from the Pacific Rim. Balkema, Rotterdam, pp 1787–1794

Leone F, Aste JP, Leroi E (1996) Vulnerability assessment of elements exposed to mass-movement: working toward a better risk perception. In: Senneset R (ed) Landslides. Balkema, Rotterdam, pp 263–269

McDonnell BA (2002) Hazard identification and visitor risk assessment at the Giant's Causeway World Heritage Site, Ireland. In: McInnes RG, Jakeways J (eds) Instability—planning and management. Thomas Telford, London, pp 527–534

Naithani AK (1999) The Himalayan landslides. Employment News 23(47):20–26

Palmer JS, Clark AR, Cliffe D, Eade M (2002) The management of risk on the Chalk Cliffs at Brighton, UK. In: McInnes RG, Jakeways J (eds) Instability—planning and management. Thomas Telford, London, pp 355–362

Rautela P, Lakhera RC (2000) Landslide risk analysis between Giri and Tons Rivers in Himachal Himalaya (India). International Journal of Applied Earth Observation and Geoinformation (JAG) 2(3–4):153–160

Ross TJ (1995) Fuzzy logic with engineering applications. McGraw-Hill, New York

Sandilands NM, Noble M, Findlay JW (1998) Risk assessment strategies for dam based hydro schemes. In: Tedd P (ed) The prospect for reservoirs in the 21st century. Thomas Telford, London

van Dine DF, Jordan P, Boyer DC (2002) An example of risk assessment from British Columbia, Canada. In: McInnes RG, Jakeways J (eds) Instability—planning and management. Thomas Telford, London, pp 399–406

Wong HN, Ho KKS, Chan YC (1997) Assessment of consequence of landslides. In: Cruden D, Fell R (eds) Landslide risk assessment. Balkema, Rotterdam, pp 111–149

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