

## An approach for GIS-based statistical landslide susceptibility zonation—with a case study in the Himalayas

**Abstract** Landslide susceptibility zonation (LSZ) is necessary for disaster management and planning development activities in mountainous regions. A number of methods, viz. landslide distribution, qualitative, statistical and distribution-free analyses have been used for the LSZ studies and they are again briefly reviewed here. In this work, two methods, the Information Value (InfoVal) and the Landslide Nominal Susceptibility Factor (LNSF) methods that are based on bivariate statistical analysis have been applied for LSZ mapping in a part of the Himalayas. Relevant thematic maps representing various factors (e.g., slope, aspect, relative relief, lithology, buffer zones along thrusts, faults and lineaments, drainage density and landcover) that are related to landslide activity, have been generated using remote sensing and GIS techniques. The LSZ derived from the LNSF method, has been compared with that produced from the InfoVal method and the result shows a more realistic LSZ map from the LNSF method which appears to conform to the heterogeneity of the terrain.

**Keywords** Landslide susceptibility zonation · GIS · Remote sensing · Himalayas

### Introduction

Landslides are amongst the most damaging natural hazards in the mountainous terrain such as the Himalayas. The study of landslides has drawn worldwide attention mainly due to increasing awareness of the socio-economic impact of landslides, as well as the increasing pressure of urbanization on the mountain environment (Aleotti and Chowdhury 1999). Malpa landslide (August 1998), Uttarkashi landslide (September–October 2003) and Badrinath landslide (July 2004) in the Himalayas are the burning examples that have caused large-scale human tragedies, material damage and associated environmental and social hazards.

Although it is yet difficult to predict a landslide event in space and time, an area may be divided into near-homogeneous domains and ranked according to degrees of potential hazard due to mass movements (Varnes 1984). Such maps are called Landslide Hazard Zonation (LHZ) or Landslide Susceptibility Zonation (LSZ) maps. In the last four decades, several qualitative and quantitative studies have been carried out to prepare landslide hazard maps. The availability of remote sensing and GIS technologies has tremendously helped the preparation of susceptibility maps with greater efficiency and accuracy than before. This is primarily due to the fact that through these technologies, it is possible to collect, manipulate and analyze a variety of spatial and non-spatial data about the causative factors (such as lithology, tectonic structures, landcover, geomorphology, etc.) responsible for the landslide activity in a region (Varnes 1984; Carrara et al. 1991; Nagarajan et al. 1998; Saha et al. 2002).

A number of methodologies for landslide susceptibility zonation have been proposed which can be grouped into six categories

(Table 1). The simplest of all, the distribution analysis only depicts direct mapping of landslide locations from field surveys or aerial photographic interpretation and thus do not provide information on predictive behavior of future landslide activity. In this type of analysis, GIS is used to digitize landslides prepared from field survey maps, aerial photographs and remote sensing images. In qualitative analysis, subjective decision rules are applied to define weights and ratings based on the experience of experts (Saha et al. 2002). The logical analytical method proposed by Bughi et al. (1996) is a variation of the above, where the field survey data on slope deformation helps to decide the numerical weights. Remote sensing and GIS techniques may be utilized here for thematic map preparation and overlay analysis.

To remove subjectivity in qualitative analysis, various statistical methods have been employed for LSZ studies. These methods can broadly be classified into three types: bivariate, multivariate and probabilistic prediction models. The bivariate models consider each individual thematic map in terms of landslide distribution and can be easily implemented in GIS (van Westen 1997). The Information Value (InfoVal) Yin and Yan 1988 and Landslide Nominal Risk Factor (LNSF) method (Gupta and Joshi 1990) are bivariate statistical analyses used to prepare landslide susceptibility maps. Multivariate methods consider various thematic at once into a complex and time-consuming data analysis processes (Carrara et al. 1991). The probabilistic prediction models (Chung and Fabbri 1999) provide quantitative estimates of future landslide activity based on prediction from past events. The ‘weight of evidence’ approach is also a kind of bivariate analysis utilizing Bayesian probability model (Lee et al. 2002a). During the last 5 years, distribution-free methods such as neural network (Arora et al. 2004) and neuro-fuzzy analysis (Elias and Bandis 2000) have also been implemented for LSZ studies. In addition to this, deterministic and landslide frequency analysis methods have also been reported for site-specific studies on landslides.

For medium-scale regional LSZ studies, the methods based on qualitative and statistical analysis have been more commonly used. Qualitative methods have the disadvantage of utilizing opinion-based weights. Therefore, to introduce objectivity in weight assignment and landslide susceptibility zoning, statistical analysis appropriate. The aim of this paper is to discuss the application of two bivariate statistical methods, namely InfoVal and LNSF for landslide susceptibility mapping in a raster-based GIS environment in a part of the Himalayas.

### The InfoVal and LNSF methods

van Westen (1997) proposed the Information Value (InfoVal) method for Landslide Hazard Zonation, which considers the probability of landslide occurrence within a certain area of each class of a thematic. This method is regarded as the simplification

**Table 1** Methodologies for various landslide hazard/susceptibility zonation (after van Westen 1994; Mantovani (1996)

LHZ/LSZ method	Main feature	For example	
Qualitative	1. Distribution analysis	Direct mapping of mass movement features resulting in a map, which gives information only for those sites where landslides have occurred in the past	Wieczorek (1984)
	2. Qualitative analysis	Direct or semi-direct methods in which the geomorphological map is renumbered to a hazard / susceptibility map or in which several maps are combined into one using subjective decision rules based on the experience of the earth scientist	Saha et al. (2002)
Quantitative	3. Statistical analysis	Indirect method in which statistical analysis are used to obtain predictions of the mass-movement from a number of parameter maps	Yin and Yan (1988), Gupta and Joshi (1990), Lee et al. (2002b), Ayalew, et al. (2004), Carrara et al. (1991), Chung and Fabbri (1999)
	4. Distribution-free methods	Neural networks and neuro-fuzzy methods, which do not depend on distributional assumptions of the data. Here, the weights are computed in an objective manner	Arora et al. (2004), Elias and Bandis (2000)
	5. Deterministic analysis	Indirect methods in which parameters are combined in slope stability calculation	Okimura and Kawatani (1986)
	6. Landslide frequency analysis	Indirect methods in which earthquakes and/or rainfall records or hydrological models are used for correlation with known landslide dates to obtain threshold values with a certain frequency	Capecchi and Focardi (1988)

of the method in Yin and Yan (1988), in which the weights of a particular class in a thematic are determined as:

$$W_i = \ln \left( \frac{\text{Densclas}}{\text{Densmap}} \right) = \ln \frac{N_{\text{pix}}(S_i) / N_{\text{pix}}(N_i)}{\sum_{i=1}^n N_{\text{pix}}(S_i) / \sum_{i=1}^n N_{\text{pix}}(N_i)} \quad (1)$$

where  $W_i$  is the weight given to the  $i$ th class of a particular thematic layer (e.g., granite or limestone in the thematic layer 'lithology'), Densclas is the landslide density within the thematic class, Densmap is the landslide density within the entire thematic layer,  $N_{\text{pix}}(S_i)$  is the number of landslide pixels in a certain thematic class,  $N_{\text{pix}}(N_i)$  is the total number of pixels in a certain thematic class, and  $n$  is the number of classes in a thematic map. The natural logarithm is used to take care of the large variation in the weights.

Thus, the weight is calculated for various classes in each thematic. The thematic are then overlaid and added to prepare a Landslide Hazard Index (LHI) map. Near-equal subdivision of LHI cumulative frequency curve into five classes yields zones of different landslide hazards (i.e., very high, high, moderate, low and very low) such that the boundaries may be adjusted subjectively to refine the suitable landslide hazard map (van Westen 1997).

In the Landslide Nominal Risk Factor (LNRF) method (Gupta and Joshi 1990), the nominal risk factor is determined and related to the weight of each class of thematic considered for the preparation of LSZ, as follows:

$$\text{LNRF}_i = \frac{N_{\text{pix}}(S_i)}{\left( \sum_{i=1}^n N_{\text{pix}}(S_i) \right) / n} \quad (2)$$

where  $N_{\text{pix}}(S_i)$  is the number of pixels containing landslides in  $i$ th thematic class, and  $n$  is the number of classes present in the particular thematic map.

An LNRF value greater than 1 implies high susceptibility to landslides. When the LNRF value is less than 1, it indicates low susceptibility. An LNRF value equal to 1 is a sign of average

landslide susceptibility. Gupta and Joshi (1990) regrouped the LNRF values broadly into three classes for each thematic, and assigned weights 0, 1 and 2 for LNRF <0.67 (low risk), 0.67 <LNRF <1.33 (moderate susceptibility) and LNRF > 1.33 (high risk), respectively. The thematic were overlaid and aggregated to prepare a LHI map. The LHI map is then classified into three susceptibility zones: low, moderate and high, keeping equal interval of LHI values.

It is observed that regrouping the LNRF values into ordinal numbers (0, 1, 2 as done by Gupta and Joshi 1990) leads to coarsening of the analytical approach and reduction in the relative importance of various thematic classes. Therefore, in this work we modify the above LNRF method, such that we directly use the computed values in further computations. Further, the term 'susceptibility' is considered here more appropriate than 'risk' or 'hazard', and therefore we call it as 'Landslide Nominal Susceptibility Factor (LNSF) method'. Another methodological improvement in this study is aimed at removing the subjectivity in segmenting the Landslide Susceptibility Index (LSI) values, which has been done using a new statistical procedure.

### Study area

The study area covers a region of about 550 km<sup>2</sup> in the Garhwal Himalayas (Fig. 1). The terrain is highly rugged with elevations ranging from about 920 to 4,250 m above mean sea level. The river Alaknanda flowing through the south-eastern part of the study area and its tributaries constitute the drainage network in the area. Geologically, the region comprises the Lesser Himalayas and the Higher Himalayas (Valdiya 1980). Structurally, the region is complex due to the presence of various thrusts, faults and intense deformations. Historically, the region has experienced numerous landslides of different dimensions, some of which have been reactivated during an earthquake on 29 March 1999 in Chamoli district (Ravindran and Philip 1999).

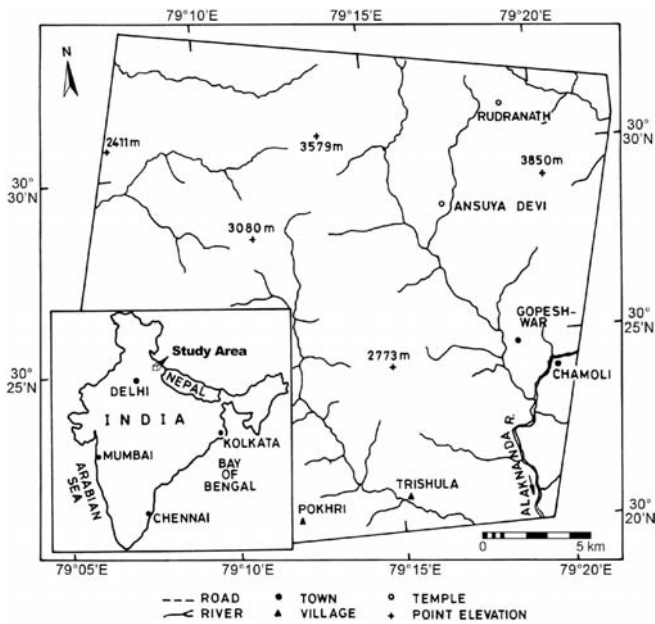


Fig. 1 Location of the study area

#### Data layer preparation

A number of thematic maps (referred to as data layers in GIS) on specific factors or parameters related to the occurrence of landslides, viz. slope, aspect, relative relief, tectonic structures, lithology, landcover and drainage density have been generated. A landslide distribution map has also been prepared. The basic data sources that have been used to generate these layers are Survey of India topographic maps (1:50,000 scale), geological and structural maps prepared by Valdiya (1980), satellite IRS-1C-LISS-III multispectral data (in green, red, near-infrared and shortwave-infrared wavelength bands at 23.5-m spatial resolution) and IRS-1C-

PAN data (broad-band 0.50–0.75  $\mu\text{m}$  wavelength region at 5.8-m spatial resolution). Besides, field surveys have been carried out for verification of landslides, landcover, geology and structural features. The above data sources have been used to generate various thematic data layers that have been resampled to  $6 \times 6 \text{ m}^2$  grid size to match the nominal spatial resolution of IRS-PAN image. A brief description of each data layer preparation is given here. More details on methodology can be found in Gupta et al. (1999).

#### Landslide distribution map

The identification and mapping of existing landslides is a prerequisite to perform statistical analysis on the relation between the distribution of landslides and influencing parameters. Since, it is not possible to reach all places to locate every landslide in mountainous region such as the Himalayas, the remote sensing images are usually great source of information as they provide synoptic view of the landscape.

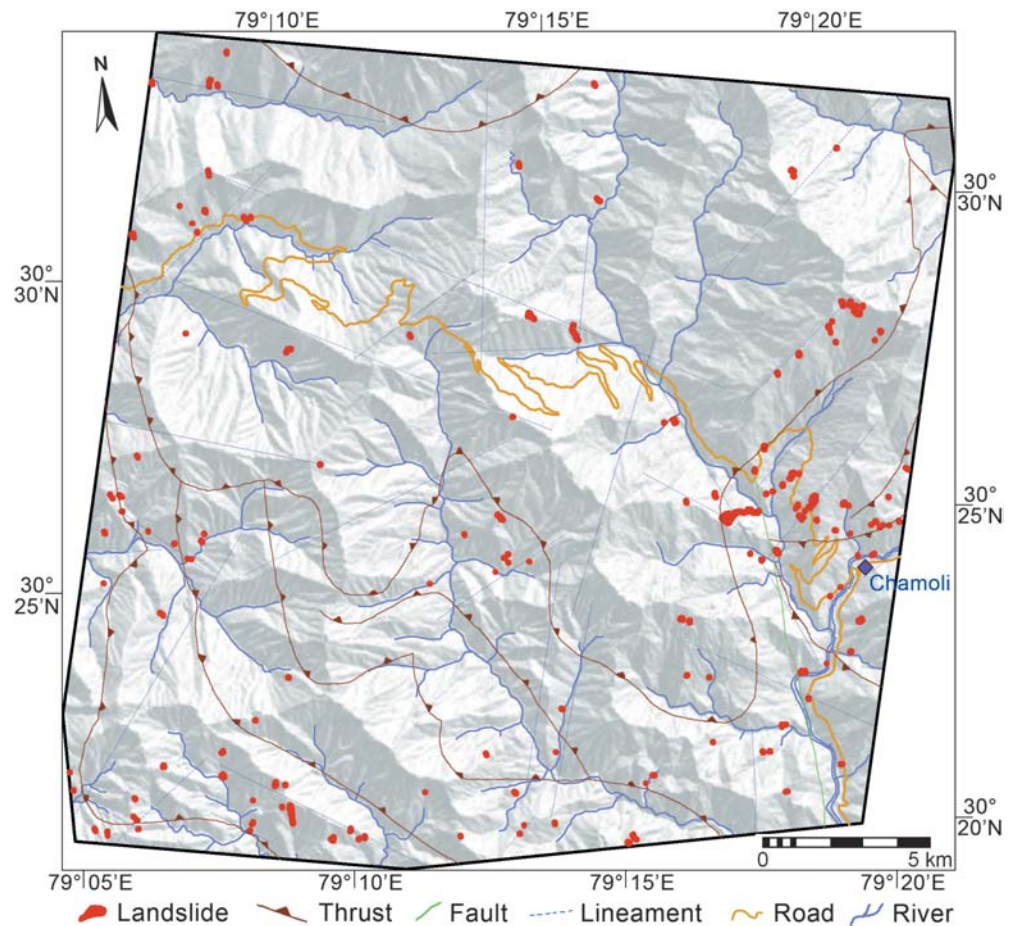
The high-resolution PAN image mentioned above for example can be used to identify and map existing landslides. On this image, landslides generally show scar and very light tones. In general, landslides in barren area can also be distinguished easily on raw images. Sometimes a simple digital image contrast stretching operation may be useful to highlight the landslides in barren areas. Besides, old landslides can be delineated on the basis of shape, landform characteristics and drainage. Moreover, PAN-sharpened multispectral image products are very useful to identify landslides, as they sharpen the boundary between stable and unstable slopes (for PAN-sharpening, see e.g., Welch and Ehlers 1987; Gupta 2003).

A total of 190 landslides of various dimensions ( $150 \text{ m}^2$ – $2 \text{ km}^2$ ) have been identified in the area using both PAN and the PAN-sharpened-LISS images. Many of the landslides have also been verified in the field. Figure 2 shows one of these landslides occurred near Gopeshwar (Fig. 1) in the eastern part of the study

Fig. 2 A typical landslide as identified from **a** IRS-PAN image and **b** the corresponding field photo (indicated by arrow)



**Fig. 3** Landslide distribution map and the tectonic structural features



area. Each landslide identified on the image has been digitized and later rasterized for further analyses.

#### DEM-based derivatives

A Digital Elevation Model (DEM) representing the terrain is a key to generate various topographic parameters, which influence the landslide activity in an area. Here, DEM has been prepared by digitizing contours at 40 m interval from the topographic map, interpolated and resampled to  $6 \times 6 \text{ m}^2$  pixel size. From this DEM, slope, aspect and relative relief thematic data layers have been prepared. Slope data layer, an important parameter in slope stability considerations, comprises of five classes (after Anbalagan 1992). Aspect is referred to as the direction of maximum slope of the terrain surface. It is divided into nine classes, namely, N, NE, E, SE, S, SW, W, NW and Flat ( $<5^\circ$ ). Relative relief data layer is formed from the difference in maximum and minimum elevation and is sliced into five classes at 30-m elevation difference.

#### Lithology

Lithology plays an important role in landslide activity. In this work, various rock formations in the study area have been grouped into five classes to prepare the lithology data layer. The five classes correspond to (a) schists and gneisses, (b) granite–granodiorite–gneiss, (c) quartzites with slates, (d) limestone with greywacke and (e) granites. The boundaries have been digitized from the geological map prepared by Valdiya (1980).

#### Tectonic structure

It is a common observation that landslide occurrence increases with proximity to tectonic structures (Fig. 3). Structurally, the study area is quite complex. Two major thrusts that pass through the area are the Main Central Thrust and the Vaikrita Thrust. Additionally, several faults and shear zones are known to traverse the area. IRS-LISS image interpretation indicates the presence of a number of lineaments in the region, which appear to have tectonic or neotectonic significance. These lineaments have been mapped and digitized to form a vector layer. On this vector layer, the traces of various tectonic structural features, viz. thrusts and faults have been superimposed, after which the vector layer has been converted into a raster layer. Subsequently, a distance function has been applied to define a buffer zone (0.5 km wide) to represent the area of influence of the structural tectonic features on the occurrence of landslides.

#### Drainage density

In mountainous regions, drainage density provides an indirect measure of groundwater conditions, which have an important role to play in landslide activity (Sarkar and Kanungo 2004). For this reason, the drainage map (scale 1:50,000) has been digitized, computed on a larger grid size of  $252 \times 252 \text{ m}^2$  and classified into three classes (low, medium and high) to generate the drainage density data layer.

**Table 2** Computed weights for classes of various thematic data layers based on landslide occurrences

Classes	Landslide (Pixel)	Area (Pixel)	LNSF weight	InfoVal weight (ln)
<b>(a) Slope</b>				
≤15°	1166	1899852	0.488	-0.219
16–25°	2462	4182712	1.031	-0.261
26–35°	3307	4286079	1.384	0.010
36–45°	2686	2821437	1.124	0.220
>45°	2325	2441452	0.973	0.220
<b>(b) Aspect</b>				
Flat	51	48558	0.038	0.318
NE	2188	2156835	1.648	0.283
E	1520	1794493	1.145	0.103
SE	2509	1986783	1.890	0.502
S	2532	2003484	1.908	0.503
SW	2015	2274792	1.518	0.148
W	563	1957136	0.424	-0.978
NW	274	1796658	0.206	-1.609
N	294	1612793	0.222	-1.431
<b>(c) Relative relief</b>				
≤30 m	2853	4557614	1.194	-0.200
31–60 m	5632	7753369	2.357	-0.051
61–90 m	2476	2318962	1.036	0.334
91–120 m	935	822424	0.391	0.397
>20 m	50	179163	0.021	-1.008
<b>(d) Lithology</b>				
Schist and gneiss	0	377411	0	-3.00 <sup>a</sup>
Granite–granodiorite–gneiss	3847	8763837	1.610	-0.555
Quartzite with slates	7066	4508249	2.957	0.718
Limestone and greywacke	0	64767	0	-3.00 <sup>a</sup>
Granite	1033	1917268	0.432	-0.350
<b>(e) Tectonic structure buffer</b>				
<504 m	9541	8156560	5.591	0.426
505–1,008 m	1984	4554560	1.163	-0.562
1,009–1,512 m	299	1996254	0.175	-1.630
1,513–2,016 m	122	724353	0.071	-1.514
2,017–2,520 m	0	149956	0	-3.00 <sup>a</sup>
2,521–3,024 m	0	49466	0	-3.00 <sup>a</sup>
3,025–3,528 m	0	383	0	-3.00 <sup>a</sup>
<b>(f) Drainage density</b>				
Low (≤310 m/m <sup>2</sup> )	10421	12654934	2.617	0.075
Medium (311–620 m/m <sup>2</sup> )	1236	2844048	0.310	-0.564
High (>620 m/m <sup>2</sup> )	289	132550	0.073	1.048
<b>(g) Landcover</b>				
Agricultural land	1830	1658013	1.379	0.367
Sparse vegetation	2082	2071261	1.569	0.274
Dense forest	685	9342146	0.516	-2.343
Settlements	861	232903	0.649	1.576
Water body	27	32679	0.020	0.078
Snow	2	39350	0	-2.703
Barren and fallow land	3806	2239843	2.867	0.799
Landslide debris	2608	10515	1.965	5.782
River sediments	45	4822	0.034	2.502

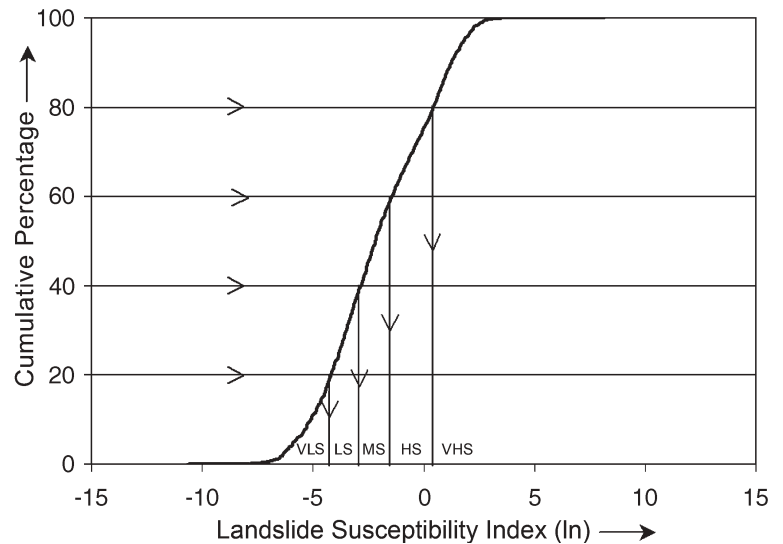
<sup>a</sup> Arbitrary value as filler

### Landcover

Landcover is also one of the key factors responsible for the occurrence of landslides, since, barren slopes are more prone to landslides. In contrast, vegetative areas tend to reduce the action of climatic agents such as rain etc. thereby preventing the erosion

due to the natural anchorage provided by the tree roots and, thus, are less prone to landslides. Based on the variation in the spectral response of various landcover classes as depicted on LISS image, nine classes have been considered that may have an impact on landslide activity in the region. These classes are dense forest,

**Fig. 4** Segmentation of LSI-values in InfoVal method (*VHS* very high susceptibility; *HS* high susceptibility; *MS* moderate susceptibility; *LS* low susceptibility; *VLS* very low susceptibility)



sparse vegetation, agricultural land, fallow-barren land, landslide debris, settlements, river sediments, water bodies and snow cover. The landcover data layer has been generated by employing multi-source image classification approach using four spectral bands (Green, Red, NIR and SWIR) of LISS image, Normalized Difference Vegetation Index (NDVI) image (generated from Red and NIR bands of LISS image) and the Digital Elevation Model. The Maximum Likelihood Classify has been used to classify the above data layers in a logical channel approach. The detailed methodology for the preparation of landcover map has been explained in Saha et al. (2004).

#### Data integration and analysis for LSZ

To evaluate the contribution of each factor towards landslide hazard, the existing landslide distribution data layer has been compared with various thematic data layers separately. The number of landslide pixels falling on each class of the thematic data layers has been recorded and weights have been calculated on the basis of both InfoVal (Eq. 1) and LNSF method (Eq. 2). These weights are given in Table 2. The weights are assigned to the classes of each thematic, respectively, to produce weighted thematic maps, which have been overlaid and numerically added according to Eq. (3) to produce a Landslide Susceptibility Index (LSI) map.

$$LSI = Sl + As + Rr + Li + St + Dd + Lu \quad (3)$$

where *Sl*, *As*, *Rr*, *Li*, *St*, *Dd* and *Lu* are distribution-derived weights for slope, aspect, relative relief, lithology, tectonic structure, drainage density and landcover respectively. Thus, two LSI maps corresponding to the InfoVal and LNSF methods have been prepared.

#### Segmentation of LSI values and generation of LSZ map

##### Information value method

The LSI values from the InfoVal method are found to lie in the range from  $-10.6643$  to  $8.1220$ . The cumulative frequency curve of LSI values has been segmented into five classes representing near-equal distribution to yield five landslide susceptibility zones, viz. very low, low, moderate, high and very high (Fig. 4).

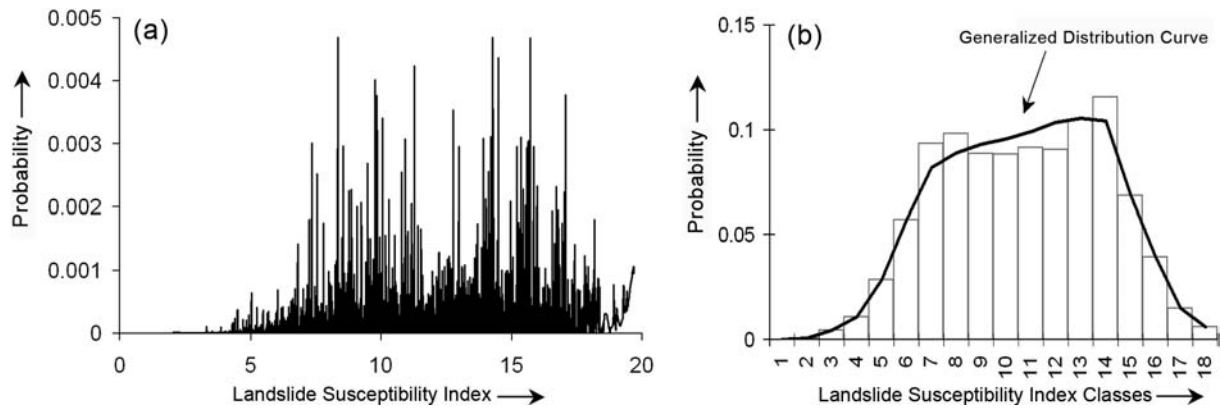
##### LNSF method

The conventional method employed to segment the LSI values for the demarcation of various susceptibility zones is often subjective. Since, the variations in weights and the respective central tendencies in thematic data layers are often large and random, we employ in this particular study, a new probabilistic approach for such segmentation. On the basis of the normalized frequency distribution of LSI values (that vary between 2.0319 and 19.6808), the probability of landslide occurrence attached to each value has been generated and depicted in Fig. 5a.

Figure 5a shows that in terms of their probability distribution, the LSI values can be classified into distinct clusters. We note that the clusters are randomly interspersed by spikes. These possibly are due to random errors in the raw data although the larger ones could represent outliers of the classes. To smoothen the effect of this randomness, the data has been sub-grouped into small and equal class-intervals and fitted to a best-fit curve (Fig. 5b). The curve is unimodal, negatively skewed and distinctly binomial. The mean ( $\mu_p$ ) and standard error ( $\sigma_p$ ) predicted from this best-fit probability distribution curve are given in Table 3. It is noteworthy that the predicted mean is equal to the observed mean and the predicted standard error is significantly less than the observed standard error. This implies that the best-fit curve derived from the proposed statistical procedure is quite reliable and accurate.

The LSI values have been segmented into five distinct classes with boundaries fixed at  $(\mu_p - 1.5m\sigma_p)$ ,  $(\mu_p - 0.5m\sigma_p)$ ,  $(\mu_p + 0.5m\sigma_p)$  and  $(\mu_p + 1.5m\sigma_p)$  where  $m$  is a positive, non-zero value. Based on a given LSZ map, the cumulative percentage of landslide occurrences in various susceptibility zones ordered from very high to very low can be plotted against the cumulative percentage of the area of the hazard zones. This curve, referred to as the success rate curve in the literature (Chung and Fabbri 1999; Lu and An 1999; Lee et al. 2002b), may be used to select the appropriate value of  $m$  decide the suitability of a particular LSZ map.

In this study, several LSZ maps and the corresponding success rate curves have been prepared for different  $m$  values. For the sake of brevity, we show here, in Fig. 6, three representative success rate curves corresponding to  $m=1.3$ , 1.4 and 2.0. The



**Fig. 5** a Frequency distribution curve of LSI values computed by LNSF method. b Curve fitting in LNSF method

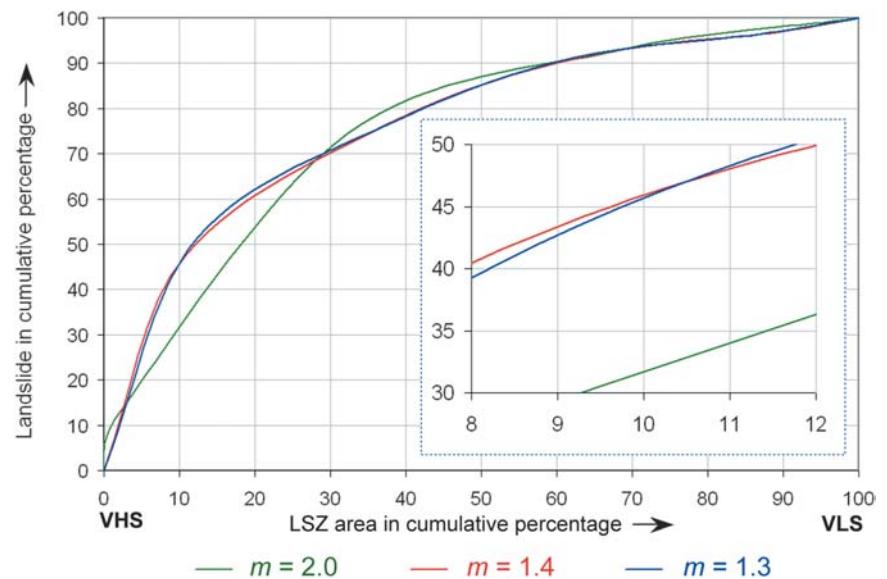
**Table 3** Statistical results for LSI-value segmentation in LNSF method

Observed mean ( $\mu_o = 12.26$ )
Observed standard error ( $\sigma_o = 3.22$ )
Number of classes made on probability distribution curve = 18
According to binomial distribution:
Predicted mean ( $\mu_p = 12.26$ )
Predicted standard error ( $\sigma_p = 1.98$ )

success of any LSZ operation can be judged by the measure that more number of landslides should fall in the very high LSZ as compared to other zones.

It can be seen from Fig. 6 that for 10% of the area, (i.e., in the very high susceptibility zone) the curves corresponding to  $m=1.3$ , 1.4 and 2.0 show the landslide occurrences of 45.5%, 46% and 32%, respectively; therefore for the first 10% of the area, the curve corresponding to  $m=1.4$  has the highest success rate. Considering further for 20% of the area, the corresponding landslide occurrences for these curves are 63%, 62% and 54%, respectively. Based on this analysis, the LSZ map corresponding to  $m=1.35 \pm 0.05$  appears to be most appropriate for the study area.

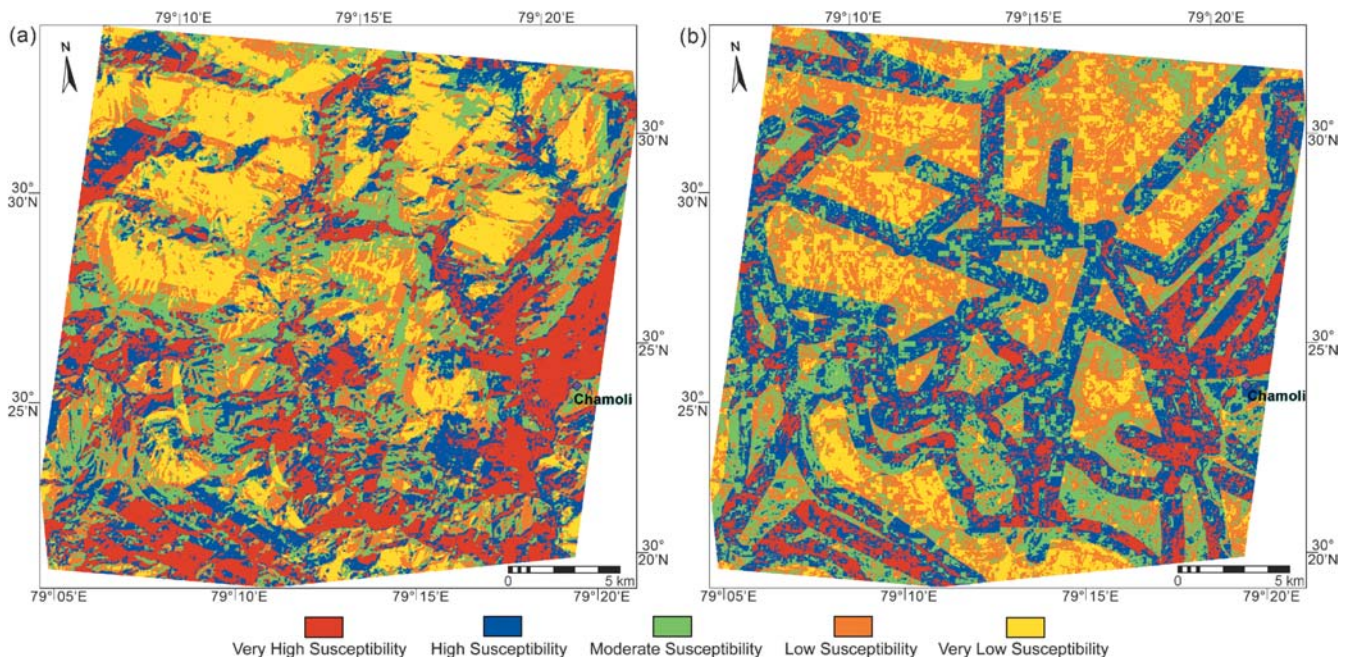
**Fig. 6** Success rate curves for choosing the best LSZ map in LNSF method



### Results and discussion

Figure 7a and b show the LSZ maps developed using the InfoVal and the LNSF methods, respectively. The following discussion provides a comparison of two methods, on the methodology of data processing, visual appearance of LHZ maps and their applicability in planning and developmental activities. The three major observations are:

1. The LSZ map is a result of a combination of various factors responsible for landslide susceptibility, where each factor has relative importance to a probable landslide activity. The structural discontinuities such as major faults, thrusts and lineaments have in general the most dominant impact on landslide occurrence along which landslide activity is likely to preferentially occur (Fig. 3). Owing to this susceptibility of the terrain, the buffer zones of structural discontinuities ought to leave some traces, called here as 'ghost-effect', on the LSZ map. These 'ghost-effects' can be clearly seen in LNSF method derived LSZ map (Fig. 7b). On the other hand, the LSZ map generated using InfoVal method does not show any 'ghost effect' and appears relatively homogeneous throughout the area



**Fig. 7** LSZ map generated using (a) InfoVal and (b) LNSF methods

thereby major influence of important structural zones and discontinuities (Fig. 7a).

- In the InfoVal method, there is a subjectivity in dividing the LSI values for generating LSZ map, as the method involves subdividing the cumulative frequency into five equal parts. This implies that each of the susceptibility zone possesses equal areas ( $\approx 20\%$ ), which is generally not the case in a geologically heterogeneous terrain such as the Himalayas. The proposed LNSF method based on a statistical criterion results in more logical boundaries of various susceptibility zones with different percentages of areas (e.g., very high (11%), high (28%), moderate (26%), low (26%), very low (10%)).
- The major application of LSZ maps is in disaster management and planning the developmental activities, which demands that the areas of very high susceptibility be properly demarcated. The very high susceptible zone in InfoVal method is 20%, which is quite high, whereas in LNSF-based LSZ map very high susceptibility zone is only 11% of the total area. Therefore, the output information, is more focused and can be of greater practical utility in landslide disaster management.

### Conclusions

Landslides cause enormous loss of life and property every year in mountainous areas. In such regions, landslide susceptibility zonation is very necessary with a view to delineate the disaster prone areas. Several methodologies have been suggested for landslide hazard/susceptibility zonation. The bivariate statistical methods are most suited for the regional-scale landslide susceptibility zonation. In such cases, remote sensing and GIS techniques can be very useful in data acquisition, processing, analysis and management.

In this study, we have applied two methods viz. InfoVal and LNSF for LSZ mapping in an area in the Himalayas and compared their results. It is observed that the LSZ map prepared from the

LNSF method is better than the one prepared by InfoVal method due to the following reasons: (1) It represents preferential distribution of higher landslide areas along structural discontinuities, which should indeed be the case, (2) It uses statistical basis of dividing the area into very high, high, moderate, low and very low susceptibility zones, and (3) It depicts a relatively small area (only 11% in LNSF as compared to 20% in InfoVal) being classed as VH susceptibility zone, which can be more meaningful for practical applications.

### Acknowledgements

A. K. Saha is grateful to the Council of Scientific and Industrial Research (CSIR), New Delhi, India, for Senior Research Fellowship. He is also thankful to German Academic Exchange Service (DAAD), Bonn for the award of DAAD Sandwich Fellowship, during which a part of this work was carried out at the Institute of Photogrammetry and Remote Sensing, Dresden University of Technology, Germany. Thanks are due to Dr. L. Ayalew, Department of Environmental Science, Niigata University, Japan and Dr. R. Anbalagan, Department of Earth Sciences, IIT Roorkee, India, for their valuable comments.

### References

- Aleotti P, Chowdhury R (1999) Landslide hazard assessment: summary review and new perspectives. *Bull Eng Geol Environ* 58:21–44
- Anbalagan R (1992) Landslide hazard evaluation and zonation mapping in mountainous terrain. *Eng Geol* 32:269–277
- Arora MK, Das Gupta AS, Gupta RP (2004) An artificial neural network approach for landslide hazard zonation in the Bhagirathi (Ganga) Valley, Himalayas. *Int J Remote Sens* 25:559–572
- Ayalew L, Yamagishi H, Ugawa N (2004) Landslide susceptibility mapping using GIS-based weighted linear combination, the case in Tsugawa area of Agano River, Niigata Prefecture, Japan. *Landslides* 1:73–81
- Bughi S, Aleotti P, Bruschi R, Andrei G, Milani G, Scarpelli G (1996) Slow movements of slopes interfering with pipelines: modelling vs. monitoring. In: *Proc 15th Int Conf OMAE, Firenze*

- Capechi F, Focardi P (1988) Rainfall and landslides: research into a critical precipitation coefficient in an area of Italy. In: Proc 5th Int Symp on Landslides, Lausanne, Switzerland 2:1131–1136
- Carrara AM, Cardinali M, Detti R, Guzzetti F, Pasqui V, Reichenbach P (1991) GIS techniques and statistical models in evaluating landslide hazard. *Earth Surf Process Landforms* 16:427–445
- Chung C-JF, Fabbri AG (1999) Probabilistic prediction models for landslide hazard mapping. *Photo Eng Remote Sens* 65:1389–1399
- Elias PB, Bandis SC (2000) Neurofuzzy systems in landslide hazard assessment. In: Proc 4th Int Symp Spatial Accuracy Assessment in Natural Resources and Environ Sci, pp 199–202
- Gupta RP (2003) Remote sensing geology. Springer, Berlin Heidelberg New York, 655 pp
- Gupta RP, Joshi BC (1990) Landslide hazard zonation using the GIS approach – a case study from the Ramganga Catchment, Himalayas. *Eng Geol* 28:119–131
- Gupta RP, Saha AK, Arora MK, Kumar A (1999) Landslide hazard zonation in a part of the Bhagirathi Valley, Garhwal Himalayas, using integrated remote sensing- GIS. *Himalayan Geol* 20:71–85
- Lee S, Choi J, Chwae U, Chang B, (2002a) Landslide susceptibility analysis using weight of evidence. In: Proc IEEE Int Geosci Remote Sens Symp, Toronto (CD-ROM)
- Lee S, Choi J, Min K (2002b) Landslide susceptibility analysis and verification using the Bayesian probability model. *Environ Geol* 43:120–131
- Lu PF, An P (1999) A metric for spatial data layers in favorability mapping for geological events. *IEEE Tran Geosci Remote Sens* 37:1194–1198
- Mantovani F, Soeters R, van Westen CJ (1996) Remote sensing techniques for landslide studies and hazard zonation in Europe. *Geomorph* 15:213–225
- Nagarajan R, Mukherjee A, Roy A, Khire MV (1998) Temporal remote sensing data and GIS application in landslide hazard zonation of part of Western Ghat, India. *Int J Remote Sens* 19:573–585
- Okimura T, Kawatani T (1986) Mapping of the potential surface-failure sites on granite mountain slopes. In: Gardiner V (ed) *Int Geomorph Part I*. Wiley, New York, pp 121–138
- Ravindran KV, Philip G (1999) 29 March 1999 Chamoli earthquake: a preliminary report on earthquake-induced landslides using IRS-1C/1D data. *Current Sc* 77:21–25
- Saha AK, Gupta RP, Arora MK (2002) GIS-based landslide hazard zonation in the Bhagirathi (Ganga) Valley, Himalayas. *Int J Remote Sens* 23:357–369
- Saha AK, Arora MK, Csaplovics E, Gupta RP (2004) Land cover classification using IRS LISS III imagery and DEM in a rugged terrain: a case study in Himalaya. *GeoCarto Int* (revised and sent)
- Sarkar S, Kanungo DP (2004) An integrated approach for landslide susceptibility mapping using remote sensing and GIS. *Photo Eng Remote Sens* 70:617–625
- Valdiya KS (1980) Geology of Kumaun Lesser Himalaya. Wadia Inst of Himalayan Geol, Dehra Dun, 292 pp
- van Westen CJ (1997) Statistical landslide hazard analysis. In: Application guide, ILWIS 2.1 for Windows. ITC, Enschede, The Netherlands, pp 73–84
- van Westen CJ (1994) GIS in landslide hazard zonation: a review, with examples from the Andes of Colombia. In: Price M, Heywood I (eds) *Mountain environments and geographic information system*. Taylor and Francis, Basingstoke, UK, pp 135–165
- Varnes DJ (1984) Landslide hazard zonation: a review of principles and practice. UNESCO, Paris, pp 1–63
- Welch R, Ehlers M (1987) Merging multiresolution SPOT HRV and Landsat TM data. *Photo Eng Remote Sens* 53:301–303
- Wieczorek GF (1984) Preparing a detailed landslide-inventory map for hazard evaluation and reduction. *Bull Assoc Eng Geol* 21:337–342
- Yin KL, Yan TZ (1988) Statistical prediction model for slope instability of metamorphosed rocks. In: Proceedings of 5th Int Symp on Landslides, Lausanne, Switzerland 2:1269–1272

**A. K. Saha · R. P. Gupta** (✉) · **I. Sarkar**

Department of Earth Sciences,  
Indian Institute of Technology Roorkee,  
Roorkee, 247667, India  
e-mail: rpgesfes@iitr.ernet.in  
Fax: +91-1332-273560

**M. K. Arora**

Department of Civil Engineering,  
Indian Institute of Technology Roorkee,  
Roorkee, 247667, India

**E. Csaplovics**

Institute of Photogrammetry and Remote Sensing,  
Dresden University of Technology,  
01062 Dresden, Germany