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Evaluation and Validation of Landslide Spatial Susceptibility in the Western Ghats of Kerala, through GIS-based Weights of Evidence Model and Area under Curve Technique

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Abstract: Landslide susceptibility mapping and spatial prediction have been carried out for the headwater region of Manimala river basin in the Western Ghats of Kerala, India, through geographic information technology and bayesian statistics, Weights of Evidence (WofE) model. The variables such as geomorphology, slope, relative relief, terrain curvature, slope length and steepness, soil type and land use/land cover are considered as factors that translate the terrain susceptible to landsliding. The quantitative relationship between landslides and the causative factors were statistically weighted using the ArcSDM extension of ArcGIS software. The posterior probability map, produced on the basis of predictive weights for each variable by combining the weighted layers in GIS, shows a high posterior probability value of 0.1 (highly possible) with a standard deviation of 0.0025. The discrete susceptibility classes in the reclassified posterior probability map reveals that the high and moderate landslide susceptibility classes cover 0.78 and 14.93% respectively of the total study area. The result was validated using the Area Under Curve (AUC) method with a separate set of landslide locations and the validation demonstrates high prediction accuracy with a prediction rate of 81.32%.

Keywords: Landslide susceptibility, GIS, Weights of Evidence, Posterior probability, Area Under Curve, Manimala river basin, Kerala.

INTRODUCTION

Prediction of landslides, the major catastrophic hydro-geological hazard, has been receiving renewed interest, mainly due to the socio-economic impacts of the increasing pressure of urbanization on the mountain environment (Corominas et al. 2003; Akgun et al. 2008; Kanungo et al. 2009; Kouli et al. 2009; Magliulo et al. 2009). Landslides affect large parts of the hilly terrain in India, especially, the Himalayas, the Western Ghats, the Eastern Ghats and the Vindhyans (NDMD, 2004). Deforestation and anthropogenic activities, together, with the unsustainable developmental projects and destructive practices, have recently increased the frequency of landslides and mass wasting in the Himalayas and the Western Ghats regions, necessitating predictive and mitigative measures. Mitigation of landslides mainly depends on risk reduction by systematic mapping and scientific analysis of landslide susceptible areas. However, such an approach is based on the assumption that future landslides occur under similar conditions as those observed in the past (Saha et al. 2005: Wang and Sassa, 2005: Clerici et al. 2006; Chen and Wang, 2007; Pandey et al. 2008).

Landslide prediction models, in general, classify the area into different zones of varying degrees of landslide susceptibility, based on an estimated influence of causative factors in landslide occurrences (Zezere, 2002; Ayalew et al. 2004; Brenning, 2005; Lee and Sambath, 2006; Jadda et al. 2009; Kanungo et al. 2009). Therefore, the determination of the relative importance of various categories of causative factors, using different types of analytical and assessment techniques, is the basic pre-requisite for landslide susceptibility modeling. The successful adaptation of bayesian formulas for arriving at the predictive models of mineral prospecting has extended their application to landslide prediction also (Bonham-Carter et al. 1988; Lee et al. 2002; Raines and Mihalasky, 2002; Carranza, 2004; Phi and Bac, 2004; Zahiri et al. 2006; Mathew et al. 2007). The advancements in the spatial data technology have led to the effective application of quantitative techniques in the development of probablistic frame work for predictive modeling and simulation of landslides (Aleotti and Chowdhury, 1999; Guzzetti et al. 1999; van Westen, 2000; Brenning, 2005; Huabin et al. 2005; van Westen et al. 2006). Among the techniques, Geographical Information System (GIS) based statistical analysis is generally considered as the most appropriate approach for landslide hazard mapping at larger and medium scales (Guinau et al. 2007; Hong et al. 2007; Magliulo et al. 2009; Pradhan and Lee, 2010).

The present paper demonstrates the application of bivariate bayesian probability model known as Weights of Evidence (WofE) based on GIS techniques, to produce a landslide susceptibility zonation map for a part of the western slopes of Western Ghats in Kerala, South India. This study also attempts to validate the applicability of the model and the reliability of the resultant landslide susceptibility zonation map in a highly undulating mountainous terrain.

STUDY AREA

Landslide evaluation and mapping have been carried out in an area of 193.30 km^2 in the eastern border of Kottayam district, Kerala, India, forming the headwater region of Manimala river basin in the western slope of the Western Ghats, a typical hilly landscape with narrow and steep valleys (Fig.1). The area forms the Koottickal, Kokkayar and Peruvanthanam villages and falls between North latitudes 9°28'00" to 9°40'00" and East longitudes 76°50'08" to 77° 02'00", with the elevation varying between 80 m and 1350 m above the mean sea level and an average slope of 20°. Geologically the region forms a part of the south Indian shield and is composed of Precambrian crystalline rocks. Charnockite is the dominant rock type followed by biotite gneiss and younger dolerite dykes. The lithological units, except the younger intrusives, are subjected to medium to high grade metamorphism and deformation resulting in well developed gneissic fabric. The study area, at many places, is covered by soil and is characterized by rugged hills with steep long side slopes on which rests the loose, unconsolidated soil and earth materials that have suffered considerable damage due to landslides. The area, as many other regions in the flanks of the Ghats, also has been affected by repeated landslides (debris flow), most of them signifying a climatic signal. Monsoon (June–November) rainfall-induced debris flow from the steep slopes of the mountain ranges occur every year, after continuous rainfall exceeding 300mm per day, causing damage to agriculture. Quantitative analysis of spatial datasets on landslides of the area is attempted to evaluate and predict the landslide susceptibility

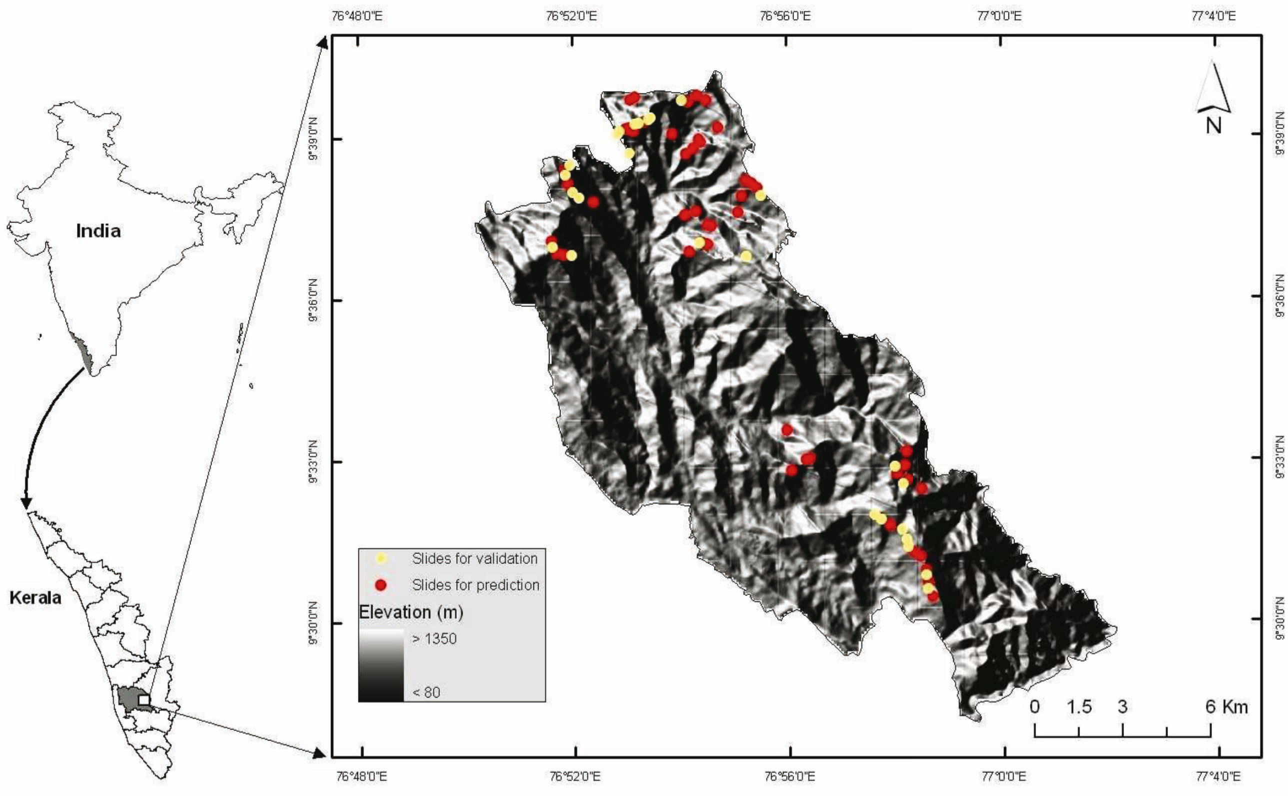

Fig.1. Location map.

areas with a view to reduce landslide-risk, employing suitable mitigation measures.

METHODOLOGY

Landslide susceptibility assessment was carried out with data-driven predictive bayesian statistical method known as Weights of Evidence (WofE) modeling. The WofE approach was initially developed for non-spatial applications in medical diagnosis, in which evidence in the form of clinical symptoms was weighted and combined to predict a patient's disease. In the late 1980s, the potential of this approach for spatial applications was recognized and WofE was implemented for mineral potential mapping in a GIS environment (Bonham-Carter et al. 1988, 1989; Raines, 1999; Harris et al. 2001; Raines and Mihalasky, 2002; Carranza, 2004). Since then, WofE has also been used in other areas of spatial data analysis, including the assessment of landslide susceptibility (Lee et al. 2002a, 2002b; van Westen et al. 2003; Lee and Choi, 2004; Phi and Bac, 2004; Thiery et al. 2004; Zahiri et al. 2006; Dahal et al. 2007; Mathew et al. 2007; Masetti et al. 2007; Moghaddam et al. 2007; Neuhauser and Terhost, 2007; Poli and Sterlacchini, 2007; Thiery et al. 2007; Tissari et al. 2007; Dahal et al. 2008; Sharma and Kumar, 2008; Barbieri and Cambuli, 2009).

Weights of evidence model is a log-linear form of bayes rule to predict a hypothesis about occurrence of an event, based on the incorporation of known evidence in a study area, where sufficient data are available to estimate the relative importance of each evidence by statistical methods (Zahiri et al. 2006; Poli and Sterlacchini, 2007). Based upon a bayesian probability framework, the WofE approach works on the basic premise that the probability of an event (e.g., landslides) occurring at a particular location in a study area, can be calculated by updating the event's prior probability of occurrence in the study area using measures of spatial association between known event occurrences and evidential or predictive maps (Bonham-Carter, 1994; Kemp et al. 2001). The method calculates the weight for each predictive factor based on the presence (positive) or absence (negative) of the training point theme units (D) within the area of each binary predictor theme (B), as indicated in Bonham-Carter et al. (1989):

$$W^{+} = ln\ \frac{P(B/D)}{P(B/\bar{D})} \tag{1}$$

$$W^{-} = ln\ \frac{P(\bar{B}/D)}{P(\bar{B}/\bar{D})} \tag{2}$$

where P is probability and *ln* is the natural log. B = presence of a potential landslide conditioning factor, $\bar{B}$ = absence of a potential landslide conditioning factor, D = presence of a landslide, and $\bar{D}$= absence of a landslide. For each factor, W^{+} is used for those pixels of a factor to indicate the importance of the presence of the factor for the occurrence of landslides. If W^{+} is positive the presence of the factor is favourable for the occurrence of landslides, and if W^{+} is negative it is not favourable. W^{-} is used to evaluate the importance of the absence of the factor for the occurrence of landslides. When W^{-} is positive the absence of the factor is favourable for the occurrence of landslides, and when it is negative, the factor is non-favourable. Weights with extreme values indicate that the factor is useful for the susceptibility mapping, while factors with a weight around zero have no relation with the occurrence of landslide. The difference between the two weights is known as the contrast, C ($C = W^{+} - W^{-}$); the magnitude of which reflects the overall spatial association between the evidential theme and the training points (Bonham-Carter et al. 1989). More details about the WofE method can also be found in Bonham-Carter et al. (1988); Raines (1999); Kemp et al. (2001); Carranza (2004); Sawatzky et al. (2004); Poli and Sterlacchini (2007). The ArcSDM extension was used in this study as a tool for automatically calculating the W^{+}, W^{-} and the statistical significance of each parameters are discussed in the analysis section.

Data Variables

Detailed mapping of landslide susceptibility zones in the study area was carried out with emphasis on recognizing factors that caused instability of the slope and associated failure. In the present study, a set of seven independent geo-environmental variables, viz., geomorphology, slope, relative relief, terrain curvature, slope length and steepness (LS), soil type and land use/land cover, derived from the Survey of India (SoI) topographic maps (scale 1:50,000) and remote sensing data were used. The most important layer that represents previous slide locations was prepared from a series of field surveys. A total of 76 landslides of various dimensions were identified in the study area and their initiation points were mapped. The landslide data set were randomly divided in two parts and 50 cases were used to assess the statistical relationship between the landslide causative variables and 26 cases were kept for validating the Landslide Susceptibility Zonation (LSZ) map. In order to make uniformity among the data resolution, all the derived parameters were scaled to a pixel size of 20 m^2, which is nearly comparable to the spatial resolution of satellite image and contour interval of SoI toposheet, from which the digital elevation model (DEM) was derived. The vast majority of the landslides in the study area are triggered by torrential and lasting rainfall events and in the present study the effect of rainfall on triggering landslides in the area was not statistically determined, considering uniform rainfall within the limits of the area.

A digital elevation model, which portrays accurate representation of land surface, was derived by digitizing contours at 20m interval from the SoI topographic map. These digitized contours were then interpolated to and resampled to $20m^2$ pixel size. The geomorphological features of the study area were derived by compiling the information from topographic map, satellite image (IRS P6 LISS III) and digital elevation model. Seven geomorphological features, viz., plateau, side slope plateau, denudational hill, denudational slope and broad valleys were identified and demarcated for the study area. The important terrain variables like slope, relative relief, terrain curvature, slope length and steepness factors were computed from the digital elevation. The slope of a surface refers to the maximum rate of change in elevation values across a region of the surface. The calculated slope of the study area shows a maximum of 64° and was regrouped into seven distinct classes of slope corresponding to their influence on terrain instability. Relative relief of the area portrays the difference between the highest and lowest points in a unit area and the relative relief map of the area shows a range between 28 – 782 m/km^2 and is grouped into five different classes, which represent different elevation zones. The terrain curvature is an important variable that controls the erosion and deposition rate of the terrain and is classified into concave, flat and convex curvatures. The LS factor of the area was also calculated and reclassified into three groups as it specifies the effects of topography on runoff velocity and erosion.

Soil depth, texture and moisture are the factors that contribute to the initiation of landslides. In the present analysis the soil type map was extracted from the soil data base of the National Bureau of Soil Survey and Landuse Planning (NBSSLUP 1999) and the vector map, produced by the digitization process, was converted to a raster image for subsequent analyses. The soil type map indicates four major types dominated by clay, loam, gravelly clay loam and gravelly clay. Vegetation cover is an important factor influencing the occurrence and movement of rainfall-triggered landslides and hence the changes in vegetation cover often result in modified landslide behaviour. Land use/land cover of the area was generated, by considering the role of vegetation in stability of slope, from the IRS P6 LISS III data of 23.5 m resolution. The land use/land cover types that can be identified in the area include rubber, cardamom, coffee, grass land, barren land, rocky out crop, tea plantation, cleared area, crop land, built-up-land, forest, forest plantations, mixed crop and water body.

WofE Analysis and Discussion of Factor Effect

The spatial association between the known landslide locations and the causative factors were determined using the Grand Weights of Evidence (GWofE) analysis techniques in the ArcSDM extension of ArcGIS software. The Grand WofE includes the calculation of weights as well as the generalization of the evidence and then the calculation of the WofE response rasters on every combination of valid weights tables for one or more evidence layers. While running the Grand WofE model in the ArcSDM extension, it will automatically calculate the statistical significance of each evidential themes by assessing the parameters such as: (1) area of each class in individual theme; (2) number of slides present in each class; (3) positive and negative weights (W^+ and W^-); (4) standard deviation of positive and negative weights; (5) contrast value (C); (6) standard deviation of contrast value and (7) studentized contrast ie, the contrast divided by its standard deviation (Stud(C)), which is used as a measure of significance of the contrast because of the uncertainties in the weights. The feature classes which have shown a strong predictive pattern were selected based on calculated positive weights and contrast values and are presented in Table 1.

The statistically assessed relationship between landslide occurrence and geomorphology indicates that among the five feature classes, denudational hills and side-slope plateau show maximum predictive contrast and probability towards the landslide susceptibility. In the case of slope, gentle slopes have a low frequency of landslides because of the generally lower shear stresses. The weighted contrast values for the slope between 25° - 35° is 1.427 and for the slope >45° is 1.899 and indicate strong probability of landslide occurrence. With respect to the relationship between landslide occurrence and relative relief, it is observed that the landslide frequency generally increases as the relief increases. In the present analysis, two distinct relative relief classes, that range between 400-600 m/km^2 and >700 m/km^2 showing the maximum predictive contrast values of 1.149 and 1.841 respectively, indicate high probability of landslide occurrence. The curvature values represent terrain morphology where the positive curvature indicates that the surface was upwardly convex at that grid while the negative curvature typifies concave surface at that grid. A value of zero implies flat surface. The estimated weighted contrast shows high probability values of 0.629

Table 1. Feature classes, identified as strong landslide predictor evidence class through WofE analysis

Theme	Class	Area (km^2)	Slides	W^+	$s(W^+)$	W^-	$s(W^-)$	Contrast	s(C)	stud(C)#
Curvature	Flat	20.398	9	0.541	0.333	-0.087	0.156	0.629	0.368	1.709
	Concave	88.518	30	0.277	0.182	-0.310	0.223	0.587	0.288	2.035
Geomorphology	Denudational hill	63.071	28	0.547	0.189	-0.429	0.213	0.977	0.284	3.429
	Side slope plateau	34.490	21	0.863	0.218	-0.349	0.185	1.213	0.286	4.234
Land use	Coffee	1.162	2	1.902	0.707	-0.034	0.144	1.937	0.722	2.682
	Mixed crops	17.640	10	0.791	0.316	-0.128	0.158	0.919	0.353	2.601
	Barren rock	6.058	3	0.656	0.577	-0.030	0.145	0.686	0.595	1.152
	Forest (degraded)	41.289	14	0.277	0.267	-0.090	0.166	0.367	0.315	1.167
	Grass land	0.486	1	2.082	1.000	-0.017	0.142	2.099	1.011	2.076
Relative relief	400-600m/km^2	46.851	25	0.731	0.200	-0.418	0.200	1.149	0.282	4.063
	> 700m/km^2	0.629	1	1.824	1.000	-0.017	0.142	1.841	1.010	1.821
Slope	25°-35°	42.791	27	0.899	0.192	-0.528	0.208	1.427	0.283	5.030
	35°-45°	7.270	4	0.762	0.500	-0.045	0.147	0.807	0.521	1.548
	>45°	0.593	1	1.882	1.000	-0.017	0.142	1.899	1.010	1.878
Soil type	Clay	41.371	15	0.344	0.258	-0.117	0.169	0.462	0.308	1.497
	Gravelly clay loam	41.946	22	0.713	0.213	-0.337	0.189	1.051	0.284	3.688
LS factor	5-15	90.498	37	0.465	0.164	-0.722	0.277	1.187	0.322	3.682

W^+ & W^- - positive and negative weights; $s(W^+)$ & $s(W^-)$ - standard deviation of positive and negative weights; s(C) - standard deviation of contrast value; stud(C) - studentized contrast

and 0.587 respectively for flat and concave curvature areas. The slope length and steepness (LS) factor is powerful predictor of soil retention on a slope. While assessing the relationship of LS factor with landslides in the study area, it is observed that the LS class of 5-15 shows a maximum contrast of 1.187 indicating a very high probability of landslide susceptibility.

The predictive probability factor analysis carried out with soil type and landslide locations indicates more number of landslide locations in gravelly clay loam and clay soil. Gravelly clay loam which covers 21% of the total study area has higher contrast value of 1.051 and suggests a strong probability of landslide occurrence followed by clay soil with a contrast value of 0.462. The land use/land cover layer was crossed with the landslide location, in order to identify the feature, which could be the control of the landslide activity in the study area. It is significant that high weighted contrast values were observed for the mixed crop, coffee plantations and grass land areas, indicating a high probability of landslide occurrence.

The final posterior probability map was generated by running the Grand Weights of Evidence tool in the ArcSDM by specifying evidential rasters with its data type and the point features to be used for the prediction. The themes can be integrated together to find the combined influence of the different input parameter classes. The posterior probabilities of each unique combination of input parameter classes were estimated and the result has been drawn. The calculated posterior probability raster (Fig. 2) was classified following the standard classification techniques, which shows a posterior probability class of impossible (0) to highly possible (0.1) and concentration of possible zones of landslide occurrence are along the eastern part of the study area.

Validation of Results

The Grand WofE module in the ArcSDM was used to generate the final posterior probability raster, which portrays the landslide susceptibility of the terrain under study. The posterior probability raster values are segmented into four discrete classes to yield four landslide susceptibility zones, viz. stable, very low susceptibility, moderately susceptible and highly susceptible (Fig. 3) and the areas under each category are presented in Table 2. The result shows that the highly susceptible zone is occupied by 0.78% of the total area with a northwest – southeast trend and patchy in nature, mainly representing the side slope plateau regions with very high slope. Moderately susceptible zone covers 14.93% of

Table 2. Landslide susceptibility classes and area covered

Landslide susceptibility class	Area (km^2)	Area (%)	Range of weighted posterior probability value	Landslide used for validation (%)
Stable	117.38	60.72	0 – 0.0001	0.0
Low susceptibility	45.55	23.57	0.0001 – 0.001	19.24
Moderate susceptibility	28.87	14.93	0.001 – 0.01	57.69
High susceptibility	1.50	0.78	0.01 – 0.1	23.07

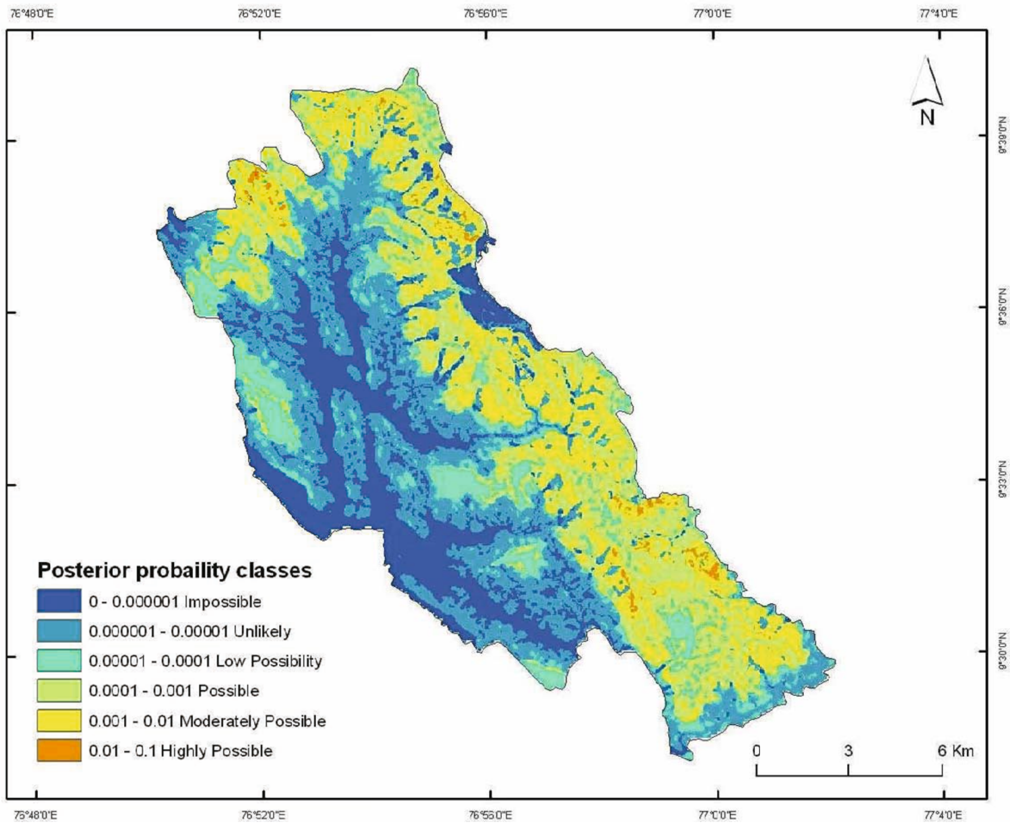

Fig.2. Posterior probability map showing areas with high probability of landslide occurrence.

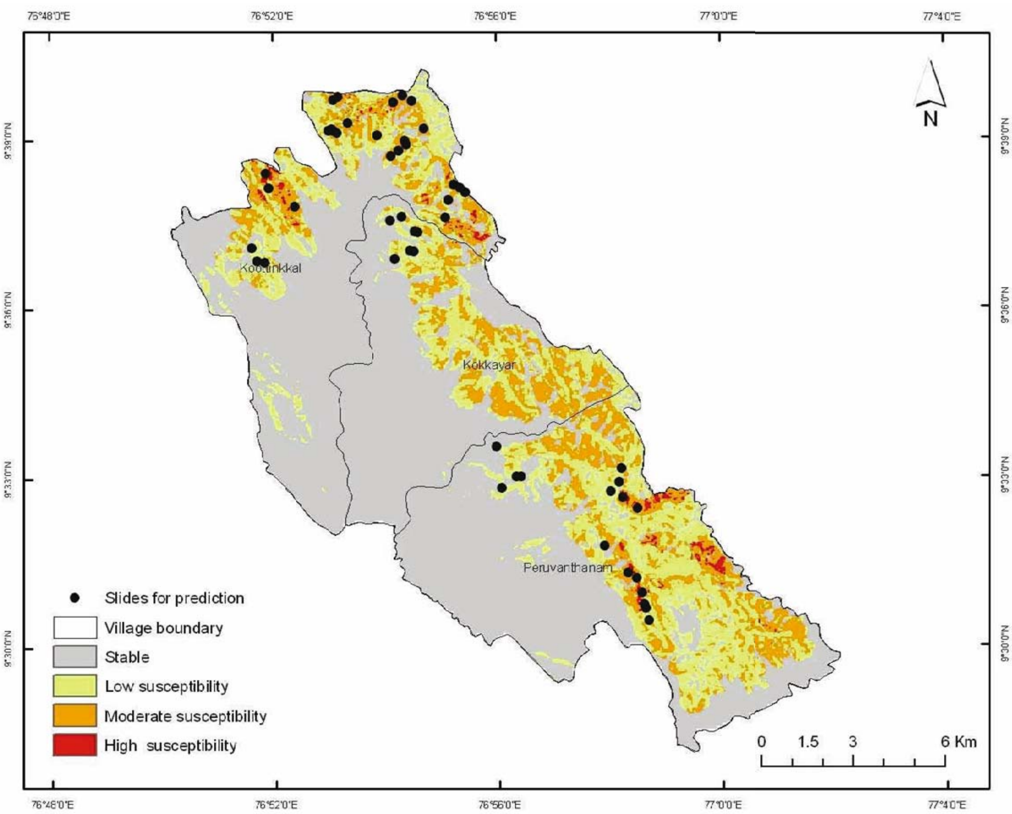

Fig.3. Classified landslide susceptibility zonation map.

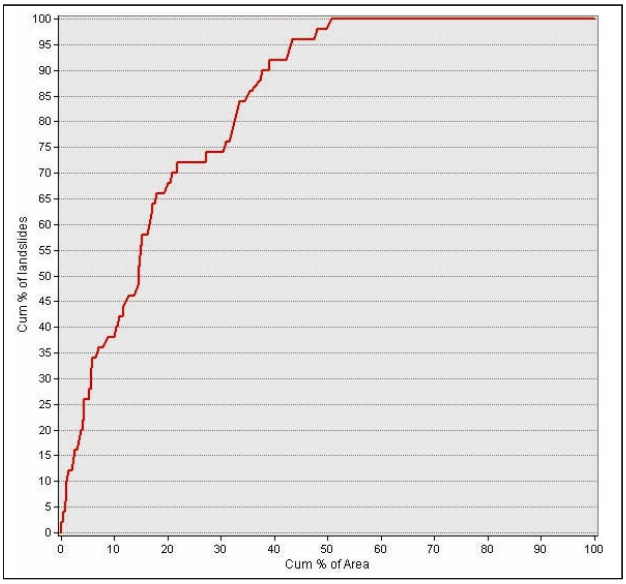

Fig.4. Area-frequency graph showing accuracy of efficiency.

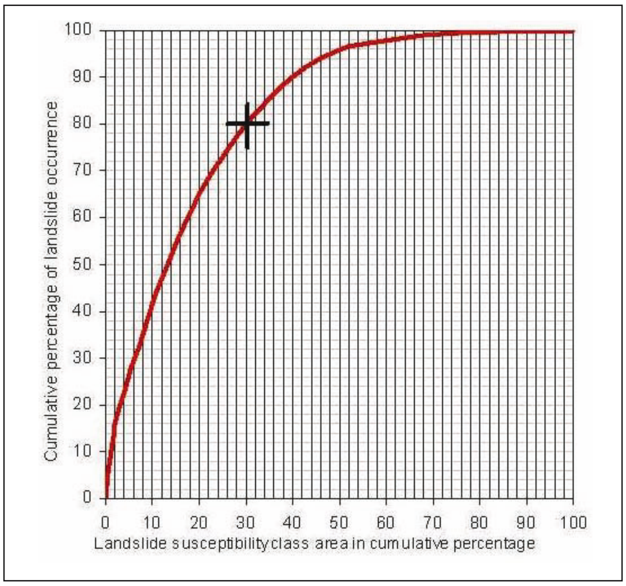

Fig.5. Prediction performance of the WofE model classification.

the total area. This zone is marked by the presence of contact between the side slope plateau and denudational hills with highly undulating terrain where more intense terrain modification is taking place. The low landslide susceptible area occupies 23.57% of the total area and shows influence of almost all the factors considered for the analysis. About 60.72% of the total area comes under the stable zone, where the terrain is well managed with low terrain undulations and slope.

The efficiency of the present model and the validity of the derived landslide susceptibility map were assessed using two different techniques. The efficiency of the model was assessed by testing the efficiency of classification of the training points using the area frequency tool. The area frequency tool uses cumulative percentage of area in the x-axis and cumulative percentage of landslides in the y-axis to draw the classification vs. efficiency graph (Fig. 4). Using this graph the efficiency area under curve was calculated and for the present model, it shows the area as 0.831 which means 83.10% of efficiency classification accuracy. The second method prediction rate curve technique was used to validate the result of reclassified landslide susceptibility map. To compare the results quantitatively, the areas under the curve were re-calculated to the total area as one, which means perfect prediction accuracy (Fig.5). The area under the prediction rate curve was estimated using the 26 validation set of landslides and it showed an area ratio of 0.8132 and the success rate of the landslide susceptibility map thus prepared was 81.32%.

CONCLUSION

The landslide susceptibility mapping of a selected portion of the Western Ghats of Kerala, India, was carried out by bayesian statistical method using the ArcSDM extention of ArcGIS software. The analysis of the relationship between previous landslide events and the contemplated causative factors, using the Grand WofE method, facilitates division of the area into stable (60.72%), low (23.57), moderate (14.93%) and high (0.78%) landslide susceptibility zones, based on the posterior probability values. The analysis also revealed that more number of previous landslide events was reported from the area under moderate susceptibility zone. The two-way method of validation of landslide susceptibility map, using the efficiency accuracy classification curve and AUC methods quantitatively represent high degree of accuracy (> 80%) of the analysis and this endorses the scalability of the proposed methods and classification scheme to similar regions. The resultant landslide susceptibility zonation map can be used to augment slope management and land-use planning on a regional scale.

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ANNOUNCEMENTS

NATIONAL SEMINAR ON GEOLOGICAL RESOURCE ASSESSMENT AND DEVELOPMENTAL PERSPECTIVE

The above seminar is being organized by the P. G. Department of Geology, Utkal University in collaboration with its Alumni Association on 27 January 2013 at Bhubaneswar. For details, please contact Prof. R.N. Hota, Organising Secretary, P.G. Department of Geology, Utkal University, Vani Vihar, Bhubaneswar – 751 004, Odisha; **Phone:** (0674) 2567488 (O); (0674) 2567183 (R); 9437176486 (Mobile); **E-mail:** rnhota@yahoo.com

NATIONAL SEMINAR ON SYNERGY OF GEOCHEMISTRY, GEOLOGY, GEOPHYSICS TOWARDS ENVIRONMENT AND HEALTH AND AGM – 2013 OF ISAG

The Indian Society of Applied Geochemists (ISAG), is organizing jointly the Annual General Body Meeting (AGM-2013) and the above national seminar sponsored by Department of Geology, University of Pune, Pune, during 14 -15, February 2013. For further details, please contact Prof. Suryaprakash Rao, E-mail: isag1993@yahoo.co.in ksprao1939@yahoo.co.in or Nitin Karmalkar, **E-mail:** nrkarmalkar@gmail.com