RESEARCH ARTICLE

Landslide Susceptibility Mapping Using Remotely Sensed Data through Conditional Probability Analysis Using Seed Cell and Point Sampling Techniques

Evangelin Ramani Sujatha · P. Kumaravel · Victor Rajamanickam G

Abstract Rapid urbanization, intense infra-structure development and increased tourism related activities have resulted in the change of landscape of the Kodaikkanal town and its surrounding, a popular hill town in Tamilnadu, South India. As an after effect, the numbers of landslides and rock-falls have increased steadily in the past decade. Landslide susceptibility analysis is carried out for this area using conditional probability analysis. The geo-spatial database for mapping landslide susceptibility consists of the factors - Relief, Slope, Aspect, Curvature, Weathering, Land use, Topographic Wetness Index and Proximity to road. Two sampling strategies – point and seed-cell are compared for landslide susceptibility mapping. The Landslide Susceptibility map developed using conditional probability method is verified using R index for both sampling strategies. The study shows that both the sampling strategies perform with good accuracy, seed cell technique excels slightly over point sampling. 86.11% of the landslides fall in the high and critical susceptible zones. The results show that conditional probability technique provides a simple tool for susceptibility analysis. The method can be used at regional scale and is a valuable input for planning purpose.

Keywords Geo-spatial · Landslide · Conditional probability · Seed cell · R index

E. Ramani Sujatha (✉)
School of Civil Engineering, SASTRA University,
Thanjavur, Tamilnadu, India
e-mail: r.evangelin@gmail.com

P. Kumaravel
Indian Institute of Astrophysics,
Kodaikkanal, Tamilnadu, India
e-mail: kumarwhale@yahoo.com

V. Rajamanickam G
Sairam Group of Institutions,
West Tambaram,
Chennai, Tamilnadu, India
e-mail: vrajamanickam@hotmail.com

Introduction

Landslides are a cause of concern in hill and mountainous terrains, manifesting in loss of property and lives, affecting urban development, resulting in loss of infra-structure facilities like roads and affect land use. Managing the losses caused by a landslide hazard, necessities the demarcation of areas highly susceptible to landslides to concentrate mitigation efforts. Landslide susceptibility assessment is crucial for safe and economic planning of engineering structures and urban infrastructure development. It is vital for designing appropriate cost-effective remedial measures. Various techniques are used to assess landslide susceptibility, which can be broadly classified as deterministic and non-deterministic methods. The different techniques used to map landslide susceptibility are discussed elaborately and compared systematically,

outlining the advantages and disadvantages of the various methods, in Aleotti and Chowdhury (1999), Guzzetti et al. (1999) and Keefer and Larsen (2007).

Deterministic methods involve analyzing specific slopes by quantifying the geotechnical and ground water parameters, applying them to specific mathematical models to find the factor of safety of these slopes (Naranjo et al. 1994; Gokeceoglu and Aksoy 1996; Shou and Wang 2003). They require detailed geotechnical data and are suitable for homogeneous ground conditions (Gokeceoglu and Aksoy 1996). Non-deterministic methods include heuristic and probabilistic methods. Heuristic or expert driven approach is qualitative and uses selective criteria, based on subjective decision rules made by the geoscientist, classifying parameters that influence the occurrence of a landslide (Aleotti and Chowdhury 1999), integrating data and assigning weights to each physical parameter causing landslide. The method requires long-term information on landslides and the physical factors causing landslides for a similar geo-environmental condition. The reproducibility of results and subjectivity in assigning weights to variables depends on the expertise of the geo-scientist. Probabilistic methods compare the spatial distribution of landslides with the factors causing landslides (Ayalew and Yamagishi 2005; Duman et al. 2005; Lee and Pradhan 2006; Magliulo et al. 2008; Bai et al. 2010; Yilmaz 2010), establishing quantitative relationship between landslide and landslide causing variable. The quantitative approach provides objectivity over qualitative analysis. Emerging techniques like fuzzy logic, artificial neural networks (Ercanoglu 2005; Ermini et al. 2005; Gomez and Kavzoglu 2005; Pradhan and Lee 2009; Pradhan and Lee 2010; Pradhan et al. 2010; Sujatha and Rajamanickam 2011) and decision trees (Nefeslioglu et al. 2010) are also used for mapping landslide susceptibility.

In this study, landslide susceptibility analysis is done using an indirect quantitative approach –conditional probability, to map landslide susceptibility in Tevankarai Ar sub-watershed, Kodaikkanal, India. Conditional probability is a simple tool to map landslide susceptibility – its input and output processes are easily understood (Duman et al. 2005; Yilmaz 2010). The physical factors considered for the study are relief, slope, aspect, curvature, land use, topographic wetness index and proximity to roads. Two sampling strategies are used – (i) Point sampling technique where landslides are considered as points and (ii) Seed

cell theory (Süzen and Doyuran 2004; Yesilnacar and Topal 2005) (i.e) landslide cells and the cells within a buffer radius of 60 m around landslide cells are used as training pixels. The present study is a unique endeavor in this area and the results of the conditional probability is validated using a temporal validation data set of landslides acquired during the period October–November 2009. The significance of the study is a successfully modeled landslide susceptibility map which delineates the area in terms of the degrees of susceptibility. It will be vital tool for land and town planners, helping them to plan suitable mitigation strategies and allocate appropriate areas for developmental activities, in particular for infra-structure developmental projects. This model can also be extended to areas of similar geo-environmental set-up.

Study Area and Landslide Characteristics

The Tevankarai Ar Sub-watershed is a part of Dindigul District in Tamilnadu, located at the eastern tip of the Western Ghats, covering an expanse of 63.44 km². Figure 1 shows the Digital Elevation Model of the study area with the landslides used as training set. It is bound by latitudes 10°13′23″ and 10°19′23″N and longitudes 77°27′8″ and 77°33′48″E. The area experiences rapid urban development with land clearing for housing and commercial establishments. There is an enormous increase in building density causing erosion and landslides. The climate is influenced by altitude - in general of temperate type. Annual rainfall is high; averaging to 1670 mm. Maximum rainfall is recorded in the months of October and November and minimum in January and February. Structural hill and valley complex with pediments and valley fills are the chief terrain features. Bedrock geology is monotonous - charnockite in varying degrees of weathering with limited soil cover ranging between nearly bare areas in the north and north-eastern parts to maximum thickness up to 3.1 m in the southern parts. The elevation is higher in the southern part of the basin and decrease towards the north and rises again in the north north–east. Few notable peaks are Mamumdi Malai Peak, 2195 m in the South and Perumalai Peak, 2337 m in the North–North East. The drainage pattern is mostly dentritic and the sub-watershed has a drainage density of 4.688 km/ km². This region is a gentle valley - nearly 87% of the slopes have a gradient less
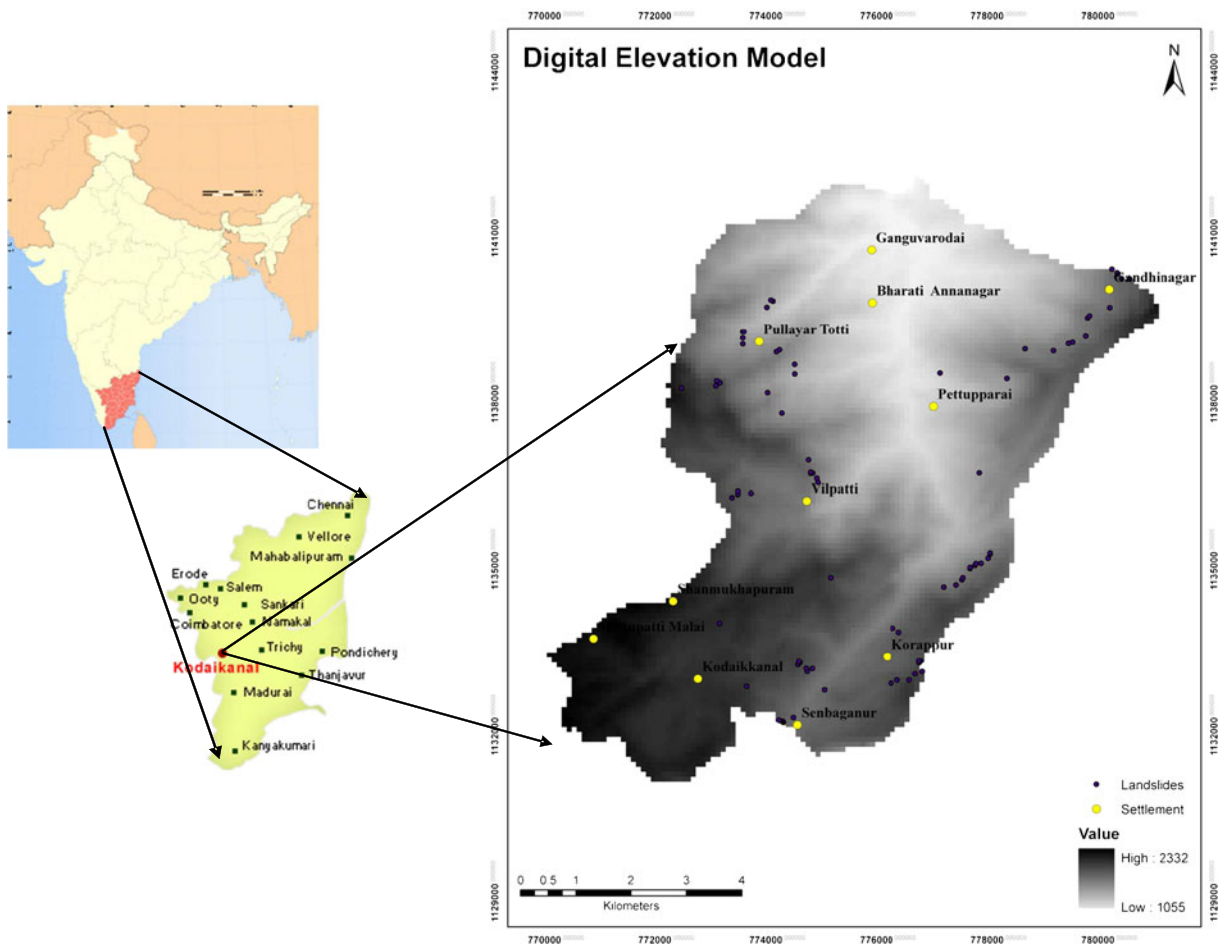
Fig. 1 Digital elevation model showing the landslide locations in the study area

than 35. The southern part of the study area bustles with human activity while the extreme northern areas are barren rock exposures with very limited settlements.

Landslides in the study are triggered by rainfall – especially during monsoons and in summer, when the summer showers are intense. Intense rainfall increases pore-pressure, lowering the shearing resistance of the formations, and thereby causing slope instability problems. The spatial distribution of the landslides in the area is observed to be controlled by both morphological and hydrological characteristics of the slopes. Anthropogenic activities like manipulating slope in the form of small terraces, irrigation of slopes, high building density and roads cause landslides in this region. The majority of the landslides are translational in nature with a few rotational slides. Debris slides,

affecting weathered material are notable in this region and convert to debris flows in where water is accumulated in the depressions, especially when the regolith is thick. Examples of landslides in the study area mapped during the field survey are shown in Fig. 2.

Data Sources and Geospatial Database

Collection of existing information and data for the area under study is the first and most important stage of landslide hazard mitigation studies (Aleotti and Chowdhury 1999). The data sources used to derive the thematic layers used for landslide susceptibility analysis are the SRTM DEM, Survey of India (SoI) topographic maps (1:25,000 scale), aerial photographs (1:50,000) and IRS ID-LISS III satellite imageries

Fig. 2 Field Photographs illustrating the characteristics and types of landslides in various parts of the study area

(2003 and 2006). Further field surveys are carried out for the collection of landslide locations and verification of land cover and topographic features. The geospatial database constructed using ArcGIS 9.2 includes eight layers of information - relief, slope, aspect, curvature, soil, land use, topographic wetness index and proximity to roads.

The decisive information layer is the one representing past landslides. The landslide data base is generated by thorough field survey and analysis of topographic maps and aerial photographs of scale 1: 25000 and 1: 50000. The landslide data set is divided into two segments based on temporal criterion. 84 cases of landslides that occurred in various years (excluding 2009) are used as training set to develop the conditional probability model and 36 cases of landslides that occurred in 2009 are used for the performance analysis of the landslide susceptibility map. SRTM DEM is widely used for the analysis of topography, geomorphology and hydrologic modeling. The factors relief, slope, aspect, curvature and topographic wetness index are extracted from the SRTM DEM of 90 m resolution and re-sampled for 30 m resolution. The maximum elevation in the study area is 2337 m and the minimum is 1050 m. Relief data layer is divided into seven classes of 200 m elevation. Aspect refers to the direction of maximum slope. It is divided into nine classes—N, NE, E, SE, S, SW, W, NW and Flat. The slope in the study area ranges between 0° and 76.57°. Slope, an important parameter in slope

stability analysis comprises of seven classes—0°–5 °, 5 °–15 °, 15 °–25 °, 25 °–35 °,35 °–45 ° , 45 °–60° and >60°. Curvature measures the rate of change of slope. It controls the velocity of water flow and hence, erosion also. It is classified into three classes such as concave, flat and convex. Topographic Wetness Index points out the topographic control on spatial variation of hydrologic conditions, influencing the spatial soil moisture pattern in the slopes. Wetness Index ranges between 1.015 and 18.304. Higher wetness index values indicate infiltration of surface water in the slopes whereas the increasing pore water pressure is directing the reduction in strength. Landslides are abundant at the lower wetness index values than at the higher wetness index values. The land use map is derived from the aerial photographs and up-dated using satellite imagery (IRS ID-LISS III, 2003 and 2006). The land use map is classified as cropland, plantation, settlements, forests, scrub, barren- fallow land and water-bodies. The proximity to road is extracted from 1: 25,000 topographic maps. Road buffer map at 50 m interval is derived from the road map.

Conditional Probability Modeling

Conditional Probability is a simple probabilistic technique that is used to assess the landslide susceptibility and is highly compatible in a GIS environment. The

results of this analysis can be easily assessed by end-users who are non-specialists (Clerici et al. 2002). The probability that an event A will occur if event B occurs is called conditional probability (Negnevitsky 2002). This approach considers a number of factors that cause landslides, which are connected with landslide occurrence. Each factor is divided into a convenient number of sub-classes, and are integrated to obtain all combinations of various factors and their sub-classes. Each pixel represents a specific combination (Unique Condition Units). Based on the principle that landslide in future is more likely to occur in a similar geo-environmental set-up which has led to the past landslide and the statistical concept that frequency and density of the landslide equals the probability that the landslide will occur, the resulting landslide density equals landslide susceptibility (Clerici et al. 2002, Duman et al. 2005; Yilmaz 2010). Conditional probability is mathematically given as in Eq. 1 (Negnevitsky 2002; Duman et al. 2005; Yilmaz 2010)

$$P(A/B) = (\text{the number of times A and B can occur})/ \atop (\text{number of times B can occur}) \quad (1)$$

The number of times that both A and B can occur is called *joint probability* of A and B, given as P (A∩B). The number of ways B can occur is the probability of B, given as P (B). Equation 1 can be written as:

$$P(A/B) = \frac{P(A \cap B)}{P(B)} \quad (2)$$

Likewise, the conditional probability of event B occurring given that event A occurs is specified as:

$$P(B/A) = \frac{P(B \cap A)}{P(A)} \quad (3)$$

Hence,

$$P(B \cap A) = P(B/A) \times P(A) \quad (4)$$

The joint probability is commutative, which implies that

$$P(B \cap A) = P(A \cap B) \quad (5)$$

Therefore,

$$P(A/B) = \frac{[P(B/A) \times P(A)]}{P(B)} \quad (6)$$

Equation 6 is the Bayesian rule and extending this principle to event A being dependent on number of mutually exclusive events B_1, B_2, B_3.......B_n (i.e) event A is the landslide and the B_1, B_2.....B_n are the factors causing landslide, the thematic layers of factors causing landslides can be integrated to obtain the landslide susceptibility map and is written as:

$$P(A) = \sum_{i=1}^{n} P(A \cap B) = \sum_{i=1}^{n} P(A/B_i) \times P(B_i) \quad (7)$$

The P (A) values for the training set selected for study is shown in Table 1 for both point and seed cell sampling techniques.

Landslide Susceptibility Analysis and Validation

GIS provides the processing platform for the slope stability using conditional probability and is used to develop the landslide susceptibility map. Landslide susceptibility map is generated using Eq. 7 for point and seed cell sampling techniques. Thus, landslide susceptibility map (Fig. 3) corresponding to the conditional probability method is prepared. High landslide susceptibility index value indicates higher susceptibility to landslides while a lower value indicates lower susceptibility to landslides. The landslide susceptibility index, which represents the cumulative probability of the various thematic layers selected for study portrays a minimum value of 0.000695 and maximum value of 0.00376 for the point sampling method and 0.00596 and 0.038453 respectively for seed cell sampling technique. The LSI values were classified into four groups using natural breaks reclassification—low, moderate, high and critical susceptibility zones (Fig. 3a and b). Natural breaks reclassification is used the jumps in the susceptibility classes and is also compatible with the findings in the field. Table 2 shows the distribution of areas and landslides in the different susceptible categories.

The relative landslide density index given by Baeza and Corominas (2001) is used for the performance analysis of the landslide susceptibility map and is defined as:

$$R = \left((n_i/N_i)/ \sum (n_i/N_i) \right) \times 100 \quad (8)$$

Table 1 Results of the conditional probability model

Theme	Class	Pixels in Class	Landslides	Point P(A)	Seed Cell P(A)
Relief (m)	1000–1200	5879	0	0	0
	1200–1400	11592	1	1.42E-05	0.000184
	1400–1600	12269	11	0.000156	0.001703
	1600–1800	12422	34	0.000482	0.00481
	1800–2000	13807	33	0.000468	0.003845
	2000–2200	11149	5	7.09E-05	0.000823
	2200–2400	3357	0	0	0
Aspect	Flat	17849	20	0.000284	0.003207
	N	4795	5	7.09E-05	0.000908
	NE	3651	4	5.68E-05	0.000326
	E	12749	8	0.000114	0.001731
	SE	5209	8	0.000114	0.00078
	S	9288	14	0.000199	0.000965
	SW	1827	1	1.42E-05	0.000227
	W	4862	12	0.00017	0.001859
	NW	10245	12	0.00017	0.001362
Slope (°)	0–5	14613	10	0.000142	0.002029
	5–15	14725	14	0.000199	0.001135
	15–25	16526	21	0.000298	0.002682
	25–35	15209	24	0.000341	0.003079
	35–45	7399	12	0.00017	0.002057
	45–60	1889	3	4.26E-05	0.000383
	>60	114	0	0	0
Curvature	Concave	27389	34	0.000482	0.004186
	Flat	15989	17	0.000241	0.006101
	Convex	27097	33	0.000468	0.001078
Weathering	Low	12577	6	8.51E-05	0.000738
	Moderate	21049	24	0.000341	0.003618
	High	17648	27	0.000383	0.003689
	Very High	19201	27	0.000383	0.00332
Land use	Cropland	8409	16	0.000227	0.002185
	Forest	10922	7	9.93E-05	0.001078
	Fallow and Barren	8168	7	9.93E-05	0.000837
	Plantation	25393	31	0.00044	0.005023
	Scrub	9425	7	9.93E-05	0.000937
	Settlement	7553	16	0.000227	0.001348
	Water bodies	605	0	0	0
Topographic Wetness Index	1	30459	50	0.000709	0.006172
	2	29378	28	0.000397	0.004271
	3	9248	6	8.51E-05	0.000922
	4	1190	0	0	2.84E-05
	5	200	0	0	0
Proximity to Road (m)	0–50	12678	45	0.000639	0.006399
	50–100	8937	22	0.000312	0.002185

Table 1 (continued)

Theme	Class	Pixels in Class	Landslides	Point P(A)	Seed Cell P(A)
	100–150	7294	3	4.26E-05	0.000752
	150–200	4744	2	2.84E-05	0.000213
	> 200	36822	12	0.00017	0.001816

where n_i is the number of landslides in the susceptibility level 'i' and N_i is the area occupied by the cells of susceptibility level 'i'. Table 2 shows the R index for each susceptibility level. It is seen that frequency of landslides increases with the susceptibility and R index also increases with the level of susceptibility. The increase in R index with the increase in susceptibility class indicates that the generated landslide susceptibility map performs well for both sampling strategies as established by authors like Baeza and Corominas (2001) and Irigaray et al. (2007).

Results and Discussion

Conditional Probability is one of the probabilistic methods used effectively for landslide susceptibility analysis and performs satisfactorily for the study area. This technique is suitable on a regional scale. Site-specific micro suitability assessment requires detailed finite slope stability analysis to assess the factor of safety, especially for construction of engineering structures. The method measures the vulnerability of a sub-class based on past landslides, thereby indicating the strength of each sub-class in causing landslide.
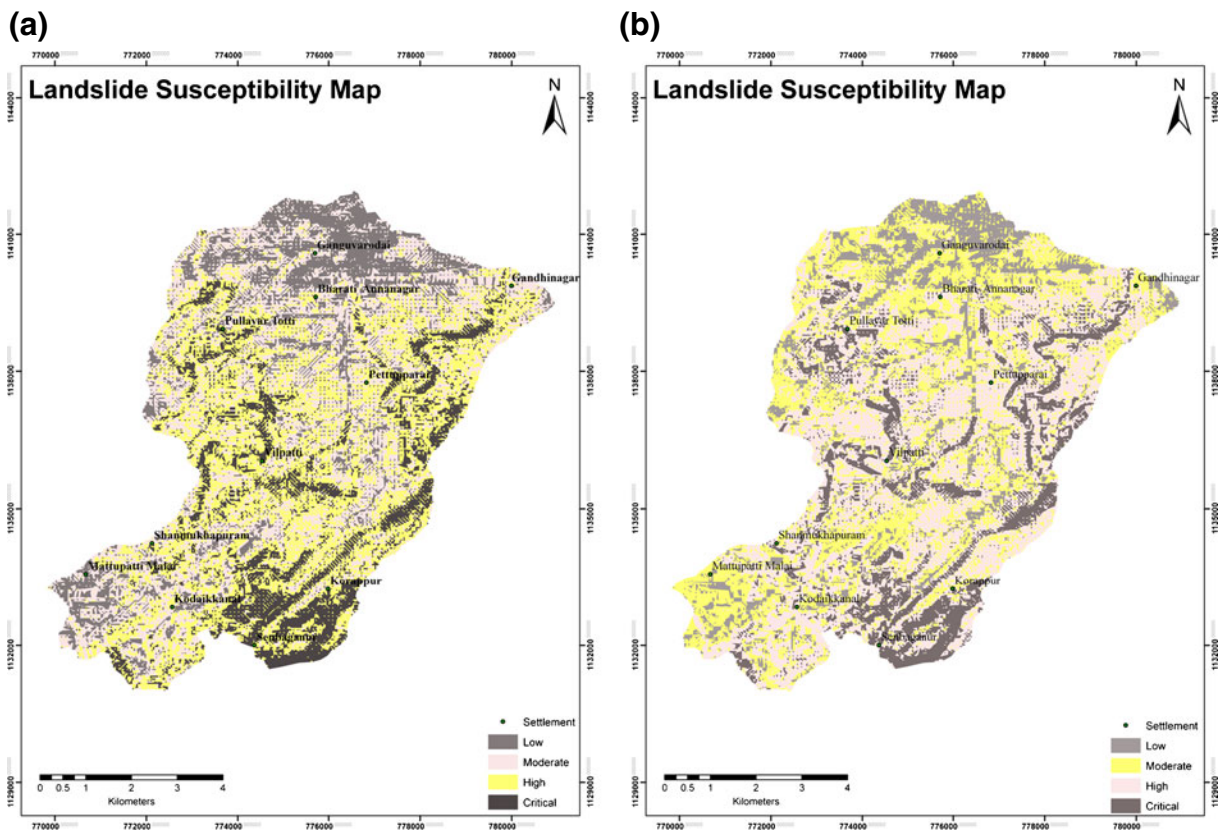

Fig. 3 a Point sampling technique b Seed cell sampling technique

Table 2 Distribution of area in susceptibility classes and corresponding R index

Susceptibility Class	Point			Seed Cell		
	Area (%)	Landslide (%)	R Index	Area (%)	Landslide (%)	R Index
Low	17.29408	5.555556	0.32124	26.85917	5.555556	0.20684
Moderate	33.98084	8.333333	0.245236	33.36786	11.11111	0.332988
High	33.80915	33.33333	0.985926	38.67329	27.77778	0.718268
Critical	14.91593	52.77778	3.53835	15.28911	55.55556	3.633668

The susceptibility analysis shows that slopes with a gradient of 25°- 35° with concave to straight slopes are more vulnerable to landslides. This shows that water retention along with slope gradient control slope instability. Altitudes between 1600 m–1800 m show more probability to failure. It is also noted that mid-altitudes between 1400 m–2000 m are vulnerable to landslides, while in lower (1000 m–1400 m) and higher (2000 m–2200 m) altitudes instability concerns are a minimum. Plantation is observed to be the most vulnerable land use category, followed by cropland and settlement. The areas within 50 m radius of roads are more susceptible to landslides. This is true as field survey shows that recurrent landslides occur along the roads every year after intense rainfall.

The conditional probabilities of weathering appear to show randomness in moderate, high and very high categories. Both sampling techniques show moderate, high and very high categories are equally susceptible to landslides. Field survey indicates that urban activity thrives in moderate and high zones as they are comparatively suitable for development. This reinforces the need for caution in pushing development activities at high rates in these regions. Thus, the results of the weathering class are consistent with the field study.

The results using point and seed cell mirror each other for all the landslide causing variables. But the results are refined in the seed cell sampling technique. This is evident in case of the land use category. Point sampling technique shows equal susceptibility for the classes' forest, scrub and fallow and barren but seed cell sampling technique has refined the results, by differentiating the susceptibilities of these categories. A similar trend is observed in the case of settlement and cropland sub-classes of land use. Seed cell sampling technique ranks settlements lower than croplands. A reason for settlements being ranked lower in

the order of probability is that the failures are localized and are strengthened before notable slides occur as the area bustles with population. Creep is also noted in areas like Indranagar and Munjikal where the density of settlement is very high. Again it is an indicator for caution in the rapid growth and urbanization. Though they are ranked next to plantation, the growth pattern and field investigation shows that there is more stress in these sub-classes, manifesting in the form of failures like tension cracks on the slopes harbouring them. The study points out that the method is successful in delineating areas of various degrees of susceptibility but is not a clear indicator to rank factors causing them. This requires an analysis and verification with detailed field study and geo-environmental assessment.

Literature shows that seed cell sampling technique performs better than point sampling technique (Süzen and Doyuran 2004; Yesilnacar and Topal 2005; Yilmaz 2010). But, the study shows that both techniques perform equally for the selected factors in the region of study. This can be due to the smaller size of the landslides observed in the region. Based on the size of landslides a pixel size of 30 m×30 m is selected and a buffer of 60 m is taken. A smaller pixel size can improve the efficiency of the seed cell sampling technique.

The landslide susceptibility map using conditional probability method portrays that the south-eastern part of the study area containing the sub-urban part of the town and the connecting hill road from the plains is more vulnerable to landslides. This area is dense with settlements, infra-structure and intense tourism related activities. The western part of the study area is also noted to be vulnerable. This region is marked with intense commercial agriculture – plantation and

cropland. Seed cell sampling technique shows smooth transition form one susceptibility zone to other than in the case of point sampling technique. Still, the study points out that for this region both methods perform equally.

Conclusions

Landslides in hill terrains cause substantial life and economic losses every year. Susceptibility mapping is an indispensable tool in these areas to define areas prone to landslide. In this study, conditional probability method is applied and tested on Tevankarai ar sub-watershed by taking into account eight factors that cause landslides. The study shows that conditional probability can be successfully used to map landslide susceptibility in this region. The susceptibility map can be used on a regional scale as a base for carrying out risk analysis to assist slope management and land use planning. The study also delineates high and very high hazard zones where finite slope stability analysis can be carried out to find the factor of safety of the unstable slopes where infrastructure projects likes road construction and widening is to be carried out. The data from the susceptibility map can be successfully integrated in the decision process through a cost-benefit analysis.

References

Aleotti, P., & Chowdhury, R. (1999). Landslide hazard assessment: summary, review and new perspectives. *Bulletin of Engineering Geology and the Environment, 58*(1), 21–44.

Ayalew, L., & Yamagishi, H. (2005). The application of GIS-based logistic regression for landslide susceptibility mapping in the Kakuda-Yahiko Mountains, Central Japan. *Geomorphology, 65*(1/2), 15–31.

Baeza, C., & Corominas, J. (2001). Assessment of shallow landslide susceptibility by means of multivariate statistical techniques. *Earth Surface Processes and Landforms, 26,* 1251–1263.

Bai, S., Lü, G., Wang, J., Zhou, P., & Ding, L. (2010). GIS-based rare events logistic regression for landslide-susceptibility mapping of Lianyungang, China. *Environmental Earth Sciences*. doi:10.1007/s12665-010-0509-3.

Clerici, A., Perego, S., Tellini, C., & Vescovi, P. (2002). A procedure for landslide susceptibility zonation by the conditional analysis method. *Geomorphology, 48*, 349–364.

Duman, T. Y., Can, T., Gokceoglu, C., & Nefeslioglu, H. A. (2005). Landslide susceptibility mapping of Cekmece area (Istanbul, Turkey) by conditional probability. *Hydrology and Earth System Sciences Discussions, 2*, 155–208.

Ercanoglu, M. (2005). Landslide susceptibility assessment of SE Bartin (West Black Sea region, Turkey) by artificial neural networks. *Natural Hazards and Earth System Science, 5*, 979–992.

Ermini, L., Catani, F., & Casagli, N. (2005). Artificial Neural Networks applied to landslide susceptibility assessment. *Geomorphology, 66*, 327–343.

Gokeceoglu, C., & Aksoy, H. (1996). Landslide susceptibility mapping of the slopes in the residual soils of the Mengen region (Turkey) by deterministic stability analysis and image processing techniques. *Engineering Geology, 44*(1–4), 147–61.

Gomez, H., & Kavzoglu, T. (2005). Assessment of shallow landslide susceptibility using artificial neural network in Jabonosa River basin, Venezuela. *Engineering Geology, 78*, 11–27.

Guzzetti, F., Carrara, A., Cardinali, M., & Reichenbach, P. (1999). Landslide hazard evaluation: a review of current techniques and their application in a multiscale study, Central Italy. *Geomorphology, 31*, 181–216.

Irigaray, C., Fernández, T., El Hamdouni, R., & Chacón, J. (2007). Evaluation and validation of landslide-susceptibility maps obtained by a GIS matrix method: examples from the Betic Cordillera (southern Spain). *Natural Hazards, 41*, 61–79.

Keefer, D. K., & Larsen, M. C. (2007). Assessing landslide hazards. *Sciences, 316*, 1136–1137.

Lee, S., & Pradhan, B. (2006). Landslide hazard mapping at Selangor, Malaysia using frequency ratio and logistic regression models. *Landslides, 4*, 33–41.

Magliulo, P., Di Lisio, A., Russo, F., & Zelano, A. (2008). Geomorphology and landslide susceptibility assessment using GIS and bivariate statistics: a case study in southern Italy. *Natural Hazards, 47*, 411–435.

Naranjo, J. L., van Westren, C. J., & Soeters, R. (1994). Evaluating the use of training areas in bivariate statistical landslide hazard analysis: a case study in Colombia. *Journal of Institute of Aerospace Survey and Earth Sciences, 1994–3*, 292–300.

Nefeslioglu, H. A., Sezer, E., Gokceoglu, C., Bozkir, A. S., & Duman, T. Y. (2010). Assessment of landslide susceptibility by decision trees in the metropolitan area of Istanbul, Turkey. *Mathematical Problems in Engineering*. doi:10.1155/2010/901095.

Negnevitsky, M. (2002). *Artificial intelligence: a guide to intelligent systems*. Great Britain: Addison-Wesley. 394 p.

Pradhan, B., & Lee, S. (2009). Landslide risk analysis using artificial neural network model focusing on different training sites. *International Journal of Physical Sciences, 3*(11), 1–15.

Pradhan, B., & Lee, S. (2010). Delineation of landslide hazard areas using frequency ratio, logistic regression and artificial neural network model at Penang Island, Malaysia. *Environmental Earth Sciences, 60*(5), 1037–1054.

Pradhan, B., Lee, S., & Buchroithner, M. F. (2010). A GIS-based back-propagation neural network model and its cross application and validation for landslide susceptibility analyses. *Computers, Environment and Urban Systems, 34*, 216–235.

Shou, K. J., & Wang, C. F. (2003). Analysis of the Chiufengershan landslide triggered by the 1999 Chi-Chi earthquake in Taiwan. *Engineering Geology, 68*, 237–250.

Sujatha, E. R., & Rajamanickam, V. (2011). Landslide Susceptibility Mapping Of Tevankarai Ar Sub-Watershed, Kodaikkanal Taluk, India, Using Weighted Similar Choice Fuzzy Model. *Natural Hazards*. doi:10.1007/S11069-011-9763-2.

Süzen, M. L., & Doyuran, V. (2004). A comparison of the GIS based landslide susceptibility assessment methods: multivariate versus bivariate. *Environmental Geology, 45*, 665–679.

Yesilnacar, E., & Topal, T. (2005). Landslide susceptibility mapping: A comparison of logistic regression and neural networks in a medium scale study, Hendek region (Turkey). *Engineering Geology, 79*(3–4), 251–266.

Yilmaz, I. (2010). The effect of the sampling strategies on the landslide susceptibility mapping by conditional probability and artificial neural networks. *Environmental Earth Sciences, 60*(5), 505–519.