## LANDSLIDE SUSCEPTIBILITY ASSESSMENT USING INFORMATION VALUE STATISTICAL METHOD: A CASE STUDY ON NORTHERN KOTA KINABALU, SABAH

Frederick Francis Tating<sup>1,2,\*</sup>, Robert Hack<sup>2</sup> & Victor Jetten<sup>2</sup>

<sup>1</sup>Minerals and Geoscience Department Malaysia (JMG), Sabah, Malaysia <sup>2</sup>Earth System Analysis Department, Faculty of Geo-information Science and Earth Observation (ITC), University of Twente, The Netherlands

\*Corresponding author email: ftating@jmg.gov.my

#### ABSTRACT

Landslides are the most frequent type of natural hazards that are often observed in hilly and mountainous areas. It may lead to not only loss of life but huge economic losses due to property damage, and other indirect effects such as disruption to transportation networks. These effects can be minimised and avoided if landslide prone areas are identified in advance by landslide susceptibility assessment. The main objective of this research is to develop a landslide susceptibility map (LSM) for the northern part of Kota Kinabalu, Sabah based on a statistical quantitative method, the information value method. The LSM was developed based on the analysis of results of spatial landslide distribution and eleven conditioning parameters. The percentage of area classified as relatively high susceptibility (high to very high) to landslides is 35.4%. These areas are mostly located at hilly areas, especially on the northern facing slopes with slope gradient between 25 to 35°. These areas are also located along old main roads (constructed more than 30 years old). Moderately susceptible areas are mostly located at foot hill areas and consist of 20.7% of the total area. Areas with relatively low susceptibility (very low to low) to landslides cover 43.9% of the total area and are mostly located at coastal, river valley and excavated areas. The area under curve (AUC) value is about 0.8022, which indicates the overall success rate of 80.2%. Due to the non-availability of medium scale LSMs for the area at present, the generated LSM map can be utilised to predict the landslide prone areas of the study area. It may also be used by the local authorities and other relevant agencies as a basis tool in land management and future planning for development in the northern Kota Kinabalu area.

**Keywords:** Landslide susceptibility map (LSM); information value method; landslide inventory; conditioning parameters; success rate curve.

## 1. INTRODUCTION

Landslides are the most frequent type of natural hazard that are often observed in hilly and mountainous areas. It may lead to not only loss of life but huge economic losses due to property damage, and other indirect effects such as disruption to transportation networks. In Malaysia, the total economic losses due to landslides reported for the period of three decades (1973 – 2007) is estimated to be about RM 3 billion (approximately USD 1 billion) (PWD, 2009). Landslide incidents and fatalities due to landslides have also increased during the same duration. The increased numbers of landslides are mostly related to expansion of development into hilly areas because of increasing population, urbanisation, deforestation and infrastructure.

Disaster and economic losses due to landslide hazard can be minimised and avoided in landslide prone areas if information about the frequency, magnitude and the characteristics of landslides within a particular area are identified in advance. However, in some countries, including Malaysia, identification and delineation of landslide prone areas have not been done yet, partly due to government policies that favour post disaster management rather than pre-disaster management (PWD, 2009). Landslide disaster management is often misunderstood as merely providing relief to victims, aiding recovery following an event and rebuilding damaged infrastructure, as a result only limited

resources and funds have been allocated for landslides hazard identification and risk management strategies in areas prone to landslides. Awareness regarding the economic and social impact of landslides begun after the collapse of Block 1 of the Highland Towers on 11 September 1993 which claimed 48 lives (Jamaludin & Hussien., 2006; Qasim *et al.*, 2013). Since then, interest in landslide investigation and management increased, as shown by the establishment of the slope engineering branch under the Public Works Department (PWD) in 2004. In addition, geological terrain mapping is conducted by the Minerals and Geoscience Department Malaysia (*Jabatan Mineral dan Geosains Malaysia*, JMG) throughout the country to make thematic maps that can be used as guidance for advice to local councils regarding constructions on hilly terrain.

Identification of landslide prone areas through susceptibility assessment is essential in order to understand landslide phenomena and its relationship with various causative factors. Landslides occur as a combination of several factors which can be distinguished into preparatory factors (such as slope angle, geology and land use) and triggering factors (such as rainfall and earthquakes). These factors can be utilised to develop a landslide susceptibility map (LSM), which delineates and ranks the slope stability in an area from low to high susceptibilities (Chacon *et al.*, 2006). Susceptibility refers to the spatial future likelihood or probability for landslides to occur (Hervas & Bobrowsky, 2009).

There are many susceptibility mapping methods published in the literature which generally can be grouped into two broad methods; qualitative and quantitative methods. Qualitative method relies on expert opinion and thus can be considered as subjective. It is commonly used as direct (geological and geomorphological) and weighting (indexing) approaches to assign susceptibility level (Soeters & van Westen, 1996). Quantitative methods are based on numerical expression of relationship between causal factors and landslides occurrences. It can be divided into two main methods: deterministic and statistical (Aleotti & Chowdhury, 1999; Ayalew & Yamagishi, 2005).

The objective of this study is to develop a LSM for the northern part of Kota Kinabalu, based on a statistical quantitative method, the information value method (Yin & Yan, 1988; Jade & Sarkar, 1993; Zezere, 2002; Yalcin, 2008; Che *et al.*, 2012). This method is also known as *landslide index method* (van Westen, 1997). At present, no appropriate and applicable landslide susceptibility mapping has been used in the planning of development and land use by the Kota Kinabalu local authorities. In addition, the parameters controlling the occurrences of landslide will also be determined and analysed. This can lead to a more in-depth knowledge on the role of landslide controlling parameters.

# 2. PREVIOUS LANDSLIDE ASSESSMENT STUDIES IN KOTA KINABALU, SABAH

Only a few landslide assessments in Kota Kinabalu, Sabah in East Malaysia have been done. Among the earliest studies is the study by Tongkul (1989) in which "weak zones" in the vicinity of Kota Kinabalu were characterised and delineated, with their implications on future construction discussed. Weak zones were classified as zones of disrupted/deformed strata (fault zone), which predominantly consist of various sizes of sedimentary blocks embedded in fine grain sedimentary materials such as shale and mudstone. These zones are the results of the tectonic activities in the past and their presence may relate to landslide incidents in natural slope and slope failure in road cut slope. However, landslides and slope failures are normally caused by set causal factors that can be analysed using several methods to delineate susceptibility to landslides.

About a decade later, Tating (2003) conducted a landslide inventory investigation in the northern part of Kota Kinabalu and related landslide occurrences with the lithology. The main controlling factors for landslides were determined based on a direct observation (heuristic) method coupled with extensive fieldwork. The result of the study shows that most of the landslides occur in areas underlain by interbedding between sandstone and shale, and some are associated with weathered thick bedded sandstone. Shallow translational landslides are the dominant type of landslides, especially in the sandstone and shale interbeds, whereas rotational landslide was mostly observed in thick bedded sandstone. Landslide causative factors are mostly due to the disturbance on natural slopes such as excavation or cut slope, vegetation clearance for agricultural and residential purposes, and weathering of the exposed rock.

Recent landslide assessments in the Kota Kinabalu area were carried out by Alvyn (2011) and Rodeano *et al.* (2011a, b, 2012a, b) using various methodologies. Alvyn (2011) carried out landslide assessment based on a probabilistic frequency ratio (PFR) model on a regional scale of 1:50,000 and concluded that the main causal factors for landslides are geomorphological factors (slope angle, slope aspect and soil types), followed by human (such as landuse and road construction) and geological (lithology and structural geology) factors.

Rodeano *et al.* (2011a, b, 2012a, and b) compared various statistical methodologies for landslide assessment at a regional scale of 1: 50,000. The results of the various landslide susceptibility maps (LSMs) show considerable differences. Seemingly different landslide assessment methods may produce different LSMs, which makes the correctness of the used methodologies questionable. The differences may be attributed to the inappropriate selections of assessment methodology, causal factor maps and the details of landslide inventory data used for regional scale assessment. Nevertheless, landslide susceptibility model validation based on the area under curve value (AUC), which is about 0.75, shows that the landslides susceptibility models are statistically accurate. It should be noted that the assessment is based on regional scale; for medium and small scale areas appropriate methodology and landslides factors should be employed.

# 3. RESEARCH METHODS

# 3.1 Landslide Inventory Map

In general, a landslide inventory map is a landslide database that records the location, date of occurrence (where known), landslide type, parameters and properties (Malamud *et al.*, 2004, Guzetti *et al.*, 2012). Landslide inventory maps are a "prerequisite dataset" towards landslide susceptibility, hazard and risk assessment (Guzetti *et al.*, 2012). It can be prepared using different techniques depending on the purpose of the inventory, extent of study area, scale of base maps, scale, resolution and characteristics of available imagery, and skills and experience of investigators (van Westen *et al.*, 2006; Guzetti *et al.*, 2012).

# 3.2 Bivariate Statistical Analysis

The fundamental concept of bivariate statistical analysis is to determine the relationship between spatial landslide distribution and landslide controlling factors (Guzetti et al., 1999). Only the location of landslide detachment area (landslide crown) is used in the analysis (Thiery *et al.*, 2007; Magliudo *et al.*, 2008) (Figure 1). This is based on the assumption that the factors controlling the occurrence of landslides in a region in the past are the same as those that will cause landslides in the future. Basically, the analysis is done by comparing landslide inventory maps with a series of landslide factor parameter maps, which results in a weighted class value (Eq. 1).

The weighted class value is determined based on the density of landslides in each parameter map determined by using the information value method (Yin & Yan, 1988; Jade & Sarkar, 1993; Zezere, 2003; Lin & Tung, 2003; Yalcin, 2008). This method is also known as landslide index ( $W_i$ ) method, in which the weighted value for a parameter class is defined as the natural logarithm of the landslide density in the class, divided by the landslide density in the entire map (van Westen, 1997). The  $W_i$  method is based on the following equation:

$$W_{i} = ln \frac{Densclass}{Densmap} = ln \frac{N_{pix} (S_{i})/N_{pix} (N_{i})}{\sum N_{pix} (S_{i})/\sum N_{pix} (N_{i})}$$
(1)

where  $W_i$  denotes the weight given to a certain parameter class; *Densclass* denotes the landslide density within the parameter class; *Densmap* denotes the landslide density within the entire map;  $N_{pix}(S_i)$  denotes the number of pixels which contain landslides in a certain parameter class and  $N_{pix}(N_i)$  denotes the total number of pixels in a certain parameter class. The natural logarithm is used to determine the influence of a certain parameter class in landslide development within the entire map. Negative values of  $W_i$  indicate that the presence of that particular parameter class has less effect on the landslide development, whereas positive values indicate a relevant relationship between the presence of such parameter class with landslide development (Yin & Yan, 1988; Zezere, 2002).



Figure 1: Ideal block diagram of a landslide. The Global Positioning System (GPS) reading for the location of landslide is taken at the landslide crown. (Source: Varnes (1978))

The landslide density per parameter class in each thematic map is calculated from the map crossing result between landslide inventory map and each of the parameter maps in a geographical information system (GIS) environment such as ILWIS. The  $W_i$  value of each parameter class is calculated by using the Eq. 1. Finally, the  $W_i$  value of each parameter class is added together according to Eq. 2 to produce a landslide susceptibility index (*LSI*) map or simply LSM:

$$LSI = W_iSl + W_iAs + W_iEl + W_iLi + W_iLu + W_iDr + W_iPr + W_iDs + W_iEx$$
(2)

where  $W_iSl$ ,  $W_iAs$ ,  $W_iEl$ ,  $W_iLi$ ,  $W_iLu$ ,  $W_iDr$ ,  $W_iPr$ ,  $W_iDs$  and  $W_iEx$  are weighted values for slope, aspect, elevation, lithology, land use, distance to road, proximity to river, distance to structural geology and road excavation time respectively. The LSI is then reclassified into five classes (very low, low, moderate, high and very high) of landslide susceptibility for the LSM. The "predictive power" of the LSM is assessed by analysing their success rate (Chung & Fabbri, 1999). In this research, the prediction rate could not be produced because multitemporal landslide data is not available. Nevertheless, the success rate result itself could indicate the quality of the map, i.e., how good the resulting weight scores describe the landslide pattern in the area (van Westen *et al.*, 2003).

#### 4. DATA PREPARATION

#### 4.1 Landslide Inventory Map

For the northern Kota Kinabalu area, a landslide inventory map was prepared from several sources of information: (1) interpreted from three series of aerial photographs which were flown during the period of 1969 to 1972 at 1:30,000 and Landsat TM satellite image (30 m resolution); (2) Landslide reports from previous landslide investigation by JMG and local researchers (e.g., Tating, 2003; Alvin, 2011; Rodeano *et al.*, 2011a); and (3) determined and collected from extensive field data collection during fieldwork campaign (8 March – 8 May 2010 and 23 March – 10 June 2011). The landslide inventory data was plotted on the base map with a scale of 1:25,000. Due to the differences in database inventory format, only the landslide location and types were used in this research.

A total of 105 landslide datasets with different dimensions and volume were recorded from the above mentioned sources (Figure 2). Most of the landslides are of a shallow translational type, while some are rotational. Most of the landslides occurred at the southeastern and middle part of the area. Most of the landslide sizes range from 150 to 1,500 m<sup>2</sup>, with the largest being about 36,000 m<sup>2</sup>. During the data collection fieldwork, landslides were characterised according to the WP/WLI (1990) definition. The date of occurrences of landslide was not recorded in the landslide inventories except for catastrophic landslides that involved the loss of life.



Figure 2: Location and distribution of landslide inventory. Most of the landslides occurred at the middle and southern parts of the study area.

#### 4.2 Selection of Landslide Preparatory Parameters

Statistical methods in determining landslide susceptibility are based on two assumptions; (1) future landslides are likely to occur at the same area where a former landslide occurred; (2) areas with similar set of geo-environmental conditions will influence the occurrence of landslide in the future in a similar way (Guzzetti *et al.*, 1999; Fell *et al.*, 2008). These assumptions may indicate that the probability spatial location of landslides in the future is governed by historical landslide distribution information and preparatory parameters for landslide initiation. Generally, the selection of preparatory

parameters depends on the nature of the study area, landslide type, failure mechanism, scale of analysis and priori knowledge of the main causes of landslides (Guzzetti *et al.*, 1999; Glade & Crozier, 2005; Jaiswal, 2011). The selected parameters should also be operational, measurable, well representing the whole study area and vary spatially (Yalcin, 2008).

In this research there are 11 preparatory parameters used for the susceptibility analysis based on field observation, landslide characteristics, and information from previous studies and reports. These are the geological (lithology, structural geology and structural geology density), topographical (slope angle, slope aspect and elevation), anthropogenic (land use/land cover (LULC), distance to road and road construction duration) and hydrological (distance to river and drainage density) parameters.

## 4.3 Geological Parameters

The geological parameters such as lithology and tectonic structures are important parameters in landslide susceptibility mapping. This is because lithological and structural variations may often lead to different susceptibility to geomorphological processes, resistance against weathering and variation in geotechnical properties (Dai *et al.*, 2001; Lee & Taib, 2005; Ayalew and Yamagishi, 2005; Dahal *et al.*, 2008; Das *et al.*, 2010). The geology of the area consists of thick sequences of fine to medium grained sandstone and red and/or gray shale beds belonging to the "Crocker Formation". The sedimentary sequence is divided into two main lithological units, i.e. Sandy and Shaly Sequences based on the lithological dominance (Tating *et al.*, 2013) (Figure 3a). The Sandy sequence consists predominantly of sandstone which is more competent and more resistant to geomorphological processes as compared to the Shaly sequence. Recent unconsolidated sediment (the Quaternary Sediment in Figure 3a) occupies most of the coastal plain and valleys between the hills. It consists of coastal and fluvial deposits.



Figure 3: Geological parameter maps used for the landslide susceptibility assessment: (a) Lithology (b) Distance to structural geology (c) Structural geology density.

Tectonic structures are mainly faults, either thrust or strike-slip faults. Thrust faults are normally associated with highly fractured zones, which consist of various sizes of rock fragments embedded in shaly and sandy matrices. This zone may contribute to slope instability and foundation problems due to their characteristics. Weathering in fractured and sheared rock zones may be very deep and rock mass strength is lower (due to high concentration of discontinuities) than the surrounding rocks. The influences of geological structures are related to the proximity to the structural features and also to the density of the structures. About 50 lineaments have been mapped from aerial photographs and satellite images by visual interpretation and verified in the field. These lineaments were buffered with 25, 50, 75, 100, 125 and 150 m distances from the lineaments mid-line (Figure 3b) to determine the effect of proximity to the structural geology features. The structural density, which is defined as the number of line elements of fixed length in a fixed area (Suzen & Doyuran, 2004), is classified into three classes i.e. 0 - 2.5, 2.5 - 5 and 5 - 7.5 line/km<sup>2</sup> (Figure 3c).

#### 4.4 Topographical Parameters

The topographical parameters consist of elevation of hill, aspect and slope angle. Aspect and slope angle are frequently used parameters in the landslide susceptibility analysis. According to Dai & Lee (2002), elevation may influence the susceptibility to landslide due to the differences of the characteristics of slope material at certain elevation of hill. However, this is may be site specific and may not be true in the study area. In this area, the magnitude and degree of disturbance due to construction of an infrastructure especially road network on side slope at certain elevation of a hill are more applicable. Slope cuttings are more extensive on side slope as compared to the hill ridge and toe. The elevation range in the study area is from 0 to 850 m msl and was reclassified into 17 classes with intervals of 50 m (Figure 4a).



Figure 4: Topographical parameter maps used for the landslide susceptibility assessment: (a) Elevation (b) Aspect (c) Slope angle.

Aspect, which is the direction of maximum slope of the terrain surface, also influences the occurrence of landslides. Aspect-related parameters, such as exposure to sunlight, drying winds, and rainfall, may

influence the moisture content and vegetation, and thus may affect the soil strength, erosion potential and susceptibility to landslides.

Slope angle has a very great influence on the susceptibility to landslide. The influence of slope angle is related to the shear strength of the material on the slope. Generally, landslide frequency will increase with higher slope angle until maximum frequency is achieved, subsequently followed by a decrease of frequency (Dai & Lee, 2002).

Aspect and slope angle were derived from a digital terrain model (DTM) with resolution of that was generated from a topographic maps using ArcGIS. Aspect was reclassified into nine classes with the interval of 45° (Figure 4b), while slope map was reclassified into six classes (Figure 4c).

## 4.5 Anthropogenic Parameters

Anthropogenic parameters are related to the effect on the environment resulting from human activities. It includes infrastructure construction and LULC. Construction of roads has significantly increased the frequency of slope failure along the road corridor. Slope excavation will disturb the strength-stress equilibrium of slope, leading to instability and it may result in development of tension cracks that facilitate the infiltration of water into the slope material. It may also increase the rate of slope material and mass deterioration. Excavation may also expose the barren slope material and mass to weathering agents thus further enhancing the rate of deterioration. Man-made fills without vegetation are also prone to erosion and weathering increasing their susceptibility to failure. However, landslide may only be confined to certain distances from the road line. In order to investigate the effective range of road construction activities to landslide susceptibility, it was buffered with 25, 50, 75, 100, 125 and 150 m distances from the road line (Figure 5a).



Figure 5: Anthropogenic parameter maps used for the landslide susceptibility assessment: (a) Distance to road (b) Road excavation time (c) LULC.

Another important anthropogenic parameter for landslide susceptibility that is related to slope excavation is the road excavation time or cut slope exposure time, which is related to the deterioration of rock mass with time. Man-made cut slopes have been designed to be stable for a certain period of

time based on a factor of safety at the time of construction, and the stability will decrease in the course of time. Some cut slopes may fail soon after the construction, due to stress relief and weathering (Huisman *et al.*, 2006; Tating *et al.*, 2013). The roads in the study area were constructed 18 to 35 years ago. Road excavation time was classified into two classes, i.e., road construction less and more than 30 years (Figure 5b).

LULC changes, especially conversion of virgin forest into plantation, increase and shifting agricultural and constructional activities, make an area more susceptible to landslides. LULC changes may also result in barren slope exposed to erosion process that eventually leads to landslide if the slope material consists of highly weathered rock and residual soil. Regeneration of secondary forest may have reduce root strength as compared to the original vegetation, thus increasing the landslide potential (Sidle & Ochiai, 2006; Sidle *et al.*, 2006; Razak, 2014). The LULC was derived from a digital topographic map with scale of 1: 25,000 and satellite imagery coupled with extensive field survey, and was classified into seven classes (Figure 5c).

#### 4.6 Hydrological Parameters

Hydrological parameters refer to the proximity of slope areas to river systems and drainage density. The drainage system may adversely affect slope stability by eroding the slope toe or/and saturating the toe material, whereas the density contribute to the regional hydrogeological properties of an area such as groundwater content. Six different buffer zones were delineated along drainage system to determine the effect of proximity to the drainage on occurrence of landslide. The buffer zones are 25, 50, 75, 100, 125 and 150 m from the drainage centre line (Figure 6a), whereas the density is classified into four classes (Figure 6b).



Figure 6: Hydrological parameter maps used for the landslide susceptibility assessment: (a) Distance to river (b) Drainage density.

# 5. **RESULTS**

## 5.1 Landslide Parameter Class Weight

The relationship between landslide distribution and landslide controlling factors is shown in Table 1. The relationship is reflected by the weight values of the parameter classes. A negative weight value of any parameters class shows that its presence may not contribute to the occurrence of landslides. On the other hand, a positive weight value indicates that the particular parameter class characteristics or occurrence may enhance the probability of landslides. A weight value which is around zero  $(\pm 0.1)$  contributes to neither presence nor absence of landslides (van Westen *et al.*, 2003).

Parameter	Class	Landslide Area		Total Area in the Class		Weight
		Pixels	%	Pixel	%	-
Lithology	Quaternary Sediment	75	17.56	96978	30.32	0.0000
	Shaly Sequence	79	18.50	62637	19.58	-0.4855
	Sandy Sequence	273	63.93	160272	50.10	0.2683
D: / /	0.05	10	0.41	22257	0.41	0.0021
Distance to	0 - 25m	19	9.41	22357	9.41	-0.6931
Structure	25 - 50m	27	13.37	22680	13.37	-0.28//
	50 - /5m	42	20.79	22143	20.79	0.1719
	75 - 100m	35	17.33	21174	17.33	0.0606
	100 - 125m	39	19.31	20274	19.31	0.1719
	125 - 150m	40	19.80	19397	19.80	0.2719
Structure Density	$0 - 2.5  \#/\mathrm{km}^2$	379	88.76	292482	85.07	0.0800
	$2.5 - 5 \#/\text{km}^2$	48	11.24	51308	14.92	-0.2877
	5 - 7.5 #/km <sup>2</sup>	0	0	21	0.01	-2.4849
A	North	107	20.74	12965	12.24	1 6262
Aspect	North	127	29.74	42803	15.54	1.0303
	Northeast	31	1.20	34/34	10.81	-0.30//
	East	30 25	8.43 5.95	43140	15.45	-0.4855
	Southeast	25	5.85	34099	10.01	-0.0190
	South	24	5.62	34349	10.69	-0.6190
	Southwest	43	10.07	34865	10.85	-0.0800
	West	19	4.45	46231	14.39	-1.1787
	Northwest	122	28.57	50997	15.87	0.6131
	0 - 5 Degree	47	11.01	137499	42.78	-1.4663
Slope	5 - 15 Degree	112	26.23	60976	18.97	0.3254
-	15 - 25 Degree	168	39.34	86405	26.88	0.3795
	25 - 35 Degree	95	22.25	34103	10.61	0.7673
	35 - 60 Degree	5	1.17	2461	0.77	0.4308
	> 60 Degree	0	0.00	0	0.00	-2.5649
Flevation	0 - 50 m	196	45 90	178454	55 51	-0 1671
Licvution	50 - 100 m	93	21.78	41300	12.85	0.5705
	100 - 150 m	14	3 28	25141	7.82	-0 7732
	150 - 200  m	2	0.47	17596	5.47	-2 56/19
	200 - 250 m	18	1 22	9892	3.08	0 3254
	250 - 250 m	8	1.22	5792	1.80	0.5254 0.0741
	200 - 350 m	0	0.47	6318	1.80	1 /663
	350 400 m	∠ 15	0.+/ 3 51	6714	2.00	0 5261
	400 450 m	13	3.04	7003	2.09	0.5201
	450 500 m	15	5.04	6746	2.10	0.3793
		22	5.15	6112	2.10	1.0726
	550 600 m	25 14	2.39	2701	1.90	1.0720
	550 - 000 III 600 - 650 m	14	5.28 0.70	2300	1.10	0.0000
	000 - 000 11	5	0.70	4377	0.75	0.0000

Table 1: Weight values obtained	from the information	value method for all	parameter classes.
---------------------------------	----------------------	----------------------	--------------------

	650 - 700m	0	0.00	1797	0.56	-2.5649
	700 - 750 m	4	0.94	1276	0.40	0.8690
	750 - 800 m	0	0.00	825	0.26	-2.5649
	800 - 850 m	0	0.00	309	0.10	-2.5649
LULC	Agriculture	9	2.11	17239	5.39	-0.9555
	Built-up Area	30	7.03	75108	23.47	-0.9555
	Forest	372	87.12	180290	56.34	0.4796
	Barren Land and Shrubs	5	1.17	21512	6.72	-0.9555
	Bare Exposed Rock	11	2.58	11339	3.54	-0.9555
	Water Body	0	0.00	2226	0.70	-2.5649
	Swampy Area	0	0.00	12276	3.84	-2.5649
	0 - 25 m	85	28.24	35753	22.47	0.2336
Distance to Road	25 - 50 m	96	31.90	31223	19.62	0.4895
	50 - 75 m	42	13.95	27219	17.10	-0.2364
	75 - 100 m	31	10.30	24259	15.24	-0.3795
	100 - 125 m	25	8.31	21435	13.47	-0.4595
	125 - 150 m	22	7.31	19258	12.10	-0.5465
	Less than 30 years	69	31.65	41836	57.73	-0.6286
<b>Excavation Time</b>	More than 30 years	149	68.35	30630	42.27	0.4906
	·					
	0 - 25 m	43	14.63	39463	20.87	-0.3747
Distance to River	25 - 50 m	58	19.73	37186	19.66	0.0000
	50 - 75 m	53	18.03	34093	18.03	0.0000
	75 - 100 m	56	19.05	30174	15.95	0.1719
	100 - 125 m	48	16.33	26263	13.89	0.1178
	125 - 150 m	36	12.24	21947	11.60	0.0000
Drainage Density	$0 - 2.5  \#/\mathrm{km}^2$	219	51.29	204011	57.02	-0.0870
	2.5 - 5 #/km <sup>2</sup>	194	45.43	116947	32.69	0.3483
	5 - 7.5 #/km <sup>2</sup>	14	3.28	34344	9.60	-1.0986
	$> 7.5 \ \text{#/km}^2$	0	0	2481	0.69	-2.4849

# 5.2 Landslide Susceptibility Map (LSM)

The calculated landslide statistical index values, generated from the analysis of eleven parameter maps range from -9.335 to 5.182. The index values were reclassified into five susceptibility classes (very low, low, moderate, high and very high) by using the natural break method. The classification was done automatically in ArcGIS. The final LSM is shown in Figure 7, where the percentages of areas classified as very low, low, moderately, high and very high susceptibilities are 16.94, 26.91, 20.74, 22.54 and 12.88% respectively.

The percentage of area classified as relatively high susceptibility (high to very high) to landslide is about 35.4%. These areas are mostly located at hilly areas, especially on northern facing slopes with slope angle between  $25-35^{\circ}$ . These areas are also located along old main road (constructed more than 30 years old). Moderately susceptible areas are mostly located at foot hill areas and consist of 20.7% of the total area. Relatively low susceptibility (very low to low) areas are mostly located at coastal, river valley and excavated areas. These areas consist of 43.9% of the total area.

# 5.3 Validation of LSM

LSMs without any validation are worthless and may not have any scientific significance (Chung & Fabbri, 2003). Validation is essential in order to ascertain that the model can be applicable for

practical purposes. Several methods to validate the quality of susceptibility map are available in the literature (such as Chung & Fabbri, 2003; Guzetti *et al.*, 2006; Frattini *et al.*, 2010).



Figure 7: Final LSM generated by using all the parameter maps. The landslide inventory locations are also shown in the map.

In this study, the validation is based on the "success rate curve" (van Westen *et al.*, 2003), which explains how well the model and controlling factors predict landslides. Success rate is calculated by ordering the LSI values of all the pixels in the LSM in descending order, and then categorising it into 100 classes with 1% cumulative intervals. The cumulative percentage of the observed landslides is plotted against the cumulative percentage area of the LSM. The success rate for the LSM is shown in Figure 8. Based on the success rate graph, it shows that the first 30% of the classes with the highest value in the LSM can predict about 74% of all landslides in the area. Apart from the success rate, the spatial efficiency or global statistical accuracy of the LSM can also be determined qualitatively by the area under the success rate curve (AUC) value (von Routte *et al.*, 2011; Pourghasemi *et al.*, 2012). AUC values lie between 0 and 1, with higher *AUC* values indicating higher prediction capability maps (Tay *et al.*, 2014). The AUC value for the generated LSM is 0.8022, which can be considered as excellent (Hosmer & Lameshow, 2000) and indicates that the overall success rate is about 80.2%.

## 6. **DISCUSSION**

The quality of the LSM depends on the quality and completeness of input parameters used in the analysis. One of the most important parameters is landslide inventory data. Landslide inventories can be prepared using various methods (Wieczoreck, 1984; Malamud *et al.*, 2004, Guzetti *et al.*, 2012). In the present study, landslide inventory is prepared mainly through aerial photographs and satellite image interpretation, extensive fieldwork, and historical records. However, details on landslides in the Kota Kinabalu area are very limited. Only some large volume big scale landslides that resulted in large infrastructure damages have been investigated and reported in detail. Furthermore, the landslide terminology and parameters recorded are sometimes inconsistent. However, in landslide susceptibility assessment, location and type of landslide are sufficient for the analysis. Therefore, only the landslides with known location and type were used in the analysis.



Figure 8: The comparison between success rate curves by using all the parameters map (red line) and without road excavation time (blue line).

Other problems of recognising and recording landslides in tropical environment are related to the rapid disappearance of landslide diagnostics features due to rapid growth of vegetation, sometimes after the failure. For older landslides, it may be impossible to identify their signature in aerial photos or satellite images due to dense forest canopy and unfavourable weather conditions (cloudy and rainy) during acquisition of optical remote sensing data. Therefore, most of the landslides recorded are along the roads and slope cut area, which is easily accessible and consist of low density vegetation. This may lead to spatial bias of the landslide incidents. In order to overcome these problems, non-optical satellite image such as LIDAR should be utilised in the future. LIDAR data has been successfully utilised for landslide inventory and identification under dense tropical forest in Malaysia (Razak *et al.*, 2013).

Among the three lithological classes, the sandy sequence shows a positive weight value, suggesting that it is prone to landslides. In the study area, most of the hilly areas consist of a competent sandy bedding sequence and are associated thick residual soil that originated from the sandstones. Any disturbance to the slope area with thick residual and weathered sandy sequence will result in slope failure. On the other hand, the shaly sequence occupies most of the low lying areas and between sandstone beds. These areas are mostly moderately to gently sloping and even though the residual soil is thick, the landslide susceptibility is low. The weight value of the quaternary sediment class suggests that it does not contribute to either the presence or absence of landslides, as most of the quaternary sediment occupies the river valleys and coastal areas.

Similar weight results are shown by the proximity to geological structural features. Negative weight values are observed for the distance from 0 to 50 m, which indicate the absence of landslides nearer to the structural features. This is also contrary to the effect of disturbance from the tectonic activities, which may contribute to the occurrence of landslides. The structural density parameter classes also show similar results; higher density of geological structures does not influence the occurrences of

landslides. Landslides may not occur at areas adjacent to geological structure unless it was excavated and exposed to the deterioration elements. The occurrences of landslides in low density areas may be attributed to other factors such as road construction.

The most dominant aspect directions are slopes oriented northwest, west, east and north, with percentage areas of 15.9, 14.4, 13.3 and 13.4%, respectively. Each of the other classes constitutes almost the same percentage of about 10%, representing about 42% of the total area. The highest positive weight values are the north and northwest direction slope aspect, indicating susceptibility to landslide. The other aspect directions show negative weight values with lower occurrence of landslides. The high occurrence of landslides on the north and northwest facing slopes is related to the rainfall distribution patterns with rain brought by the southwestern monsoon.

Based on the slope angle classes, negative weight values are associated with slopes with gradient less than  $5^{\circ}$  and more than  $60^{\circ}$ . The slope classes from  $5-15^{\circ}$  to  $25-35^{\circ}$  show an increasing positive weight value, while there is a decrease at slope with gradients  $35-60^{\circ}$ . The highest value of positive weight is at slope class of  $25-35^{\circ}$ , indicating high probability of landslide occurrences within this slope class.

Generally, elevation of less than 350 m and more than 600 m (except for the elevation of 700-750 m) do not contribute to the occurrence of landslides. Most landslides occurred at the elevation classes of 350-600 and 700-750 m. This is due to the fact that much of the slope disturbances are concentrated at these elevations. Some villages and private residential areas are constructed at this elevation due to its strategic location with beautiful scenery overlooking the coastal area and cooler weather conditions. Several private roads are also constructed to link these villages to the main road, enhancing the slope disturbance. At the higher elevations, most of the area consists of virgin forests and forest reserves in which any human activities are prohibited.

Based on the LULC, landslides mostly occurred within the forest areas. This is due to the fact that shifting cultivation, road construction and deforestation for private residential areas are carried out at forested areas. Barren land/shrubs and exposed rock areas are mostly observed near the coastal area; these originate from the excavation and flattening of isolated hills. Even though these areas have been disturbed and exposed to weathering agents, some areas are relatively flat and thus not very prone to landslides.

Based on the distance to road alignment, most slope failures (60.14%) occurred within the range of 0 to 50 m as indicated by the positive weight value. It also shows the occurrence of landslides related to the disturbance due to the construction of roads; after 50 m from the road alignment, landslide occurrences become less, indicated by the negative weight value.

Landslide occurrences and temporal factors for the road construction relationship indicate that landslides are mostly observed at roads constructed more than 30 years old. This is due to fact that deterioration of cut slope reduces the value of geotechnical parameters (intact rock strength, cohesion and friction) of slope material and mass, thus reducing the factor safety to unstable conditions. Generally, roads constructed less than 30 years are less prone to landslides. Even though the road excavation time factor seems to be influential in controlling the occurrences of slope failure along the road due to the rock mass deterioration process, it does not contribute to the overall reliability of the generated LSM. This is as this parameter only exerts influence along roadcuts and not the whole study area. Furthermore, its effect is also already accounted for by the distance from road parameter. As the road excavation time parameter in determining the slope stability along roads by using geotechnical methods such as slope stability probability classification (SSPC) (Das *et al.*, 2010). SSPC is based on rigorous field data analyses of geotechnical parameters that are critical to slope failure conditions (Hack *et al.*, 2003). Therefore, for specific areas, such as along the road networks, geotechnical methods are appropriate to be used.

The influences of river and geological structures on the occurrences of landslides are based on distance/proximity from the parameter features and density of the parameter. Density functions attribute to the regional (km<sup>2</sup>) influence of the particular parameters, whereas the proximity functions evaluate the local situation (m<sup>2</sup>) (Suzen & Doyuran, 2004). Negative weight value for the distance between 0 to 25 m indicates that the proximity to main river/stream does not influence the landslide occurrences. This is contrary to the conventional effect of river/stream to the occurrence of landslides, i.e. slope undercutting and saturation effects. This is due to the fact that most of the main rivers are located at the lowland and flat areas, in which both sides of river banks are covered with mangrove trees. In the hilly area, most of the river banks are also covered with trees that may prevent bank erosion. The weight values for the other classes of proximity to the main rivers fluctuated around zero, indicating low relationship with landslide occurrence. Similarly, the drainage density factor map analysis also shows a non-significant relationship. Higher drainage density seems to be not related to landslide occurrence, contrary to effect of higher moisture content that may contribute to slope instability due to the presence of excessive water. In tropical areas, the presence of water may encourage vegetation to thrive thus enhancing slope stability due to their root action. However, slope instability may occur if the area is deforested.

Although, some of the landslides factors and landslide incidence relationships are insignificant, the results can be used to understand their contributions based on their factual condition and occurrence in the field. For example, river distance and density factors map show insignificant relation with the landslide incidents. This can be explained by the abundance of trees thriving along the riverbanks, which impeded slope erosion and landslide.

# 7. CONCLUSION

In this study, the information value method was used to develop a LSM for the northern Kota Kinabalu area. Eleven conditioning parameters were used in the assessment. The selection of the conditioning factors was based on the consideration of relevance and field observation, landslide characteristics and information from previous studies and reports, and the availability of data for the study area.

Generally, the percentage of area classified as relatively high susceptibility (high to very high) to landslide is about 35.4%, which are mostly located at hilly areas, especially on northern facing slopes with slope angle between 25-35°. These areas are also located along old main road that constructed more than 30 years old ago. Moderately susceptible areas are mostly located at foot hill areas and consist of 20.7% of the total area. Relatively low susceptibility (very low to low) areas are mostly located at coastal, river valley and excavated areas. These areas consist of 43.9% of the total area.

Based on the success rate value, 30% of the area with the highest susceptibility can predict about 74% of all landslides in the area whereas the AUC value is about 0.8022, which indicates that the overall success rate of 80.2%. The LSM can be utilised as a preliminary assessment tool in land management and future planning for development in the northern Kota Kinabalu area.

## REFERENCES

- Alleotti, P. & Chowdary, R. (1999). Landslide hazard assessment: summary review and new perspectives. *Bull. Eng. Geol. Env.*, **58**: 21-44.
- Alvyn, C.M. (2011). Landslide Hazard Mapping in Kota Kinabalu Area using GIS and Remote Sensing. MSc Thesis. Universiti Malaysia Sabah (UMS), Malaysia.
- 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: 15-31.

- Chung, C.F. & Fabbri, A.G. (1999). Probabilistic prediction models for landslide hazard mapping. *Photogramm Eng. Rem. S.*, **65**: 1389-1399.
- Chung, C.F., Fabbri, A.G. (2003). Validation of spatial prediction models for landslide hazard mapping. *Nat. Hazards*, **30**: 451-472.
- Chacon, J., Irigaray, C., Fernandez, T. & El Homdouni, R. (2006). Engineering geology maps: landslides and geographical information systems. *Bull. Eng. Geol. Env.*, **65**: 341-411.
- Che, V.B., Kervyn, M., Suh, C.E., Fontijn, K., Ernst, G.G.J., del Marmol, M.-A., Trefois, P. & Jacobs, P. (2012). Landslide susceptibility assessment in Limbe (SW Cameroon): A field calibrated seed cell and information value method. *Catena*, **72**: 83-98.
- Varnes, D.J. (1978). Slope movement Type and Processes. *In*: Schuster, R. L., and Krizek, R.J., (Eds), *Landslides: Analysis and Control*. Transportation Research Board, National Research Council, Special Report No. 176, Washington D.C., pp. 12 - 33.
- Dahal, R. K., Hasegawa, S., Nonomura, A., Yamanka, M., Masuda, T. & Nishino, K. (2008). GISbased weights of evidence modeling of rainfall-induced landslides in small catchments for landslides susceptibility mapping. *Environ. Geol.*, 54: 311-324.
- Dai, F.C. & Lee, C.F. (2001). Terrain-based mapping of landslide susceptibility using a geographical information system: a case study. *Can. Geotech. J.*, **38**: 911-923.
- Dai, F.C. & Lee, C.F. (2002). Landslide characteristics and slope instability modelling using GIS, Lantau Island, Hong Kong. *Geomorphology*, **42**: 213-228.
- Das, I., Sahoo, S., van Westen, C., Stein, A. & Hack, R. (2010). Landslide susceptibility assessment using logistic regression and its comparison with a rock mass classification system, along a road section in the northern Himalayas (India). *Geomorphology*, **114**: 627-637.
- Fell, R., Corominas, J., Bonnard, C., Cascini, L., Leroi, E. & Savage, W.Z. (2008). Guidelines for landslide susceptibility, hazard and risk zoning for land use planning. *Eng. Geol.*, **102**: 85-98.
- Frattini, P., Crosta, G. & Carrara, A., (2010). Techniques for evaluating the performance of landslide susceptibility models. *Eng. Geol.*, **111**: 62-72.
- Glade, T. & Crozier, M.J. (2005). The nature of landslide hazard and impact. *In*: Glade, T., Anderson, M. G. & Crozier, M.J. (Eds), *Landslide Hazard and Risk*. Wiley, London, pp. 43 74.
- Guzzetti, F., Carrara, A., Cardinali, M. & Reichenbach, P. (1999). Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, Central Italy. *Geomorphology*, **31**: 181-216.
- Guzetti, F., Reichenbach, P., Ardizzone, F., Cardinalli, M. & Galli, M. (2006). Estimating the quality of landslides susceptibility models. *Geomorphology*, **81**: 166-184.
- Guzetti, F., Mondini, A. C., Cardinali, M., Fiorucci, F., Santangelo, M. & Chang, K-T. (2012). Landslide inventory maps: New tools for an old problem. *Earth-Sci. Rev.*, **112**: 42-66.
- Hack, R., Price, D. & Rengers, N. (2003). A new approach to rock stability a probability classification (SSPC). *Bull. Eng. Geol. Environ.*, **62**: 167-184.
- Hervas, J. & Bobrowsky, P. (2009). Mapping: Inventories, Susceptibility, Hazard and Risk. *In*: Sassa, K. & Canutti, P. (Eds), *Landslides Disaster Risk Reduction*. Springer, Berlin, pp. 321-349.
- Huisman, M., Hack, H.R.G.K. & Nieuwenhuis, J.D. (2006). Predicting rock mass decaying engineering lifetime: the influences of slope aspect and climate. *Environ. Eng. Geosci.*, **12**: 39-51
- Hosmer, D.W. & Lameshow, S. (2000). Applied Logistic Regression, 2<sup>nd</sup> Ed., John Wiley and Sons, London.
- Jade, S. & Sarkar, S. (1993). Statistical model for slope instability classifications. *Eng. Geol.*, **36**: 71-98.
- Jaiswal, P., van Westen, C, J. & Jetten, V. (2010). Quantitative landslide hazard assessment along a transportation corridor in southern India. *Eng. Geol.*, **116**: 236-250.
- Jaiswal, P. (2011). Landslide Risk Quantification Along Transportation Corridors Based on Historical Information. PhD Thesis, University of Twente, Enschede.
- Jamaludin, S. & Hussien, A.N. (2006). Landslide hazard and risk assessment: The Malaysian experience. 10<sup>th</sup> IAEG Int. Cong., Nottingham, United Kingdom, Paper number 455.
- Lee, S. & Talib, A.T. (2005). Probabilistic landslide susceptibility and factor effect analysis. *Environ. Geol.*, **47**: 982-990.

- Lin, M.L. & Tung, C.C. (2003). A GIS-based potential analysis of the landslides induced by the Chi-Chi earthquake. *Eng. Geol.*, **71**: 63–77.
- 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. *Nat. Hazards*, 47: 411-435
- Malamud, B.D., Turcotte, D.L., Guzetti, F. & Reichenbach, P. (2004). Landslide inventories and their statistical properties. *Earth Surf. Proc. Land*, **29**: 687 711.
- PWD (Public Works Department)., (2009). National Slope Master Plan 2009 2023. Public Works Department (PWD), Malaysia.
- Pourghasemi, H.R., Pradhan, B., Gokceoglu, C., Moezzi, K.D. (2012). In: Pradhan, B. & Buchroithner, M. (Eds.), Terrigenous Mass Movements: Detection, Modelling, Early Warning and Mitigation Using Geoinformation Technology. Springer Science & Business Media, New York.
- Qasim, S., Harahap, I.S.H. & Osman, S.B.S. (2013). Causal factors of Malaysian landslides: A narrative study. *Res. J. Appl. Sci. Eng. Technol.*, **5**: 2303-2308.
- Razak, K.A., Santangelo, M., van Westen, C.J., Straatsma, M.W. & de Jong, S.M. (2013). Generating an optimal DTM from airborne laser scanning data for landslide mapping in a tropical forest environment. *Geomorphology*, **190**: 112-125.
- Razak, K. A., (2014). Airborne Laser Scanning for Forested Landslides Investigation in Temperate and Tropical Environments. PhD Thesis. University of Twente/University of Utrecth, Enschede.
- Rodeano, R., Jamaluddin, T.A. & Talip, M.A. (2011a). Aplication of GIS in landslide risk assessment (LRA): A case study of the Kota Kinabalu area, Sabah, Malaysia. *Bull. Geol. Soc. Malaysia*, 57: 69-83.
- Rodeano, R., Jamaluddin, T.A., Talip, M.A. & Hassan , S. (2011b). Landslide Hazard Factors (LHF) by Community perception survey in Kota Kinabalu, Sabah. *Borneo Sci.*, **29**: 32-45.
- Rodeano, R., Jamaluddin, T.A. & Talip, M.A. (2012a). Integration of GIS using geostatistical interpolation techniques (kriging) (GEOSTAINT-K) in deterministic models for landslide susceptibility analysis (LSA) at Kota Kinabalu, Sabah, Malaysia. J. Geogr. Geol., 4: 18-32.
- Rodeano, R., Jamaluddin, T.A. & Talip, M.A. (2012b). Landslide susceptibility mapping (LSM) at Kota Kinabalu, Sabah Malaysia using factor analysis model (FAM). J. Adv. Sci. Eng. Res., 2: 80-103.
- Soeters, R. & van Westen, C.J. (1996). Slope instability recognition analysis and zonation. In: Turner, K.T. & Schuster, R.L., (Eds.). Landslides: Investigation and Mitigation. Transportation Research Board, National Research Council, Special Report no. 247, Washington D.C., pp. 129-177.
- Suzen, M.L. & Doyuran, V. (2004). Data driven bivariate landslide susceptibility assessment using geographical information systems: a method and application to Asarsuyu catchment, Turkey. *Eng. Geol.*, **71**: 303-321.
- Tating, F.F. (2003). The Geology and Landslide in the Northern Kota Kinabalu, Sabah, Malaysia. Kumamoto University, Kurokami Kumamoto, Japan
- Tating, F. F., Hack, R. & Jetten, V., (2013). Engineering aspects and time effects of rapid deterioration of sandstone in the tropical environment of Sabah, Malaysia. *Eng. Geol.*, **59**: 20-30.
- Tay, L.T., Sh. Alkhasawneh, M., Lateh, H., Md. Hossain, K. & Kamil, A. A., (2014). Landslide hazard mapping of Penang Island using Poisson Distribution with dominant factors. J. Civil Eng. Res., 4: 72-77.
- Thiery, Y., Malet, J.-P., Sterlacchini,S., Puissant, A. & Maquaire, O. (2007). Landslide susceptibility assessment by bivariate methods at large scales: Application to a complex mountainous environment. *Geomorphology*, **92**: 38-59.
- Tongkul, F. (1989). Weak zones in the Kota Kinabalu Area, Sabah, East Malaysia. Sabah Soc. J., 9: 11 pp.
- van Westen, C.J. (1997). Statistical landslide hazard analysis. *In*: van Westen, C.J. (Ed.), *ILWIS 2.1 for Windows Application Guide*. ITC Publication, Enschede, pp. 73–84.

- van Westen, C.J., Rengers, N. & Soeters, R. (2003). Use of geomorphological information in indirect landslide susceptibility assessment. *Nat. Hazards*, **30**: 399-419.
- van Westen, C.J., Castellos, E. & Kuriakose, S.L. (2008). Spatial data for landslide susceptibility, hazard, and vulnerability assessment: An overview. *Eng. Geol.*, **102**: 112-131.
- Varnes, D.J., (1978). Slope movement: types and process. *In*: Schuster, R. L. & Krizek, R.J. (Eds.). *Landslides: Analysis and Control*. Transportation Research Board, National Research Council, Special Report No. 176, Washington D.C., pp. 11 - 33.
- von Routte, J., Papritz, A., Lehman, P., Rickli, C. & Or, D. (2011). Spatial statistical modeling of shallow landslides-Validating predictions for different landslide inventories and rainfall events. *Geomorphology*, **133**: 11 22.
- Wieczorek, G. F., (1984). Preparing a detailed landslide-inventory map for hazard evaluation and reduction. *Bull. Int. Assoc. Eng. Geol.*, **21**: 337-342.
- WP/WLI (International Geotechnical Societies' UNESCO Working Party for World Landslide Inventory). (1990). A suggested method for reporting a landslide. *Bull. Intern. Assoc. Eng. Geol.*, 41: 5-12.
- Yin, K. J. & Yan, T.Z. (1988). Statistical prediction model for slope instability of metamorphosed rocks. *In*: Bonnard, C. (Ed.), *Landslides*. *Proc.* 5<sup>th</sup> *Int. Symp. Landslides*, Balkema, Rotterdam, pp. 1269 – 1272.
- Yalcin, A. (2008). GIS-based landslide susceptibility mapping using analytical hierarchy process and bivariate statistics in Ardesen (Turkey): Comparisons of results and confirmations. *Catena*, **72**: 1-12.
- Zezere, J.L. (2002). Landslide susceptibility assessment considering landslide typology. A case study in the area north of Lisbon (Portugal). *Nat. Hazards Earth Syst. Sci.*, **2**: 73-82.