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Analytical Hierarchy Process Method for Mapping Landslide Susceptibility to an Area along the E-W Highway (Gerik-Jeli), Malaysia

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ABSTRACT

In this study, the Analytical Hierarchy Process (AHP) method was used to produce a landslide susceptibility map for an area located in the central northern part of Peninsular Malaysia. The study was carried out using remote sensing data, field surveys, historical data and Geographic Information System (GIS) tool. Eleven factors that influence the occurrence of landslide were chosen for this study: Slope gradient, slope aspect, curvature, distance from road, drainage density, lithology, foliation dip, topographic/bedding relationship, lineament density, soil and rainfall. The Landslide Susceptibility Index (LSI) was computed from the combined weighed thematic maps of factors based on the assigned weights and ratings given by the AHP method. The AHP results were verified with existing landslide locations, which yielded the accuracy rate of 80.97%. Hence the landslide susceptibility map generated with the AHP method is useful for preventing or minimizing possible landslides and could be adopted in the proper planning for land use and construction in the future.

Key words: GIS methodology, AHP, landslide susceptibility mapping, east-west highway Malaysia

INTRODUCTION

Landslides are dangerous natural hazards that take heavy tolls on human lives and properties. Landslides often occur in tropical countries such as Malaysia. It is one of the main constraints for development projects in the highlands of the country. Most of these landslides are shallow rainfall-induced landslides that normally occur in steep hilly areas and highlands as an aftermath of heavy rainfall during monsoon season.

However, the risk of landslide incidents could possibly be minimized if the knowledge of the potentially landslide prone areas are known in prior. Generally, the prediction of occurrence of a potentially landslides in future is represented in the form of landslide susceptibility map. Landslide hazard mapping is essential for land use activities and management (Moghaddam *et al.*, 2007). Varnes (1984) indicates that the occurrences of landslide hazard can be evaluated based on the possibility of incidence of this conceivably ruining phenomenon within a particular period of time and within a given area. These early timely indication maps of slope stability prone areas are mandatory tools for various experts such as engineers, geologists, planners and decision makers. These susceptibility maps will help in selecting the appropriate sites for development of agriculture, construction and many other activities.

The Geographical Information Systems (GIS), enables data acquisition, storage, retrieval, modeling and manipulation. The GIS systems have the capability to incorporate various geographical technologies including remote sensing and global positioning systems hence, they have become very vital for landslide susceptibility mapping. The analytical and combinational capacity of GIS has enabled the production of techniques used in landslide assessment for generating more precise maps, detailing the probable landslide hazard prone areas.

Landslide susceptibility mapping can vary from simple methods that use a minimum data to sophisticated mathematical methods that use practical mathematical methods using complex databases in computer-based Geographic Information System (GIS). For assessing landslide hazard different methodologies are proposed which are mainly grouped as: qualitative and quantitative methods. Qualitative approaches are based on the site-specific experience of experts and the susceptibility/hazard areas are determined directly in the field or by combining different index maps. Whereas, quantitative methods calculate susceptibility/hazard probability based on the numerical expressions of the relationship between causative factors and landslides (Solaimani *et al*., 2009). The two main types of quantitative methods are deterministic and statistical (Aleotti and Chowdhury, 1999). The deterministic models are physically based models which are used only to assess and examine the slope stability for small areas due to the need of comprehensive geotechnical data. Hence, statistical methods in landslide evaluation are generally used in large areas. In statistical methods, the role of all the factors that cause landslides is defined based on the computed associations between those factors and landslide distributions. They are based on a general theory which claims that, the landslides in the future will be more likely to occur, due to the existence of the same conditions that have caused landslides in the past.

In this study, landslide-hazardous areas are analyzed and mapped using the landslide-occurrence factors through the heuristic approach named Analytic Hierarchy Process (AHP). This GIS-based AHP method has been applied in previous studies which has proved to be very effective and valuable method to landslide susceptibility mapping (Ercanoglu *et al*., 2008; Yalcin, 2008).

MATERIALS AND METHODS

Study area: The study area lies in the central northern part of Peninsular Malaysia along the E-W highway between 5°:24":6' N to 5°:45":56.5' N latitude and 101°:7":53.6' E to 101°:50":26' E longitude, with a total area of 1205 km² (Fig. 1). It is characterized by rugged hills and mountainous terrain covered by thick rain forest. The study area is frequently subjected to landslides following heavy rains, especially, alongside the highway since it was constructed. The common types of landslides identified in the area were rock slumps, rock falls, wedge slides, toppling, soil slides and soil slumps. From the lithological standpoint, ten units described in Table 1 have been identified from the geological maps of the area. The study area is dominated by the three main rock types, namely sedimentary, igneous and metamorphic. Igneous and metamorphic rocks cover the middle and eastern part of the area while the sedimentary rocks are commonly found in the west.

Landslide influencing data layers

Geology: In the domain of landslide susceptibility mapping both the lithology and structural geology play an important role. Lithology is a primary parameter conditioning landslide occurrences as various lithological units have diverse susceptibilities to landslides. Hence, a lot of researchers have utilized lithology as an input factor to measure the vulnerability of landslides (Akgun *et al*., 2008; Bai *et al*., 2010; Mezughi *et al*., 2011). In this study, geological maps produced by Minerals and Geoscience Department Malaysia at a scale of 1:63, 300 covering the study area and the

Table 1: Lithological units

Unit	Description
LU 1	Granite
LU 2	Metagreywacke and metasandstone
LU 3	Quartz-chlorite schist, sericite schist, graphitic schist and phyllite
LU 4	Quartz-mica schist, quartz-graphite schist and minor amphibole
LU 5	Metatuff of rhyolitic composition
LU 6	Chert, shale, slate and metasiltstone
LU 7	Metarenite
LU 8	Phyllite and slate
LU 9	Marble with calcareous metasediments
LU 10	Granite, granodiorite and syenite

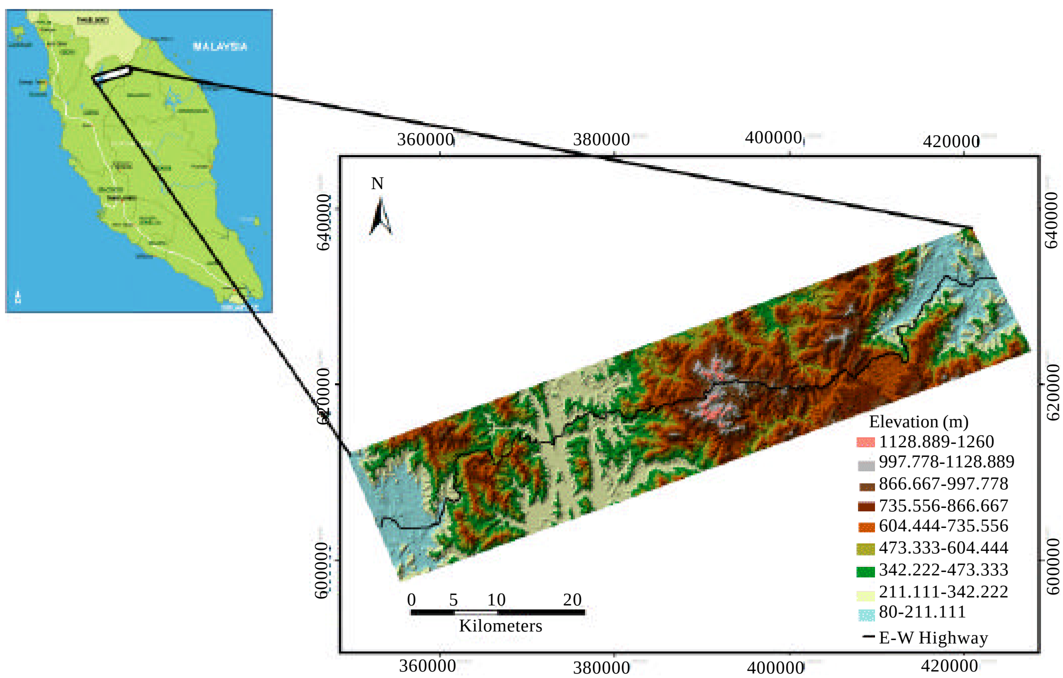

Fig. 1: Location of the study area shown with the TIN map

geologic formations were identified. The structural details such as strata dip and foliation dip, were acquired from the above mentioned maps and from field studies. A total of 200 readings representing strata dip and strike and 230 reading representing foliation dip and strike were digitized as points and then they were interpolated to generate strata and foliation dip maps.

Fractures are also considered as important geological structures which influence landslides. They can be detected from satellite images where they appear as linear to curvilinear features (lineaments). It has generally been observed that the probability of landslide occurrence increases near to lineaments which describe weakness zones. This study has used Landsat-7 ETM+image to extract lineaments using various image processing and enhancement techniques. The interpreted lineaments were digitized in vector mode and converted to shape file to generate the lineament density map using the line density analyst extension on ArcGIS 9.2.

Topography: The Digital Elevation Model (DEM) represents the terrain surface which is very important to generate many of topographic parameters which control landslide activity in the area.

The DEM was produced from a Triangulated Irregular Network (TIN) model, acquired from contour lines and elevation points on the 1:50,000 scale topographic maps with a contour interval of 20 m. Slope angle, slope aspect and curvature are the significant topographic factors that control landslide occurrence. They are automatically acquired from DEM and categorized into different classes.

Slope: The slope angle is the primary factor is used in the slope stability analysis (Lee and Min, 2001) and since it directly influences landslides, it is often employed in generating landslide susceptibility maps (Mancini *et al*., 2010; Kolat *et al*., 2006). According, to Anbalagan (1992) many previous studies indicate that the slope gradient is proportional with the susceptibility of landslide occurrences. Hence, the slope factor plays a vital role in generating landslide susceptibility maps. The relief of the study area varies between 60 to 1200 m from mean sea level and therefore, it becomes responsible for the major slope variation in the area that ranges from 0 to 88°.

Aspect: The slope aspect is another frequently used and still-debated instability factor as different conclusions are drawn by different authors in different areas (Ercanoglu *et al*., 2004; Lee, 2005). The slope aspect contribute to landslide occurrence when the slope face intense rainfall, sunlight and drying winds. It will ultimately affect the other factors like the flora distribution, degree of water saturation, evapotranspiration of the slope and the soil thickness. Climatic aspects like the intensity of the rain and the amount of sunshine could influence landslides in that particular slope, for instance the hillsides that receive dense rainfall are considered to be more prone to landslides because, soils of these hillsides reach saturation faster, causing the increase of pore water pressure. The saturation capacity is also controlled by a few factors like the slope curvature, soil type, permeability, porosity and land cover.

Curvature: Curvature represents the morphology of the topography which plays a significant role in the landslide phenomenon. It is considered as a factor that controls landslide occurrences due to its effect on the hydrological conditions of the soil cover. Generally, after rain fall, the soil in concave slope will retain and preserve more water than soils in convex slope. However, in a lot of places the convex slopes represent the outcrop of strong bedrock. Subsequently, the concave slope areas have a very high prospect for a landslide incidence than the convex areas. In the curvature raster file, the positive curvature values specify that the surface is convex at those cells. In contrast the negative principles designate that the surface is concave at those cells. A value of zero specifies that the surface is flat.

Topography/bedding relationship: The different geometric relationships between bedding attitude and slope aspect can be considered as a factor that controls landslide occurrence which is used in susceptibility mapping. Slope stability can be influenced by geological structures as result of the angular relationship between bedding attitude, slope aspect and slope angle (Wen *et al*., 2004; Wu *et al*., 2004; Jaboyedoff *et al*., 2004). In this study, dip angle and dip direction measurements were taken from geological maps and from field surveys. The readings of the dip direction and angle were interpolated using ordinary kriging to produce dip angle and dip direction map, while the slope aspect and slope angle map were calculated from DEM. Bedding direction and slope aspect datasets were overlaid and according to their relationship four classes were identified as following:

Class 1: Layers dip opposite the slope
Class 2: Layers dip as the slope and incline equal to the slope

Class 3: Layers dip as the slope and incline more than the slope
Class 4: Layers dip as the slope and incline less than the slope

Classes 1, 2 and 3 represent the stable condition, while class 4 represents the unstable condition because the bedding plane daylights on the slope's free face.

Drainage: The proximity of the slopes to the stream networks is yet another important factor that influences slope stability. Streams have a major role in the slope stability by saturating the soil until the water level causes the increase in the pore soil pressure and they can also heavily influence the slope stability by toe erosion. According, to Cevik and Topal (2003) the higher stream density the lower is the penetration of water into soil and the faster is the movement of surface flow. Generally, the penetration happens on slopes adjacent to the streams, which have a high permeability such as alluvium. In order to produce drainage density map in this study, the drainage were digitized from topographic maps of scale 1:50.000 and a drainage density map was calculated using the line density analyst extension on ArcGIS 9.2. The drainage density map was classified into five equal intervals classes.

Rain fall: Among the natural activities the rainfall is the primary catalyst that induces the landslides. Rainfall is the main triggering factor for Landslides in the area where most of the landslides occurred after heavy rainfall. A rainfall map was generated by this study based on annual rainfall data collected from three meteorological stations for the period of 2000, 2005 and 2009. The rainfall map was generated using interpolation method. Based on the analysis the maximum rain fall recorded in the eastern part of the area is 3970 mm year^{-1} and the lowest rainfall is recorded in the western part is 1590 mm year^{-1}.

Distance from road: Roads are considered as one of the important anthropogenic factors controlling slope stability. Landslides might happen on the road and on slopes of road sides (Pachauri *et al.*, 1998). It has been observed that, many landslides occur close to roads. The reason for this is the extraction of materials from the lower portion of the slopes during road construction, which eventually makes the slope lose to support and also due to the frequent vibrations generated by vehicles predispose hill slopes to failure. During the field visits of this study, most landslides were detected due to road construction work. In this study the road distance map was generated by digitizing the road network from the topographic maps and the area was classified into five distance buffer classes, computed at 100 m intervals from both sides of the roads to determine the effect of the road on the stability of slope.

Soil: Soil is another significant factor that is employed to evaluate the occurrence of landslides. The topsoil cover on a slope has an influence on landslide occurrence as observed in the field. For this study, a soil map was prepared using 32 soil samples collected in the field from residual soils formed by weathering processes on the rocks. The soil samples were classified in the laboratory based on the Unified Soil Classification System (USCS). The study has identified the following types of soil: SILT-sandy and SAND-silty.

AHP method: The Analytic Hierarchy Process (AHP) is a structural framework that enhances the realization of complicated decisions by decomposing the issue in a hierarchical structure. This approach breaks down a composite, amorphous circumstance into its components parts, organizing these parts or judgments on the relative significance of every variable and synthesizing the judgments to establish the variables that have the maximum priority and must be acted upon to influence the resulting situation (Saaty, 1990).

The AHP is a subjective approach that is employed in landslide susceptibility evaluation depending on understanding and knowledge of the experts to decide the factors affecting the landslide process. It is utilized to ascertain the relative importance of all the criteria (factors) and sub criteria (classes) that contribute to landslide susceptibility to compute its weight. This is implemented by constructing a hierarchy of decision criterions (causative factors) that are compared to each other in pair-wise assessment in a matrix in which every factor is rated with other factors by giving a score value. The scores are provided based on the comparative precedence of the factor for influencing landslides and depending on the estimation of an expert following the rating system (Table 2) introduced by Saaty (1977). The ranking of the relative priority of the criteria is performed by allotting a weight between 1 that signifies equal importance and 9 that indicates extreme importance to the more vital criterion, whereas, the reciprocal of this value is assigned to the other factor in the pair. When the factor on the vertical axis of the matrix is more significant than the feature on the horizontal axis, the value differs between 1 and 9. On the other hand, the value differs between the reciprocals between 1/2 and 1/9. To compute an average weight for each factor, the columns are initially normalized by dividing the elements of every column by the sum of the column and then summing all the elements in each resultant row and divide this sum by the number of elements in the row. The summary of the outcome for this computation are illustrated in Table 3.

As the comparisons are accomplished by personal or subjective judgments, some degree of inconsistency may occur, hence, Consistency Ratio (CR) which is an index of inconsistency, is employed to specify that the matrix judgments were randomly generated (Saaty, 1980). The CR is acquired as follows:

$$CR = \frac{CI}{RI}$$

where, CI is the consistency index which is expressed as:

$$CI = \frac{(\lambda_{max} - n)}{(n-1)}$$

where, λ_{max} is the major or principal eigenvalue of the matrix and it is computed from the matrix and n is the order of the matrix.

The Random Consistency Index (RI) is the average of the consequently constancy index based on the order of the matrix proposed by Saaty (1980). Table 2 illustrates the value of the Random Consistency Index (RI) for matrices of order 1 to 10 acquired by approximating random indices using a sample size of 500 (Saaty, 2000).

The acceptable CR range varies based on the size of matrix i.e., 0.05 for a 3 by 3 matrix, 0.08 for a 4 by 4 matrix and 0.1 for all larger matrices, $n \geq 5$ (Saaty, 2000; Cheng and Li, 2001). Thus, a CR of 0.1 or less is a practical level of reliability (Malczewski, 1999) whereas, a CR above 0.1 needs revision the judgment in the matrix due to conflicting treatment of particular factor ratings.

RESULTS AND DISCUSSION

After the application of the AHP, the acquired weight values of causative factors (W_i) and the ranking values (R_i) of the different classes in these factor layers were acquired from the

Table 2: Scale of relative importance suggested by Saaty (1977)

Intensity of importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to objective
3	Weak importance of one over another	Experience and judgment slightly favor one activity over another
5	Essential or strong importance	Experience and judgment strongly favor one activity over another
7	Demonstrated importance	An activity is strongly favored and its dominance demonstrated in practice
9	Absolute importance	The evidence favoring one activity over another is the highest possible order of affirmation
2,4,6,8	Intermediate values between the two adjacent judgments	When compromise is needed

1/9 1/8 1/7 1/6 1/5 1/4 1/3 1/2 1/1 1 2 3 4 5 6 7 8 9

Less important ← → **More important**

Eigenvalues of the AHP matrixes that articulates the relation between various factors and of the matrixes that represent the relationship between classes in a factor. The consistency of the weights and ratings are validated by taking the principal eigenvectors of each matrix and computing the consistency index CI and consistency ratio CR. In all cases of the gained class weights with $CR_s<0.1$, the ratio illustrates a sensible level of consistency in the pair-wise comparison that was adequate to identify the class weights. In this study, the CR ranges between 0.00 and .0987, signifying a rational level of consistency in the pair-wise comparison, that is reasonable to identify the factor weights. After computing the weight of each factor and the rate of each class using AHP method, the Landslide Susceptibility Index (LSI) was calculated by summing up each factor's weight multiplied by class weight of every referred factor (for that pixel) written as follows:

$$LSI = \sum_{i=1}^{n} (W_i \times R_i)$$

where, LSI is the calculated landslide susceptibility index of the given pixel, R_i and W_i are class rating value and the factor weight for factor i which is derived using AHP technique (Table 3). The LSI values characterize the comparative susceptibility of a landslide occurrence, hence, if the index is higher the area will be more prone to landslides.

To verify the results, the LSI was compared with known landslides. The LSI was assessed in terms of its predictive power validity by calculating the prediction rate curve. To produce the prediction rate curve, the computed index values of all cells in the targeted area were arranged in descending order and divided into 100 equal classes ranging from very highly susceptible classes to non susceptible classes. Then, the 100 classes were overlaid and intersected with known landslides to establish the percentage of landslide incidences in each susceptible class. Figure 2 illustrates the prediction rate curve as a line graph. The Fig. 2 also indicates the satisfactory results, highest susceptibility pixels that envelop 10% of the study area includes 56% of known landslides, while the 20% high susceptible area covers more than 68% of landslides. Later, the prediction of the map was validated more precisely using the Area Under the Curve (AUC) by ascertaining that the ideal prediction will have highest AUC of 1. In our study, the AUC was found to be 0.8097.

Table 3: Pair-wise comparison matrix with classes ratings (R_i) and factor weights (W_i)

Factors		1	2	3	4	5	6	7	8	9	10	11	R_i
Slope gradient (Degree)													
1	0-5	1											0.0469
2	5-15	2	1										0.0744
3	15-30	4	3	1									0.1635
4	30-60	7	5	2	1								0.3893
5	>60	5	4	5	1/2	1							0.3259
Consistency ratio: 0.078													
Slope aspect													
1	Flat	1											0.0201
2	N	7	1										0.1818
3	NE	5	3	1									0.1379
4	E	3	1/5	1/2	1								0.0621
5	SE	7	1/3	1	1/3	1							0.0836
6	S	7	1	5	5	4	1						0.2783
7	SW	5	1/3	1	3	1	1/4	1					0.0957
8	W	3	1/5	1/4	1	1/3	1/5	1/3	1				0.0397
9	NW	5	1/4	1	4	1	1/4	1	3	1			0.1008
Consistency ratio: 0.0875													
Lineament density (km km^{-2})													
1	<0.5	1											0.0508
2	0.5-1	2	1										0.0818
3	1-1.5	3	2	1									0.1329
4	1.5-2	5	4	2	1								0.2644
5	2-2.5	7	5	5	2	1							0.4702
Consistency ratio: 0.0174													
Drainage density (km km^{-2})													
1	<0.876												10.4162
2	0.876-1.752	1/2	1										0.2618
3	1.752-2.629	1/3	1/2	1									0.1611
4	2.629-3.505	1/4	1/3	1/2	1								0.0986
5	3.505-4.382	1/5	1/4	1/3	1/2	1							0.0624
Consistency ratio: 0.0152													
Topographic/bedding													0.0650
1	Class 1	1											
2	Class 2	4	1										0.2231
3	Class 3	2	1/2	1									0.1079
4	Class 4	7	3	7	1								0.6040
Consistency ratio: 0.0185													
Foliation angle (Degree)													
1	<5	1											0.040
2	5-15	2	1										0.065
3	15-30	4	3	1									0.147
4	30-60	7	5	2	1								0.255
5	>60	9	6	4	3	1							0.493
Consistency ratio: 0.027													
Distance from road (m)													
1	100	1											0.4544
2	200	1/2	1										0.2855
3	300	1/4	1/2	1									0.1394
4	400	1/5	1/5	1/2	1								0.0827

Table 3: Continue

Factors		1	2	3	4	5	6	7	8	9	10	11	R_i
5	1000	1/9	1/7	1/4	1/3	1							0.0380
Consistency ratio:	0.0209												
Lithology													
1	LU 1	1											0.080
2	LU 2	3	1										0.130
3	LU 3	1/3	1/3	1									0.044
4	LU 4	1/3	1/3	1	1								0.047
5	LU 5	1/4	1/5	1/3	1/4	1							0.025
6	LU 6	3	2	6	6	7	1						0.205
7	LU 7	2	1	4	4	5	1/3	1					0.125
8	LU 8	3	2	7	7	8	2	3	1				0.256
9	LU 9	1/5	1/6	1/5	1/5	1/3	1/6	1/5	1/7	1			0.027
10	LU 10	1	1/3	3	3	4	1/4	1/4	1/5	1/2	1		0.061
Consistency ratio:	0.0987												
Rainfall (mm year^{-1})													
1	<2000	1											0.067
2	2000-2500	2	1										0.121
3	2500-3000	4	2	1									0.233
4	> 3000	7	5	3	1								0.579
Consistency ratio:	0.0105												
soil													
1	Sand-silty	1											0.250
2	Silt-sandy	2	1										0.750
Consistency ratio:	0.00												
Curvature													
1	Concave	1											0.681
2	Convex	1/3	1										0.216
3	Flat	1/7	1/2	1									0.103
Consistency ratio:	0.002												
Data Layers		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**W_i**
1	Slope angle	1											0.185
2	Slope aspect	1/7	1										0.018
3	Lineament density	1/2	5	1									0.086
4	drainage density	1/4	4	1/2	1								0.062
5	Bedding angle/Aspect	1/6	3	1/6	1/5	1							0.031
6	Foliation angle	1/5	2	1/5	1/4	2	1						0.037
7	Distance from road	1	7	4	5	6	5	1					0.203
8	Lithology	1/2	5	3	4	5	4	1/2	1				0.132
9	Rainfall	1/2	6	2	4	6	4	1/2	1	1			0.129
10	Soil		1/3	6	4	3	3	3	1/3	1/2	1/2	1	0.099
11	Curvature	1/7	3	1/6	1/5	1/4	1/5	1/9	1/7	1/6	1/5	1	0.020
Consistency ratio:	0.0798												

Consequently, it indicates that the prediction precision of the acquired map is 80.97% with respect to the ideal value of 100%, which is comparatively satisfied.

Finally, all the identified values of LSI were categorized into five classes by employing the natural breaks algorithm to signify five classes of the Landslide Susceptibility Zone (LSZ) of the area; namely, i) very high, ii) high, iii) moderate, iv) low and v) very low susceptibility zones (Fig. 3). The five susceptibility zones were overlaid and crossed with the landslide location map. Figure 4 shows a histogram that abridges the outcome of the complete process.

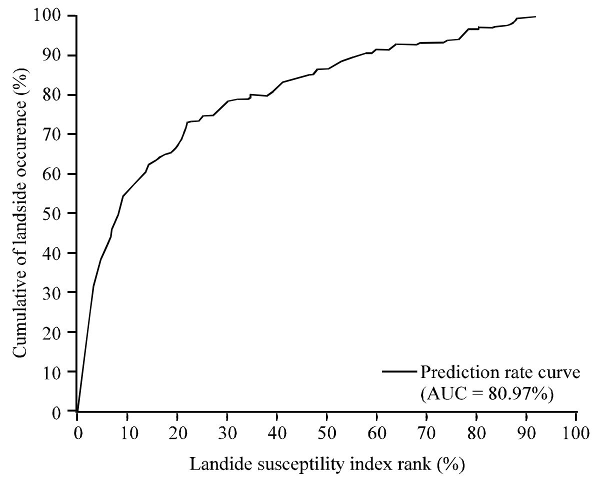

Fig. 2: Cumulative frequency diagram showing percentage of study area classified as susceptible (x-axis) in cumulative percent of landslide occurrence (y-axis)

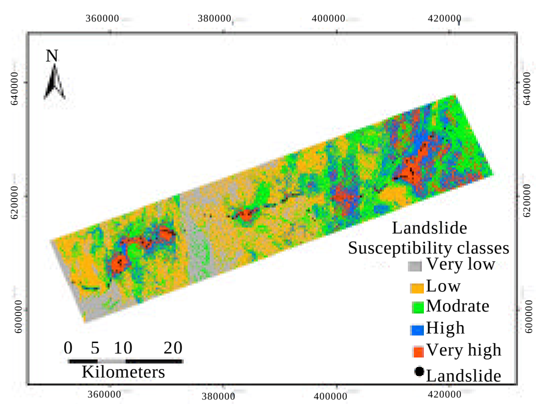

Fig. 3: Landslide susceptibility map of the study area

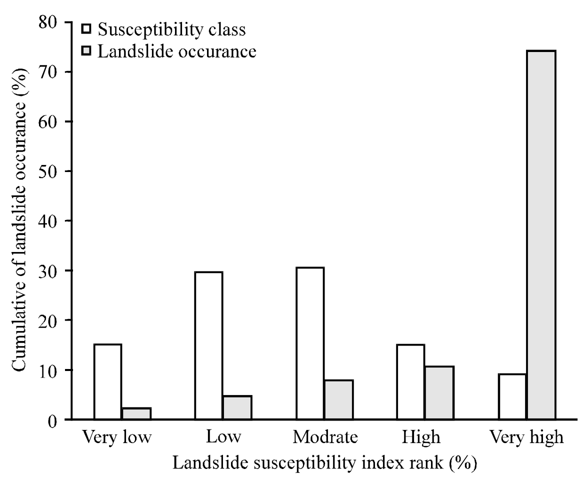

Fig. 4: The percentage distribution of the susceptibility classes and landslide occurrence

CONCLUSION

This study has provided a landslide susceptibility assessment model with the aid of GIS for a landslide prone area located in central northern Malaysia. This model is cost effective and capable of quickly contributing to the landslide assessment by manipulating data and performing the essential analysis. In order to accomplish this purpose ten landslide control factors were employed in the analysis which includes: slope gradient, slope aspect, curvature, distance from road, drainage density, lithology, foliation dip, topographic/bedding relationship, lineament density, soil and rainfall. An Analytical Hierarchical Process was implemented in order to obtain the weights for every factor and class using direct pairwise comparison, later based on these weights, thematic maps of factors were combined by weighted overly techniques and the landslide susceptibility map of the study area was created.

The obtained map was classified into five susceptibility classes which specified that the high and very high susceptible zones include about 24.3% of the total area, while about 45.2% were classified as low and very low susceptible zones and 30.4% is moderately susceptible zone. At the end, the map was validated with known landslides data based on the Area Under Curve (AUC) method, by which the prediction precision of 80.97% was established.

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