Landslide Susceptibility Assessment for Cameron Highlands using Analytical Hierarchy Process

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Abstract: ***Landslides susceptibility assessment has been conducted to identify the landslide-prone areas by using Geographical Information System (GIS) through Analytical Hierarchy Process (AHP) technique. Ten predictive or causative factors, such as digital elevation map (DEM), aspect, slope, curvature, geology, land use, fault, river, road and rainfall are used to map the susceptibility of landslides.Five classification zones of landslide susceptibility area are classes to very high, high, moderate, low and very low zone. The classification zones were compared and validated using a landslide inventory map produce from the integration of historical data and field survey using area under curve (AUC) method. The AHP techniquefinalresult shows 78.0% accuracy of landslide prediction, which considered as a fair result and it is acceptable. The mitigation measures for planning safe urbanization can be formulated using this susceptibility map.***

Keywords: Landslide, susceptibility map, analytical hierarchy process, area under curve

I. INTRODUCTION

Cameron Highlands was recorded as an area highly prone to landslide, whether small or big, it will causes harmful and damage to the farming/agricultural, property and loss of life [1], [2], [3]. Consequently, efficient assessment of landslide hazard is highly important to monitor and mitigate this tragedy as well.Landslide Susceptibility Maps (LSM) actas a main role in the planning, management of land use and risk mitigation risks [4]. The aim of LSM is to focus the regional distribution of possibly unstable slopes based on a thorough research of landslide factors [5].

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LSMoffers information on the probability of landslides in an area due to local terrain circumstances and these techniques can be divided based on the chosen method or characteristics, which is qualitative and quantitative methods [6].

Qualitative methods denote levels of susceptibility using specialist understanding in descriptive terms, while quantitative methods study the correlation between landslide and causative factor to predict probabilities of occurrence. [6], [7].The qualitative method limitation is that the precision depends on the understanding of the professionals conducting the research, while quantitative methods investigate the correlation between landslide and causative factor to predict the probability of occurrence using weighting causative factors of landslide [7].

Thus far, there have been many efforts to predict landslides and prevent the damage using appropriate science instruments. Nevertheless, a landslide susceptibility evaluation of hilly areas requires to be carried out carefully using suitable methodologies to anticipate all related effects[8], [9]. However, it is significant to consider various causative factors that cause landslides while using significant models to map the susceptibility of landslides.Landslide susceptibility assessment normally uses various causal factors and indicator. The causal factors are varying from existing data, time availability, types of landslides, historical data from one research to another depends to its objectives and the condition of the study area and also the level of the landslide hazard [10]. Just because of that, a clear image of the possible event should be taken into consideration the causal factors that led to the landslide need to be studied.

II. METHODOLOGY

Study Area and Landslide Predictive/Causative Factor

Cameron Highland, Pahang was recorded as the highest frequency of landslide occurrences in Malaysia. This location was chosen as the study area for landslide susceptibility assessment. The landslide predictive or causative factor in this case study was selected based on the objectives of the research, historical records and available data such as satellite data. The objective is therefore to create maps of landslide susceptibility and to highlight the most vulnerable areas and/or safer areas to landslides. Analytical Hierarchy Process (AHP) from heuristic (based on expert knowledge) was used to produce the Cameron Highlands LSM.

Ten (10) factors contributing to a landslide which are digital elevation map (DEM), aspect, slope, curvature, geology, landuse, fault, river, road and rainfall are selected based on the condition of the study area.Landsat 8, ALOS Palsar and Sentinel data were extracted using ERDAS and ARCGIS to produced ten factors Constructed a spatial database and converted into a vector-type spatial database to develop predictive or causative factors for assessing landslide susceptibility as shown in Fig.1.

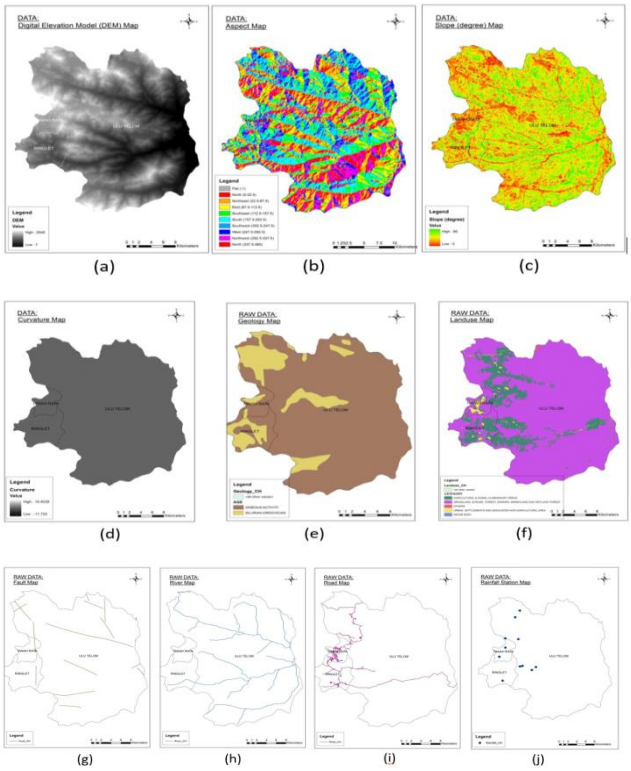

Fig. 1 Landslide Classification and Predictive Factors: (a)Digital Elevation Map; (b) Aspect; (c) Slope;(d) Curvature; (e) Geology; (f) Land use; (g)Fault; (h) River; (i) Road and (j) Rainfall Station

Ranking/Weight age of Landslide Parameter

In order to obtain the influence factor or weight age (in percentage) of each parameter, three simple steps are used; Pair-wise Comparison Matrix, Normalized Matrix and Consistency Analysis.

1) Step 1: Pair-Wise Comparison Matrix:Ranking and pair wise value are determined in term of integer values from 1 (equal importance) to 9 (extreme importance) as shown in Table I. The higher number means the chosen parameter is considered more important or contributes more to landslide occurrences compared with the parameter being compared with.

Table. 1 The Scale of Comparison (Modified From Saaty, 2000)

Scale	Degree of preference
1	Equal importance
3	Moderate importance
5	Strong or essential importance
7	Very strong importance
9	Extreme importance
2,4,6,8	Intermediate values
Reciprocals	Opposites

A pair-wise comparison as shown in Fig. 2was constructed based on five criterions which are C1, C2, C3, C4 and C5. By comparing two criterions, the importance values are assigned to green-coloured boxes according to comparison value on Table 1. If, in any case, The vertical axis factor is more important than the horizontal axis factor, values from value one to value nine are assigned. Since there are five criteria or parameters used, the comparison matrix has 25 boxes. However, due to the symmetrical nature of the pair-wise comparison, only ten values were required to be filled in which is at the upper triangular half of the matrix (green-coloured boxes). The diagonal (greycoloured boxes) and the lower triangular half (uncoloured boxes) represent equal and reciprocals value respectively.

The diagonal boxes of a pair-wise comparison matrix (grey coloured boxes) are comparing the same criteria. Hence, it has equal importance which is 1. Column 2 and row 1 are referred. When C1 has a very strong importance compared to C2, value 7 is assigned to the intersection box which was referred to Table 1. Automatically, the opposite box (column 1 row 2) has the reciprocal value of 1 which is 1/7. These simple steps are repeated until all green-coloured boxes at the upper triangle are filled.

		column 1	column 2	column 3	column 4	column 5
		C1	C2	C3	C4	C5
row 1	C1	1.000	7.000	3.000	1.000	1.000
row 2	C2	0.143	1.000	0.140	0.200	0.200
row 3	C3	0.333	7.143	1.000	1.000	1.000
row 4	C4	1.000	5.000	1.000	1.000	1.000
row 5	C5	1.000	5.000	1.000	1.000	1.000
row 6	**Sum**	**3.476**	**25.143**	**6.140**	**4.200**	**4.200**

Fig. 2 A total of 11 rainfall station at Cameron Highlands displayed using ArcGIS application

2)Step 2: Normalized Matrix:The second step is to normalize the matrix by adding together the digits in each column as shown in row 6. Then, Each column entry is then split by the sum of the column to give its standard score where the sum of each vertical column is equivalent to 1. Each row is summed up as shown in the greycoloured column in the Fig.3.

Normalized Matrix								Consistency Measures
	C1	C2	C3	C4	C5	TOTAL	AVERAGE	(must be equal to n)
C1	0.288	0.278	0.489	0.238	0.238	1.531	0.306	5.38
C2	0.041	0.040	0.023	0.048	0.048	0.199	0.040	5.08
C3	0.096	0.284	0.163	0.238	0.238	1.019	0.204	5.10
C4	0.288	0.199	0.163	0.238	0.238	1.126	0.225	5.15
C5	0.288	0.199	0.163	0.238	0.238	1.126	0.225	5.15
Sum	1.000	1.000	1.000	1.000	1.000	5.000		
							n	5
							CI	0.04
							RI	1.12
							Consistency Ratio	0.04

Fig.3Table of normalized matrix in Excel spreadsheet

3) Step 3: Consistency Analysis:Analysis of consistency consists of three tiny steps ; calculate the measure of consistency, calculate the consistency index (CI) and calculate the consistency ratio (CR). The matrix multiplication function (MMULT) is used to calculate the consistency metric in Microsoft Excel was used. The result

is shown in the orange-colored column where the consistency measures must be equal or near to value n. In this case, 'n' represent the order of the matrix involves in this case study. Consistency index (CI) reflects the consistency of one's judgment and it is calculated using the formula shown below:

$$CI = \frac{\lambda max - n}{n-1} \text{(Eq. 1)}$$

where λmax = the largest or principle Eigenvalue of the matrix or the average value of consistency measure,

n = the order of the matrix.

The consistency ratio (CR) is used to specify the likelihood of random generation of matrix judgments [9]. A CR of 0.1 or lower is considered acceptable in common practice. Any higher value at any level indicates that the judgments warrant re-examination and the matrix for pair comparison must be modified and adjusted. The CR is calculated using the following formula:

$$CI = \frac{CI}{RI} \text{(Eq. 2)}$$

where CR = Consistency index,

RI = Random inconsistency indices for n – 10 (Saaty, 1980).

Once the influence factor has been checked with consistency ratio (CR), these values now can be exported to ArcGIS, the medium where LSM was produced. ArcGIS calculator was used to generate the LSI by giving weight or influencing factor to each factor using Equation 1. LSI was classified into five susceptibility classes which are very low susceptibility (VLS), low susceptibility (LS), moderate susceptibility (MS), high susceptibility (HS) and very high susceptibility (VHS).

$$LSI = (W_1*X_1) + (W_2*X_2) + \ldots + (W_n*X_n) \quad \text{(Eq. 3)}$$

where LSI = Landslide susceptibility index from heuristic method,

$W_{1\ldots n}$ = Weight of infulencing factor,

$X_{1\ldots n}$ = Predictor variable/Influence factor.

Area under Curve (AUC)

The area under the curve (AUC) method is used as one of the validation technique in this study, which has been implemented and used by many researcher and expert. Upon generation of the susceptibility map using the AHP technique, the landslide hazard map of Cameron Highland produced from the actual landslide eventshave been compared to these susceptibility maps. Landslide Classification and Predictive factors have been used and the frequency ratio has been compared. In all cases, their area under curve was calculated based on the rate of curve previously generated.Based on the given rates, we can determine the accuracy of the models and factors predicting landslides event at study area.Therefore, to evaluate the prediction pattern, it is possible to evaluate the area under curve and the order must be in descending order for the index of values calculated from all cells in the study areathat has been performed.Then the ordered cell values were divided into 100 classes, with an accumulation of 1 percent intervals. The results of the rates check appear as a line. The area under curve was recalculated as the total area is 1, which means perfect prediction accuracy to compare the resulting quantities.

III. RESULTS AND ANALYSIS

Ranking/Weightage of Landslide Parameter

According to this study, digital elevation map, aspect and slope are ranked based on High-hills Guidelines from Ministry of Natural Resources and Environment (NRE). In the NRE guideline, only four classes are being used to range these classes. But in this study, five classes are being considered. Hence, the rank or weights are modified accordingly based on the NRE guidelines. This can be seen in Table II.

Table. 2 Rank/ Classes and their Reference that has are being used in this Study

1.Digittal Elevation Map	Class	Ranking/ Weight age	5.Distance From Drainage/Stream	Ranking/ Weight age	8.Distance From Fault	Ranking/ Weight age
<150m	Low Land	5	<1,000m	1	<1,000m	1
150-300m	Hill	4	1,000-2,000m	2	1,000-2,000m	2
300-750m	Highland	3	2,000-3,000m	3	2,000-3,000m	3
750-1,000m	Highland	2	3,000-4,000m	4	3,000-4,000m	4
>1,000m	Mountain	1	>4,000m	5	>4,000m	5
Source: modified from NRE Guidelines (2005)					Source: modified from Matori et al. (2011)	

2.Aspect	Ranking/ Weightage	6.Distance From Road	Ranking/ Weightage	9.Landuse	Ranking/ Weightage
Flat	1	<500m	1	Agricultural Area	5
North, North	2	500-1,000m	2	Grassland, Shrubs, Forest, Swamps	4
East, Southeast,South, Northwest 3	3	1,000-1,500m	3	Urban, Settlements & Non-Agri	3
Southwest	4	1,500-2,000m	4	Water Bodies	2
Northeast, Northwest	5	>2,000m	5	Others	1
Source: modified from NRE Guidelines (2005)				Source: modified from Matori et al. (2011)	

3.Slope	Class	Ranking/ Weightage	7.Geology	Ranking/ Weightage	Rainfall (mm/year)	Ranking/ Weightage
0-15 degree	Low Risk	5	Silurian Ordovician – Schist	3	1 <1,000	5
15-25 degree	Moderate Risk	4	Igneous Activity - Granite	4	1,000-1,500	4
25-35 degree	High Risk	3			1,500-2,000	3
35-45 degree	High Risk	2			2,000-2,500	2
>45 degree	Very High Risk	1			>2,500	1
Source: modified from NRE Guidelines (2005)			Source: modified from Matori et al. (2011)		Source: modified from Matori et al. (2011)	

4. Curvature	Ranking/ Weightage
<-8.4	4
-8.4- (-2.1)	2
-2.1-4.2	1
4.2-10.5	3
>10.5	5
Source: modified from Matori et al. (2011)	

Influence Factor using Pair-wise Comparison Matrix

By referring to Fig. 4, elevation parameter has the highest influence factor which is 20 percent while the lowest influence are distance from drainage and distance from road with 3 percent respectively. The total of influence factor must be equal to 100 percent.

	Average/ Priority Vector	Consistency Measures
1. Elevation (m)	20	10.59
2. Slope Aspect	7	10.43
3. Slope Angle	17	10.58
4. Curvature	8	10.52
5. Distance From Drainage (m)	3	10.54
6. Distance From Road (m)	3	10.44
7. Geology	8	10.48
8. Distance From Fault (m)	14	10.60
9.Landuse	6	10.33
10. Rainfall (mm/yr)	14	10.63
Sum	100.000	
	n	10
	CI	0.06
	RI	1.49
	Consistency Ratio	0.04

Fig.4 Influence factor of landslide parameterwhich will be used in ArcGIS

Landslide Susceptibility Mapping in ArcGIS

Once all data has been imported into ArcGIS platform and the necessary ranking/weightage and influence factor has been calculated, all data must be reclassify according to different classes.Using AHP technique, the LSM is overlay with the data of landslide inventory map where it includes the current landslide areas.

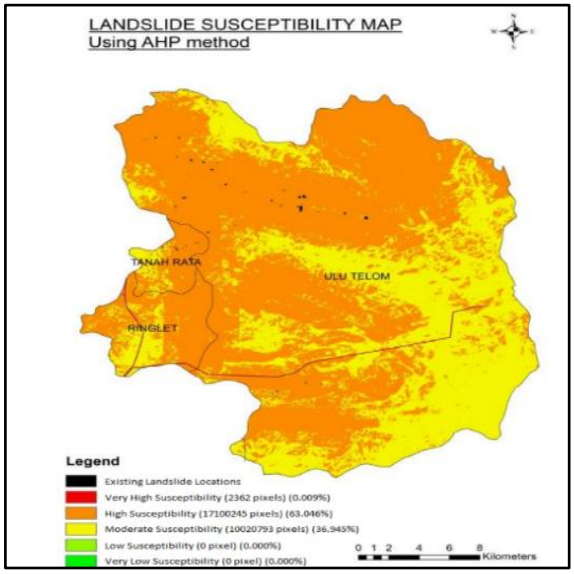

Fig. 5 Landslide susceptibility map using AHP technique overlay with landslide inventory map

Referring to Fig. 5, it shows that the current landslides (black) were position at the high susceptibility area (orange).As for the count (number of pixels), most of the study area is in high landslide susceptibility area (63 percent) while very high susceptibility area has very low pixel count (39 percent).

Validation and Accuracy

Landslide susceptibility results wasanalysis and validated using actual landslide areas from Google Earth's aerial view and field survey.At that moment, the inventory to be used for validation purposes were added about 50 active landslides that were captured during site surveying. The landslide inventory map consisting of data actual base on Google Earth's aerial view and field survey which is active landslides has been overlaid with the LSMgenerated by the AHP technique and the outcomes have been tabulated as shown in Table 3. Generally, the active landslide should be spotted on critical slope at the actual site. However, in this study the landslide can be identified at either high or very high susceptibility area. If there is an active landslide occurin the area of low susceptibility, the susceptibility map may be found to be incorrect or misleading due to existing data is inaccurate.

Table. 3 Percentage of Existing and Active Landslides on the Landslide susceptibility Area

Landslide Susceptibility (Area)	% of Landslide
Very High	0
High	18
Moderate	82
Low	0
Very Low	0

Table.3show the validation results. Based on this table, within the high susceptibility area there are 18 percent (%) of active landslide falls, while the remaining 82 percent (%) are in a moderate susceptibility area. Others give 0 percent (%) for very high, low and very low susceptibility area.

Area under Curve (AUC)

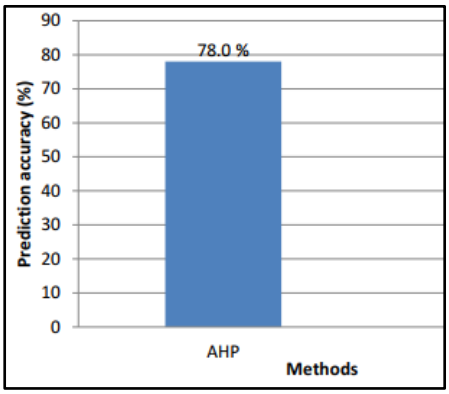

Fig. 6 Accuracy of landslide prediction

From the result (Fig. 6), AHP technique obtained 78.0% accuracy of landslide prediction. The accuracy obtained is classified as fair results as refer to the traditional academic point system.

IV. CONCLUSION

In this research, the integration of the analytical hierarchy process (AHP) and geographical information system (GIS) was perfomedto generateLSM for Cameron Highland. Based on the validation and accuracy assessment results, there are 18% of active landslide was found within the high susceptibility area while the remaining 82% were in moderate susceptibility area. The landslide prediction accuracy based on Area Under Curve (AUC) is 78%, which is classified as afair result.This outcome can be used to formulate recommendations and mitigation measures for notifying and informing the public by local authorities.

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