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EVALUATION AND DEVELOPMENT OF CUT-SLOPE ASSESSMENT SYSTEMS FOR PENINSULAR MALAYSIA IN PREDICTING LANDSLIDES IN GRANITIC FORMATION

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Abstract. A slope assessment is carried out to predict the probability of occurrence and the degree of severity of landslides in a given area. This paper evaluates four existing slope assessment systems (SAS) for predicting landslides at micro level of assessment developed by the Public Works Department of Malaysia, namely the Slope Maintenance System (SMS), Slope Priority Ranking System (SPRS), Slope Information Management System (SIMS) and the Slope Management and Risk Tracking System (SMART). From the results of this study, it appears that none of the existing SAS is satisfactory for predicting landslide in granitic formation, due to various reasons such as the use of hazard score developed from another country, insufficient database, and the use of data base derived from different rock formations. Two new SAS were developed, i.e. Model A using ten-variables equation that is based on the stepwise discriminant analysis, and Model B using nine-variables equation that is based on the stepwise linear regression analysis. These two new models appear to be suitable for predicting landslides in granitic formations than the existing four SAS.

Keywords: Discriminant analysis, granitic formation, landslide, slope assessment system

Abstrak. Penilaian cerun dijalankan bagi meramal kebarangkalian berlakunya kejadian tanah runtuh dan juga tahap kemusnahannya di sesuatu kawasan yang dinilai. Dalam kertas kerja ini, empat sistem penilaian cerun (SAS) sedia ada bagi meramal kejadian tanah runtuh pada skala mikro yang telah dibangunkan oleh Jabatan Kerja Raya (JKR) Malaysia iaitu *Slope Maintenance System* (SMS), *Slope Priority Ranking System* (SPRS), *Slope Information Management System* (SIMS) dan *Slope Management and Risk Tracking System* (SMART) telah dikaji. Daripada hasil kajian, adalah jelas tiada sebarang satu SAS sedia ada yang sesuai bagi meramal kejadian tanah runtuh di kawasan yang didasari batuan granit. Ini adalah kerana beberapa sebab yang jelas iaitu antaranya skor bahaya yang digunakan diadaptasi dari negara luar, pengkalan data yang terhad, dan juga pengkalan data yang digunakan adalah daripada formasi batuan yang berbeza. Dalam kajian ini, dua SAS baru telah dibangunkan iaitu Model A yang menggunakan persamaan sepuluh parameter yang dibentuk dari analisa *discriminant*, dan Model B yang menggunakan persamaan sembilan parameter yang dibentuk dari analisa *linear regression*. Kedua-dua model baru ini jelas menunjukkan ia lebih sesuai bagi meramal kejadian tanah runtuh di kawasan didasari batuan granit.

Kata kunci: Analisa *discriminant*, formasi granit, tanah runtuh, sistem penilaian cerun

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1.0 INTRODUCTION

Landslide is defined as the movement of a mass of rock, debris or earth down a slope [1]. The word landslide also refers to the geomorphic features that result from the event. Other terms referring to landslide include slope failures, slope instability and terrain instability [2]. Landslide may occur almost anywhere, from man-made slopes to natural, pristine ground. Most slides often occur in areas that have experienced previous sliding. All landslides are triggered by similar causes.

Landslides have caused large numbers of casualties and huge economic losses in hilly and mountainous areas of the world. In tropical countries where annual rainfall can reach as high as 4500 mm and high temperatures around the year, cause intense weathering of rock mass and formation of thick soil profile [3]. With these set of climate and geological condition, combined with other causative factors, landslide is one of the most destructive natural disasters in tropical region. Malaysia is one of the countries located in the tropical region, and where granite rocks dominate virtually every mountain range with summits exceeding 2000 m. During the period of 1993 to 2004, there were some 13 major landslides reported in Malaysia, involving both cut and natural slopes, which resulted in more than 100 deaths.

Social and economic losses (and lives) due to landslides can be reduced by means of effective planning and management which involved landslide hazard assessment, slope assessment for landslide prediction, mitigation measures, and warning systems [4, 5].

Slope Assessment System (SAS) for predicting the probability of occurrence and likely severity of the landslides in a given area can be carried out by various approaches. According to Varnes [6], Soeters and van Westen [7] and van Westen *et al*. [8] there are four methods of slope hazard assessment, namely landslide inventory, heuristic approach, statistical approach and deterministic approach. Hussein *et al.* [9] described another assessment method called the overall score evaluation method. Irigaray & Chacón [10] discuss six methods of assessment namely percentage of rupture zones, intervals of critical slope angle, matrix, indexing, value of information and multiple regression. Ali [11], Rosenbaum *et al*. [12] and Tangestani [13] described the use of fuzzy set theory analysis for evaluating landslide hazard. Fractal dimension, a mathematical theory that describes the quality of complex shapes of images in the nature is claimed to be suitable for measuring landslides complex topography [14, 15]. Results of these SAS can be presented in the form of landslide hazard map, which is useful in planning development, and in slope maintenance and management. It can also be combined with landslide consequences analysis to produce landslide risk map which can be used in prioritizing maintenance works and in emergency and rescue preparedness.

In Malaysia, there are several government departments involve in reducing of landslide hazard and their consequences, namely the Department of Mineral and Geosciences (DMG), Center of Remote Sensing (MACRES) and the Public Works Department (PWD). The SAS developed by MACRES and DMG are meant for macro level of assessment whereas the SAS developed by the PWD are meant for micro level of assessment.

To date, the reliability or accuracy of the existing SAS in predicting landslides in Malaysia have never been evaluated despite that they are very crucial in any SAS. Incorrect prediction will expose lives and economy to danger or hazard if a slope or an area that should had been rated as a High Hazard Level is incorrectly rated as Low Hazard Level, or vice versa.

This paper presents an evaluation of the reliability and accuracy of four existing SAS in assessing landslide at the micro level. They are the Slope Maintenance System (SMS), Slope Priority Ranking System (SPRS), Slope Information Management System (SIMS), and the Slope Management and Risk Tracking System (SMART). The development of a new SAS meant for slopes in granitic formations (an area where the weathering profile is underlain by granitic rock mass) is also described.

2.0 SLOPE ASSESSMENT SYSTEMS AND FIELD SITES

In evaluating the reliability and accuracy of the existing slope assessment systems in predicting landslides, field data were collected from existing cut and natural slopes. The number of recent landslides or failed slope was then compared with the number of slopes classified as high and very high hazard that actually failed. A good prediction is when many, if not all, the predicted slope will actually fail (or have actually fail for the case of back analysis). There are four SAS that have been developed by the PWD of Malaysia for predicting landslide at the micro level. They are the SMS, SPRS, SIMS and SMART.

The SMS was developed in 1996 by the PWD for long-term preventive measures in prioritizing landslide prevention and slope stabilization works [16]. Statistical method using discriminant and factor overlay analysis based on slope type (cut and natural slope in granitic formation) were used to determine the hazard values [17, 18]. Six parameters were considered namely, age of slope in years, number of culverts, erosion, percentage of feature uncovered, feature aspects, and rock condition profile.

The SPRS was developed in 1999 as a tool for quick assessment of all slopes in Malaysia so that repair work can be prioritized and carried out. This system was also developed to identify budget requirements for slope repairs. The hazard score used in SPRS was established using heuristic method with associated ratings of 0, 1 and 2 were used according to the definitions of each parameter by Hussein *et* *al*. [19]. The hazard attributes for cut slope include slope angle, height of slope, slope cover, surface drain, natural water path, seepage, ponding, erosion, slope failure, surroundings upslope, soil type, weathering grade and discontinuities.

The SIMS was developed in 2002 jointly by the PWD and the Japanese International Cooperation Agency [20]. The hazard score used was adopted from Japanese experience in Japan. Parameters considered include topography, slope geometry, material, geological structure, deformation, surface conditions and counter-measure effectiveness.

The SMART is the latest slope management system developed by the PWD. The hazard score or instability score (IS) ranges from 0 to 1 and is derived through the integration of results from three assessment methods: statistical method (using stepwise discriminant function analysis and then converted into probability), deterministic method (the factor of safety determine by combined hydrology and stability model or CHASM and then converted to the probability using Monte-Carlo Analysis) and, when appropriate, expert knowledge [21]. The system was developed based on the Tamparuli-Sandakan road, in Sabah, Malaysia where there have been numerous failures. This road is underlain largely by the meta-sediment formation.

In Malaysia, the total length of roads had increased by more than three folds, from 21,914 km in 1980 to 78,433 km in 2003 [22]. About 30% of these roads traverse through or are located in hilly and mountainous areas. Landslide occurrences along these hilly and mountainous roads have been reported from time to time, in both cut and natural slopes. Normally landslides occurred during the rainy season, from October to January every year. A study conducted in 2000 along six selected hilly and mountainous roads shows that out of 444 landslides, 420 occurred in cut and natural slopes [20].

Granite is the major rock that dominates virtually all the major mountain ranges with summits exceeding 2,000 meter in Malaysia [23]. More than 75% of the roads that traverse through the hilly and mountainous areas are cut through and/or underlain by the granite rock formation. At least four major trunk roads traverse through the Main Range granite formation of Peninsular Malaysia, namely the East-West highway (Gerik-Jeli), the Tapah – Cameron Highland road, the Kuala Kubu Baru – Gap road and the Kuala Lumpur – Bentong Old road (see in Figure 1). These four roads have experienced numerous numbers of landslides in the past.

For evaluating the accuracy and reliability of the existing SAS in predicting landslides, slope assessment data along three different sites underlain by granitic formation, namely the Gunung Raya road in Langkawi Island, Malaysia (Site A), and the East-West highway (Gerik-Jeli, Site B) and the Kuala Kubu Baru – Gap road (Site D) of the Main Range granite were used (see Figure 1). The slope inventory data such as slope height, slope angle, soil type, weathering grades, were collected / compiled for ten years period, from 1994 to 2004. These data were obtained from previous records as well as through site visits (walkover survey). Landslide occurrences were determined either from written historical records, differences seen in multi-date aerial photo, or difference between older sketches of the data collection performa and the current site conditions. Data prior to the occurrence of the landslides were used as input for the SAS.

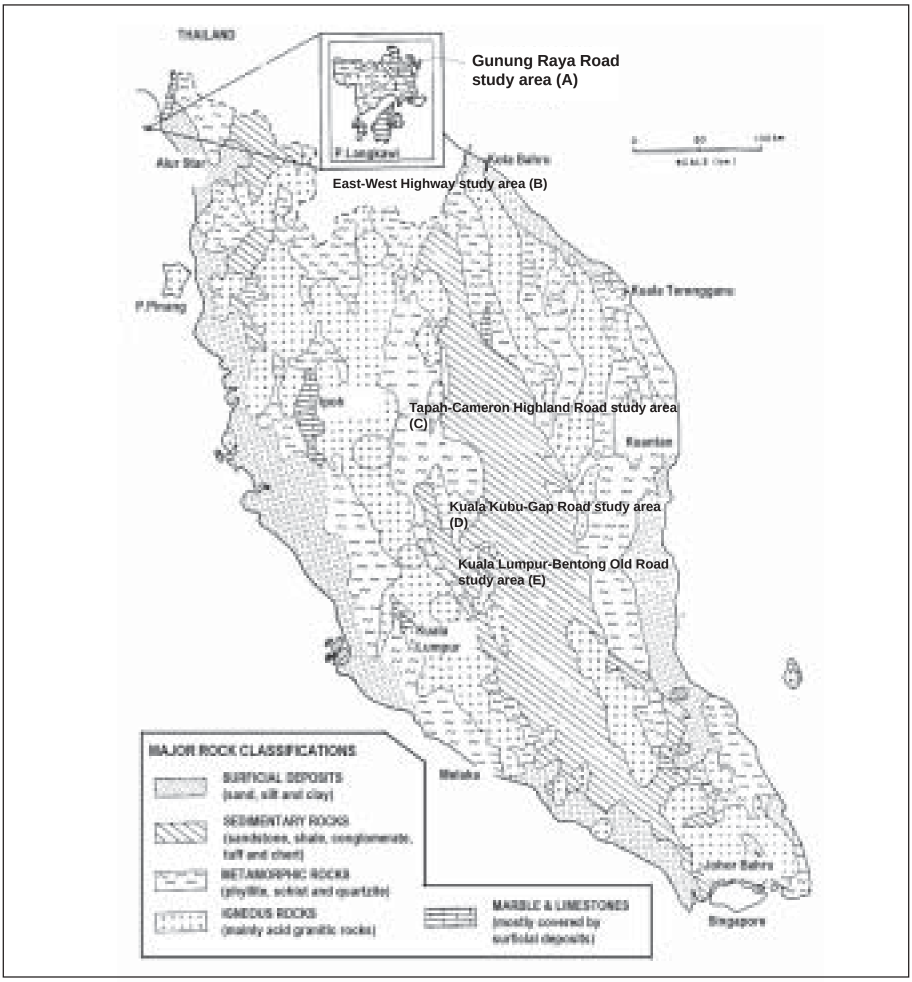

Figure 1 Locations of field sites and general geology of Peninsular Malaysia (General geology is after Komoo & Mogana [24])

For the case of the Gunung Raya road (Site A), there were 15 numbers of landslides that had occurred after a period of heavy rainfall in September 2003. Generally the types of landslide that occurred along this road were shallow slides and severe sheet erosion. One big deep-seated landslide occurred at KM 5.9 that caused one fatality. For the case of the East-West highway, 20 numbers of landslides were reported from 1994 to 2001. More than 100 landslides occurred during a period of heavy rainfall in 2003 at site D along the Kuala Kubu Baru – Gap road. Most of these were shallow-seated landslides.

3.0 EVALUATION OF THE EXISTING SAS

Thirty four (34) number of cut and natural slopes along the Gunung Raya road, 53 number of cut and natural slopes of the East-West Highway and 52 number of cut and natural slopes along the Kuala Kubu Baru – Gap Road were assessed using the four slope assessment systems, namely the SMS, SPRS, SIMS and SMART. The results obtained in term of number of slopes classified as high and very high hazard, and numbers of slopes that actually failed are shown in Table 1.

Table 1 Summary of comparative study on four existing SAS in predicting landslide

Prediction	SMS	SPRS	SIMS	SMART
(1) Number of assessed slopes	139	139	139	139
(2) Numbers of recent landslide or failed slope	44	44	44	44
(3) Numbers of slope classified as high and very high hazard	65	71	2	72
(4) Number of slopes classified as high and very high hazard that actually failed	17	23	1	27
(5) Percentage of (4) compared with (2)	39%	52%	2%	61%

From the table above, it can be seen that the SAS, except for the SIMS, predicted a larger number of slopes with 'high' and 'very high hazard' compared to the actual failure. In term of actual failure, only the SMART and the SPRS systems appear to give prediction accuracy of higher than 50%, i.e. percentage of number of slopes classified as high and very high hazard that actually failed. The reasons for the apparent poor predicting capability of the existing SAS can perhaps be listed as follows.

For the case of the SIMS, it used hazard score developed from other country (Japan). This appeared to be its main defect. The SMS was developed based on statistical analysis of data from the same East West highway. It appeared that its database was not sufficient in term of number of selected sites and samples taken. For the case of the SPRS, the accuracy obtained was fair, giving the system simplistic approach of assigning hazard score with only 0, 1 and 2. Whilst for the case of the SMART, its current database derived only from the meta-sediment formations was apparently not sufficient to be extrapolated for the granitic formations considered in this study.

4.0 DEVELOPMENT OF THE NEW SAS

Due to the apparent lack of accuracy of the existing SAS in predicting landslides, attempt was made in this study to develop a new SAS, as an alternative to the existing ones. The same slope inventory data of failed and stable slopes (or without sign of failure) was analyzed using two statistical analyses, namely the (i) stepwise discriminant analysis (Model A), and (ii) stepwise linear regression analysis (Model B). The Statistical Package for the Social Science (SPSS) computer software was used as a tool in analyzing the data instead of stepwise discriminant analysis which was used in both SMART and the SMS.

Statistical analysis was chosen because there is abundant database on slopes and landslides collected for the past ten years that could be used. The linear models produced by the statistical analysis could easily be applied and verified by others. This is good in term of objectivity compared to other methods such as the heuristic method which depends on the experience of the geomorphologists, and could not be easily verified by others.

In the stepwise discriminant analysis, data on numerous slope variables (such as slope angle, slope height, percentage of slope uncovered by vegetation) prior to landslide or slope failure occurrences were compiled, separated into failed and stable group and subsequently analyzed. Through the analysis, the significant variable(s) in discriminating the failed and stable group and their regression coefficient as the best predictors for future landslide occurrences were determined. In this analysis, the model of discrimination was built step-by-step. Specifically, at each step all variables were reviewed and evaluated to determine which would contribute most to the discrimination between the groups. Those variables were then being included in the model, and the process started again. The general regression model used for the computation of discriminant function (Y) representing the instability score is as shown below;

$$Y = d_1V_1 + d_2V_2 + \ldots + d_nV_n + C \tag{1}$$

where $d_1, d_2, \ldots d_n$ are discriminant coefficient, $V_1, V_2, \ldots V_n$ are significant variables and C is a constant or model error.

In the stepwise linear regression analysis, the slope data of the failed and stable group was lumped together and analyzed step-by-step to determine the best parameter(s) that fit the linear equation model of both the failed and stable groups. The linear regression model used for computation of regression function (Y) representing the instability score is similar to Equation (1).

139 numbers of cut and natural slopes of granitic formations from the three sites; the Gunung Raya road (Site A), the East-West highway (Site B) and the Kuala Kubu Baru – Gap road (Site S) were used in the development of the new SAS. The slopes features were then divided into two groups: 86 numbers of failed slopes and 53 numbers of stable slopes.

From the available data, 22 numbers of variables for every slope features that are related to the landslide occurrences were selected in the development model as listed in Table 2. All slope data in the form of continuous variables were transformed into various classes or scores and they were used in the statistical analysis and regression equation for the computation of instability score (individual discriminant and regression function scores).

Table 2 Sub-variables of slope feature used in the models development

Sub-variables	**Ranges (Classes)**	**Sub-variables**	**Ranges (Classes)**
Slope feature	Near crest (1)	Main cover type	Trees (1)
location/position	Mid-slope (2)		Shrub (2)
	Near toe (3)		Grass (3)
Height of slope	<10 (1)		Artificial cover (4)
(m)	10 to 20 (2)	% of feature	< 10 (1)
	20 to 30 (3)	uncovered	10 to 30 (2)
	> 30 (4)		> 30 (3)
Slope angle	<45 (1)	Soil type	Sandy (1)
	45 to 63 (2)		Silty (2)
	>63 (3)		Clayey (3)
Feature aspect	0 to 90 (1)	Presence of rock	Yes (0)
in degrees	90 to 180 (2)	exposure	No (2)
	180 to 270 (3)	% rock exposure	0 to 25 (1)
	270 to 360 (4)		26 to 50 (2)
Plan profile	Concave (1)		51 to 75 (3)
	Straight (2)		76 to 100 (4)
	Convex (3)	Weathering grade	I to II (1)
Cross profile shape	Concave (1)		III to IV (2)
	Straight (2)		V to VI (3)
	Convex (3)	Rock condition	Grade III or less (1)
Feature area (m^2)	< 2,500 (1)	profile	Grade III and Grade VI (2)
	5,000 to 7,500 (2)		Grade IV to Grade VI (3)
	7,500 to 10,000 (3)		Grade IV to Grade VI with
			corestone boulders (4)
	>10,000 (4)		Colluvium (5)
Distance to ridge	< 50 (1)	Bench drain	Yes (0)
(m)	50 – 149 (2)		No (2)
	150 – 249 (3)	Horizontal drain	Yes (0)
	> 250 (4)		No (2)
Batter/Bench	< 5 (1)	Roadside drain/	Yes (0)
height (m)	5 – 9.9 (2)	Toe drain	No (2)
	10 – 14.9 (3)	Number of water	0 (0)
	15 – 19.9 (4)	courses within	1 (1)
	> 20 (5)	features	2 (2)
Slope shape	Simple (1)	Erosion	No (0)
	Planar (2)		Yes (2)
	Asymmetrical (3)		
	Compound (4)		

In Model A, discriminant analysis was conducted using significant value of 0.15 to add and 0.20 to delete the variables from the analysis. The result of the analysis showed that there are ten significant variables that could separate the failed and stable slopes, namely; slope angle, feature area, distance to ridge, slope shape, percentage (%) of feature uncovered, presence of rock exposure, rock condition profile, bench drain, horizontal drain and erosion. Discriminant function was then calculated using general regression formula (Equation (1)) and using canonical discriminant function coefficients as shown in Table 3.

Table 3 Ten-variable used in the Model A and its un-standardized canonical discriminant coefficients

Variables	Label	Coefficients
Slope angle	angle	0.533
Feature area	feat_are	0.626
Distance to ridge	dst_ridg	0.359
Slope shape	slp_shp	-0.183
% of feature uncovered	uncover	0.415
Presence of rock exposure	rexp	0.340
Rock condition profile	rxcpro	0.421
Presence of bench drain	bench_d	0.746
Presence of horizontal drain	hori_d	0.394
Presence of erosion	erosion	0.686
Constant		-7.653

The ten-variable equation for Model A produced from the analysis is as follows:

$$\begin{aligned} Y = {} & 0.533(\text{angle}) + 0.626(\text{feat\_are}) + 0.359(\text{dst\_ridg}) - 0.183(\text{slp\_shp}) \\ & + 0.415(\text{uncover}) + 0.340(\text{rexp}) + 0.421(\text{rxpro}) + 0.746(\text{bench\_d}) \\ & + 0.394(\text{hori\_d}) + 0.686(\text{erosion}) - 7.653 \end{aligned} \tag{2}$$

Discriminant function of both the failed and stable slopes then could be computed using this equation (Equation (2)). All variables in the equation should be replaced by actual variables (in form of classes or ranges) of the assessed slope. The boundary of discriminant function separating these two groups (failed and stable) was calculated using the mean average of this two groups, which could be determined statistically as shown in the histogram and normal curve plot as in Figures 2 and 3.

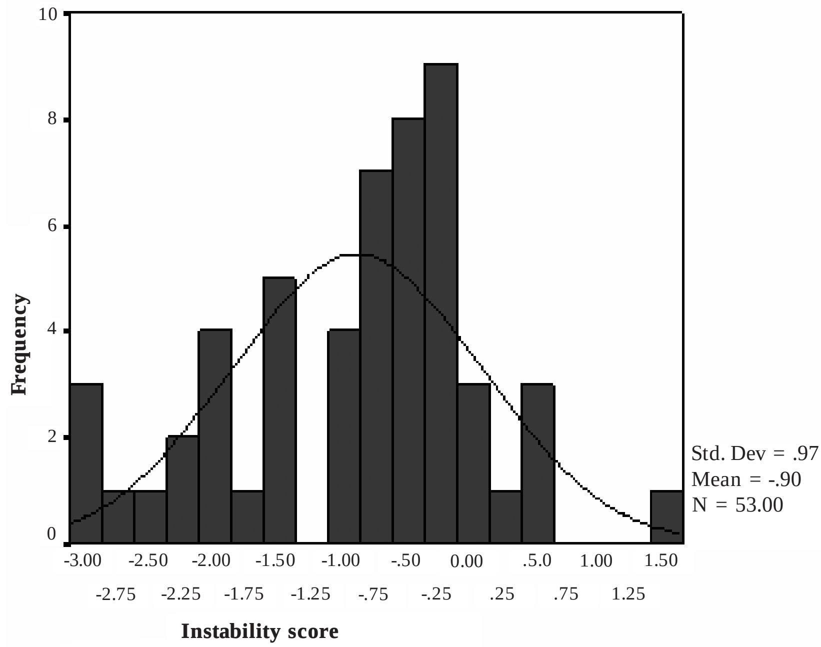

Figure 2 Histogram plot and normal curve of stable slope for Model A

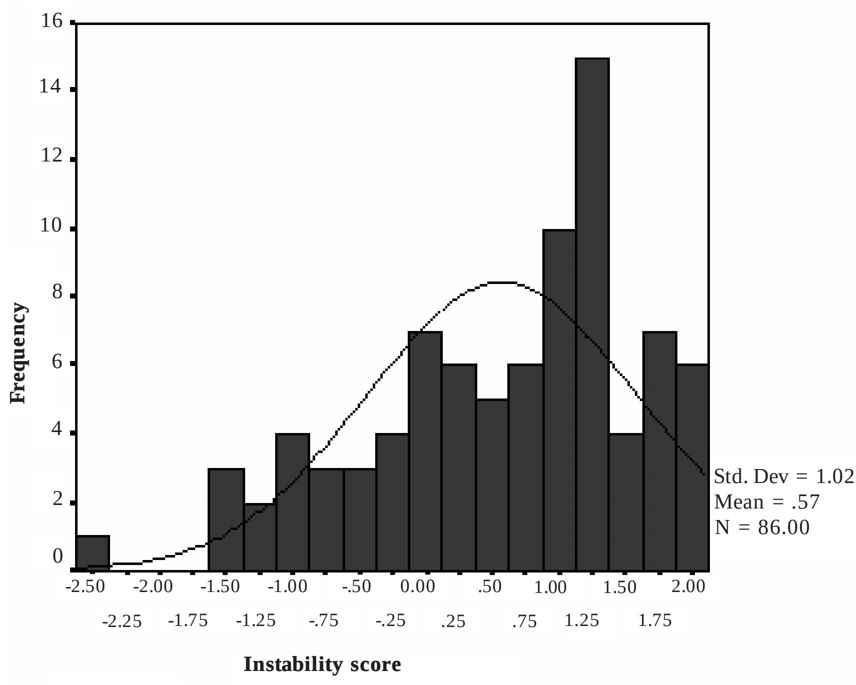

Figure 3 Histogram plot and normal curve of failed slope for Model A

Group means for the stable and failed slopes are -0.90 and 0.57 respectively. The value of discriminant function separating these two groups (noted as g) can be calculated using Equation (3) as follows,

$$g = (Y_f + Y_s) / 2, \tag{3}$$

where, Y_f = Mean of failed group
Y_s = Mean of stable group

Value of g for Model A is;

$$\begin{aligned} g &= (0.57 - 0.90)/2 \\ &= -0.165 \end{aligned}$$

Using this g value, the boundary condition separating failed and stable slopes for Model A is as follows,

Stable if $Y < -0.165$, or otherwise failed

The hazard rating was designed using the maximum and minimum value of discriminant function. For Model A, the maximum value of discriminant function was 5.385 and the minimum value was -6.031. Table 4 below shows the hazard rating designed for Model A.

Table 4 Hazard rating designed for Model A

Range	Rating
2.61 to 5.385	Very high
– 0.165 to 2.61	High
– 3.098 to – 0.165	Low
– 6.031 to – 3.098	Very low

Accuracy (or known as overall correctly classified) of Model A in classification of failed and not failed slope within 139 slopes used in the development of the model was analyzed. The accuracy of produced by the models is 79.9%, at par compared to other earlier researchers [25-27].

For the case of Model B, the stepwise linear regression was used to fit an observed independent data set (failed or stable slopes) using a linear combination of independent variables (e.g. slope angle, slope height, etc.). The result of this statistical method was a number of independent variables correlated to the dependent variable used in the analysis. The linear equation combining the values of the independent data set of these variables with coefficients established by the regression can be developed. With significant value of F-statistic to add at 0.1 and to delete at 0.15, there were nine independent variables determined as the best set of variables to predict failed and stable slopes. They were the slope angle, feature area, distance to ridge, slope shape, percentage of feature uncover, presence of rock exposure, presence of bench drain, presence of horizontal drain and presence of erosion, as shown in Table 5.

Table 5 Nine variables used in the Model B and its un-standardized coefficients

Variables	Label	Coefficients
Slope angle	angle	0.111
Feature area	feat_are	0.138
Distance to ridge (m)	dst_ridg	0.076
Slope shape	slp_shp	-0.048
% of feature uncovered	uncover	0.097
Presence of rock exposure	rexp	0.102
Presence of bench drain	bench_d	0.171
Presence of horizontal drain	hori_d	0.086
Presence of erosion	erosion	0.172
Constant		0.159

Where Y is dependent variable function representing instability score of failed and stable slopes, whereas angle, feat-are, dst-ridg, slp-shp, uncover, rexp, bench-d, hori-d and erosion represent independent parameters (or sub-parameters) as listed in Table 5**.**

The nine-variable linear regression equation produced from the analysis is as follows:

$$\begin{aligned} Y = {} & 0.111(\text{angle}) + 0.138(\text{feat\_are}) + 0.076(\text{dst\_ridg}) - 0.048(\text{slp\_shp}) \\ & + 0.097(\text{uncover}) + 0.102(\text{rexp}) + 0.171(\text{bench\_d}) + 0.086(\text{hori\_d}) \\ & + 0.172(\text{erosion}) + 0.159 \end{aligned} \tag{4}$$

The instability scores (Y) for failed and stable slopes were then calculated using nine-variables equation (Equation 4) above. A high value instability score indicated that the slope feature fall within the unstable area. The values of independent variables used in the computation were the classes of variables or sub-variables as listed in Table 2. The boundary of the instability score (Y) separating these two groups (failed and stable slopes) were calculated using a mean value of their instability scores. Mean values of instability score for proposed model was determined statistically, i.e. 1.620 (Figure 4).

Using these mean values, the boundary condition separating instability scores of failed and not failed slopes for all significant value to be used in the proposed models is as follows:

Not failed if $Y < 1.620$, or otherwise failed.

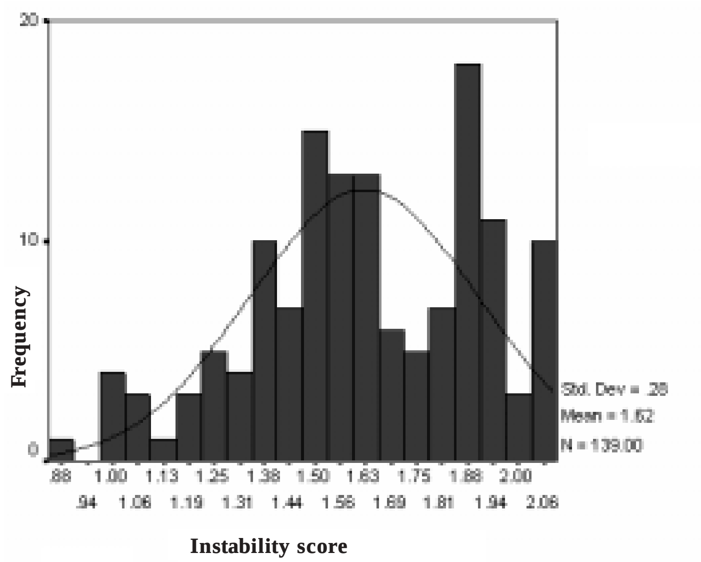

Figure 4 Histogram plot and normal curve of instability score of Model B

The hazard rating was designed using the maximum and minimum value of instability score (*Y*). The maximum value of instability score (*Y*) was 2.653 and the minimum value was 0.389. Table 6 below shows the hazard rating designed for Model B.

Table 6 Hazard rating for Model B

Instability score	**Hazard rating**
2.137 to 2.653	Very high
1.620 to 2.137	High
1.005 to 1.620	Low
0.389 to 1.005	Very low

Similar process of accuracy evaluation of Model B in classification of failed and not failed slope within 139 slopes used in the development of the model was analyzed, and found out that the accuracy produced by the models was 79.14%, also at par compared to other researchers earlier works.

5.0 COMPARISON OF THE EXISTING SAS WITH THE NEW SAS

It is of interest to compare the performance of the four existing SAS with the new SAS in predicting landslides. For this purpose, two new sites underlain by granitic formation (other than those used to developed the new SAS) were considered. Data from 21 slopes along the Tapah – Cameron Highland road (Site C), and 15 slopes along Kuala Lumpur – Bentung old road (Site E, see Figure 1) were used. Heavy rainfall caused a number of landslides along both roads. Some 13 recent landslides occurred along the Tapah – Cameron Highland road between 1994 and 2000. For the case of the Kuala Lumpur – Bentung old road, 12 landslides occurred after a period of heavy rainfall in November 2003. The results of the comparative study are shown in Table 7.

Table 7 Comparison of the existing SAS with the new SAS for predicting landslides in granitic formation

	Model A	Model B	SMS	SPRS	SIMS	SMART
(1) Number of assessed slopes	36	36	36	36	36	36
(2) Numbers of recent landslide or failed slope	25	25	25	25	25	25
(3) Numbers of slope classified as high hazard	28	24	7	20	0	8
(4) Number of slopes classified as high hazard that actually failed	24	21	6	17	0	7
(5) Percentage of (4) compared with (2)	96%	84%	24%	68%	0	28%

The new SAS exhibits a better capability in predicting landslides in the granitic formation terrain. The number of slopes classified as high to very high hazard match closely with the actual failures. Likewise the percentage of correct prediction was over 80%. Model A that was based on the stepwise discriminant analysis on ten variables, appeared to be slightly better than Model B, which was based on the stepwise linear regression analysis on nine variables.

6.0 CONCLUSIONS

(i) There are four existing slope assessment systems for predicting landslides at the micro level of assessment developed by the Public Works Department of Malaysia, namely the Slope Maintenance System, Slope Priority Ranking System, Slope Information Management System, and the Slope Management and Risk Tracking System. From this study, it appears that none of the existing SAS is satisfactory for predicting landslide in area underlain by granitic formation. The reasons for the apparent poor predicting capability of the existing SAS are several. For the case of the SIMS, it uses hazard score developed from other country (Japan) which is its main defect. For the case of the SMS, it appears that its database is not sufficient. While for the case of the SPRS, it uses very simplified approach of assigning hazard score with only 0, 1 and 2. While for the case of the SMART, its current database derived from the meta-sediment formations which is apparently not suitable to be extrapolated for the granitic formations considered in this study.

(ii) Two new SAS have been developed, i.e. Model A using ten-variables equation that is based on the stepwise discriminant analysis, and Model B using nine-variables equation that is based on the stepwise linear regression analysis. These two developed models appeared to show a good capability in predicting landslides in granitic formations. Model A appears to be slightly better than Model B.

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