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Landslide susceptibility mapping along PLUS expressways in Malaysia using probabilistic based model in GIS

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Abstract
PLUS Berhad holds the concession for a total of 987 km of toll expressways in Malaysia, the longest of which is the North-South Expressway or NSE. Acting as the 'backbone' of the west coast of the peninsula, the NSE stretches from the Malaysian-Thai border in the north to the border with neighbouring Singapore in the south, linking several major cities and towns along the way. North-South Expressway in Malaysia contributes to the country economic development through trade, social and tourism sector. Presently, the highway is good in terms of its condition and connection to every state but some locations need urgent attention. Stability of slopes at these locations is of most concern as any instability can cause danger to the motorist. In this paper, two study locations have been analysed; they are Gua Tempurung (soil slope) and Jelapang (rock slope) which are obviously having two different characteristics. These locations passed through undulating terrain with steep slopes where landslides are common and the probability of slope instability due to human activities in surrounding areas is high. A combination of twelve (12) landslide conditioning factors database on slope stability such as slope degree and slope aspect were extracted from IFSAR (interoferometric synthetic aperture radar) while landuse, lithology and structural geology were constructed from interpretation of high resolution satellite data from World View II, Quickbird and Ikonos. All this information was analysed in geographic information system (GIS) environment for landslide susceptibility mapping using probabilistic based frequency ratio model. Consequently, information on the slopes such as inventories, condition assessments and maintenance records were assessed through total expressway maintenance management system or better known as TEMAN. The above mentioned system is used by PLUS as an asset management and decision support tools for maintenance activities along the highways as well as for data quality checking and integrity. In this study, TEMAN data were further analysed and subsequently integrated with landslide susceptible map for Gua Tempurung and Jelapang area in Perak.

1. Introduction

Landslides carry high economic and social loses to many organizations in Malaysia and not exception to highway industry like PLUS Berhad. Occurrences of landslides are prevalent in hill complexes both in the highlands and lowlands including along the highways. These landslides have caused loss of lives and properties in recent years. While agriculture in landslide occurring areas has caused severe soil erosion downstream, hill construction projects for infrastructure and residential purposes were the main triggering factors of landslides.

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Planners have taken cognizance that developable areas in the gentle terrain have become scarce and encroachments into the more sensitive hilly areas particularly in the highlands are inevitable. Development planning in the hills based on landslide considerations is of paramount importance. In this context a national landslide hazard zoning map is a prerequisite to assist in decision making for approving developments in the prone areas [54]. To further strengthen this initiative, landslide detection and monitoring system should also be developed to for timely mitigation measures.

Landslides have always posed serious threats to settlements and structures in Malaysia that support transportation, natural resources and tourism. They cause considerable damage to highways, waterways, properties, livestock and pipelines. Though most of these landslides occurred on cut slopes or embankments alongside roads and highways in mountainous areas still there are records of landslides in other areas. Few landslides occurred near high-rise apartments and in residential areas, causing death to human being.

In the recent years, remote sensing and GIS have played major roles in carrying out analytical analysis in natural hazard particularly in development of landslide susceptibility map (LSM) for authorities [1, 33, 34]. The advancement in GIS technology provides a significant contribution in analyzing and producing LSM [50, 52, 53, 55, 59, 63]. They are studies done by experts and scientists around the world in Frequency Ratio (FR) and probabilistic analysis to produce LSM [1, 11, 17, 64, 65].

Recently, a large number of landslides have triggered along east coast highways and other highways in peninsular Malaysia. The extent of damages can be reduced or minimized if a long term early warning system predicting the landslide prone areas would have been in place. The landslides that occurred in the New Klang Valley Express Highways (NKVE) region in the year 2003 have woken up the highway authorities and other organizations towards the seriousness of landslide management and prevention. The October 2002 landslide in Kuala Lumpur is fresh in the memory of the people as completely destroyed a few houses and killed six members of a family. Landslides in Malaysia are mainly triggered due to the tropical rainfall and flash floods causing failure of the rock surface along the fracture, joint and cleavage planes. The geology of the country is quite stable but continuous development and urbanization leads to deforestation and weathering, erosion of the covered soil masses causing serious threat to slopes.

In 2006 and 2010, there were studies done in landslide hazard and risk analysis for Penang Island [34, 54] using a frequency ratio and logistic regression model. These models did not provide the weightage for landslide causative parameters. Weight determination can only be done through the ANN (Artificial Neural Networks) and fuzzy logic models amongst others [7, 18, 27, 53, 54, 55, 56, 64]. There was a study [77] done regarding soil erosion to see the impact of development affecting Ringlet reservoir in Cameron Highland. However their study is very limited for the soil erosion along the reservoir area only. EWarns, a real-time GPS based transmitter has been developed [72] to monitor the rainfall information for some stretches of highways and tourism locations in Cameron Highland. In last few years, landslide hazard evaluation using GIS and data mining such as fuzzy logic, and artificial neural network methods have been applied by researchers in different countries [16, 22, 48, 36, 37]. However their result output cannot be directly used in the Malaysian landslide hazard analysis. This is due to the changes in the geographical environment set up, litho types and different climatic condition etc. The local geographical settings cause different landslide types according to completely different mechanisms and are absolutely incomparable.

There are two main issues highlighted in this paper. Firstly is regarding the combination of twelve (12) parameters extracted from highly optical and non-optical based satellite images by using remote sensing techniques to form a highly reliable landslides susceptibility map at two different sites. e.g. soil and rock slopes. Secondly is how landslides susceptibility databases been integrated with TEMAN databases which are comprised of inventory, condition assessment and maintenance records to further improve the current slopes ranking in PLUS.

2. Study area and data

Gua Tempurung and Jelapang in Perak are the two locations which were selected for this analysis. These locations are shown in Figure 1. The selections of the study area are based on the following criteria:-

a. There are scars of slope failure at the higher part of the slopes in the west outside of the right of ways (ROW). Although they do not pose any threats to the highway but geomorphological study of this area should be conducted to determine the slopes stability at the east side area which may have a direct impact on the highway.
b. There are lineaments across in the Jelapang area which may have higher influence to the stability of rock slopes of the area.
c. There is debris flow event (debris flow) in the Gua Tempurung area in 2004 that was originated from outside of the ROW. Further studies should be undertaken to prevent the event from recurring.
c. Criteria of water catchments for both study area are different.

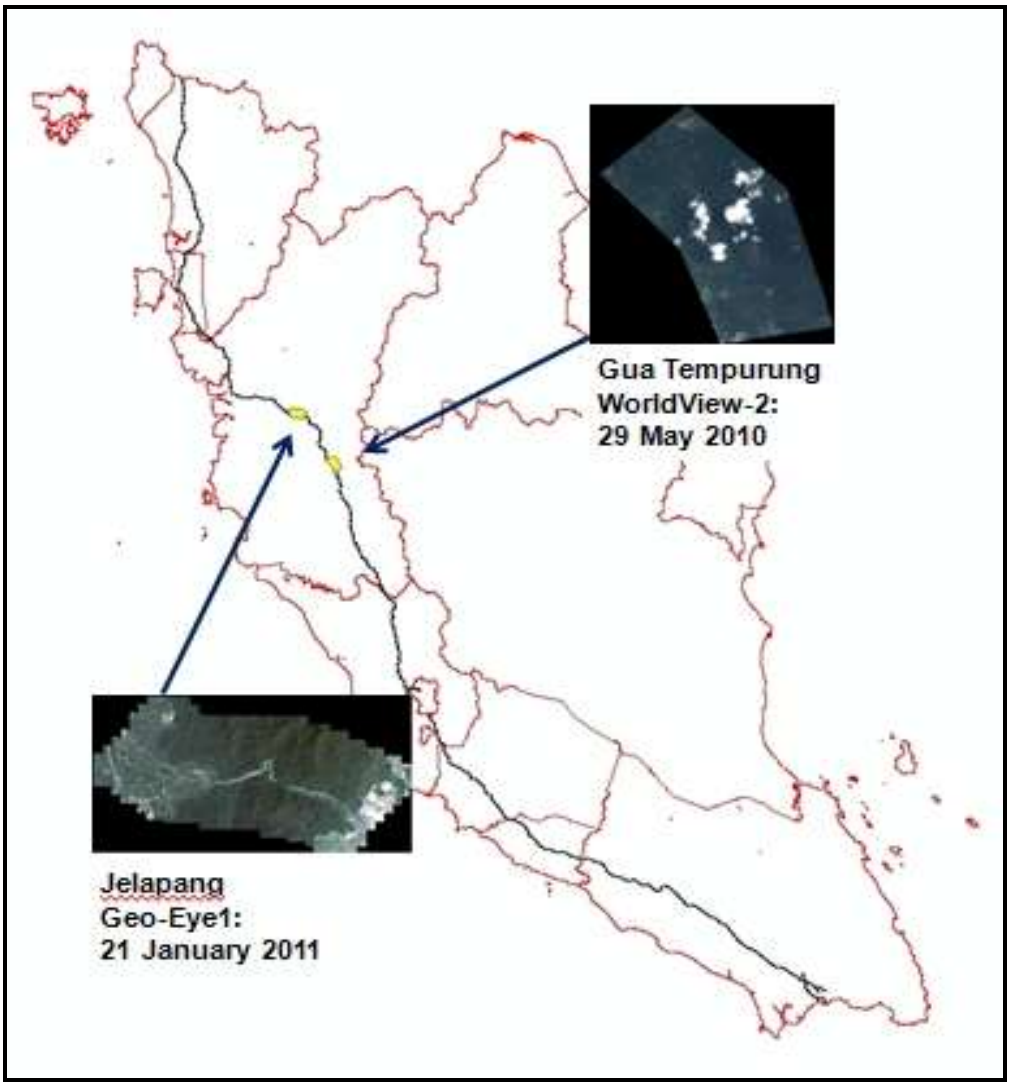


Figure 1. Location map of the study area.

3. Methodology

The research methodology is implemented into five phases: data preparation, modelling, GIS works (e.g. preparation of LSM), the accuracy assessment of the model, the data integration and preparation of landslide hazard maps. Illustration of the overall methodology is shown in Figure 2.

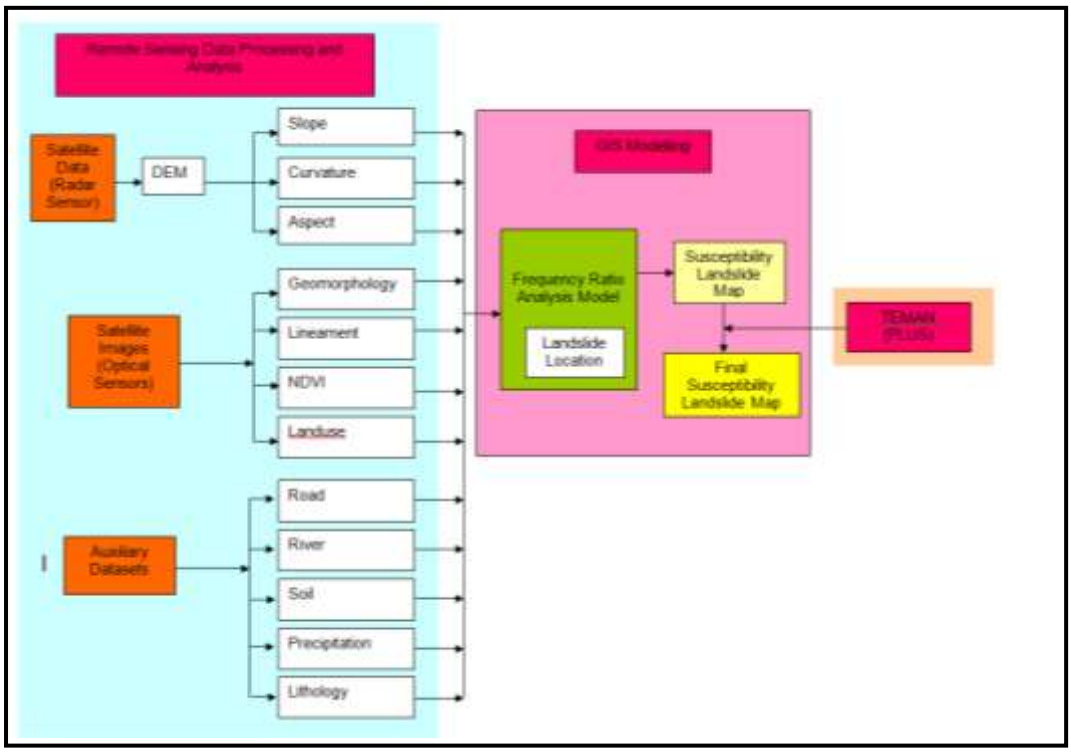


Figure 2. Overall methodology adopted in this study.

3.1 *Data preparation*

Several types of data have been used to extract the important parameters for GIS modelling. The data sources and their parameters are shown in Table 1.

Table 1. Data source.

Bil.	Data Sources	Extracted Parameters
1.	Geology Map	Lithology
2.	Geology Map/ Image Satellite Landsat TM	Geomorphology
3.	Land use map	Soil type
4.	Rainfall Data	Total of rainfall
5.	Topography Map	Drainage Road
6.	IFSAR Data	Lineament Cut slope Aspect angle Curvature
7.	High resolution satellite image (WorldView-2/GeoEye)	Normalized Difference Vegetation Index (NDVI) Land use

3.2 *Cut slope*

Cut slope is correlated with gravitational force. Hence, a steep cut slope is more likely to collapse rather than gentle cut slope. The classification of cut slopes in this study is shown in Table 2.

Table 2 : Classification of slope angle.

Bil.	Slope Angle
1.	0-15°
2.	16-25°
3.	26-35°
4.	>35°

3.3 *Curvature*

Curvature is one of the factors that contribute to landslide and divided into few types such as concave, convex or flat. Concave is capable of storing more water rather than a flat surface and a convex surface is proven otherwise. Hence, the concave surface is highly potential that could trigger landslide compare to the other surface types. The classification of curvature is summarized in Table 3.

Table 3 : Curvature classification.

Bil.	Curvature
1.	Convex
2.	Flat
3.	Concave

3.4 *Aspect angle*

Aspect angle means orientation of slope surface in 360° winds direction. Aspects angle are classified as flat angle (-1 °), North (337.5 ° -360 °, 0 ° - 22.5 °), the Northeast (22.5 ° - 67.5 °), East (67.5 ° - 112.5 °), Southeast (112.5 ° - 157.5 °), South (157.5 ° - 202.5 °), West (202.5 ° - 292.5 °) and Southwest (292.5 ° - 337.5 °). The aspect angle influences landslides thru certain factors such as exposure to the sun, wind (air factor) and rain. The aspect angles' classification is shown in Table 4.

Table 4 : Aspect angle classification.

Bil.	Aspect Angle
1.	Flat (-1)
2.	N (0°-22.5°)
3.	NE (22.5°-67.5°)
4.	E (67.5°-112.5°)
5.	SE (112.5°-157.5°)
6.	S (157.5°-202.5°)
7.	SW (202.5°-247.5°)
8.	W (247.5°-292.5°)
9.	NW (292.5°-337.5°)

3.5 *Lineament*

Lineament is known as a straight feature such as faults, sinkholes lines and lines of volcanoes. In the study of landslides, lineament is associated with the presence of cracks in the rock that affect slope stability. The lineaments classification is shown in Table 5.

Table 5 : Lineament classification.

Bil.	Distance from lineament (m)
1.	100
2.	200
3.	300
4.	400
5.	>400

3.6 *Normalized difference vegetation index (NDVI)*

Normalized difference vegetation index (NDVI) is used to indicate a plant cover that influences the presence of water in an area. In this research, satellite images (high spectral resolution) are used to extract this information. Its value is between -1 and +1 with positive values indicate areas with vegetation cover, while a negative value means otherwise. The NDVI classification is shown in Table 6.

Table 6 : NDVI classification.

Bil.	NDVI Value	NDVI Classification
1.	< -0.5	Unclassified
2.	(-0.5) - 0.1	Cloud
3.	0.1 – 0.2	Water
4.	0.2 – 0.4	Fairly Vegetated, bare land
5.	> 0.4	Dense Vegetated

3.7 *Geomorphology*

Geomorphology describes the landform of an area. Generally it is divided into five main groups, alluvial, denudational, marine, karst and others. Each group has its own criteria, which representing its topography. For example, alluvial is located at flat area compared to denudational which is located at high topographic area. The detailed of geomorphological classification is shown in Table 7.

Table 7 : Geomorphology classification.

Bil.	Group of Geomorphology	Geomorphology Classification
1.	Alluvial	Active Floodplain Floodplain Infilled Valley Waterbody Paneplain Alluvial Plain
2.	Denudational	Denudational Hill Residual Hill Piedmont Scarp Structure Hill Pediment Isolated Hill Structure Denudational Hill Structure Denudational Hill (With Folding)
3.	Karst	Limestone Cuesta Isolated Limestone Hill
4.	Marine	Sand Bar/Sand Beach Coastal Ridges And Swales Mud Flat
5.	Others	Land Outside Of Coastal Zone Sea Water

3.8 *Land use*

Land use shows land cover of an area that is due to human activities. In general, low vegetated area is more likely to have landslides against the highly vegetated area. In this research, the classification of land use is shown in Table 8.

Table 8 : Land use classification.

Bil.	Land Use Classification
1.	Agricultural Land
2.	Barren Land
3.	Moderately Vegetated Area
4.	Sparsely Vegetated Area with Less Ground Cover
5.	Urban and Associated Area
6.	Water Body
7.	Thickly Vegetated Area

3.9 *Road*

Slope that is nearer to the road can cause instability to the area. Hence, the distance from the constructed road to the slope is one of the factors that is considered for this research. Technical review reveals that the closer distance from road to slope, the higher possibility of landslide. The distance from road to the slope can be classified in Table 9: -

Table 9 : Road classification.

Bil.	Distance from Road (m)
1.	40
2.	80
3.	120
4.	160
5.	200
6.	>200

3.10 *River*

The slope area that is closer to the river is more likely to have landslide due to erosion. The closer distance from slope to river is the higher possibility of landslide occurrences. The distance from the road to the river can be classified in Table 10.

Table 10 : River classification.

Bil.	Distance from river (m)
1.	50
2.	100
3.	150
4.	>150

3.11 *Soil type*

Soil type is one of the Quasi-static factors that need to be considered in landslide analysis. Usually landslide occurred on slopes that are characterized as loam and sand. This is because these two types of soil are less elastic than the clay and peat. The soil classification is shown in Table 11.

Table 11 : Land use classification.

Bil.	Land Use Classification
1.	Organic
2.	Sand
3.	Loamy
4.	Sandy Loam
5.	Sandy Clay Loam
6.	Clay Loam
7.	Silty Clay Loam
8.	Sandy Clay
9.	Silty Clay
10.	Clay
11.	Peat

3.12 *Total rainfall*

Total rainfall is one of dynamic variables factor that is closely related to landslide. This is because water from rainfall can be easily seeping into the ground and subsequently increased ground water level. Eventually this situation will weaken the soil structure. However, based on this fact the landslide is actually proportional directly to the amount of rainfall in the area. The rainfall classification is shown in Table 12.

Table 12: Rainfall classification.

Bil.	Total Rainfall Annually (mm)
1.	1-1000
2.	1001-1200
3.	1201-1500
4.	1501-1750
5.	1751-2000
6.	2001-2250
7.	2251-2500
8.	2501-2750
9.	2751-3000
10.	3001-3250
11.	3251-3500
12.	3501-3750
13.	3751-4000
14.	>4001

3.13 *Lithology*

Lithology or rock type is one of the key factors that contribute to landslides. Generally there are three types of rocks and they are igneous, sedimentary and metamorphic. The classification of lithology is shown in Table 13.

Table 13: Lithology classification.

Bil.	Lithology Classification
1.	Sand (mainly marine)
2.	Clay and silt (marine)
3.	Peat, humic clay and silt
4.	Clay, silt, sand and gravel – undifferentiated (continental)
5.	Shale, mudstone, siltstone, hyalite, slate and hornfels
6.	Sandstone/metasandstone
7.	Conglomerate
8.	Limestone / marble
9.	Schist
10.	Ignimbrite
11.	Acid to Intermediate volcanic : mainly pyroclastic, rhyolites to dacitic composition
12.	Intermediate to basic volcanism : mainly pyroclastic
13.	Acid Intrusive (undifferentiated)
14.	Intermediate Intrusive (undifferentiated)
15.	Basic intrusive, mainly gabbro
16.	Ultrabasic intrusive, commonly altered to serpentine
17.	Vein quartz
18.	Clay, silt, sand, peat and minor gravel
19.	Cross-bedded sandstone with subordinate conglomerate and shale/mudstone.Volcanics are locally present.
20.	Interbedded sandstone, siltstone and shale; widespread volcanics, mainly rhyolitic to dacitic tuffs. ConglomeSert local.
21.	Phyllite, slate and shale with subordinate sandstone and schist. Prominent development of limestone throughout the succession.
22.	Phyllite, slate, shale and sandstone; argillaceous rocks are commonly carbonaceous. Limestone and acid to intermediate volcanics.
23.	Phyllite, schist and slate; limestone and sandstone locally prominent. Some interbeds of conglomerate and chert and rare volcanics.
24.	Schist, phyllite, slate and limestone. Minor intercalations of sandstone and volcanics
25.	Sandstone/metasandstone with subordinate siltstone, shale and minor conglomerate.

3.14 *GIS modelling*

GIS modelling that is used to produce LSM for this research is Frequency Ratio Model (FR) [1, 33, 35, 54, 56, 59]. FR is the ratio of the total pixel in landslide area against total pixel of research area. FR is calculated to obtain the probability of landslides occurrence in each class. Probability values for each class are then will be added together to get landslide susceptibility index (LSI) [54].

$$LSI = Fr_1 + Fr_2 + Fr_3 + \ldots + Fr_n \quad (1)$$

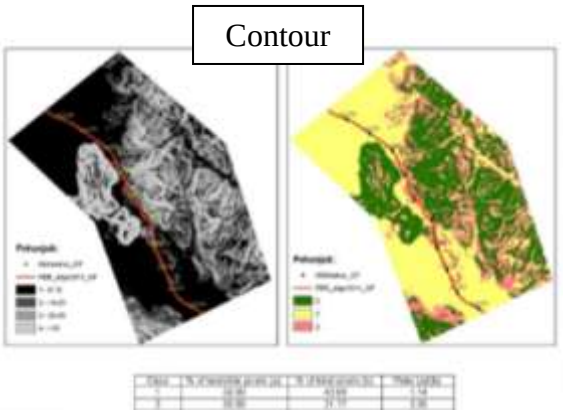
Subsequently, LSI is used to generate a LSM. The values of this index are classified into four classes, namely very high, high, medium, and low which indicates the landslides probability.

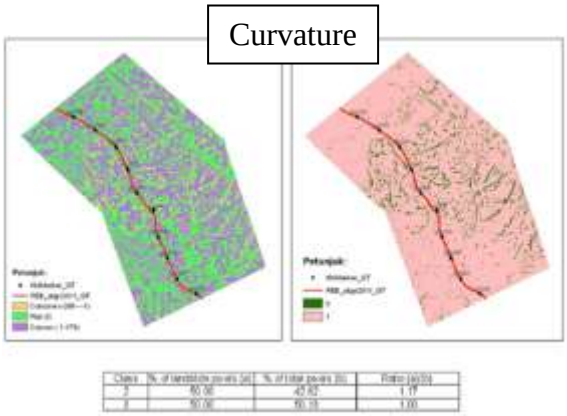
3.15 *Accuracy assessment model*

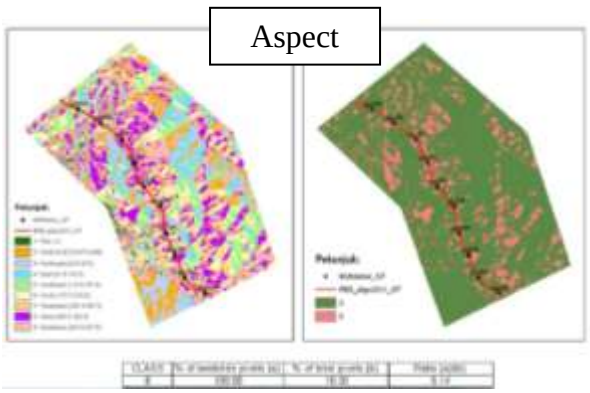
Area under the Curve (AUC) is used to determine the accuracy of the model for this study [34]. For this purpose, a graph of cumulative percentage of landslides ratio is compared with cumulative percentage of landslide pixel for Jelapang and Gua Tempurung area and they are plotted separately. The data for the Jelapang and Gua Tempurung is in Figure 6 and Figure 94, respectively. AUC values obtained from each of the plotted graph determined the accuracy of analysis results for this area.

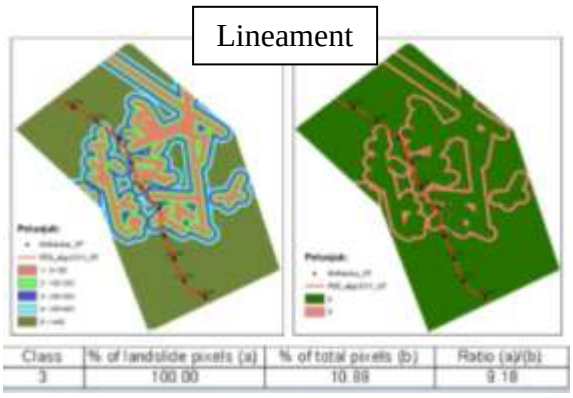
4. Results and discussion

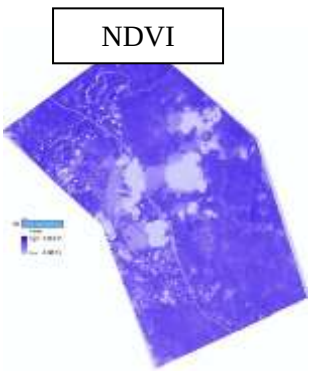
4.1 The following are some of the samples for parameters extraction from FR technique for optical and non-optical based data :-

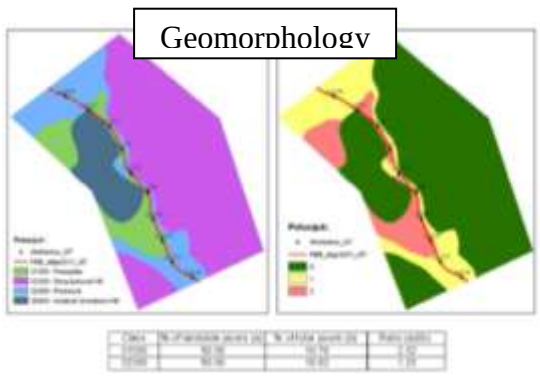












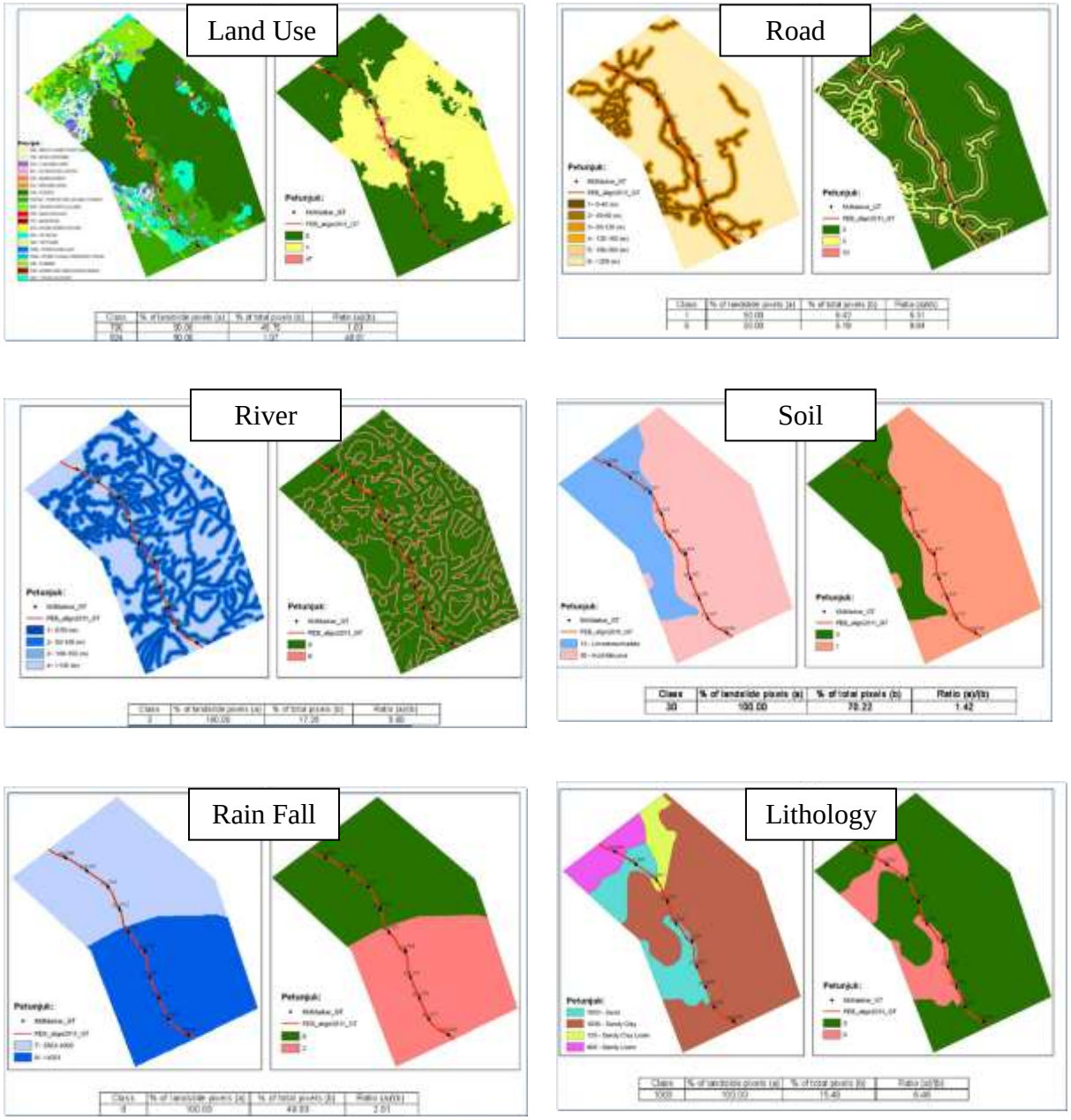


Figure 3. Samples of parameters extraction from satellite data.

4.2 *Landslide susceptibility map of Gua Tempurung*

They are two types of LSM for Gua Tempurung area produced in this study, namely: -

a) LSM for the entire study area (Figure 4) and
b) LSM for engineered slopes at Gua Tempurung (Figure 5).

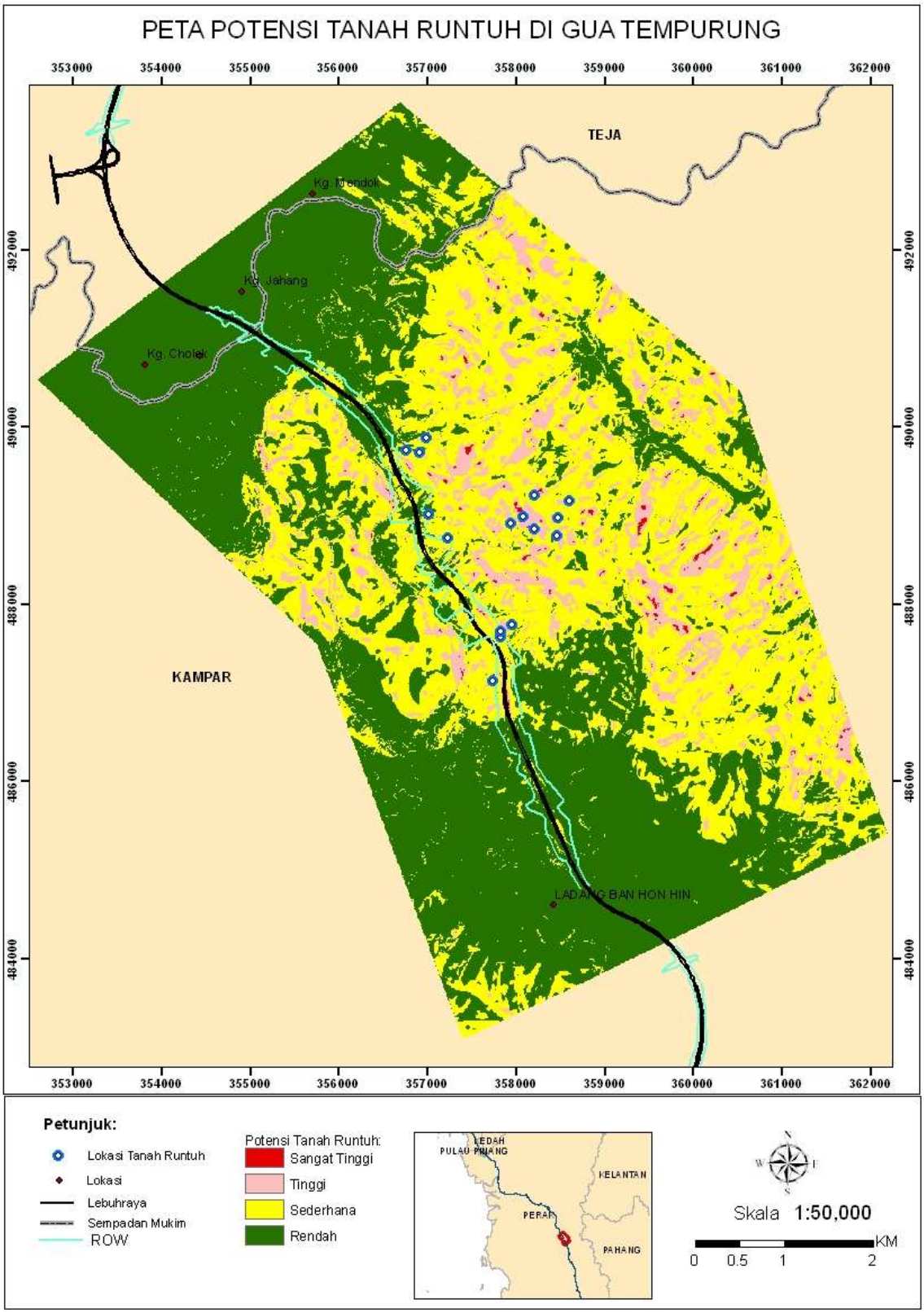


Figure 4. LSM for Gua Tempurung.

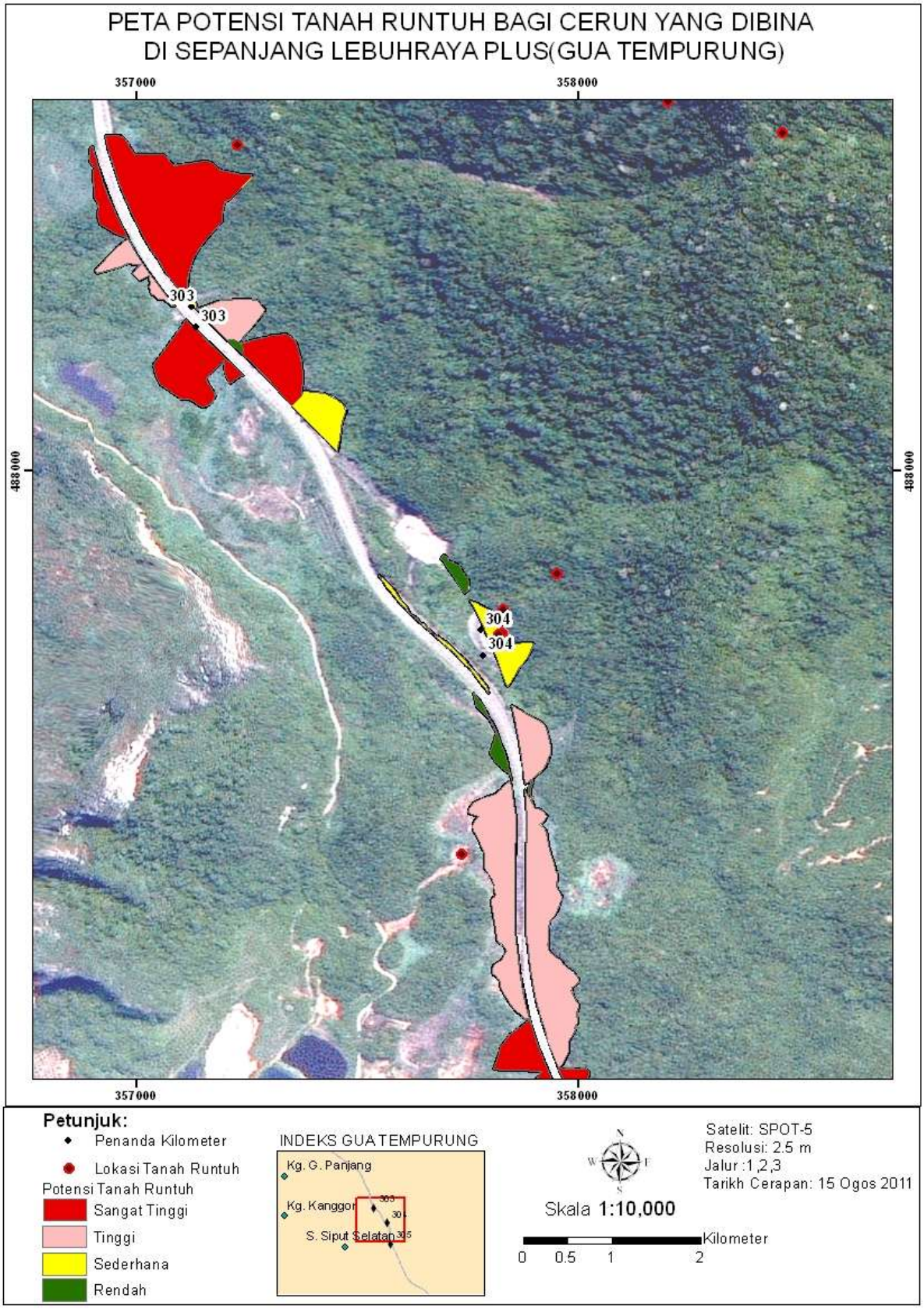


Figure 5. LSM for engineered slopes at Gua Tempurung.

4.3 *Accuracy assessment model*

Based from the following graph in Figure 6, the landslide cumulative ratio versus landslide cumulative pixel shows the area under the curve (AUC) is at 0.7406 which gives an accuracy of 74% for the model of Gua Tempurung. From this graph, it is shown that 51.55% of landslides at Gua Tempurung is located in lower class, 39.5% is in the medium class while 8.7% and 0.3% are in high and very high class, respectively.

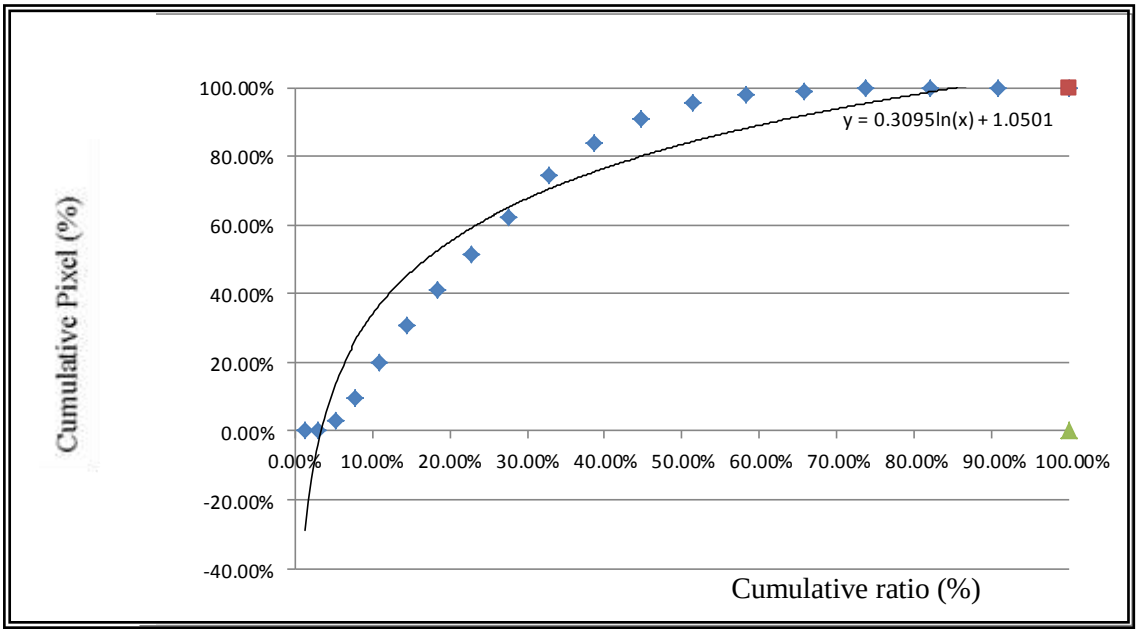


Figure 6: Cumulative ratio against pixel.

4.4 *Landslide susceptibility map for Jelapang Area*

LSM for the entire area of research in Jelapang is shown in Figure 7 while Figure 8 shown LSM for engineered slopes in Jelapang area.

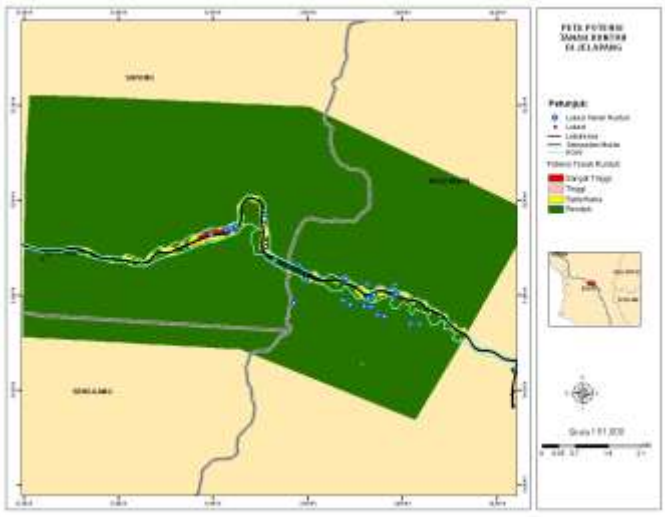


Figure 7: LSM for Jelapang.

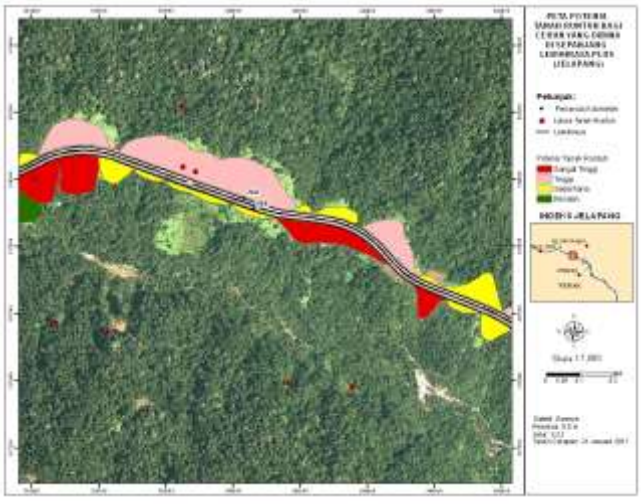


Figure 8: LSM for engineered slopes at Jelapang.

4.5 *Accuracy assessment model*

From the following graph in Figure 9, cumulative ratio versus cumulative pixel shows that the 98% of landslides at Jelapang are located in Lower class, 1.11% in medium class while 0.28% and 0.02% are in high and very high class, respectively. Area under curve (AUC) value obtained is 0.98 which gives an accuracy of 98% for this model.

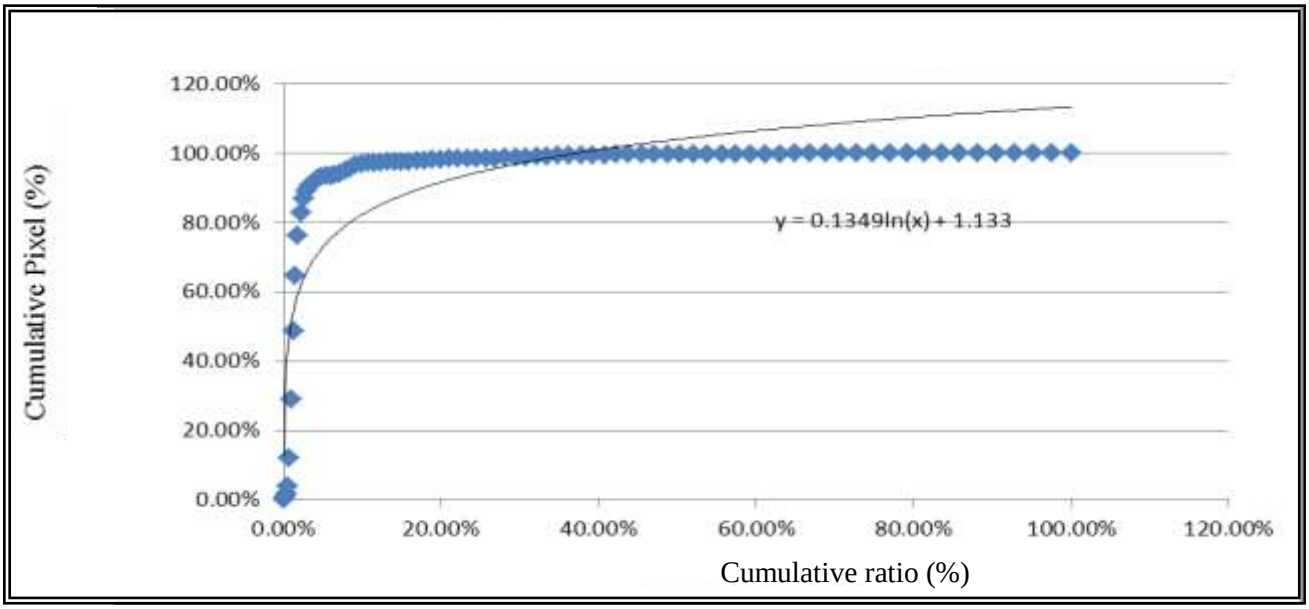


Figure 9: Cumulative ratio against pixel for Jelapang.

4.6 *Observation and analysis*

The followings are the observation on LSM (e.g. Figure 3, 4, 6 and 7). They are four (4) classes of susceptible landslides for both locations. The area is shown in percentage as follows:

Table 14: Percentage of landslides susceptible at Gua Tempurung and Jelapang.

Bil.	Landslides Susceptible Classification	Percentage at Gua Tempurung (%)	Percentage at Jelapang (%)
1	Very High	0.3	0.1
2	High	8.7	0.3
3	Medium	39.5	1.1
4	Low	51.5	98.5
Total		100	100

They are 43 landslides susceptible locations identified at both research locations. The breakdown of the landslides susceptibility locations following its classes are as follows:

Table 15: Total landslides susceptible locations at Gua Tempurung and Jelapang.

Bil	Landslides Susceptible Classification	Number of landslides at Gua Tempurung	Number of landslides at Jelapang	Total
1.	Very High	0	2	2
2.	High	2	5	7
3.	Medium	7	5	12
4.	Low	8	14	22
Total		17	26	43

The following are the main parameters that are dominant in which could trigger landslides in both research areas.

Table 16: Main criteria of landslides at Gua Tempurung dan Jelapang.

Bil	Parameters	Criteria at Gua Tempurung	Criteria at Jelapang
1.	Slope Angle	35° – 90°	35° – 90°
2.	Geomorphology	Denudational Hill	Denudational Hill
3.	Land use	Sandy Clay	Sandy Clay
4.	Precipitation	2251 – 2500mm	1751-2000 mm

There are 152 numbers of engineered slopes which are maintained by PLUS along the research area. The breakdown of the landslides susceptibility locations after integrated with TEMAN data is shown in table 17 as follows :-

Table 17: Numbers of slope based on its classification for Gua Tempurung and Jelapang.

Bil	Landslides Susceptible Classification	Number of Slope at Gua Tempurung	Number of slope at Jelapang	Total
1	Very High	9	1	10
2	High	4	5	9
3	Medium	15	60	75
4	Low	22	36	58
Total		50	102	152

5. Conclusion

Frequency ratio based mapping of landslide for Gua Tempurung and Jelapang area showed that these locations even located at hilly area but they are very much stable, there are only 7 out of 26 locations which are shown in Gua Tempurung and 2 out of 17 locations at Jelapang area are categorised as high and very high for landslides. The parameters that influenced slope failure for both locations were identified namely slope angle, geomorphology, soil type and precipitation. The quality of this model are then proven via calculation of AUC which shows that the landslide susceptibility map produced in this research paper can be used for planning and preventive measures. The integration with TEMAN data has further improved the LSM for the areas.

In conclusion, frequency ratio is one of the useful statistical based methods for LSM. LSM is a fundamental towards understanding better of hazard and disaster risk maps. There are many useful GIS based techniques either qualitative or quantitative to analyse the correlation between landslides and its influence parameters.

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