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Landslide Risk Analysis Using Machine Learning Principles: A Case Study of Bukit Antrabangsa Landslide Incidence

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Abstract: A quantitative analysis of landslides was carried out in this research to ascertain the risk that will be incurred on housing development built along hillside slopes. The study uses results from the most recent landslides analysis of GIS data and soft computing techniques to describe a concept for determining risk in a housing development situated on the hillside. The concepts presented by this study are timely, which means that computations define the time in which the housing development becomes vulnerable to landslides. The general idea enclosed in this research was to merge recent landslides analysis with real-life situations. The study location for this research was an already developed area situated along the hillside slopes of Bukit Antrabangsa, Malaysia. The approach includes predicting landslides using a novel machine-learning algorithm ensemble, the random subspace technique. The prediction process relates to the probability of occurrence of the slides responsible for the vulnerability of the housing development. A landslides prediction technique that employs GIS data to develop a geospatial database and machine learning algorithms for predicting future occurrences was used to produce the landslides inventory. The study area's landslide inventory was then used as reference locations to predict landslide occurrence under the influence of ten landslide predisposing factors. Prediction results were evaluated for accuracy using the ROC (receiver operator characteristics) and calculated the AUC (area under the curve). Other parameters used to decide the quality of the models include the RSME (root-mean-square error), the MAE (mean absolute error), and the F-measure. The results obtained from the statistical analysis of the model show that the model has high predictive and success rates. The soft computing results now gave ways to obtain a timely probability of occurrence of the slides using a deterministic approach. The analysis was concluded by providing a conceptual equation to determine the timely probability of the slides using the available hazard information.

Keywords: landslide risk mapping, random subspace, failure, machine learning, risk analysis, hillside development.

使用机器学习原理进行滑坡风险分析：武吉安特拉邦沙滑坡事件的案例研究

摘要：本研究对山体滑坡进行了定量分析，以确定沿山坡建造房屋的风险。该研究使用地理信息系统数据和软计算技术的最新滑坡分析结果来描述确定位于山坡上的住房开发风险的概念。本研究提出的概念是及时的，这意味着计算定义了住房开发易受山体滑坡影响的时间。这项研究的总体思路是将最近的滑坡分析与现实情况相结合。这项研究的研究地点是位于马来西亚武吉安特拉邦沙山坡上的一个已经开发的地区。该方法包括使用一种新颖的机器学习算法集合，即随机子空间技术来预测滑坡。预测过程与导致住房开发脆弱性的滑坡发生

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的概率有关。使用地理信息系统数据开发地理空间数据库和预测未来事件的机器学习算法的滑坡预测技术被用于生成滑坡清单。然后将研究区的滑坡清单用作参考位置，以预测在十个滑坡易感因素影响下的滑坡发生。使用鹏（接收者操作员特征）评估预测结果的准确性并计算曲线下面积（曲线下面积）。用于决定模型质量的其他参数包括RSME（均方根误差）、MAE（平均绝对误差）和F度量。模型的统计分析结果表明，该模型具有较高的预测率和成功率。软计算结果现在提供了使用确定性方法获得幻灯片发生的及时概率的方法。通过提供一个概念方程来结束分析，以确定使用可用危险信息的幻灯片的及时概率。
关键词：滑坡风险测绘、随机子空间、故障、机器学习、风险分析、山坡开发。

1. Introduction

Landslide incidence is rising worldwide due to increasing demand to put infrastructures in the hilly regions. Several efforts have been made, ranging from mapping to other empirical studies, with the sole intention of identifying more suitable areas to prevent the dangers of the slides. Some of these approaches to analyzing the landslides were compelling but ineffective in many landslide incidences. Any landslide analysis's primary role is to provide early warning to the people living around the area. This theory did not always go well in developed regions due to the ineffectiveness of some qualitative judgments in initial landslide investigations [1]–[5].

The risk caused by landslides can be assessed in three significant ways: the first approach is the probabilistic approach [6]–[9]. Using probabilistic procedures, the authors consider the risk involved in many hazards, including landslides. They evaluate the risk and safety of the environment using Bayesian statistics principles to discuss each hazard separately. Research works by [10]–[12] explained how the random finite element method could enhance the performance of several landslide parameters in the probabilistic approach of risk assessment. Secondly, the complex network methods were utilized to analyze the risk involved in landslides; for example, [13] discussed articles that used the complex network to establish risk assessment of landslides. They use such methods to evaluate and develop many hazard risk chains, including landslides. The third and final category uses remote sensing data such as the GIS (Geographic information system) to analyze the risk by producing risk maps of study areas. Various researchers, such as [13]–[17], have reported how GIS data can map specific areas and establish the area's risk.

However, this paper evaluated the risk in the developed housing area caused by landslides using the third category of risk computations. Discussions accompanied this objective on the mechanics of slope deterioration leading to landslides as a function of the infrastructural risk. Han [13] identified remote sensing technology and GIS as better ways to analyze landslide risk and other naturally occurring or human-caused hazards. Their methods detect the effects of disasters on human lives, environments, and properties. In another study, statistics and GIS have been identified as significant and effective ways to analyze landslides and compute the risk in an area [16]. However, the study has recognized GIS as a medium used to analyze landslides effectively and produce risk maps. Overall, GIS technologies help us identify landslide hazard locations and evaluate and map the risk into zones depending on its intensity.

Establishing landslides risk assessment is challenging, especially with the continued destructions caused by landslides within housing developments by hillsides. This study developed landslides risk assessment models using soft computing techniques that involve GIS data and machine learning algorithms. The method shall help analyze the landslides in the study area (Bukit Antrabangsa housing developments) and produce predicted risk maps. The maps or landslides models will be used to establish further the vulnerability of the area's elements (housing units). The concept differs from previous studies that either produce risk maps from other forms of landslide analysis. Previous studies, e.g. [16], [19]–[22], were subjective in their judgments for landslides risk analysis. Others use probabilistic approaches to conclude the risk incurred on infrastructures from landslide activities [9], [23]. Only a handful of studies harness GIS data for pure risk assessment and computation of vulnerability of a specific infrastructure group such as the hillside housing development. These studies can be improved by integrating soft computing techniques to use machines and compute predicted risk maps, which will be used to assess the overall risk of housing developments.

2. Geography of the Study Area

The study area referred to as the "hillside town" is located at Ulu Klang within Ampang's district in Selangor, Malaysia (Fig. 1). The city is prominent for its development of housing infrastructures, primarily for celebrities and political figures. Geographically, the area lies on longitude 3° 12′ 00″ towards the north and latitudes 101° 46′ 01″ east. Development in the city has been on the rise. It is accommodated in different grassland terrains of flat swampy areas that rise to over 420m of natural vegetation above sea level [24]. The area is characterized by the following soil composition (Table 1). Records of housing development in the area revealed that housing development had reached about 65% of the Bukit Antrabangsa land area. About 85% of the housings were built with reinforced concrete materials.

Most of Malaysia's regions experience tropical monsoon rain, which is responsible for many landslide events and erosions along the hilly terrains, even though most zones' geology is stable [25]. Records from Malaysia's geological survey reveal that granite rock formation from the Triassic age is underlying the study area and its surroundings. As a part of the significant granite range, which is sometimes referred to as the Kuala Lumpur granite, the area has an extended metamorphosed clastic and calcareous Paleozoic rock region. The residual granites exist in different decompositions, forming the residual soils overlying the parent rock materials [25]–[28].

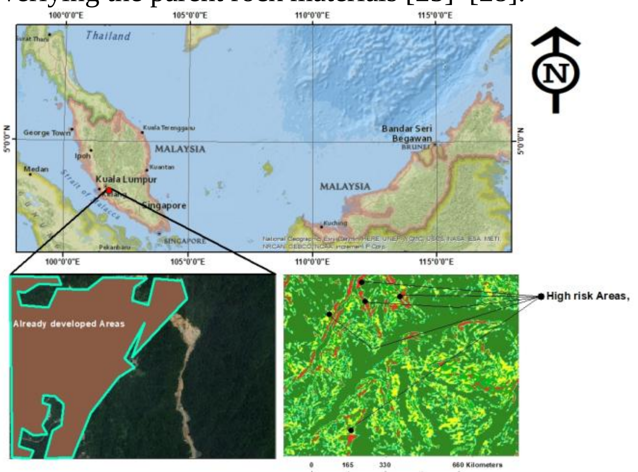


Fig. 1 The study location (Bukit Antrabangsa, Kuala Lumpur, Malaysia)

The slopes that formed the study area's terrain experience a load combination of short and high-intensity rainfall preceded by relatively long but low rainfall intensity (antecedent rainfall). The nature of the slope failures includes either a shallow slide caused by suction reduction attributed to the wetting front from precipitation or a deep-seated slide caused by rising groundwater level due to a combination of parallel bedrock infiltration and vertical infiltration through the unsaturated zone.

Table 1 Characteristics of Bukit Antrabangsa soil [24]

Soil characteristics	**Value**
Unit weight $(\gamma) kN/m3$	18.50
Specific Gravity (G_s)	2.65
Shear Strength Parameters	**Value**
Frictional angle ($\varphi \circ$)	23
Cohesion (c) kPa	8.70
Permeability (m/s)	2.4048 x 10^{-3}
Porosity	43.00
Soil texture	**Value**
Silt	17.5
Sand	45.00
Clay	37.50

2.1. Background History of Rainfall-Induced Landslides in Malaysia

With the hypothesis on the effect of rainfall on our study area's landslide events, it is essential to look into the history of Malaysia's rainfall-induced landslides in general. Malaysia's geographical settings and the nature of its terrains and climate made the country vulnerable to landslides. Many writers have reported how landslides in Malaysia have engulfed money in compensatory measures or even life losses [14], [25], [28]–[31]. From the literature, non-stop rainfall causes instability in slopes which is the primary cause of landslides. However, the impact has decreased significantly by developing early warning measures like the development of susceptibility maps, hazard maps, determining landslide risk, etc. [3], [4], [32]. Table 2 shows some of the recorded landslide events in Malaysia, from the 1960s to date (internet sources).

Table 2 Major landslide events in Malaysia

S/No.	Landslide Events (Location)	Date	Casualties
1	Ringlet, Cameron Highlands, Pahang	1/5/1961	
2	Pantai Remis landslides	21/10/1993	
3	Highland Towers, Taman hill view Ulu Klang Selangor	11/12/1993	48 Deaths
4	Genting highland slip road Karak highway	30/6/1995	20 Deaths
5	North-South Expressway, Gua Temperung, Perak	6/1/1996	
6	Mudflow near Pos. Dipang Orang Asli, Kampar, Perak	29/8/1996	44 Deaths
7	Bukit Antrabangsa Ulu Klang, Selangor	15/5/1999	Many Deaths from trapped people.
8	Taman Hillview Ulu Klang Selangor	20/11/2002	1
9	New Klang Valley expressway rockfall	12/12/2003	Closes the expressway for over six months
10	Kampung Parsir, Ulu Klang, Selangor	31/5/2006	4 Deaths
11	Lorong 1 Kampung Baru Cina, Kapit, Sarawak	26/12/2007	2 Deaths
12	43 story construction site at Bukit Ceylon, Kuala Lumpur	12/2/2009	1 Death
13	The Children's Hidaya madrasah Al-Taqwa in FELCRA Semungkis, Hulu Langat, Selangor	21/5/2011	16 Deaths (about 15 Children)
14	88 residents moved out due to ground movement in Puncak Setiawangsa, Kuala Lumpur	29/12/2002	

Continuation of Table 2

15	The Kingsley hill housing construction area at Putra sites	4/1/2013	Lots of properties are buried in mud
16	Kuala Lumpur-Kerak expressway	11/11/2015	Road closure
17	Taman Idaman, Serendah Selangore	26/11/2016	Evacuated about 340 persons
18	Paya Terubong, George Town Penang	19/10/2018	
19	Genting highland road	7/11/2019	

3. Materials and Methods

The methods used in this research involved: firstly, developing a hazard map using a machine learning ensemble of random forests with decision trees and GIS. Secondly, we interpret the generated maps and provide timely hazard maps for the area. The following research [16], [22], [26], [33], [34] concentrated on an individual discussion on landslides risk probabilities or spatial analysis of landslides to develop its hazard map. The database for this research comprises satellite maps, geological data, meteorological data, write-ups and publications, site visitation reports, and landslides historical records. Finally, the database is put to rigorous data preprocessing to extract the relevant information needed for the analysis.

In the first phase, an inventory map of landslides was developed. The landslides inventory map was generated using landslides' historical records, site investigation reports, and satellite image data analyzed with GIS software. These data were obtained from the IGM (Institute of Geology Malaysia. One hundred thirty-six major and minor landslide locations obtained for the past 20 years were identified to constitute our inventory. Ten landslides predisposing factors were selected using the relief-F process. These factors comprise slope angle, elevation, aspect, profile curvatures, plan curvatures, SPI (Stream Power Index), STI (Sediment Transport Index), Lithology, soil type, and rainfall [35]–[37]. High-resolution DEMs of (50x50)cm resolution obtained from IGM were used to build the spatial models (slope angle, slope aspect, curvatures, elevation, STI, and SPI) [32], [38]. Data obtained from Malaysian Meteorological Departments in Sabah and Sarawak was used to build the rainfall model [39]–[41]. Other factors like the soil type and the lithology model were developed by digitizing geological maps [42]–[44]. These geological maps were collected from the Malaysia Geological Department in Sabah and Sarawak.

After creating the models, data extraction and its preparation for running the predictions with the machine learning algorithms followed. Numerical representation of the maps was exported to ML platforms as datasets for training and validation processes. The training process defines the prediction of the future occurrence of landslides. Simultaneously, the validation usually reveals the algorithms' prediction ability and accuracy. The predicted datasets are implemented on ArcMap software to produce the susceptibility map. Finally, we obtain the hazard map from the susceptibility map by ranking the landslides' locations into respective landslide hazard zones with different severity levels [38].

The second stage of the research starts with identifying the landslide's failure mechanisms using a root course analysis of the factors that influence the slides in the first place. The predisposing factors selected from the beginning serve as the variables. These factors are the target variables used to compute the timely risk-hazards maps probabilities of failure that cause ground movement leading to landslides. Thus, the second stage of this research focuses on providing the risk hazard maps for the housing development situated at the toes of hills for a 12-years return period at an interval of 4 years.

3.1. Machine Learning

3.1.1. The Random Subspace Machine Learning Ensembles

Landslides are generally very difficult to study or analyze because of their dynamic nature and the involvement of many variables in deciding their occurrence. The initiation of these movements and the degree to which they can occur are determined by the progressive or extreme evolution of natural events resulting from geological, tectonic, geomorphological, climatic, and human activity [45]. However, landslide analysis in recent years has improved significantly due to the involvement of machine learning techniques. The machine learning technique involves learning from data to establish a pattern in the data. Statistical Data from landslides comprising all the predisposing factors is practically impossible to interpret using manual means. However, with the help of these machines, the learning process can be done accurately [46]. The random subspace ensemble technique was used in this research to train the datasets. At the same time, validation was carried out using the ROC/AUC (receiver operator characteristics/area under the curve), F-measure, RSME, and MAE statistical indicators.

Many researchers reported the random forest as an ensemble of machine learning that employs many trees in parallel positions [47]–[49]. Random subspace (RSS) methods were used to construct the ensemble used for this research. The RSS ensemble was first built to enhance the training performance of random forest classifiers. Random subspace algorithms demand a lesser cost of computations over other ensemble classifiers. The method adopted by the RSS was to multiply trees in the forest to increase diversity between the trees of the ensembles. This phenomenon also stops the classifiers from functioning on random subsets within their futures. Every classifier learns within a defined subset, say n. it then makes accurate selections at random from the group. The method was observed to perform with larger subsets or more extensive features. The descriptive learning information is spread across each member in the training sets (Fig. 2).

Consider a random subset with an X-features out of Z-features used to train a certain N-number of weak learners, where $X = \{x | x = [\sqrt{Z} + 0.5] \pm 2, \pm 4, x \in N, Z \in N\}$, M denotes basic integers (e.g., M=$[3, 5, 7, 9, 11]$, Z = 50, $[\sqrt{Z} + 0.5]$ = 7) and N = $\{n | 1 \le n \le 100, n \in N\}$; hence the basic principles of the random subspace ensemble follow the steps:

1) Selecting an N-number of the subsets containing an X feature choosed randomly from Z-features;
2) Conducting training on N-weak learners using each random subset;
3) Computing the prediction by majority voting.

4. Results

4.1. Landslide Prediction

Ten landslide conditioning factors were chosen out of the many factors listed for consideration. A relief-F method selected the most influencing factors observed to have contributed significantly to landslide occurrence within the study area. The technique has been used efficiently for future selection. It effectively assigns weights to dependents and interdependent variables and places them by rank [50]. Factors with higher weights are ranked first, indicating that the factors have higher contributions to the landslide occurrence, and the same applies to all the factors in the selection. The factors were used to build the ten landslides' spatial models (Fig. 3a-j). Soft computing procedures which use factors that contributed to landslides occurrence to analyze the slides have been utilized effectively by many researchers [19], [51], [52]. The inclusion of landslides conditioning factors has dramatically increased landslides prediction accuracy because it takes care of their dynamic natures.

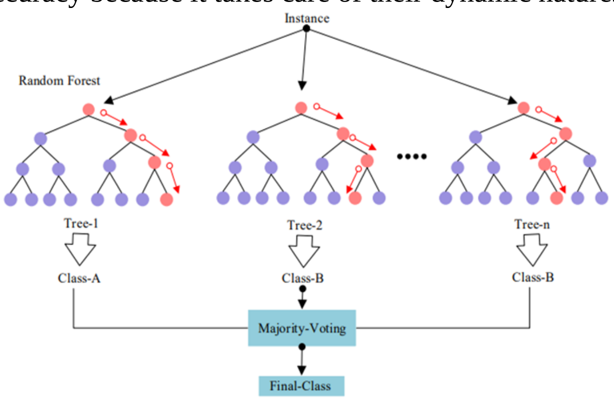


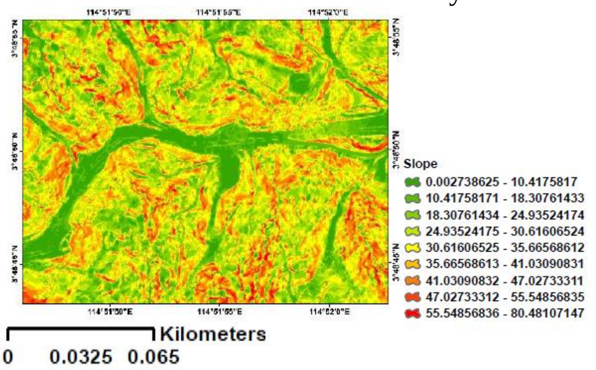
Fig. 2 The random subspace classifiers

The spatial data layers obtained include the slope angle spatial layer, a conditioning factor selected based on its importance to the landslide's occurrence. The slope map (Fig. 3a) provides details of the terrain's angle of inclination made with the horizontal plane. With higher slope angle values, landslides are expected to occur [12]. Slopes have been reported to relate to translational and rock landslides. However, this statement depends significantly on other factors such as the soil's nature, rainfall intensity, and other hydrological features within this study area [33], [54]. The slopes from this study area range from 0°, signifying flatlands, to about 80° along higher terrains. The second factor is the slope aspect (Fig. 3b), another essential factor that signifies the slope's orientation in a given study area. The slope orientation in a space is crucial because it influences landslides in evapotranspiration, the dry and wet winds, rainfall effects, and direct sunlight [22], [55].

The slope elevation (Fig. 3c) describes the terrain's height above the main sea level. In many texts, slope elevation or altitude is considered an essential factor because it relates to the gravitational force on the material. Loos materials that form slope surfaces are more likely to slide and cause landslides in higher terrains or altitudes [43]. The elevation values from this study area ranged between 400 m to a little above 800 m high. Profile curvature (Fig. 3d) is a landslide influencing factor that affects the disposition of slope surface materials that moves down slopes due to surface runoffs. In contrast, the plan curvature (Fig. 3e) manages the effects of surface runoff convergence and divergence [50], [56].

Soil nature type is another significant factor influencing landslide occurrence in an area. The soil data layer for this study area has indicated five soil types with variant properties, as shown in Fig. 3f. Again, an area's lithological formation has been utilized for many decades when predicting landslides' occurrence. The lithological model (Fig. 3g) of this study location was developed by digitizing the information obtained from a geological survey map of the area [30]. Sediment transport index STI (Fig. 3h) characterizes the erosion rate within the study location and the rate flow of the erosion materials. The STI for this research was developed using the DTM of the study area. Another important factor determining water in an erosion flow scenario is the Stream power index SPI (Fig. 3i). The SPI for this research was also carved out from the high-resolution DTM of the study area.

The last and most significant factor of landslide occurrence is rainfall or precipitation. Many researchers view rain as a trigging factor to landslides [58], [59]. Knowing that rainfall is a significant factor in landslides occurrence makes it familiar in almost all landslides analysis in areas that experiences rain as a form of precipitation. (Fig. 3j) indicates the distribution of rainfall and its intensities within the study location. This data layer was developed by building rainfall data obtained from rainfall stations in the study area.



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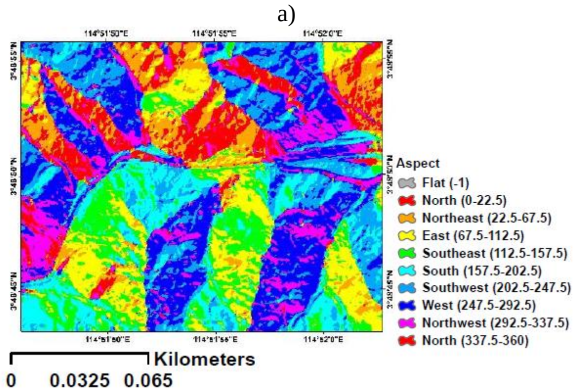

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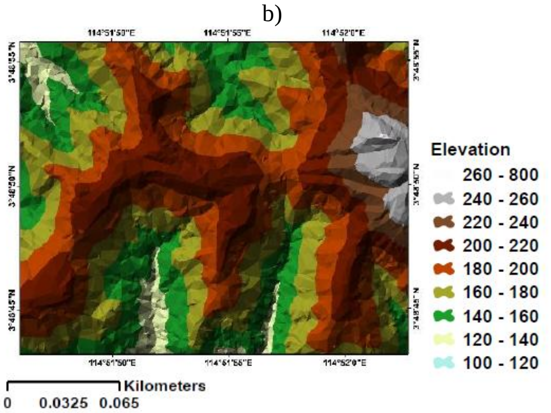

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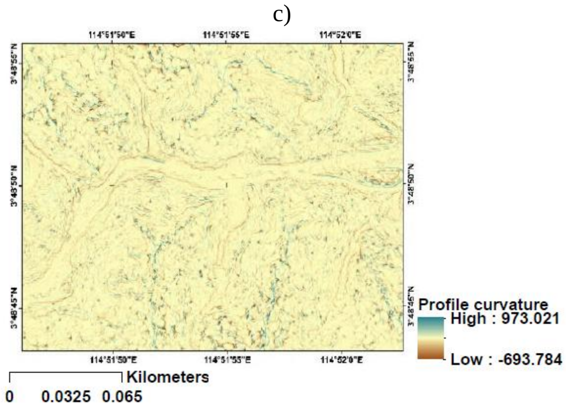

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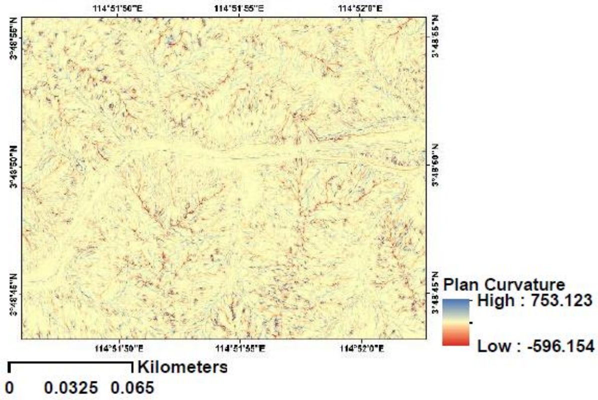

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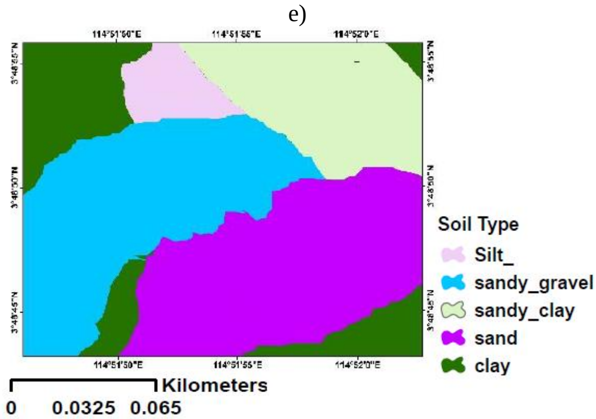

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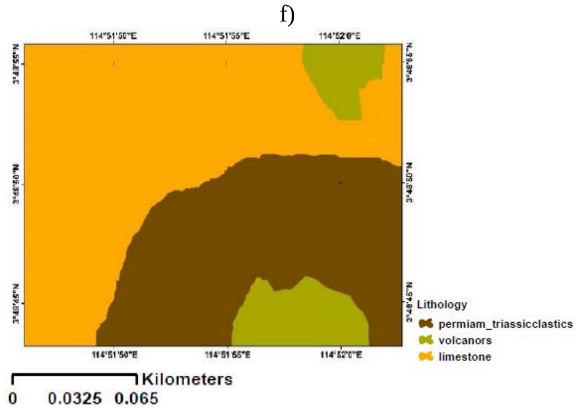

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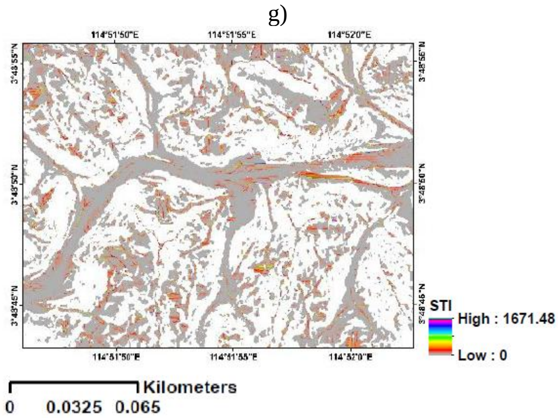

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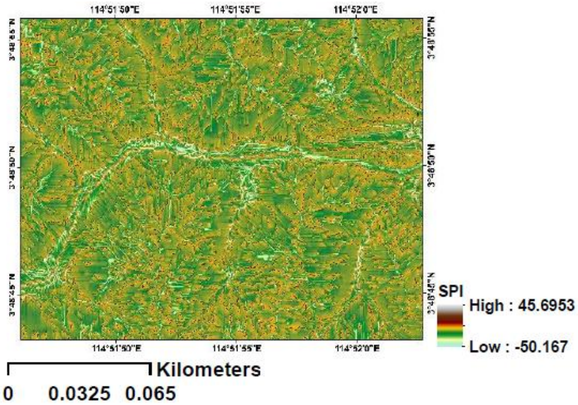

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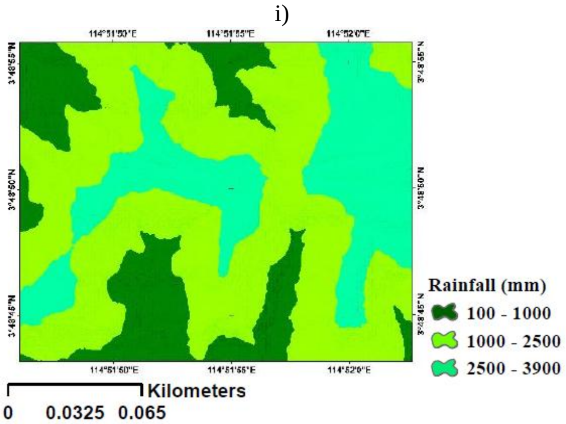

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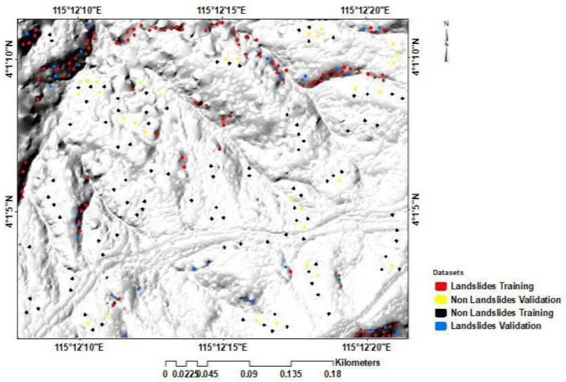

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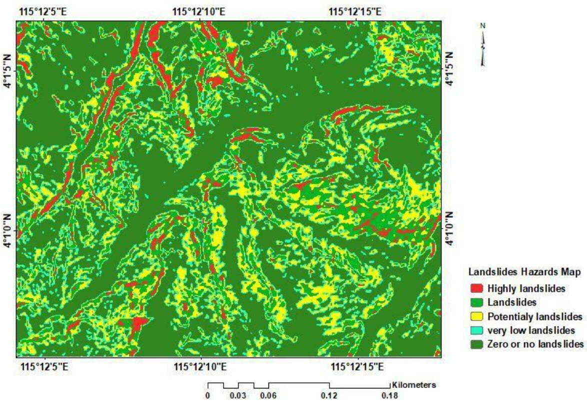

l)

Fig. 3 a) Slope angle; b) Aspect; c) Elevation; d) Profile curvature; e) Plan curvature; f) Soil type; g) Lithology; h) Sediment transport index (STI); i) Stream power index (SPI); j) Rainfall; k) Landslide inventory/datasets; l) Landslide hazard map

Similarly, the same number of non-landslides locations were provided and were divided into (70%) for training and (30%) for validations. The non-landslide locations serve as the algorithms' reference points or target values during the training or learning [61]. The validation process was conducted by developing the Receiver Operating Characteristics (ROC) and calculating the area Under the ROC Curve (AUC). The remaining performance indices, such as the RMSE, F-measure, and MAE, were also computed from the established confusion matrix analysis [62].

The build-up for the training process was done using the random subspace (RSS) technique. The procedure established ensembles of decision trees (DT) and random forest (RF) [48]. Machine learning ensembles have turned out to perform better than individual algorithms because the ensembles put together unique algorithms' predictive ability to form the ensembles' function. The technique employed was to build the classifiers and allow them to train in a predetermined future space. The RSS uses several future spaces besides the single space used by many other algorithms. This future distinct it from other ensembles [56]. The ensemble is expected to serve better when dealing with datasets with many redundant features such as landslides and their conditioning factors and help handle overfitting issues.

4.2. Evaluation of the Predicted Model

A confusion matrix was developed to obtain the models' prediction accuracy and success rate. True positive (TP), false positive (FP), accuracy, and recall helped determine the model's F-measure, ROC, RMSE, and MAE. These statistical metrics will further entail the model's behavior in the presence or absence of data. As stated earlier, these metrics are derived from confusion matrix's four operations: true positive (TP), false positive (FP), true negative (TN), and false-negative (FN).

Table 3 presents the results of the various values obtained after the computation of the statistical metrics. It observed that the algorithms had performed well in the model development. The values obtained from the evaluation show that all the four metrics (ROC/AUC, RSME, MAE, and F-measure) have shown that the model has good predicting accuracy. In addition, the success rate returned positives with values obtained above the benchmark [48].

The ROC is developed by plotting sensitivity on the y-axis against 100-specificity on the x-axis (Fig. 4) [60]. The sensitivity here refers to the landslide's pixels classified as "landslides" from the initial stages. While 100-specificity signifies the number of pixels count of the non-landslide locations and is classified as "non-landslide."

Table 3 Results of the statistical evaluation for the models

	Training	**Testing**
ROC/AUC	0.762	0.759
RSME	0.232	0.498
MAE	0.444	0.487
F-Measure	0.641	0.615

The similarity of the graph also indicates the accuracy levels between the models' output values (Table 3) and the observed data [53], [57]. The developed AUC graph obtained high predictive values of 0.762 against a testing value of 0.759. These figures entail that the algorithm used displayed an outstanding predictive capability. Overall, the predicted landslides hazard model developed (Fig. 3l) has higher accuracy and can be used to plan future developments in the area. With this kind of map developed using intelligent predictions to predict future landslides, high-risk areas can be avoided.

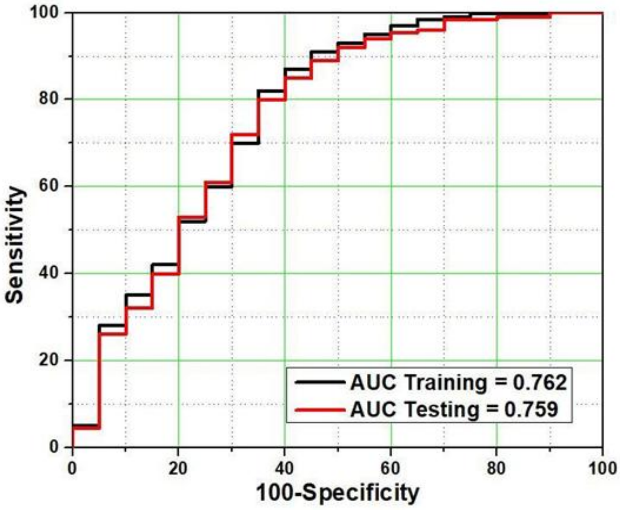

Fig. 4 Plots of the AUC values for both the training and testing datasets

5. Computation of the Landslide Risk

The risk related to landslides defined the probability of an element being affected by the landslides. The landslides happen in a particular area of a certain magnitude and risk exposure [18]. The mathematical expression below explains further;

$$R_{ie|t} = f(H_i, V_e)|t \qquad (1)$$

where:

$R_{ie|t}$ is the risk within the period of landslides event;

H_i is the hazard of ith intensity;

V_e is the vulnerability of the exposed element.

From Equation (1), it can be understood that the risk can easily be computed with a known value of the hazard and vulnerability of the housing developments at a specific time. The hazard rate is established using soft computing procedures. Information about the vulnerability is extracted from the hazard maps. The timing can be controlled by the soft computing procedures, and the probabilities will be computed within the timeframe.

6. Conclusions

In conclusion, this research has extensively studied and presented ways to incorporate the recent landslides analysis of soft computing to risk analysis. Over the years, many different studies were conducted to determine the risk of hillside development due to landslides using many empirical methods. The research provides the path that will improve the computations of risk analysis associated with landslides on a timely basis. The time-dependent probabilities targeted the vulnerable features of sloppy terrain easily affected by landslides. Early investigations on the Bukit Antrabangsa landslides incidence suggested that a combination of runoff water and pipe leakages triggers the landslides event.

The statement was in line with the findings on the major causes of landslides in Malaysia. With information on the landslides triggering factor using the soft-computing procedures, it is easier to compute the landslides' timely probabilities of those factors. However, previous studies might not have captured it because most reports were conducted qualitatively. Nevertheless, the processes conducted for this research were significant enough to bridge the following gaps.

a) The approach was so robust to consider factors that influence the landslides rather than just assertions.

b) This approach captured more extensive areas and used fewer resources in the shortest time possible.

c) Intelligently predicted the future occurrence of landslides in the area.

d) Validation of prediction results revealed that this approach is more accurate than the reports on investigations from the area.

e) The predicted results were obtained from probability expressions to help planners establish the risk incurred due to landslides in the study area.

The spatial model developed (Fig. 3l) showing five different landslide zones or hazard zones was obtained by implementing the trained datasets on ArcMap GIS software. The produced map was then normalized and reclassified to define the boundary conditions. The locations indicated in red signify areas of high landslide susceptibility. A quick check by back-dating the predicted locations and comparing them with the inventory locations indicates some accuracy in the predictions. If a similar procedure were used for housing development and planning in the area, the landslides incidences that claim lives and considerable damages to properties would have been avoided. The classification has also validated the selection of the landslides conditioning factors. A quick check on this also reveals that the areas with high susceptibility to landslides were predicted on spots with higher inclination angles and higher elevations. Although some unprecedented undulations exist within the study area, the proportion of zero or non-landslides regions multiplies the landslides predicted regions. However, this signifies the area's suitability for development despite the undulation that the high-risk zones need to be avoided. In line with this, careful observation should be given to the variables' uncertainties when computing the landslide's hazard and risk.

The finding from this study can be handy for practicing geotechnical engineers in predicting the reliability of an area. Furthermore, the research can help enhance time-dependent risk probabilities for many infrastructures and not just hillside development alone. From the concepts presented, helpful information can be harnessed to properly plan, maintain, and manage natural and engineered slopes.

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Definition of Terminologies

Landslides - the movement of a portion of the earth's soil or rock mass from one place to another, usually under a gravitational force.

Risk - measures the probability of an event's effect on our lives and properties as a product of consequence and probability (referred to as loss of lives and property due to landslide activities).

Hazards - when the landslide process is capable of causing an undesirable life loss, it is termed hazardous.

Element at risk - any factors that can become affected by the landslide events. For instance, all human and animal populations, economic activities, housing developments, and constructions such as roads, to mention a few, are elements that can be affected by landslides.

Vulnerability - the amount of loss attributed to a particular element or elements within the area affected by the hazards (landslides).

Event - here referred to as "landslides."

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