The use of geospatial data from GIS in the quantitative analysis of landslides

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Abstract. This study was conducted in order to compare two advanced technique used in establishing landslides susceptibility maps. The study considers a method of landslides analysis using the analytical hierarchy process (AHP) to check the occurrence of landslides in the study area through the establishment of a landslides susceptibility map based on the causative factors of landslides in the area. To further check and validate the process, it was compared with a more recent approach that is the soft computing (machine learning) technique. After the comparison, the enhanced analytical hierarchy process performed wonderfully well but not better than the machine learning method of analysis. Using the AHP methods, it was able to identify rainfall precipitation to be the major trigger mechanisms while 12 other conditioning factors were also identified. From the results obtained, it was observed that a good portion of the study area can be said to be susceptible to landslides. The analysis suggested that though the slides were fully triggered by rainfall precipitation, other factors such the geological and hydrological conditions facilitate the rapid occurrences of the phenomenal landslides in the study area. Validation was carried out by comparison of obtained results with inventories.

1. Introduction
The landslides phenomenon has been such a complex issue to deal with especially when trying to understand the conditions that were involved in the slides. This is because there is no single condition that works for every landslide in every location [1] [2]. Site and environmental conditions which play a key role in the stability or instability of slopes definitely vary from place to place. Until these conditions with their behaviors are carefully studied and observed, the successes recorded so far in the aspect of landslides analysis wouldn’t have been there. There were many approaches established by research over the decades in order to have a better understanding on the phenomenal landslides. Thus, a lot of research have come up with ways on how to get the insight on how landslides behave in general for instance, the development of susceptibility of landslides and zoning of the landslides occurrence in an area helps to tell us how the landslides will occur in that area and its intensity or severity in this case was further revealed by the introduction of landslides hazards analysis [3].
In all the cases, much emphasis was paid to what actually caused the movement of the slopes and it was discovered that most certainly, there is actions from within and without the slope’s environment. Those factors from without like the environmental conditions are seen as the landslides controlling factors, though some of the environmental conditions does more of a triggering of landslides than just controlling. For instance, rainfall precipitation is seen by many to be the major form of trigger
mechanism than just a conditioning factor. This was archived through many of the landslides events studied and so far that discovered landslides to have been triggered by continuous rainfall precipitation event when other complex conditioning factors are not there.

In general, it was agreed that until adequate and reliable data for any landslides events is available only then quality and reliable results is assured. Most of these studies are built on the past knowledge of landslides occurrence in any area to be studied. The selection of the most appropriate method of study to be carried out should also vary from place to place and is equally important in the quality of the final results.

Maps creation for landslides studies has over the years undergone a lot of transformation and has also seen and is seeing a lot of improvements. Maps help us to study a whole bigger area and give explicit information/indications of areas that are susceptible to landslides. The introduction of landslides zonation and subsequently, the development of landslides hazard maps was also a very useful addition to the general analysis of landslides [4].

Analysis of landslides found so far in the literature goes in two ways, the qualitative approach which drives bases from the opinion of experts and the quantitative approach which is a data base method [5]. These involve methods such the logistic regression, linear combinations, statistical approaches, analytical hierarchy methods etc. Most recently, there exist procedures that uses the two approaches [6], that is to use expert opinion to come up with an inventory and then make validations after the analysis with the quantitative methods. So far, it has not been established placing one approach over the other due to the complexity of landslides but it has been observed that the quantitative approach produce more accurate prediction results than the forma. Though the qualitative approach give more information when it comes to the selection of conditioning factors or predictors [6] because it identifies the site conditions like geological and geomorphological factors to be taking into consideration.

This paper has focussed on the use of data mined from geospatial information by the help of GIS to build up the database used in the analysis. It replaces the tedious work done which involved collecting real time samples to the laboratories to establish values of the database [7]. The geospatial data obtained was used to established landslides conditioning models which served as predictors and subsequently developed the landslides susceptibility map of the study area after analysing the data obtained using the AHP and compared with SVM models. The research uses intelligent prediction which involves the use of machine learning algorithms to predict the future occurrence of landslides and build up the susceptibility map in GIS. The research further uses the analytical hierarchy process to build up the landslides inventory in the study area and then validation was carried out [8].

2. General characteristics of the study area

Malaysia being a tropical rainforest is a country that experiences rainfall throughout the year. Considering this phenomenon with the nature of the terrains in the regions, it makes Malaysia in a landslides alert zone [9]. Records have shown that, there were series of landslides events recorded across the country especially in the southern region of Malaysia where other factors contributing to the occurrence of landslides in those places were observed to be higher than the remaining regions [10].

LAWAS (figure 1) below is a place in the Sarawak region of Malaysia, and has the following under listed information in table 1 below. The study area has also many different faults in different directions, many simple flow tributaries exist in the elevations with natural vegetation which features trees and shrubs in the form of thick vegetation that makes access difficult to some parts of the area. There were records of few rural settlements with few infrastructures which could potentially become bigger cities in the near future [10] [11].
3. Materials and Methods

As stated earlier, this research extracts data for the whole analysis from geospatial sources that was obtained through satellite imagery and maps. Geospatial data helps us to capture more and accurate information about the happenings on the surfaces of the area we wish to study for over a long period of time. This gives us access to data from very complex areas were access to quality and actual data is almost impossible. Indeed, geospatial data made landslides analysis easier and increases accuracies of the results of the analysis [12].

3.1. Quantitative Analysis of Landslides

When trying to solve problems associated with landslides, we make considerations between the landslides activities and the factors that presumably control the landslides. The quantitative method of landslides analysis here employs the use of numerical data from the constituted parameters that will now forms the basis for the analysis. Research has so far identified or categorize the quantitative method into two categories namely, the deterministic approach and the statistical approach [13], [14].

This research has employed the use of GIS tool to extract numerical data to fully analyse slides form the study area and produce susceptibility maps. Geospatial Data was integrated to producing landslides susceptibility in the study area with the support of the AHP and machine learning methods as well.

3.2. Analytical hierarchy process (AHP)

The use of logic to eventually analyse, separate and integrate problems from decision making could be said to be an analytical hierarchy process [8]. The process has over the years been used by many to enhance the decision making and also, it provides a comprehensive methodology in making combinations between empirical data and subjective judgements by an expert. The process involve use of 9 point scales put together on a criteria bases and which allows you to make ratings of a relative preference against options on a one to one bases [15]. AHP goes by making or representing linguistic expressions in places of numerical values and vice-versa, table 2.

| Scale Values | Explanations in words                  |
|--------------|---------------------------------------|
| 1            | Of equal importance                    |
| 3            | Of moderate importance                 |
| 5            | Of strong importance                   |
| 7            | Of very strong importance              |
| 9            | Extremely importance                   |
| 2,4,6,8      | Intermediate values                    |
| Reciprocals  | For inverse comparison                 |

The corresponding values representing the expressions known as weights are further calculated using the right eigenvector in accordance to the maximum absolute Eigen-value. A matrix formed
from judgement of the number of weights assigned is checked for consistency by calculating the consistency index (CI) using the below expression;

$$CI = \frac{\lambda_{max} - n}{n-1} \pi r^2$$ (1)

Where CI = consistency index
\(\lambda_{max}\) = Principal eigenvalue of the matrix.
n = number or order of the matrix formed

While the consistency ratio is computed from,

$$CR = \frac{CI}{RI}$$ (2)

Where RI is the average resulting consistency index, this factor is a function of the matrix order [8]. For an overall consistency of the matrix, the CR should be less than 0.1 [15].

3.3. Machine learning
A type of computational learning theory where the performance and computational analysis was conducted with the help of designed algorithms is known to be Machine learning process. In a broader perspective, it is the process of using these designed algorithms as interface to allow the computer to learn from an available data, study the data and establish a pattern and then draw up predictions without the action of a human intervention or without being explicitly programmed. There are virtually many and different types of these algorithms today, the choice for the algorithms selection has remained open, but lately being decided by the nature and type of analysis. SVM has being selected for use in this research work [16].

3.3.1. The Support Vector Machines (SVM)
The Support Vector Machine is a very popular machine learning algorithms that has been used for different landslides analysis. It can be deduced that, the progresses made or recorded so far by the SVM was remarkably outstanding when compared to other machine learning algorithms like the decision tree, random forest, regressions etc. [5].

SVM have been used to produce predictions in landslides analysis and was observed to produce very good prediction results when compared to other landslides statistical approaches. In some of the works, it has been used as an ensemble, which is a combination of SVM with other algorithms with the aim of enhancing the accuracy performance of the targeted objectives [17]. This research has adopted the use of the SVM algorithms due to above mentioned reasons. The outcome of the susceptibility map developed turns out to be more accurate when compared to the AHP methods. The algorithms have gone a long way in reducing the rate of error in computations and the complexity in the many data involved in the computations [18].

3.4. Landslides conditioning factors and selection of influencing data layer
Data used for analysis in this research was mostly images from satellite in which a Digital Elevation Model (DEM) was developed. The landslides models that have to do with terrains and should serve as predictors were derived from the DEM. The DEM is a source for topographic attributes responsible for landslide events data in the region. A high resolution DEM 50 X 50 cm was used to develop all related landslides models with the help of GIS tool called the ArcGIS. These models help in the analysis of the landslides in the area and machine learning algorithms was employed to enhance the prediction capabilities of the general model. The selections of the most influencing factors that contributed to the occurrence of landslides in the area was carried out using expert judgments and are explained in the subsequent sub-subsections.

3.5. Analysis of the parameters
The analysis comprises a formation of a geo-database of eleven (11) landslides influencing factors. As stated earlier, one of the goals of this research is to source for data or mine the data from satellite images in order to build up the database. The table below highlighted the data base build up and the primary source of extractions of each factor.
The parameters were selected after careful observation on the environmental factors of the area was made together with an adequate study of the past landslides event which is a key to future landslides occurrence in the area. In addition to this, a selection of proper channels was made in the analytical hierarchy process. DEM analysis on ArcGIS was helpful to reveal the terrain information, talking of slope, aspect, elevations, curvatures etc. Weightages was assigned to individual factor or predictor and values were obtained by the use of AHP to help in ascertaining the actual influence of the parameters or predictors in the area.

| Table 3. Geospatial Data and their sources. |
|-------------------------------------------|
| **Class of Data**                         | **Layer developed** | **Layer Type** | **Data Source**                  |
| Satellite Image (DEM)                     | Slope Angle         | Points, Line and Polygon | Landsat 8 Satellite Imageries    |
|                                           | Slope Aspect        |                             |                                  |
|                                           | Slope Elevation     |                             |                                  |
|                                           | Curvatures          |                             |                                  |
|                                           | Flow Accumulation   |                             |                                  |
| Drainage map/Lineaments map              | Distance to tributaries/rivers | Polygon | Extracted from satellite Imagery |
|                                           | Distance to Lineaments |                             |                                  |
| Geological/Land use/land cover/Soil Maps | Lithology           | Polygon/Grid | Department of Mineral Resources |
|                                           | Land use/Land cover |                             | Department/Department of Land Development |
|                                           | Soil Texture        |                             |                                  |
| Hydrological data                         | Rainfall            | Grid                       | Meteorological Station          |
|                                           | Precipitation       |                             |                                  |

3.5.1. Slopes Angle
One of the major factors that directly affect landslides occurrence in an area is the slope. This is the inclination that terrains make with the plains. The map of the slope model was obtained from the DEM, while relevant information on the slope angles was extracted from the developed map in ArcGIS. Figure 4 below elaborates on the slope angles in percentages, as it can be noticed that the areas with higher slopes that ranges from 55° to a little bit over 80° is shown in red colour. Similarly, for the remaining categories of the slope angles also represented in different colours.

3.5.2. Slope Aspect
In any landslides analysis, it is very important to consider the way the slopes are situated within its environments. The positioning of the slopes affects factors such as exposure to rainfall, wind, sun light etc. These factors affect the stability of the slopes and enhanced the occurrence of landslides in an area because it deals with the slope directly, and can cause a lot of discontinuity. For this research, the aspect map was developed from the DEM, and was classified to the number of levels as shown in Figure 5 [21].

3.5.3. Slope Elevation
Any detailed analysis of landslides should consider the effect of altitude (elevation) in the slopes forming the terrains. This factor directly associates with the stability or instability in the materials forming the slopes. Literature have so far confirmed that landslides are always likely to occur in higher altitudes and that the higher the altitude, the more rapid the movements of the material on the surfaces of slopes [21].

3.5.4. Rainfall
Talking about one of the features that triggers the occurrence of landslides in an area is the rainfall intensity of within that area. The analysis of landslides must contain rainfall intensity data of the study area. While other research has to compute the intensity of the rainfall using the formulae (Eq.3), this research obtained its data from the meteorological stations within the study area already computed.
\[ I = \frac{a}{(t_d + b)^c} \]  
Where

\( I \) = average rainfall intensity (mm/hr or inch/hr)  
\( t_d \) = storm duration (minutes) 
\( a, b, c \) = Constants depending on the units employed and the return frequency of storm.

3.5.5. Flow Accumulation

This is the phenomenon that defines the amount of rain that has fallen within a watershed. It is the feature that relates the soil particles forming the slope to the amount of water necessary to cause any form of instability. DEM from the sturdy area was used in ArcGIS to establish the flow accumulation model within the sturdy area and relevant info was deduced from the model such as data extraction for the analysis in both the AHP methods and the Machine learning processes. The accumulated flow was calculated for each of the classes obtained from the flow accumulation model [22].

3.5.6. Curvatures

The curvature has been selected as a conditioning factor because of its ability to affect the flow of surface water. The curvature can be viewed from the intersections of contour lines, and different shape of these curves affects the velocity of the flow. Details of the morphology of the topography can also be obtained from the curvature model of the study area [23].

3.5.7. Lineaments

When checking the seismic triggers in places that are elevated, it is important to consider the parameters that control the slope stability. These are factors that check the effect of distances of features like the slope of the terrains to fault lines or seismic action lines, the activities of landslides are sure to increase when moving closer to the fault lines [24].

3.5.8. Lithology

Landslides are generally related to the lithology of the surrounding area and it is a determining factor to the geomorphology of any area. This is seen as degradation of rock materials through chemical and physical processes which causes the variance in the structure of the soil materials that influences the occurrence of landslides. The lithological formation affects factors such as soil strength, permeability conditions and soil shear conditions [25].

3.5.9. Distances to Rivers

Degree of saturation has been a very important parameter affecting the stability of slopes. Presence of rivers near the foot of the slopes tends to saturate the slopes and makes it overcome its factor of safety. This made it very important to check the behaviour of such water bodies (streams, rivers, ponds etc.) in the analysis of landslides. The presence of these types of water bodies also contribute in eroding the foot of the slopes there by causing instability in the slopes which eventually leads to the failure of the slopes in a phenomenon called landslides. Initially or traditionally, field investigations were the major methods used in identifying these water bodies and their distance to the foot of the slopes, but nowadays, the introduction of GIS helps greatly in identifying all the needed information about the water bodies in relation to the slopes. This research uses the same procedure and mined the basic information about the rivers and their distances to the major and minor slopes by delineating the watersheds features on ArcGIS [26].

3.5.10. Land cover/land use

In trying to find information about the anthropogenic characteristics of a place, we talked about the land use/land cover. This factor has a contribution to the occurrence of landslides in any area [27]. Due to less human activities in the study area, the land use map has been divided into the following categories; Pasture lands, Wood lands, Compound pasture lands and Residential areas [28].
4. Results and Discussion

4.1. Development of the landslides susceptibility Map

With the introduction of the GIS software and soft computing, it was easy to play around with the geodatabase from the development of the landslides models that allows us to extract data for analysis and subsequently interpreting the predicted results in the form of susceptibility maps and makes zonation. Hence, the landslides susceptibility map was obtained from the results of the analysis conducted that is from the raster data models produced from the weighted values of our conditioning factors. All data obtained in vector forms are converted to raster data model formats, modified factors with assigned
weights from their respective classes are multiplied by their respective pixel values to give that of the required map [29].

4.2. Validation
There are virtually many ways to validate results obtained from the analysis of landslides conducted using GIS based geospatial data mining. One can run a quick background check of the areas predicted to have slide in the past and compare such findings with the inventory or history of slides in the area [30]. Other ways are the application of correlated coefficient and cross-checking of the procedures, this has to involve making considerations in the produced spatial model’s accuracy as the reflected and correlated coefficients with the cross-checking procedure. The criteria weightings obtained from the AHP methods forms the empirical determination that shall be the basis for the validation. For this research, the number of slides was determined from the inventory of the landslides events computed form satellite images. While we have our computed landslides susceptibility mapping obtained from our analysis, it was easy to find the correlation ranked in percentages for the various landslides zones or degrees in the study area. After the computations, it was observed that there is some 94.7% accuracy of landslides susceptible areas that corresponds directly to landslides inventory in the study area.

5. Conclusion
It was an objective of this research to help in exploring and understanding of landslides in our environments and the study of its dynamism in other to make it safer for human lives and their properties. The use of GIS and its related tools has greatly shortened the time we spent, the energy and money we put to come up with empirical data for the analysis of naturally occurring landslides in our environments. More so, these naturally occurring phenomena usually involve very large areas of the environments and sometimes occur in very complex places were access to actual data will be very difficult or even almost impossible.

In this research, it uses one of the recent ways of conducting landslides analysis which have been found to be very effective. That is the use of data mined from geospatial sources such as the satellite imagery and the use of such approximate data to make full analysis of the landslides and produces susceptibility map, hazard maps and even conduct hazard risk analysis of the area. The database contained some eleven landslides conditioning factors that were considered as the most contributing factors to slides in the study area and they form the source of our data for this analysis. AHP matrix was fully computed based on the landslides conditioning models developed from the geospatial data in ArcGIS software using ArcMap tools. After the enhanced analysis using AHP and SVM, the results were transferred and used to produces a detailed susceptibility maps and classification of the areas into very low landslides, low landslides, moderate landslides, high landslides and very high landslides

Figure 8. The landslides susceptibility map of the study area using AHP.

Figure 9. The landslides susceptibility map of the study (SVM model).
zones can be noticed from the map. Validation of the map and the whole process of the analysis were conducted and accuracy level of about 94.7% was established. Overall, the use of geo-spatial data to analyse landslides and produce landslides susceptibility has been found to be very useful and it’s accurate to rely on. It has save time and has given the room to analyse such a very big area within the limited time and resources available. In the near future and with continuous exploration in this field, this process will be reliably enough to draw conclusions on the behaviour of naturally occurring phenomenon as it has shown a very promising potentials in the analysis of such natural hazards [31].

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