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GIS-ASSISTED RAIN-INDUCED LANDSLIDE SUSCEPTIBILITY MAPPING OF BENGUET USING A LOGISTIC REGRESSION MODEL

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ABSTRACT:

Landslides are a major concern in disaster risk reduction and management in Southeast Asia due to the region's geographic location and setting. These are massive downward movement of rock, soil and/or debris under the influence of gravity. Benguet, lying within the Cordilleran mountains of the Philippines, is landslide prone. The increasing demand for sustainable development and expansion of human settlements and infrastructures deems landslides as a problem for the mountainous province. More than half of Benguet's land area is highly susceptible to landslides. Hence, landslide potential identification and assessment, associated with topography, is vital in ensuring efficiency while minimizing collateral damage and unwanted casualties. This study developed a logistic regression model to map susceptibility to rainfall-induced landslides. Causative factors for the analysis in this study include rock types, soil types, land use, elevation, slope, aspect, precipitation, topographic wetness index (TWI), normalized difference vegetation index (NDVI), and leaf area index (LAI). These layers were prepared using GIS. Based on the logistic regression, the most statistically significant variables were aspect, elevation, and leaf area index (LAI). The model considered with the combination of the causative variables resulted with an R squared value of 86% which indicates good variability for the conditioning factors used for the mapping procedure. Results indicate that 69% of Benguet is highly susceptible to landslides, 7% area is moderately susceptible to landslides, and 24% area is low susceptible to landslides.

1. INTRODUCTION

1.1 Background of the Study

Benguet, along the southwestern portion of the Cordillera Administrative Region, is dominantly mountainous as it lies within the Cordillera mountains. Due to its topographic landscape and characteristics, landslide is the predominant hazard in Benguet. Defined as the movement of rock, debris, or earth down a slope, landslides are a type of "mass wasting," which denotes any down-slope movement of soil and rock under the direct influence of gravity. Landslides are site-specific and have multiple causes. Slope movement occurs when gravity acting down-slope exceeds the strength of the Earth's composition. Rainfall, snowmelt, water level fluctuations, stream erosion, ground water variations, earthquakes, volcanic activity, and human disturbance can trigger landslides (USGS, 2018).

The Philippines receives rainfall of 965 to 4,064 millimeters annually (PAGASA). In this light, rain-induced landslides also require attention and concern. Rain-induced landslide susceptibility mapping is necessary to easily identify areas landslides caused by rainfall. assessment is also fundamental in order to classify the areas in terms of required disaster risk reduction and management and response. Records show that Southeast Asia's steep hill slopes, seasonally dry periods, excessive rainfall intensities, and unstable soils are the main causes of frequent landslides (Shahabi, 2015). New techniques and accurate data are used in landslide susceptibility mapping in the tropical environment.

GIS is a very promising tool for the effective analysis of geologic hazards. It is an ideal tool for landslide modeling for an efficient environment for analysis and display of results while collecting, storing, retrieving, and transforming spatial data from the real world. GIS incorporates spatially varying data related to landslides including ground elevation, soil and rock type, precipitation and land cover (Miles et al., 1999). The causative and control factors affecting landslide susceptibility can be determined.

1.2 Objectives

The study aims to assess the susceptibility of areas in Benguet to rainfall-induced landslides by examining co-occurrences of various factors in areas where landslides have occurred.

1.3 Study Area

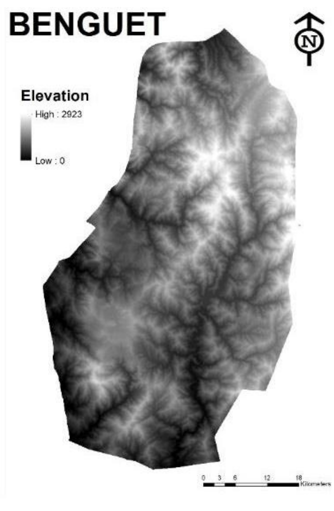

Figure 1. Elevation Map of Benguet.

The study area involves the province of Benguet, Philippines. Benguet lies on the southernmost portion of the Cordillera Administrative Region which covers an area of 2,826.59 square kilometers (1,091.35 sq. mi). The province is bordered northeast by Mountain Province and Ifugao, southeast by Nueva Vizcaya, south by Pangasinan, west by La Union, and northwest by Ilocos Sur. It is geographically located between 16°11' and 16°56' north latitudes and 120°28' to 120°53' east longitude. It has mountainous terrain of peaks, ridges, and canyons which makes it favorable for landslides. Records also show that a number of landslides had already occurred in the study area for the past few years.

2. RELATED LITERATURE

2.1 Causative factors

Slope has considerable influence on slope stability, which can be explained as the form between any section of the surface and a horizontal datum. Aspect and related factors including exposure to sunlight, winds and precipitation are vital factors in instigating landslides. Land use is affected by human activities and alterations in the environment. Land use is affected by human activities and alterations in the environment. Lithology can be regarded as one of the most vital conditioning factors in LSM because strength and the rocks and soils permeability are influenced directly by lithological characteristics (Kalantar et al., 2018). Lithology is one of the most important factors that influence the type and mechanism of the landslides because different types of rocks and soils are having different internal structures, mineral compositions, and thus susceptibility to landslide occurrences (Ercanoglu, 2005). Erosion of the slide forming slopes is caused by flowing water in the river. Ground mass adjacent to river is saturated and thus affects slope stability besides undercutting the slope face (Saha et al. 2002). Geomorphological units in this area include alluvial flood plain, colluvium deposits, low to highly dissected hills, rock ridges, river valleys and transported material on mid slopes. Excavation of roads in hilly areas creates instability of slopes and results in landslides; however, it depends on the topographic condition and nature of road construction (Pham et. al 2015).

On the one hand, rainfall is considered to be a triggering factor that significantly influences landslide occurrences (Shahabi et al. 2014). Rainfall affects soil properties such as decreasing of soil shear strength. Rains also cause liquefaction of soil material and even flow of soil/ debris mass enhancing the susceptibility of soil masses to landslides (Highland & Bobrowsky 2008).

2.2 Logistic Regression

Logistic regression is a multivariate regression technique considering several physical parameters which may affect the probability of landslide occurrences. The dependent variable can only have two values which is ether the presence or absence of landslide. For landslide susceptibility mapping, the main aim of LR is to find the best-fit model describing the relationship of the presence or absence of landslides using a set of independent parameters (Solaimani et al., 2013).

Kalantar (2018) explains that independent variables in the LR could be designated as 0 and 1, denoting the landslide absence and presence. Model output varies between 0 and 1 and represents landslide susceptibility. The LR is based on the logistic function Pi, determined as

$$P = \frac{\exp(z)}{(1+\exp(z))}, \tag{1}$$

where P denotes the probability related to a certain observation, and z is defined as

$$\mathbf{Z} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \tag{2}$$

where p/1 – p is the so-called odds or likelihood ratio. c0 is the constant of the equation and $\beta_1, \beta_2 ..., \beta_n$ are the coefficients of variables $X_1, X_2 ..., X_n$. Z varies from $-\beta_0$ to $+\beta_0$. The probability (p) varies from 0 to 1 on an S-shaped curve. The closer predicted probability of any landslide raster point to 1, the more probable a landslide is to occur and the closer probability to 0, the least probable is landslide occurrence. The advantages of logistic regression are that despite making an appropriate link function to the usual linear regression models, this technique does not assume linearity of relationship between the independent variables and does not assume variables having equal statistics variances, and in general has less stringent requirements (Mousavi et al., 2011).

In general, during susceptibility modeling, there are two main processes: the construction and evaluation of the model followed by the construction and evaluation of the susceptibility maps (Chen et al., 2017).

3. MATERIALS AND METHODS

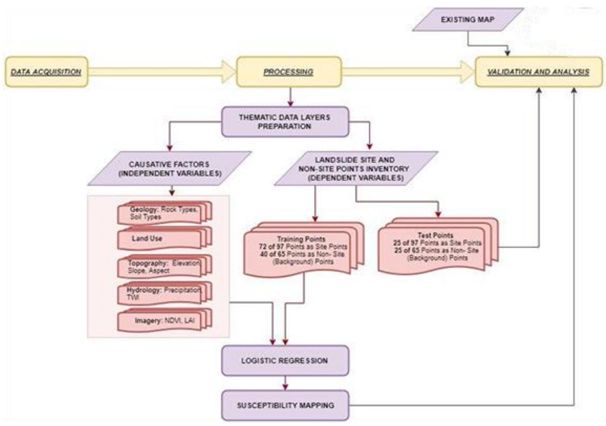

Figure 2. Flowchart of the methodology

3.1 Data Acquisition

The needed datasets and/or maps for the implementation of the Logistic Regression, landslide susceptibility mapping, validation and analysis were acquired from different sources. The digital elevation model (DEM) with the resolution of 5 x 5 m was collected from Philippines' National Mapping and Resource Information Authority (NAMRIA). The datasets for the rock types, soil types, land use, precipitation and Benguet's population density were downloaded from the PhilGIS' website (https://www.philgis.org/). Satellite images from Copernicus (https://scihub.copernicus.eu) and Planet (https://www.planet.com/) were collected to derive other needed datasets for the study. Then, a Rain-Induced Hazard Map of Benguet was acquired from Philippines' National Disaster Risk Reduction and Management Council's (NDRRMC) website (http://ndrrmc.gov.ph).

3.2 Processing

Thematic Data Layers Preparation

Landslide site points and non-site points inventory as dependent variables

A landslide inventory map is an essential basis for landslide susceptibility assessment (Conforti et al. 2014a) and may give clues to the locations of future landslides based from the distribution of the past movements. The inventory map was prepared through multi-temporal satellite imagery (from Planet) from year 2016 to 2018 interpretations. A total of 97 landslide site points have been mapped in the study area.

Landslide susceptibility mapping aims to identify areas that are prone to landslides and those that are not, which requires landslide sites and landslide non-site (background) points. A total of 65 non-landslide samples were selected randomly from the study area.

Finally, landslide site and non-site points were randomly split into two parts to build training points which will be used in the regression model as dependent variables and test points which will be used for the validation of the generated landslide susceptibility model from regression. For training points overlaid on the elevation map as shown in Figure 4a, 72 landslide site points and 40 landslide non-site (background) points were used. On the other hand, for test points overlaid on the elevation map as shown in Figure 4b, 25 landslide site points and 25 landslide non-site (background) points were used.

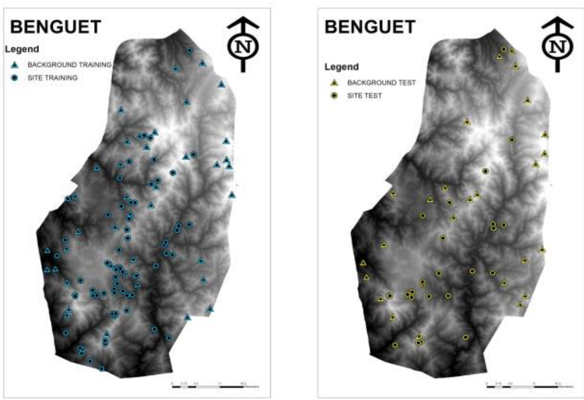

Figure 3. Location of points for developing the landslides susceptibility model (left) and for validating the model (right).

The sets of points consist of locations where landslides occurred (site) and where landslides did not occur (background)

Causative factors as independent variables

In this study, 10 factors were chosen according to the literature review and the general geo-environment of the study area. These conditioning factors are rock types, soil types, land use, elevation, slope, aspect, precipitation, topographic wetness index (TWI), normalized difference vegetation index (NDVI), and leaf area index (LAI).

The data acquired/derived for the 10 factors were either categorical or continuous. Categorical or also known as discrete data or discontinuous data, mainly represents objects has known and definable boundaries. Attributes can be assigned to the map features and used to describe, label, and identify them. Rock types, soil types, and land use are categorical data since they label or identify the objects on the study area with known or definable boundaries. Whereas for the continuous or non-discrete data, the transition between possible values on a continuous surface is without abrupt or well-defined breaks between values. Datasets for the elevation, slope, aspect, precipitation, TWI, NDVI, and LAI are continuous data since they are continuous across the entire surface of the study area.

Using Sentinel-2 imagery of the study area, NDVI was computed in ArcMap using Raster Calculator and the equation: $\mathrm{NDVI} = \frac{\mathrm{NIR-Red}}{\mathrm{NIR+Red}}$. Using the same image, LAI was computed using the ESA SNAP software using the Biophysical Processor tool under Thematic Land Processing. Next, TWI was determined by first computing the slope and flow accumulation under the Spatial Analyst tools and then computing the equation: $\mathrm{TWI} = \ln\left(\frac{\mathrm{Flow\ Accumulation}}{\mathrm{Slope}}\right)$ using Raster Calculator.

The acquired categorical datasets for the rock types, soil types, and land use were categorized according to classes and weighted from being least prone to most prone to landslides based on literature review using the ArcGIS 10.3 software. Rock types were reclassified into 6 classes (1-Neogene, 2-Oligocene Miocene, 3-Upper Miocene Pliocene, 4-Pliocene quaternary, 5-Undifferentiated, and 6-Recent), soil types were reclassified into 10 classes (1-Rough Mountainous Land, 2-Mountain Soil, 3-Loam, 4-Gravelly Loam, 5-Gravelly Clay Loam, 6-Clay Loam, 7-Sandy Loam, 8-Silt Loam, 9-Clay, and 10-Sandy Clay), and land use were reclassified into 6 classes (1-Closed and Open Forest, 2-Grasslands and Shrubs, 3-Farmlands, 4-Open Barren, 5-Inland Water, and 6-Built-up).

On the other hand, the acquired/derived continuous datasets need not to be reclassified. The DEM data was applied to extract elevation, slope, aspect, and topographic wetness index (TWI) of the study area using ArcGIS 10.3 software. The derived aspect has 10 classes (Flat, North, Northeast, East, Southeast, South, Southwest, West, and Northwest). The Sentinel images were adopted to extract normalized difference vegetation index (NDVI) and leaf area index (LAI) also using the ArcGIS 10.3 software. The acquired monthly precipitations were averaged to get the annual precipitation of the study area.

Finally using the ArcGIS 10.3 software, all thematic maps were resampled with Kriging method to convert them into the same resolution of 5 m x 5 m. These 10 causative factors which will then be used as the set of independent variables for the implementation of Logistic Regression.

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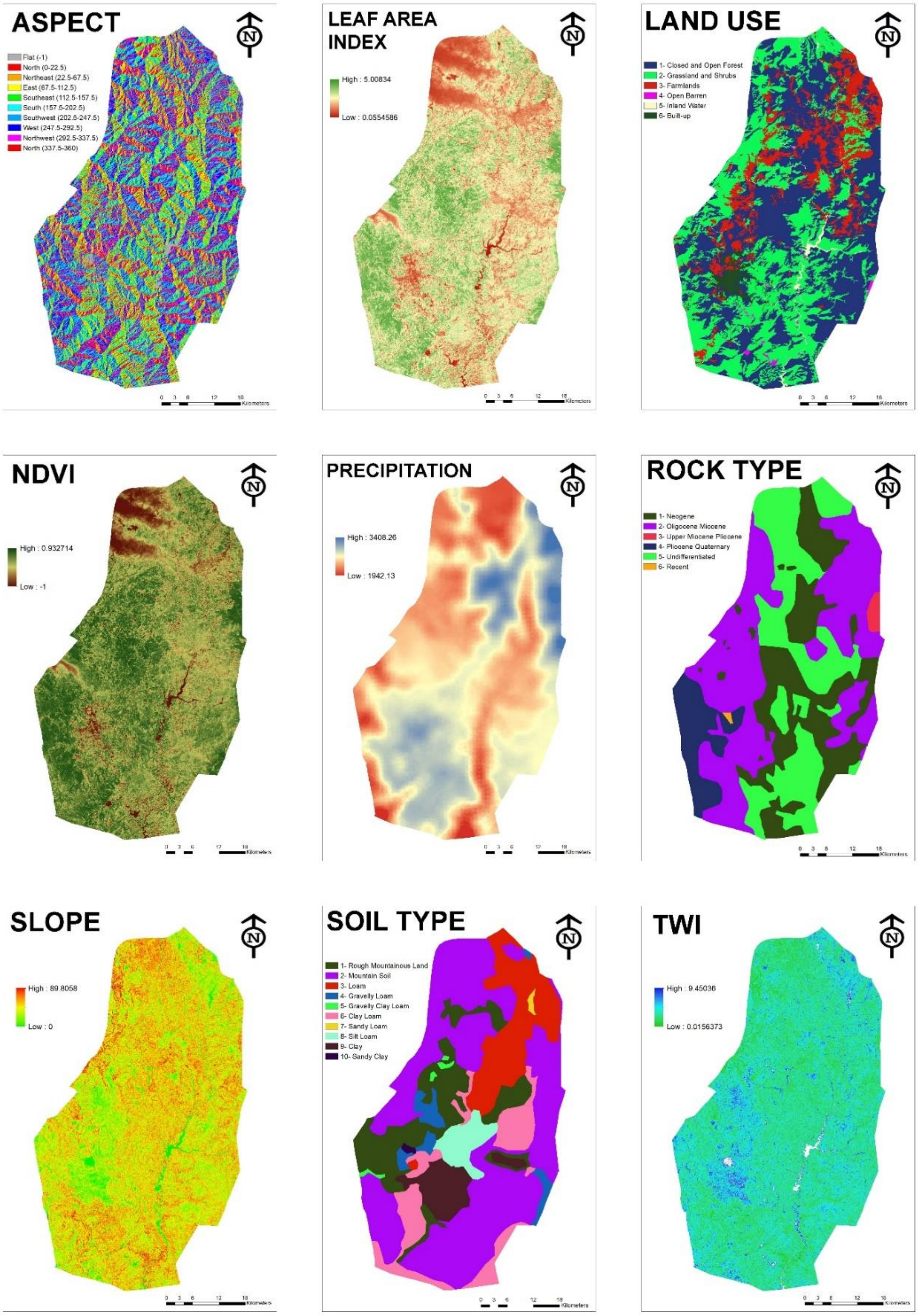

Figure 4. Thematic maps of the independent variables used

Logistic Regression and Susceptibility Mapping

Once all the independent and dependent variables (the causative factors and the site and non-site points respectively) had been acquired and prepared, the data sets were loaded into ArcMap. Values of all the independent variables were then extracted to all the training site points and training non-site points and was saved as a CSV file.

R software was then used to perform logistic regression on the extracted values. R is a free software which provides various statistical techniques as well as software facilities for data manipulation, calculation, and graphical display. The result of running the software, in the case of logistic regression, yields different statistics such as deviance residuals, estimates, standard error, and probability scores of each factor.

From R, the estimates or the coefficients of all the independent variables were obtained. The sign of these coefficients determines the effect a variable has on the occurrence of an event. A positive coefficient indicates that as the value of the factor increases, the probability of a landslide occurring also increases. A negative sign on the other hand, presents the opposite and results to a decrease in probability of an occurrence as the value of the factor increases (Ayalew & Yamagishi 2005). The probability score of each independent variable was also analyzed in order to determine which of the factors are statistically significant in the model.

The regression coefficients of the independent variables were then expressed as Equation 2 using the factor data sets and Raster Calculator in ArcGIS to produce a raster output of the model. Equation 1 was then applied on the raster output, again using Raster Calculator, to produce the final landslide susceptibility map of the study area. The range of values of the resulting map falls between 0 and 1 indicating the probability of an occurrence with values closer to 0 as having lower susceptibility and values closer to 1 as having higher susceptibility to landslide. The resulting map was then classified into three (3) classes namely, LOW, MODERATE, and HIGH using natural breaks.

3.3 Validation and Analysis

Validation is an important component in the development of landslide susceptibility mapping and its quality determination (Pourghasemi et al. 2012a). The validity of the final rain-induced landslide susceptibility map produced in this study was assessed in two different ways.

The first method involves comparing the resulting map to existing rain-induced landslide susceptibility maps. The published and existing map used was obtained from the National Disaster Risk Reduction and Management Council.

For the second method, the site and non-site points allotted for testing was utilized. The percentage of these landslide and non-landslide points falling under the three set classes (LOW, MODERATE, and HIGH) was computed to test the accuracy and assess the validity of the generated map.

The total area of Benguet under each category of susceptibility was then computed to determine how much of the Benguet province is prone to the occurrence of rain-induced landslides.

4. RESULTS AND DISCUSSIONS

4.1 The Logistic Regression Model

In creating the landslide susceptibility map, logistic regression was used to determine the relationship between the presence or absence of a landslide occurrence with a set of independent variables which were the different factors that the researchers determined to contribute to the formation of landslides.

The R-Statistics software was used to perform the logistic regression and generate the first model. Shown in the table below are the resulting coefficients and probability scores of each factor contributing to the occurrence of landslides. The computed R-squared for the model, also computed in R-Statistics, was 86.71% indicating good variability for the conditioning factors used for the mapping procedure.

Table 1. The coefficients and probability scores of each factor

Factors	Coeffecient	Pr (>|z|)
Aspect	0.02993	0.0872*
Elevation	-0.01176	0.068*
LAI	-12.422425	0.0738*
Land Use	-0.776476	0.6530
NDVI	18.285584	0.5334
Precipitation	0.002717	0.6361
Rock Type	-0.183611	0.7043
Soil Type	-0.156665	0.6133
Slope	-0.057361	0.8855
TWI	-0.222676	0.9757
AIC	41.402	
R-squared	86.71%	

Based on the table above, aspect, NDVI, and precipitation exacerbate the landslide susceptibility of the specific study area to landslide as indicated by the positive sign of their coefficients. A positive coefficient means that as the factors increases, the odds of landslides occurring also increases. The rest of the independent variables had a negative coefficient indicating their negative effect in landslide formation. The probability scores of each independent variable are also shown in the table above. This shows how much the different variables are explaining why or why not an occurrence is present in a specific area. The smaller the probability score, the more statistically significant a variable is. Aspect, elevation, and LAI had the smallest probability scores and are the most statistically significant among the 10 variables.

However, NDVI and LAI have opposing coefficient signs in the model, whereas the two should theoretically have the same effect considering that they are both dictated by the vegetation in the study area. This prompted the researchers to create two additional models, one without NDVI and another without LAI, as the two variables may have been redundant in the regression of the first model. The table below shows the coefficients and probability scores of the independent variables for two new models.

Table 2. The coefficients and probability scores of each factor for the two new models.

Factors	Without NDVI		Without LAI	
	Coeffecient	Pr (>|z|)	Coeffecient	Pr (>|z|)
Aspect	0.027308	0.0856*	0.027866	0.0705*
Elevation	-0.01168	0.0704*	-0.011073	0.0514*
LAI	-10.11729	0.0368*		
Land Use	-0.735163	0.6778	-0.404129	0.7931
NDVI			-79.24242	0.0255*
Precipitation	0.002675	0.6479	0.002923	0.6073
Rock Type	-0.201477	0.6809	-0.29604	0.5249
Soil Type	-0.149076	0.6324	-0.134619	0.6576
Slope	-0.030829	0.9466	0.094644	0.7723
TWI	0.295995	0.9722	2.755788	0.6494
AIC	39.47		40.02	
R-squared	86.67%		86.29%	

In both models, the variable that was not removed yielded high statistical significance and a negative coefficient indicating its negative effect in landslide formation. In choosing which model was to be used, the R-squared value and the Akaike's Information Criterion (AIC) of both models from R-Statistics were considered. The Akaike's Information Criterion (AIC) is a measure of the performance of a model. When comparing several models, the lower the value of the AIC, the better the model.

The model with LAI obtained a higher R^2 value of 86.67% and a lower AIC of 39.47 whereas the model with NDVI obtained an R^2 value of 86.21% and AIC of 40.02. Based from this, the researchers used the model with LAI in generating the landslide susceptibility map of the study area.

In the final model, the aspect, precipitation, and topographic wetness index have the prominent role in the occurrence of landslides in the study area as indicated by the signs of their coefficients. However, it may be noted that the probability score of precipitation is not as high as that of aspect. This may be due to the dataset obtained for the said variable being an average of the monthly rainfall. Aspect, elevation, and LAI are the most statistically significant among the 9 independent variables.

The coefficients of the independent variables were then utilized to formulate Equation 1 which was used to determine the probability of landslide occurrence. The susceptibility map was then generated using the obtained equation of the model.

$$
\begin{aligned}
Z = 37.695 &+ (Aspect \times 0.027) + (Elevation \times -0.012) + (LAI \times -10.117) \\
&+ (Land\ use \times -0.735) + (Precipitation \times 0.003) + (Rock\ type \times -0.201) \\
&+ (Soil\ type \times -0.149) + (Slope \times -0.031) + (TWI \times 0.296)
\end{aligned} \tag{3}
$$

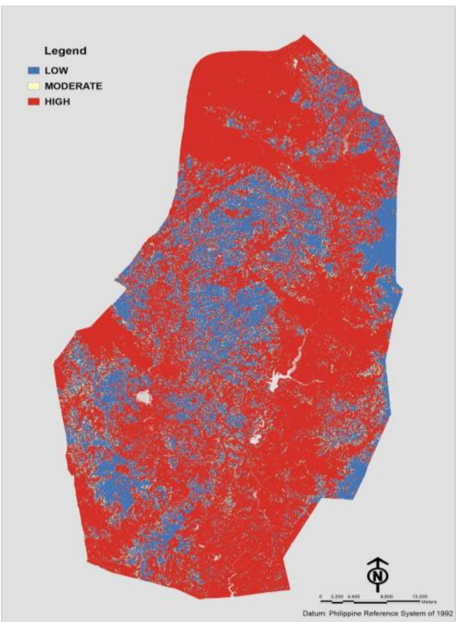

Figure 5. Logistic regression generated map.

Figure 5 shows the map generated using Logistic regression. It is raster-based output using ArcGIS 10.3 software. Using Natural breaks as a mean of data classification, which then divide the resulting continuous data into 3 sub classes namely low, moderate, and high susceptible. It was then used in order to infer the natural groupings at the same time to identify the best group with similar values and to maximize the differences between set of points (ArcGIS Pro). Doing so, it can show the percentage area coverage per class.

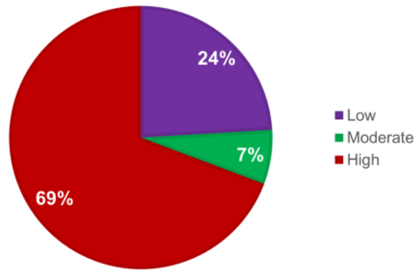

Figure 6. Percentage area coverage for the three degrees of susceptibility.

Based on Figure 6, it shows that most of the area in Benguet will be highly susceptible to Rain-Induced Landslide with an area percentage of 69%. With only 24% and 7% for moderate and low chance of landslide that may take part respectively.

4.2 Validation using existing maps from NDRRMC

Validation is an essential component in the development of landslide susceptibility and determination of its quality (Pourghasemi et al. 2012a). The landslide susceptibility maps were verified by comparing the output susceptibility map with existing Benguet Rain-Induced Landslide Hazard Map coming from National Disaster Risk Reduction and Management Council (NDRRMC).

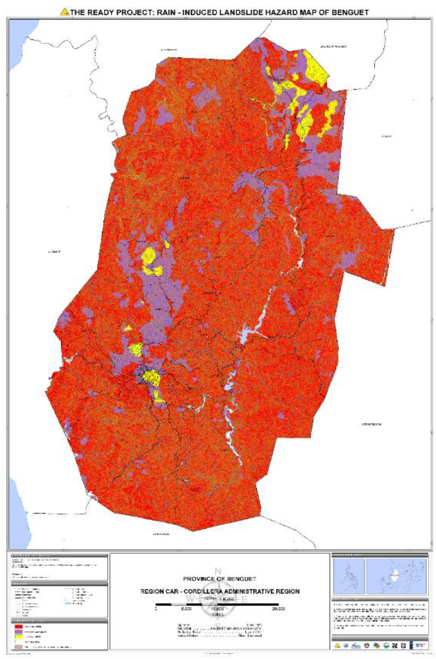

Figure 7. Rain-induced landslide susceptibility map from NDRRMC

Both maps, existing rain-induced landslide susceptibility map from NDRRMC, and the generated map agree that most of the area in the province of Benguet have high susceptibility to rain-induced landslide as indicated by the red areas in both maps. However, the area with lower susceptibility in the generated map seem to be larger than that of the existing map. Differences in the two maps may be explained by the various factors or independent variables considered in making the maps as having different conditioning factors used in a model would yield different results.

The produced susceptibility map will be useful as an aid in prediction to which areas have high probability of risk from landslide occurrences through different factors considered. It also can act as validation or new set of information for the community within the area of interest. Also, the resulting map can be implemented such that it can allow delineating of zones wherein precaution measures will prevail. It can also be used to extract information to set standards and/or requirements for the use of land or places that can be associated to sloped area which have a higher chance of risk from landslides and can be used for land stability.

4.3 Validation using set of landslide site points and non-site points

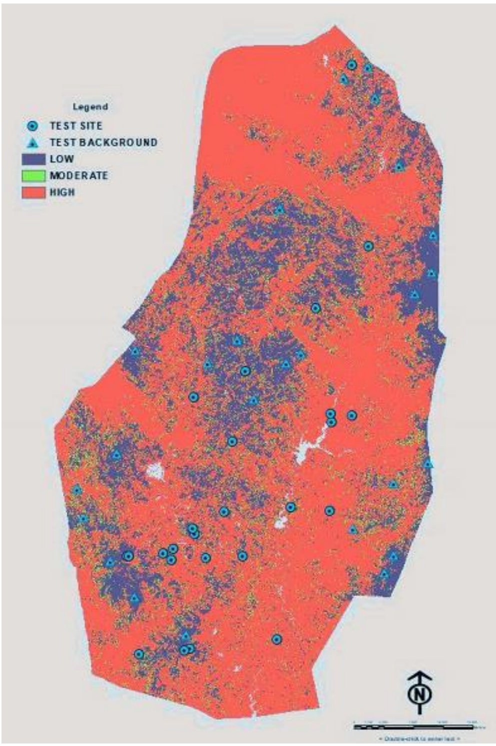

Figure 8. Site and non-site points overlaid on the generated map.

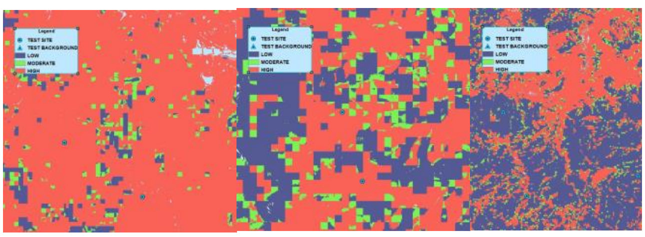

Figure 7. Validation using set of landslide site points and non-site points.

Another way of validating the generated Rain-Induced Landslide Map would be using another set of site points and non – site points. These 2 set of points would be different from the set of points used in modeling through logistic regression. Hence, it is the same method used when obtaining this set of points. 25 points were then used as validation points. Then it was graphed in order to see the percentage of those points that expected to be seen.

Table 3. Test Percentage Validation for site and non-site points.

Test Percentage Validation	Low	High
Site Points	8%	92%
Non-site Points	84%	16%

Based on the results displayed in Table 3, it shows that 92% (23 out of 25) of the test site points occurred to be highly susceptible from the landslide map generated which is to be expected since this site points were ground truth data wherein there were landslide occurrences. Also, from Table 3, it shows that 84% (21 out of 25) of the test non – site points are low susceptible to rain-induced landslide map produced which also needed to be expected since non – site points assumed to be the places that has a very low chance of landslide occurrences. Through this validation, it implies that the generated map produced can be considered as accurately modeled in predicting future landslide occurrences.

4.4 Problems Encounters

Problems were encountered by the researchers in doing the study. One major problem encountered is the limitation of data. With many possible factors available that may affect the model, only some were accessible since most have no data available, or it takes time to request data which can delayed this study. Another is that since the datasets for the independent variables were acquired from different sources, as a result, they have different cell sizes. As a solution to this, resampling and interpolation were done. Lastly, the resampled and interpolated uniform cell size of 5mx5m for the datasets was an enormous file size for the software to handle which makes it crash or prolongs its processing time.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

In this study, a rain-induced landslide susceptibility map was successfully modeled using logistic regression which is a multivariate regression technique considering several physical parameters which may affect the probability of landslide occurrences in Benguet, Philippines.

97 dependent variable points were used as training and test sites for the methodology. These sites represent past landslide occurrences from year 2016-2018. Given the current circumstances, it is assumed that landslides will most probably occur again in these sites.

A total of nine (9) conditioning factors were considered for the rain-induced landslide susceptibility map namely: elevation; slope; aspect; Topographic Wetness Index (TWI); precipitation; rock type; soil type; land use; and Leaf Area Index (LAI). These nine factors were considered as the independent variable using logistic regression approach for modeling the probabilistic map for rain-induced landslide in Benguet and are the combinations of factors that gave the lowest AIC and at the same time a higher R squared value among the three models made.

With resulting of 86% value of R squared indicates good variability for the conditioning factors used for the mapping procedure. Considering the generated map, 69% of the area cover of Benguet is highly susceptible to landslide and with only 7% and 24% for moderate and low chance of landslide that may take part respectively.

5.2 Recommendations

The researchers recommend the following:

Use other statistical models for analyzing and interpreting data. In addition, accuracies of these models must be compared and analyzed in order to determine the best fit model in cases of landslide susceptibility mapping.

Consider more causative factors to be implemented in the research. The greater number of variables entail greater variability and correlation which shall result in better models of the desired phenomenon (e.g. landslide). Also, more accurate data must be obtained so that deviations from the true values are not exaggerated. In short, higher data resolutions, data within longer time periods and greater number of data sources are fundamental to produce accurate susceptibility maps.

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