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A REVIEW OF LANDSLIDE SUSCEPTIBILITY ASSESSMENT MODELS

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Abstract - *Landslides are always a threat to human society, worldwide. Being able to accurately estimate landslide susceptibility spatially and temporally is foundational to the management of many landslide-prone areas around the world. Landslide occurrences are largely controlled by different and manifold causative factors. Topography, lithology, tectonics, rainfall, vegetation, and human activities all affect the natural stability of slopes and determine the susceptibility of a landscape to landslides. Therefore, characterizing the spatial patterns of landslide occurrences under natural geo-environmental causatives factors over the large-scale landscape is an extremely difficult task with field surveys alone. This paper reviews three landslide susceptibility assessment methods viz-a-viz, Multinomial Logistic Regression Model (MLR), Deep Learning Model (DL) and Logistic Regression Model (EBF-LR). As a replacement for field methods, modelling the landslide susceptibility is an attractive alternative that can provide analytic frameworks for quantifying and understanding the underlying patterns of this phenomenon under various local conditions.*

Key Words: Landslide susceptibility, Deep learning, Logistic regression model, Multinomial logistic regression model, spatial patterns

1.INTRODUCTION

Landslides are always a threat to human society, worldwide. Being able to accurately estimate landslide susceptibility spatially and temporally is foundational to the management of many landslide-prone areas around the world. Landslide occurrences are largely controlled by different and manifold causative factors. Topography, lithology, tectonics, rainfall, vegetation, and human activities all affect the natural stability of slopes and determine the susceptibility of a landscape to landslides. Therefore, characterizing the spatial patterns of landslide occurrences under natural geo-environmental causatives factors over the large-scale landscape is an extremely difficult task with field surveys alone. As a replacement for field methods, modelling the landslide susceptibility is an attractive alternative that can provide analytic frameworks for quantifying and understanding the underlying patterns of this phenomenon under various local conditions. (Juan Du et al., 2020).

This technical paper gives a review of different susceptibility methods used in three different journals which was located three different parts of the world. The first paper has used the method of Multinomial Logistic Regression Model for the easy preparation of landslide susceptibility at Jilong Valley, Tibet (Juan Du et al., 2020). In the second paper it has used the method of Deep Learning Model for the preparation of landslide susceptibility at Muong Lay (Dong Van Dao et al., 2020). The third paper shows the method of Logistic Regression Model for the preparation of landslide susceptibility at southern western ghats in Kerala, India (B Feby et al., 2020). It is thought that such a study would be helpful for the prediction of landslide susceptibility of hilly areas.

2. MODEL STUDIES

2.1Multinomial Logistic Regression Model

Study area is located on the southern flank of the Great Himalayan range in Tibet, China. The Jilong Valley is characterized by conspicuous spatial variations in temperature and precipitation (Fig-1). The intensity of rainfall caused by the south-west monsoon tends to decrease with increasing altitude, which is reflected in

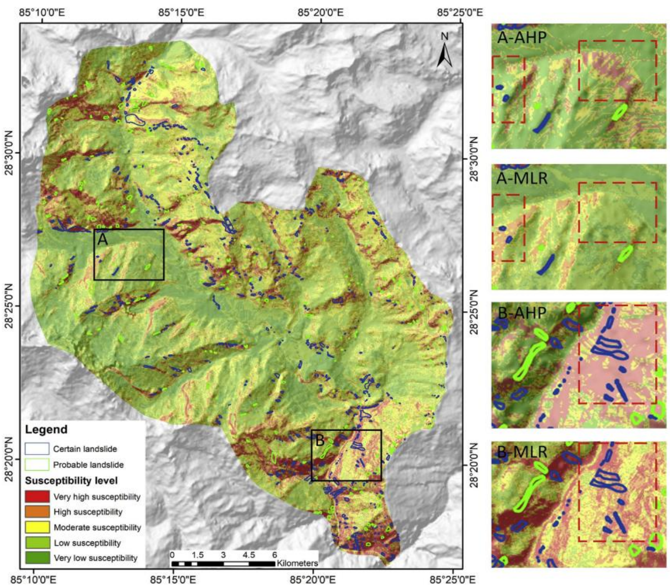

Fig -1: Susceptibility map based on MLR model

the distribution and types of vegetation. The temperature decreases at higher altitudes, which explains the distribution of seasonal and permanent snow. The precipitation and average temperature increase from north to south. The altitude of the lower boundary of seasonal and permanent snow and the upper boundary of vegetation gradually increases from north to south (Juan Du et al., 2020).

In terms of the landform and types of landslides, the study was divided into three segments. The lower segment (LS) extends from Jilong Port to Chongse Village and is characterized by the typical deeply dissected narrow canyon landform. On the steep hillslopes, the rock outcrops are intensively incised by joints, which cause rock falls and rockslides. On the gentle slopes and in the tributary gullies, rainfall triggers the activation of colluvial sediments leading to soil landslides and debris flows. The middle segment (MS) extends from Chongse Village to Rema Village and is characterized by deeply dissected broad valley landforms with fluvial terraces, proluvial fans, and sediments from debris flows. Rock falls and rockslides are distributed on the steep hillslopes . Rockslides located at high altitude often transform into rock avalanches that run out along the steep slopes. The upper segment (US) from Rema Village to the north boundary of the study area is a deeply dissected narrow canyon, where the intruded granitoid is the primary lithology. The valley floors and tributary gullies are dominated by moraine deposits, which are the primary source material of debris flows caused by rainstorms and glacier meltwater. As in LS, the steep hillslopes in the US are also prone to rock falls and rockslides (J Du et al., 2020).

2.2 Deep Learning Model

Vietnam has long been affected by various natural disasters such as climate change, arsenic pollution, radiation geo-hazard, debris flood, coastal erosion, sea level rise, earthquake, tsunami, volcanism, and landslides in particular. The study area is the Muong Lay district in the northwest of Vietnam. The approximately 11,403 km^2 area is characterized by rugged topography, with the elevation and slope gradients of 125–1778 m and 0–73%, respectively. The district enjoys a tropical monsoon climate with average temperature of 22–23 °C and an average rainfall of 1483 mm/year (Fig-2). The most important active fault in this district is the Dien Bien Phu Fault (DBPF) that follows a north-south orientation (D Van Dao et al., 2020).

A DL algorithm that benefits of several hidden layers is capable of mining underlying patterns of environmental phenomena. During the training course, the conditioning factors with the highest predictive utility are organized hierarchically to recognize the spatial patterns of the historical landslides adequately. This classification scheme provides a predictive model with the highest possible predictive accuracy and generalization capability. Overall, these results are supported by those reported by Sameen et al. (2019) who showed that while the performance of SVM and ANN models decreased during the validation phase, the deep learning model demonstrated a robust performance in both training and validation phases (D Van Dao et al.,2020).

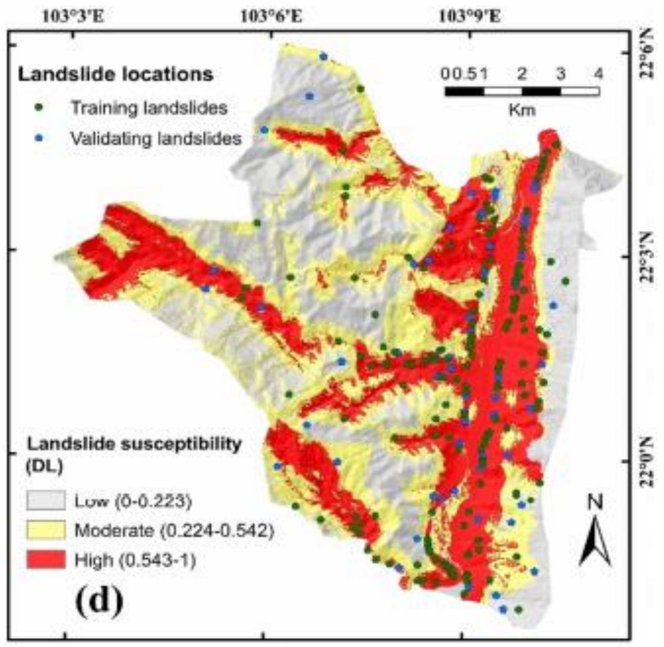

Fig.-2: Landslide susceptibility maps produced by DL method

2.3 EBF-LR Model

Study area lies in the windward slopes of Southern Western Ghats, characterized by rugged hills and deep valleys. The region is administratively located in the Malappuram district, northern part of Kerala state in India and it is geographically situated between 11◦ 07′ 37.93′′ to 11◦ 31′ 40.45′′N latitudes and 76◦ 02′ 53.95′′ to 76◦ 18′ 46.50′′E longitudes, covering an area of 770 km2. The average annual rainfall of the district is 3000 mm and more than 90% of its precipitation is the contribution of South-West monsoon (Indian Meteorological Department). The study area forms a part of moderately dissected slopes with relatively thin cover of overburden material comprising mainly soil and debris (Fig-3). The study area is experiencing repeated slope failures in the onset of every Indian summer monsoon (South-West monsoon). Out of the 83 past landslide slides, 82 are occurred in 2018 and remaining one (Kavalappara landslide) occurred in 2019 caused wide spread damage to life and property. Most of these landslides are occurred during the episodes of long and persistent downpours (B Feby et al., 2020).

Both reliable and accurate landslide susceptibility maps are essential to take action to safeguard the life and property from the future landslide calamity. Such maps are progressively made feasible by advanced hybrid data mining techniques. In this study, a hybrid integration of EBF and LR are used for the prediction of landslide susceptibility mapping. For this, a landslide inventory of 83 past landslides are collected and analyzed with twelve landslide conditioning factors viz., lithology, LU/ LC, NDVI, slope angle, slope aspect, profile curvature, distance to stream, distance to roads, distance to lineaments, soil texture, topographic wetness index and average annual rainfall. The predictive ability of the variables are assessed by using Pearson correlation method. Thereafter, landslide susceptibility modelling was carried out using EBF, LR and integrated EBF-LR methods. The predicted models are validated using ROC-AUC, K index, sensitivity, specificity, MAE and RMSE. The analyses shows that hybrid EBF-LR model higher prediction accuracy with ROC-AUC value of 0.935 and K index 0.719 over other methods. It is also noted EBF-LR model have least prediction error with MAE value of 0.221 and RMSE of 0.456, indicates the efficiency of proposed hybrid EBF-LR method (Table-1, 2).

This study proposes a novel EBF-LR based susceptibility map for the study area with 93.5% accuracy. The main advantage of the integrated model is that it is free from the uncertainties. Uncertainties can be analyzed at the stage of EBF implementation and if it is satisfactory, the integrated EBF-LR model can be implemented (B Feby et al., 2020).

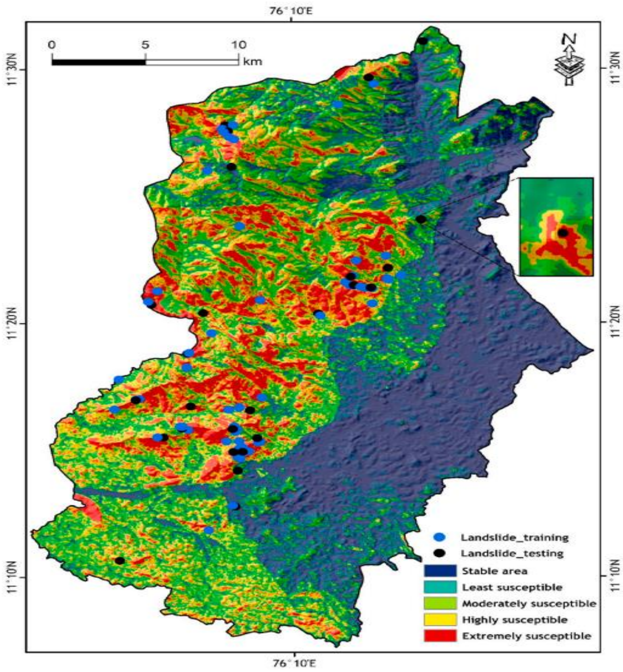

Fig- 3: Landslide susceptibility map generated from EBF-LR method.

3. COMPARISON OF MODELS STUDIED

To check the accuracy of each susceptibility level of EBF-LR model, frequency ratio (FR) method is implemented (Table-1,2). The highest FR value of 4.45 is shown in extremely susceptible class whereas higher susceptibility category have only 0.96. Absence of landslides in stable areas indicate the efficiency of the predicted model. Therefore, the model is highly consistent in predicting those areas, which have higher probability of landslide occurrence in future (Fig-4).

Table-1: Performance evaluation using training data set [Feby et al., 2020]

Models	Sensitivity	Specificity	Accuracy	K
EBF	0.814	0.789	0.802	0.603
LR	0.804	0.800	0.802	0.603
EBF-LR	0.879	0.759	0.819	0.638

Table-2: Model validation using testing data set (Feby et al., 2020]

Models	Sensitivity	Specificity	Accuracy	MAE	RMSE	K
EBF	0.870	0.815	0.840	0.317	0.557	0.680
LR	0.792	0.769	0.780	0.298	0.475	0.560
EBF-LR	0.885	0.833	0.860	0.221	0.456	0.719

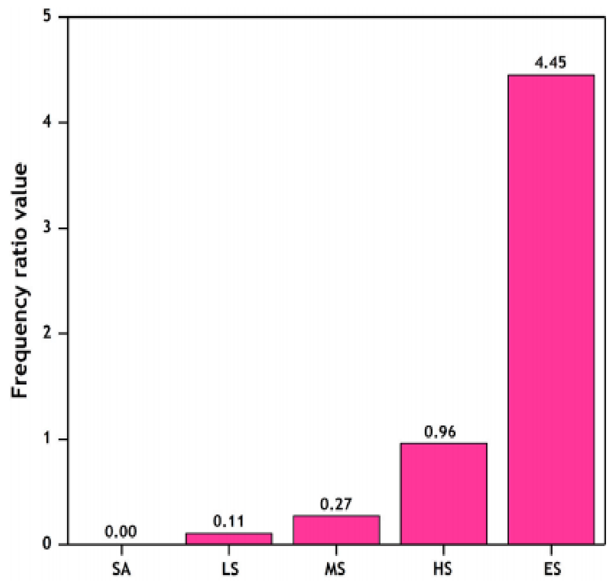

Fig.-4: Frequency ratio values of landslide susceptibility levels. (SA = stable area, LS = least susceptible, MS = moderately susceptible, HS = highly susceptible, ES = extremely susceptible) [Feby et al.,2020].

4. CONCLUSIONS

Governments and geologists work together with land managers to obtain reliable estimates of landslide susceptibility and take action to ensure the human society in the future. Such efforts need to be supported by powerful predictive models that are progressively made feasible by advanced data-processing techniques. Within this seminar report, different model for the landslide prediction were reviewed. The DL model was successful in both training and validation phases and significantly improved the capability of the prediction of the future landslide in comparison with other models. The main disadvantage of the DL model is its computation time that may restrict its values when dealing with big datasets of large-scale landscapes. The multinomial regression method was, proposed as it is a method for landslide susceptibility mapping to overcome the problems of an incomplete landslide inventory, complicated geological setting, and the uncertainty of landslide interpretations using remote sensing images. Both reliable and accurate landslide susceptibility maps are essential to take action to safeguard the life and property from the future landslide calamity. Such maps are progressively made feasible by advanced hybrid data mining techniques. Thus, a hybrid integration of EBF and LR are used for the prediction of landslide susceptibility mapping. Overall, these results suggest that the monitoring and early warning systems need to be implemented in at least 30% of the land area which is prone to landslides to provide timely and critical information on landslide activities for supporting more informed decisions.

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BIOGRAPHIES

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