

AN EVALUATION OF LANDSLIDE SUSCEPTIBILITY MAPPING USING REMOTE SENSING DATA AND MACHINE LEARNING ALGORITHMS IN IRAN

B. Kalantar ^{1,*}, N. Ueda ¹, H. A. H. Al-Najjar ², M. B. A. Gibril ³, U. S. Lay ⁴, A. Motevalli ⁵

¹RIKEN Center for Advanced Intelligence Project, Goal-Oriented Technology Research Group, Disaster Resilience Science Team, Tokyo 103-0027, Japan – ([bahareh.kalantar](mailto:bahareh.kalantar@riken.jp), [naonori.ueda](mailto:naonori.ueda@riken.jp))@riken.jp

²Centre for Advanced Modelling and Geospatial Information Systems (CAMGIS), Faculty of Engineering and IT, University of Technology Sydney, 2007 NSW, Australia – HusamAbdulrasoolHammadeh.AL.NAJJAR@student.uts.edu.au

³Research Institute of Sciences and Engineering, University of Sharjah, Sharjah 27272, UAE - mbgibril@sharjah.ac.ae

⁴Department of Civil Engineering, Faculty of Engineering, Universiti Putra Malaysia, Serdang, Selangor, Malaysia - usmansirly@gmail.com

⁵Department of Watershed Management Engineering, College of Natural Resources, Tarbiat Modares University, Noor, Mazandaran, Iran - motevalli.alireza@yahoo.com

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ABSTRACT:

Landslide is painstaking as one of the most prevalent and devastating forms of mass movement that affects man and his environment. The specific objective of this research paper is to investigate the application and performances of some selected machine learning algorithms (MLA) in landslide susceptibility mapping, in Dodangeh watershed, Iran. A 112 sample point of the past landslide, occurrence or inventory data was generated from the existing and field observations. In addition, fourteen landslide-conditioning parameters were derived from DEM and other topographic databases for the modelling process. These conditioning parameters include total curvature, profile curvature, plan curvature, slope, aspect, altitude, topographic wetness index (TWI), topographic roughness index (TRI), stream transport index (STI), stream power index (SPI), lithology, land use, distance to stream, distance to the fault. Meanwhile, factor analysis was employed to optimize the landslide conditioning parameters and the inventory data, by assessing the multi-collinearity effects and outlier detections respectively. The inventory data is divided into 70% (78) training dataset and 30% (34) test dataset for model validation. The receiver operating characteristics (ROC) curve or area under curve (AUC) value was used for assessing the model's performance. The findings reveal that TRI has 0.89 collinearity effect based on variance-inflated factor (VIF) and based on Gini factor optimization total curvature is not significant in the model development, therefore the two parameters are excluded from the modelling. All the selected MLAs (RF, BRT, and DT) shown promising performances on landslide susceptibility mapping in Dodangeh watershed, Iran. The ROC curve for training and validation for RF are 86% success rate and 83% prediction rate implies the best model performance compared to BRT and DT, with ROC curve of 72% and 70% prediction rate, respectively. In conclusion, RF could be the best algorithm for producing landslide susceptibility map, and such results could be adopted for the decision-making process to support land use planner for improving landslide risk assessment in similar environmental settings.

1. INTRODUCTION

Globally, man encounter challenges in resolving check and balances between the search for shelter and the growing risk of environmental hazard as a result of climate change. The most densely populated regions around the world are the hills and mountainous areas, which are often prone to numerous forms of natural hazard including landslides. Landslide is a complex gravitational flow that initiates mass movements. Different categories of landslides and associated triggering factors have been reported in the literature with ambiguous definitions (Lollino et al. 2015; Pradhan et al. 2017a).

A number of models with diverging steps of generalization have been established and investigated in geospatial science for evaluating landslide susceptibility. The models are categorized into five classes (Pradhan et al. 2017b), which include bivariate statistic, multivariate statistic, expert-based, machine learning and hybrid models. The individual models are subdivided into numerous subcategories with holds associated merits and demerits.

Applications of these model groups in landslide mapping are reported in the literature these include analytic hierarchy process (AHP) (Sharma and Mahajan 2018) that requires expert knowledge, and fuzzy analytic hierarchy process (FAHP) (Yang et al. 2017) have incorporated expert-based model, which inventory data is not a requisite in the learning process. Nevertheless, the decision on the contributions of the landslides conditioning variables is subjective.

Other landslides analytical models subclass like the weight of evidence (WOE) (Ilija and Tsangaratos 2016), statistical index (SI) (Razavizadeh et al. 2017), and frequency ratio (FR) (Sharma and Mahajan 2018) fits in the bivariate statistical models. While the logistic regression (LR) (Du et al. 2018), discriminate analysis (DA) (Pham and Prakash 2017), partial least squares (PLS) regression (Pradhan et al. 2017b) are multivariate statistical models group. The bivariate numerical models determine the impact of landslides conditioning variables on the menace incidence although, the focal drawback of this approach is the notion of conditional objectivity. On the other hand, the multivariate numerical models investigate the

* Corresponding author

value) and concave (positive values) (Figure 3d and 3e). The land cover classes are dry farming, highly dense forest, mixed forest and orchard, agriculture, mixed agriculture and orchard, orchard, mixed orchard and agriculture, Sandy/dune and urban area were illustrated in (Figure 2a). Lithology was used as mentioned in previous section (Figure 2b). However, the TWI, STI, and SPI were ordered into five classes as shown in Figure 3f, 3g, and 3h, respectively. Finally, Distance to stream and Distance to fault were categorized into five classes, see (Figure 3i and 3j).

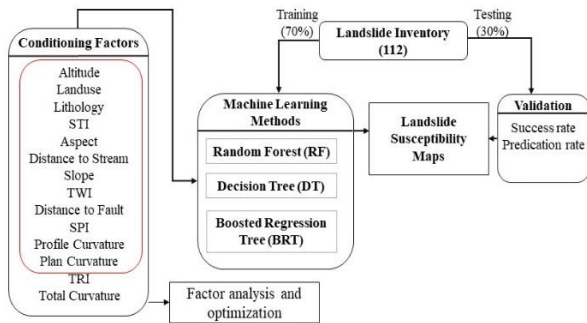


Figure 2. Overall workflow of this study.

3.2 Landslide Inventories

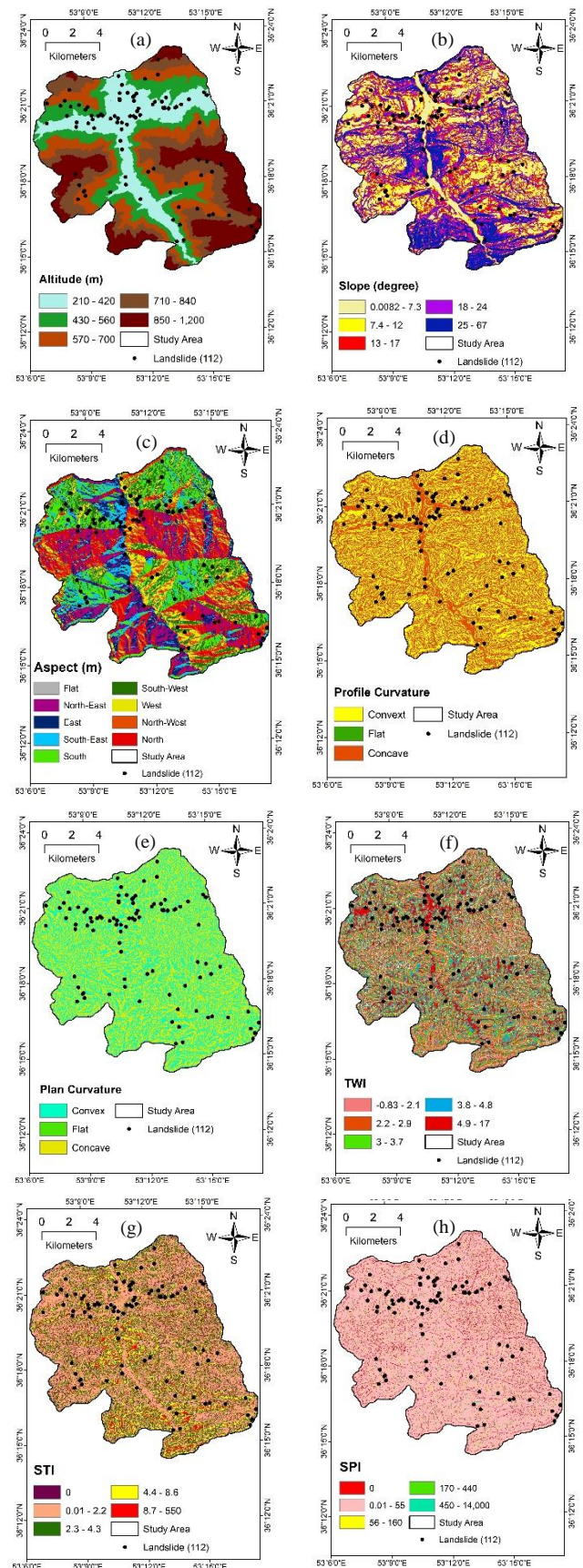
112 randomly landslide inventories points have been obtained with 14 different landslides conditioning variables (independent variables). The inventory is sourced from visual interpretation, previous reports, aerial photographs and satellite images. 70% of the landslide inventories were used for training and 30% was used for testing (Hong et al. 2018).

In a successful prediction model, there must be a dependent variable (y) and independent or predictors variable (x_1, \dots, x_n). To develop the landslides susceptibility maps, we considered two rejoinders (landslide denoted by 1 and no landslide denoted by 0) as the (y) variable and the conditional variable as x -variables. The generated datasets are continuous in natures and subjected to pre-processing that involve a check for multicollinearity effects, out layer evaluation feature contribution. Although, the variables were normalized prior to the model development to get rid of large dissimilarity and concentration on the certain variable principal dispersals. In view of this, variable scale domination of different variables; then the dataset has a unit (1) variance and zero (0) mean through individual conditioning variable. Hence, z-score normalization was utilized, that could present as follows:

$$\text{norm}, X_{ij} = \frac{X_{ij} - \text{mean } X_j}{\text{std } X_j} \quad (5)$$

3.3 Statistical Analysis and Optimization

The next step is factor analysis was applied in the pre-process section to assess for the presence and eliminate of collinearity effect in a given landslide conditioning parameters and outlier values in the inventory dataset (Pradhan et al. 2017b). Multi-collinearity denotes signifies the existence of a strong relationship amongst the independence or conditioning variable with one another in the model. Note that the presence of multi-collinearity reduces the model performance by increasing the error term.



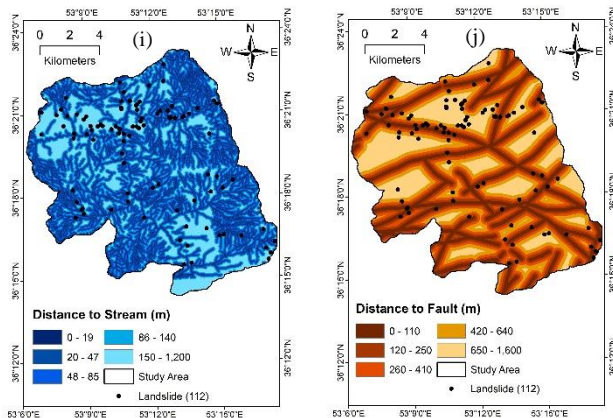


Figure 3. Conditioning factors.

Researchers have developed and recommended a various approach to address multi-collinearity such as (a) discarding highly correlated features (b) Linear combination of the highly correlated features and (c) implementing progressive simulations, which explain multi-collinearity effect (Pradhan et al. 2017b). We adopted the highly related features discard approach using an estimation of variance-inflated factor (VIF) as the following equation:

$$VIF = \frac{1}{1 - R^2} \quad (6)$$

where R^2 = multi correlation coefficient between individual feature and the other features in the model.

In the current study, the factors with a VIF greater than 4.00 is removed. Table 1 displays the estimated VIF values. The VIF values show that the TRI (VIF = 4.16) is the factor which suffers multi-collinearity in the dataset. Therefore, TRI is discarded (Pradhan et al. 2017b).

Factor optimization is another important stage in landslide susceptibility mapping. A large number of conditioning factors could increase the training sample size and computational cost. Consequently, the estimated regression coefficients are misled when the number of factors increased. In this research, attributes of factor optimization that include *Chi-square* and Gini importance was applied to identify the important features and get rid of the insignificance variables at 0.05 (95%) confidence level, used for further analysis. Table 2, shows the results of the model input selected based on their significant importance. Accordingly, the factors optimizations' attributes have all agreed in selecting three factors (altitude, land use and lithology), which are considered the most important features for the prediction of landslide susceptibility in Dodangeh watershed.

Factor	Multi-collinearity and Statistics summary			
	Means	Standard Dev.	Multiple	VIF
TWI	2.71	1.63	0.66	1.78
TRI	2.77	1.39	0.87	4.16
Total Curvature	1.94	1.00	0.62	1.63
STI	2.61	1.07	0.73	2.19
SPI	1.96	0.57	0.49	1.33
Slope	3.02	1.39	0.85	3.71
Profile Curvature	2.09	0.99	0.37	1.16
Plan Curvature	2.02	1.00	0.49	1.32

Lithology	8.33	3.01	0.26	1.07
Land use	2.13	1.60	0.18	1.03
Distance to Stream	103.67	128.25	0.11	1.01
Distance to Fault	416.40	311.96	0.07	1.00
Altitude	2.62	1.4801	0.62	1.62
Aspect	185.26	103.59	0.14	1.02

Table 1. The estimated Variance Information Factor (VIF) for landslide conditioning variables.

Variables	Chi-square (X^2) method		Gini Method		
	(X^2)	p-values	Gini	IV	Cramer's V
Altitude	69.284	0.000	0.354	1.424	0.539
Land use	63.483	0.000	0.367	1.188	0.514
Lithology	35.529	0.000	0.463	0.319	0.271
TRI	21.823	0.000	0.462	0.313	0.274
STI	14.162	0.006	0.465	0.065	0.262
Aspect	11.802	0.160	0.465	0.284	0.261
Distance to Stream	10.892	0.091	0.477	0.188	0.211
Slope	9.336	0.053	0.479	0.180	0.204
TWI	4.852	0.434	0.485	0.119	0.170
Distance to Fault	4.754	0.689	0.489	0.032	0.146
SPI	2.813	0.244	0.493	0.050	0.111
Profile	1.460	0.226	0.496	0.026	0.080
Curvature Plan	0.017	0.893	0.499	0.0003	0.008
Total Curvature	0.000	1.000	0.500	0.000	0.000

Table 2. The factors importance based on factor optimization (Chi-square and Gini).

3.4 Machine Learning Algorithm (MLA)

This study employed three MLAs (RF, DT and BRT) in developing the landslide susceptibility models using R 3.0.2 (an open source software). RF approach is an ensemble machine learning method that creates a large amount of DT; used to describe the spatial relationship that exists in landslide events. In contrast to other algorithms, RF has different procedures for essential factors. A recommended procedure is the influence on the classification accuracy because the value of the factor in a developed tree-like structure was evaluated randomly (Pradhan et al. 2017b). Application of RF method in landslides susceptibility has used the gain of high modification among the different trees, which permit individual tree to choose a class association or membership and allocation groups of a particular class are based on highest number of the supported polls. This ensemble exhibited a promising performance on complex datasets, with a simple preparation and processes (Stumpf and Kerle 2011).

The second approach is the DTs, which have reported to be an effective data-mining tool capable of predicting both continuous and categorical (discrete) response features (Lee et al. 2006). Integrated nodes in the model are splits into different observation. Existing components of the initial nodes begin to nurture a tree via the training data and the explanatory features resulted in a number of division of child nodes. It is possible for the algorithm to further produce more division from the child nodes but advance split is not allowed at the node terminal. The model prediction ability depends on the structure of the tree nodes terminal; this procedure has numerous advantages. The most paramount importance of the model is the ability to predict

complex relationships between variables and give a simple explanation of a DT (Bui et al. 2012). Moreover, complex mathematical equations are not associated with DTs model for any predictions. Finally, the demerits attributed to this model involves their proneness to filthy data and allowed limited attributes result. for more details on DT equations, the interested reader is directed to (Bui et al. 2012).

BRT is a hybrid of statistical and machine learning methods, aimed at improving the performance of a model through appropriate integration of various models for prediction of an event (Schapire 2003). The latest development in BRT approach is demonstrated in modelling the occurrences of natural hazard that is not linear in nature and prove adequate in conducting complex nonlinear relationships. In-depth feature or data, pre-processing (transformation and outlier detection) is not necessary for this approach because the correlation effects between variables are reported automatically (Elith et al. 2008). The two approaches that made up BRT are regression and boosting, which produces intuitive results represented in a simple visualize on DTs. Some outstanding characteristics of the DT models exist in literature, which includes, unaffected to outlier and surrogate approach is used to amend missing data in model input variables (Elith et al. 2008; Breiman et al. 1984). The boosting algorithm purposely employed to enhances model performance accuracy because it is capable of detecting numerous irregular procedural search better than to discover a solitary optimal or extreme forecasting control instruction (Schapire 2003). Addition of several appropriate trees in the BRT model will surmount the model's weakness.

3.5 Validation of the Model's Performance

The initial analyses consist of the ability to create successfully landslide susceptibility models emphasis on address the highly susceptible area, this so-called success rate. The prediction rates are the ability of the test dataset to assess accurately the performances of the models' prediction strength. Note that, a landslide is not evenly distributed in the area. There is not concrete thumb rule regarding the ratio of training and test dataset. Hence, in this research, the landslides inventory was divided into training (70%) and test (30%) set. The popular approach to decide the accurate performance of analytical investigation (Razavi Termeh et al. 2018). In this study models performance was conducted using receiver operating characteristic (ROC) curves (AUC) were considered (Pourghasemi et al. 2013); using success rate and prediction rate for the assessments of the robustness of individual machine learning algorithms in landslide susceptibility mapping (Pham et al. 2018). The ROC (AUC) value is categorized into scales in relation to qualitative classes 50% to 60% is poor, 60% to 70% is average, 70% to 80% is good, 80% to 90% is very good and 90% to 100% is exceptional (excellent) (Razavi Termeh et al. 2018; Yesilnacar and Topal 2005).

4. RESULT AND DISCUSSION

4.1 Relative Importance Analysis of Landslide Conditioning Parameters

Concerning the predictors' contribution in the model development, *chi-square* results in Figure 4, shows that altitude (DEM) (69.28%), Landuse (63.48%) were the most contributing parameters, next by Lithology (36.53%), TRI (22.82%), STI (14.16%), Aspect (12.80%), Distance to stream (10.89%), the minimum importance conditioning parameters were slope (9.34%), TWI (4.85%), Distance to the fault (4.75%), SPI (2.81%), Profile Curvature (1.46%), Plan curvature (0.02%) and no significance conditioning parameters is Total curvature (0.00%). Therefore, all these conditioning parameters except total curvature were utilized as thematic

layers dataset were selected as input predictors in generating the landslide susceptibility maps. Since the analytical report of *chi-square* revealed their participation in the landslide prediction in Iran.

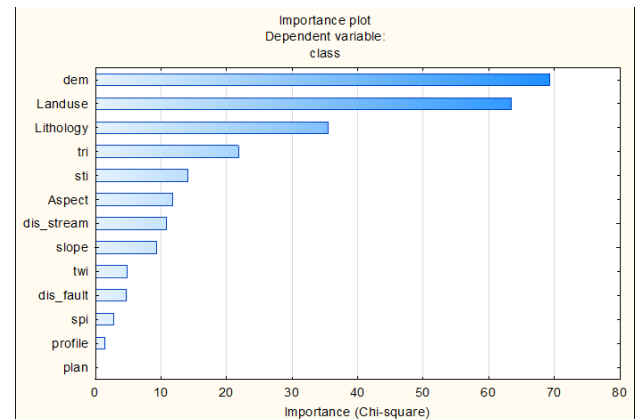


Figure 4. The important plot of conditioning factors using Chi-square.

The emergence of altitude and land use as the most contributing conditioning parameters to landslide occurrence; justifies the logical anthropogenic activities, which has backward effects on the natural environments and manifested on the altitude. These factors were proved leading factor capable to accelerate landslide activities in the study area.

Factor analysis showed that the TRI with VIF values of 4.16 is the highly correlated factors and need to be removed. On the other hand, results of factor optimization indicated that total curvature with chi-square and information value equal to zero was found to be statistically not significant. Important factors in predicting landslides in Dodangeh watershed which are altitude (Chi-square value = 69.284, information value = 1.424), land use (Chi-square value = 63.483, information value = 1.188), and lithology (Chi-square value = 35.529, information value = 0.319). On the other hand, total curvature (Chi-square value = 0.00, information value = 0.00) is removed as its important value is zero.

4.2 The Coefficient of the Conditioning Parameter

The developed coefficient for each factor is shown in Table 3, from different machine learning algorithms. The RF algorithm estimates values range from 0 to 1; altitude reveal to yield the highest estimated value of 1 and the lowest coefficient is 0.073 for plan curvature. Meanwhile, the DT generated coefficient results that presented land use factor with the highest coefficient value of 1, the conditioning factor differs from the RF. It is observed that at the bottom estimates for both DT and RF models, shown a consistency in their coefficient results, though DT minimum coefficient values are 0.044 on plan curvature. Finally, the BRT highest coefficient result is similar to the RF model on the same conditioning parameters altitude. Hence, the developed output model using the RF, DT and BRT models are presented in Figure 5.

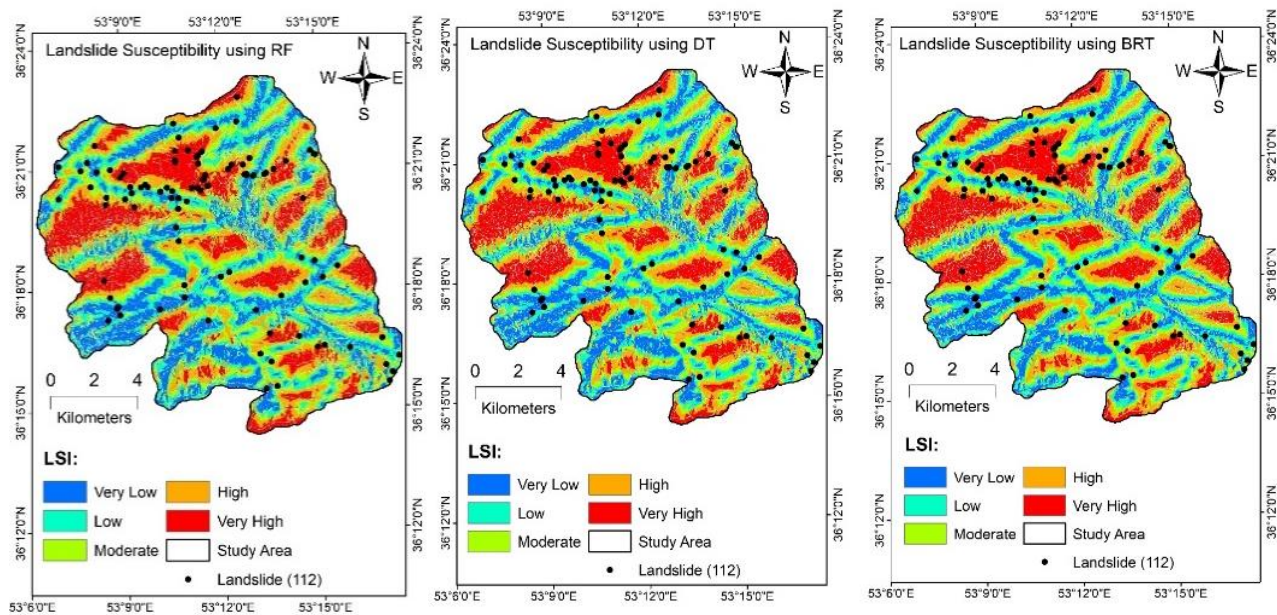


Figure 5: Landslide susceptibility maps produced by the RF, DT, and BRT.

Factor	Coefficients		
	RF	DT	BRT
Altitude	1.000	0.635	1.000
Landuse	0.811	1.000	0.614
Lithology	0.348	0.284	0.841
STI	0.370	0.258	0.374
Aspect	0.496	0.331	0.762
Distance to Stream	0.428	0.250	0.616
Slope	0.215	0.183	0.445
TWI	0.194	0.151	0.548
Distance to Fault	0.402	0.284	0.844
SPI	0.130	0.063	0.416
Profile Curvature	0.155	0.068	0.136
Plan Curvature	0.073	0.044	0.212

Table 3. Estimated coefficients of landslide conditioning factors by the RF, DT, and BRT.

4.3 Validation of the Models

The predictive and consistency strength of these approaches for landslide susceptibility was evaluated by success curve using the training data and prediction rate curves drawn from testing data that were not included in the training process) (Bui et al. 2018). The ROC approach used in this study owing to its reputation, satisfactory and efficiency to quantitatively estimates of models. The observed findings for this study on the success rate and prediction rate curve for the three machine learning approaches were shown in Figure 6. In comparison, the RF models proved to outperformed other machine learning

models with the success rate AUC value of 0.86 (86%) and prediction rate AUC value 0.83 (83%). While the DT model have corresponding AUC values for success rates and prediction rates of 0.72 and 0.70 respectively, and BRT have the AUC values for success rates and prediction rates of model 0.75, and 0.72 (Table 4).

Methods	Success rate	Prediction rate
RF	0.86 (86%)	0.83 (83%)
BRT	0.75 (75%)	0.72 (72%)
DT	0.72 (72%)	0.70 (70%)

Table 4. Success and predication rates for RF, DT, and BRT.

The prediction rate was derived from the (30%) testing dataset, which was used in the evaluation of the capability of the models in predicting landslides zones. However, the highest predictive model strength for landslide susceptibility areas in the Dodangeh watershed was evidence by the RF model follow by BRT and then DT (Figure 6). RF model emerged to be the global best model in both training rate and prediction rate for landslide modelling in the study area.

So far, the findings of this study have been compared with similar research in the same line. The results of this study agreed with the findings of Pradhan et al. (2017b) that investigated and compared SVM, RF and DT models. Their result revealed RF model the best compared to SVM and DT. There is a need for advanced research in environmental hazards now due to the rising human population resulting in high demand in shelter and infrastructures; that require an accurate report on the hazard risk-free or suitable area setting.

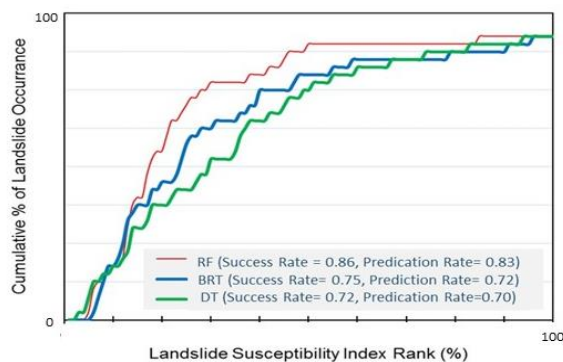


Figure 6: Success and prediction rates for the machine learning models.

5. CONCLUSION

This research evaluated and verified machine learning (RF, DT, and BRT) models in landslide susceptibility mapping with a case study at Dodangeh watershed, Mazandaran province, Iran. A GIS database model was created using 112 sample points of landslide inventory coupled with 12 landslides conditioning parameters. The AUC values for the success rates and prediction rate was detailed from the model's validations.

Research findings indicated RF model to have the best AUC values of success rate (0.86) and prediction rate (0.83) rate, following BRT model (success=0.75, prediction=0.72) and DT model (success=0.72, prediction=0.70). The results displayed efficacy of the three machine learning models to predict landslide susceptibility maps with significant accuracy. The research is relevant to reliable urban planning managers and engineers, as a tool for the adequate decision-making process.

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