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CONVENTIONAL AND MODERN APPROACHES IN LANDSLIDE SUSCEPTIBILITY MAPPING: A METHODOLOGICAL REVIEW

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ABSTRACT

Landslides pose significant risks to infrastructure, the environment, and human lives, underscoring the importance of mapping landslide susceptibility for effective hazard management. This report provides a comprehensive analysis of conventional and modern methods used in landslide susceptibility mapping to understand diverse approaches and advancements in the field. It begins by exploring traditional methods, often reliant on deterministic and statistical models using historical landslide data and geological factors, yet limited in capturing the complex dynamics of landslide occurrences. The review then examines contemporary strategies incorporating remote sensing and GIS technologies. Machine learning approaches like artificial neural networks, decision trees, and support vector machines are emphasized for their ability to handle intricate correlations in landslide susceptibility variables. To ensure accurate assessments, various performance analysis methods are discussed. The review concludes with insights into method effectiveness and the importance of different factors in landslide susceptibility mapping, followed by identifying research gaps for future studies.

Keywords: Landslide Susceptibility mapping, Machine Learning Model, GIS Model, Hybrid Model.

INTRODUCTION

Landslides, defined as the downward movement of rock, soil, and organic matter under gravity's pull, can wreak havoc on infrastructure and lead to severe casualties. While no specific regions or causes can be pinpointed for landslides, literature suggests that increased urbanization, deforestation, and climate change significantly contribute to their occurrence [1].

The aftermath of a landslide can be challenging to manage, but with proper preparedness and mitigation plans, the resulting fatalities can be significantly reduced. Essential to these plans is Landslide Susceptibility Mapping (LSM), which provides crucial information about landslide-prone areas to policymakers. LSM, a complex task, is the spatial prediction of landslides based on an area's local geomorphological conditions [2, 3]. It considers various internal factors related to landslides, such as geotechnical properties, geological conditions, hydrological factors, vegetation cover, and topographic attributes. LSM is formally defined as the division of land surface into near homogeneous zones, ranked according to potential and actual landslide hazards [4]. Numerous methods and approaches exist for LSM, including geomorphological mapping, landslide inventories analysis, heuristic terrain susceptibility zoning, physically based numerical modelling, and statistical methods [5,6]. Over time, more sophisticated LSM techniques have emerged, such as inventory analysis, bi-variate and multivariate, probabilistic frequency ratio, logistic regression, and advanced methods like fuzzy logic, which includes Analytical Hierarchy Process, Probabilistic Frequency Ratio, and analysis with artificial neural network [7-16]. These techniques can be categorized as Qualitative or Quantitative, depending on the method of correlating the factors used for LSM [6].

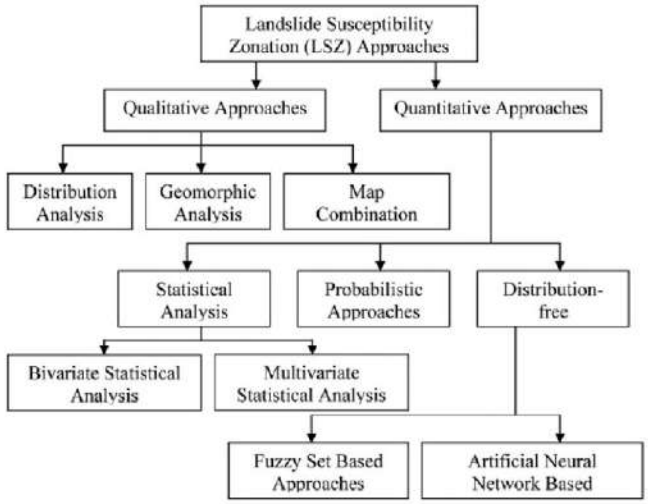

Figure 1. Categorization of Different Approaches used of Landslide susceptibility Mapping [4]

LANDSLIDE SUSCEPTIBILITY MAPPING

Susceptibility to landslides pertains to the likelihood or probability of a landslide occurring in a particular area, thus making landslide susceptibility maps a popular tool for indicating potential landslide-prone areas based on various factors influencing landslides. Assessing landslide susceptibility can be done using different methods depending on the available data [6]. However, the production of a landslide susceptibility map may be challenging with limited data, emphasizing the importance of data quality [17][18].

From previous case studies, key factors influencing landslides include slope angle, curvature, aspect, soil type, geology, distance to rivers, and drainage. Researchers generally concur that slope angle and aspect are the most influential variables in landslide spatial analysis ([19], [20]-[21]). This could be attributed to the slope angle's significant role in slope stability analysis, directly impacting shear strength [22].

Susceptibility, in this context, refers to the extent to which future slope movements can affect the terrain [23]. It has been proposed that understanding fundamental questions such as the location, nature, and mechanism of landslide occurrence is essential for defining landslide susceptibility in a particular area [5]. A landslide susceptibility map categorizes slope conditions as stable or unstable, indicating the likelihood of a landslide occurrence. Additionally, it serves as an indicator of relative hazard and the total density or frequency of likely landslides [24].

OBJECTIVES AND METHODOLOGY

Core Objective of this review paper is to provide a comprehensive review of different methods used in landslide susceptibility mapping. This paper also gives brief insights into use of different method in different regions and context.

The methodology used for writing the review paper involves a comprehensive literature review of different methods from conventional to modern approaches in landslide susceptibility mapping. The intent of writing this paper is to provide a systematic review of the various methods used in landslide susceptibility mapping, their merits, and demerits, and to identify areas for future research.

The review covers the most relevant papers for different methods used in landslide susceptibility mapping from 1988 to 2023. The statistics show that there are many papers existing in landslide susceptibility mapping. However, for the purpose of this review, the focus was on the most relevant methods and papers. This approach ensures that the review is comprehensive, up-to-date, and provides valuable insights into the current state of research in landslide susceptibility mapping.

A total of 166 papers were selected from different sources such as Google Scholar and Scopus. Different keywords used for searching the database includes Landslide Susceptibility mapping, qualitative approach in landslide susceptibility mapping, Quantitative approach in landslide susceptibility mapping, Modern approaches in landslide susceptibility mapping, Ensemble methods, Deep learning models, Hybrid models in landslide susceptibility mapping. These papers were chosen based on their relevance to the topic, the methods used. The selection of papers was done in a way to ensure a comprehensive coverage of the topic, including both conventional and modern approaches in Landslide susceptibility mapping.

Conventional Approaches in Landslide Susceptibility Mapping

Qualitative Approach: Qualitative methods entail subjectivity in the creation of thematic layers that contribute to landslides. These thematic layers are later integrated to develop landslide susceptibility maps for the respective areas. This approach, known as the knowledge-driven approach, relies heavily on expert knowledge of landslides in specific locations. Consequently, the weighting of each factor is determined based on personal expertise and experience.

Distribution Analysis is the simplest and straightforward approach for LSM and is also known as landslide inventory approach. Landslide inventory is defined as the simplest form of landslide information in which location, date of occurrence and other landslide related information is recorded [25]. Slope failure by a single event or cumulative effect of many events can be understood from the landslide inventory maps [26]. Spatial distribution of existing Landslides is provided on a map either as polygons (affected areas) or as point events [27]. Landslide inventory map has significant role to play in landslide hazard assessment and quality and completeness of the landslide inventory map has significant influence on the landslide susceptibility mapping. In a study inventory map for different parts of Italy were compared. Correlation is established between Geomorphological landslide maps, landslide distribution inventory and multi temporal landslide inventories after compiling them [28]. The result of the study revealed that susceptibility prediction analysis is good with the complete landslide inventory map. In a study done by [29], three landslides inventory were compared using universal frequency area statistics. The study highlights significance of data quality and completeness and results of the study reveals that number of landslide event increased rapidly with increase in landslide up to maximum value and then decrease was seen with the power law function. In the study [30] prepared the inventory maps using aerial photographs and GIS database. The time consumption is more in distribution approach and the process is cumbersome and costly but the information which these maps provide can serve as first-hand information for studying the landslide susceptibility in that area. Geomorphic Analysis approach is direct qualitative approach which relies upon the expert/investigator's opinion to estimate the potential and actual slope failures [6]. In this approach, LSM is done by the researcher by directly conducting study on field and collecting other relevant information about the area and based on the field study, landslide susceptibility maps are created and no rule imply here in this type of assessment. In this approach the landslide susceptibility map evolves from detailed geomorphological maps. The quality of the geomorphic map is subjective to ability of the researcher and complexity of the area [31-32]. This approach has some inherent limitation which are due to subjectivity involved in the study. It becomes complicated task to compare the maps prepared by different experts and the updating the existing landslide susceptibility mapping becomes difficult when new data is available. This approach also consumes more time and resources as this will need extensive field survey.

In ***Map Combination*** approach, preparation of thematic layer involves the landslide causative factors such as lithology, lineament, slope and aspect, land use/cover, and drainage. As mentioned in [33], this approach starts with Selection of the landslide causative factors which is followed by thematic Data layer preparation and assigning weights and ratings to the factors. Subsequently after completing preliminary steps discussed above, these thematic Data layer is integrated and landslide susceptibility map is prepared. The study conducted by [34] in New Zealand, different types of soil erosion and their severity was studied and thematic layer was prepared based on the geological factors such as lithology, topography, and slope for landslide susceptibility mapping using Map combination approach. [1] [2] Before the availability of GIS and other data information system, landslide susceptibility mapping using this approach was done by manual interpretation and superimposing of the data. But with the availability of the GIS, and other remote sensing features, it is easy to prepare different thematic layers considering different landslide causative factors in a region. One such study was done by [35] in which GIS based approach was used in landslide susceptibility mapping for the catchment of Ramganga in Himalayas. In this study, landslide causative factors were studied, and then after assigning the weight to the different factors landslide susceptibility mapping was done. One another study was also reported which used GIS and remote sensing for assessing the landslide hazard [36]. One major limitation observed in this method was assigning the weight to the landslide causative factor, because weight is assigned based on the knowledge of expert or researcher. Hence the weight assigned may be subjective to the researcher and it varies from expert to expert as well as region to region. It is also difficult to extrapolate one existing model for other areas [4].

Quantitative Approach: As observed from the discussion for qualitative approaches, it was noted that in all the methods based on qualitative approach subjectivity is involved which makes the landslide susceptibility mapping quite a complex task. To counter the complexity of qualitative approach and reduce the subjectivity, quantitative approaches can be deployed which is more data driven as compared to the heuristic (knowledge based) approach. To say in a brief, quantitative approach is based on statistical analysis and it studies the probability of occurrence of the landslide in any landslide susceptible zone [6]. Statistical approach reduces the subjectivity associated with the qualitative approach. Statistical approach gives the comparison between spatial distribution of existing landslides and landslide causative factors [5]. In this approach, analysis of functional distribution between the known and inferred instability factors and the present and historical landslide distribution is done [6,24,37,38,39]. In [38], literature review stressed the use of GIS in landslide hazard assessment. Further, [24] has also given a comprehensive review on application of GIS in mapping engineering geology and discussed the general concepts of landslide mapping with the statistical concepts which involves inventory preparation, identifying and weight assignment to Causative factors and preparing the susceptibility and hazard map.

In bivariate statistical method, each data layer of causative factors is compared with the existing landslide distribution to prepare landslide mapping [4]. Some important bivariate method includes, Weight of evidence model, frequency analysis approach, weighted overlay method and information value method. Log linear form of Bayesian probability model for LSM is known as weight of evidence model. This uses the landslide occurrence as training points to derive the output. This method is based on calculation of positive and negative weights to define the degree of spatial association variables class and landslide occurrence [40]. For landslide susceptibility mapping in Italian Alps [41] used WOE model. Four maps were prepared and compared based on the success rate curves. The map with Area under Curvature of 88% was selected as best performing model. One other study done for LSM in alpine environment in Italian Alps by [42] also used WOE method and validation was done and best performing model was selected with success rate of 88%. In a study for LSM in south eastern Alps in Italy, [43] used the anthropogenic factors for LSM using WOE model. For landslide susceptibility mapping in Rudra Prayag district of Garhwal Himalaya with semi-automatically created inventories, [44] used weight of evidence model. There are also few other works published in the recent past which used WOE model in spatial data prediction [45-47].

The method which relates the landslide causative factors with landslide frequency is Weighted overlay method. For LSM in Rudra Prayag district of Garhwal Himalaya [48] has used WOE method. In that study, based on the relationship of causative factors with landslide frequency, numerical weights were assigned to causative factors and then data layers were overlaid to prepare the LSM. Some other studies also used this WOE method to know the importance of the landslide causative factors in studying landslide occurrence [49-51]. Bivariate discriminant function can also be used for ranking and weighing the landslide explanatory variables [52].

The method based on observed relationship between landslide occurrence and the causative factors in Frequency Ratio Approach. It is noted that to establish spatial relationship between landslide location and explanatory variables, Frequency Response Approach (FRA [3]) can be used [11]. Based on relationship with landslide occurrence, frequency ratio for each sub class of individual causative factor is calculated and then by summing up the frequency ratio values of each other landslide susceptibility index is calculated. In Penang region of Malaysia comparison of LSM by frequency ratio method and logistic regression was done by [11]. To assess the spatial distribution of landslides in south west Calabria, Italy frequency area statistics was used [52]. For Penang region of Malaysia LSM was prepared using this method by [53] and results with accuracy of 80.03% was obtained and they also found the incorporating the precipitation data in the LSM will improve the prediction accuracy. To map the Landslide susceptibility in Romania frequency ratio method was used by [54]. Few other studies are also noted in which frequency analysis approach was used [48], [55-57]. Another bivariate statistical method based on relationship between landslide occurrence and landslide parameters is Information Value Method [58]. The comparative study for LSM based on logistic regression and IVM method in GIS environment was done by [59]. For GIS based landslide susceptibility mapping for Sikkim Himalayas, IVM was used by [60]. An integrated model for LSM was developed using Global Positioning system, Geographical Information System and Remotely Sensed Data [61]. There are noted evidence of several other studies which have used IVM with different combinations and methods to develop the Landslide susceptibility map [4, 55], [62-67]. There are several other studies which have done landslide hazard evaluation based on guidelines released by Bureau of Indian Standards in 1998. BIS standard revealed that based on rating of Causative factors using LHEF, landslide mapping should be performed. Six different factors were identified by BIS which are slope morphometry, relative relief, land use-land cover, hydrological condition, lithology, and structure. This method involves the dividing of study areas into small units and assigning weight to them and then total estimated hazard is obtained by adding weights of all variables for all units and then landslide susceptibility map is produced. To study the effectiveness of BIS based Landslide Hazard Evaluation Factor, study was conducted in Darjeeling Himalayas by [45].

In Multivariate Statistical Method the relative contribution of each thematic layer data in total susceptibility is considered. This method involves huge amount of data analysis and which involves using external statical packages along with GIS packages. This method is very much time consuming. The most frequently used statistical analysis for LSM is discriminant approach and multiple regression analysis [55, 68-70]. The percentage calculation of landslide area for each pixel and landslide present -absence data layer is produced which follows application of multivariate statistical method to reclassify the hazard for given area. Most used methods for multivariate statistical analysis are logistic regression model, conditional analysis, multiple regression model, Discriminant analysis and Artificial Neural Network.

The use of Logistic regression is done to predict the absence or presence of characteristics based on the values of set of predictor variables. In LSM, Logistic regression finds the best fitting model for relationship between presence or absence of landslides based on the causative factors [71]. This logistic regression model generates the coefficient and if the coefficient is positive, it indicates that landslide might occur. Logistic Regression is the statistical method of slope instability which is built on assumption that the factor which caused slope failure will generate landslide in that area in future [6]. LSM for Hong-King was done based on Digital Elevation Model in GIS environment using LR method [72]. The study done by [73] assessed the landslide susceptibility in the black sea region of Turkey using Logistic regression. For landslide susceptibility classification they used unique condition Unit for mapping unit.

There is one other commonly used method under multivariate analysis is Discriminant analysis. Discriminant analysis defines the difference between landslide causative factors for landslide occurrence and non-landslide occurrence group and weights are assigned to those factors [74]. For slope instability units, Standardized Discriminant Function coefficient is computed based on relative importance of causative factors classified in landslide affected and landslide free group. Relative importance of each variable is revealed by SDFC in Discriminant function as slope a predictor of slope instability. The higher coefficient value of the variable indicates the association of the variable with presence or absence of the landslide. In a study done by [75], Discriminant analysis with 46 thematic layers in GIS environment was used for landslide susceptibility mapping. Landslide susceptibility mapping study done by [76] LSM study was done by dividing region into hydrological units based on the drainage network and geology of area to define mapping unit. Discriminant function was used for terrain-based classification on landslide susceptibility mapping. LSM was done using LR and DA in GIS environment by [77]. A comparative study was done between the maps produced by multivariate approach for mapping unit like pixels, topographical mapping units and slope units in which TMU has shown larger susceptibility area then pixels [78].

The modern method in landslide susceptibility mapping with multivariate approach is Artificial Neural Network (ANN). ANN is system which has capability of learning like humans. The learning algorithm which is used is back propagation which governs the rules for weight assignment. The effectiveness of this model for LSM is proved in several researches [79-83]. There are several records of studies for LSM using Multivariate approach and have proved to be more objective method for landslide hazard assessment in complex geo-environmental settings [71,78,80,84]. Multivariate method gives more accurate results compared to other statistical methods but it involves complex calculations. Comparative contribution of each causative factor in landslide occurrence can be studied using this method.

Probabilistic approach compares different causative factors with the landslide distribution within a probabilistic framework. To determine the spatial, temporal, and size probability of landslides probabilistic approach for landslide hazard assessment is used [26]. Probabilistic approach includes favourability function, Bayesian probability, certainty factor etc. The relationship between landslide distribution and thematic is transferred to the values based on probability distribution function. This approach comes in quantitative approach but still some subjectivity is involved in it [4]. Using frequency area distribution function landslide size, temporal and spatial probability of landslides was computed in a study done by [26]. They used poison probability model to determine exceedance probability of landslide in each mapping unit. In another study done by [85] quantitative landslide hazard assessment done in Nilgiris Hilles; India used frequency volume statistics to obtain probability of landslide magnitude for different return period. The study results revealed landslide occurrence is directly related to the amount of rainfall in the region. For Nilgiris hills in India, spatial probability was used for producing hazard and risk information for planning risk mitigation. Several other studies are also there which have used probabilistic approach [86 – 92].

LSM involves consideration of many variables and their relationship needs to be established. For better results multicriteria decision making approach is very useful. To derive priority scales, measurement is done pairwise and is subjective to judgement of the experts in Analytical Hierarchy Process (AHP) [93]. In AHP there are four steps which includes; Problem definition, Goal, and alternative identification, generating Pairwise comparison matrix, weight determination and priority selection. Numbers from 1 to 9 is assigned to variable related to landslide and its importance and comparison matrix are generated. After generating comparison matrix, consistency ratio and index (CR and CI) is calculated. Comparative study for the LSM generated by Logistic regression, Multicriteria Decision Approach and Likelihood Ratio Method was done by [94] for Azmir, Turkey using Area under Curvature method. In comparative study done by (Ayalew & Yamagishi, 2005) LSM produced using LR and AHP was compared and results revealed that LR method gave more details then AHP. When these maps were compared for landslide activity map then AHP based maps showed the better results as compared to LR models[71].The probabilistic approach which identifies the minimum rainfall required to cause landslide and studies different rainfall related parameters which causes rainfall is known as rainfall threshold method. Most used parameters for designing rainfall threshold includes antecedent rainfall, rainfall intensity, and duration of rainfall. The critical rainfall threshold is dependent on soil properties, wet soil bulk density, water density, slope angel and upslope drainage. As noted by [95], rainfall threshold decreases with increasing seasonal accumulation and comes to constant at 11 mm/day. To predict the landslide in Seattle, Washington, USA cumulative rainfall threshold was used [86]. Comparative study of the model was done with historical records and results revealed that with this method almost 90% of historical events of landslide was captured and researchers have advised to use cumulative rainfall threshold and exceedance rainfall intensity duration threshold together. Physical based model is used to study the physical processes responsible for landslide events. This Physically based model [4] is independent of history and can be also used in the area where past records of landslide is not available. Transient ground water response of slope to rainfall is accounted in this model. In a study [96], use *Transient Rainfall Infiltration and Grid-based Slope Stability* (TRIGRS) to model the rainfall induced shallow landslides in central Umbria region of central Italy. In this study, past records of landslides and rainfall events were used to calibrate the model. Researchers argued that for better results in TRIGRS, information about spatial distribution of physical properties of the surface is needed. In a study done by [97], real time susceptibility of the shallow landslides was assessed for Emilion Apennine in North Italy. When researchers compared SLIP (Shallow Landslide Instability Prediction) and TRIGRS (Transient Rainfall Infiltration and Grid Based Slope Stability) models of landslide susceptibility analysis in GIS environment, results revealed that each model has identical capability for prediction. Four different physically based model was compared in a study done by [98]. The study involved Shallow Land sliding Stability (SHALSTAB), Stability Index Mapping (SINMAP), TRIGRIS and STARWAR + PROBSTAB (storage and Redistribution of water on agricultural and revegetated slope+ Probability of Stability) models in western Ghats of Kerala, India. The results of study revealed that STARWAR+PROBSTAB model is best suitable in spatial-temporal probabilities of shallow landslides assessment. Based on hydrological parameters, High Resolution Slope Stability Simulator (HIRESSS) model was used for predicting landslides and model involved Global Circulation Model for analyzing rainfall parameters [99]. From the review of several studies, it is very much clear that spatial information related to landslide occurrence plays vital role in Landslide Susceptibility Mapping. [5] The combination of Remotely sensed data and Geographical Information System (GIS) have proven evidence of generating and processing good quality of spatial information. The development in earth observation techniques have played vital role in detecting landslides, mapping, monitoring, and analyzing hazard [100].

Modern Approaches in Landslide Susceptibility Mapping

The modern approaches refers to Machine learning which is new emerging trend in landslide susceptibility mapping and gaining popularity among researchers. There are enough number of literatures available which deals with different machine learning model for landslide susceptibility mapping. This machine learning models are classified as conventional, hybrid, ensemble and deep learning models which are discussed in the proceeding sections of this paper.

Standalone ML Methods: This methods are standalone machine learning models popular in Landslide susceptibility mapping and has shown good accuracy in prediction. Most popular method in this category involves, Random Forest Method, Support vector machine, Logistic Regression, Artificial Neural Network, and Naïve Bayes method.

Random Forest model develops many trees based on the input data and predicts by taking votes or average of the decision tree. This method is ensemble of Decision Tree's [101,102]. More number of trees will reduce the overfitting but will also increase the complexity in computation. Random forest when used for classification, each decision tree will predict a class and most voted class is considered as result. While doing regression analysis average of the individual trees will give the estimation of dependent variable. The predictive ability of the model is dependent on the input variables (Causative factors) and this makes the selection of input variables most critical task [103]. Many studies with the use of this model have been recorded. In study done by [104], RF model was used for classification. In a study 50 "ntrees" and 8 "mtry" was used which gave 98.3% success rate and AUC prediction value was 97.7%. As noted in [105] no specific rule exists for value of ntree and mtry in RF. A study done by [106] used the classification model with the equation shown below and the RF model was trained on 700 landslides pixels.

$$\boldsymbol{o} = (\boldsymbol{i}) = \boldsymbol{max}\left[\sum\nolimits_{\boldsymbol{k}} \quad \boldsymbol{f}(\boldsymbol{d})\right]$$

Where; input data is indicated by I, output computed is indicated with o and f(d) is Indicator function which is defined as;

$$f(d) = \{1, if\ d\ is\ 'YES'\ 0,\ \ Otherwise$$

In above equation, YES indicates landslide zone and OTHERWISE indicates non-landslide zone. The value of k was selected as 1000 after parameters tuning and at each node 3 features were tested. Out of Bag (OOB) method which is used for measuring prediction error was used for measuring accuracy of the RF model and results revealed that model has accuracy of 98%. In a comparative study done by [107], comparison between traditional statistical model (certainty Factor), Conventional ML models like SVM and RF, and hybrid of CF-SVM and CF-RF was done. The RF model in study used 500 decision trees with 3 randomly selected features and 464 landslide and non-landslide samples were used to train the model. Testing of the model was done on 200 test samples and out of that 200 samples 156 gave the accurate prediction and prediction accuracy of 78% was noted for the RF model.

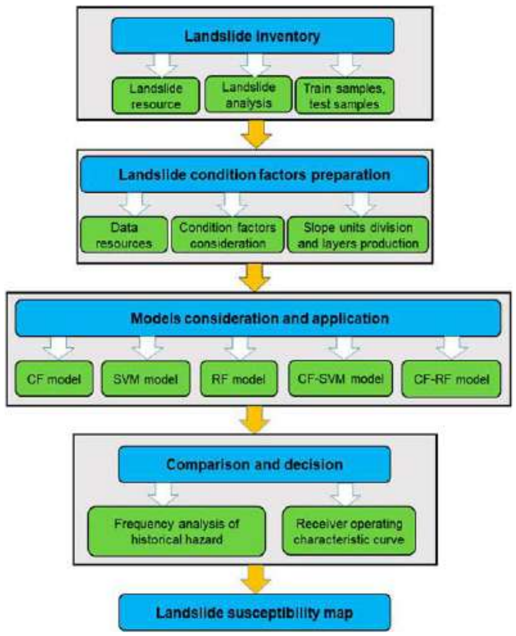

Figure 2. Flow of Study [107]

In a study done by [108], RF was used for feature selection. The study focused on improvement of the classification model removing irrelevant features and careful selection of the causative factor. The study was conducted with 500 trees and four features. The study showed the AUC performance of 0.93. The study was done using 2100 landslide data groups divided into two groups, first group of 1050 points was used for training and remining 1050 for training [101]. The study used STATISTICA for implementing RF in landslide susceptibility mapping. The AUC for the RF method used in study was 0.7394. The literature proves that, RF is quite popular method for mapping landslide susceptibility. The use of RF is prevalent due to some inherent advantages like easy implementation, better ranking of causative factors which helps in eliminating the irrelevant factors and gives the higher accuracy in prediction.

Support Vector Machine is categorised as supervised ML model and can be used to solve classification and regression model. Support Vector Machine (SVM) is a concept used for classifying data into different groups by drawing a line or hyperplane between them. In classification, the best hyperplane is the one with the maximum margin, which is the maximum distance between the hyperplane and the data points. The SVM model is trained to find this hyperplane. However, in real-life scenarios, data is often not linearly separable, making the maximum margin approach unsuitable. In such cases, a soft margin, which allows for some misclassification, is more appropriate. To handle nonlinear datasets, SVM uses a mathematical function called a Kernel, which transforms the input data into a higher-dimensional space, making it easier to separate the classes. Basic classification function in SVM is given by below equation where coordinates numbers are given by n, xi defines parameters in vector x in original space, y gives class label, hyperplane parameters are given by weight w and bias b, and sgn gives the sign function.

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$$\boldsymbol{y = sgn(f(x)) = sgn\left(\sum_{i=1}^{n} wixi + b\right) = sgn(w.x + b)}$$

The modified equation for classification is given as below;

$$f(x) = sgn\sum_{i=1}^{m} \alpha_i \gamma_i (x_i \,.x) + b$$

In the above equation weight is given by; w = ∑ m i=1 αiyixi, i = 1, ..., m where αi denotes the weight of the ith training example as a support vector. For dealing with non-linear decision boundary, SVM datasets are mapped into higher dimension space where data is linearly separated. Datapoints xi is replaced by φ(xi) which produces higher dimension mapping. Kernel function is used to produce value like dot product of higher dimensional vector. The equation (16) describes the decision function using Kernel trick.

$$f(x) = sgn\sum_{i=1}^{m} \alpha_i \gamma_i k(x_i \,,x) + b$$

In a study done by [109], four kernel function namely, linear, polynomial degree of 2, sigmoid, and RBF, was used to generate LSM. For training the model ENVI5.1 software was used and for visualization results was exported to ArcGIS software. The results revealed that RVF-SVM gave best success rate and prediction rate. In success rate, RBF-SVM was followed by polynomial-SVM, linear-SVM, and sigmoid-SVM. In prediction rate RBF-SVM was followed by linear-SVM, polynomial-SVM, and sigmoid-SVM. The study done by [110] used gaussian radial function with parameter γ = 2 and penalty factor C = 100 for model fitting. The datasets were divided into two random sets where 50% was used for model training and other 50% for model performance. The next step in study swapped the training datasets with testing datasets and arithmetic mean of both give the accuracy of the model. The study was done using multiple iterations and the accuracy for them was, for 1% = 71. 0, for 5% = 71.0, and for 50% = 88. An open-source package LIBSVM was used for study. From the study it was observed that small datasets can give good accuracy in susceptibility prediction. SVM has the least false positive rate for a standard ground class which is considered essential in risk assessment and based on the available literature SVM has been proved to be effective method in landslide susceptibility mapping [111].

Logistic Regression is supervised ML method used for binary classification problem. This model is predecessor of ANN as ANN is generalization of logistic regression [112]. Its name suggest that model is regression model but in actual it is classification model [113]. This model does not require linear relationship between input and output variables [114]. This method gives probability of event by dividing events occurring and events not occurring. Weights are assigned to the inputs of the logistic regression and there is exponential relationship between weights and output [116]. This model can be given by below equation;

$$Logistic\ Function = \frac{1}{1 + e^{-x}}$$

In above equation, input variable is given by x, and logistic function is natural log of odds. Here the probability of 0.5 transforms to the logistic function 0. The range of logistic function is between 0 to 1 and is given by P > [0, 1] [113]. Logistic regression predicts outcome as Yes/No, Success/Failure, Occur/Not occur. Taking causative factors as input variables, we can determine the occurrence of landslide in the study area. As noted by [117], logistic regression is the most common multivariate method and, in their study, they find the relationship between causative factor and occurrence or non-occurrence of landslides. In a study done by [118], some common ML models were used with convolution neural network and hybrid model were studied. They used, SVM, LGR and RF with CNN. CNN has better learning capabilities and after learning it extracts features which will improve the performance of the ML model. From the results of their study, it is revealed that when the combination of LGR and CNN is used, better predictive capability is observed as compared to other hybrid model under study. Overall accuracy of the LGR-CNN model was 79.82%. From the results of the study, it is evident that hybrid models can perform better as compared to the traditional ML models. One other study done by [119] did the comparative evaluation between SVM, LGR, ANN and conditional probability. The study done by x` [120], used LGR and CART as benchmark model while using Random Subspace based Classification and Regression Tree (RRSCART). As an input 14 causative factors were taken and 203 landslide locations were considered. The results revealed that RSSCART has training AUC of 0.852 and validation AUC of 0.827 which was better than both LGR and CART.

Artificial Neural Network resembles the working of biological neurons and their interconnection to process the information parallelly. The basic architecture of this method has interconnected neurons arranged in different layers. There are three types of layers, the first is input layer, then number of hidden layers and output layer. Every connection between neurons in the model is assigned a numerical value known as weight. To give the output hi of the hidden neuron i, equation given below is used; in which σ () is the activation function, number of input neurons is defined by N, weight is represented by Vij and inputs to the input neuron is represented by Xj and threshold of hidden neuron is given by [121].

$$h_i = \sigma\left(\sum_{j=1}^{N} V_{ij}x_j + T_i^{hid}\right)$$

In a research done by [122] used 14 causative factors with different weights assigned to it as an input variable. The model was trained using back-propagation algorithm. The main aim of the study was to determine the weight of the causative factors. Validation for the trained model was done by taking the existing data from Korea's Youngin, Jang hung, and Boeung regions. The model evaluation showed the highest accuracy of 81.36% and lowest of 71.72% when tested in nine different locations. The main factors such as slope, land cover and lineament distance were having highest weights whereas soil type and forest density has lowest weight. In a comparative study [123], studied the Mamdani Fuzzy Interference System and ANN for LSM. This study is more significant because there is no literature for LSM available which has previously used FIS. From the comparative study it was observed that ANN has less uncertainty as compared to FIS and prediction accuracy for both the model was satisfactory. The AUC value for ANN was 0.94 whereas FIS was 0.88. The study done by [124] also used ANN for LSM and used back propagation algorithm for training the model. Small numerical values between 0 to 1 was used for assigning the weight to the input variables and then network output was calculated and compared with the expected output, if the results align with each other than process is continued and if not, then weights are reassigned using correction rule. The AUC value of 0.84 showed that the model has good prediction accuracy. Two different ANN structures were studied by [125] which were composed of single and double hidden layers. The ANN model was trained with four different training algorithms namely, batch backpropagation, quick propagation, conjugate gradient descent algorithms, and Levenberg–Marquardt algorithm. The CGD algorithm was observed to be slower than other but also gave the highest success rate in AUC and best prediction accuracy. The study was done by [126] which classified four types of landslides namely complex, slide, rockfall and slow and for all four types LSM was done using MLP-ANN model. The software named as ArcGIS were used for mapping and MATLAB for supervised learning. AUC value of more than 0.9 was observed for MLP-ANN model and from overall review it is evident that ANN has very high prediction accuracy.

The learning algorithm based on 'Bayes' rule is known as ***Naïve Bayes model***. Naïve Bayes works on assumption that the classification features are independent of other features in class [127]. In the practice, assumption of independence is often violated and NB therefore offers competitive accuracy.

There are certain features of Naive Bayes which are as listed below;

1. NB model offers efficient computation time as there is linear relationship between training and classification time and number of features.
2. There very less possibility of variance as search is not included in the model but also chances of high bias are associated with this model.
3. NB models offers cumulative learning. It learns from the lower order probability from the available training data and then it updates when new training data is available.
4. NB model can predict posterior probabilities directly.
5. There is no effect of noise as all the features are utilized for prediction.
6. There is no effect of missing features at as all the features are used for prediction and hence it makes the missing feature unnoticeable.

In a study [128] used NB model for LSM using 17 Landslide causative factors vectors and occurrence and non-occurrence vector. For classification, NB classifier was used which is given by below equation.

$$Y_{NB}f(x) = \{argmaxP(y_i), y_i = [event, non - event], \prod_{i=1}^{17} P\left(\frac{x_i}{y_i}\right)$$

$$P\left(\frac{x_i}{y_i}\right) = \frac{1}{\sqrt{2\pi\alpha}} e^{\frac{-(x_i - \eta)^2}{2\alpha^2}}$$

In above equation conditional probability was given by P(xi/yi), where P(yi) represents prior probability of yi, standard deviation α for xi, η indicates the mean. The prediction accuracy of 78.3% was obtained and success rate of 79.2%. The main aim of the study was to utilize NB model for damage control by providing preventive support measure. For comparative evaluation of the model [129] studied RF, SVM and NB models. Study was done using eleven landslide causative factors and NB model was implemented using e1071 Library in R. The NB model was employed to classify pixels into landslide and non-landslide classes and the model demonstrate accuracy in range of 96% to 97%. In a case study two ML models, SVM and NB was used with fractal theory for landslide susceptibility mapping. The study was conducted using 10 Landslide Causative Factors. Prediction accuracy for the ML model with FRT for selecting non-landslide locations was higher with AUC value of 0.96 for SVM and 0.98 for NB. When non-landslide location was selected randomly, AUC value came out to be 0.708 for SVM and 0.727 for NB and this indicated that there is significance of non-landslide locations in Landslide susceptibility mapping and it can affect the accuracy of generated LSM. The study done by [130] implemented NB algorithm with R 3.0.2 and the Rminer package for LSM modelling. The model performance was evaluated using AUC and RMSE where AUC value for model was 0.91 and RMSE value was 0.464.

Hybrid ML Models: The accuracy of the ML models in generating LSM is dependent on the landslide causative factors. There should be wise use of landslide causative factors to get the better accuracy in landslide susceptibility mapping. Hybrid techniques are combination of different ML models or combination of ML model with feature selection and optimization techniques. For selecting causative factors, conventionally multicollinearity analysis was involved by calculating VIF and Tolerance (TOL) [131-133]. Other co-relation method noted in the survey are such as Pearson's Co-relation analysis, CFS , CAE and spearman's rank correlation coefficient [134-137]. Novel hybrid model was studied by [138] which combined Rough Set (RS) theory with SVM. The study aimed to map the landslide susceptibility at a regional scale using multisource data. For selection of Landslide causative factors RS was used and SVM for prediction of landslide susceptibility. Overall good fit was observed while using combination of RS-SVM for LSM as compared to that of individual SVM model. In a hybrid model study done by [139], considered local environmental factors using GWR method for sake of better prediction accuracy. The hybrid model of GWR-PSO-SVM was used for generating LSM. For defining Landslide causative factors, SPSS Clementine 12 software was used. The AUC value of the GWR-PSO-SVM hybrid model was 0.978.

The hybrid model using sequential minimal optimization and SVM was studied by [140]. Use of SMO included several benefits like fast, easy, and simple algorithm implementation. This model gives better results with extensive datasets, less input and reduced complexity of the problem. When SMO-SVM compared with other hybrid models such as cascade generalization optimization-based SVM and other ML: models such as NB-tree and SVM, SMO-SVM outperformed with AUC value of 0.824. In a study done by [133], quantitative prediction of landslide was done. Hybrid model with Fractal dimension, Index of Entropy and SVM was used in the study. The hybrid model Fractal-IOE gave the AUC value of 0.85 and Fractal-SVM gave the AUC value of 0.97. The results revealed that hybrid model gave better results than standalone IOE or SVM model. To determine spatial agreement of ML-based LSM and reduce uncertainties in landslide studies, [141] used combination of KNN, MLP, RF, and SVM ML models. It was observed that there was better spatial agreement with correlation coefficients when hybrid models were used. The study showed better prediction accuracy than individual ML models but due to secondary source of input data there was lower RMSE accuracy. Hybrid model using GeoSOM, RF, and ensemble ML model consisting of ANN-SVM-Gradient boosting decision tree (GBDT) was used in a study of [142]. For clustering study locations GeoSOM was used, for feature selection RF and Pearson correlation coefficient was used and for generating LSM ANN-SVM-GBDT was used. Random selection of non-landslide locations imposed the possibility of error in the model and time consumed for the model was also more as compared to other hybrid models. In a study done by [118], CNN was integrated with SVM, RF, and LGR.CNN was used for feature selection and LSM was generated using different ML models. It was noted in study that overfitting was the problem with this type of hybrids. For improving predictive performance of ML models, FRT was included to select the non-landslide locations [143]. The study showed that there was better accuracy for SVM and NB model when FRT was used for selecting landslide and non-landslide locations. The combination of Bayesian optimization (BO) with RF and GBDT was explored by [144]. Prediction accuracy of RF and GBDT was observed to be improved with the use of BO. The integration of multi-boost with radial basis function neural network (RBFN) and Credal decision tree (CDT) was studied by [136]. The results revealed that CDT had the best AUC value of 0.77 with the use of multi-boost whereas for combined model AUC was lower as compared to other studies.

Ensemble Models: The method of combining of different conventional ML models using different averaging or voting systems is known as Ensemble methods. The limitation of one model is compensated by other model and hence when this ensemble approach is used there is improvement in prediction accuracy and generating LSM [145]. There is enough literature available which proves that ensemble techniques are useful in improving accuracy of the LSM. Some studies have used Light GBM [146] based on decision tree. The RF is the basic ensemble model used for generating LSM and is recorded in many studies, [137, [146-151]. Due to its simplicity, lower computation and robustness, RF is the most preferred ML model. Another popular model is random subspace which is used by many researchers [150,152], [153-155]. This algorithm was proposed in the study done by [153]. This model used the different features in entity space and this the key difference in this method as compared to other techniques [153]. Overfitting is the main problem with this model. Another ensemble model based on decision tree is canonical correlation forest (CCF) [156]. As compared to RF and RotFor, this method is advanced. CCF method uses many decision trees for predicting unknown samples using majority voting method. Another decision tree-based algorithm is Chi-squared automatic interaction detection (CHAID) [157]. For automatic classification, CHAID can be useful as it can analyze many Landslides Causative Factors.

Deep Learning Models: Deep learning models can find intricate structures in data with higher dimension [158] and therefor they can achieve higher performance. Deep learning models are representation learning techniques with number of representation layers. Representation Layers of the Deep Learning methods involve; batch normalization, flatten, dense, and dropout layer. The consistent data distribution for learning is done by batch representation layer. Class distribution is done by dense layer and improvisation in generalization of the model is done by drop out neuron layer. One other vital component for DL architecture is Activation function and should be differentiable and selected according to the model requirement. For landslide susceptibility mapping, Sigmoid Activation Function is generally used dur to non-linear nature of landslide susceptibility mapping [159]. Some of the popular Deep Learning methods include CNN, LSTM, DNN (deep neural network) and RNN. CNN model has three essential components which are; convolution, down sampling, and fully connected layers. Convolution layer extracts the feature information from previous layer by using multiple kernels. As compared to fully connected network, convolution layer allows training with lesser number of parameters. After convolution layer, activation function comes into play and most effective and popular activation function is Rectified linear unit function. The down sampling layer reduces size of feature and tendency of overfitting [160]. It is observed that DNN has been popular choice for natural hazard studies. DNN includes, fully connected layers, dropout layers, hyperparameters for random search, activation function, and optimization algorithm [161]. In temporal data processing RNN has proved to be successful. As contrast to CNN, RNN can process sequential data with recurrent hidden states, which learns from former and present state [162]. However, for long data processing RNN is not accurate. To overcome the limitations of RNN, LSTM came into existence which has advanced recurrent structure. The memory cell is the basic building block in LSTM and this cell has gates to control the stored information. The input gates regulate the status of cell and for that gate decides that how much memory from the previous state is retained or forgotten [159].

In a study done by [163], CNN was used for the first time in landslide susceptibility mapping study. Three different CNN architectures were constructed from three data representation algorithms 1D, 2D, 3D. The historical landslide data taken from Yunshan County, China was divided into ratio of 70:30 for training and validation purpose and 16 Landslide causative factors were selected. The evaluation of the proposed CNN was done using OA, MCC, ROC, and AUC measures. While making a comparative study of the proposed CNN model with Optimized SVM, DNN and LeNet 5, it was observed that CNN-2D gave the highest AUC value of 0.813. From the study it was concluded by researchers that CNN is more practical approach in landslide prevention and management than conventional ML models. Comparative study between DNN and CNN was done while taking Iran as an area of study for landslide susceptibility mapping in a study done by [164]. Entire Region of Interest was converted to raster format for mapping landslide susceptibility. Susceptibility indices of each pixel was calculated to test that trained model of CNN and RNN. The LSM was generated by converting the indices and then landslide susceptibility was categorized into five different categories. The AUC value of CNN was 0.85 and RNN was 0.88.

To overcome the limitations of DL model such as lack of model variance and limited generalizability, a study was conducted by [159]. In this study the network architecture consists of two main parts, first part consists of RNN-CNN-LSTM layer blocks which was used for feature extraction and the second part was for dense and dropout layer for class prediction. To find the batch size, number of layers, epoch, loss function, and optimizer, trial and error method was employed. Overall accuracy of the DL model was improved by 7% with the proposed model. Improvement of 4% was also noted in the AUC value of map generated for landslide susceptibility. The AUC values of the models are as; LSTM (0.86), RNN (0.91), CNN (0.92), and the highest of all models is CNN-RNN-LSTM (0.93). In a comparative study done by [165], hybrid CNN-DNN based LSM was compared with the conventional ML models. In this proposed study, CNN was used for feature extraction and DNN for sorting pixel into susceptibility groups. AUC value of 0.90 for CNN-DNN was achieved. A stacking-based ensemble model was used with CNN and RNN to generate LSM [162]. The AUC value for the LR, RNN, CNN and CNN-RNN are 0.87,0.900,0.904, 0.918 respectively. CNN was compared with conventional ML models in study done by [160], which revealed that CNN based model has best predictive performance. A Deep learning framework with integration of spatial response feature and ML classifier was developed by [166]. This method is executed in three steps. The first step involves depth wise separable convolution used for spatial feature extraction to prevent multifactor feature confusion. The second step is spatial pyramid pooling which extracts the response features to obtain features under different scales. The last step merges the high-level feature into ML classifiers for more effective feature classification. The AUC values of SR-RF, SR-SVM, and SR-LGR are 0.92, 0.915, and 0.903 respectively. The study done by [161] explored CNN, RNN, DNN, LSTM methods. The CNN architecture was 1D and included one layer for convolution, flattening and pooling and two fully connected dense layers. To avoid overfitting, dropout layer was used. To select the kernel size, number of neurons in fully connected layers, activation function and number of filters, Keres Tuner Library was used. For training the model, Adam Optimization Algorithm was used and Sigmoid as an activation function. The LSTM in study used one bi-directional layer, one layer for dropout and two fully coupled layer. The RNN model used simple RNN layer using Keres library. The architecture was same as other model and it consisted, one RNN layer, one dropout layer and two fully connected layer. The AUC value for DNN, LSTM, CNN and RNN are 87.3, 86.5,85.6, and 82.9 respectively.

CONCLUSION

This review paper provides a comprehensive overview of various methods used in landslide susceptibility mapping, highlighting their merits and demerits.

It is evident that each method has its strengths and weaknesses, and the choice of method should be guided by the specific requirements of the study, the available data, and the expertise of the researchers

One key insight from this review is the importance of landslide causative factors in landslide susceptibility mapping. These factors, which includes different topological, Hydrological, and geological factors such as slope, aspect, soil type, and rainfall, Lithology, distance to fault and density of fault play a crucial role in determining the susceptibility of a region to landslides. Therefore, any susceptibility mapping exercise should give due consideration to these factors.

The Table 1 below gives the brief overview of the merits and demerits of the different methods used in landslide susceptibility mapping.

Table I. Summary of different methods used in landslide susceptibility mapping

Method	Type	Merits	Demerits
Distribution Analysis	Qualitative	Comprehensive method, considers multiple factors and utilize the human intelligence which can give better insights.	Subjectivity is involved in this method as human intervention is there and data is totally based on expert knowledge. It is also time-consuming and difficult to update due to larger subjectivity.
Map Combination Approach	Qualitative	Integration of multiple factors in the study is possible.	Subjective weighting increases chances of error and is difficult to extrapolate.
Multivariate Statistical Approach	Quantitative	This method considers relative contribution of each factor and gives good accuracy.	It consumes more time due to complex calculations.
Bivariate	Quantitative	Simple method and	There is compromise with

Method	Type	Merits	Demerits
Statistical Approach		interpretation are also easy.	accuracy when compared to other multivariate methods.
Logistic Regression	Quantitative	Finds best fitting model.	Requires large data sets which makes process lengthy.
Frequency Ratio Approach	Quantitative	Simple, easy to interpret	Less accurate than multivariate methods
Analytical Hierarchy Process	Quantitative	It is uses multiple factors which can give good idea about relative contribution of different factors.	It involves complex calculations which requires more computational resources.
Random Forest Method	Modern/Machine learning Standalone model	Overfitting is reduced as compared to other methods.	Increases computational complexity with a greater number of trees and chances of overfitting reduces with increased number of trees.
Support Vector Machine	Modern/Machine learning Standalone model	Gives High accuracy compared to other models in the segment.	Requires large data sets which makes process lengthy.
Artificial Neural Network	Modern/Machine learning Standalone model	It offers good prediction accuracy.	It is complex to interpret the data generated by this model and is a complex task.
Naive Bayes	Modern/Machine learning Standalone model	Simple and fast method as compared to other methods in the same context.	Features are assumed to independent to each other and presence or absence of any feature does not affect the model.
Hybrid Models	Modern/Machine Learning	Combines strengths of multiple models	Complexity in model compiling and upto certain extent overfitting is observed in the mode.
Ensemble Models	Modern/Machine Learning	Reduces bias and variance.	Overfitting is the major issue in ensemble models.
Deep Learning Models	Modern/Machine Learning	Gives High accuracy and capable of handling complex patterns of data.	Requires large data sets and complex calculations are involved.

In conclusion, a thorough examination of various machine learning models reveals Support Vector Machine (SVM) as the predominant choice for landslide susceptibility mapping, while ensemble methods, artificial neural networks, random forests, and hybrid approaches are gaining traction. However, exploration into deep learning and decision trees in this domain appears comparatively limited. Building upon these findings, several avenues for further research emerge. Firstly, optimization in the number of trees and random inputs in Random Forests could enhance accuracy, alongside exploring SVM with different kernels. From the review it is identified that there is a need for more research focusing on machine learning models and advanced techniques in the Himalayan regions, particularly in less-studied areas like the Sutlej basin, utilizing ensemble models and deep learning methods for comparison with conventional approaches. Investigating less-explored Deep Learning models such as Transformer, LSTM, and RNN could yield insights into their potential for higher accuracy in landslide susceptibility mapping. Lastly, exploring Transfer Learning models to apply knowledge from data-rich locations to areas with limited data could streamline training processes and dataset sizes without compromising accuracy. These avenues signify promising directions for future investigations in landslide susceptibility mapping.

REFERENCES

[1] Turner A. K., & Schuster R. L. (1996). Landslides Investigation and Mitigation.

[2] Brabb, E. E. (1984). Innovative approaches to landslide hazard and risk mapping. International Synopsis, Landslides, 307–324.

[3] Brabb E. E. (1991). Brabb, 1991. Journal of International Geoscience, 14(1).

[4] Kanungo, D. P., Arora, M., & Sarkar, S. (2009). Landslide Susceptibility Zonation (LSZ) Mapping-A Review. www.em-dat.net

[5] Aleotti, P., & Chowdhury, R. (1999). Landslide hazard assessment: summary review and new perspectives. In Bull Eng Geol Env (Vol. 58). Springer-Verlag.

[6] Guzzetti, F., Carrara, A., Cardinali, M., & Reichenbach, P. (1999). Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, Central Italy. In Geomorphology (Vol. 31).

[7] Dahal, R. K., Hasegawa, S., Nonomura, A., Yamanaka, M., Masuda, T., & Nishino, K. (2008). GIS-based weights-of-evidence modelling of rainfall-induced landslides in small catchments for landslide susceptibility mapping. Environmental Geology, 54(2), 311–324. https://doi.org/10.1007/s00254-007-0818-3

[8] Dai, F. C., Lee, C. F., Li, J., & Xu, Z. W. (2001). Assessment of landslide susceptibility on the natural terrain of Lantau Island, Hong Kong. In Cases and solutions Environmental Geology (Vol. 40, Issue 3). Springer-Verlag.

[9] Ercanoglu, M., Gokceoglu, C., & Van Asch, T. W. J. (2004). Landslide Susceptibility Zoning North of Yenice (NW Turkey) by Multivariate Statistical Techniques. In Natural Hazards (Vol. 32).

[10] Karnawati, D., Fathani, T. F., Ignatius, S., Andayani, B., Legono, D., & Burton, P. W. (2011). Landslide hazard and community-based risk reduction effort in Karanganyar and the surrounding area, central Java, Indonesia. Journal of Mountain Science, 8(2), 149–153. https://doi.org/10.1007/s11629-011-2107-6

[11] Lee, S. (2005). Application of logistic regression model and its validation for landslide susceptibility mapping using GIS and remote sensing data. International Journal of Remote Sensing, 26(7), 1477–1491. https://doi.org/10.1080/01431160412331331012

[12] Lee, S., & Min, K. (2001). Statistical analysis of landslide susceptibility at Yongin, Korea. Environmental Geology, 40(9), 1095–1113. https://doi.org/10.1007/s002540100310

[13] Pradhan, B., Singh, R. P., & Buchroithner, M. F. (2006). Estimation of stress and its use in evaluation of landslide prone regions using remote sensing data. Advances in Space Research, 37(4), 698–709. https://doi.org/10.1016/j.asr.2005.03.137

[14] Sarkar, S., Kanungo, D. P., Patra, A. K., & Kumar, P. (2008). GIS based spatial data analysis for landslide susceptibility mapping. Journal of Mountain Science, 5(1), 52–62. https://doi.org/10.1007/s11629-008-0052-9

[15] Sarkar, S., & Anbalagan, R. (2008). Landslide hazard zonation mapping and comparative analysis of hazard zonation maps. Journal of Mountain Science, 5(3), 232–240. https://doi.org/10.1007/s11629-008-0172-2

[16] Van Westen, C. J. (1997). Statistical landslide hazard analysis.

[17] R J Fabbri, A G Chung and C F Cendrero A 2003 Is Prediction of Future Landslides Possible with a GIS? Nat Hazards 30 487–499

[18] J Coe, J Godt, R Baum, R Bucknam and J Michael 2004 Landslide susceptibility from topography in Guatemala Landslides Eval. Stab. Terrain Eval. Stabilisation 1 69–78

[19] A D Regmi et al. 2014 Application of frequency ratio, statistical index, and weights-of-evidence models and their comparison in landslide susceptibility mapping in Central Nepal Himalaya Arab. J. Geosci. 7 725–742

[20] M Teixeira, C Bateira, F Marques and B Vieira 2015 Physically based shallow translational landslide susceptibility analysis in Tibo catchment, NW of Portugal Landslides

[21] B C Vieira, N F Fernandes, O Augusto Filho, T D Martins and D R Montgomery 2018 Assessing shallow landslide hazards using the TRIGRS and SHALSTAB models, Serra do Mar, Brazil Environ. Earth Sci. 77 260-274

[22] Q Q Wang, Y Guo, W Li, J He and Z Wu 2019 Predictive modeling of landslide hazards in Wen County, northwestern China based on information value, weights-of-evidence, and certainty factor Geomatics, Nat. Hazards Risk 10 820–835

[23] P Reichenbach, M Rossi, B D Malamud, M Mihir, and F Guzzetti 2016 A review of statistically-based landslide susceptibility models Earth-Science Rev. 180 60–91[15] J Chacón, C Irigaray, T Fernández and R El Hamdouni 2006 Engineering geology maps: Landslides and geographical information systems Bull. Eng. Geol. Environ. 65 341–411

[24] J Chacón, C Irigaray, T Fernández and R El Hamdouni 2006 Engineering geology maps: Landslides and geographical information systems Bull. Eng. Geol. Environ. 65 341–411

[25] Cruden D (1991) A simple definition of a landslide. Bull-Int Assoc Eng Geology 43:27–29

[26] Guzzetti, F., Reichenbach, P., Cardinali, M., Galli, M., & Ardizzone, F. (2005). Probabilistic landslide hazard assessment at the basin scale. Geomorphology, 72(1–4), 272–299. https://doi.org/10.1016/j.geomorph.2005.06.002

[27] Wieczorek G.F. (1984). Preparing a Detailed Landslide-Inventory Map for Hazard Evaluation and Reduction. Bulletin of the Association of Engineering Geologists, 3, 337–342.

[28] Galli, M., Ardizzone, F., Cardinali, M., Guzzetti, F., & Reichenbach, P. (2008). Comparing landslide inventory maps. Geomorphology, 94(3–4), 268–289. https://doi.org/10.1016/j.geomorph.2006.09.023

[29] Guzzetti, F. (2003). LANDSLIDE HAZARD ASSESSMENT AND RISK EVALUATION: LIMITS AND PROSPECTIVES.

[30] Colombo, A., Lanteri, L., Ramasco, M., & Troisi, C. (2005). Systematic GIS-based landslide inventory as the first step for effective landslide-hazard management. Landslides, 2(4), 291–301. https://doi.org/10.1007/s10346-005-0025-9

[31] Hansen A, Frank C A, Kirk P A, Brimicombe A J, & Fung Tung. (1995). Application of GIS to Hazard Assessment, With Particular Reference to Landslides in Hong Kong. In Carrara A & Guzzetti F (Eds.),

Geographical Information System in Assessing Natural Hazard (pp. 135–175). Kulwer Academic Publisher.

[32] Paola Reichenbach, Mirco Galli, Mauro Cardinali, Fausto Guzzetti, & Francesca Ardizzone. (2005). Geomorphological Mapping to Assess Landslide Risk: Concepts, Methods and Applications in the Umbria Region of Central Italy. In T. , A. M. G. , C. M. J. Glade (Ed.), Landslide Risk Assessment (pp. 429–468). J. Wiley.

[33] Soeters R., & Westen V. (1996). Slope Instability, Recognition, Analysis and Zonation.

[34] Eyles, G. O. (1983). The Distribution and Severity of Present Soil Erosion in New Zealand. New Zealand Geographer, 39(1), 12–28.

[35] Gupta, R. P., & Josh1, B. C. (1990). Landslide Hazard Zoning Using the GIS Approach A Case Study from the Ramganga Catchment, Himalayas. In Engineering Geology (Vol. 28).

[36] Mckean, J., Buechel, S., & Gaydos, L. (1991). Remote Sensing and Landslide Hazard Assessment. Photogrammetric Engineering & Remote Sensing, 57(9), 1185–1193.

[37] Carrara, A., Sorriso-Valvo, M., & Reali, C. (1982). Analysis Of Landslide Form and Incidence by Statistical Techniques, Southern Italy (Vol. 9).

[38] Huabin, W., Gangjun, L., Weiya, X., & Gonghui, W. (2005). GIS-based landslide hazard assessment: An overview. In Progress in Physical Geography (Vol. 29, Issue 4, pp. 548–567). Arnold. https://doi.org/10.1191/0309133305pp462ra

[39] van Westen, C. J., Castellanos, E., & Kuriakose, S. L. (2008). Spatial data for landslide susceptibility, hazard, and vulnerability assessment: An overview. Engineering Geology, 102(3–4), 112–131. https://doi.org/10.1016/j.enggeo.2008.03.010

[40] Pardeshi, S. D., Autade, S. E., & Pardeshi, S. S. (2013). Landslide hazard assessment: recent trends and techniques. http://www.springerplus.com/content/2/1/523

[41] Blahut, J., van Westen, C. J., & Sterlacchini, S. (2010a). Analysis of landslide inventories for accurate prediction of debris-flow source areas. Geomorphology, 119(1–2), 36–51. https://doi.org/10.1016/j.geomorph.2010.02.017

[42] Sterlacchini, S., Ballabio, C., Blahut, J., Masetti, M., & Sorichetta, A. (2011a). Spatial agreement of predicted patterns in landslide susceptibility maps. Geomorphology, 125(1), 51–61. https://doi.org/10.1016/j.geomorph.2010.09.004

[43] Piacentini, D., Troiani, F., Soldati, M., Notarnicola, C., Savelli, D., Schneiderbauer, S., & Strada, C. (2012a). Statistical analysis for assessing shallow-landslide susceptibility in South Tyrol (south-eastern Alps, Italy). Geomorphology, 151–152, 196–206. https://doi.org/10.1016/j.geomorph.2012.02.003

[44] Martha, T. R., van Westen, C. J., Kerle, N., Jetten, V., & Vinod Kumar, K. (2013). Landslide hazard and risk assessment using semi-automatically created landslide inventories. Geomorphology, 184, 139–150. https://doi.org/10.1016/j.geomorph.2012.12.001

[45] Ghosh, S., Van Westen, C. J., Carranza, E. J. M., Ghoshal, T. B., Sarkar, N. K., & Surendranath, M. (2009). A quantitative approach for improving the BIS (Indian) method of medium-scale landslide susceptibility. Journal of the Geological Society of India, 74(5), 625–638. https://doi.org/10.1007/s12594-009-0167-9

[46] Neuhäuser, B., Damm, B., & Terhorst, B. (2012). GIS-based assessment of landslide susceptibility on the base of the Weights-of-Evidence model. Landslides, 9(4), 511–528. https://doi.org/10.1007/s10346-011-0305-5

[47] Schicker, R., & Moon, V. (2012). Comparison of bivariate and multivariate statistical approaches in landslide susceptibility mapping at a regional scale. Geomorphology, 161–162, 40–57. https://doi.org/10.1016/j.geomorph.2012.03.036

[48] Sarkar, S., Kanungo, D. P., & Mehrotra, G. S. (1995). Landslide Hazard Zonation: A Case Study in Garhwal Himalaya, India. Mountain Research and Development, 15(4), 301–309.

[49] Cardinali, M., Reichenbach, P., Guzzetti, F., Ardizzone, F., Antonini, G., Galli, M., Cacciano, M., Castellani, M., Salvati, P., & snc, T. (2002). Natural Hazards and Earth System Sciences A geomorphological approach to the estimation of landslide hazards and risks in Umbria, Central Italy. In Natural Hazards and Earth System Sciences (Vol. 2).

[50] Parise, M. (2002). Natural Hazards and Earth System Sciences Landslide hazard zonation of slopes susceptible to rock falls and topples. In Natural Hazards and Earth System Sciences (Vol. 2).

[51] Preuth, T., Glade, T., & Demoulin, A. (2010). Stability analysis of a human-influenced landslide in eastern Belgium. Geomorphology, 120(1–2), 38–47. https://doi.org/10.1016/j.geomorph.2009.09.013

[52] Goswami, R., Mitchell, N. C., & Brocklehurst, S. H. (2011). Distribution and causes of landslides in the eastern Peloritani of NE Sicily and western Aspromonte of SW Calabria, Italy. Geomorphology, 132(3–4), 111–122. https://doi.org/10.1016/j.geomorph.2011.04.036

[53] Lee, S., & Pradhan, B. (2006). Probabilistic landslide hazards and risk mapping on Penang Island, Malaysia.

[54] Bălteanu, D., Chendeş, V., Sima, M., & Enciu, P. (2010). A country-wide spatial assessment of landslide susceptibility in Romania. Geomorphology, 124(3–4), 102–112. https://doi.org/10.1016/j.geomorph.2010.03.005

[55] Jade, S., & Sarkar, S. (1993). Statistical models for slope instability classification. In Engineering Geology (Vol. 36).

[56] Kanungo, D. P., & Sarkar, S. (1996). Terrain analysis and spatial assessment of landslide hazard in parts of Sikkim Himalaya. In Article in Journal of the Geological Society of India. https://www.researchgate.net/publication/257679254

[57] Pachauri, A. K., & Pant, M. (1992). Landslide hazard mapping based on geological attributes. In Engineering Geology (Vol. 32).

[58] Sarkar, S., Kanungo, D. P., Patra, A. K., & Kumar, P. (2006). GIS Based Landslide Susceptibility Mapping-A Case Study in Indian Himalaya ENGINEERING OF DISASTER MITIGATION AND HEALTH MONITORING FOR SAFE AND SMART BUILT ENVIRONMENT-A NETWORK PROJECT Under CSIR-12TH FIVE YEAR PLAN View project Advance research in engineering and earth science View project. https://www.researchgate.net/publication/242073557

[59] Wang, H. B., & Sassa, K. (2005). Comparative evaluation of landslide susceptibility in Minamata area, Japan. Environmental Geology, 47(7), 956–966. https://doi.org/10.1007/s00254-005-1225-2

[60] Sharma, L. P., Patel, N., & Debnath, P. K. (2009). Geographical Information System Based Landslide Probabilistic Model with tri-variate approach-a case study in Sikkim Himalayas Digital India Land Record Modernization Program, Core Banking Solution View project IEEE International Conference on Advanced Computational and Communication Paradigms (ICACCP-2017) View project. https://www.researchgate.net/publication/261925928

[61] Akbar, T. A., & Ha, S. R. (2011). Landslide hazard zoning along Himalayan Kaghan Valley of Pakistan-by integration of GPS, GIS, and remote sensing technology. Landslides, 8(4), 527–540. https://doi.org/10.1007/s10346-011-0260-1

[62] Arora, M. K., Das Gupta, A. S., & Gupta, R. P. (2004). An artificial neural network approach for landslide hazard zonation in the bhagirathi (ganga) valley, Himalayas. International Journal of Remote Sensing, 25(3), 559–572. https://doi.org/10.1080/0143116031000156819

[63] Balasubramani K, & Kumaraswamy K. (2013). Application of Geospatial Technology and Information Value Technique in Landslide Hazard Zonation Mapping: A Case Study of Giri Valley, Himachal Pradesh Coastal Zone Management: Global Perspectives, Regional Processes, Local Issues. A Special Volume by Elsevier. View project Application of Geospatial Technologies View project. Disaster Advances, 6(1). https://www.researchgate.net/publication/234062937

[64] Lin, M. L., & Tung, C. C. (2004). A GIS-based potential analysis of the landslides induced by the Chi-Chi earthquake. Engineering Geology, 71(1–2), 63–77. https://doi.org/10.1016/S0013-7952(03)00126-1

[65] Pereira, S., Zêzere, J. L., & Bateira, C. (2012). Technical Note: Assessing predictive capacity and conditional independence of landslide predisposing factors for shallow landslide susceptibility models. Natural Hazards and Earth System Science, 12(4), 979–988. https://doi.org/10.5194/nhess-12-979-2012

[66] Ray, P. K. C., Dimri, S., Lakhera, R. C., & Sati, S. (2007a). Fuzzy-based method for landslide hazard assessment in active seismic zone of Himalaya. Landslides, 4(2), 101–111. https://doi.org/10.1007/s10346-006-0068-6

[67] Ray, P. K. C., Dimri, S., Lakhera, R. C., & Sati, S. (2007b). Fuzzy-based method for landslide hazard assessment in active seismic zone of Himalaya. Landslides, 4(2), 101–111. https://doi.org/10.1007/s10346-006-0068-6

[68] Atkinson, P. M., & Massari, R. (1998). Generalized Linear Modelling Of Susceptibility To Land sliding In The Central Apennines, Italy. Computer and Geosciences, 24(4), 373–385.

[69] Clerici, A., Perego, S., Tellini, C., & Vescovi, P. (2002). A procedure for landslide susceptibility zonation by the conditional analysis method. Geomorphology, 48, 349–364. www.elsevier.com/locate/geomorph

[70] Yin, K. L., & Yan T Z. (1988). Statistical prediction models for slope instability of metamorphosed rocks. Proceedings of 5th International Symposium on Landslides, Lausanne, 1269–1272

[71] Ayalew, L., & Yamagishi, H. (2005). The application of GIS-based logistic regression for landslide susceptibility mapping in the Kakuda-Yahiko Mountains, Central Japan. Geomorphology, 65(1–2), 15–31. https://doi.org/10.1016/j.geomorph.2004.06.010

[72] Rowbotham, D. N., & Dudycha, D. (1998). GIS modelling of slope stability in Phewa Tal watershed, Nepal. In Geomorphology (Vol. 26).

[73] Can, T., Nefeslioglu, H. A., Gokceoglu, C., Sonmez, H., & Duman, T. Y. (2005). Susceptibility assessments of shallow earthflows triggered by heavy rainfall at three catchments by logistic regression analyses. Geomorphology, 72(1–4), 250–271. https://doi.org/10.1016/j.geomorph.2005.05.011

[74] Lee, C.-T., Huang, C.-C., Lee, J.-F., Pan, K.-L., Lin, M.-L., & Dong, J.-J. (2008). Statistical approach to storm event-induced landslides susceptibility. In Hazards Earth Syst. Sci (Vol. 8). www.nat-hazards-earth-syst-sci.net/8/941/2008

[75] Guzzetti, F., Reichenbach, P., Cardinali, M., Galli, M., & Ardizzone, F. (2005). Probabilistic landslide hazard assessment at the basin scale. Geomorphology, 72(1–4), 272–299. https://doi.org/10.1016/j.geomorph.2005.06.002

[76] Calvello, M., Cascini, L., & Mastroianni, S. (2013). Landslide zoning over large areas from a sample inventory by means of scale-dependent terrain units. Geomorphology, 182, 33–48. https://doi.org/10.1016/j.geomorph.2012.10.026

[77] Ohlmacher, G. C., & Davis, J. C. (2003). Using multiple logistic regression and GIS technology to predict landslide hazard in northeast Kansas, USA. Engineering Geology, 69(3–4), 331–343. https://doi.org/10.1016/S0013-7952(03)00069-3

[78] Van Den Eeckhaut, M., Reichenbach, P., Guzzetti, F., Rossi, M., & Poesen, J. (2009). Combined landslide inventory and susceptibility assessment based on different mapping units: an example from the Flemish Ardennes, Belgium. In Hazards Earth Syst. Sci (Vol. 9). www.nat-hazards-earth-syst-sci.net/9/507/2009

[79] Catani, F., Casagli, N., Ermini, L., Righini, G., & Menduni, G. (2005). Landslide hazard and risk mapping at catchment scale in the Arno River basin. Landslides, 2(4), 329–342. https://doi.org/10.1007/s10346-005-0021-0

[80] Ercanoglu, M. (2005). Landslide susceptibility assessment of SE Bartin (West Black Sea region, Turkey) by artificial neural networks. In Natural Hazards and Earth System Sciences (Vol. 5).

[81] Pradhan, B. (2009). Landslide risk analysis using artificial neural network model focusing on different training sites The manifestation of VIS-NIRS spectroscopy data to predict and mapping soil texture in the Triffa plain (Morocco) View project. In Article in International Journal of Physical Sciences. https://www.researchgate.net/publication/228662309

[82] Pradhan, B. (2010). Remote sensing and GIS-based landslide hazard analysis and cross-validation using multivariate logistic regression model on three test areas in Malaysia. Advances in Space Research, 45(10), 1244–1256. https://doi.org/10.1016/j.asr.2010.01.006

[83] Tien Bui, D., Pradhan, B., Lofman, O., Revhaug, I., & Dick, O. B. (2012). Landslide susceptibility assessment in the Hoa Binh province of Vietnam: A comparison of the Levenberg-Marquardt and Bayesian regularized neural networks. Geomorphology, 171–172, 12–29. https://doi.org/10.1016/j.geomorph.2012.04.023

[84] Conoscenti, C., Di Maggio, C., & Rotigliano, E. (2008). GIS analysis to assess landslide susceptibility in a fluvial basin of NW Sicily (Italy). Geomorphology, 94(3–4), 325–339. https://doi.org/10.1016/j.geomorph.2006.10.039

[85] Jaiswal, P., van Westen, C. J., & Jetten, V. (2011). Quantitative assessment of landslide hazard along transportation lines using historical records. Landslides, 8(3), 279–291. https://doi.org/10.1007/s10346-011-0252-1

[86] Chleborad, A. F., Baum, R. L., Godt, J. W., & Leahy, P. P. (2006). Rainfall Thresholds for Forecasting Landslides in the Seattle, Washington, Area-Exceedance and Probability. http://www.usgs.gov/pubprod

[87] Das, I. Chandra. (2011). Spatial statistical modelling for assessing landslide hazard and vulnerability. s.n.].

[88] Floris, M., & Bozzano, F. (2008). Evaluation of landslide reactivation: A modified rainfall threshold model based on historical records of rainfall and landslides. Geomorphology, 94(1–2), 40–57. https://doi.org/10.1016/j.geomorph.2007.04.009

[89] Ghosh, Saibal. (2011). Knowledge guided empirical prediction of landslide hazard. s.n.].

[90] Guzzetti, F., Galli, M., Reichenbach, P., Ardizzone, F., & Cardinali, M. (2006). Natural Hazards and Earth System Sciences Landslide hazard assessment in the Collazzone area, Umbria, Central Italy. In Natural Hazards and Earth System Sciences (Vol. 6).

[91] Jaiswal, P., & van Westen, C. J. (2013). Use of quantitative landslide hazard and risk information for local disaster risk reduction along a transportation corridor: A case study from Nilgiri district, India. Natural Hazards, 65(1), 887–913. https://doi.org/10.1007/s11069-012-0404-1

[92] Polemio, M., & Sdao, F. (1999). The role of rainfall in the landslide hazard: the case of the Avigliano urban area (Southern Apennines, Italy). In Engineering Geology (Vol. 53).

[93] Saaty, T. L. (2008). Decision making with the analytic hierarchy process. In Int. J. Services Sciences (Vol. 1, Issue 1).

[94] Akgun, A. (2012). A comparison of landslide susceptibility maps produced by logistic regression, multi-criteria decision, and likelihood ratio methods: A case study at İzmir, Turkey. Landslides, 9(1), 93–106. https://doi.org/10.1007/s10346-011-0283-7

[95] Gabet, E. J., Burbank, D. W., Putkonen, J. K., Pratt-Sitaula, B. A., & Ojha, T. (2004). Rainfall thresholds for land sliding in the Himalayas of Nepal. Geomorphology, 63(3–4), 131–143. https://doi.org/10.1016/j.geomorph.2004.03.011

[96] Salciarini, D., Godt, J. W., Savage, W. Z., Conversini, P., Baum, R. L., & Michael, J. A. (2006). Modeling regional initiation of rainfall-induced shallow landslides in the eastern Umbria Region of central Italy. Landslides, 3(3), 181–194. https://doi.org/10.1007/s10346-006-0037-0

[97] Montrasio, L., Valentino, R., & Losi, G. L. (2011). Towards a real-time susceptibility assessment of rainfall-induced shallow landslides on a regional scale. Natural Hazards and Earth System Science, 11(7), 1927–1947. https://doi.org/10.5194/nhess-11-1927-2011

[98] Kuriakose, S. Lukose. (2010). Physically-based dynamic modelling of the effects of land use changes on shallow landslide initiation in the Western Ghats, Kerala, India. s.n.].

[99] Mercogliano, P., Segoni, S., Rossi, G., Sikorsky, B., Tofani, V., Schiano, P., Catani, F., & Casagli, N. (2013). Brief communication A prototype forecasting chain for rainfall induced shallow landslides. Natural Hazards and Earth System Science, 13(3), 771–777. https://doi.org/10.5194/nhess-13-771-2013

[100] Tofani, V., Segoni, S., Agostini, A., Catani, F., & Casagli, N. (2013). Technical note: Use of remote sensing for landslide studies in Europe. Natural Hazards and Earth System Science, 13(2), 299–309. https://doi.org/10.5194/nhess-13-299-2013

[101] Kim, J. C., Lee, S., Jung, H. S., & Lee, S. (2018). Landslide susceptibility mapping using random forest and boosted tree models in Pyeong-Chang, Korea. Geocarto International, 33(9), 1000–1015. https://doi.org/10.1080/10106049.2017.1323964

[102] Liu, Y., Wang, Y., & Zhang, J. (2012). LNCS 7473 - New Machine Learning Algorithm: Random Forest. In LNCS (Vol. 7473).

[103] Liu, L.-L., Yang, C., & Wang, X.-M. (2020). Landslide susceptibility assessment using feature selection-based machine learning models. In GECE.

[104] Akinci, H., & Zeybek, M. (2021). Comparing classical statistic and machine learning models in landslide susceptibility mapping in Ardanuc (Artvin), Turkey. Natural Hazards, 108(2), 1515–1543. https://doi.org/10.1007/s11069-021-04743-4

[105] Taalab, K., Cheng, T., & Zhang, Y. (2018). Mapping landslide susceptibility and types using Random Forest. Big Earth Data, 2(2), 159–178. https://doi.org/10.1080/20964471.2018.1472392

[106] Pham, Q. B., Achour, Y., Ali, S. A., Parvin, F., Vojtek, M., Vojteková, J., Al-Ansari, N., Achu, A. L., Costache, R., Khedher, K. M., & Anh, D. T. (2021). A comparison among fuzzy multi-criteria decision

making, bivariate, multivariate and machine learning models in landslide susceptibility mapping. Geomatics, Natural Hazards and Risk, 12(1), 1741–1777. https://doi.org/10.1080/19475705.2021.1944330

[107] Zhao, Z., Liu, Z. yuan, & Xu, C. (2021). Slope Unit-Based Landslide Susceptibility Mapping Using Certainty Factor, Support Vector Machine, Random Forest, CF-SVM and CF-RF Models. Frontiers in Earth Science, 9. https://doi.org/10.3389/feart.2021.589630

[108] Micheletti, N., Foresti, L., Robert, S., Leuenberger, M., Pedrazzini, A., Jaboyedoff, M., & Kanevski, M. (2014). Machine Learning Feature Selection Methods for Landslide Susceptibility Mapping. Mathematical Geosciences, 46(1), 33–57. https://doi.org/10.1007/s11004-013-9511-0

[109] Chen, W., Chai, H., Zhao, Z., Wang, Q., & Hong, H. (2016). Landslide susceptibility mapping based on GIS and support vector machine models for the Qianyang County, China. Environmental Earth Sciences, 75(6). https://doi.org/10.1007/s12665-015-5093-0

[110] Marjanović, M., Bajat, B., & Kovačević, M. (2009). Landslide susceptibility assessment with machine learning algorithms. International Conference on Intelligent Networking and Collaborative Systems, INCoS 2009, 273–278. https://doi.org/10.1109/INCOS.2009.25

[111] Marjanović, M., Kovačević, M., Bajat, B., & Voženílek, V. (2011). Landslide susceptibility assessment using SVM machine learning algorithm. Engineering Geology, 123(3), 225–234. https://doi.org/10.1016/j.enggeo.2011.09.006

[112] Dreiseitl, S., & Ohno-Machado, L. (2002). Logistic regression and artificial neural network classification models: A methodology review. Journal of Biomedical Informatics, 35(5–6), 352–359. https://doi.org/10.1016/S1532-0464(03)00034-0

[113] Subasi, A. (2020). Machine learning techniques. In Practical Machine Learning for Data Analysis Using Python (pp. 91–202). Elsevier. https://doi.org/10.1016/b978-0-12-821379-7.00003-5

[114] Belyadi, H., & Haghighat, A. (2021). Chapter 5 - Supervised learning. In H. Belyadi & A. Haghighat (Eds.), Machine Learning Guide for Oil and Gas Using Python (pp. 169–295). Gulf Professional Publishing. https://doi.org/https://doi.org/10.1016/B978-0-12-821929-4.00004-4

[115] Bartosik, A., & Whittingham, H. (2021). Chapter 7 - Evaluating safety and toxicity. In S. K. Ashenden (Ed.), The Era of Artificial Intelligence, Machine Learning, and Data Science in the Pharmaceutical Industry (pp. 119–137). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-820045-2.00008-8

[116] Kavzoglu, T., Colkesen, I., & Sahin, E. K. (2019). Machine learning techniques in landslide susceptibility mapping: A survey and a case study. In Advances in Natural and Technological Hazards Research (Vol. 50, pp. 283–301). Springer Netherlands. https://doi.org/10.1007/978-3-319-77377-3_13

[117] Fang, Z., Wang, Y., Peng, L., & Hong, H. (2020). Integration of convolutional neural network and conventional machine learning classifiers for landslide susceptibility mapping. Computers and Geosciences, 139. https://doi.org/10.1016/j.cageo.2020.104470

[118] Yilmaz, I. (2010). Comparison of landslide susceptibility mapping methodologies for Koyulhisar, Turkey: Conditional probability, logistic regression, artificial neural networks, and support vector machine. Environmental Earth Sciences, 61(4), 821–836. https://doi.org/10.1007/s12665-009-0394-9

[119] Li, Y., & Chen, W. (2020). Landslide susceptibility evaluation using hybrid integration of evidential belief function and machine learning techniques. Water (Switzerland), 12(1). https://doi.org/10.3390/w12010113

[120] Wang, S. (2003). Chapter 5 ARTIFICIAL NEURAL NETWORK. In Interdisciplinary Computing in Java Programming. The Springer International Series in Engineering and Computer Science (Vol. 743). Springer, Boston, MA. https://doi.org/https://doi.org/10.1007/978-1-4615-0377-4_5

[121] Choi, J., Oh, H. J., Won, J. S., & Lee, S. (2010). Validation of an artificial neural network model for landslide susceptibility mapping. Environmental Earth Sciences, 60(3), 473–483. https://doi.org/10.1007/s12665-009-0188-0

[122] Lucchese, L. V., de Oliveira, G. G., & Pedrollo, O. C. (2021). Mamdani fuzzy inference systems and artificial neural networks for landslide susceptibility mapping. Natural Hazards, 106(3), 2381–2405. https://doi.org/10.1007/s11069-021-04547-6

[123] Yilmaz, I. (2009). A case study from Koyulhisar (Sivas-Turkey) for landslide susceptibility mapping by artificial neural networks. Bulletin of Engineering Geology and the Environment, 68(3), 297–306. https://doi.org/10.1007/s10064-009-0185-2

[124] Can, A., Dagdelenler, G., Ercanoglu, M., & Sonmez, H. (2019). Landslide susceptibility mapping at Ovacık-Karabük (Turkey) using different artificial neural network models: comparison of training algorithms. Bulletin of Engineering Geology and the Environment, 78(1), 89–102. https://doi.org/10.1007/s10064-017-1034-3

[125] Harmouzi, H., Nefeslioglu, H. A., Rouai, M., Sezer, E. A., Dekayir, A., & Gokceoglu, C. (2019). Landslide susceptibility mapping of the Mediterranean coastal zone of Morocco between Oued Laou and El Jebha using artificial neural networks (ANN). Arabian Journal of Geosciences, 12(22). https://doi.org/10.1007/s12517-019-4892-0

[126] Azeraf, E., Monfrini, E., & Pieczynski, W. (2020). Using the Naive Bayes as a discriminative classifier.

[127] Lee, S., Lee, M. J., Jung, H. S., & Lee, S. (2019). Landslide susceptibility mapping using Naïve Bayes and Bayesian network models in Umyeonsan, Korea. Geocarto International. https://doi.org/10.1080/10106049.2019.1585482

[128] Imtiaz, I., Umar, M., Latif, M., Ahmed, R., & Azam, M. (2022). Landslide susceptibility mapping: improvements in variable weights estimation through machine learning algorithms—a case study of upper Indus River Basin, Pakistan. Environmental Earth Sciences, 81(4), 112. https://doi.org/10.1007/s12665-022-10233-y

[129] Youssef, A. M., & Pourghasemi, H. R. (2021). Landslide susceptibility mapping using machine learning algorithms and comparison of their performance at Abha Basin, Asir Region, Saudi Arabia. Geoscience Frontiers, 12(2), 639–655. https://doi.org/10.1016/j.gsf.2020.05.010

[130] Kutlug Sahin, E., & Colkesen, I. (2021). Performance analysis of advanced decision tree-based ensemble learning algorithms for landslide susceptibility mapping. Geocarto International, 36(11), 1253–1275. https://doi.org/10.1080/10106049.2019.1641560

[131] Li, R., & Wang, N. (2019). Landslide susceptibility mapping for the Muchuan County (China): A comparison between bivariate statistical models (WoE, EBF, and IoE) and their ensembles with logistic regression. Symmetry, 11(6). https://doi.org/10.3390/sym11060762

[132] Zhang, T. yu, Han, L., Zhang, H., Zhao, Y. hua, Li, X. an, & Zhao, L. (2019a). GIS-based landslide susceptibility mapping using hybrid integration approaches of fractal dimension with index of entropy and support vector machine. Journal of Mountain Science, 16(6), 1275–1288. https://doi.org/10.1007/s11629-018-5337-z

[133] Hu, X., Zhang, H., Mei, H., Xiao, D., Li, Y., & Li, M. (2020). Landslide susceptibility mapping using the stacking ensemble machine learning method in lushui, southwest China. Applied Sciences (Switzerland), 10(11). https://doi.org/10.3390/app10114016

[134] Pham, B. T., Vu, V. D., Costache, R., Phong, T. Van, Ngo, T. Q., Tran, T. H., Nguyen, H. D., Amiri, M., Tan, M. T., Trinh, P. T., Le, H. Van, & Prakash, I. (2022). Landslide susceptibility mapping using state-of-the-art machine learning ensembles. Geocarto International, 37(18), 5175–5200. https://doi.org/10.1080/10106049.2021.1914746

[135] Wang, G., Lei, X., Chen, W., Shahabi, H., & Shirzadi, A. (2020). Hybrid computational intelligence methods for landslide susceptibility mapping. Symmetry, 12(3). https://doi.org/10.3390/sym12030325

[136] Song, J., Wang, Y., Fang, Z., Peng, L., & Hong, H. (2020). Potential of ensemble learning to improve tree-based classifiers for landslide susceptibility mapping. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 4642–4662. https://doi.org/10.1109/JSTARS.2020.3014143

[137] Peng, L., Niu, R., Huang, B., Wu, X., Zhao, Y., & Ye, R. (2014). Landslide susceptibility mapping based on rough set theory and support vector machines: A case of the Three Gorges area, China. Geomorphology, 204, 287–301. https://doi.org/10.1016/j.geomorph.2013.08.013

[138] Yu, X., Wang, Y., Niu, R., & Hu, Y. (2016). A combination of geographically weighted regression, particle swarm optimization and support vector machine for landslide susceptibility mapping: A case study at Wanzhou in the three gorges area, China. International Journal of Environmental Research and Public Health, 13(5). https://doi.org/10.3390/ijerph13050487

[139] Pham, B. T., & Prakash, I. (2019). Evaluation and comparison of LogitBoost Ensemble, Fisher's Linear Discriminant Analysis, logistic regression and support vector machines methods for landslide susceptibility mapping. Geocarto International, 34(3), 316–333. https://doi.org/10.1080/10106049.2017.1404141

[140] Adnan, M. S. G., Rahman, M. S., Ahmed, N., Ahmed, B., Rabbi, M. F., & Rahman, R. M. (2020). Improving spatial agreement in machine learning-based landslide susceptibility mapping. Remote Sensing, 12(20), 1–23. https://doi.org/10.3390/rs12203347

[141] Wang, Y., Feng, L., Li, S., Ren, F., & Du, Q. (2020). A hybrid model considering spatial heterogeneity for landslide susceptibility mapping in Zhejiang Province, China. Catena, 188. https://doi.org/10.1016/j.catena.2019.104425

[142] Hu, Q., Zhou, Y., Wang, S., & Wang, F. (2020). Machine learning and fractal theory models for landslide susceptibility mapping: Case study from the Jinsha River Basin. Geomorphology, 351. https://doi.org/10.1016/j.geomorph.2019.106975

[143] Rong, G., Alu, S., Li, K., Su, Y., Zhang, J., Zhang, Y., & Li, T. (2020). Rainfall induced landslide susceptibility mapping based on bayesian optimized random forest and gradient boosting decision tree models—a case study of shuicheng county, china. Water (Switzerland), 12(11), 1–22. https://doi.org/10.3390/w12113066

[144] Kavzoglu, T., & Teke, A. (2022). Predictive Performances of Ensemble Machine Learning Algorithms in Landslide Susceptibility Mapping Using Random Forest, Extreme Gradient Boosting (XGBoost) and Natural Gradient Boosting (NGBoost). Arabian Journal for Science and Engineering, 47(6), 7367–7385. https://doi.org/10.1007/s13369-022-06560-8

[145] Zhang, H., Song, Y., Xu, S., He, Y., Li, Z., Yu, X., Liang, Y., Wu, W., & Wang, Y. (2022). Combining a class-weighted algorithm and machine learning models in landslide susceptibility mapping: A case study of Wanzhou section of the Three Gorges Reservoir, China. Computers & Geosciences, 158, 104966. https://doi.org/https://doi.org/10.1016/j.cageo.2021.104966

[146] Kalantar, B., Ueda, N., Saeidi, V., Ahmadi, K., Halin, A. A., & Shabani, F. (2020). Landslide susceptibility mapping: Machine and ensemble learning based on remote sensing big data. Remote Sensing, 12(11). https://doi.org/10.3390/rs12111737

[147] [148] Liang, Z., Wang, C., & Khan, K. U. J. (2021). Application and comparison of different ensemble learning machines combining with a novel sampling strategy for shallow landslide susceptibility mapping. Stochastic Environmental Research and Risk Assessment, 35(6), 1243–1256. https://doi.org/10.1007/s00477-020-01893-y

[148] Nhu, V. H., Shirzadi, A., Shahabi, H., Chen, W., Clague, J. J., Geertsema, M., Jaafari, A., Avand, M., Miraki, S., Asl, D. T., Pham, B. T., Ahmad, B. Bin, & Lee, S. (2020). Shallow landslide susceptibility mapping by Random Forest base classifier and its ensembles in a Semi-Arid region of Iran. Forests, 11(4). https://doi.org/10.3390/F11040421

[149] Saha, S., Roy, J., Pradhan, B., & Hembram, T. K. (2021). Hybrid ensemble machine learning approaches for landslide susceptibility mapping using different sampling ratios at East Sikkim Himalayan, India. Advances in Space Research, 68(7), 2819–2840. https://doi.org/10.1016/j.asr.2021.05.018

[150] Sahin, E. K., Colkesen, I., & Kavzoglu, T. (2020). A comparative assessment of canonical correlation forest, random forest, rotation forest and logistic regression methods for landslide susceptibility mapping. Geocarto International, 35(4), 341–363. https://doi.org/10.1080/10106049.2018.1516248

[151] Hu, X., Huang, C., Mei, H., & Zhang, H. (2021). Landslide susceptibility mapping using an ensemble model of Bagging scheme and random subspace–based naïve Bayes tree in Zigui County of the Three Gorges Reservoir Area, China. Bulletin of Engineering Geology and the Environment, 80(7), 5315–5329. https://doi.org/10.1007/s10064-021-02275-6

[152] Pham, B. T., Vu, V. D., Costache, R., Phong, T. Van, Ngo, T. Q., Tran, T. H., Nguyen, H. D., Amiri, M., Tan, M. T., Trinh, P. T., Le, H. Van, & Prakash, I. (2022). Landslide susceptibility mapping using state-of-the-art machine learning ensembles. Geocarto International, 37(18), 5175–5200. https://doi.org/10.1080/10106049.2021.1914746

[153] Pham, B. T., Nguyen-Thoi, T., Qi, C., Phong, T. Van, Dou, J., Ho, L. S., Le, H. Van, & Prakash, I. (2020). Coupling RBF neural network with ensemble learning techniques for landslide susceptibility mapping. Catena, 195. https://doi.org/10.1016/j.catena.2020.104805

[154] Shirzadi, A., Soliamani, K., Habibnejhad, M., Kavian, A., Chapi, K., Shahabi, H., Chen, W., Khosravi, K., Pham, B. T., Pradhan, B., Ahmad, A., Bin Ahmad, B., & Bui, D. T. (2018). Novel GIS based machine learning algorithms for shallow landslide susceptibility mapping. Sensors (Switzerland), 18(11). https://doi.org/10.3390/s18113777

[155] Kutlug Sahin, E., & Colkesen, I. (2021). Performance analysis of advanced decision tree-based ensemble learning algorithms for landslide susceptibility mapping. Geocarto International, 36(11), 1253–1275. https://doi.org/10.1080/10106049.2019.1641560

[156] Althuwaynee, O. F., Pradhan, B., Park, H. J., & Lee, J. H. (2014). A novel ensemble decision tree-based CHi-squared Automatic Interaction Detection (CHAID) and multivariate logistic regression models in landslide susceptibility mapping. Landslides, 11(6), 1063–1078. https://doi.org/10.1007/s10346-014-0466-0

[157] Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. In Nature (Vol. 521, Issue 7553, pp. 436–444). Nature Publishing Group. https://doi.org/10.1038/nature14539

[158] Kavzoglu, T., Teke, A., & Yilmaz, E. O. (2021). Shared blocks-based ensemble deep learning for shallow landslide susceptibility mapping. Remote Sensing, 13(23). https://doi.org/10.3390/rs13234776

[159] Liu, R., Yang, X., Xu, C., Wei, L., & Zeng, X. (2022). Comparative Study of Convolutional Neural Network and Conventional Machine Learning Methods for Landslide Susceptibility Mapping. Remote Sensing, 14(2). https://doi.org/10.3390/rs14020321

[160] Habumugisha, J. M., Chen, N., Rahman, M., Islam, M. M., Ahmad, H., Elbeltagi, A., Sharma, G., Liza, S. N., & Dewan, A. (2022). Landslide Susceptibility Mapping with Deep Learning Algorithms. Sustainability (Switzerland), 14(3). https://doi.org/10.3390/su14031734

[161] Li, W., Fang, Z., & Wang, Y. (2022). Stacking ensemble of deep learning methods for landslide susceptibility mapping in the Three Gorges Reservoir area, China. Stochastic Environmental Research and Risk Assessment, 36(8), 2207–2228. https://doi.org/10.1007/s00477-021-02032-x

[162] Wang, Y., Fang, Z., & Hong, H. (2019). Comparison of convolutional neural networks for landslide susceptibility mapping in Yanshan County, China. Science of the Total Environment, 666, 975–993. https://doi.org/10.1016/j.scitotenv.2019.02.263

[163] Thi Ngo, P. T., Panahi, M., Khosravi, K., Ghorbanzadeh, O., Kariminejad, N., Cerda, A., & Lee, S. (2021). Evaluation of deep learning algorithms for national scale landslide susceptibility mapping of Iran. Geoscience Frontiers, 12(2), 505–519. https://doi.org/10.1016/j.gsf.2020.06.013

[164] Azarafza, M., Azarafza, M., Akgün, H., Atkinson, P. M., & Derakhshani, R. (2021). Deep learning-based landslide susceptibility mapping. Scientific Reports, 11(1). https://doi.org/10.1038/s41598-021-03585-1

[165] Wei, R., Ye, C., Sui, T., Ge, Y., Li, Y., & Li, J. (2022). Combining spatial response features and machine learning classifiers for landslide susceptibility mapping. International Journal of Applied Earth Observation and Geoinformation, 107. https://doi.org/10.1016/j.jag.2022.102681Turner A. K., & Schuster R. L. (1996). Landslides Investigation and Mitigation.