A COMPREHENSIVE REVIEW ON LANDSLIDE SUSCEPTIBILITY ZONATION TECHNIQUES

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Abstract: This review paper provides an overview of recent research on landslide susceptibility. Landslides are a natural phenomenon that can cause significant damage to infrastructure and endanger human lives. The paper presents an in-depth analysis of the factors that contribute to landslide susceptibility, including geological, hydrological and anthropogenic factors. It also discusses various methods and techniques used to assess landslide susceptibility, including statistical models, geographic information systems (GIS) and remote sensing. The paper examines the advantages and limitations of these methods and highlights the need for an integrated approach that combines multiple techniques to improve accuracy and reliability. Additionally, the paper discusses the challenges associated with developing landslide susceptibility maps and emphasises the importance of considering uncertainties and risk assessments. The review paper concludes by identifying the gaps in current research and suggesting potential directions for future studies. Overall, this review paper provides a comprehensive analysis of landslide susceptibility, which can serve as a valuable resource for researchers, practitioners and policymakers working in this field.

Keywords: natural hazards, landslides, landslide susceptibility zonation techniques, ensembled approach

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Introduction

Natural hazards are naturally occurring events that endanger human life, property and the environment. These dangers encompass a vast array of phenomena, including earthquakes, volcanic eruptions, floods, hurricanes, tornadoes, landslides and wildfires. Natural hazards can be caused by natural processes such as plate tectonics, weather patterns and climate change, as well as by human activities such as deforestation, urbanisation and land-use change. Natural hazards can have devastating effects, resulting in loss of life, population displacement, infrastructure destruction and economic losses. A combination of physical, social, economic and environmental factors influences the susceptibility to natural hazards. Natural hazards are more likely to have an impact on vulnerable communities, such as those living in poverty or in areas with inadequate infrastructure.

Natural hazards can be mitigated through risk management strategies such as disaster preparedness, early warning systems and community-based disaster risk reduction. These strategies combine structural and non-structural measures, such as physical infrastructure, education and awareness, and capacity building. Globally,

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natural hazards pose a significant challenge to human societies. Effective risk management strategies, informed by scientific research and community participation, are essential for mitigating the risks associated with natural hazards and minimising their impact on human life, property and the environment (Nautiyal et al. 2021).

A landslide is a geological phenomenon that occurs when masses of rock, earth or debris move down a slope due to the influence of gravity (Petley 2012). Landslides can be triggered by various factors such as heavy rainfall, earthquakes, human activities and changes in the natural environment (Frattiniet al. 2010). They can have devastating effects on the environment, property, infrastructure and human life.

Landslides are a significant geological hazard that affects many regions worldwide, including the United States, Europe, Asia and Africa (Sidle, Ochiai 2006). In the United States, landslides cause billions of dollars in damages and claim dozens of lives each year (USGS 2021). In Europe, landslides are a significant concern, especially in mountainous regions, where they pose a threat to transportation, tourism and human settlements (Mikoš et al. 2012). In Asia, landslides are common in the Himalayan region, where they are triggered by monsoon rainfall, earthquakes and human activities such as deforestation and road construction (Bhandari et al. 2021). In Africa, landslides are a growing concern, especially in urban areas where they threaten human settlements and infrastructure (Nyandwi et al. 2017).

Overall, landslides are a significant geological hazard that poses a threat to human life and infrastructure. Understanding the causes and mechanisms of landslides is crucial for developing effective strategies to mitigate their impact and reduce their occurrence. Landslide susceptibility mapping is an essential tool for identifying areas that are prone to landslide hazards. The need for landslide susceptibility mapping arises from the increasing frequency and severity of landslides worldwide, resulting in significant loss of life, property damage and environmental degradation (Sharma et al. 2019, Kumar et al. 2020). According to the International Landslide Centre (ILC), landslides account for over 11,500 fatalities worldwide annually (Guzzetti 2006). In addition, landslides are responsible for significant economic losses, with an estimated annual cost of over $10 billion worldwide (Gariano, Guzzetti 2016).

Landslide susceptibility mapping can be performed using various approaches, including statistical, deterministic and probabilistic methods (Van Den Eeckhaut et al. 2018). These approaches utilise different input variables, including topography, geology, soil properties and land use, to produce a map of areas susceptible to landslides. These maps can be used by decision-makers, planners and engineers to mitigate landslide hazards and reduce the risk of loss of life and property damage (Lee et al. 2019). Various studies have shown the effectiveness of landslide susceptibility mapping in mitigating landslide hazards. For example, in Taiwan, landslide susceptibility mapping was used to identify areas susceptible to landslides and implement measures such as reforestation and slope stabilisation to reduce landslide risks (Lin et al. 2018). Similarly, in Nepal, landslide susceptibility mapping was used to develop a landslide risk management plan that included early warning systems and the implementation of mitigation measures in high-risk areas (Dhital et al. 2021).

Map scaling in geographic information systems (GISs) from landslide susceptibility zonation (LSZ) involves adjusting the size and proportions of geographic data layers to create meaningful and accurate maps. The process begins with acquiring various data layers related to slope, aspect, lithology, land cover, rainfall and past landslide occurrences. These data layers may have different resolutions and scales, requiring preprocessing and standardisation to ensure compatibility. Analytical methods are then applied to assess landslide susceptibility, taking into account the scald data layers. The resulting maps depict different levels of landslide susceptibility, aiding in interpretation, decision-making and planning for land use and mitigation measures. Throughout the process, maintaining a consistent and appropriate scale is crucial to accurately represent spatial patterns and facilitate the usability of the maps.

In conclusion, landslide susceptibility mapping is a crucial tool for identifying areas at risk of landslide hazards and implementing mitigation measures to reduce the risk of loss of life and property damage. With the increasing frequency and severity of landslides worldwide, the need for landslide susceptibility mapping is becoming more critical. Therefore, it is essential to continue developing and improving landslide susceptibility mapping techniques to reduce the impact of landslides on communities and the environment. Recent studies have also focussed on improving landslide susceptibility mapping techniques by integrating new technologies and data sources. For example, the use of remote sensing data and GIS analysis has shown promise in accurately identifying landslide-prone areas (Rahmati et al. 2020). In addition, machine learning algorithms such as support vector machines (SVMs), artificial neural networks (ANN) and decision trees have been used to improve the accuracy of landslide susceptibility mapping (Kavzoglu, Sahin 2021).

Furthermore, researchers have also investigated the impacts of climate change on landslide susceptibility. A study by Regmi et al. (2020) analysed the relationship between landslide occurrences and precipitation variability in the Indian Himalayas, finding that the frequency and intensity of landslides have increased due to climate change. Another study by Sattar et al. (2020) investigated the effects of glacier retreat on landslide susceptibility in the Karakoram Mountains, finding that the melting of glaciers has led to an increase in landslide occurrences. Overall, the field of landslide susceptibility mapping continues to evolve, with new techniques and data sources being integrated to improve accuracy and better understand the impacts of climate change on landslide occurrences.

Landslide susceptibility mapping can be performed using a variety of techniques, each with its own strengths and limitations. Some of the commonly used techniques are briefly described below:

1. **Statistical Methods:** These methods are based on the analysis of statistical relationships between landslide occurrence and various causative factors. Some of the commonly used statistical methods are logistic regression (LR), discriminant analysis and ANNs. These methods have been found to be effective in many regions, including the Indian Himalayas (Gokceoglu et al. 2005, Bhandary, Sitharam 2014).
2. **Index-based Methods:** These methods involve the combination of various causative factors into a single index, which is then used to determine landslide susceptibility. The most commonly used index-based method is the weight of evidence (WoE) method, which has been found to be effective in many regions, including the Indian Himalayas (Lee, Talib 2005, Maiti, Bhattacharya 2012, Kumar et al. 2018, 2019, 2022).
3. **Expert-based Methods:** These methods rely on the expert knowledge and judgement of geologists, engineers and other professionals to identify and map areas of high landslide susceptibility. These methods are often used in conjunction with other techniques, such as statistical and index-based methods. Expert-based methods have been found to be effective in many regions, including the Indian Himalayas (Akgun et al. 2012, Bhattacharya et al. 2013, Laura et al. 2023, Zhou et al. 2023).
4. **Machine Learning Methods:** These methods involve the use of various machine learning algorithms, such as decision trees, SVMs and random forests, to model the relationships between landslide occurrence and causative factors. Machine learning methods have been found to be effective in many regions, including the Indian Himalayas (Kumar et al. 2018, Barman et al. 2019).

The different techniques used in landslide susceptibility assessment models are shown in Figure 1.

Each of these techniques has its own strengths and limitations and the choice of technique depends on various factors such as data availability, complexity of the terrain and the objective of the study. Landslides are complex phenomena that can be triggered by a variety of causative factors, including geological, hydrological and anthropogenic factors. Understanding these factors is crucial in landslide susceptibility mapping and hazard assessment. Geological factors, such as lithology, structure and soil type, play a significant role in landslide occurrences. Different types of rocks and soils have varying properties, such as permeability, shear strength and cohesion, which can affect their susceptibility to failure (Sidle et al. 2018). In addition, structural features, such as bedding planes, joints and faults, can act as planes of weakness, making slopes more susceptible to sliding (Akgun et al. 2012). Hydrological factors, including precipitation, groundwater

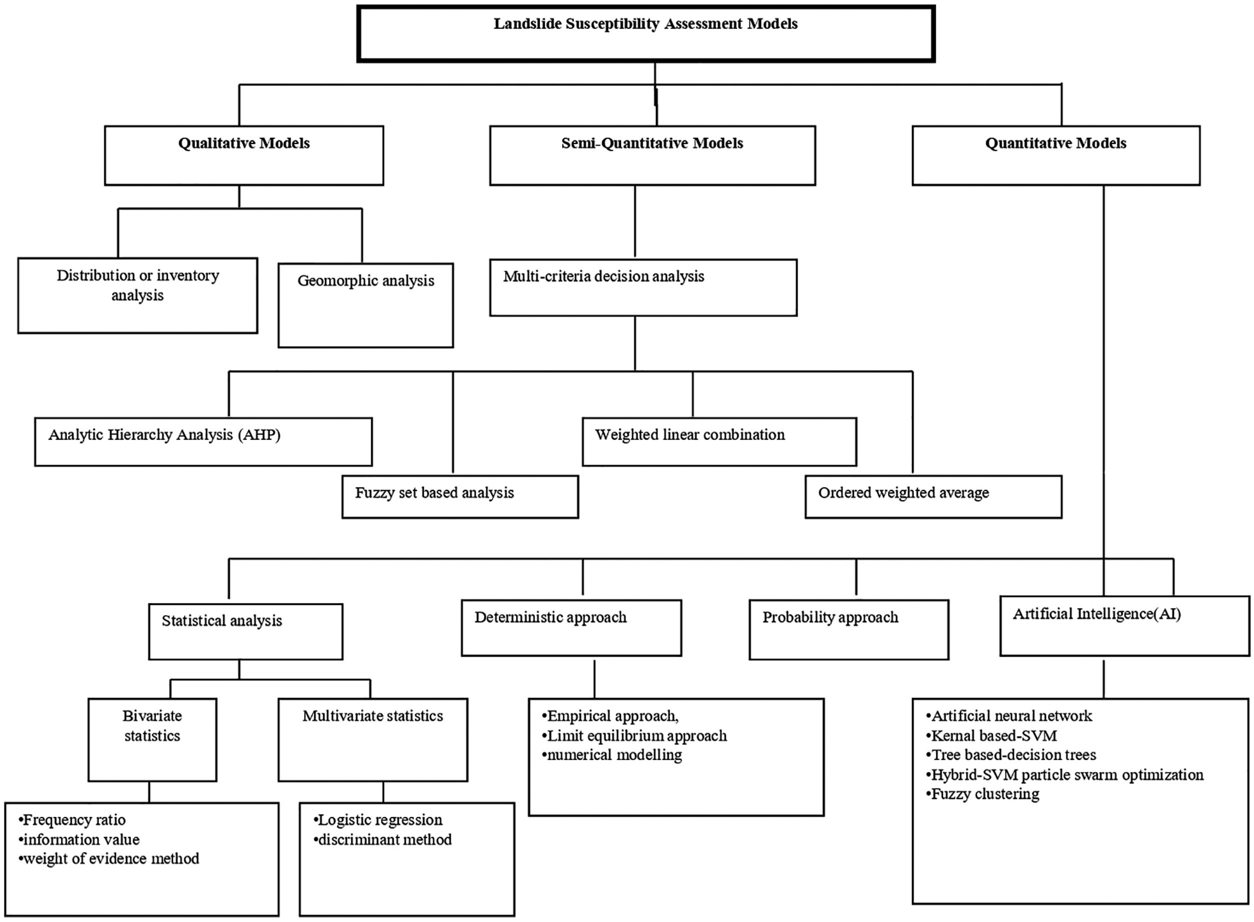

Fig. 1. Landslide susceptibility studies using different models (Shano et al. 2020).

and surface water, also play a significant role in landslide occurrences. High-intensity rainfall events can saturate the soil and increase pore water pressure, reducing the shear strength of the soil and making it more prone to failure (Huang et al. 2020). Groundwater can also cause slopes to fail by increasing the weight of the soil, and by altering the pore water pressure and effective stress within the slope (Caine 1980). Surface water, such as rivers and streams, can erode the base of slopes, increasing their steepness and making them more susceptible to sliding (Ercanoglu et al. 2020).

Anthropogenic factors, such as land-use change, deforestation and construction activities, can also contribute to landslide occurrences. Land-use change, such as converting forests into agricultural land or urban areas, can alter the water balance of the slope and increase erosion (Shrestha, Aryal 2016). Deforestation can also increase the likelihood of landslides by removing tree roots that stabilise the soil (Wu et al. 2017). Construction activities, such as excavation, slope cutting and filling, can alter the slope geometry and increase the pore water pressure within the slope, making it more prone to failure (Lee et al. 2020). In summary, geological, hydrological and anthropogenic factors all contribute to the occurrence of landslides. Understanding these factors is crucial in landslide susceptibility mapping and hazard assessment, and can help to mitigate the risk of landslides in vulnerable areas.

Landslide susceptibility techniques

Frequency ratio (FR) method

FR is a statistical method used for landslide susceptibility mapping (Thakur, Kumar 2013, Sharma, Kumar 2015, Nath, Roy 2018, Kumar et al. 2019, Fatah et al. 2023, Thambidurai et al. 2023, Yadav et al. 2023). This method is based on the statistical analysis of the relationship between the landslide locations and the factors that may influence the landslide occurrence. The FR method has been widely used for landslide susceptibility mapping in different regions of the world, including the Himalayas. The FR method is a ratio of the number of landslides to the number of non-landslides in a given area for a particular parameter. It provides a value for the susceptibility of the study area for each parameter. The formula for the FR method is as follows:

$$\mathrm{FR} = \frac{\text{(Number of landslides in a specific zone / Total number of landslides)}}{\text{(Number of non-landslide points in the same zone / Total number of non-landslide points)}} \quad (1)$$

The output of the FR method is a susceptibility map, where the areas with higher FR values indicate a higher probability of landslide occurrence. The FR method has advantages such as its simplicity and ease of use, which make it a suitable method for rapid mapping in areas with limited data. However, the FR method has some limitations. It assumes that each parameter is independent of every other, which may not be the case in reality. In addition, it does not take into account the spatial correlation of the parameters, which may lead to the overestimation or underestimation of the landslide susceptibility in some areas. Despite its limitations, the FR method is a useful tool for preliminary landslide susceptibility mapping in areas with limited data. It can also be used in conjunction with other methods to improve the accuracy of landslide susceptibility mapping.

Advantages:

- Easy to use and understand: The FR method is a simple and intuitive method that can be easily used by non-experts. It only requires the knowledge of the occurrence of landslides and the related causative factors,
- High accuracy: Studies have shown that the FR method provides high accuracy in landslide susceptibility mapping (Lee et al. 2019, Tangestani et al. 2019),
- Provides quantitative results: The FR method provides quantitative results in the form of susceptibility values that can be used for further analysis and decision-making,
- Can handle missing data: The FR method can handle missing data by ignoring the variables with missing values (Pradhan 2010).

Disadvantages:

- Over-reliance on past occurrences: The FR method heavily relies on past occurrences of landslides to predict future susceptibility, which may not always be accurate due to changing environmental and climatic conditions,
- Limited applicability: The FR method is limited in its applicability to areas with similar geological and environmental conditions. It may not be suitable for areas with vastly different conditions,
- Ignores the spatial relationships between variables: The FR method ignores the spatial relationships between variables, which may lead to the oversimplification of complex environmental conditions (Bai et al. 2010),
- Biased results: The FR method may produce biased results if the occurrence of landslides is not evenly distributed over the study area (Pradhan 2010).

Information value (IV) method

The IV method is a statistical method used in landslide susceptibility mapping (Kumar et al. 2019, Yadav et al. 2023). It is a measure of the strength of the relationship between a binary response variable (landslide occurrence or non-occurrence) and an explanatory variable (e.g., slope, aspect, lithology, etc.). The IV method can be used to rank the importance of different explanatory variables and to identify the most influential factors in landslide occurrence.

The formula for IV is as follows:

$$\mathrm{IV} = \ln(\text{odds ratio}) \times (P_{\text{event}} - P_{\text{non-event}}), \quad (2)$$

where:

- ln indicates natural logarithm,
- odds ratio = (number of events/total events)/(number of non-events/total non-events),
- P_{event} represents the proportion of events in the total events,
- $P_{\text{non-event}}$ the proportion of non-events in the total non-events.

The IV method is commonly used in LR models to identify the most important predictors of landslide occurrence. The IV values range from 0 to infinity, with higher values indicating stronger relationships between the explanatory variable and landslide occurrence. An IV value of 0 indicates that the explanatory variable has no predictive power for landslide occurrence. The IV method has been widely used in landslide susceptibility mapping studies, including in the Indian Himalayas (Sharma et al. 2019, 2021). It has been shown to be an effective method for identifying the most important landslide-causative factors and for producing accurate landslide susceptibility maps.

Advantages:

- The IV method is simple and easy to use. It does not require extensive knowledge of statistical and mathematical techniques,
- It can be applied to both categorical and continuous variables,
- The method can be used for both binary and multiclass classification problems,
- The method has been shown to be effective in identifying the most important variables in landslide susceptibility mapping,
- It can be used to compare the relative importance of different variables.

Disadvantages:

- The method assumes of independence of variables, which may not always be true,
- The method does not take into account the interaction between variables,
- The method may not work well for imbalanced datasets,
- The results of the method can be sensitive to the choice of threshold values,
- The method may not be suitable for datasets with a large number of variables.

Weight of evidence (WoE) method

The WoE method is a statistical approach used for landslide susceptibility mapping (Neupane et al. 2023), which evaluates the relationships between the landslide occurrences and the potential landslide-causative factors by quantifying the WoE supporting the presence or absence of the factors (Carrara et al. 1992). The WoE method is based on the Bayesian probability theory and provides a simple and objective means of evaluating the likelihood of an event occurring. The method quantifies the evidence that a particular factor is associated with the landslide occurrence and produces a WoE factor map showing the spatial distribution of the factors contributing to landslide occurrence (Ohlmacher, Davis 2003).

The formula for the WoE method is:

$$\mathrm{WoE} = \frac{\ln(\text{number of landslide occurrences / number of non-landslide occurrences})}{(\text{number of landslide occurrences in the study area / number of non-landslide occurrences in the study area})} \quad (3)$$

The WoE method has several advantages, including its simplicity, objectivity and ability to handle missing data. The method is also able to evaluate the relative importance of each factor in the susceptibility analysis. However, the method requires a large number of samples to provide reliable results and is sensitive to the choice of the reference data used in the analysis (Lee et al. 2019). Overall, the WoE method is a useful tool for landslide susceptibility mapping in areas with limited data and can provide valuable information for land-use planning and decision-making.

Advantages:

- WoE method is easy to implement and interpret, making it suitable for use by non-experts,
- It can handle both categorical and continuous variables, providing more flexibility in model development,
- It has been shown to perform well in landslide susceptibility mapping studies in various regions,
- The method can provide valuable insights into the relationships between landslide occurrence and the factors influencing it.

Disadvantages:

- The WoE method assumes that the relationship between the explanatory variables and the dependent variable is linear. However, this may not always be the case in reality, leading to model errors,
- The method may not capture the interactions between variables, which could affect the accuracy of the susceptibility map,
- It requires a large dataset to provide reliable results, which may not be available in all regions.

The results of the method may be sensitive to the choice of weight and cut off values used in the analysis.

Logistic regression (LR) analysis

LR analysis is a statistical technique used to model the probability of an event occurring (Yadav et al. 2023). In the context of landslide susceptibility, LR analysis can be used to identify the factors that are most strongly associated with the occurrence of landslides. According to Chae et al. (2012), LR analysis is a widely used method for landslide susceptibility assessment. The technique allows for the identification and quantification of the factors that contribute to landslide occurrence, by estimating the probability of landslide occurrence based on the values of the independent variables. The model coefficients provide information on the strength and direction of the association between each independent variable and the probability of landslide occurrence.

To use LR for landslide susceptibility analysis, the landslide occurrence data are typically used as the dependent variable, with the landslide or non-landslide status of each location as the binary outcome. The independent variables, which are the factors that are thought to influence landslide occurrence, can include a variety of physical and environmental variables such as slope, geology, land use, precipitation and vegetation cover. Once the model is developed, it can be used to produce a landslide susceptibility map, which shows the probability of landslide occurrence across the study area. Areas with a higher probability of landslide occurrence are often considered to be more susceptible to landslides.

Advantages:

- LR can handle both continuous and categorical independent variables,
- The output of LR is easy to interpret, as the coefficients indicate the strength and direction of the association between each independent variable and the probability of landslide occurrence,
- LR can be used to develop landslide susceptibility maps, which can be useful for land-use planning and risk management,
- LR is a widely used and well-established statistical technique.

Disadvantages:

- LR assumes that the relationship between the independent variables and the log odds of landslide occurrence is linear, which may not always be the case,
- LR assumes that the independent variables are independent of each other, which may not always be true in practice,
- LR can be sensitive to outliers and influential data points,
- LR assumes that the data are representative of the population, which may not always be the case.

Artificial neural networks (ANN) method

ANN is a computational method inspired by the structure and function of biological neural networks. It consists of interconnected nodes or neurons that process information in a parallel, distributed manner. ANN has been widely used in various fields, including landslide susceptibility mapping. According to Ayalew et al. (2004), ANN is a powerful tool for modelling complex nonlinear relationships between landslide occurrence and various contributing factors. In the context of landslide susceptibility mapping, ANN can be used to classify the input data into landslide or non-landslide categories based on the relationship between the input variables and the output class.

ANN models are typically trained using a supervised learning approach, where the model is trained on a set of input–output pairs to learn the relationship between the input variables and the output class. The model can then be used to predict landslide susceptibility for new locations based on their input variables. The advantage of ANN is that it can handle complex nonlinear relationships and is less sensitive to outliers than other statistical techniques. However, ANN requires a large amount of training data and can be computationally intensive.

Advantages:

- ANNs can handle complex nonlinear relationships between landslide occurrences and their contributing factors,
- ANNs are capable of learning from past examples and can generalise to new situations,
- ANNs can handle missing data and noisy input data to some extent,

- ANNs can perform well on large and complex datasets,
- ANNs can provide insights into the relative importance of different input variables in predicting landslide susceptibility.

Disadvantages:

- ANNs require a large amount of training data, which may not be available in some cases,
- ANNs are highly sensitive to the choice of model parameters, such as the number of hidden layers, the number of neurons per layer and the learning rate,
- ANNs are often considered to be black-box models, as it is difficult to interpret the relationship between the input variables and the output class,
- ANNs may be affected by overfitting if the training dataset is too small or if the model is too complex.

Support vector machines (SVM) method

SVM is a machine learning method used for classification and regression analysis. SVM is based on the concept of finding the hyperplane that maximises the margin between the two classes. SVM has been widely used in landslide susceptibility mapping due to its ability to handle nonlinear relationships and its good performance on small and high-dimensional datasets. According to Gokceoglu et al. (2005), SVM is a powerful tool for landslide susceptibility mapping, as it can effectively classify the input data into landslide or non-landslide classes based on the relationship between the input variables and the output class. In the context of landslide susceptibility mapping, SVM can be used to identify the most important factors contributing to landslide occurrence and to develop accurate landslide susceptibility maps.

SVM works by transforming the input data into a high-dimensional feature space, where the classes can be separated by a hyperplane. The optimal hyperplane is selected based on the margin between the two classes, with the goal of maximising the margin while minimising the classification error. SVM can handle both linear and nonlinear relationships by using different types of kernel functions. The advantage of SVM is that it can handle high-dimensional data and can provide a clear separation between the two classes. However, SVM requires careful selection of model parameters, such as the kernel function and the regularisation parameter, and can be computationally intensive.

Advantages:

- SVM can handle high-dimensional data and can provide a clear separation between the two classes,
- SVM can handle nonlinear relationships between landslide occurrences and their contributing factors,
- SVM is less prone to overfitting than other machine learning methods, such as decision trees and ANNs,
- SVM can be used to identify the most important factors contributing to landslide occurrence and to develop accurate landslide susceptibility maps,
- SVM can be combined with other machine learning methods, such as random forest, to improve its performance.

Disadvantages:

- SVM requires careful selection of model parameters, such as the kernel function and the regularisation parameter, which can be time-consuming and require expert knowledge,
- SVM can be sensitive to the choice of the kernel function, which can affect the performance of the model,
- SVM is computationally intensive and may not be suitable for large datasets,
- SVM can be affected by outliers and noise in the input data,
- SVM does not provide a probabilistic estimate of landslide susceptibility, which may be important in some applications.

Random forest-based technique

Random forest is a machine learning algorithm used for classification and regression analysis. In the context of landslide susceptibility mapping, random forest has been widely used due to its ability to handle high-dimensional data and its good performance on large and complex datasets. Random forest works by constructing a multitude of decision trees based on random subsets of the input data and input variables. Each tree provides a classification result, and the final prediction is made based on the majority vote of all trees. Random forest can handle nonlinear relationships between landslide occurrences and their contributing factors and can identify the most important factors contributing to landslide susceptibility.

According to Kavzoglu and Sahin (2009), random forest is a powerful tool for landslide susceptibility mapping, as it can provide accurate and robust results even in the presence of noisy and missing data. Random forest can also provide information on the relative importance of each input variable, which can help to identify the most critical factors for landslide susceptibility. One advantage of random forest is that it can handle large and complex datasets with a large number of input variables. However, random forest can be computationally intensive and may require careful selection of model parameters, such as the number of trees and the maximum depth of each tree.

Advantages:
- Random forest is an ensemble method that combines multiple decision trees, which can lead to better prediction accuracy and more robust results compared to single decision trees,
- Random forest can handle large and complex datasets with a large number of input variables, and can identify the most important variables contributing to the prediction,
- Random forest is less prone to overfitting than other machine learning methods, such as ANNs and SVMs,
- Random forest can provide information on the relative importance of each input variable, which can help to identify the most critical factors for the prediction,
- Random forest can be used for both classification and regression tasks.

Disadvantages:
- Random forest can be computationally intensive and may require a large amount of memory, especially for large datasets with a large number of input variables,
- Random forest can be difficult to interpret compared to single decision trees, as it involves multiple decision trees with different splitting rules,
- Random forest can be sensitive to the choice of model parameters, such as the number of trees and the maximum depth of each tree,
- Random forest does not provide a probabilistic estimate of the prediction, which may be important in some applications.

Ensemble approaches

Ensemble approaches are machine learning techniques that combine multiple models to improve the accuracy and robustness of landslide susceptibility mapping (Fatah et al. 2023, Matougui et al. 2023). The most common ensemble methods used in landslide susceptibility mapping are bagging, boosting and stacking.

Bagging (Bootstrap Aggregating) involves creating multiple models using random subsets of the input data and input variables, and then aggregating the results to produce a final prediction. Bagging can reduce the variance and improve the generalisation ability of the models.

Boosting involves iteratively training multiple weak models, with each subsequent model focussing on the errors of the previous models. Boosting can improve the accuracy and robustness of the models, and is especially useful when dealing with imbalanced data.

Stacking involves combining multiple models with different architectures or algorithms, and using a meta-model to learn the optimal way to combine the results of the base models. Stacking can improve the accuracy and robustness of the models by combining the strengths of different methods.

Ensemble approaches have been shown to improve the accuracy and robustness of landslide susceptibility mapping compared to single models. For example, Kavzoglu, Sahin (2011) used a bagging ensemble of decision trees to map landslide susceptibility in the Yenice region of Turkey, and found that the ensemble approach outperformed single decision trees and other machine learning methods. Another study by Pham et al. (2018) used a stacking ensemble of LR, SVMs and random forest to map landslide susceptibility in the Song Pha watershed of Vietnam, and found that the stacking approach improved the prediction accuracy compared to single models.

Advantages:
- Improved prediction accuracy: Ensemble methods combine multiple models, which can lead to improved prediction accuracy compared to single models,

- Robustness: Ensemble methods can reduce the impact of noisy or irrelevant features in the input data, which can improve the robustness of the models,
- Reduced overfitting: Ensemble methods can reduce overfitting by combining multiple models and using techniques such as bagging, which involves training each model on a different subset of the input data,
- Applicability to different types of data: Ensemble methods can be applied to different types of data, including categorical, numerical and mixed data,
- Interpretability: Some ensemble methods, such as stacking, can provide insights into the relative importance of different models or features.

Disadvantages:

- Computationally intensive: Ensemble methods can be computationally intensive, as they require training multiple models and combining their results,
- Difficulty in interpretation: Some ensemble methods, such as bagging and boosting, can be difficult to interpret, as they involve combining multiple models with different weights,
- Parameter tuning: Ensemble methods may require tuning of various hyperparameters, which can be time-consuming and require expertise,
- Data preprocessing: Ensemble methods may require careful preprocessing of input data, including feature selection and normalisation.

Conclusion

There is no one 'best' method for landslide susceptibility modelling as the choice of method depends on various factors such as the type and amount of input data, study area and research objectives. However, comparing the performances of different methods can help identify which among these are most suitable for a particular application. Several studies have compared the performances of different methods for landslide susceptibility modelling, including LR, ANNs, decision tree, SVM and random forest. The choice of methods compared and evaluation criteria vary between studies.

For example, a study by Wu et al. (2019) compared the performance of LR, random forest, SVM andANN for landslide susceptibility modelling in the Three Gorges Reservoir Area of China. They evaluated the models using various criteria, including receiver operating characteristic (ROC) curves, area under the curve (AUC) and prediction accuracy. The results showed that the random forest model outperformed the other models in terms of prediction accuracy and AUC.

Another study by Chen et al. (2020) compared the performance of decision tree, SVM, random forest andANN for landslide susceptibility modelling in the Wu River Basin of China. They evaluated the models using criteria such as ROC curves, AUC and prediction accuracy. The results showed that the decision tree and random forest models performed better than the other models. A study by Dou et al. (2020) compared the performance of LR, random forest and SVM for landslide susceptibility modelling in the Sichuan Province of China. They evaluated the models using criteria such as AUC, prediction accuracy and kappa coefficient. The results showed that the random forest model had the highest AUC and prediction accuracy, while the SVM had the highest kappa coefficient.

In conclusion, LSZ approaches in geosciences encompass a range of methods, including statistical-based approaches, geotechnical-based approaches, index-based approaches, machine learning approaches and hybrid approaches. These methods are widely adopted to assess and map areas prone to landslides by considering various influencing factors such as slope, aspect, lithology, land cover, rainfall and seismicity. The selection of LSZ approach depends on the available data, study area characteristics and the specific objectives of the analysis. The aim is to provide accurate and reliable assessments of landslide susceptibility, aiding in interpretation, decision-making and planning for land-use and mitigation measures. Overall, the choice of the 'best' model for landslide susceptibility modelling depends on the specific application and evaluation criteria used. Therefore, it is recommended to compare the performance of different methods using various criteria to identify the most suitable method for a particular study area and research objectives.

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Author's contribution

Kanwarpreet Singh: Conceived and design the analysis. Vanshika Bhardwaj: Collected the data and contributed to the analysis. Abhishek Sharma: Writing and reviewing of paper. Shalini Thakur: Perfomed the analysis tool.

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