A Review of Various Landslide Susceptibility Mapping Techniques Used in Nepal

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Abstract

A landslide is one of the most destructive geological hazards in Nepal. For systematic mitigation and management of landslide, comprehensive landslide evaluation and hazard zonation are essentially needed. During recent decades, various susceptibility mapping methods have been applied to identify landslide-prone areas in Nepal. This review article analyzes the strengths, limitations, and effectiveness of methods such as Frequency Ratio (FR), Weight of Evidence (WoE), Analytical Hierarchy Process (AHP), Logistic Regression (LR), and Artificial Neural Networks (ANN), in mapping landslide susceptibility and underlines significant research gaps through a review of various past studies from Nepal. FR and WoE are user-friendly, but they require extensive historical data, whereas AHP relies on expert judgment without the need for previous information. LR and ANN are very accurate and reliable but are resource-intensive. There is a great research gap that needs to discuss how factors such as local conditions, selection of training data, and data quality interact to influence the effectiveness of the methods and lead to different predictions in different areas. Further, the models also do not incorporate some vital parameters like groundwater modelling and soil depth that are very crucial for improvement of accuracy and interpretation of landslide dangers. Finally, suitable models need to be employed so that a critical study of susceptibility can be conducted and landslide management strategies can be more effective.

Keywords: Analytical Hierarchy Process; Artificial Neural Network; Frequency Ratio; Landslide; Landslide susceptibility; Logistic Regression; Weight of Evidence

1. Introduction

A landslide refers to the process of rocks, soil, or debris sliding down a slope (Cruden, 1991). A landslide is one of the most serious geological hazards in Nepal. It causes loss of life, injuries to people, damage to infrastructures and blockage of rivers. The process of identifying landslide prone locations by comparing the past distribution of landslides with factors causing them is called Landslide Susceptibility Mapping (LSM) (Brabb, 1984). The aim of Landslide Susceptibility Mapping (LSM) is to provide a quantitative assessment of the probability of landslides happening in particular location, which can be applicable for disaster risk reduction and land-use planning.

To minimize the impact of landslides, various factors have to be considered, including geology, geomorphology, land use, land cover, rainfall, seismicity, and anthropogenic activities. (Raghuvanshi et al., 2014). These factors spatially interact among themselves to cause a landslide in an area. Analysis of their association with past landslides is thus necessary for future predictions (Chimidi et al., 2017). The techniques of landslide hazard evaluation and zonation are applied to analyze the factors and categorize risks.

Several techniques are used in Nepal for the zonation of landslide susceptible areas. Frequency Ratio (FR), Weight of Evidence (WoE), Analytical Hierarchy Process (AHP), Logistic Regression (LR), and Artificial Neural Networks (ANN) are some of the commonly used methods. Each method has its own benefit and drawback compared to the other methods. (Leroi, 1997). The primary goal of this research is to present a summary of techniques used in landslide susceptibility mapping and hazard zonation, highlighting the advantages, disadvantages and efficacy of each method. Further, the study also intends to identify research gaps through critical evaluation of past studies in Nepal.

2. Data types and Software for Landslide Studies

The first step in studying landslides involves collecting data through field visits, remote sensing and verifying using Google Earth Pro (Craig et al., 2020). The data collection method for landslide studies depends on the study scale, goals, and accessibility to the study area. Landslide susceptibility and hazard zoning studies require data on elements such as landslide inventory and triggering factors (Sreedevi and Yarrakula, 2016). Landslides are typically triggered by three main factors: rainfall, seismic activity and human activities (Hong et al., 2015). In our review, we found that the literature considers a variety of factors. Although there are no standard selection criteria, the most frequently incorporated factors are slope, aspect, rainfall, proximity to fault, distance from roads, distance from drainage, Stream Power Index (SPI), Topographic Wetness Index (TWI), curvature, land use land cover (LULC), altitude, lithology, Sediment Transport Index (STI). After selection of factors, factor maps are prepared.

Where the gradient of the slope is larger, the higher will be the shear stress on soil or other unconsolidated materials, and thus increases the tendency to failure. (Oh and Lee, 2011). Slope map can be generated using a Digital Elevation Model (DEM) using slope algorithm of Surface-Spatial Analyst tool in ArcMap.

Slope aspect simply denotes the direction of slope. The south-facing slopes in the Himalayas are usually barren, receive heavier orographic rainfall, and have more rapid mass movements. (Chauhan et al., 2010). Aspect map can be prepared using a Digital Elevation Model (DEM) using aspect algorithm of Surface-Spatial Analyst tool in ArcMap.

The higher the rainfall rates are the higher the risks of landslides. (Addis, 2023). Precipitation data can be extracted from CHRS Data Portal.

Places near sites of faults are most likely to encounter frequent landslides due to increased seismic activities that might cause the slope failure. (Chen et al., 2018). Fault lines can be obtained from geological map and fault map by buffering in ArcMap.

This proximity to roads may affect the landslide chances because road constructions and their maintenance have the potential to destabilize slopes, hence resulting in increased landslide possibilities. (Yalcin, 2008). The map can be obtained from the Department of Survey, Government of Nepal (GoN).

The streams may act to undermine slope stability both by erosion at the base of slopes or by saturation of materials within the water level of the stream, thereby weakening it. (Çevik and Topal, 2003). The map can be generated from the vector map of rivers by applying buffering and rasterizing with the help of ArcMap software.

The Stream Power Index reflects the erosive power of water flow. The higher the SPI value, the more erosion and run off is expected to be, hence an increase in landslide occurrences. SPI map can be prepared from the DEM produced by the topographic map provided by the Department of Survey, Nepal.

The Topographic Wetness Index is an approach to calculate the tendency of water to accumulate in a particular landscape. With a higher TWI value, more accumulation and saturation of water results in the potential rising chance of landslide occurrence by weakening slope stability (Devkota et al., 2013). The map can be obtained from the DEM produced by the topographic map provided by the Department of Survey, Nepal.

Curvature is a measure of the bend or shape of a slope. Positive curvature (convex) can decrease the accumulation of water and consequently reduce erosion, while negative curvature (concave) serves to increase the collection of water, further increasing erosion and possibly increasing landslide susceptibility (Mancini et al., 2010). Curvature map can be generated using a Digital Elevation Model (DEM) using aspect algorithm of Surface-Spatial Analyst tool in ArcMap.

LULC defines the classification of land based on its use and the vegetation or other surface materials upon it. Forestland promotes runoff water regulation and infiltration to keep slopes stable, whereas cultivated lands destroy slope stability because of increased saturation and erosion (Devkota et al. 2013). The map can be obtained from Department of Survey, GoN.

Higher the altitude higher will be the chance of landslide. (Pachauri and Pant, 1992). The map can be generated using a Digital Elevation Model (DEM) using Spatial Analyst tool in ArcMap.

There is abundance association between the type of rock and the related mass movement phenomena. (Sidle et al., 1985). The map can be obtained using geological map prepared by Dhital et al., 1995.

The Sediment Transport Index quantifies the possible sediment movement over a landscape. High STI values refer to those areas with potentiality for sediment transport, which results in a further rise of erosion and, thus, of landslide probability (Bannari et al., 2017). The map can be obtained from the DEM in SAGA GIS.

After the preparation of the factor maps, both factor maps and landslide inventory are imported to a GIS platform using ArcMap software (Yilmaz, 2010).Then, these maps are processed according to specific formulas and models necessary for producing the landslide susceptibility map. Other software like SPSS/ real statistics and Ms. Excel are also used for statistical analysis and data management.

3. Methodology

Landslide susceptibility is evaluated using various approaches worldwide. All techniques can be broadly categorized into three types: qualitative, semi-quantitative, and quantitative. The qualitative analysis relies on the evaluator's subjective knowledge (Raghuvanshi et al., 2014). Semi-quantitative approach includes multi-criteria decision analysis approach which is used to make decisions by merging numerous information derived from various sources. (Feizizadeh and Blaschke, 2012). The quantitative approach includes statistical, probabilistic and deterministic free techniques which are objective in nature. (Raghuvanshi et al., 2014; Kanungo et al., 2006; Girma et al., 2015). The most commonly used techniques in Nepal are Frequency Ratio (FR), Weight of Evidence (WoE), Logistic Regression (LR), Analytical Hierarchy Process (AHP) and Artificial Neural Network (ANN).

3.1 Frequency Ratio Approach

This model calculates the ratio of landslide occurrences in relation to the study area. This model assumes that the probability of landslide occurrence is proportional to the probability of its absence in relation to specific factors. (Bonham-Carter, 1994). The simplicity and effectiveness of the FR model make it a popular choice for mapping landslide susceptibility.

$$FR = \frac{\%landslides}{\%\ \text{Area}} \tag{1}$$

'FR' is the Frequency Ratio for the factor class, '%Landslides' is the percentage of landslides in a factor class and '% Area' is percentage of the area of the factor class (Regmi et al., 2014).

The Landslide Susceptibility Index (LSI) can be obtained by summing each of the FR values of each factor as follows:

$$LSI = \sum FR \tag{2}$$

A ratio value greater than 1 shows a stronger relationship with landslide occurrences, while a less-than-1 ratio shows a weaker relationship with that attribute of the particular factor.

3.2 Weight of Evidence (WoE)

The Weight-of-Evidence (WoE) method is a statistical tool used to determine the future probability of landslides by assessing the past historic landslides and analyzing the significant factors and their relative roles in contributing landslides. (van Westen, 2002).

The calculations for both past and future probabilities of a landslide occurrence (L), based on the existence or non-existence of any parameter class (Ni), are conducted using the following equations.

$$\text{Past Probability} = P(L) = \frac{\text{Pix (Landslide)}}{\text{Pix (Tot.)}} \tag{3}$$

$$\text{Future Probability} = P(L/N) = \frac{\text{Pix (L Ni)}}{\text{Pix (Ni)}} \tag{4}$$

Where, Pix (L) and Pix (Tot.) are the number of pixels of the landslides and number of pixels of the total area, respectively.

Positive (C+) and negative (C-) weights are calculated using following equations:

$$C+ = \text{loge}\left[\frac{(P\ (Ni|L)}{(P\ (Ni\ /\bar{L})}\right] \qquad C- = \text{loge}\left[\frac{(P\ (\bar{N}i\ |\ L)}{(P\ (\bar{N}i\ /\bar{L})}\right] \tag{5}$$

where, C+ and C- indicates that factor class has contribution and no contribution C- in landslide occurrence respectively.

For each class, the total weight can be calculated as:

$$C_{tot} = (C+) + (C-) - (C_{min}) \tag{6}$$

where, Cmin = the sum of all negative weights. The contrast value (C) is finally calculated as; C= (C +) – (C –) (Gadtaula and Dhakal, 2019).

3.3 Analytical Hierarchy Process

The analytical hierarchy process (AHP) is a semi-quantitative approach that aids decision-making by assigning weights through pairwisse comparisons (Saaty, 1980). In the implementation of AHP, various factors are evaluated against one another to ascertain their relative importance in achieving the overall objective, where Saaty's Fundamental scale (Table 1) was made a base for assigning numerical values to each pair.

Table 1. Fundamental scales for pair wise comparison

Importance Rank	Degree of Preference	Explanation
1	Equal importance	Two criteria contribute equally to the objective
3	Moderately importance of one over another	Judgement and experience slightly to moderately favour one criteria over another
5	Strongly important	Judgement and experience essentially favour one criteria over another
7	Very strongly important	Experience and judgements is strongly favoured over another and its dominance is showed in practice
9	Extremely important	The evidence favouring a criteria over another is the highest degree probable of an affirmation
2,4,6 and 8	Intermediate values between two adjacent judgements	Used to represent compromising between the preferences in weights 1, 3, 5, 7 and 9
Reciprocals	Opposites	Used for inverse comparison

As per Saaty (1980), landslide hazard zones are prepared by following procedures:

a. Establishment of pair-wise comparision matrix
b. Assigning weight values to each class of factors
c. Zonation of the study area

3.4 Logistic Regression

Logistic regression establishes a multivariate relationship between a dependent and several independent variables. (Atkinson and Massari 1998). It can be expressed by the following equation:

$$L = \frac{\exp(k)}{1+\exp(k)} \quad (7)$$

where L is the probability of occurrence of landslides. The following equation is used to derive k:

$$Z = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn \quad (8)$$

In this context, 0 denotes the intercept of the model, while 1, 2, ..., n signify the partial regression coefficients. The variables X1, X2, ..., Xn correspond to the independent variables. (Devkota et al., 2013).

The initial step in the analysis is converting the landslide inventory map and factor maps in raster format into ASCII format. This is followed by the use of statistical software (SPSS) to test the relationship between landslide occurrences and the influencing factors. Landslide occurring probability is then calculated using a number of equations and finally, susceptibility map can be obtained by converting the file into the raster format (Yilmaz, 2010).

3.5 Artificial Neural Network

Artificial neural networks (ANN) are used as computational tools in landslide susceptibility zonation (Gomez and Kavzoglu, 2005). In comparison to conventional statistical techniques like multivariable regression, linear regression and autocorrelation, they provide a flexible substitute (Singh et al., 2003). The complex interactions between input and output elements related to landslides can be efficiently investigated by using ANN.

Landslide simulation is frequently carried out using the multi-layer perceptron (MLP) neural network, a well-liked ANN architecture. MLPs are artificial neurons that are networked together. They are composed of three layers: an input layer, a hidden layer, and an output layer. Based on input data, they work together to detect patterns and provide predictions.

Weights and biases in the Artificial Neural Network (ANN) model link the neurons; a learning method modifies these parameters to create correlations between the input and output data. Artificial neural networks (ANNs) are superior to traditional techniques at identifying patterns and trends in intricate or imprecise datasets. They successfully manage imprecise and fuzzy data and support continuous, categorical, and binary data without imposing assumptions. Because they predict events based on past data, neural networks are a useful tool for estimating the chance of landslides.

3.6 Validation methods

For the validation of landslide susceptibility computational models, various accuracy assessment techniques can be employed. Among them, the receiver operating characteristic (ROC) curve is the most commonly used method in Nepal. The ROC examines the performance of a model's classification by plotting the False positive Rate (FPR) on the X-axis and the True Positive Rate (TPR) on the Y-axis (Gorsevski et al., 2006). Each threshold in predictions provides a different FPR and TPR pair, making up the ROC curve. The key metric derived from the ROC curve is the Area Under Curve (AUC). It represents the overall capability of the model to distinguish between classes, with values ranging from 0.5 (random guessing) to 1 (perfect classification) (Roy et al., 2019). The closer the ROC curve gets to the (0, 1) point, the higher the AUC will be, reflecting better model performance (Yu et al., 2023). FPR and TPR can be calculated as:

$$\text{FPR} = \frac{False\ Positives}{False\ Positives + True\ Negatives}$$

$$\text{TPR} = \frac{True\ Positives}{True\ Positives + False\ Negatives} \qquad (9)$$

Similarly, other methods such as F-score, mean absolute error (MAE), root mean square error (RMSE), chi-square test and the relative landslide density index can also be used.

4. Past Studies

Numerous studies in Nepal have used different methods like FR, WOE, AHP, LR and ANN to assess landslide susceptibility, and each method has shown different success rates.

Regmi et al. (2014) analyzed landslides in the Bhalubang-Shiwapur area, Nepal. The area is characterized by altitude ranging from 170m to 960m, rugged topography, steep slopes and deeply dissected gullies. Distance from highway is the most influential factor in this study area. Additionally, other eleven factors: slope, aspect, curvature, altitude, SPI, TWI, sediment transport index (STI), lithology, distance from faults, land use and distance from rivers were considered. Frequency Ratio and Weights-of-Evidence models were used for the study. The WoE model achieved an 83.39% success rate and 79.59% prediction rate, while the FR model had had slightly lower values at 83.31% and 78.58%, respectively. The software used for the preparation of LSM was ArcMap 9.3.

Neupane et al. (2023) carried out landslide susceptibility mapping in Lakhandehi Khola watershed in the Sarlahi District, Nepal. The altitude of the area ranges from 181m to 706m. Slope is the leading factor in this study area. Other eight factors: aspect, curvature, stream density, TWI, land use, geology, distance from river and distance from road were incorporated in the study. They applied two bivariate models, specifically the Frequency Ratio (FR) and the Weight of Evidence (WoE). The results indicated that WoE outperformed FR with a prediction rate of 75.62% compared to 71.09% for FR.

Poudyal et al. (2010) carried out landslide susceptibility mapping in the Panchthar district of Nepal. The area is characterized by altitude ranging from 440m to 2496m, rugged and highly dissected topography with high relief. Precipitation and stratigraphic condition are the most contributing factors in this study area. Similarly, other factors: slope, aspect, curvature, distance from drainage, land use, stream power index (SPI), TWI, combined length-slope, distance from lineament played significant roles. Landslide susceptibility maps were generated utilizing the Frequency Ratio and Artificial Neural Network methodologies, which were based on ten factors associated with landslide occurrences. The accuracy of the susceptibility maps created through the Frequency Ratio method was 82.21%, while the accuracy achieved by the neural networks was 78.25. The software used in this research are Arc/View GIS (ESRI, Redlands, CA, USA) and MATLAB (The Math-Works, Inc., Natick, MA, USA).

Devkota et al. (2013) performed landslide susceptibility mapping at road section of Mugling–Narayanghat road section in Nepal Himalaya by comparing three models: Certainty Factor, Index Of Entropy and Logistic Regression models. The study area belongs to Mahabharat Range, on the north of Churia Range and has higher mountains with steep slopes. The leading factor for landslides in this study area is lithology. Likewise, the factors: altitude, slope, aspect, curvature, SPI, TWI, STI, land use, distance from faults, distance from rivers and distance from roads also played additional roles. After validation of models through Area Under Curve (AUC) method, the highest prediction accuracy was shown by index of entropy which is 90.16%.

The accuracy of Logistic Regression model was found 86.29% and certainty factor model was 83.57%. The software used for the preparation of LSM was ArcMap 9.3.

Bist et al. (2020) applied the Analytical Hierarchy Process (AHP) to analyze landslide susceptibility in the Kaligandaki hydro-catchment of Syangja, Nepal. The area is characterized by altitude ranging from 400m to 2000m, where two streams- Andhikhola and Phidikhola mixes up with Kaligandaki river in the western part of the study area. Eight factors: slope, land use, lithology, aspect, road, river, fault and precipitation were considered in the study area. They validated the map's accuracy using a chi-square test, which yielded significant and high values. The software used for susceptibility map preparation was ArcGIS 10.5.

Kayastha et al. (2012) employed the Analytical Hierarchy Process (AHP) to assess landslide within the Tinau watershed. The altitude of the study area ranges from 165m to 1940m. Slope was the most influential factor in this study area. Additionally, other factors: aspect, annual rainfall, land use, relative relief, distance from streams, slope shape and distance from faults, folds were used for the study. The examination of the success rate curve demonstrated that the landslide susceptibility zonation map had an overall success rate of 77.54%.

Dahal (2013) employed a Logistic Regression(LR) model for landslide susceptibility mapping in the Nepal Himalaya. The study area is densely populated hilly area with inclusion of few parts of Kathmandu, Mugling and Gorkha. Excessive rainfall and human activities are the main causes of slope instability in this region. Other factors such as: slope, aspect, relief, curvature, drainage density, wetness index, land cover, lithology, lineament proximity, stream proximity and road proximity also played additional roles in landslides. The model achieved a prediction rate of over 82%. The softwares used in the study are GIS software ILWIS 3.3 and statistical software (SPSS).

Gautam et al. (2021) carried out landslide susceptibility mapping in high mountainous area of Sindhupalchowk district, Nepal. The altitude of the region ranges from 796m to 5832m. Rainfall induced landslides were mapped in the study area along with consideration of other factors: slope, aspect, elevation, geological formation, proximity to river, proximity to road, land cover, soil type, and curvature. They applied four models, Frequency Ratio, Logistic regression, Artifcial neural network and Support vector machine (SVM). The results indicated that the best method for rainfall-induced landslides in high mountainous region is ANN with accuracy of 86.9%, followed by 85.6% for LR, 81.2% for SVM and 80.1% for FR. The software used in the study was ArcGIS 10.3.

Landslide susceptibility mapping methods often represent their prediction and success rate differently from one physiographic region to another, regions due to factors such as local conditions, training data selection, and data quality. These differences simply demonstrate that there is no universally best method for landslide susceptibility mapping. It is, therefore, important to do more research for a proper understanding of how these factors interact with a view to determining the effectiveness of different methods in differing regions (Gautam et al., 2021). Additionally, the current models exclude key parameters such as groundwater modeling and soil depth, which affect the occurrence of landslides by a great margin. These parameters should be integrated with susceptibility models in order to enhance the accuracy of the models and provide full insight into the danger of landslide occurrences.

5. Advantage and Limitation of each method

FR and WoE are statistical methods based on the relationship between historical landslides and contributing factors. The weightage for each causal factors can be determined statistically in these methods (Dai and Lee, 2001). The primary benefit of these techniques lies in their applicability across extensive regions, allowing for an easy observation of the individual impacts of each factor and factor classes on landslides (Shano et al., 2020). Both methods are considered one the simplest methods because of their simplicity in input, computations and output processes which can be comprehended easily. (Poudyal et al., 2010). The main limitation of these methods is that there is need of collection of huge number of past landslide data. There is the need of inputting the distribution, classification and scope of past landslide data (Negassa and Kala, 2015).

The results produced by the use of FR and WoE show similar accuracy, however, FR is considered as simpler method because it does not require preliminary conversion of data unlike WoE (Ozdemir and Altural, 2012).

The main advantage of Analytical Hierarchy Process is that there is no need of past historical data for assigning weightage to the factors. It simply needs the judgement and evaluation of expert for relative contribution of each factor classes. However, the subjectivity that lies in assigning weightage and ratings to factor classes is one of the major limitations of AHP (Raghuvanshi et al. 2014). Because of this, it is challenging to determine the actual weights of the conditioning components and impossible to account for the nonlinear correlations between the conditioning elements and the landslides. (Ge et al., 2018).

The utilization of binary dependent variables in landslide susceptibility mapping is one of the major benefits of Logistic Regression method. Despite being a widely used measure, Logistic Regression has the significant drawback of producing average parameters for the study, which may vary locally within different regions (Pourghasemi et al., 2013). The lengthy input, computation, and output processes associated with using LR are still another major issue. Because processing the large volumes of data in statistical software can be extremely challenging, they necessitate converting data into ASCII or various formats (Yilmaz, 2010).

The absence of statistical variables during the procedure is the primary benefit of employing ANN techniques. With the use of ANN techniques, it is possible to define target classes in relation to their distribution across all source data sets, which makes it easier to integrate data from sources like remote sensing and geographic information systems. Plus, it takes less time than conventional statistical methods and allows for pixel-by-pixel computation. With the help of this strategy, incomplete or imperfect data may be managed and interactions between complicated or non-linear factors can be analyzed (Chacón et al., 2006). The complexity of the underlying processes in the hidden layers of the ANN and the amount of processing time required to modify the data format for usage in GIS are its two main disadvantages. (Basma and Kallas, 2004).

6. Results

Different methods show varying effectiveness, either in their predicting ability or in the process of using the methods. Among these, LR and ANN are highly accurate. In some cases, like Nepal Himalayas (areas of Kathmandu, Mugling and Gorkha), LR has shown prediction rates over 82% (Dahal, 2013), even though this method is complex and data-intensive. ANN has also shown good prediction rates in the past studies – 86.9% in highly mountainous region of Sindhupalchowk district (Gautam et al., 2021), and it deals with complex and non-linear relationships accurately. FR and WoE have shown considerable accuracy, wherein FR showed an 83.31% success rate and 78.58% prediction rate in the Bhalubang-Shiwapur area, while WoE showed an 83.39% success rate and 79.59% prediction rate in the same area (Regmi et al., 2014). Although these methods require intense past data, it is user-friendly and simple. AHP has been applied in the Kaligandaki hydro-catchment and the Tinau watershed, securing a success rate reaching as high as 77.54% (Kayastha et al., 2012). It doesn't require data from past events, but sometimes it relies on the subjectivity of a researcher. For the validation of models, every researcher, Dahal et. al (2013), Gautam et al., (2021), Regmi et al., (2014) and Kayastha et al., (2012) used AUC- ROC curve. While these methods have shown considerable success in different regions of Nepal, their precision differs across physiographic zones because of variations in local conditions, factor selection and data quality. No single method is universally best, so more research is needed to come up with models for specific locations and determine the factors behind best performances.

7. Challenges

There are several challenges that arise during the execution of landslide susceptibility mapping. One of the primary issues is the inaccessibility of areas with high landslide susceptibility, which complicates the extrapolation of results. For instance, Gautam et al., (2021) faced some difficulties in regions above 4000 meters, where it was very difficult to identify the landslides on the satellite images like Google Earth because of year-round snow cover. That means this has very much influenced how they have collected data about them in terms of completeness and accuracy. Similarly, the extreme slopes with rugged topography render field investigations challenging on-site gathering and analyzing data. Besides, there is also a lack of recent and good-quality topographic data and sufficient landslide inventories in Google Earth Pro, which restricts mapping efficiency. On top of that, the variability in seasonal rainfall can further complicate access to reliable data, which may reduce overall accuracy of landslide susceptibility mapping.

8. Conclusions and Recommendation

Proper dealing with landslides requires a thorough assessment of susceptibility. The phenomenon of landslides is influenced by range of natural factors and external factors, and it is necessary to employ appropriate models for evaluating these factors accurately. This review paper has provided a detailed examination of the different methodologies utilized in Landslide Susceptibility Mapping (LSM) and hazard zonation in Nepal. The techniques discussed include Frequency Ratio (FR), Weight of Evidence (WoE), Analytical Hierarchy Process (AHP), Logistic Regression (LR), and Artificial Neural Networks (ANN), each having its own strengths and weaknesses. Past studies show that Frequency Ratio (FR) and Weight of Evidence (WoE) provide reliable results with high success rates when historical data is sufficient. Analytical Hierarchy Process (AHP), Logistic Regression (LR), and Artificial Neural Networks (ANN) provide advanced analysis but the methods are complex and hefty. Therefore, an appropriate approach can be chosen based on data availability and research insights. There is a significant research gap that necessitates discussion on how factors such as: local conditions, training data selection, and data quality interact in influencing the effectiveness of a method, and how this results in a variety of predictions across different regions. Besides, the models ignore critical factors such as groundwater dynamics and soil depth, which are of prime importance to improve the accuracy and understanding of landslide risks. These parameters should be considered for the best result. Frequency Ratio (FR) model is recommended for beginners due to its simplicity and ease of interpretation. FR and WOE should be employed when the interaction of several factors and their contribution to the landslide has to be understood. The Analytical Hierarchy Process (AHP) is preferred when there is lack of past historic landslide data. For advanced and detailed results, Logistic Regression (LR) and Artificial Neural Networks (ANN) are recommended. As past data is the base for the prediction of landslides in FR, WoE, ANN and LR, the quantity of data should be enough and the quality should not be compromised. This will increase the performance for each method in terms of prediction accuracy to help in better land-use planning and disaster risk management strategies.

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