Shahrood University of Technology

Journal of Mining and Environment (JME)

Journal homepage: www.jme.shahroodut.ac.ir

Iranian Society of Mining Engineering (IRSME)

Landslide Susceptibility Assessment using Remote Sensing and GIS-a Review

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Article Info

Received 5 January 2023

Received in Revised form 12 January 2023

Accepted 1 February 2023

Published online 1 February 2023

DOI:10.22044/jme.2023.12580.2283

Keywords

Landslide

GIS

Landslide Depicting Factors

LSZ Methods

Validation

Abstract

Natural hazards are naturally occurring phenomena that might lead to a negative impact on the environment and also on the life of living beings. These hazards are caused due to adverse conditions of weather and climate events, and also due to certain human activities that are harmful to the environment. Natural hazards include tsunamis, earthquakes, volcanic activity, landslides, etc. Among these natural hazards, landslides are among the most common natural hazards resulting in loss of life and property each year, leading to socio-economic impact; thus to avoid such losses, a comprehensive study of landslides is required. Landslides generally occur in hill region with steep slopes, heavy precipitation, loose shear strength of soil or due to many human activities like afforestation or construction activities. To resolve the problem of landslides in a hilly region, much research is conducted annually, providing a predicted landslide susceptibility zonation (LSZ) mapping of the area of research. The predicted landslide susceptibility maps are verified based on the past landslide data, an area under the curve (AUC), and other methods to provide an accurate map for landslide susceptibility in any area. In this study,93 research articles are reviewed for analysis of LSZ, and various observations are made based on the recent trends followed by various researchers over the world over the past ten years. The study can be useful for many researchers to practice their research on landslide susceptibility zonation.

1. Introduction

Natural hazards are naturally occurring phenomena that might lead to a negative impact on the environment and also on the life of living beings. Among them, landslides are the most destructive and disruptive to the natural and social environment in the modern period. A landslide occurs when rocks disintegrate and decay under gravity, producing mass movement downwards. Landslides are described as almost all variations of mass movement on the slope including a few like rock falls, topples, and particles that go with the drift that contains very little or no true sliding [1]. According to Brusden, landslides are a unique type of mass movement and a process that does not involve a transport medium such as water, air, or ice [2]. "A landslide in its intensive way is a very rapid mass wasting process that causes the down-slope motion of mass of rock, debris, or earth driven by a variety of external stimulation," Hutchinson [3]. Courture R defines a landslide as "a movement of a mass of soil (earth or debris) or rock down a slope." [4].

Landslides are particularly common in mountainous or steep terrain [5]. Landslides are caused by heavy rains, earthquakes, erosion, deforestation, severely unstable slopes, deep excavations, vegetation removal, rock fall, and mining. Landslips are one of the most threatening natural hazards in mountainous terrain [1]. Every year, thousands of people die in landslides around the world, and these disasters have huge economic effects on both local and global economies. Landslides are growing increasingly common as the world's population increases. The need to protect natural and agricultural areas has driven human development to think about it [6]. As a

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result of human manipulations on mountain slopes such as the expansion of built-up and agricultural land, as well as overgrazing, the country's landslide disaster problem has worsened.

In addition to the Himalayas, Northeastern hill ranges, Western Ghats, Nilgiris, Eastern Ghats, and Vindhyans, which encompass around 15% of the continent, rock-fall and snow slip are among the primary hydro-geological hazards that jeopardize vast portions of India [7].The Himalayas include landslides of every sort, name, and description including huge, ancient, and recent landslides. A bewildering assortment of landslide risks threatens the Northeastern region. Landslides in West Bengal's Darjeeling district, and those in Sikkim, Mizoram, Tripura, Meghalaya, Assam, Nagaland, and Arunachal Pradesh, are a continual threat, causing billions of rupees in economic losses [8].

Nowadays, the technique used to determine the LSZ is Remote Sensing (RS) and Geographical Information System (GIS). With the help of RS and GIS tools, the landslide hazard maps can be produced for analysis of disaster-prone areas, and after this, the preventive measures and mitigation can be suggested against landslides in that particular region or area. It is capable of enhancing organizational integration. GIS collects, analyze, manages, and displays spatially related data by combining software, technology, and data. GIS would allow for the viewing, querying, comprehending, creating, and analyzing data in several forms, such as globes, maps, charts, and reports, to emphasize relationships, trends, and patterns. A Geographic Information System (GIS) is designed to assist people in answering questions and solving problems by analyzing the data and delivering it clearly and concisely. GIS technology can be incorporated into any enterprise information system's foundation. Numerous employment options would be available [9]. Existing maps, digital data, and RS are used to collect the data. This study focuses on using Aeronautical Reconnaissance Coverage Geographic Information System software (Arc GIS).

Rock falls are one of the most common sources of the calamity in the world, and the annual death toll from landslides is staggering. Landslides are usually caused by the earth's geological movement. It significantly impacts livelihoods since it can limit access to land for years, resulting in loss of life, infrastructure ruin, roadway damage, and the destruction of seeds and food reserves. The world has been watching Japan recently as it has been struck by one natural disaster after another, one of which are landslides, which have resulted in a dip in the economy and a decline in natural resources such as naturally occurring trees [10].

The most destructive effect of a landslide in any country is the loss of human and animal lives. Movement is slowed because mud, pebbles, and debris flowing down the hill create barriers on essential traffic corridors such as highways and railways. Consequently, the flow of goods and persons is constrained. When a landslide occurs, numerous homes, buildings, roadways, and other infrastructure are damaged. Much money is spent on infrastructure reconstruction, mass rehabilitation, and assistance for damaged persons. When landslides occur on the slopes of a river valley, the sliding debris may reach the valley floor, partially or entirely obstructing the river channel. A landslide dam is an accumulation of avalanche debris blocked by a river. It has the potential to decrease the water supply available to surrounding communities [11].

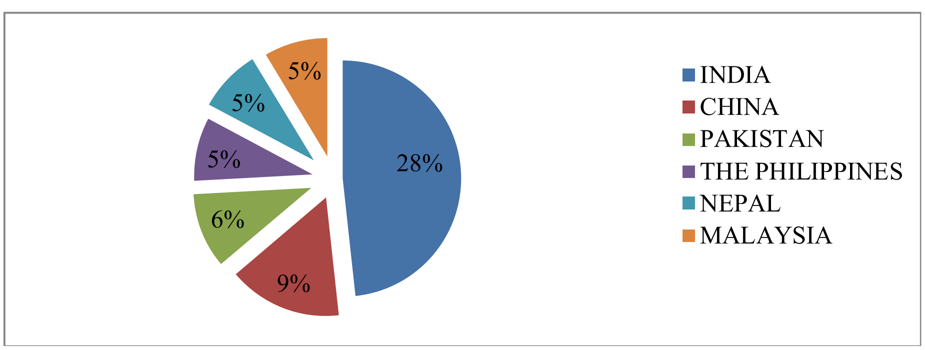


Figure 1. According to the findings published in the European Geosciences Union's Natural Hazards and Earth System Sciences journal countries that experienced the most construction-related landslides.

2. Literature Review

Due to the increase in landslides, many types of research works were conducted regarding LSZ mapping in different parts of the world, which led to predicted mapping of LSZ maps of that area that helped in taking proper mitigation measures while working in the landslide-prone areas. Every map in the LSZ analysis is primarily considered in 30 m cell size because the lesser the area, the higher the spatial resolution considered, and a scale of 1:50,000 is provided for the map reason being that it can cover a bigger area and allow one to see the whole picture of landscape around easily. Different methods predict the LSZ maps. Literature shows different approaches for LSZ analysis that the researcher may use based on the objective of the research, spatial scope of the studied region, availability of data, and local topographical conditions. Each model applied to different areas pros and cons, which can impact overall prediction rate and the interpretability of susceptibility.

The results are then validated using past landslide data, post-field surveys, landslide density analysis, receiver operating characteristics (ROC) curve analysis, an area under ROC curve analysis, success rate or prediction rate curve analysis, and many more methods. The validation of the map is important as it is done to check the accuracy of the predicted map. For this study, 93 articles about LSZ mapping using GIS were studied, and the observations made were discussed (Table 1).

Table 1. Methods applied by Different authors for LSZ mapping [5, 12-103].

Author(s) name	Year	Method(s)	Factors	No. of LSZ
Temesgen *et al*.	2001	Statistical approach	5	2
Dai *et al*.	2002	Logistic Regression (LR) model	7	4
Ohlmacher *et al*.	2003	LR model	3	4
Lee *et al*.	2004	Artificial Neural Network (ANN) model	7	Range (0-100)
Ayalew *et al*.	2004	Weight Linear Combination (WLC) method	6	5
Sarkar *et al*.	2004	Frequency Ratio (FR) model	8	4
Ayalew *et al*.	2005	Analytic Hierarchy Process (AHP), LR	3	5
Ayalew *et al*.	2005	LR model	7	5
Ermini *et al*.	2005	ANN model	5	4
Yesilnacar *et al*.	2005	ANN model, LR model	19	4
Gomez *et al*.	2005	ANN model	9	4
Kanungo *et al*.	2006	Weight of Evidence (WOE) method ANN model, Fuzzy logic procedure, ANN-fuzzy logic	6	5
Eeckhaut Den *et al*.	2006	LR model	10	4
Neaupane *et al*.	2006	Analytic network process	5	3
Pradhan *et al*.	2007	ANN model	10	4
Neuhauser *et al*.	2007	WOE method	6	5
Thiery *et al*.	2007	WOE method	7	4
Akgun *et al*.	2008	FR model, WLC method	6	5
Kamp *et al*.	2008	Multi-criteria evaluation	8	4
Yalcin A.	2008	AHP, statistical index method, WOE method	7	5
Melchiorre *et al*.	2008	ANN, cluster analysis	6	Range (0-10)
Garcia-Rodriguez *et al*.	2008	LR model	7	5
Nefeslioglu *et al*.	2008	LR model, ANN model	6	4
Wang *et al*.	2009	Trapezoidal fuzzy number weighting approach	6	4
Yilmaz I.	2009	FR model, ANN model, LR model	8	5
Kawabata *et al*.	2009	ANN model	6	Range (0-100)
Saito *et al*.	2009	Decision tree-based modelling	7	3
Kouli M.	2010	WLC method	9	5
Bai *et al*.	2010	LR model	14	4
Das *et al*.	2010	LR model	8	4
Nandi *et al*.	2010	FR model, LR model	7	4

Continuous of Table 1.

Pradhan *et al*.	2010	ANN model	15	5
Regmi *et al*.	2010	WOE method	17	3
Yalcin *et al*.	2011	FR model, AHP, statistical index method, weighting factor method, LR model	10	5
Ghosh *et al*.	2011	AHP	6	4
Khezri S.	2011	AHP	8	4
Oh *et al*.	2011	Adaptive neuro-fuzzy inference system	7	5
Ilanloo M.	2011	Fuzzy logic approach	9	5
Choi *et al*.	2012	FR model, LR model, ANN model	6	4
Bui *et al*.	2012	Adaptive neuro-fuzzy inference system	10	5
Mohammady *et al*.	2012	FR model, Dempster-Shafer, WOE method	13	5
Xu *et al*.	2012	Support Vector Machine (SVM) model	6	Range (0-1)
Das *et al*.	2012	LR model	11	5
Pradhan B.	2013	Decision tree model, SVM model, adaptive neuro-fuzzy inference system	10	5
Kayastha *et al*.	2013	AHP	11	4
Ozdemir *et al*.	2013	FR model, WOE method, LR method	18	4
Pareek *et al*.	2013	Information Value (IV) model	7	5
Wang *et al*.	2013	LR model	13	5
Chen *et al*.	2014	IV model	10	5
Umar *et al*.	2014	FR-LR	14	5
Niu *et al*.	2014	SVM, GA-SVM	9	5
Conforti *et al*.	2014	ANN model	10	5
Bayes A.	2015	AHP, WLC, ordered weight average	9	3
Guo *et al*.	2015	FR model, WOE model	11	5
Wang *et al*.	2015	LR model, bivariate statistical analysis, multivariate adaptive regression spline model	11	5
Conoscenti *et al*.	2015	LR Model, Multivariate Adaptive Regression Spline Model	16	3
Anbalagan *et al*.	2015	FR model, fuzzy logic approach	8	5
Dehnavi *et al*.	2015	Step-wise Weight Assessment Ratio Analysis (SWARA), Adaptive Neuro-Fuzzy Inference System (ANFIS), SWARA-ANFIS	12	5
Leonardi *et al*.	2016	Fuzzy logic approach	5	5
Kumar *et al*.	2016	AHP	13	5
Erener *et al*.	2016	LR model, AHP, association rule mining model	11	5
Zhang *et al*.	2016	Statistical approach with AHP	9	5
Partriche *et al*.	2016	LR model, AHP	7	4
Chimdi *et al*.	2017	FR model	9	5
Kumar *et al*.	2017	SVM technique	8	4
Nicu I.C.	2017	FR model	7	4
Chen *et al*.	2017	Logistic model tree, random forest model, classification andregression tree model	12	5
Singh *et al*.	2017	FR model, IV model	9	5
Chawla *et al*.	2018	Particle swarm optimization-SVM technique	12	4
Kumar *et al*.	2018	ANN model	7	3
Pham *et al*.	2018	Rotation forest-based SVM, rotation forest-based ANN, rotation forest-based decision trees, rotation forest-based naive bayes	10	5
Aditian *et al*.	2018	FR model, LR model, ANN model	7	5
Mandal *et al*.	2018	AHP	17	6
Abija *et al*.	2019	AHP	9	3
Bera *et al*.	2019	AHP	10	5
Pham *et al*.	2019	Reduced Error Pruning Trees (REPT), Bagging REPT, multi-boost REPT, rotation forest-based REPT, random subspace-based REPT	10	5

Continuous of Table 1.

Demir G.	2019	Index of entropy model, FR model	6	5
Shahri *et al.*	2019	ANN model	14	5
Bappaditya *et al.*	2020	AHP	8	4
Chowdhuri *et al.*	2020	Evidential Belief Function (EBF), Geographically Weighted Regression (GWR), Random Forest (RF), RF-EBF, RF-GWR	16	5
Mersha *et al.*	2020	FR model, WOE method	7	5
Sharma *et al.*	2020	IV model	10	5
Banshtu *et al.*	2020	FR model, fuzzy logic approach	8	5
Abu El- Magd *et al.*	2021	Random forest, K-nearest neighbor, naïve bayes	7	5
Getachew *et al.*	2021	WOE method	9	5
Tran *et al.*	2021	Naive bayes, multi-layer perceptron neural network classifier, alternating decision tree	10	5
Ngo *et al.*	2021	Linear discriminant analysis, LR, radial basis function network	10	5
Abdo H.G.	2022	FR model, statistical index model	13	5
Mekonnen *et al.*	2022	AHP	11	5
Dam *et al.*	2022	Shannon Entropy (SE) model, WOE method	10	5
Khaliq *et al.*	2022	Random forest model, LR model	13	4
Alsabhan *et al.*	2022	WOE method, IV model, FR model	8	5
Saha *et al.*	2022	Multi-layer Perception Neural Nets (MLP)-bagging, Kernel Logistic Regression (KLR)-bagging, Random Forest (RF)-bagging, Multi-variate Adaptive Regression Splines (MARS)-bagging	17	5

The focus of one's research should be on examining many facets. Figure 2 can be used as a resource for the researchers performing the study. The graphic displays the number of publications released in various nations for mapping landslide susceptibility. The R software was used to analyze different research articles so that a detailed overview could be given to the researcher interested doing their research on the LSZ analysis.

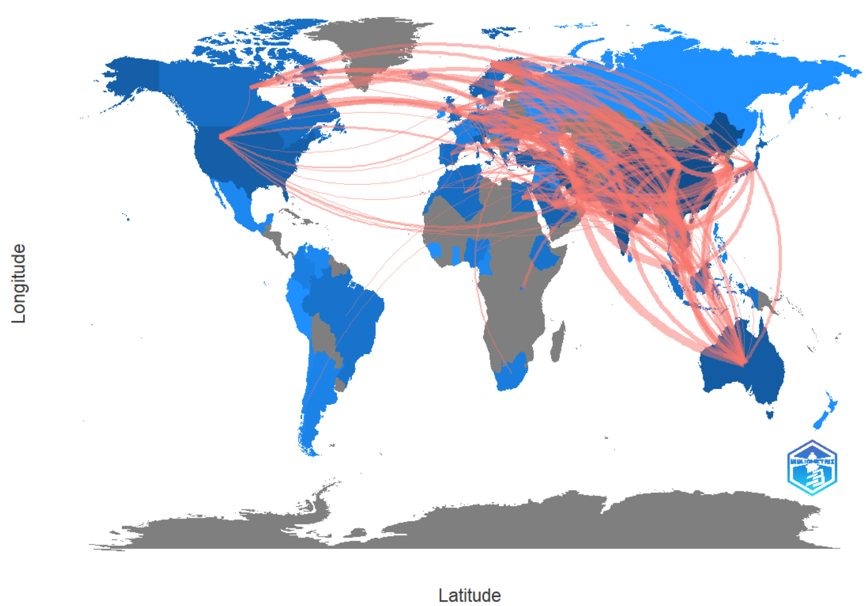
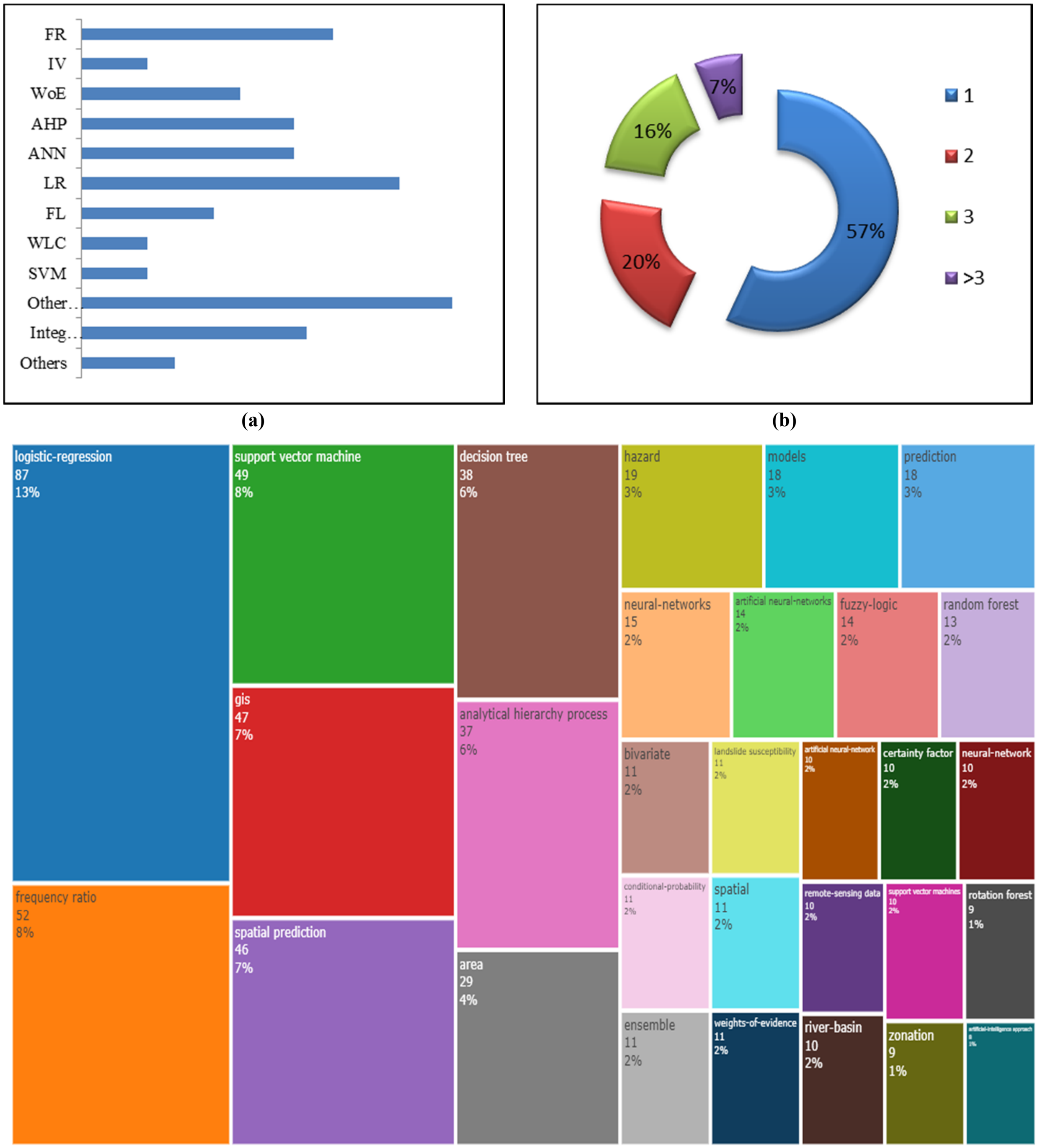


Figure 2.Articles published for LSZ over different countries.

Some more information was extracted from R for the researcher's benefit including the frequency of methods used in recent years (Figure 3 (a)), the number of methods applied for LSZ mapping (Figure 3 (b)), and different keywords used by researchers in recent years (Figure 3 (c)). With the help of these, one can eliminate the chance of repeating the research over the area.



(a) (b) (c)

Figure 3. (a) Frequency of applying different methods for LSZ; (b) Number of methods applied for LSZ; (c) Tree describing different keywords used by the researcher over recent years.

3. Methodology

Any research project in any discipline requires a proper technique. Similarly, in LSZ mapping, a brief notion of the approved approach by various scholars is mapped in Figure 4, which will aid the researcher's job. Different phases in methodology must be completed in the correct order to accomplish the research.

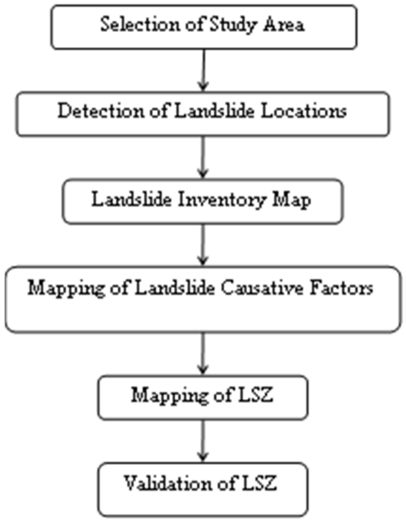


Figure 4. Flow chart of procedure to be followed by the researcher for LSZ mapping.

3.1. Selection of studied area

The area to be selected is of the utmost importance, as all analysis pertaining to the landslide will be conducted on that specific region; it should also be in the researcher's best interest as to which area should be selected. The area to be investigated should have important data that is readily available and understood. Extraction of the studied area can be accomplished in several ways including using the polygon tool or polyline tool in Google Earth, digitizing a map and then extracting the required polygon using GIS, downloading a natural polygon from USGS Earth Explorer using satellite images that adequately cover the area, and many others. Consequently, any approaches can be used to pick the studied area, and then the subsequent steps can be taken.

3.2. Detection of past landslide locations

Earth observation techniques and satellite photos are used extensively to detect the location of landslides. The data on landslides is also accessible on a social platform including the cause and casualties of landslides in a given region. The discovery of landslide areas is also possible through field surveys. Satellite imaging gives data in real-time that can be used to detect the locations of landslides.

3.3. Landslide inventory map

Various landslide-determining factors such as slope, rainfall, and lithology are used to create landslide maps. In addition to illustrating the location and nature of a landslide, an inventory map may also depict additional geomorphological elements associated with landslides. In mapping landslides, legends are utilized, which must fit the project's objectives and all geomorphological standards. Remember that every classification of landslides is subject to simplification, geomorphological deduction, and subjectivity. To minimize the disadvantages of mapping, the mapping should be validated using external data accessible for the designated studied region.

3.4. Preparation of landslide determining factors

Most landslides are caused by slopes, rainfall or an increase in development in hilly regions. However, these are only a few of the elements that create landslides; many other cause landslides; therefore, mapping is necessary for the right zonation of landslides. The determining factors are:

a). Geological

The geology of any region has a substantial effect on the mass movement that occurs there. The region's physical constitution and elements are among the geological considerations. Numerous social networking sites offer geology maps for various countries that can be digitized for mapping the geology of any study area.

b). Topographical

In reference to the elevation, topographical elements include slope, slope aspect (direction of slope), plan curvature, and profile curvature. GIS can be used to map topographical features using Digital Elevation Model (DEM) derived from Cartosat 1 satellite images received through USGS Earth Explorer.

c). Hydrological

Rainfall is one of the most influential factors influencing landslides in hilly locations; therefore, its examination is required for landslide zonation mapping. For rainfall mapping, at least the ten-year average is considered. Climatic Research Unit (CRU) provides rainfall information for all regions. Other elements such as drainage density, flow direction, and watershed also contribute to the occurrence of landslides. These characteristics are mapped using the DEM provided for the studied region.

d). Land coverage (LULC)

LULC is used to provide the user with an understanding of the existing landscape. Due to increased land usage in hilly regions, the hill's surface is becoming disturbed, resulting in a rise in landslides. Thus mapping of LULC is essential for analyzing the annual data on national databases that enable the monitoring of temporal dynamics of agriculture, forest conservation, surface water bodies, etc., on an annual basis. Landsat images for a specific region can be obtained through USGS Earth Explorer using Landsat 8/9 data of Cartosat Level-2. Supervised classification can then be used in GIS to map every feature and validate it using Google Earth pro or base map for that region.

e). Geotechnical

The predominant failure mode of soil is shear, making soil type a crucial factor in landslides. A critical element of landslide research is estimating the slope's stability and offering appropriate alternatives. Most of these studies are conducted by conducting a complete geotechnical investigation on the landslide, collecting soil samples from the landslide location, analyzing its specific physical features, and estimating its stability factor. These results are then utilized to develop a 2D model for the slope stability of the region.

Thematic maps like slope, slope aspect, curvature, elevation, and hillshade are derived from the digital elevation model (DEM). Some layers such as soil, rainfall, geology, and lithology are made based on the past data available at various sources. The maps are prepared in ArcMap using various tools like spatial analyst tools, data management tools, geostatistical analyst tools, and conversion tools.

3.5. LSZ mapping

All the determining factors are considered in mapping for the predicted LSZ. The LSZ is usually divided into five categories, i.e. low to high zones. According to various causative factors, landslide zonation maps categorize a region based on its potential instability towards landslides. Therefore, it is accomplished by gathering consistent and accurate data in the form of a landslide inventory about the occurrence of previous landslides. Recognizing the instability factors causing the landslides depends heavily on the updated inventory of landslides [104].There are various techniques for the calculation of LSZ (Figure 5).

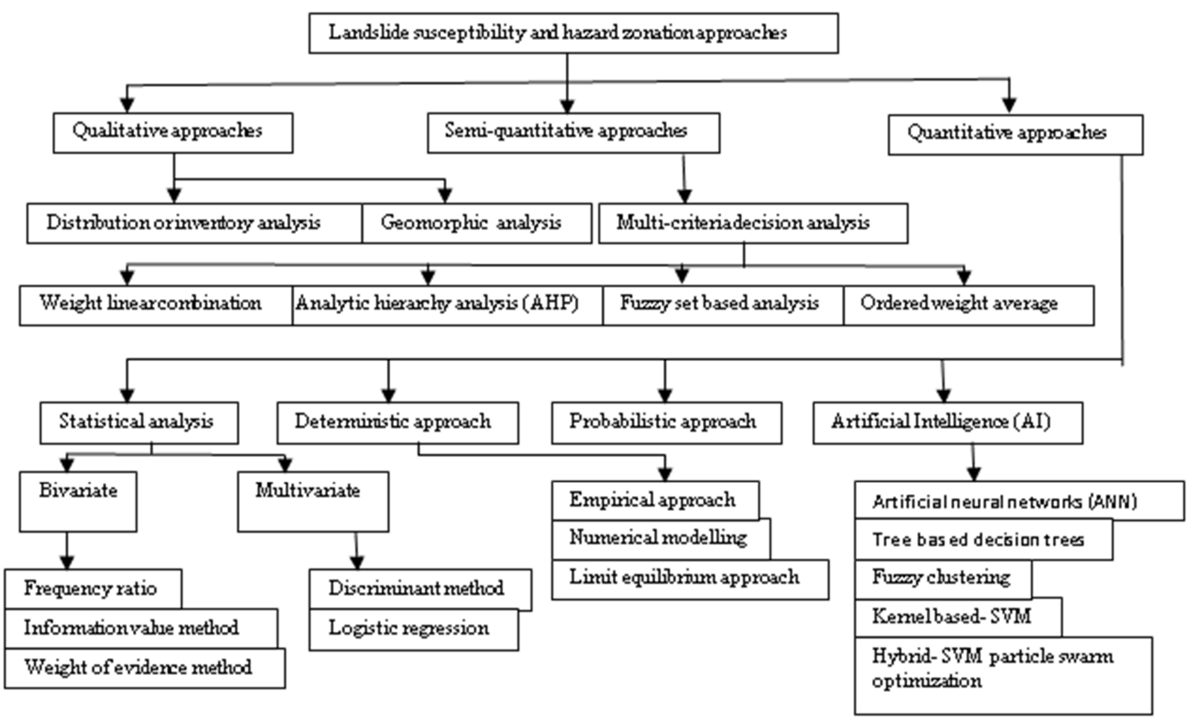


Figure 5.LSZ techniques.

3.5.1. Frequency ratio (FR) method

FR is a bivariate statistical approach for LSZ mapping by defining a relationship between the landslide occurrence area and the landslide determining factors of the studied area [5, 98, 104-112]. The FR for mapping landslide susceptibility is determined as the ratio of the percent of landslide pixels in each class to the percent of the class pixel of the study area. Mathematically it is represented as:

$$FR = \frac{\frac{N_l}{N_{lt}}}{\frac{N_c}{N_{ct}}} \quad (1)$$

where N_l is the number of landslide pixels in a particular class, N_{lt} is the number of landslide pixels in the entire study area, N_c is the number of pixels in a specific landslide determining factor, and N_{ct} is the number of pixels of landslide determining factor of an entire research area.

If FR>1, there is a strong interdependence between landslide occurrence and the determining factor.

If FR<1, there is weak interdependence between landslide occurrence and the determining factor.

The landslide susceptibility index (LSI), which shows the area's vulnerability to landslides, is calculated. The LSI is calculated as:

$$LSI = \sum_{i=1}^{n} \mathrm{FR_i} * \mathrm{L_i} \quad (2)$$

where n is the number of determining factors, FR_i is the FR value of the particular landslide determining factor, and L_i is the particular landslide determining factor. Further, these LSI values are classified using natural breaks in ArcGIS. The higher the LSI value, the higher the probability of landslides and vice versa.

Advantages

- Capable of dealing with both numerical and categorical data.
- Robust and simple to understand.
- Frequently used for a quick analysis of LSZ.

Limitations

- Only shows linear relationship between factors, avoiding the real-time non-linear relationship.
- Affects weight distribution when large numbers of landslides are located in a particular class, eventually affecting the resulted LSZ map.
- Relative importance of factors neglected.
- No intensive field surveys.

3.5.2. Information value (IV) method

IV is a bivariate statistical technique for mapping landslide susceptibility by estimating the relation between landslide-causing elements and the chance of rock mass movement occurring in the research area [104, 113-122]. Information value is the ratio of the logarithms of conditional probability to the logarithm of prior probability. Mathematically it is represented as:

$$IV = log\left(\frac{Conditional\ Probability}{Prior\ Probability}\right) \quad (3)$$

where IV is information value, conditional probability (eq. iv) is the ratio of the number of landslide pixels in a particular class (N_l) to the total number of pixels in that class (N_c), and prior probability (eq. v) is the ratio of total landslide pixels in the entire study area (N_{lt}) to the total number of pixels of the entire studied area (N_t).

$$Conditional\ probability = \frac{N_l}{N_c} \quad (4)$$

$$Prior\ probability = \frac{N_{lt}}{N_t} \quad (5)$$

If IV>0.1, it indicates a strong interrelationship between the class of factors that cause landslides and the chance that they will occur; if IV<0.1, it indicates a weak interdependency; and if IV is negative, it indicates that the class of factors that causes landslides does not contribute significantly to the probability that they will occur.

The landslide probability will increase as the LSI value rises, and vice versa. The LSI value in the raster calculator is depicted as:

$$LSI = \sum_{i=1}^{n} \mathrm{IV_i} * \mathrm{L_i} \quad (6)$$

where n is the number of landslides determining factors, IV_i is the information value of a particular determining factor, and L_i is the landslide determining factor.

Advantages

- The use of positive and negative weights simplifies the modelling process and makes it more understandable to users.
- Scaling of input features is not required.
- If new information becomes available, the database can be updated quickly.

Limitations

- Results may vary from user to user for the same area, as it is based on the GIS derived landslide information.
- The model is affected when no information is available for a particular class having considerable larger area that might affect the final output of LSZ.

3.5.3. Weight of evidence (WOE) method

The mineral potential was predominantly evaluated using the WOE method, which is normally regulated by the Bayesian Probability approach [123]. The WOE method is simple compared to other statistical methods and efficient in terms of time [124-131]. In this method, the weight of the landslide-causing factor (Z) is determined based on the occurrence and non-occurrence of landslide (R) over that area.

$$W_i^+ = \ln\left[\frac{P\left(\frac{Z}{R}\right)}{P\left(\frac{Z}{\bar{R}}\right)}\right] \quad (7)$$

$$W_i^- = \ln\left[\frac{P\left(\frac{\bar{Z}}{R}\right)}{P\left(\frac{\bar{Z}}{\bar{R}}\right)}\right] \quad (8)$$

where P is the probability of occurrence of landslide, Z represents the presence of landslide determining factor, $\bar{Z}$ represents the absence of landslide determining factor, R represents the presence of occurrence of landslide, $\bar{R}$ represents the absence of occurrence of landslide, W_i^+ is the positive correlation between landslide determining factor and occurrence of landslide, and W_i^- is the negative correlation between landslide determining factor and occurrence of landslide.

After determining the positive and negative correlations between the landslide determining factor and the occurrence of landslides, the weight contrast of each landslide determining factor is determined as:

$$W_{f_i} = W_i^+ - W_i^- \quad (9)$$

Here, W_{f_i} is the weight contrast that is determined individually for each landslide determining factor and with the help of it landslide susceptibility index (LSI) that is determined as:

$$LSI = \sum_{i=1}^{n} W_{f_i} \quad (10)$$

The LSI is then reclassified into different zones for the entire studied area ranging from low to high.

Advantages

- Log-based assessment of factor class in order to determine its relative importance in landslide occurrences.
- Non-parametric method.
- No parametric model tuning is required.

Limitations

- The limitations of landslide evidence (incomplete inventory) support non-relevant predictions.
- Interdependency between different factor classes is required.

3.5.4. Analytical hierarchy process (AHP)

AHP is a multi-criteria decision analysis semi-quantitative approach used for landslide susceptibility mapping [110, 130, 132-142]. This is analyzed by developing pair-wise balancing matrix by allocating rank to each determining factor against another factor (Table 2) [143]. The rank is assigned based on the degree of preference for factors influencing landslips [144]. After determining the pair-wise comparison matrix, the weight for each determining factor is calculated.

Table 2. Matrix of pair-wise comparison [143].

C	A_1	A_2	…	A_n
A_1	a_{11}	a_{12}	…	a_{1n}
A_2	a_{21}	a_{22}	…	a_{2n}
:	:	:	…	:
A_m	a_{m1}	a_{m2}	…	a_{mn}

Consistency Ratio (CR) is used to determine whether the matrix is generated randomly or not; if CR=<0.10, then it is assumed that the matrix is randomly generated, and if CR>0.10, then the matrix is automatically rejected. The value of CR is determined using Equation (xi) [145]:

$$CR = \frac{CI}{RI} \quad (11)$$

Here, RI is a random index, and CI is the consistency index. The consistency index is given as[145]:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (12)$$

where λ_{max} is the principal or largest eigen value for the matrix, and n is the order of the matrix.

Table 3. RI value for matrix order (n) [145].

n	1	2	3	4	5	6	7	8	9
RI	0.00	0.00	0.58	0.90	1.12	1.14	1.32	1.41	1.46

Advantages

- Ease of configuration.
- Considers the matrix only if CR is less than 0.10.
- Frequently employed to define and/or explain the trade-offs in multi-objective analysis.

Limitations

- May produce an excessively complicated pair-wise comparison matrix that does not generalize the situation in real life.
- According to professional judgment, the rank of factors' relative importance can change.
- Sensitive to subjective evaluations, which can vary from person to person.

3.5.5. Artificial neural network model

The Artificial Neural Network (ANN) model is an artificial intelligence technique used in ArcGIS for mapping landslide susceptibility [146-154]. This strategy was initially utilized in the medical area but has since been implemented in various other fields as well. ANN imitates the human learning process by comparing weight differences between actual output and target output [155]. This method requires multi-layer perceptron software such as MATLAB or R, with input, hidden, and output layers (Figure 6).

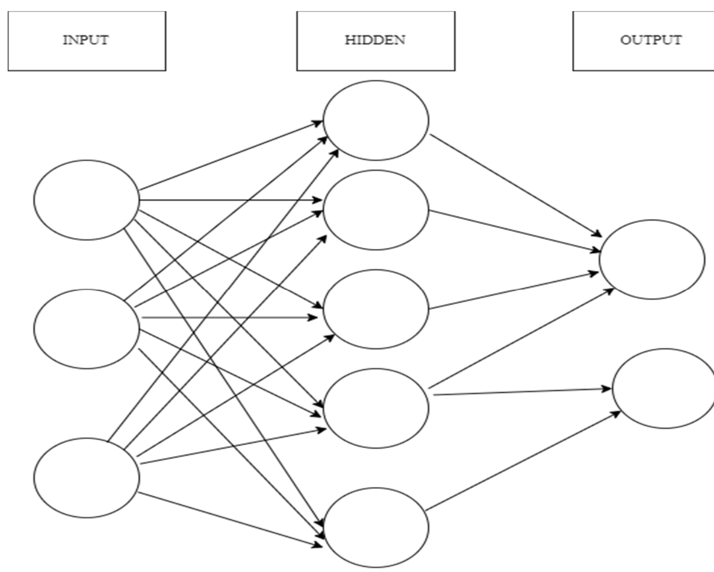


Figure 6. Architecture of ANN.

Predictions of landslide susceptibility mapping are more precise using this method than with previous statistical approaches. The result of this method is weighted for each node, and the error is evaluated using the back-propagation method to determine if there is a difference between the expected and actual output.

Advantages

- Takes into account the non-linear relationship between landslides and their causes.
- The output is accurate and adaptable to the needs.
- Minimizing the possibility of human error during computation.
- It is possible to achieve reliable prediction accuracies.

Limitations

- The availability of a large number of algorithms makes it difficult for the evaluator to choose the most effective one.
- High computational cost compared to other modelling approaches and highly data-intensive.

3.5.6. Logistic regression (LR) method

LR method is a multivariate statistical approach for LSZ mapping that provides a multivariate regression relationship between the dependent and independent variables [116,122,125,128, 156-163]. This method requires a software like MATLAB, SPSS or R to provide the coefficient of each landslide determining factor. Mathematically it is represented as:

$$X = \frac{1}{1 + e^{-a}} \tag{13}$$

where X is the chance of occurrence of amass movement whose value ranges from 0 to 1, and a is the linear combination of predictors.

If a = [-1, 0], less chance of occurrence of landslides

If a = (0, 1], more chance of occurrence of landslides

Mathematically a is given as:

$$a = \beta_0 + \sum_{i=1}^{n} \beta_i + x_i \tag{14}$$

where β_0 is the slope of logistic regression analysis, β_i is the coefficient of logistic regression analysis, and x_i is an independent variable.

Advantages

- Non-parametric method.
- It is not necessary for landslides and their explanatory variables to have a linear relationship, nor even that are they normally distributed.
- Aids in the evaluation of the causes of landslides using regression coefficient analysis.
- The absolute probability of a landslide occurring is calculated by taking into account a specific set of circumstances.

Limitations

- Highly susceptible to the problem of multi-collinearity, so the factors under consideration should be independent from one another.
- The logit function is used in the LR model to combine the regression coefficients of the factors to create the LSZ map. However, because the LR model is so sensitive to collinearity problems, such consideration frequently calls for mutually exclusive parameters.

3.5.7. Support vector machine (SVM) model

Landslide susceptibility mapping employs the machine learning technique of SVM, which analyses data for distribution and regression analysis [148, 151, 153, 156, 159, 161, 164-170]. The primary function of SVM is to discriminate between factors using a decision surface known as the hyperplane and the data points nearest to the hyperplane, known as support vectors, which are crucial components of the training set [171].

Four types of kernels are provided by SVM classifiers in prediction [172]; they are:

- Radial basis function
- Polynomial
- Sigmoid
- Linear

Multi-layer perceptions like hyperplane with high margins exhibit greater resistance to noise, which is one benefit the SVM offers over other machine learning methods [173].

Advantages

- Unaffected by the types of data and their statistical distribution.
- Before modelling, no presumptions required to be taken into account.
- The parallel-combination function of the causal factors is taken into consideration for prediction.
- The likelihood of human error in computation is reduced.

Limitations

- Highly data intensive and computational cost is higher than other modelling approaches.
- For performance optimization, the maximum number of models requires parameter tuning.
- Complex modelling processes are frequently difficult to understand and end up being a "black box" for users.

3.6. Validation of constructed map

As all the produced models are merely prediction models, they are meaningless until their validation is accomplished, and they become accessible for future study. By partitioning the data, one subset is utilized for prediction modeling, and the other subset is used for validation of the predicted model based on the historical pattern of the area. Among the strategies used to validate a produced map is the time partition technique. This method assumes that the time and space distribution of prior landslides in the research area has been gathered. It can then be used to create a model for predicting future landslides for the following 35 years. In this method, a prediction model is created based on the past landslides of the research region, and the area is then separated using aerial photographs into two parts: one prior to the year under consideration and the other of all years following the year under consideration. The portion considered previous to the year is used to obtain the anticipated image, and the remaining portion is used to validate the predicted image using the prediction-rate curve.

4. Conclusions

The review mainly concentrated on 93 LSZ-related articles from the past ten years published worldwide. After carefully examining the papers, it was observed that there was no one established methodology for LSZ mapping. It was also observed that ensembled techniques and machine learning techniques had been adopted more frequently recently; this may be due to the more accurate prediction rate of these techniques. This paper explained how RS and GIS were utilized. It is somewhat challenging to properly compare the various LSZ mapping techniques used by different researchers because they all used different factors, making it impossible to draw an accurate conclusion. Most researchers concentrate on factors like slope, aspect, soil, drainage density, and lithology. It was also noted that some studies had not carried out the crucial LSZ validation, so it is important to carry out an appropriate validation of LSZ maps. All of these suggestions aim to raise LSZ's level of quality. Comparative landslide assessment is preferable using qualitative and quantitative based approaches. For future land use, these considerations must be taken into account. Landslide zonation may facilitate decision-making during the implementation of a terrain development project. It is always preferable to avoid high-risk areas but if this is not possible, precautions must be taken to reduce the likelihood of landslides. Because of the growth in the number of landslides in hilly areas, it is necessary to restrict construction operations there. As afforestation affects slope stability, it should be encouraged in hilly regions. However, nature should not be harmed.

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ارزیابی حساسیت زمین لغزش با استفاده از سنجش از دور و GIS، یک مقاله مروری

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چکیده:

مخاطرات طبیعی پدیده‌هایی هستند که به طور طبیعی رخ می‌دهند که ممکن است بر محیط زیست و همچنین زندگی موجودات زنده تأثیر منفی بگذارند. این خطرات به دلیل شرایط نامطلوب جوی و رویدادهای اقلیمی و همچنین به دلیل فعالیت‌های خاص انسانی که برای محیط زیست مضر است، ایجاد می‌شود. خطرات طبیعی شامل سونامی، زلزله، فعالیت‌های آتشفشانی، رانش زمین و غیره است. در میان این مخاطرات طبیعی، زمین لغزش از شایع ترین مخاطرات طبیعی است که هر ساله منجر به تلفات جانی و مالی می‌شود که منجر به اثرات اجتماعی-اقتصادی می‌شود. بنابراین برای جلوگیری از چنین خساراتی، مطالعه جامع زمین لغزش‌ها ضروری است. لغزش معمولاً در مناطق تپه‌ای با شیب‌های تند، بارندگی‌های شدید، استحکام برشی سست خاک یا به دلیل بسیاری از فعالیت‌های انسانی مانند جنگل‌کاری یا فعالیت‌های ساختمانی رخ می‌دهد. برای حل مشکل زمین لغزش در یک منطقه تپه‌ای، تحقیقات زیادی سالانه انجام می شود که نقشه پهنه بندی حساسیت زمین لغزش (LSZ) پیش بینی شده از منطقه مورد تحقیق را ارائه می‌دهد. نقشه‌های پیش بینی شده حساسیت زمین لغزش بر اساس داده‌های زمین لغزش گذشته، یک منطقه زیر منحنی (AUC) و روش‌های دیگر برای ارائه یک نقشه دقیق برای حساسیت زمین لغزش در هر منطقه تایید شده است. در این مطالعه ۹۳ مقاله تحقیقاتی برای تحلیل LSZ بررسی شده و مشاهدات مختلفی بر اساس روندهای اخیر که توسط محققان مختلف در سراسر جهان طی ده سال گذشته دنبال شده است، انجام شده است. این مطالعه می‌تواند برای بسیاری از محققین مفید باشد تا تحقیقات خود را در زمینه پهنه‌بندی حساسیت زمین لغزش انجام دهند.

کلمات کلیدی: زمین لغزش، GIS، عوامل نشان دهنده زمین لغزش، روش‌های LSZ، اعتبار سنجی.