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A REVIEW OF STATISTICAL APPROACHES USED FOR LANDSLIDE SUSCEPTIBILITY ANALYSIS WITH THE HELP OF REMOTE SENSING AND GIS TECHNOLOGY

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ABSTRACT

Aim of the study
The goal of the present study, which was undertaken as a review, was to provide a critical analysis of statistical methods, used for landslide susceptibility modelling and associated terrain zonation from 2010 to 2023.

Material and methods
To critically review pertinent literature, the authors systematically searched for and compiled a substantial database using 139 articles that have been peer-reviewed. We assigned 5 categories/sub-categories of data for each article in the literature database, including the authors who have worked in landslide susceptibility, the trends in journal publishing on the subject, the periodic pattern of articles published from 2010 to 2023 (March), major factors that are considered for landslide susceptibility analysis, and the models that are used for landslide susceptibility analysis. Then these data are represented in graphical visualisation form.

Results and conclusions
There has been an increase in the number of publications from 2019 onwards on the topic of landslide susceptibility. In 20.8% of the studies, the Frequency Ratio (FR) model and Logistic Regression (LR) model have been chosen as the most popular approach for determining landslide vulnerability. Other than the logistic regression and frequency ratio model, other models like Fuzzy, Weight of Evidence (WoE), Artificial Neural Networks (ANN), Support Vector Machine (SVM), and Random Forest (RF) are also popular for landslide susceptibility analysis.

Keywords: review, landslides, statistical model

INTRODUCTION

Numerous researchers have studied landslide susceptibility, hazard, and risk because landslides are considered among the most typical geological hazards and they frequently result in fatalities and casualties (Li et al., 2017). The identification of landslide-prone locations, land use planning and management, and risk mitigation can all benefit from this research (Holec et al., 2013). In worldwide literature on the subject, one of the most important topics is the evaluation of landslide susceptibility as it is a major and complex

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challenge to forecast the occurrence of a landslide (Bui et al. 2016a,b). In order to simulate and analyse landslip susceptibility, many methodologies and strategies have been developed (Bui et al., 2016b). Heuristic, statistical, and deterministic models can be used to classify landslip susceptibility approaches. These models can be categorised as either quantitative or qualitative. According to the aspects that the researchers choose to emphasise, the exact classification of the assessment methods will vary. The experts' judgement in deciding the weight of each component affecting the landslip event could lead to errors in the heuristic models because they are subjective (Dahal et al., 2008). Additionally, there is a chance that the researcher may interpret the data according to his or her own preferences and will see what they want to see (Hjort and Luto et al., 2013). Mathematical relationships are the foundation of deterministic models. The physical rules that must be calculated with the objective of establishing the connection between driving and resisting forces are what the deterministic models rely on. Deterministic models can only be used on a limited scale (in a small area) because they require extensive data on slopes, hydrology situations, lithological types, soil qualities, the geometry of slopes, and discontinuity aspects (Youssef and Pourghasemi, 2021). Since statistical approaches are data-driven, inaccurate data selection and preparation could result in major errors in the outcomes. For modelling and model evaluation, these methodologies in particular necessitate a thorough inventory of landslide data. The availability of data, the scope of the study, and the appropriate approach to analysis and modelling, each have an important bearing on the accuracy of landslide sensitivity maps. (Baeza and Corominas et al., 2001). Complex drivers like geology, geomorphology, topography, and seismic variables interact to generate landslides. According to Abuzied et al. (2016), these elements can be separated into two primary categories: conditioning and trigger factors. In general, factors that condition an environment include lithology, drainage density, land use land cover, slope degree, aspect, altitude, fault, and soil type, whereas factors that cause an event include precipitation, earthquakes, and human action. The goal of the analysis of landslide susceptibility is to spatially identify the areas that are susceptible to landslides by utilising statistical models, data mining, and soft computing methods, as well as geographic information systems GIS (Cárdenas and Mera, 2016; Khali et al., 2023; Behera and Rawat, 2023a,b). The Kashmir earthquake of October 8, 2005, with a magnitude of Mw7.6, caused thousands of landslides in Northern Pakistan and India's Himalayan region which are in six geographically distinct locations., while varying in terms of geology, and human activity. In order to analyze this phenomenon, with the help of GIS technology and images from ASTER satellite, an inventory of 2000 plus landslides was created and assessed. The most important factors that caused the landslides, such as elevation, lithology, slope aspect, faults, land use land cover, stream density, and highways, were determined by a multi-criteria assessment. The findings showed four classifications of landslip susceptibility, with lithology playing a major role, especially in highly fractured rocks including dolomite, clastic deposits, shale, limestone, and slate. Particularly in moderately elevated areas on south-facing slopes, landslides were more probable to happen close to faults, streams, and roadways. Landslides have been discovered to be more common in agricultural, grassland, and shrubland areas than on wooded slopes. The necessity for immediate mitigation measures was highlighted in other landslide-prone areas as the chances of a landslide occurring in that zone are very high. The remaining part of the area was classified as stable, with very low landslide risk. This research indicates that landslides caused by earthquakes happen in areas that are affected by some specific factors, and that road development and deforestation have both had a major impact on land sliding in the western region of the Himalayas following and prior to earthquakes (Kamp et al., 2008).

METHODOLOGY

Using the keywords "landslide susceptibility" and "GIS and remote sensing" as search terms, a total of 225 articles are downloaded from the Scopus journal database but it is only in 139 research papers that, a statistical approach is being used for landslide susceptibility zonation. For this review paper, we are using only those research papers that are related to the statistical approach and in which remote sensing and

GIS are carried out for landslide susceptibility analysis. The input data in these articles were satellite images through which different parameters inventory map was generated. 77 out of these 139 research papers were published between from 2010 and 2018, and 62 papers were published from 2019 till present. The next phase is classifying the articles according to the year they were published. The publication's date, journal name, model's type and major factors affecting landslides were recorded in a database. This database was created in an Excel sheet, using this data different graphs were generated.

RESULTS AND DISCUSSION

Periodic pattern of articles published

According to the database in the year 2010 to 2018, 77 research papers were published whereas from 2019 to March 2023, 62 papers have already been published. Using the database a graph was generated (Figure 1) in which the number of papers published per year were shown. So on the basis of this information, we can conclude that the average number of research papers published in 2010–2018 is 9 per year, and from 2019 to March 2023 the average number of research papers published is 14 per year. The findings also showed that the highest number of research papers was published in 2021 i.e., 17.

The trends in journal publishing

Landslide susceptibility indexing papers have primarily been published in the following journals: Environmental Earth Sciences, Remote Sensing, Disaster Advances, Journal of Indian Society of Remote Sensing, Landslides and Natural Hazards. 25% of the papers relating to landslide susceptibility between 2010 and 2023(Jan–Mar) were published in those 6 journals. According to this review, 73 journals have published research papers on landslide susceptibility from 2010–2023(Jan–Mar). Environmental Earth Science has published a total of 14 papers.

Models used in landslide susceptibility

Numerous researchers have studied landslide susceptibility, hazard, and risk because it is the most prevalent geological danger and it frequently results in fatalities and casualties (Li et al., 2017). Locating landslide-prone areas, managing and planning for land use, and reducing risk can all benefit from this research (Holec et al., 2013). Methods for measuring landslide susceptibility might be either quantitative or qualitative. Heuristic, statistical, and deterministic models can be used to classify landslide susceptibility approaches and can be categorised as either quantitative or qualitative. According to the aspects that the researchers choose to emphasise, the exact classification of the assessment methods will vary. In the

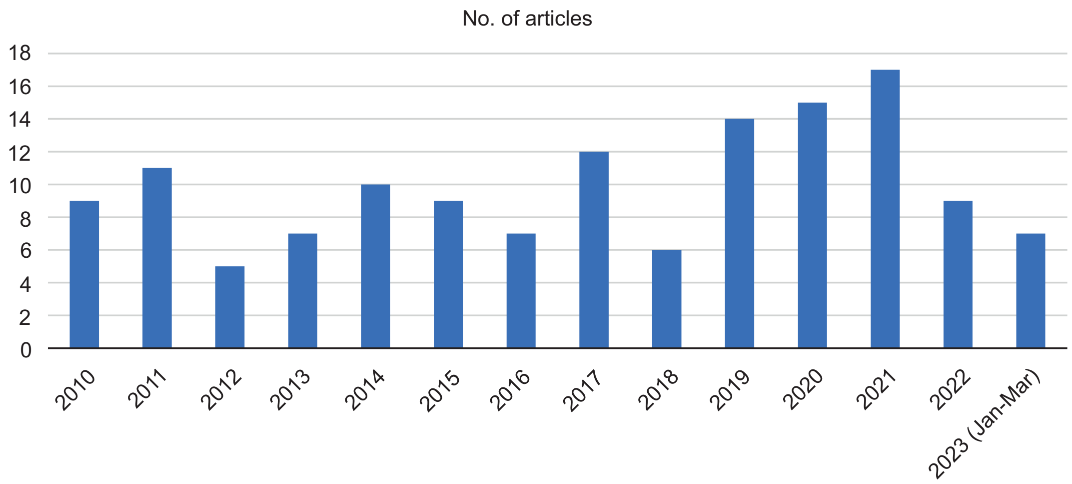

Fig. 1. As per the database, the number of papers on landslide susceptibility using a statistical model, published per year from 2010 to 2023 (Jan–Mar)

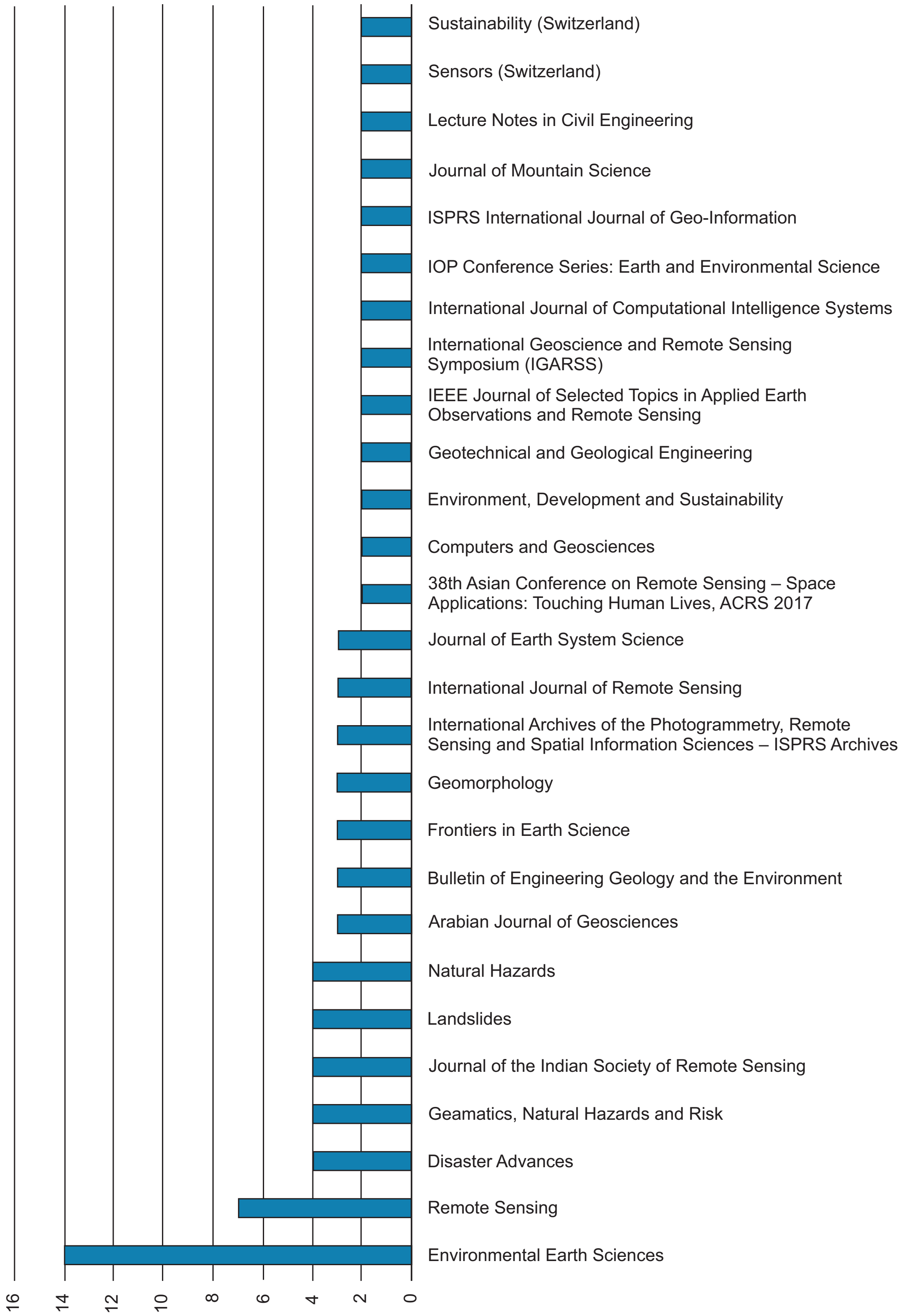

Fig. 2. Number of papers published by journals according to the database, during the period 2010–2023 (Jan– Mar)

current study, 23 models were employed to evaluate the sensitivity of the 139 articles published between the years 2010 and 2023 (Jan–Mar). According to the results, the most common model was the Frequency Ratio (FR) model and the Logistic Regression Model, both with 29 cases. Other than that, Fuzzy, WoE, ANN, SVM and RF are also popular according to the results.

Bivariate statistical models, such as logistic regression or the bivariate statistical index (BSI), are used in landslide susceptibility analysis for several specific reasons. Multiple factors, including topography, geological characteristics, land cover, and rainfall, among others, influence landslide susceptibility. Bivariate models allow for the simultaneous consideration of two factors at a time. This can help assess how pairs of factors interact and jointly contribute to landslide occurrence. Bivariate analysis can provide insights into the correlations between individual factors and landslides. It's important to note that while bivariate models have their advantages, they are limited in capturing the full complexity of landslide susceptibility, as landslides are influenced by a combination of factors working together. For a more comprehensive analysis, multivariate statistical models, such as logistic regression, decision trees, or machine learning algorithms, are typically employed to consider multiple factors simultaneously. In practice, bivariate models are often used as a preliminary step to gain insights into the relationships between individual factors before developing more sophisticated multivariate models for a more accurate and comprehensive landslide susceptibility analysis.In the context of landslide susceptibility analysis, decision trees and CHAID (Chi-squared Automatic Interaction Detection) differ in how they approach the problem and handle geospatial data. Decision trees can handle both categorical and continuous geospatial data, which is important in landslide susceptibility analysis where you may have a mix of data types such as elevation (continuous) and land cover types (categorical). Decision trees can adapt to these varied data types. CHAID is primarily designed for categorical data, which may limit its ability to handle continuous variables. While it can work with categorical target variables (e.g., landslide occurrence), it may not be as versatile when dealing with a combination of continuous and categorical predictor variables. Decision trees can become complex, especially when applied to geospatial data with multiple variables and complex relationships. The resulting tree may require pruning to avoid overfitting and improve interpretability. CHAID typically produces simpler trees because it focuses on the significance of relationships between categorical variables. This simplicity can make CHAID models more interpretable, which can be advantageous in scenarios where clear communication is vital. In the context of landslide susceptibility analysis, the choice between a decision tree and CHAID depends on the nature of the data, the research objectives, and the need for interpretability. Decision trees are more versatile, and capable of handling mixed data types, while CHAID is more tailored to specific scenarios involving categorical data. The choice should be guided by the specific characteristics of the dataset and by the goals of the analysis.

ANN and DNN are both types of neural network models used in machine learning and data analysis, including for tasks like landslide susceptibility analysis. An ANN typically consists of a single hidden layer between the input and output layers. It may have a limited number of neurons in that hidden layer. A DNN, as the name suggests, consists of multiple hidden layers, usually more than one. DNNs are characterized by their depth, and they can have several hidden layers, making them deeper and more complex. ANN models are relatively shallow and less complex compared to DNNs. They may struggle to capture highly complex, non-linear patterns in data. DNN models are more complex due to their depth and the presence of multiple hidden layers. This complexity allows them to model intricate relationships within data, making them more suitable for tasks that involve a high degree of complexity, such as landslide susceptibility analysis.

In landslide susceptibility analysis, the choice between ANN and DNN models depends on the complexity of the data and the availability of training data. DNNs are better suited for capturing intricate patterns in geospatial data, but they may require more data and computational resources. ANN models can be simpler and more accessible for smaller datasets. Support Vector Machines (SVM) and Generative Adversarial Networks (GANs) are two distinct machine learning techniques used for different purposes, including landslide susceptibility analysis. SVM is a supervised learning model primarily used for classification and regression tasks. In landslide susceptibility analysis, SVM is commonly used as a binary or multi-class classifier to predict the susceptibility of areas to landslides. SVM is trained using labelled data, which means you need a dataset with historical landslide occurrence data (positive class) and non-landslide data (negative class) to train the model. The model then learns to create a decision boundary that separates these classes. SVM is trained using labelled data, which means you need a dataset with historical landslide occurrence data (positive class) and non-landslide data (negative class) to train the model. Again, the model learns to create a decision boundary that separates these classes. GANs are a class of unsupervised learning models used for data generation. They consist of a generator and a discriminator, which compete to generate and evaluate data samples, respectively. GANs require large amounts of unlabeled data for training. In landslide susceptibility analysis, SVM is typically used for classification, making predictions about the susceptibility of specific areas based on their geospatial features. GANs, on the other hand, are not typically used for direct susceptibility analysis but could potentially be used to generate synthetic data to augment a dataset, especially when data is scarce. The choice between the two models depends on the specific goals and data availability in the analysis. One of the primary uses of GANs in landslide susceptibility analysis is data augmentation. GANs can generate synthetic geospatial data that resembles real landslide-related data. This is especially useful when there's a scarcity of labelled data for training traditional models like Support Vector Machines (SVM) or Deep Neural Networks (DNN). By generating synthetic data points, GANs can help improve the training and performance of other models. GANs can be employed to enhance the quality of remote sensing imagery, such as satellite or aerial photographs. Improved image quality can lead to more accurate feature extraction and a better understanding of the terrain, geology, and land cover characteristics that influence landslide susceptibility. GANs can be used to simulate different scenarios for risk assessment, such as predicting the impact of changes in land cover, urbanization, or precipitation patterns on landslide susceptibility. This can aid in land-use planning and disaster mitigation. GANs are most effective when used in combination with traditional machine learning models to enhance the quality and quantity of data available for training and analysis.

The "Index of Entropy" is a concept related to information theory and entropy, and it can potentially play a role in landslide susceptibility analysis, particularly in the context of feature selection or assessment of the complexity of geospatial data. In landslide susceptibility analysis, you typically work with a variety of geospatial features such as topography, land cover, geological characteristics, rainfall, and more. The Index of Entropy can be used to measure the level of disorder or uncertainty within these features. By calculating the entropy of different variables, you can identify which features carry the most information or exhibit the highest variability. These informative features can be selected for inclusion in your susceptibility model. The specific role of the Index of Entropy in landslide susceptibility analysis would depend on how it is integrated into the modelling process. It can be used as a tool for data preprocessing, feature selection, model assessment, or exploratory data analysis. Ultimately, it can contribute to the development of more informative and accurate landslide susceptibility models by identifying key variables and assessing data complexity. Random Forest is well suited for predictive modelling in landslide susceptibility analysis. It can effectively predict the susceptibility of specific areas to landslides based on a combination of geospatial features, such as topography, geology, land cover, rainfall, and more. Random Forest models can handle both binary (presence/absence of landslides) and multi-class classification tasks. Random Forest is known for its high predictive accuracy. It's particularly effective when dealing with complex and non-linear relationships between features and landslide occurrences. The ensemble of decision trees reduces overfitting and can capture intricate patterns in the data. WoE can be used to evaluate the relationship between individual geospatial variables (e.g., topography, geology, land cover) and landslide susceptibility. It calculates the strength of association between each variable and the occurrence of landslides. Variables with higher WoE values are considered more influential in the analysis. By calculating WoE values for different geospatial factors, you can quantify the risk associated with each factor. This information can be valuable for identifying high-risk areas and assessing the likelihood of landslides based on the presence of specific factors. It's important to note that the application of WoE to landslide susceptibility analysis would require adaptation and validation. While WoE is commonly used in specific fields like credit scoring, it is not a standard technique in geospatial analysis. As such, careful consideration of data quality, model development, and validation is crucial to ensure its effectiveness and suitability for the specific requirements of landslide susceptibility analysis.

Multiple regression model quantifies the strength and direction of relationships between geospatial variables and landslide susceptibility. You can determine whether an increase or decrease in a particular variable leads to a corresponding change in landslide likelihood. While multiple regression has it's advantages, it's important to acknowledge its limitations, such as its assumption of linearity and the potential for overfitting if not carefully managed. CNNs can be applied to process and analyze remote sensing imagery, such as satellite or aerial photographs, which can be rich sources of geospatial information. These networks can identify and extract features like land cover, topography, and vegetation, which are essential for assessing landslide susceptibility. CNNs are effective feature extractors. They can automatically learn and extract relevant features from satellite or aerial images, such as textures, shapes, and patterns, which can be used as input features for other models like logistic regression or decision trees in landslide susceptibility analysis. While CNNs can contribute to landslide susceptibility analysis through image processing and feature extraction, they are typically part of a broader approach that includes other machine-learning models. The choice of modelling techniques depends on the nature of the data, and on specific research objectives, and on the availability of geospatial information.

Fuzzy Logic and ANFIS are both mathematical models used for modelling complex, uncertain, and nonlinear systems. They share some similarities but have distinct differences. Fuzzy logic is a mathematical framework for dealing with uncertainty and imprecision. It uses linguistic variables and membership functions to represent and manipulate vague or uncertain information. ANFIS is a hybrid model that combines elements of fuzzy logic and artificial neural networks. It uses neural networks to adaptively learn and tune the fuzzy inference system. Fuzzy logic systems are less expressive than ANFIS in terms of handling complex, data-driven relationships, as they rely on manually crafted rules. ANFIS can capture complex, data-driven relationships and can approximate a wide range of functions when trained with appropriate data.

Table 1. According to the database, analysis of landslide susceptibility using different statistical models using the database created in this research

ID Model	Description	Total
ANFIS	Adaptive neuro-fuzzy inference system	8
ANN	Artificial neural network	17
BS	Bivariate statistical	7
CHAID	Chi-square Automatic Interaction Detection	3
CNN	Convolutional neural network	1
DNN	Deep neural network	3
DT	Decision trees	4
FR	Frequency ratio	29
FUZZY	–	18
GAN	Generative adversarial networks	1
GASVM	Genetic algorithm-support vector machine	1
IoE	Index of Entropy	3
IVM	information value model	2
LMV	Linear multi-variate	1
LR	Logistic Regression	29
MS	Multivariate statistical	4
MR	Multiple regression	1
RF	Random forest	8
SVM	Support vector machine	21
WoE	Weights of Evidence	17

Authors who have worked on landslide susceptibility articles

The study of 139 articles on the susceptibility of landslides revealed that 110 authors contributed to those manuscripts. Only 5.7% of the articles were published by a single author, whereas 21.5% research papers had two authors and the remaining 70.5% were published in collaboration by more than two authors. Between 2010 and 2023 (Jan–Mar), each author produced 1.26 articles on average. Only three authors (2.72%) have published more than three items, compared to 69.7% who published one, and 7.9% who published two.

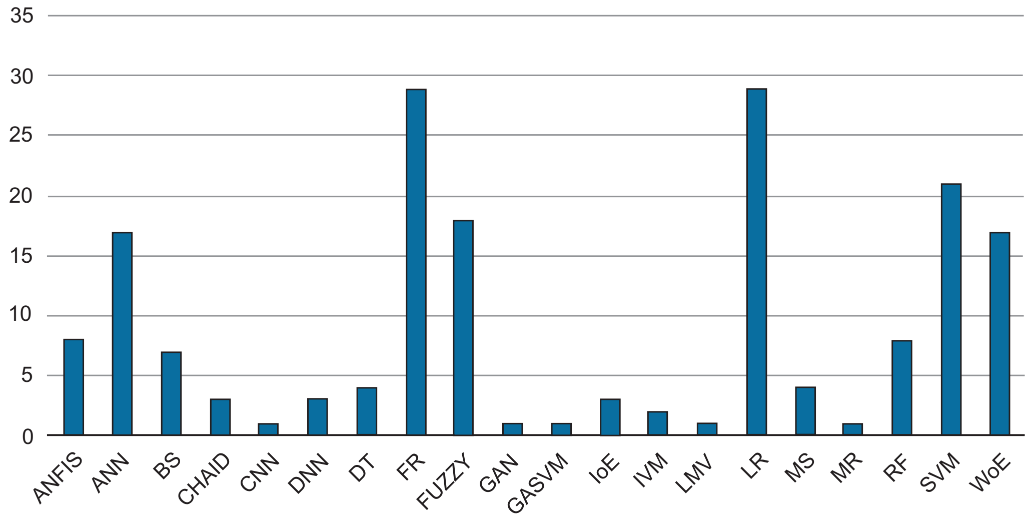

Fig. 3. As per the database, number of articles published according to the database using different statistical models during the period 2010–2023 (Jan–Mar)

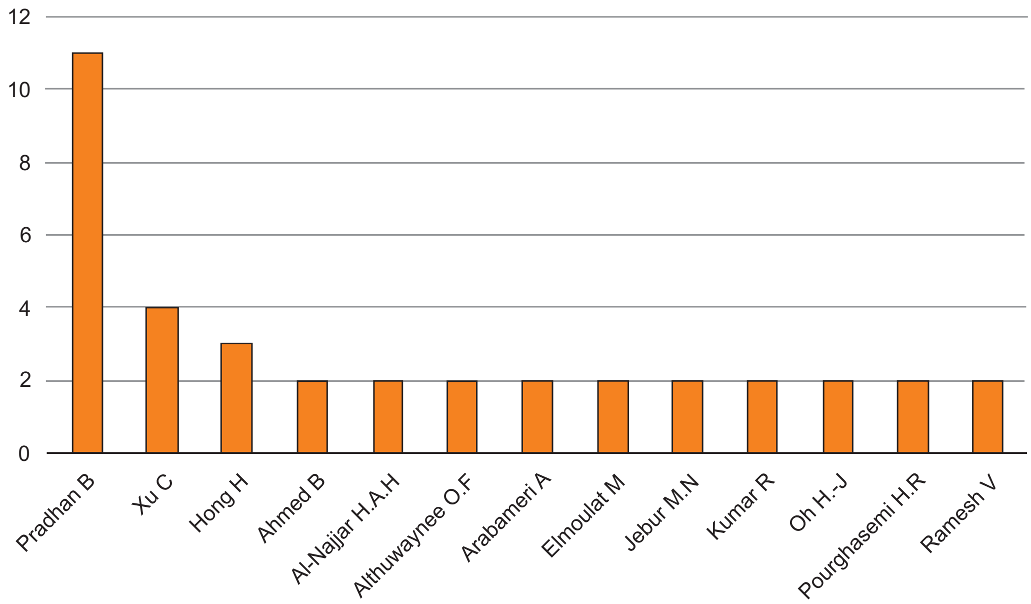

Fig. 4. Using database, the number of articles published by authors who have used different statistical model during the period 2010–2023 (Jan–Mar)

Condition factors and trends

For the analysis of landslide susceptibility, here in this review, we are using Remote Sensing (RS) and GIS data. Remote sensing data is valuable for landslide susceptibility analysis as it provides a means to capture information about the Earth's surface from a distance. Various kinds of RS data were considered for this purpose, such as satellite images (Optical, SAR, hyperspectral or multispectral), aerial photography, and remote sensing-derived DEM's. In order to research landslides and determine their hazards, other RS methods, including RADAR, LiDAR, UAVs, etc., have also been deployed. The processing of enormous amounts of data, however, grew challenging with the advancement of RS methods and the discovery of several landslide causative elements. This was made possible by GIS, which makes it simple to store, edit, analyse, and display vast volumes of geographical data. In order to map landslides and forecast potential dangers, RS and GIS have been widely employed (Gupta et al., 2008). In this study, landslide susceptibility analysis relies on a variety of geospatial data to assess the likelihood of landslides occurring in specific areas. The choice of data depends on the specific characteristics of the region and the availability of data being studied. Some of the GIS data that are reviewed in this review paper are

i) Topographic data for DEM and DTM data, so that we can extract the slope, aspect, curvature, drainage density and distance from drainage data;
ii) Precipitation data for understanding the climatic conditions in that area;
iii) Geological data, providing information about rock types, soil types and geological formations;
iv) Land cover and vegetation data, giving information about land cover and vegetation density. This information helps in understanding the impact of human activity and vegetation on landslides;
v) Human activity and infrastructure data as human activity and construction can alter the landscape and potentially increase landslide susceptibility;
vi) Soil data as it influences soil stability and landslide potential, and
vii) Past landslide data, which are valuable for identifying landslide-prone zones and understanding the history of landslides in the region.

The number of parameters assumed in the given study depends on the availability and quality of data that may vary from one region to another.

Although this does not always indicate a strong performance in their predictive potential, multiple data inputs have been required by the wide variety of techniques and models used in the assessment of landslide vulnerability (Bui et al., 2016a, b). The proper factor selection is influenced by the landslide mechanism and type, the features of the studied region, the scope of the research, the availability of data, and the methodology (Manzo et al., 2013). However, there is no single, fixed set of guidelines or recommendations for choosing the important factors

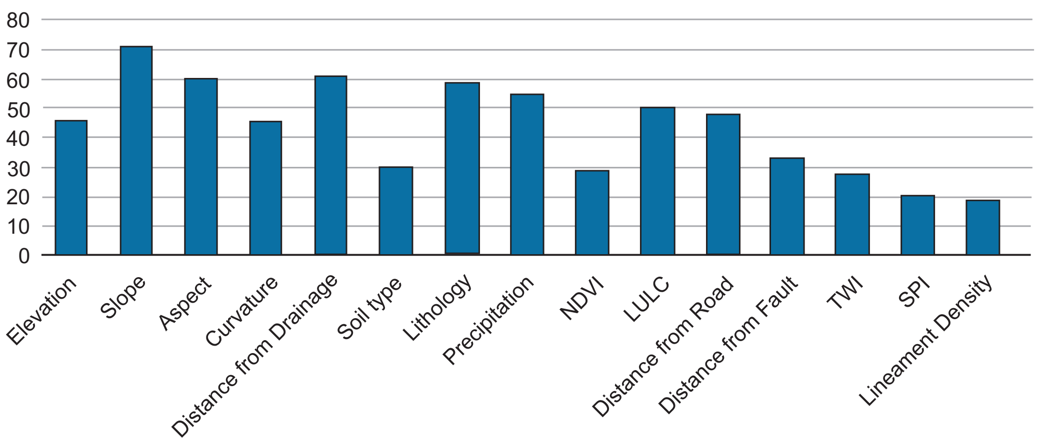

Fig. 5. As per the database, the number of articles published according to the database, using different factors responsible for landslide susceptibility during the period 2010–2023 (Jan–Mar)

that influence the likelihood of a landslide. Instead, the findings show that different studies use different variables. In order to improve the selection of the input variables in future research, a list of parameters utilised in landslide susceptibility assessment should be provided.

32 factors from the 139 publications we looked at were utilised to gauge landslide vulnerability, out of which only 15 factors are most commonly used.

Over 60% of the research (139 articles) evaluated slope gradient as the most important component in landslide susceptibility study. The most often cited factors in papers on landslide susceptibility are: Distance from Drainage, Aspect, Lithology, Precipitation, Land Use Land Cover (LULC), Distance from Road, Slope Elevation, and Curvature. A different set of factors (Distance from Fault, Soil Types, NDVI, TWI, SPI, and Lineament Density) is used in more than 15% of the cases with a medium level of frequency compared to the previously mentioned factors.

CONCLUSIONS

In the last five years, there has been a significant rise in the quantity of publications published on landslide susceptibility, going from an average of 9.5 articles per year between 2010 and 2018 to 14.5 articles between 2019 and 2023 (Jan–Mar). All the research done in the field of landslide susceptibility and the models used for this agenda can give a chance or improve the strategy related to creating awareness for better land-use planning and preventing or mitigating cases of land-slide damage. This research can be used for mapping different hazard zones. By identifying the low-risk hazard zone, we can use those zones for development activities in future whereas the high-risk hazard zone mapping is required to reduce the risk to life and infrastructure. Various mitigation schemes and policies can be adapted to do so. FR and LR models can be used in other areas for landslide susceptibility analysis. These susceptibility maps greatly help engineers and development planners as they can select locations for development purposes. The outcome of this research can provide a base for urban development slope management and land use planning. However, we should note it is good to mention that the output map is not suitable to use for detailed design purposes. In order to increase accuracy, we require more data. Landslide susceptibility maps elaborated using the FR and LR models are cost-effective and can be used for the planning and harvesting of timber and road construction. Using such maps, foresters and development managers can make decisions and take precautions accordingly. This will reduce the risk of adverse conditions. Research in this field also helps in developing techniques for remote sensing, tools used for modelling, data accessibility, and GIS, which could all be contributing factors to this growth. 29.4% (41 articles) of the papers assessed in this article were published in seven journals, including Environmental Earth Sciences, Remote Sensing, Disaster Advances, Geomatics, Natural Hazards and Risk, Landslides, Natural Hazards, and Journal of the Indian Society of Remote Sensing. 23 models were utilised in the 139 published studies that we reviewed. The FR and LR model, which were applied in 20.8% of the articles published in the period 2010–2023 (Jan–Mar), is the one that is most frequently used among them for determining landslide susceptibility. Slope instability is one of the most important parameters that should be considered for landslide susceptibility analysis.

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PRZEGLĄD MODELI STATYSTYCZNYCH STOSOWANYCH DO ANALIZY PODATNOŚCI OSUWISKOWEJ ZA POMOCĄ TELEDETEKCJI I TECHNOLOGII GIS

ABSTRAKT

Cel pracy
Celem niniejszych badań, które mają charakter przeglądowy, była krytyczna analiza metod statystycznych stosowanych do modelowania podatności osuwiskowej oraz powiązanej z podatnością osuwiskową klasyfikacji terenu, stosowanej w latach 2010–2023.

Materiał i metody
W celu dokonania krytycznej analizy i przeglądu literatury fachowej, autorzy systematycznie przeszukiwali i kompilowali obszerną bazę danych, na którą ostatecznie złożyło się 139 zrecenzowanych artykułów naukowych. Każdemu z artykułów w bazie literatury tematu przypisano 5 kategorii i podkategorii, dotyczących: autorów, którzy zajmowali się zagadnieniem podatności osuwiskowej; trendów oraz tematów podejmowanych w czasopismach i wydawnictwach naukowych; okresowości/częstotliwości artykułów opublikowanych od 2010 roku do marca 2023 roku; głównych czynników uwzględnianych w analizie podatności osuwiskowej; oraz modeli stosowanych w analizie podatności osuwiskowej. Dane te następnie zaprezentowano w formie wizualizacji graficznej.

Wyniki i wnioski
Od 2019 roku wzrosła liczba publikacji na temat podatności osuwiskowej. W 20,8% badań za najpopularniejsze metody określania podatności osuwiskowej uznano model Współczynnika Częstotliwości (*Frequency Ratio*; FR) i model Regresji Logistycznej (*Logistic Regression*; LR). Oprócz modelu Regresji Logistycznej i Współczynnika Częstotliwości f, w analizie podatności na osuwiska spotyka się inne popularne modele, takie jak Model Rozmyty (*Fuzzy*), Metoda Transformacji Zmiennej Objaśniającej (*Weight of Evidence*; WoE), Sztuczne Sieci Neuronowe (*Artificial Neural Networks*; ANN), Maszyna Wektorów Nośnych (*Support Vector Machine*; SVM) i Las Losowy (*Random Forest*; RF).

Słowa kluczowe: artykuł przeglądowy, osuwiska, model statystyczny