International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0063

e ISSN: 2584-2854
Volume: 04 Issue: 03
March 2026
Page No: 397 - 403

A Review of Current Techniques for Debris Flow Susceptibility Assessment

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Abstract

In the mountain region, debris flows are among the most recognized geological natural hazards, due to their unpredictability, rapid movement, and extensive runout distribution, which have been documented for several centuries. For reliable and efficient mitigation measures, debris flow susceptibility assessment (DFSA) is an essential approach. Over the past few decades, numerous methods have been developed to evaluate debris flow susceptibility. In this article, the authors study and discuss current techniques for DFSA in detail. These techniques are grouped into the following approaches: Qualitative, Semi-quantitative, and Quantitative. 30 research articles published between 2016 and 2025 were analyzed. Across the studies, 25 susceptibility assessment techniques were identified; among these, random forest (RF), logistic regression (LR), Support vector machine (SVM), and extreme gradient boosting (XGBoost) are most frequently employed. Overall, this article provides a comprehensive discussion of debris flow susceptibility assessment and serves as a valuable reference for scientists and researchers.

Keywords: *Debris Flow, Susceptibility, Machine-learning*

1. Introduction

Natural hazards are responsible for a huge number of fatalities and property losses worldwide each year (Vargas-Cuervo et al. 2019; Lee et al. 2020; Daud et al. 2024). In mountain regions, Landslides are among the most common geological natural hazards, recorded for several centuries (Park et al. 2016). According to the World Disaster Report by the International Federation of the Red Cross and Red Crescent Societies (2001), Approx 42% of total casualties from flooding, Avalanches, and landslides, in major countries like China, Japan, India, Italy, Taiwan, and the USA (Zhang et al. 2019; Dash et al. 2022; Huang et al. 2022; Li et al. 2025). The classification of landslides was first formally proposed by D.J. Varnes, based on the types of movement and material (D.J Varnes 1978), as summarized in Table 1. The various types of movement include falls, topples, slides (rotational and translational), spreads, flows, and complex movements. The materials involved are soil and rock. Soil is subdivided into predominantly fine (earth) and predominantly coarse (debris). Among all landslide types, debris flows are among the most recognized natural disasters due to their unpredictability, rapid movement, and extensive runout (Li et al. 2017) According to Varnes, Debris flow is a two-phase solid-liquid mass movement, a mixture of water and various-sized particles, materials like sediments, detritus, and muds that occur in gullies or on steep hilly areas with a bulk density of 1.5 to 2.2 g/m3 and a flow rate of 1 m/s to 10 m/s, depending on rainfall intensity and duration (Sharma et al. 2023; Yanting and Yonggang 2023; Ming et al. 2025). To prevent or minimize damage from debris flow, it is essential to act before the event occurs (Lee et al. 2020). The debris flow susceptibility assessment (DFSA) is an essential approach for early warning, prevention, and disaster mitigation (Zhao et al. 2024). Several studies have been carried out on DFSA. The reliability of DFSA depends on the dataset, mapping unit, causative factor, and modelling approach (Cama et al. 2016; Kang and Lee 2018; Gao et al. 2021b). In this article, review the current techniques adopted by researchers between 2016 and August 2025 for DFSA.

2. Methodology

To execute the review process, a literature database was compiled by searching the "Web of Science"

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e ISSN: 2584-2854
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platform for the following keyword combination: "Debris flow + Susceptibility." Different inclusion criteria were adopted during the literature search. Only peer-reviewed journal articles published in the English language from 2016 to 2025. After screening the studies based on inclusion, exclusion, and abstract criteria, 30 research articles were finally selected for critical analysis

Table 1 Landslide Classification System.

Type of Movement		**Type of Material**			**Recommended**
		Soil		**Bed Rock**	
		Predominantly Fine	**Predominantly Fine**		
Falls		Earth fall	Debris fall	Rockfall	Geotextile nailing
Topples		Earth topples	Debris topple	Rock topples	Soil nailing
Slide	Rotational	Earth slump	Debris slump	Rock slump	Earth/rock fill buttress
	Translational	Earth block slide	Debris block slide	Rock block slide	Reinforced earth
Lateral spreads		Earth spread	Debris spread	Rock spread	Check dams
Flows		Earth flow	Debris flow	Rock flow	Check dams
		Soil creep		Deep creep	Deep piles
Complex		A combination of two or more principal types of movement			

Source: (D.J Varnes 1978)

2.1. Pattern of Journal Publication

According to the literature database, more than 50% of the articles were published in the following top ten journals: Journal of Mountain Science, Natural Hazards, Remote Sensing, Bulletin of Engineering Geology and the Environment, Engineering Geology, Geomorphology, Water, Landslides, Applied Sciences, and Environmental Earth Sciences. Out of these ten journals, Bulletin of Engineering Geology and the Environment was the most cited. The maximum percentage of the studies is in China, as shown in Fig. 1.

3. Results

Debris flow susceptibility assessments (DFSA) are among the well-considered research topics worldwide and play a crucial role in infrastructure management and disaster prevention strategies (Liang et al. 2020). Debris flow is a typical non-linear process, and a wide variety of approaches are used to anticipate its occurrence. Based on the literature database, this section provides a holistic review of recent techniques adopted by researchers to assess DFS.

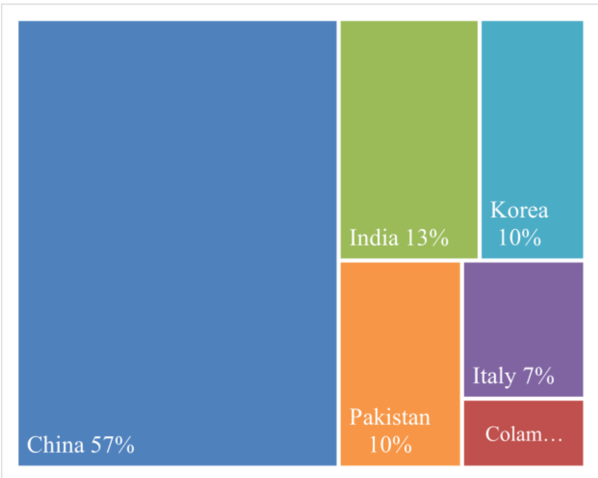

Figure 1. Location of the studies.

3.1 Approaches for Assessing Debris Flow Susceptibility

The database lists 25 techniques for assessing debris flow susceptibility. Selection of techniques

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depending on the purpose of the study, data availability, terrain conditions, etc. (Li et al. 2024b). These techniques were classified into three primary approaches: qualitative, semi-quantitative, and quantitative approaches (Wen et al. 2025). After reviewing, it has been observed that 84% (21 in number) of techniques were applied less than 5 times, indicating that these are less significant than those that are frequently applied in analysis, as summarized in Table 2.

Table 2 Technique Used for Debris Flow Susceptibility Assessment

Variable	Count
Adaptive Boosting (AdaBoost)	2
Analytic Hierarchy Process (AHP)	1
Artificial Neural Network (ANN)	4
Categorical Boosting (CatBoost)	2
Certainty Factor (CF)	1
Convolutional Neural Network (CNN)	4
Decision Tree (DT)	3
Deep Neural Network (DNN)	2
Extreme Gradient Boosting (XGBoost)	6
Frequency Ratio (FR)	2
Fuzzy C-means (FCM)	1
Index of entropy (IoE)	3
Information Gai Ratio (IGR)	1
Information Value (IV)	3
Light Gradient Boosting (LGBoost)	1
Logistic Regression (LR)	10
Naïve Bayes (NB)	1
Natural Gradient Boosting (NGBoost)	1
Principal Component Analysis (PCA)	1
Random Forest (RF)	11
Rock Engineering System (RES)	1
Steady State Infinite Slope Method	1
Support Vector Machine (SVM)	8
TRIGRS	1
Weight of Evidence (WoE)	3

Qualitative Approach: - The qualitative approach represents some of the earliest methods, the physical model (Huang et al. 2022) based on field surveys and landform characteristics, which rely on visual interpretation, field observation, and historical records(Liang et al. 2020). Map combination approach, distribution approach based on the assumption that areas with a high density of past landslides or debris flows are more likely to experience future occurrences. These qualitative approaches are simple, cost-effective, and suitable in small regions with limited data.

Semi-quantitative Approach: - In addition to qualitative approaches, semi-quantitative approaches have been extensively employed in debris flow and landslide susceptibility assessment, as they provide a structured framework that combines expert knowledge with numerical evaluation. Analytic Hierarchy Process (AHP) (Gao et al. 2021a).

Quantitative Approach: -To estimate future projections, the quantitative approach uses statistical, deterministic, and machine-learning techniques to analyze the intrinsic relationships between debris flow and its causative factors. (Cama et al. 2016) . Statistical methods, such as logistic regression, frequency ratios, fuzzy logic, weight-of-evidence, and certainty factor techniques, were employed due to their simplicity and interpretability (Bera et al. 2021). Over the last few decades, deterministic approaches have been developed, focusing on physics-based numerical models such as TRIGRS (Fusco et al. 2021) are particularly valuable for site-specific hazard assessments but often require detailed, reliable field data, which can restrict their regional applicability and make it a challenging task to determine the optimal model. Now, researchers have employed machine learning techniques to establish nonlinear and complex correlations between debris flow occurrences and causative factors (Ming et al. 2025), According to the analysis, the most frequently applied techniques are random forest (RF), logistic regression (LR), support vector machine (SVM), and extreme gradient boosting (XGBoost).

Random Forest: - RF is a highly flexible, robust machine learning algorithm (Si et al. 2020) which can be applied to both regression and classification tasks,

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e ISSN: 2584-2854
Volume: 04 Issue: 03
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as well as feature selection tasks (Wu et al. 2020; Zhou et al. 2024; Wen et al. 2025). By combining and training multiple decision tree models to enhance the predictive performance (Li et al. 2024a; Ming et al. 2025). Each tree is constructed using a randomly selected subset to reduce the risk of overfitting (Gao et al. 2024). Specifically:

- The random subset ensures an independent tree for classification or regression to boost the generalization and accuracy of the model.
- The model handles high-dimensional data without feature selection

Logistic Regression: - Logistic regression is a logarithmic model fitted to the maximum likelihood method (Cama et al. 2016), which is used to analyze one or multiple regression variables (Cao et al. 2023). The LR model has been widely used to evaluate DFS due to its high reliability and robustness. It is widely used for the classification task to forecast a solution based on probability (Aslam et al. 2023) . It transforms the binomial categorical dependent variables into a logit variable, which describes the relationship between the occurrence of debris flow (where 0 indicates absence and 1 indicates presence). The standard logistic regression formula is equation 1 (Vargas-Cuervo et al. 2019; Li et al. 2024b).

$$P = \frac{1}{1+ e^{-z}} \quad (1)$$

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n \quad (2)$$

$$\mathrm{P} = \frac{e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots\beta_n X_n}}{1+e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots\beta_n X_n}} \quad (3)$$

Where P is the probability, Z is the linear fitting equation, β0, β1, β2…βn are the LR coefficients, and ($X1$, $X2$…, Xn) Influence factors.

Support Vector Machine: - Based on statistical learning theory and the idea of structural risk minimization, Vapnik proposed the support vector machine (SVM) in the 1990s (Qing et al. 2020) . It is a type of supervised machine learning classifier that performs binary classification and regression tasks. The primary objective of SVM is to identify the ideal hyperplane that separates data points of various classes with the maximum margin, as defined by equation 8, thereby minimizing classification error and improving model robustness (Qing et al. 2020; Huang et al. 2022). When the dataset is not linearly separable, SVM employs four kernel functions: linear functions (LF), sigmoid functions (SF), radial basis functions (RBF), and polynomial functions (PF). Among the four types of kernel functions, the RBF is the most adaptable for classifying data with complex characteristics (Gao et al. 2021a) .

$$y_i[w \times x_i + b] \geq 1 - \delta_i, \delta_i > 0 \quad (4)$$

$$LF : k\,(x, y) = x^T y + c \quad (5)$$

$$SF : k\,(x, y) = \tanh(ax^T + c) \quad (6)$$

$$RBF : k\,(x, y) = \exp(-\gamma||x - y||^2) \quad (7)$$

$$PF : k\,(x, y) = (ax^T y + c)^2 \quad (8)$$

In equation 8, x_i (i = 0, 1, 2, 3, …, n) is the chosen causative factor, y_i (i = 0, 1, 2, 3 …, n) is the variable in the training set (1 represent debris flow, 0 represent non-debris flow), w representing the hyperplane direction, b represents displacement, and δ_i is the relaxation factor.

Extreme gradient boosting (XGBoost):- In ensemble machine learning methods, it is one of the most efficient gradient boosting algorithms, giving the best results in supervised machine learning tasks such as classification, regression, and ranking, with minimal computational resources (Chen et al. 2016; Dash et al. 2024). The main advantage of this technique is that it is very simple to implement and can manage big datasets. The primary objective of employing this technique is to solve the overfitting problem by minimizing the loss function using gradient descent (Qing et al. 2020). The maximum tree depth, number of boosting iterations, shrinkage, minimum loss reduction, and subsamples are some of the hyperparameters.

Conclusion

Debris flow has become one of the recognized natural disasters in countries such as China, Italy, India, Pakistan, and Korea, posing a constant risk to infrastructure and society due to its unpredictability, rapid movement, and long-distance runout distribution. To prevent or minimize damage from debris flows, it is crucial to act before the event occurs. The researcher employed several approaches to produce a debris flow susceptibility assessment, facilitating a safer strategic plan to mitigate debris flow hazards. However, the current context still has shortcomings, primarily in the selection of appropriate modeling techniques and their validation methods. Therefore, we present a holistic review of recent techniques adopted in debris flow susceptibility assessments.

In this review, we primarily focused on the 30 research articles published between 2016 and 2025 for the following combination of keywords (Debris flow + Susceptibility). Upon reviewing the literature database, it has been observed that most studies (57%) are conducted in China, while the rest of the world has few studies. Over the last few years, the Indian subcontinent has experienced numerous debris flows across almost all landslide-prone areas. Therefore, future debris flow studies and mapping should consider all those previously untouched landslide-prone regions. Due to advances in computer technology, debris flow susceptibility assessment (DFSA) has gradually shifted from qualitative to quantitative approaches. In the quantitative approach, machine learning techniques have also received extensive attention because they can more accurately describe the nonlinear relationship between debris flow occurrence and causative factors. The most reliable techniques are random forest (RF), logistic regression (LR), Support vector machine (SVM), and Extreme gradient boosting (XGBoost). Talking about the validation of the technique/model, where ROC and ACC are the ones that are used the most in the studies. This highlights the scope for exploring other validation techniques. It is also noted that most studies employed a single approach, rather than a mixed or multiple approach, which is a good option for future studies. This review database helps scientists and researchers working in debris flow susceptibility assessment for future studies.

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