Review Paper:

A review paper on Landslide Susceptibility Mapping using Geospatial Technology and Machine Learning Techniques

Kollipara V. Ramana[1*], Chitikela N. Vara Laxmi[2], Kodimela Anil[3], Jampana N.S. Suryanarayana Raju[4] and Parupalli Sridhar[5]

1. Civil Engineering Department, Lakireddy Balireddy College of Engineering (A) Mylavaram, INDIA
2. School of Spatial Information Technology, IST, JNTUCEK, Kakinada, INDIA
3. Department of Civil Engineering, Bapatla Engineering College, Bapatla, INDIA
4. Civil Engineering, S.R.K.R. Engineering College, Bhimavaram, INDIA
5. Water Resources Development Division, ESCI, INDIA

*laxman.satya51@gmail.com

Abstract

Landslides are among the most frequent and devastating natural hazards, often resulting in significant loss of life, property damage and disruption to infrastructure and agriculture. As a serious geo-environmental issue, landslides present complex challenges for both prediction and control. Landslide Susceptibility Mapping (LSM) has emerged as a valuable tool for identifying high-risk areas and supporting disaster mitigation strategies. In recent years, numerous researchers have applied geospatial technologies in combination with statistical methods and machine learning techniques to enhance the accuracy of LSM. Review papers play a crucial role in helping researchers and academicians to identify knowledge gaps and to evaluate existing methodologies by synthesizing findings from previous studies. This review is based on a comprehensive collection of research studies focused on LSM using geospatial and machine learning approaches, aiming to provide insights into current practices and future research directions. The analysis reveals that machine learning models, particularly Random Forest (RF), Support Vector Machine (SVM) and Gradient Boosting Decision Trees (GBDT), consistently outperform traditional statistical methods like Logistic Regression (LR) and Frequency Ratio (FR) in predictive accuracy.

Studies have reported AUC values exceeding 0.95 for RF models, indicating excellent predictive capabilities in various geographical contexts. Furthermore, the integration of Bayesian optimization techniques has enhanced model performance, with improvements in prediction accuracy up to 7% for GBDT models. Hybrid models, combining algorithms such as SVM with metaheuristic optimization methods, have also demonstrated superior performance, effectively capturing complex, nonlinear relationships inherent in geospatial data. In conclusion, the adoption of advanced machine learning and hybrid models has significantly improved the accuracy and reliability of LSM. These methodologies offer robust tools for disaster risk management, enabling more effective identification of high-risk areas and informing mitigation strategies. Future research should focus on enhancing model interpretability and integrating real-time data to further refine susceptibility assessments and support proactive landslide risk reduction efforts.

Keywords: Statics Model, Machine learning Models, Geospatial Technology.

Introduction

Landslides are among the most common natural hazards, causing significant loss of life and economic damage[84]. They occur when gravitational forces overcome the resisting strength of earth materials on a slope[88]. As severe geo-hazards, landslides extensively impact both the built environment and natural ecosystems[30], damaging infrastructure such as highways, pipelines and buildings, resulting in over 400 deaths annually worldwide[32]. Globally, landslides are responsible for substantial damage, causing an estimated 56,000 deaths across 4,900 fatal events between 2004 and 2016, resulting in approximately $20 billion economic losses annually.

In India, landslides represent a major hazard, accounting for about 18% of global landslide incidents during the same period. Approximately 12% of India's land area is vulnerable to landslides, particularly in the Himalayan region and the Western Ghats. Kerala, located in the Western Ghats, is one of the most landslide-prone states, recording 2,239 landslides between 2015 and 2022, which account for nearly 59.2% of all reported landslides in India during that period. In 2024, the Wayanad district experienced a devastating landslide event resulting in significant displacement, infrastructure damage and economic losses, highlighting the increasing vulnerability of the region to such geo-environmental hazards.

It is asserted that although landslide prediction remains a complex process due to variations across both space and time, it is possible to categorize regions into homogeneous zones based on landslide probability. By analyzing geological, geomorphological, hydrological and climatic factors, areas prone to similar levels of landslide risk can be systematically identified. This zoning approach enables better risk management, targeted mitigation efforts and informed land-use planning in vulnerable regions.

In recent years, the increased availability of Geographic Information Systems (GIS) and Remote Sensing (RS) data has opened new avenues for landslide analysis and risk reduction[18,20]. The advanced progress of GIS technologies offers an effective means to systematically collect, manage, organize, extract and analyze local terrain and climatic conditions[60]. Modern machine learning (ML) algorithms, in particular, leverage the comprehensive information stored in GIS databases to create highly accurate mapping correlations that predict landslide susceptibility[10,11].

Since the early 2000s, the application of machine learning algorithms for GIS-based landslide modeling has gained considerable momentum[4,5]. To assess landslide susceptibility, researchers have traditionally adopted three major categories of techniques: heuristic, statistical and deterministic methods[23]. Due to their ability to handle nonlinear relationships and multivariate datasets which are common in landslide studies, machine learning models including decision trees, support vector machines, random forests and deep learning techniques, have become increasingly popular and effective tools[49]. These advanced approaches significantly enhance the accuracy and reliability of landslide hazard assessments.

Effective GIS-based statistical analyses require comprehensive data on past landslides, preparatory factors and triggering conditions. Identifying and assessing landslide-prone areas are critical for developing effective strategies to prevent or mitigate potential damage. This process greatly benefits from the use of remote sensing and GIS-derived thematic layers.

Key layers commonly employed in landslide susceptibility mapping include Digital Elevation Model (DEM), elevation, slope, aspect, plan curvature, profile curvature, lithology, geological age, faults, roads, rivers, Stream Power Index (SPI), Sediment Transport Index (STI), Topographic Roughness Index (TRI), Topographic Wetness Index (TWI), land cover, Normalized Difference Vegetation Index (NDVI) and precipitation. These factors are widely recognized as essential conditioning parameters and are frequently used as input layers in various studies. The number and type of layers utilized vary across studies depending on data availability and specific research objectives. For instance, Rong et al[70] and Hong et al[32,33] used 18 layers, Wei et al[85] included 12 layers, Shano et al[76,77] used 8 layers, Jennifer et al[34] considered 13 layers and Azarafza et al[10,11] employed 17 layers in their respective analyses.

Despite variations in the selection of conditioning factors across different studies, certain thematic layers such as slope, lithology, land use/land cover (LULC), drainage density and proximity to faults, are widely recognized and utilized in landslide susceptibility mapping. The choice of these layers often depends on the specific objectives of the study and the availability of data as evidenced by various researchers listed in table 1.

Methodology: In the realm of Landslide Susceptibility Mapping (LSM), a diverse array of computational models has been employed, broadly categorized into Statistical Methods, Artificial Intelligence/Machine Learning (AI/ML) Methods and Hybrid Methods. Statistical approaches, such as Logistic Regression (LR) and Frequency Ratio (FR), have been included in LSM due to their simplicity and interpretability. These methods facilitate the quantification of relationships between landslide occurrences and conditioning factors, offering insights into the contributing variables. However, their linear nature may limit the capture of complex, nonlinear interactions inherent in geospatial data.

To address these complexities, AI/ML techniques have gained prominence. Models like Support Vector Machines (SVM), Random Forests (RF) and Artificial Neural Networks (ANN) excel in handling high-dimensional datasets and modeling intricate, nonlinear relationships between multiple conditioning factors and landslide occurrences. For instance, RF models have demonstrated high accuracy in various studies, effectively managing overfitting and providing robust predictions.

Similarly, SVMs are renowned for their generalization capabilities, especially in scenarios with limited training data. These AI/ML methods leverage historical landslide inventories and conditioning factors to learn patterns and predict susceptibility with enhanced precision. The selection and integration of these methodologies in this study are informed by the specific objectives and data availability, aiming to enhance the accuracy and reliability of the landslide susceptibility maps produced. The models utilized by various researchers, as detailed in table 2, underscore the diverse methodological approaches adopted in the field of LSM.

Discussion

Here we discuss the results of various researchers concerning Landslide Susceptibility Mapping (LSM) models. Rong et al[70] conducted a study comparing Random Forest (RF) and Gradient Boosting Decision Tree (GBDT) models, both before and after Bayesian optimization. The results demonstrated that all proposed models achieved high accuracy suitable for LSM applications. Notably, the performance of RF surpassed that of GBDT without Bayesian optimization. However, after applying Bayesian-optimized hyperparameters, the prediction accuracy of RF and GBDT models improved by 1% and 7% respectively with the Bayesian-optimized GBDT model emerging as the most effective among the four models evaluated.

Four bivariate models were compared: Evidential Belief Function (EBF), Weights of Evidence (WoE), Shannon Entropy (SE) and Frequency Ratio (FR). The Area Under the Curve (AUC) results indicated success rates of 0.80, 0.86, 0.84 and 0.85 for EBF, WoE, SE and FR respectively. In terms of prediction rates, WoE achieved 0.84, followed by FR at 0.83, SE at 0.82 and EBF at 0.79. Consequently, the WoE model, having the highest AUC, was identified as the most accurate method among the four implemented for identifying regions at risk of future landslides. Wei et al[84] evaluated four ensemble models: Extreme Gradient Boosting (XGBoost), Bagging, Gradient Boosting Decision Trees (GBDT) and Adaptive Boosting (AB).

Table 1
Data sets considered by various researchers

Layers	**Resolution**
DEM Downloaded from websites[30-33,35,48,76,77,84,86]	12.5m
	30m
	25m
Elevation[10,11,32-34,70-72,76,77,85,86]	
Slope[10,11,32-34,70-72,76,77,85,86]	
Aspect[32-34,70-72,76,77,85,86]	
Plan curvature[32,33,70-72]	
Profile curvature[10,11,32,33,70-72,85,86]	
Lithology[32,33,70-72,85,86]	
Geological age[34,70-72,76,77]	
Faults[10,11,32,33,70-72,76,77,85,86]	
Roads[10,11,32-34,70-72,85,86]	
Rivers[10,11,32,33,70-72]	
SPI[32-34,70-72]	
STI[32,33,70-72]	
TRI[32,33,70-72]	
TWI[32-34,70-72,85,86]	
Landcover[32-34,70-72,76,77,85,86]	
NDVI[32,33,70-72,85,86]	
Precipitation[32-34,70-72,85,86]	

Table 2
Various methodologies considered by several researchers

Category	**Techniques/Methods**
Statistical Methods	Evidential Belief Function (EBF)[19,21,24,46,87]
	Weights-of-Evidence (WoE)[9,12,13,50,58,68]
	Likelihood Ratio (LR)[36,39,40,81]
	Frequency Ratio (FR)[41,43,61,75,91]
	Information Value (InV) Model [1,74,78,88]
	Logistic Regression (LR)[37,45,80,90]
	Discriminant Analysis[8,26]
	Bayesian Probability[14,27,77]
	Certainty Factor (CF)[79,83]
	Analytic Hierarchy Process (AHP)[1,25,56,57,62,63,92]
AI/ML Methods	Random Forest (RF)
	Decision Trees (DT)[87]
	Support Vector Machine (SVM)[28,60]
	Naïve Bayes (NB)[42,59]
	Bayesian Networks (BN)[17,70-72,82]
	Artificial Neural Networks (ANNs)[16,47]
	Maximum Entropy (MaxEnt)[15,65]
Other/Hybrid Methods	Fuzzy Logic [2,3,51,66,67,94]
	Index-based Methods
	Data Overlay Techniques
	Expert Systems and Knowledge-Driven Approaches

All models achieved an AUC greater than 0.8, indicating their suitability for accurate landslide susceptibility mapping. Among them, the XGBoost model demonstrated the best performance, with a sensitivity of 92.86%, specificity of 90.00% and accuracy of 91.38%. The Bagging model followed with a sensitivity of 89.29%, specificity of 86.67% and accuracy of 87.93%, outperforming GBDT and AB models. Jennifer et al[34] applied Frequency Ratio (FR) and Logistic Regression (LR) models to assess landslide susceptibility in the Nilgiris District, Tamil Nadu, India.

The results indicated that approximately 8.78% and 23.22% of the study area were classified as very high landslide susceptibility zones based on the FR and LR models respectively. Mersha and Meten[50] conducted a study in the Simada area, northwestern Ethiopia, utilizing FR and WoE models. The predictive rates achieved were 88.2% for the FR model and 84.8% for the WoE model, indicating that the FR model exhibited better performance in landslide susceptibility mapping. Deng et al employed the r.slopeunits method to extract slope units and applied the Information Value-Random Forest (IV-RF) model for landslide susceptibility assessment. Their results showed that under optimal parameters, the model achieved an AUC of 0.905 and an F1 score of 0.908, indicating high internal homogeneity and external heterogeneity in the slope units. The model's performance, validated through AUC-ROC and statistical parameters such as precision, recall, accuracy and F-score, demonstrated a good degree of adjustment and acceptable predictive capacity.

Conclusion

Based on the comparative analysis of various landslide susceptibility mapping (LSM) models, it is evident that while traditional statistical methods like Frequency Ratio (FR) and Logistic Regression (LR) provide foundational insights, they often fall short in capturing the complex, nonlinear relationships inherent in geospatial data. Machine learning (ML) models, particularly Random forest (RF) and Gradient Boosting Decision Trees (GBDT), have demonstrated superior predictive capabilities. Notably, the integration of Bayesian optimization techniques has further enhanced the performance of these models, with studies indicating improvements in prediction accuracy by up to 7% for GBDT models. These advancements underscore the importance of model optimization in achieving more accurate and reliable LSM outcomes.

Furthermore, the emergence of hybrid models that combine the strengths of different algorithms, has shown promising results in LSM applications. For instance, the integration of Convolutional Neural Networks (CNN) with RF and Cat boost has led to improved accuracy and robustness in susceptibility mapping. These hybrid approaches effectively address the limitations of individual models by capturing both spatial features and complex decision boundaries. As the field progresses, the adoption of such ensemble and hybrid methodologies is likely to play a pivotal role in enhancing the precision and applicability of LSM, thereby contributing to more effective disaster risk management and land-use planning strategies.

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