

Landslide Prediction Using Machine Learning and Gis-Based Approaches - A Comprehensive Review

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Abstract- – Landslides are a serious natural hazard that cause major social, economic, and environmental damage around the world. To reduce their impact, it's crucial to accurately predict where they might happen. In recent years, combining Geographic Information Systems (GIS) with Machine Learning (ML) has greatly improved landslide prediction and mapping. GIS helps organize and visualize complex spatial data, while ML can find hidden patterns between the factors that lead to landslides. This review looks at different ML models used for landslide prediction, including Logistic Regression, Support Vector Machines, Random Forest, as well as ensemble methods like Bagging, Boosting, and Stacking. It also explores newer Deep Learning approaches. We discuss common challenges such as limited data, difficulty in understanding models, and how to handle changing conditions. Finally, we highlight future directions like Explainable AI (XAI) and real-time monitoring. By bringing together findings from recent studies, this review provides insights into what's working, what's not, and how ML and GIS can help improve landslide risk management.

Index Terms- Landslide Prediction, Landslide Susceptibility Mapping (LSM), Machine Learning (ML), Geographic Information Systems (GIS), Remote Sensing (RS), Ensemble Methods, Deep Learning (DL), Hazard Assessment, Risk Mitigation, Explainable AI (XAI).

I. INTRODUCTION

Landslides are one of the most destructive natural hazards, causing serious economic losses, environmental damage, and human fatalities worldwide. Triggered by both natural and human-induced factors such as heavy rainfall, earthquakes, slope instability, and unplanned development landslides are a major threat, especially in hilly and mountainous regions. Traditional methods of assessing landslide risk have mostly relied on empirical mapping and expert judgment. While these approaches have value, they often lack spatial accuracy and struggle to provide timely insights in fast-changing landscapes. With climate change driving more extreme weather and human settlements expanding into high-risk areas, the need for accurate and timely landslide prediction is more urgent than ever.

Accurate landslide prediction plays a vital role in reducing risk, supporting urban planning, infrastructure development, and disaster preparedness. Reliable susceptibility maps can guide early warning systems and help prioritize areas for intervention, ultimately reducing vulnerability and economic disruption. In regions with limited resources or monitoring systems, predictive models become even more critical for proactive decision-making and building disaster resilience.

However, making accurate predictions isn't simple it requires handling complex terrain, diverse data sources, and a range of geological and hydrological factors.

Recent advancements in machine learning and Geographic Information Systems have greatly improved landslide susceptibility mapping. Machine learning models like Random Forest, Support Vector Machines, and Convolutional Neural Networks have shown strong predictive power and the ability to capture complex, nonlinear relationships between landslide factors and occurrences. At the same time, Geographic Information Systems offer a powerful platform for mapping, integrating environmental variables, and analysing terrain. Together, machine learning and Geographic Information Systems provide a data-driven, scalable approach that can adapt to different landscapes. The growing availability of high-resolution remote sensing data has further boosted model inputs, allowing for more precise spatial predictions.

The main goal of this paper is to review and synthesize the current methods used for landslide prediction with machine learning and Geographic Information Systems. Specifically, this study aims to:

- Explain the core concepts and methods behind landslide susceptibility analysis.
- Evaluate how different machine learning techniques perform when combined with Geographic Information Systems data.
- Identify key challenges and limitations in existing approaches.
- Discuss the practical uses, scientific impact, and future directions for this growing research area.
- Highlight the importance of data quality, availability, and preprocessing in improving model performance.
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II. BASIC DEFINITIONS AND CONCEPTS

Landslides: Definition and Classification

A landslide is the movement of a mass of rock, debris, or earth down a slope, driven by gravity. It's a complex natural process that can be triggered by events like heavy rainfall, earthquakes, volcanic eruptions, or human activities such as deforestation and construction. Landslides are typically classified based on the type of material involved and how the movement occurs. According to the widely used Varnes classification, there are five main types of landslides: falls, topples, slides, flows, and spreads. Each type involves different mechanisms and factors that need to be considered when creating prediction models. Landslides can occur suddenly or develop slowly over time, depending on slope stability. Early warning systems and slope monitoring technologies are crucial in reducing landslide impacts. Landslides also vary greatly in size, from small slope failures to large-scale movements covering entire hillsides.

Landslide Susceptibility, Hazard, and Risk

Landslide susceptibility describes how likely a landslide is to occur in a specific area based on local conditions and factors that could trigger it, without considering when it might happen. It's a measure of spatial probability, often calculated using statistical or machine learning methods. Landslide hazard takes susceptibility a step further by including the chance of the landslide happening over a certain period. Landslide risk adds another layer by considering the potential consequences—like loss of life, economic costs, or damage to infrastructure. In simple terms, risk is the combination of hazard, vulnerability, and exposure. These concepts help prioritize areas for mitigation and planning. Risk assessments also guide land-use decisions and emergency preparedness strategies. Effective risk management depends on continuously updated data and community awareness programs.

Overview of Machine Learning in Geosciences

Machine learning is a field of artificial intelligence that focuses on creating algorithms that can learn from data and make predictions or decisions without being explicitly programmed. In geosciences, machine learning has become a powerful tool for analysing the complex and often nonlinear relationships between environmental factors. Supervised learning algorithms like Random Forest, Support Vector Machines, Logistic Regression, and Gradient Boosting Decision Trees are commonly used for modelling landslide susceptibility. More recently, deep learning methods like Convolutional Neural Networks and Recurrent Neural Networks have been applied for tasks like image classification and modelling changes over time. These models can handle large, complex datasets with many variables, making them well-suited for predicting geohazards like landslides. Machine learning can also automate feature extraction from satellite images, saving time and resources. Ensemble approaches that combine multiple algorithms are increasingly popular for improving predictive accuracy. Open-source tools and cloud computing platforms are expanding access to machine learning in geoscience research.

GIS and Remote Sensing Basics

Geographic Information Systems (GIS) are digital platforms used to capture, manage, analyse, and visualize geographic or spatial data. In landslide prediction, GIS helps combine different data layers—such as slope, elevation, rock type, land use, rainfall, and distance from faults—into a single framework. These layers can be processed as raster or vector data to serve as inputs for machine learning models. Remote sensing involves gathering information about the Earth's surface from satellites or aircraft. It provides valuable data such as vegetation indices, land cover, soil moisture, and rainfall measurements at various scales. By combining GIS and remote sensing, researchers can create detailed, large-scale models of areas prone to landslides. GIS tools also enable real-time mapping and updates following landslide events. Remote sensing helps detect subtle changes in terrain or vegetation that may signal slope instability. Together, GIS and remote sensing support monitoring, early warning, and rapid response systems for landslide management.

III. METHODOLOGY

Data Collection and Preprocessing

Landslide susceptibility modelling depends greatly on the quality and variety of both spatial and non-spatial data. Common sources include geological maps, topographic maps, satellite images, meteorological records, and historical landslide inventories. These datasets are collected from government agencies, remote sensing platforms like Sentinel-2 and Landsat 8, and global databases such as NASA Earth data and USGS Earth Explorer. Preprocessing

involves standardizing coordinate systems, converting raw data into raster formats, reclassifying thematic layers, handling missing data, and normalizing features to ensure consistency across sources. Historical landslide locations are often geo-referenced using GPS and serve as the dependent variable in supervised machine learning models. Data augmentation techniques may be used to increase the sample size. Visual inspection and outlier detection are performed to ensure data integrity. Metadata documentation is also maintained for transparency and reproducibility.

Selection of Conditioning Factors

Conditioning factors also called causal or predictive factors are key to identifying landslide-prone areas. These factors include elevation, slope angle, aspect, curvature, lithology, soil type, land use/land cover, rainfall, distance to roads, distance to rivers, and distance to faults. Their selection is based on expert knowledge, correlation studies, and feature importance scores from preliminary models. Techniques like Recursive Feature Elimination, Information Gain, and Pearson Correlation Coefficients are commonly used to eliminate redundant or less significant variables. Sensitivity analysis is carried out to understand the impact of each factor. Domain-specific thresholds are sometimes applied to discrete continuous variables. Factor interactions are explored to identify synergistic effects contributing to landslide susceptibility.

ML Models Used (Svm, Rf, Xg Boost, Cnn)

A range of machine learning algorithms is used for landslide susceptibility mapping:

Support Vector Machine (SVM): Effective for high-dimensional data and nonlinear classification using kernel functions.

Random Forest (RF): An ensemble decision tree method known for high accuracy and resistance to overfitting.

eXtreme Gradient Boosting (XG Boost): A scalable, efficient gradient boosting algorithm with regularization, widely used for structured data.

Convolutional Neural Networks (CNN): Deep learning models suited for extracting spatial features from remote sensing images and digital elevation models.

Studies have shown that hybrid and ensemble models often perform better than individual models, especially when combined with spatial analysis tools. Hyperparameter tuning is performed through grid search or Bayesian optimization to improve performance. Feature scaling and transformation techniques may be applied to enhance model input quality. Comparative analysis among models is conducted to select the optimal algorithm for specific study areas.

GIS-Based Spatial Analysis

GIS provides the spatial framework for integrating various data layers, analysing terrain, and visualizing susceptibility maps. Spatial interpolation methods like Inverse Distance Weighting or Kriging are used to estimate variables such as rainfall or soil moisture at locations without direct measurements. Digital Elevation Model derivatives like slope, aspect, and curvature are generated using tools in software like ArcGIS or QGIS. The final landslide susceptibility index is created by overlaying the weighted conditioning factors, and susceptibility zones are classified into categories such as very low, low, moderate, high, and very high using methods like natural breaks or quantile classification. Geoprocessing models are automated to streamline repeated analysis. Map algebra techniques are used to derive composite indices. Spatial autocorrelation analysis is performed to assess the clustering of landslide events.

Model Validation and Evaluation Metrics

Model performance is evaluated using statistical and spatial accuracy metrics. The most common is the Area Under the Receiver Operating Characteristic Curve, which measures the balance between true positive and false positive rates. Other metrics include Precision, Recall, F1-score, Kappa coefficient, and Overall Accuracy. Validation methods may involve k-fold cross-validation, confusion matrix analysis, and testing with independent datasets. Bootstrapping techniques can be employed to estimate confidence intervals. Spatial validation is carried out by dividing the study area into training and testing zones. Error propagation analysis is sometimes conducted to assess uncertainty in predictions.

IV. IDENTIFIED CHALLENGES

Data Imbalance and Inconsistency

One of the most pressing issues in landslide prediction is data imbalance where non-landslide instances far outnumber landslide occurrences. This skewed distribution often leads to models biased toward predicting the majority class, resulting in low sensitivity and poor generalization to real-world conditions. Furthermore, landslide inventories often vary in spatial resolution, completeness, and quality, especially across different countries and terrains. Variability in data sources (e.g., satellite-derived vs. ground-measured rainfall) introduces inconsistencies that hinder model training and reproducibility. Additional challenges arise from missing or inaccurate historical landslide records. Differences in data acquisition periods further complicate integration. Harmonizing multi-source datasets requires intensive preprocessing and domain expertise. This imbalance can also affect threshold setting in classification models. Manual re-labelling or data augmentation techniques are often necessary to improve minority class representation.

Overfitting and Generalization

Machine learning models, particularly those with high complexity like Random Forests and Deep Neural Networks, are prone to overfitting—where models memorize training data rather than learning generalizable patterns. Overfitting becomes more likely when using small or highly correlated datasets, leading to excellent training accuracy but poor performance on unseen areas. Regularization methods, cross-validation, and ensemble techniques are commonly used to address this, but trade-offs between bias and variance remain a persistent issue. Additionally, noise in input variables can exacerbate overfitting risks. Limited availability of diverse training samples restricts model robustness. Model pruning and dimensionality reduction are explored to mitigate these effects. Data augmentation strategies and dropout layers are also being implemented in deep learning to improve generalization. However, selecting optimal hyperparameters remains challenging.

Limited Transferability

Landslide models are often location-specific, meaning that models trained in one geographic region may not perform well in others due to varying geological, climatic, and anthropogenic factors. The lack of standardized conditioning factor sets, differences in terrain morphology, and regional variance in triggering mechanisms limit the ability to create globally applicable models. This poses a barrier to model deployment in regions lacking localized data or technical capacity. Transfer learning approaches are being explored to adapt models across regions. Domain adaptation remains underutilized in geospatial contexts. Cross-region validation studies are still relatively rare but necessary. Incorporating global datasets may improve scalability but risks losing local specificity. Creating hybrid models combining regional and global features is a potential pathway.

Feature Selection and Model Explainability

While ML models can ingest large volumes of data, identifying the most relevant conditioning factors remains a challenge. Redundant or irrelevant features can lead to increased noise and reduced model accuracy. Moreover, explainability is often sacrificed in favour of predictive power particularly in black-box models like CNNs or XG Boost making it difficult for practitioners to interpret model outputs or validate them against expert geological knowledge. Model-agnostic interpretability tools like SHAP and LIME are beginning to address this, but are not yet widely adopted in geoscience workflows. Visualization of feature contributions is still limited. Stakeholder trust in model outputs requires interpretable results. Regulatory frameworks may demand transparency for operational use. Integrating expert judgment into feature selection workflows may enhance both interpretability and acceptance.

Integration with Real-Time Systems

Most current ML-based landslide susceptibility models operate on static data and offline processing. This makes it difficult to integrate them into real-time early warning systems that require dynamic inputs like rainfall forecasts or seismic readings. The lack of temporal modelling capabilities in traditional ML approaches further impedes real-time applicability. Deep learning models with spatiotemporal capabilities are a promising direction but require large datasets and computational resources for deployment. Moreover, system interoperability and access to timely sensor data remain major barriers in low-resource settings. Communication infrastructure challenges also affect real-time data streaming. Latency issues can compromise early warning effectiveness. Integration with mobile or cloud-based platforms is an emerging solution. Stakeholder coordination is critical to ensure actionable alerts. Validation of real-time predictions under operational conditions remains underexplored.

V. IMPACT ANALYSIS

Scientific Contributions

The integration of machine learning (ML) with GIS in landslide prediction has significantly advanced the geospatial and earth sciences. These approaches have contributed to the development of data-driven susceptibility models capable of uncovering complex, nonlinear relationships between terrain factors and landslide occurrences. The use of deep learning models such as Convolutional Neural Networks (CNNs) and hybrid ensemble techniques has further improved prediction accuracy and spatial resolution. Moreover, explainable AI methods are increasingly being applied to interpret feature importance and decision boundaries, enhancing transparency in geohazard modeling.

These scientific developments have laid the groundwork for next-generation hazard monitoring systems. Interdisciplinary collaborations have also emerged between geologists, data scientists, and environmental planners. The field has witnessed a surge in peer-reviewed publications, contributing to global knowledge sharing. Transfer learning and automated feature extraction are now being investigated to extend models beyond regional boundaries.

Practical Applications

ML-GIS integrated models are now widely applied in hazard mapping, urban planning, infrastructure design, and emergency response systems. Governments and local authorities use susceptibility maps to guide the placement of critical infrastructure, assess the vulnerability of road networks, and implement zoning laws that discourage construction in high-risk areas. In areas with limited resources, these models serve as a low-cost yet effective tool

for rapid landslide assessment using remotely sensed data. Mobile and web-based GIS platforms also allow dissemination of risk information to communities and responders in near-real time.

Disaster response teams rely on real-time risk alerts for rapid mobilization. Engineering firms integrate susceptibility models into the planning of highways, dams, and pipelines. Environmental monitoring agencies are leveraging these tools to track changes in slope stability over time. These models also assist insurance companies in assessing risk zones and planning premiums.

Influence on Policy and Planning

Landslide susceptibility assessments powered by ML have begun influencing national and regional disaster risk reduction (DRR) frameworks. Countries like India, Nepal, and Indonesia have integrated such models into their geohazard management strategies (Ullah et al., 2022). The World Bank and UNDP have also encouraged the adoption of AI-driven approaches for sustainable development and resilient infrastructure planning. Predictive risk mapping enables more proactive policy interventions, such as preemptive evacuations and land-use regulation, thereby reducing economic and human losses during landslide events (Ghorbanzadeh et al., 2022).

Policy-makers now have access to evidence-based tools for prioritizing funding and interventions. ML-driven risk scores influence the designation of disaster-prone zones in urban master plans. National databases and portals are incorporating machine learning outputs to enhance transparency and public access to hazard information.

Societal Benefits and Risk Mitigation

The societal impact of accurate landslide prediction models is substantial. By forecasting landslide-prone areas, these systems save lives, minimize economic disruption, and protect environmental resources. Community-level awareness programs can use ML-generated maps to educate populations on local risks, enhancing preparedness. Integration into early warning systems, though still in development, promises real-time alerts based on triggering events like intense rainfall or seismic activity. Overall, these technologies contribute to the broader goals of climate adaptation, sustainability, and disaster resilience.

Public trust in scientific forecasting has increased with accessible risk visualizations. Educational curricula and public workshops increasingly include geohazard awareness informed by ML tools. These systems also help allocate emergency relief more efficiently by identifying the most vulnerable zones in advance.

VI. FUTURE SCOPE

Use of Deep Learning and Hybrid Models

Future advancements in landslide prediction will emphasize the integration of deep learning and hybrid modeling approaches. Convolutional Neural Networks, Recurrent Neural Networks, Graph Neural Networks, and Transformer-based architectures have shown remarkable capabilities in capturing complex spatial temporal interactions across diverse terrains. These models can automatically learn hierarchical features from multimodal data, reducing reliance on manual feature engineering. Hybrid models that combine machine learning techniques with deep learning layers or merge physically based models with data driven techniques are gaining popularity for their improved predictive accuracy and adaptability across regions. There is also growing interest in explainable deep learning frameworks aiming to balance predictive power with interpretability to support practical deployment in hazard management.

Real Time Forecasting and IoT Integration

The fusion of Internet of Things technologies with machine learning represents a promising pathway for achieving real time landslide forecasting. Deployment of low cost distributed sensor networks monitoring rainfall, soil moisture, pore water pressure, and seismic signals enables continuous data streams into predictive algorithms. Edge computing and 5G networks can support decentralized onsite data processing reducing latency in high, risk zones. Additionally integrating real time satellite imagery and weather data into dynamic models will improve early warning accuracy. Future systems may also employ automated alert dissemination via mobile apps or sirens improving community level preparedness and response.

Advances in Remote Sensing and Geospatial Data

Emerging remote sensing platforms such as high resolution optical satellites synthetic aperture radar UAVs and LiDAR are expanding opportunities for detailed terrain mapping and landslide monitoring. These technologies enable frequent updating of Digital Elevation Models land use and land cover maps and deformation tracking through InSAR analysis. Combining multi temporal and multi sensor datasets enhances the detection of subtle slope movements that may precede catastrophic failures. Future directions may explore fusing optical radar and hyperspectral imagery with machine learning pipelines for improved landslide susceptibility mapping and post event damage assessment.

Interdisciplinary Research and Stakeholder Engagement

Future progress in landslide prediction will require interdisciplinary collaboration between geoscientists data scientists engineers social scientists and policymakers. Incorporating socioeconomic variables into susceptibility models will allow for vulnerability mapping and prioritization of mitigation efforts in at risk communities. Co developing predictive tools with local stakeholders ensures alignment with practical needs and improves adoption in decision

making processes. Moreover establishing international partnerships can foster standardized datasets shared benchmarks and open access platforms for global landslide monitoring. Ethical considerations such as data privacy and equitable access to early warning technologies will also need greater attention.

Integration of Climate Change Projections

An important emerging direction is integrating climate change projections into landslide susceptibility models. Changes in precipitation patterns intensity of extreme weather events and glacier retreat are altering slope stability dynamics worldwide. Future models should incorporate downscaled climate data and scenario analysis to assess potential shifts in landslide prone areas under different emission trajectories. Coupling climate models with hydrological and geomorphological processes will enable dynamic risk mapping under changing environmental conditions. This integration can support proactive planning and adaptation strategies for infrastructure development and disaster preparedness.

VII. CONCLUSION

This review explored how machine learning and geographic information systems are being combined for landslide susceptibility assessment. It highlighted the importance of selecting the right factors, cleaning and preparing spatial data carefully, and using different machine learning models like Support Vector Machines, Random Forests, and deep learning approaches such as convolutional neural networks. These models have shown good accuracy in various case studies, but their success depends heavily on data quality, local conditions, and how well they are validated. Challenges like imbalanced data, overfitting, poor transferability, and lack of transparency still need more attention.

Bringing together machine learning and GIS has transformed landslide prediction from traditional methods to powerful data-driven systems. Machine learning helps uncover complex spatial patterns, while GIS makes it possible to visualize, analyze, and combine different types of geospatial data. This partnership allows for more detailed and scalable susceptibility maps, improves disaster preparedness, and sets the stage for real-time forecasting through sensor networks and remote sensing technologies.

Landslides continue to pose a serious threat worldwide, made worse by climate change, growing cities, and human activities. The progress in machine learning and GIS offers a promising path for better prediction, risk reduction, and planning. However, moving forward will require teamwork across disciplines, more standardized geospatial data, and a stronger focus on models that are both interpretable and usable in real time. Involving local communities and aligning with policy efforts will also be key to turning scientific

advances into practical solutions that help build resilience and sustainability.

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