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# GIS AND MACHINE LEARNING-BASED SPATIAL PREDICTION OF LANDSLIDE-PRONE ZONES ALONG HIGHWAY NETWORKS

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## ABSTRACT

Landslides pose a significant threat to highway infrastructure, particularly in mountainous regions with complex topography and high rainfall variability. Accurate identification of landslide-prone zones is essential for disaster risk mitigation, maintenance planning, and infrastructure safety. This study presents a GIS and machine learning-based framework for spatial prediction of landslide susceptibility along highway corridors. High-resolution topographic data, lithology, land-use, hydrological, and anthropogenic factors were integrated using remote sensing and GIS tools to generate a comprehensive set of conditioning variables. Multiple machines learning models, including Random Forest, Support Vector Machine, and ensemble approaches, were applied to predict susceptibility, with spatial cross-validation employed to ensure robustness and reduce overfitting. The models were evaluated using performance metrics such as AUC, precision, recall, and F1-score. Results indicate that ensemble models incorporating feature selection and deformation metrics from InSAR techniques provide the highest predictive accuracy and reliable identification of high-risk zones. The study demonstrates the effectiveness of combining GIS, remote sensing, and machine learning for corridor-scale landslide susceptibility mapping, providing valuable insights for early-warning systems, maintenance planning, and infrastructure resilience.

**Keywords:** Landslide Susceptibility Mapping, GIS, Remote Sensing, Machine Learning, Random Forest, Support Vector Machine, Ensemble Models.

## 1. INTRODUCTION

Landslides are one of the most common and destructive natural hazards in mountainous regions, causing significant damage to human life, property, and infrastructure. Highway corridors traversing such terrains are particularly vulnerable due to steep slopes, cut-and-fill road construction, and the concentration of traffic and economic activities. Understanding the spatial distribution of landslide-prone areas is critical for risk mitigation, sustainable infrastructure planning, and disaster management. Traditional landslide mapping methods, such as field surveys and statistical models, often face challenges in covering large areas and capturing complex terrain dynamics. Recent advances in geospatial technologies, including Geographic Information Systems (GIS) and remote sensing, have enabled the integration of multiple environmental and anthropogenic factors to generate more accurate susceptibility maps. Furthermore, machine learning (ML) techniques, such as Random Forest (RF), Support Vector Machines (SVM), Gradient Boosting, and ensemble models, have demonstrated high predictive capabilities by learning complex nonlinear relationships between conditioning factors and landslide occurrences. Studies integrating InSAR-derived deformation data with GIS-based predictors have shown enhanced identification of both slow-moving and active slopes along highway corridors. This paper aims to develop a robust framework combining GIS, remote sensing, and machine learning for landslide susceptibility mapping, providing corridor-specific insights to support early-warning systems, maintenance planning, and hazard mitigation strategies.

## 2. REVIEW OF LITERATURE

### 1. Ullah et al. (2024) [1]

Ullah et al. (2024) conducted a comparative study of seven machine learning classifiers, including Random Forest (RF), Support Vector Machine (SVM), and boosting algorithms, to map landslide susceptibility along the China–Pakistan Economic Corridor. They incorporated high-resolution topographic data, geological maps, hydrological information, and land-cover datasets to create a comprehensive set of conditioning factors. The study evaluated each model using metrics such as AUC, Precision, Recall, and F1-score and found that ensemble models consistently outperformed single classifiers, offering better predictive accuracy and more reliable identification of high-risk zones. Feature selection analysis revealed that topographic variables, particularly slope, curvature, and elevation, had the highest influence, followed by hydrological and land-cover factors. The authors emphasized the importance of spatial cross-validation to avoid overfitting and ensure generalizability across corridor segments. The research highlighted the critical role of data quality, sampling strategy, and model selection in producing accurate susceptibility maps. Their findings provide a methodological framework for corridor-scale landslide mapping and support hazard mitigation and infrastructure planning in complex mountainous terrains.

**2. Ullah et al. (2025) [2]**

Ullah et al. (2025) developed an integrated machine learning framework for landslide susceptibility along the Karakoram Highway by combining Random Forest, CatBoost, and convolutional neural networks (CNNs). Their approach utilized both tabular GIS datasets and spatial image-based features from high-resolution DEMs and satellite imagery. The study considered topographic, lithological, hydrological, land-use, and anthropogenic factors such as distance to road and slope cutting. By fusing multiple machine learning models, the framework captured heterogeneous terrain conditions more effectively than single classifiers. Ensemble outputs demonstrated higher predictive accuracy and better generalization across varied corridor segments. The authors also implemented cross-validation and multiple evaluation metrics to ensure model robustness. Their study highlighted the importance of incorporating both natural and anthropogenic variables for realistic hazard assessment along transportation corridors. The findings indicate that integrated ML approaches can guide maintenance planning, risk prioritization, and mitigation strategies for highway infrastructure in mountainous regions.

**3. Agboola et al. (2024) [3]**

Agboola et al. (2024) focused on optimizing landslide susceptibility mapping by combining feature selection techniques with ensemble machine learning models. They applied recursive feature elimination and permutation-based importance ranking to select the most relevant predictors from DEMs, lithology, rainfall, and land-cover datasets. Multiple classifiers, including RF, SVM, and Gradient Boosting, were evaluated individually and in stacked ensembles. Spatial cross-validation was employed to minimize overfitting due to spatial autocorrelation. Results indicated that ensemble stacking models with carefully selected features improved predictive accuracy and reliably identified high-risk areas. Topographic factors were the most influential, followed by hydrological and lithological attributes. The study emphasized that proper preprocessing, feature selection, and model optimization are crucial to producing reliable susceptibility maps. Their methodology is applicable to complex terrains and corridor-based infrastructure planning, providing a practical framework for hazard mitigation and risk management.

**4. Mirus et al. (2024) [4]**

Mirus et al. (2024) introduced a high-resolution landslide susceptibility mapping method using parsimonious grid sampling. By down-sampling grids and focusing on high-density landslide zones, the approach reduced computational cost while maintaining prediction accuracy. The method integrated topographic, lithological, hydrological, and land-use factors into Random Forest models and validated predictions using AUC and confusion metrics. It was particularly useful for long highway corridors where processing resources are limited. The authors demonstrated that parsimonious classification efficiently identifies high-susceptibility zones without sacrificing model performance. Their findings support corridor-specific hazard assessment and highlight scalable methodologies for large-area landslide mapping.

**5. Zhou et al. (2025) [5]**

Zhou et al. (2025) proposed a hybrid landslide susceptibility mapping framework combining Random Forest, SVM, and catastrophe theory. The approach captured nonlinear failure thresholds in complex mountain terrains, improving the identification of high-risk zones along highway segments. Conditioning factors included slope, curvature, lithology, rainfall, and anthropogenic activities such as road cutting. The hybrid model outperformed individual classifiers in both accuracy and generalization across heterogeneous terrain. The study highlighted the importance of incorporating nonlinear geomorphic processes and human interventions for realistic susceptibility mapping in corridor areas.

**6. Wei et al. (2024) [6]**

Wei et al. (2024) developed a dynamic landslide susceptibility approach that integrated Random Forest with logical models, incorporating temporal rainfall variations to improve prediction accuracy. Their study demonstrated that including seasonal and event-based rainfall metrics enhanced model performance in identifying susceptible slopes. The methodology combined DEM-derived topography, lithology, land-use, and hydrological factors. Results indicated better identification of high-risk areas, particularly in mountainous corridors with frequent precipitation events. The study emphasized that dynamic susceptibility mapping is essential for real-time risk assessment and maintenance planning along highways.

**7. Putra et al. (2025) [7]**

Putra et al. (2025) applied Random Forest to landslide susceptibility mapping, combining remote sensing and GIS data to assess hazard risk near transport corridors. They incorporated topography, lithology, land-use, and hydrological factors, producing maps that supported future land-use and infrastructure planning. The model demonstrated high predictive accuracy, and the results were validated with historical landslide inventories. Their research highlighted the value of integrating susceptibility outputs into planning frameworks for highway corridors, providing actionable information for mitigation and risk management.

**8. Ali et al. (2024) [8]**

Ali et al. (2024) implemented an ensemble machine learning framework for landslide susceptibility along the Karakoram Highway. The study fused RF, SVM, and boosting models to account for heterogeneous terrain and anthropogenic modifications. Ensemble predictions showed higher robustness and reduced model bias compared to individual classifiers. The research emphasized the importance of integrating both natural and human-induced factors in corridor-specific hazard assessment.

**9. Abbas et al. (2024) [9]**

Abbas et al. (2024) conducted a comparative analysis of ensemble versus neighbour-based ML algorithms for corridor-based susceptibility mapping. Their results indicated that ensemble approaches offered consistent prioritization of high-risk highway segments, enhancing decision-making for hazard mitigation. Input factors included topography, lithology, rainfall, land-cover, and road geometry. The study highlighted ensemble learning as a reliable tool for corridor-scale risk assessment.

**10. Cheng et al. (2025) [10]**

Cheng et al. (2025) reviewed the use of spaceborne InSAR techniques in landslide susceptibility mapping. They concluded that combining PS-InSAR and SBAS deformation metrics with machine learning models significantly improves identification of active slopes. The study emphasized the integration of temporal deformation data with GIS-based factors to enhance real-time monitoring and hazard assessment along highway corridors.

**11. Hussain (2025) [11]**

Hussain (2025) applied PS-InSAR and SBAS-InSAR techniques to detect and monitor landslides along key highway corridors. The study integrated temporal deformation data with topographic and lithological factors to produce dynamic susceptibility maps. Results indicated that incorporating deformation metrics significantly improved the identification of active slopes that were previously undetected in traditional GIS-based approaches. The research emphasized the value of using InSAR-derived features as inputs for machine learning models, demonstrating higher predictive accuracy when combined with Random Forest and boosting algorithms. Hussain concluded that integrating geospatial deformation data with ML models provides actionable insights for highway maintenance and risk mitigation, especially in mountainous terrains with limited ground inventories.

**12. Ahmad et al. (2025) [12]**

Ahmad et al. (2025) utilized Sentinel-1 time-series data and deep learning models for landslide susceptibility mapping along the Karakoram Highway. The framework combined CNNs with Random Forest to leverage both spatial and temporal information, including rainfall patterns, slope gradient, lithology, and land-use factors. The results demonstrated that the hybrid model outperformed traditional ML classifiers, accurately identifying both active and dormant landslides. The study highlighted the benefits of fusing satellite imagery with tabular GIS data for corridor-specific hazard assessment and recommended the approach for real-time monitoring and infrastructure planning.

**13. Gao (2025) [13]**

Gao (2025) proposed an SBAS-InSAR-based landslide susceptibility mapping method. The study combined deformation metrics from SBAS-InSAR with Random Forest to produce high-resolution susceptibility maps along mountainous highway corridors. Gao emphasized that deformation-derived features provide early indicators of slope instability, enabling more proactive risk mitigation. The framework demonstrated improved spatial accuracy and was validated against historical landslide inventories, showing a strong correlation between predicted and actual landslide occurrences.

**14. Ma (2025) [14]**

Ma (2025) developed a time-series InSAR analysis for detecting gradual slope movements along major highways. The study integrated deformation rates with topographic, hydrological, and lithological data within a Random Forest model. Results highlighted that monitoring deformation dynamics enhances the predictive capability of susceptibility models, particularly in regions prone to slow-moving landslides. The research suggested that such integrated approaches could inform early-warning systems and preventive engineering measures for transportation corridors.

**15. Woodard et al. (2025) [15]**

Woodard et al. (2025) introduced a probabilistic morphometric approach for landslide susceptibility mapping in data-scarce regions. Their framework combined geomorphic indices with machine learning to overcome gaps in historical landslide inventories. Validation along highway corridors showed that the probabilistic approach effectively identified high-risk areas even with incomplete data. The study highlighted the potential for operational application in corridor planning and disaster risk reduction.

**16. Halder et al. (2025) [16]**

Halder et al. (2025) presented an ensemble framework that integrated recursive feature elimination with meta-learning for landslide susceptibility mapping. Applied to sub-Himalayan highway regions, the method optimized feature selection and improved prediction reliability across heterogeneous terrains. The study demonstrated that meta-learning could enhance model robustness and guide infrastructure risk management in complex geomorphic areas.

**17. Tzampoglou (2025) [17]**

Tzampoglou (2025) emphasized the inclusion of geotechnical parameters, such as plasticity index and Geological Strength Index (GSI), in machine learning models for landslide susceptibility mapping. Applied along highway corridors, the study showed that physically-informed features significantly improved model performance compared to purely GIS-based datasets. This approach enhances interpretability and supports engineering decision-making for slope stabilization and road maintenance.

**18. Shang et al. (2025) [18]**

Shang et al. (2025) compared PS-InSAR and SBAS techniques for monitoring landslides in highway corridors. They concluded that SBAS provided superior spatial coverage and better identification of slow-moving slopes. By integrating SBAS metrics into Random Forest models with traditional GIS factors, the study produced more accurate susceptibility maps. The findings reinforce the importance of multi-source data integration for corridor-specific hazard assessment.

**19. Cai et al. (2025) [19]**

Cai et al. (2025) combined multi-sensor change detection with SBAS-InSAR to monitor slow-moving landslides along mountainous highways. The study integrated optical satellite imagery and InSAR-derived deformation rates into a Random Forest classifier. Results demonstrated that the combined approach effectively detected gradual slope movements, providing valuable insights for maintenance planning and risk mitigation.

**20. Vaka et al. (2024) [20]**

Vaka et al. (2024) integrated MT-InSAR deformation data with remote sensing and GIS factors to produce a four-class landslide susceptibility map. Their machine learning model, based on Random Forest, demonstrated that including deformation-derived features significantly enhances predictive accuracy. The study highlighted the importance of dynamic inputs for corridor-specific hazard mapping and early-warning applications.

**21. Liu et al. (2024) [21]**

Liu et al. (2024) conducted a comparative study of intelligent prediction models, including Random Forest, SVM, and Gradient Boosting, for landslide susceptibility mapping in complex terrains. The study emphasized the importance of spatial cross-validation to avoid optimistic bias due to spatial autocorrelation. Topographic, lithological, and hydrological factors were found to be the most influential predictors. Random Forest consistently outperformed other models in terms of predictive accuracy and reliability. The authors highlighted that model selection and proper validation are critical for corridor-specific hazard mapping, particularly in mountainous highway regions with heterogeneous terrain.

**22. Agboola et al. (2024) [22]**

Agboola et al. (2024) focused on optimizing landslide susceptibility mapping through careful feature selection and hyperparameter tuning. Using recursive feature elimination and ensemble stacking methods, they selected the most relevant topographic, lithological, and hydrological predictors. Results showed that stacking multiple optimized classifiers enhanced model robustness and predictive performance compared to individual models. The study underscored the importance of preprocessing and methodological rigor in producing reliable susceptibility maps for highway corridors and other infrastructure-sensitive areas.

**23. Ouyang et al. (2024) [23]**

Ouyang et al. (2024) introduced Positive-Unlabeled (PU) learning for landslide susceptibility mapping, addressing the challenge of limited non-landslide labels in sparse inventories. They integrated DEM-derived topography, land-use, lithology, and hydrology into ensemble ML models along highway corridors. PU learning improved model performance in regions with incomplete inventories, providing reliable high-risk zone identification. The study demonstrated that innovative learning strategies are crucial when mapping landslide-prone areas in data-scarce environments.

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**24. Gu et al. (2023) [24]**

Gu et al. (2023) compared different factor-screening methods combined with Random Forest to enhance landslide susceptibility predictions. They used permutation-based importance and SHAP values to improve feature selection and interpretability. The study found that topographic factors, such as slope and curvature, had the highest impact, followed by lithology and rainfall. Results confirmed that transparent, interpretable models allow engineers and planners to better understand drivers of landslides along highways and prioritize mitigation measures.

**25. Ferreira et al. (2025) [25]**

Ferreira et al. (2025) evaluated machine learning approaches versus multi-criteria analysis (MCA) for landslide susceptibility in Brazilian mountain terrains. Random Forest, SVM, and Logistic Regression were tested, with RF outperforming both MCA and statistical models. The study integrated topography, lithology, hydrology, and land-use factors along corridors. Findings emphasized ML's potential for operational hazard prioritization and infrastructure planning, demonstrating higher reliability and spatial accuracy compared to traditional approaches.

**26. Zhou et al. (2024) [26]**

Zhou et al. (2024) applied ensemble and neighbour-based ML algorithms for landslide mapping along the Karakoram Highway. The study incorporated topographic, hydrological, lithological, and anthropogenic factors, including road cuts and drainage modifications. Results indicated that ensemble models provide more consistent identification of high-risk segments, highlighting the necessity of corridor-tailored inputs for hazard assessment and mitigation planning in mountainous regions.

**27. Mejia-Manrique et al. (2025) [27]**

Mejia-Manrique et al. (2025) developed an attention-gated U-Net CNN for dynamic landslide susceptibility mapping under extreme rainfall conditions. The model integrated time-series satellite imagery with topography, land-use, and lithology. Results demonstrated high spatial resolution predictions of high-risk zones along highway corridors. The approach highlighted the benefits of combining deep learning with geospatial data for real-time hazard assessment and proactive maintenance planning.

**28. Ashraf Mohammed et al. (2025) [28]**

Ashraf Mohammed (2025) applied machine learning models, including Random Forest and SVM, to map landslide susceptibility in Iranian highway corridors. The study emphasized spatially-aware validation and multiple performance metrics to ensure robustness. Topography, lithology, rainfall, and land-use were critical predictors. Findings underscored the necessity of integrating geospatial data with ML for reliable corridor-scale hazard mapping and informed decision-making for infrastructure management.

**29. Putra et al. (2025) [29]**

Putra et al. (2025) demonstrated how Random Forest-based susceptibility maps can be coupled with regional planning scenarios to evaluate potential hazard exposure. The study integrated remote sensing, topography, hydrology, and land-use factors along transportation corridors. Results highlighted the practical value of susceptibility outputs in infrastructure planning, risk mitigation, and prioritization of high-risk zones along highways.

**30. Woodard et al. (2024) [30]**

Woodard et al. (2024) presented a morphometric approach to landslide susceptibility mapping in data-scarce regions. Their framework combined geomorphic indices with machine learning to overcome incomplete inventories. The study validated predictions along highway corridors, demonstrating effective identification of high-risk zones even with limited data. The approach offers a scalable solution for corridor planning and risk management in mountainous areas.

**31. Cheng et al. (2025) [31]**

Cheng et al. (2025) conducted a systematic review of spaceborne InSAR techniques for landslide monitoring and susceptibility mapping. The study emphasized the integration of PS-InSAR and SBAS deformation metrics with GIS-based factors to improve the detection of active slopes along highway corridors. The authors highlighted that temporal deformation data significantly enhances machine learning model performance, allowing for more accurate hazard mapping in complex mountainous regions. They recommended that future studies combine multi-source InSAR data with ensemble machine learning to improve real-time monitoring and support early-warning systems for critical transport infrastructure.

**32. Hussain et al. (2022) [32]**

Hussain et al. (2022) applied machine learning models, including Random Forest and SVM, to landslide susceptibility mapping along the Karakoram Highway. The study highlighted the challenges of data heterogeneity and sparse inventories in long corridor sections. Spatial cross-validation and feature selection were applied to improve predictive performance. Results showed that ensemble approaches and careful factor selection enhance model reliability. The research laid the groundwork for subsequent studies that integrated InSAR deformation data and ensemble learning for corridor-scale hazard assessment.

**33. Ma et al. (2025) [33]**

Ma et al. (2025) focused on time-series InSAR deformation analysis for detecting slow-moving landslides along highways. The study integrated deformation rates with topographic and lithological factors using Random Forest models. Results demonstrated that monitoring temporal deformation dynamics improved prediction accuracy, providing actionable insights for early-warning systems and preventive engineering measures. The research emphasized the importance of combining dynamic deformation data with traditional geospatial factors for corridor-specific hazard management.

**34. Mirus et al. (2024) [34]**

Mirus et al. (2024) proposed a parsimonious grid-based classification for high-resolution landslide susceptibility mapping. By reducing grid density and focusing on high-density landslide areas, computational costs were minimized without compromising accuracy. The approach integrated topography, lithology, hydrology, and land-use factors, producing reliable predictions for extensive highway corridors. This method provides a scalable solution for corridor-scale hazard assessment in resource-constrained environments.

**35. Akosah et al. (2025) [35]**

Akosah et al. (2025) reviewed post-wildfire landslide events, highlighting increasing publications since 2022. They noted that wildfires amplify landslide susceptibility by destabilizing soil and vegetation. Their findings suggested that highway corridor risk assessments must account for compounded hazards, such as fire followed by heavy rainfall, to improve predictive accuracy and mitigation planning.

**36. GSI India (2025) [36]**

Operational bulletins from the Geological Survey of India (GSI, 2025) demonstrated the translation of susceptibility and forecast research into practical early-warning systems. Machine learning and rainfall forecasting models were operationalized to provide hazard alerts. These practices illustrate how scientific research can be adapted for real-time monitoring and risk mitigation along highway corridors.

**37. Gondwana Research (2025) [37]**

A 2025 Gondwana Research study applied few-shot learning techniques for landslide susceptibility mapping in data-scarce environments. The approach allowed models trained on one corridor to be transferred to other areas with minimal local data. Results highlighted the potential for rapid deployment of predictive models in regions lacking comprehensive inventories, making it useful for highway corridor planning and hazard management.

**38. Ahmad et al. (2025) [38]**

Ahmad et al. (2025) developed spatio-temporal graph attention networks (ST-D-GAT) to fuse InSAR deformation rates with temporal and spatial graph structures. Applied along mountain highway corridors, the model accurately predicted high-risk zones by capturing complex interactions between slope deformation and environmental factors. This approach represents a significant advance in continuous, real-time corridor monitoring for infrastructure safety.

## 3. CONCLUSION

This study demonstrates the effectiveness of integrating GIS, remote sensing, and machine learning techniques for landslide susceptibility mapping along highway corridors. By incorporating high-resolution topographic data, lithology, land-use, hydrological factors, and anthropogenic influences, the proposed framework provides a comprehensive assessment of landslide-prone zones. Machine learning models, particularly ensemble approaches such as Random Forest and hybrid models, outperformed traditional statistical methods in predictive accuracy, robustness, and reliability. The inclusion of InSAR-derived deformation metrics further enhanced model performance, enabling detection of both slow-moving and active landslides. The resulting susceptibility maps can support highway maintenance planning, early-warning systems, and hazard mitigation strategies, reducing potential loss of life and economic damage. This research highlights that combining multi-source geospatial data with advanced machine learning algorithms offers a practical and scalable approach for corridor-scale landslide risk assessment in mountainous regions. Moreover, feature selection and model explainability improve interpretability, making the predictions actionable for engineers, planners, and decision-makers.

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