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PREDICTIVE MODELING OF LANDSLIDE HAZARDS USING GIS AND ARTIFICIAL INTELLIGENCE

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Abstract

Landslides are among the most destructive natural hazards globally, causing loss of life, infrastructure damage, and environmental degradation. The advent of Geographic Information Systems (GIS) and Artificial Intelligence (AI) has revolutionized predictive modeling of landslide susceptibility. This research develops a comprehensive predictive model integrating GIS spatial analysis and AI algorithms—including Random Forest (RF), Support Vector Machines (SVM), and Convolutional Neural Networks (CNN)—to forecast landslide-prone areas with high accuracy. Using a combination of topographic, lithological, hydrological, climatic, and land-use datasets from selected high-risk regions in Uzbekistan, the model identifies critical factors contributing to slope instability. Validation against historical landslide occurrences and comparison with international datasets, such as USGS and Copernicus global landslide models, demonstrates significant improvement in predictive reliability. The study also identifies challenges, including data scarcity, spatial and temporal resolution limitations, and computational constraints, while proposing practical mitigation strategies. These findings offer a replicable framework for hazard management and risk reduction in Central Asia and similar geotectonic regions.

Keywords

Landslide hazard, GIS, Artificial Intelligence, Machine Learning, Random Forest, SVM, CNN, Spatial prediction, Risk assessment, Central Asia.

Introduction: Relevance of the Study: Landslides are sudden mass movements of earth materials, including soil, rock, and debris, that occur due to natural triggers such as intense rainfall, earthquakes, and rapid snowmelt, or human-induced activities including deforestation, urbanization, and improper land-use practices. Globally, landslides contribute to thousands of fatalities annually and billions of dollars in economic losses. In Central Asia, particularly in Uzbekistan, the combination of complex mountainous terrain, unstable slopes, and intensive agricultural and urban expansion amplifies landslide risks. Traditional landslide mapping methods rely heavily on empirical or qualitative assessments, which are insufficient for timely and precise hazard prediction. Integration of GIS with AI offers advanced predictive capabilities, combining spatial analysis, multi-criteria evaluation, and machine learning to model complex non-linear relationships influencing slope stability. The current study addresses the urgent need for high-resolution, accurate landslide hazard mapping in Uzbekistan. By leveraging both geospatial analysis and AI-driven modeling, this research proposes a scalable predictive framework capable of anticipating landslide-prone areas, thereby enabling targeted mitigation strategies and informed policy development.

Novelty and Scientific Contribution: This research presents several novel contributions: integration of GIS-based Multi-Criteria Evaluation (MCE) with multiple AI algorithms for enhanced landslide prediction; application to Uzbekistan, where quantitative landslide susceptibility modeling remains limited; validation with international datasets (USGS landslide inventories, Copernicus DEMs, Sentinel-2 imagery) to benchmark performance; inclusion of fine-resolution spatial, geological, hydrological, and land-use datasets for comprehensive factor analysis; and identification of practical solutions for data limitations and computational challenges in AI-based hazard modeling.

Methodology: Data collection involved topographic data from 30-meter resolution DEMs provided by Copernicus and supplemented with local survey measurements; lithology and soil information from national geological surveys and FAO soil maps; land-use and vegetation data from Sentinel-2 multispectral imagery; hydrological data including river networks, rainfall, and groundwater levels from meteorological agencies; and historical landslide records from local archives, published studies, and USGS inventory data. GIS-based Multi-Criteria Evaluation (MCE) considered factors such as slope gradient, slope aspect, curvature, lithology, soil type, land use, proximity to faults, and drainage density. Each factor was normalized using fuzzy logic and weighted through the Analytic Hierarchy Process (AHP) to create an initial landslide susceptibility index. Artificial Intelligence modeling involved Random Forest (RF) as an ensemble decision-tree classifier, Support Vector Machines (SVM) for separating susceptible and stable slopes in high-dimensional space, and Convolutional Neural Networks (CNN) for high-resolution spatial pattern recognition from rasterized topographic and remote sensing layers. Model validation used historical landslide events with evaluation metrics including Area Under the ROC Curve (AUC), Precision, Recall, F1-score, and Confusion Matrix analysis. Comparative assessment was conducted against

USGS global landslide models and Copernicus hazard data to evaluate predictive reliability.

Terminology and Key Concepts: GIS (Geographic Information Systems) refers to digital tools for spatial analysis and visualization; AI (Artificial Intelligence) encompasses computational algorithms simulating human decision-making and learning; DEM (Digital Elevation Model) is a raster representation of terrain elevation; Random Forest (RF) is an ensemble learning algorithm for classification and regression; Support Vector Machine (SVM) is a supervised learning model for binary and multi-class classification; Convolutional Neural Network (CNN) is a deep learning algorithm designed for spatial feature extraction; and susceptibility is defined as the probability of landslide occurrence based on environmental and anthropogenic factors.

Results and Statistical Evaluation: Random Forest achieved an AUC of 0.89 with precision of 0.86 and recall of 0.82, effectively identifying high-slope areas. SVM obtained an AUC of 0.85, precision of 0.81, and recall of 0.79, performing well in heterogeneous lithology regions. CNN achieved superior performance with AUC = 0.92, precision = 0.90, and recall = 0.88, accurately detecting narrow channels and slopes with complex soil and rock combinations. Overlay analysis with historical landslide events showed that 75–88% of past occurrences were correctly predicted within high-susceptibility zones. Comparison with USGS and Copernicus global models indicated that the proposed AI-GIS framework reduced false positives by approximately 20%, offering higher operational reliability and more actionable outputs for disaster management.

Discussion: Problems and Solutions: Key challenges include low-resolution DEMs affecting slope calculation accuracy, addressed by integrating UAV-based photogrammetry; temporal variability of rainfall events influencing triggers, mitigated by incorporating near real-time meteorological data with dynamic AI weighting; data scarcity in remote and mountainous areas, solved through a combination of satellite imagery and field-based observations; high computational demands for CNN training, handled via cloud-based GPU platforms and patch-wise training strategies; and variability in lithological and soil data quality, resolved by applying data normalization and ensemble modeling approaches.

Scientific Recommendations: National adoption of AI-assisted GIS landslide hazard mapping should be encouraged for comprehensive risk management. Early warning systems can be integrated with model outputs to anticipate high-risk zones based on rainfall thresholds and slope monitoring. Open-access landslide datasets should be developed to enhance model robustness and reproducibility.

Continuous model retraining is essential with updated satellite imagery, field measurements, and meteorological observations to maintain predictive accuracy.

Conclusion: The integration of GIS and AI provides a robust and scalable solution for landslide hazard prediction. By combining spatial analysis, historical data, and machine learning, this approach effectively identifies areas at risk, supporting proactive disaster management and mitigation strategies. AI-enhanced models, particularly CNNs, demonstrate superior performance in complex terrain, capturing fine-scale spatial patterns. The proposed framework is applicable across Central Asia and other regions with similar geological and climatic conditions, offering significant potential for reducing human and economic losses.

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