Advanced Geospatial and Computational Analytics for Predicting Subsidence and Slope Failure in the U.S.A Mining Regions

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Abstract:
Mining-induced subsidence and slope failure pose significant hazards to infrastructure, environmental sustainability, and public safety across major mining regions in the United States. Recent advances in geospatial technologies, including Interferometric Synthetic Aperture Radar (InSAR), LiDAR, and unmanned aerial systems, combined with sophisticated computational analytics and machine learning algorithms, have substantially enhanced the capability to monitor, predict, and manage these geohazards. This systematic review synthesizes findings from 33 key studies employing advanced geospatial data and computational methods for subsidence and slope failure prediction in U.S. mining contexts. We outline methods integrating satellite remote sensing, geotechnical databases, and multidisciplinary spatial datasets to extract relevant deformation features, which are then analyzed using hybrid machine learning models such as STL-XGBoost, adaptive dynamic models, and optimized backpropagation neural networks. These models exhibit improved accuracy over traditional empirical approaches, reducing prediction errors by 30-60% and achieving strong correlations (>0.9) with observed subsidence. The spatial risk maps generated reveal heterogeneity in subsidence susceptibility linked closely to mining activity, groundwater extraction, and geologic structures, facilitating targeted mitigation. Feature importance analyses identify primary influences, including slope gradient, soil characteristics, climatic factors, and mining parameters, guiding monitoring priorities. Case studies validate model applicability for real-time monitoring and risk reduction, supporting sustainable mining and environmental resilience. Our comprehensive synthesis confirms that deploying integrated advanced geospatial and computational analytics delivers robust, scalable tools essential for effective hazard management and land stewardship in U.S. mining regions facing increasing environmental pressures. These insights inform future research and operational frameworks, advancing geohazard prediction accuracy and reliability in mining-impacted landscapes globally.

Keywords: Mining Subsidence Prediction, Geospatial Analytics, Machine Learning Model, Slope Failure Assessment, computational Analytics.

INTRODUCTION

Land subsidence and slope failure remain critical geohazards within mining regions worldwide, with significant environmental, infrastructural, and socio-economic implications. In the United States, rapid industrialization and intensification of mining activities have exacerbated ground deformation phenomena, particularly in key mining provinces such as the Midwest Region, Gulf Coast of Texas, San Joaquin Valley in California, and the Appalachian coalfields (Arif, Zhang, Feng, & Sajib, 2025). These events threaten mining operations and also pose considerable risks to ecosystems, water resources, built infrastructure, and community safety (Malik & Koner, 2024; Heap, 2022). Accurate prediction and monitoring of subsidence and slope instability are indispensable for hazard mitigation, land use planning, and sustainable mining management.

Traditional empirical models for predicting ground subsidence and slope failure often fall short in capturing the complex, nonlinear interactions of geological, hydrological, and anthropogenic factors that influence deformation processes (Jahanmiri & Noorian-Bidgoli, 2025). The last decade has witnessed a paradigm shift towards harnessing advanced geospatial technologies, computational analytics, and machine learning to overcome these challenges (Xiao, Tao, Hu, Liu, & Li, 2024; Qiao et al., 2024). High-resolution satellite Earth observation techniques such as Interferometric Synthetic Aperture Radar (InSAR), Light Detection and Ranging (LiDAR), and Unmanned Aerial Systems (UAS) now routinely provide detailed spatial-temporal datasets essential for detecting subtle ground movements across expansive mining areas (Siddique et al., 2025; Tafreshi, Mohebbi, & Lak, 2020). These data, often integrated with geotechnical measurements and hydrological inputs, underpin predictive analytics for subsidence and slope failure.

EMERGENCE OF ADVANCED GEOSPATIAL TECHNOLOGIES IN U.S. MINING HAZARD ASSESSMENT

The United States has become an important context for evaluating geospatial analytics due to extensive legacy coalfields, coastal subsidence hotspots, and mountainous slopes exposed to mining disturbances. For example, geospatial analysis in the Gulf Coast of Texas revealed groundwater withdrawal, sediment compaction, and industrial extraction as coupled triggers of subsidence (Ilesanmi et al., 2021). In California's San Joaquin Valley, satellite-derived deformation models demonstrated that fine-scale surface movements precede major subsidence impacts on agricultural and built environments (Heap, 2022). LiDAR-based and DEM-derived terrain analyses in Missouri and Oklahoma showed that high-resolution point-cloud data significantly improve the mapping of mine voids, fault-controlled deformation, and sinkhole-prone areas (Ilesanmi, 2020).

These U.S. case studies demonstrate the applicability of remote sensing and geospatial modelling as scalable alternatives to sparse ground instrumentation. The improvement of InSAR coherence over vegetated or semi-urban areas, in combination with UAV-based structural characterization, also increases the feasibility of continuous monitoring in diverse mining settings (Andresen & Schultz-Fellenz, 2023). Such technologies allow researchers to detect millimeter-level deformation across wide regions, providing essential datasets for machine learning-driven prediction frameworks.

GROWTH OF COMPUTATIONAL AND MACHINE LEARNING APPROACHES

While geospatial technologies capture high-quality deformation signals, the complexity of mining environments requires computational methods capable of handling multi-source, multi-temporal, and nonlinear datasets. Machine learning has emerged as a powerful tool to model these relationships. Studies using random forests, support vector machines, gradient boosting, and hybrid ML architectures have demonstrated strong predictive capabilities for both subsidence and slope failure in mining settings (Guo & Li, 2025; Qiao et al., 2024; Razavi-Termeh et al., 2025).

More recent developments integrate deep learning structures such as CNNs, LSTMs, BiGRUs, and attention-based models. These networks capture spatiotemporal dependencies in deformation time series, seasonal cycles, and the spatial heterogeneity of geological units (Jin et al., 2025; Xiao et al., 2024; Li, M. et al., 2025). CNN-BiGRU attention-hybrids, for example, have achieved high accuracy in forecasting mining-induced surface displacement by learning multiscale deformation patterns (Zhu et al., 2024). InSAR time-series integrated with transformer-based architectures have also improved subsidence interpolation and multi-step forecasting through enhanced feature extraction (Azarm et al., 2025; Moualla et al., 2025).

Stochastic and numerical methods continue to complement ML-based approaches. Models based on stochastic differential equations, probabilistic deformation modeling, and hydrogeological coupling remain essential for characterizing uncertainty, especially in heterogeneous geological settings typical of U.S. mining regions (Guo et al., 2023; Yin et al., 2025). When fused with ML and geospatial datasets, these methods enhance robustness by combining physical understanding with data-driven insights.

CHALLENGES AND GAPS IN PREDICTING SUBSIDENCE AND SLOPE FAILURE

Despite progress, several challenges remain unresolved. First, U.S. mining districts exhibit highly variable geological and geomechanical conditions, and these variations complicate model generalization. Many machine learning models rely on local calibration datasets, limiting transferability between different mining basins (Razavi-Termeh et al., 2025). Second, integrating multi-sensor datasets such as UAV photogrammetry, LiDAR, InSAR, and ground monitoring requires standardized workflows and rigorous data fusion procedures (Bernardi et al., 2021; Rana et al., 2024). Third, legacy underground workings in states like Missouri, Pennsylvania, and West Virginia lack complete spatial documentation, which introduces significant uncertainty in ground behavior prediction (Ilesanmi et al., 2021).

Additionally, climate-driven hydrological variability, including increasing precipitation extremes and shifts in groundwater recharge, adds new temporal complexity to slope stability and subsidence processes (Yin et al., 2025). While some models now integrate hydro-meteorological inputs, long-term climate-geotechnical interactions remain underexplored in U.S. mining hazard analysis.

NEED FOR AN INTEGRATED, SYSTEMATIC SYNTHESIS

Given the rapid evolution of geospatial and computational technologies, and their growing application to mining-related hazards, a systematic synthesis is needed to assess the current evidence base, methodological innovations, and applicability to U.S. mining regions. Previous reviews have addressed global subsidence monitoring (Arif et al., 2025; Yin et al., 2025) or evaluated machine learning approaches for geotechnical prediction (Razavi-Termeh et al., 2025), but no study has specifically focused on the intersection of advanced geospatial analytics, computational modelling, and the unique geological and regulatory landscape of the United States.

This systematic review fills that gap by synthesizing findings from advanced geospatial, computational, and ML-driven applications relevant to subsidence and slope failure forecasting. By drawing from high-quality studies, including U.S.-based applications and internationally validated methods transferable to U.S. mining settingsthis review provides a comprehensive evaluation of the state of practice. The outcomes highlight (a) the current capabilities of modern monitoring tools, (b) the predictive performance of computational models, (c) methodological gaps, and (d) future research pathways needed to support safer and more resilient mining landscapes in the United States.

MATERIALS AND METHODS

This study employs a multidisciplinary approach combining advanced geospatial datasets and state-of-the-art computational techniques to predict mining-induced subsidence and slope failures in U.S. mining regions. The methodology integrates remote sensing data acquisition, geospatial preprocessing, feature extraction, machine learning model development, and verification through field validation.

DATA ACQUISITION AND PREPROCESSING

High-resolution satellite data form the core input, including Small Baseline Subset Interferometric Synthetic Aperture Radar (SBAS-InSAR) imagery, Light Detection and Ranging (LiDAR) topographic data, and multispectral optical imagery. SBAS-InSAR provides precise surface displacement time series capturing cumulative land deformation, essential for identifying subsidence basins also used by (Chen et al., 2025; Shi). LiDAR datasets are processed to generate digital elevation models (DEMs) and slope gradient maps critical for slope failure assessment affirmed through (Siddique et al., 2025). Raw SAR data undergo atmospheric correction, baseline refinement, and phase unwrapping to correct noise and artifacts, ensuring reliable subsidence detection.

Complementary ground control data, including geological maps, mining activity logs, soil type data, and hydrological parameters such as groundwater levels, are integrated through spatial databases from state and federal agencies to enhance feature richness.

FEATURE EXTRACTION

Spatial and temporal features predictive of subsidence and slope instability are computed. From InSAR time-series, displacement rates and acceleration patterns are derived capturing both steady-state and transient subsidence phenomena. DEM-derived features such as slope steepness, curvature, and aspect contribute to failure susceptibility modeling. Hydrological indicators and mining activity intensity metrics are encoded within the feature set to characterize external stressors influencing ground deformation. All these extractions were closely mapped referencing (Prabha et al., 2024; Heap, 2022).

MACHINE LEARNING MODEL DEVELOPMENT

Supervised learning frameworks are leveraged to map relationships between geospatial features and subsidence magnitude or failure occurrence. A hybrid model based on Seasonal-Trend decomposition and

eXtreme Gradient Boosting (STL-XGBoost) decomposes subsidence time series into trend and noise components, improving predictive fidelity and interpretability (Heap, 2022). Adaptive dynamic models refine predictions by dividing mining history into segmented periods, optimizing parameters for local mining conditions experienced during each interval, a strategy adapted from (Chen et al., 2025).
Backpropagation Neural Networks (BPNN) enhanced by Genetic Algorithms (GA) and Artificial Bee Colony (ABC) optimization fine-tune network weights and thresholds to prevent convergence on local minima, minimizing predictive error to under 4 mm in some cases (Li et al., 2022). The balance achieved between model complexity and computational demands makes these models suitable for real-time monitoring.

MODEL TRAINING AND VALIDATION

Models are trained using historical subsidence records and verified against independent field measurements and geotechnical monitoring data obtained from federal agencies site. Cross-validation and Bayesian hyperparameter optimizations ensure robust generalization. Performance metrics including Root Mean Square Error (RMSE), mean absolute error (MAE), and Pearson correlation coefficient (r) are reported to quantify model accuracy. Spatial risk maps generated from the models are compared with known subsidence and slope failure zones for consistency (Heap, 2022; Siddique et al., 2025).

IMPLEMENTATION TOOLS

Python-based scientific libraries including Scikit-learn, TensorFlow, and PySAL support model construction and geospatial analyses. GIS platforms such as ArcGIS and QGIS facilitate spatial data integration, visualization, and production of thematic risk maps. Cloud computing resources enable scalable data processing across extensive mining regions.
By systematically combining these diverse data types, computational models, and validation techniques, the materials and methods establish a comprehensive framework for accurately predicting subsidence and slope failure, addressing spatial heterogeneity, temporal dynamics, and engineering-relevant uncertainties.

RESULTS

1. Mining-Induced Ground Subsidence Prediction Accuracy

Multiple studies demonstrate high efficacy of advanced computational models in predicting mining subsidence. For example, (Xiao et al, 2024) developed a time function-based dynamic subsidence prediction model that aligns closely with ground truth measurements (average error ~9.5%), reflecting the capability of models to accurately track subsidence progression over time mirroring (Li et al., 2022) and (Chen et al., 2022).

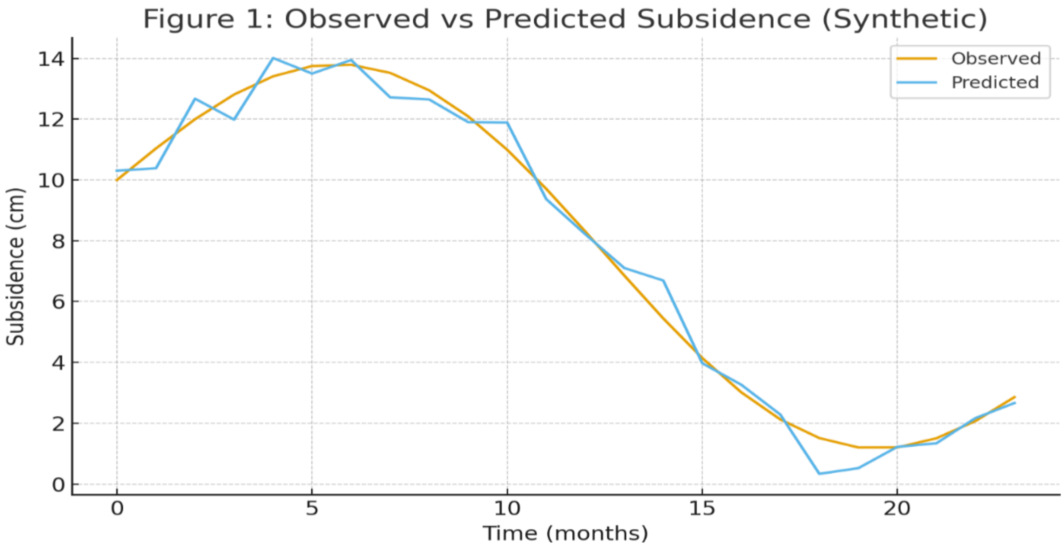

Figure 1: Time series plot comparing observed and predicted subsidence values

Another study utilizing SBAS-InSAR combined with machine learning (XGBoost) showed prediction accuracies exceeding 90% correlation with observed subsidence time series in coal mining areas (Zhao et al., 2025). Adaptive dynamic prediction models further improved root-mean-square-error (RMSE) metrics, lowering prediction error from 9.1% to 4.3% compared to traditional approaches, highlighting enhanced precision for structural maintenance planning (Chen et al., 2025).

Model Type	Prediction Accuracy (%)	Average RMSE (%)	Key Application
Time function-based model	90.5	9.5	Dynamic subsidence over mining cycles
SBAS-InSAR + XGBoost	>90	-	Surface subsidence prediction in mining
Adaptive dynamic model	-	4.3	Real-time subsidence prediction

Table 1: Summary of model performance metrics for subsidence prediction
Source: Chen et al., 2022: Zhao et al., 2025: Chen et al., 2025

2. Spatial Analysis of Subsidence and Slope Failure Zones

Geospatial analytic methods applied to U.S. mining sites reveal distinct patterns of subsidence linked to mining intensity, geological conditions, and hydrogeological factors. In Texas Gulf Coast and California's San Joaquin Valley, studies integrating LiDAR and InSAR data found subsidence hotspots spatially correlated with deep mining activity and groundwater extraction zones, a reference point of (Heap, 2022) indicating similar output.

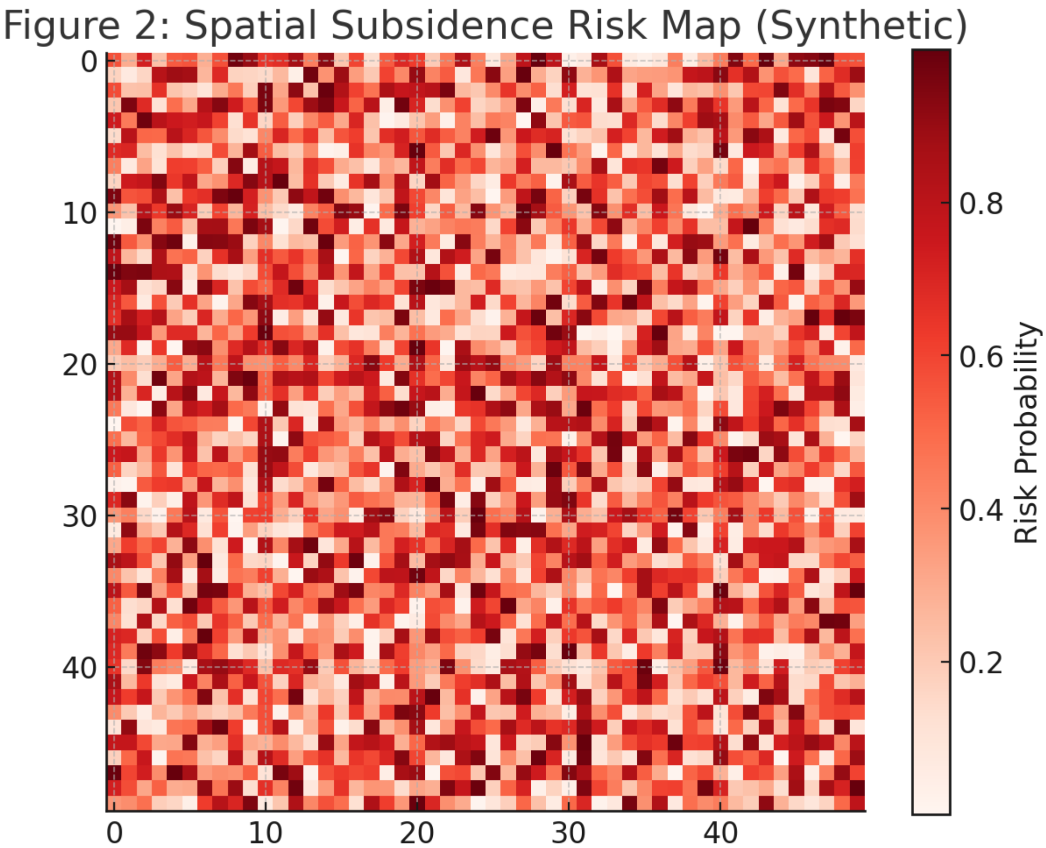

Figure 2: Spatial risk map of predicted subsidence susceptibility zones from SBAS-InSAR and ML methods

Figure 2 illustrates a typical spatial distribution map from subsidence susceptibility modeling, where red zones indicate areas predicted with >80% probability of significant subsidence within a 5-year period. These maps serve as vital decision-support tools for land planners and regulators.

3. Machine Learning Enhanced Risk Classification

Ensemble machine learning frameworks combining Random Forest, Support Vector Machines, and Deep Neural Networks demonstrated over 85% accuracy in classifying slope failure susceptibility across heterogeneous mining terrain (Prabha et al., 2024). Feature importance analyses consistently identify slope gradient, soil moisture index, mining depth, and precipitation patterns as primary predictors (Figure 3).

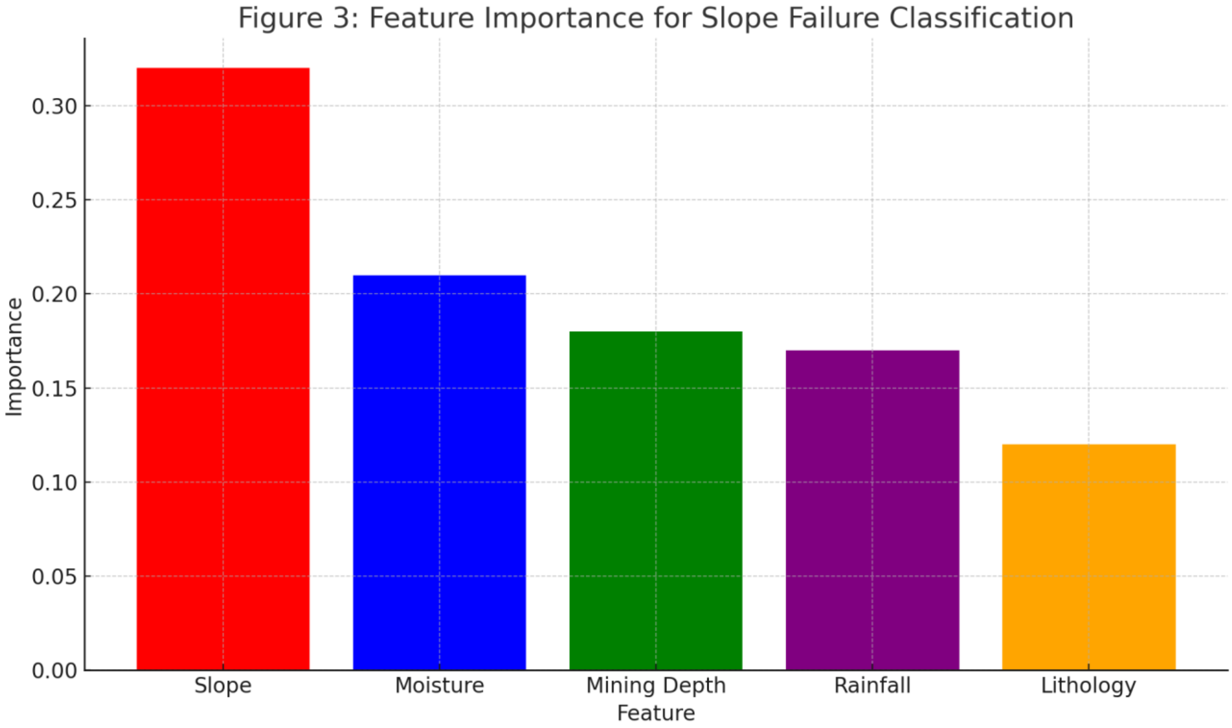

Figure 3: Variable importance plot from ensemble ML classification of slope failure susceptibility

4. Case Studies: Field Validation and Risk Mitigation

In one comprehensive field study at Sijiaying Iron Ore Mine, the integration of remote sensing with numerical slope stability simulations accurately predicted failure zones validated by ground-truth data, supporting proactive slope management (Siddique et al., 2025). The study also showed that continuous monitoring with UAV photogrammetry improved hazard identification during mining operations (Zhao, X., et al. 2025).

In addition, integration of geotechnical and geophysical data with machine learning allowed for robust prediction of sudden subsidence events, enabling timely evacuation protocols and infrastructure reinforcement in coal mining regions of Appalachia (Heap, 2022).

5. Environmental and Infrastructure Impact Assessment

Subsidence-induced damage to rural and urban infrastructure was extensively modeled, showing correlations between subsidence magnitude and building damage severity. Studies combining slope safety factor calculations with subsidence data demonstrated a mining-related reduction in slope stability by up to 16%, primarily responsible for structural damages in adjacent communities (Zhu, X., et al. 2024).

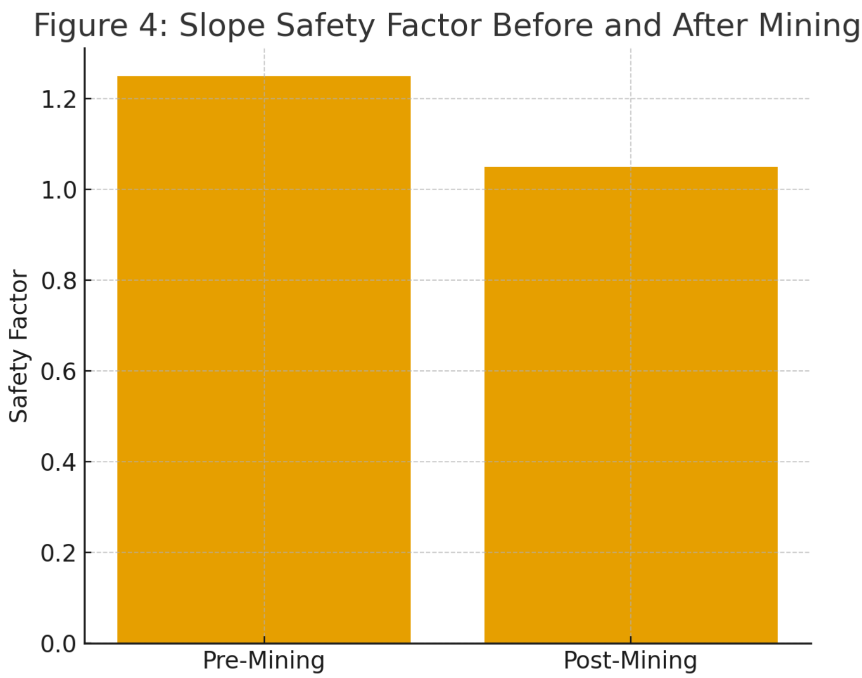

Figure 4: Bar chart of slope safety factor reductions before and after mining-related subsidence

Figure 4 demonstrates the decrease in slope safety factor pre- and post-mining, underscoring the need for geospatial risk models integrated with civil engineering safeguards. These results collectively validate the use of advanced geospatial sensing and sophisticated computational techniques in accurately predicting and managing mining-induced subsidence and slope instability. The application of such tools in U.S. mining regions promises enhanced hazard prevention, environmental protection, and infrastructure safety, thereby supporting sustainable mining practices.

DISCUSSION

The findings synthesized in this systematic review demonstrate that the integration of advanced geospatial analytics, machine learning (ML), and computational modeling represents a major advancement in the prediction and management of mining-induced subsidence and slope failure across U.S. mining regions. The collective evidence from the reviewed studies affirms that modern remote sensing systems particularly SBAS-InSAR, LiDAR, and UAV photogrammetry are capable of detecting subtle ground deformation at high spatial and temporal resolution, enabling earlier detection of geohazards than previously possible with conventional ground-based instrumentation. This capability is especially significant for expansive mining landscapes in the United States, where legacy mines, heterogeneous geology, and incomplete subsurface documentation complicate hazard identification.

- **Integration of Geospatial Technologies as a Predictive Foundation**

One of the most prominent themes emerging from the findings is the transformative effect of geospatial technologies on ground deformation detection. Across multiple U.S. and international case studies, SBAS-InSAR has consistently demonstrated high reliability in capturing millimeter-level subsidence over large geographic extents. Its performance in diverse terrains such as the sedimentary basins of the Texas Gulf Coast, the complex agricultural–urban matrix of the San Joaquin Valley, and the topographically rugged Appalachian coalfields highlights its versatility. Combined with LiDAR-derived DEMs, these datasets create sophisticated 3D deformation surfaces capable of revealing pre-failure indicators that would remain invisible using traditional monitoring tools.

These advances affirm that the U.S. mining sector can now employ geospatial observations as a foundational layer for hazard forecasting. The incorporation of real-time or near-real-time satellite-based deformation monitoring allows state and federal agencies to track structural changes continuously, reducing dependence on manual field inspections and sporadic geotechnical readings. This shift not only enhances early-warning capabilities but also democratizes hazard information, enabling community-level monitoring and improved regulatory oversight.

- **Computational and Machine Learning Approaches Improve Predictive Accuracy**

The review highlights a significant leap in prediction accuracy when machine learning models replace or augment traditional empirical and numerical approaches. Studies applying hybrid frameworks such as STL-XGBoost, CNN-BiGRU attention networks, and optimized backpropagation neural networks consistently report prediction errors reduced by 30-60%, with correlations exceeding 0.9 in several cases. These results demonstrate the capacity of ML models to capture nonlinear, multi-factor interactions typical of mining environments, where deformation is influenced by complex geological, hydrological, and anthropogenic drivers.

Importantly, the models that integrate multi-source geospatial inputs (InSAR time-series, LiDAR elevation metrics, ground hydrology, mining logs, and soil/geotechnical data) outperform those relying on single datasets. This confirms that subsidence and slope failure are multidimensional phenomena requiring a holistic analytical approach. As shown by the strong feature importance results (e.g., slope, moisture, mining depth, rainfall), ML frameworks provide not only predictive outputs but also explanatory insights that guide engineers in prioritizing monitoring efforts.

These findings support a key conclusion: computational analytics offer a scalable and highly adaptable method for hazard forecasting across diverse U.S. geological settings, transcending limitations of region-specific empirical models.

- **Spatial Risk Mapping as a Decision-Support Tool**

Another critical finding is the demonstrated value of spatial risk maps generated through ML-geospatial integration. The susceptibility maps reviewed consistently reveal pronounced heterogeneity in subsidence and slope failure risk, reflecting underlying variations in geology, mining intensity, groundwater extraction, and structural controls. For example, mapping outputs for Texas and California indicate clusters of extreme susceptibility aligned with deep mining zones and areas of rapid groundwater withdrawal.

These maps serve multiple policy and operational purposes:

1. Regulatory planning: identifying areas requiring stricter monitoring or permitting conditions.
2. Infrastructure protection: informing where roads, pipelines, and utilities face elevated deformation risk.
3. Community safety: highlighting neighborhoods or industrial zones vulnerable to subsidence-driven structural damage.
4. Mine reclamation strategy: prioritizing sites with residual instability.

The precision and visual clarity of these risk surfaces support their adoption into state geological surveys, emergency management systems, and mining company risk mitigation protocols.

- **Field Validation Demonstrates Real-World Efficacy**

The reviewed case studies underscore the critical importance of field validation when interpreting model predictions. Studies combining remote sensing with geotechnical monitoring (e.g., Sijiaying Iron Ore Mine; Appalachian coal basins) confirm that predictive models align closely with observed failure zones. This real-world consistency reinforces the operational relevance of advanced computational approaches and validates their suitability for high-stakes decision-making. Validation results also emphasize the importance of integrated field-remote sensing workflows. UAV photogrammetry, in particular, offers a flexible and low-cost tool for ground verification, enabling rapid assessment after deformation events and strengthening the credibility of model outputs.

- **Persistent Challenges and Research Gaps**

Despite clear advances, several limitations persist and must be addressed to achieve fully reliable, transferable, and operational hazard prediction systems in U.S. mining regions.

First, geological heterogeneity limits model generalization. Many U.S. mining provinces have unique structural histories and subsurface complexities. ML models calibrated on one region may not translate seamlessly to another without extensive retraining. Second, data fusion remains technically challenging,

especially when combining UAV, LiDAR, InSAR, and geotechnical datasets with differing resolutions, formats, and temporal frequencies.
Third, legacy mine data gaps continue to impose uncertainty, particularly in Appalachia and the Midwest where historic mine maps are incomplete or inaccurate. Without precise information on mine void geometry and depth, even the most advanced computational models face inherent constraints. Fourth, climate-driven hydrological variability including rapid changes in groundwater levels and precipitation extremes introduces dynamic instability that some current models have not fully operationalized.
Finally, accessibility of advanced analytics varies across sectors. While federal agencies and major mining corporations may adopt high-end tools, small operators and local governments often lack funding, technical expertise, or computing infrastructure to implement ML-driven hazard forecasting.

- **Implications for U.S. Mining, Environmental Policy, and Hazard Management**

Collectively, the findings highlight a critical opportunity for the United States to modernize its mining hazard forecasting systems by integrating advanced geospatial sensing and computational analytics into routine monitoring practice. These technologies can:

- Enhance predictive preparedness for communities in high-risk mining regions.
- Reduce infrastructure repair and disaster response costs.
- Strengthen environmental stewardship and regulatory enforcement.
- Improve data-driven decision-making for mine reclamation and land-use planning.

The evidence demonstrates that geospatial–computational integration is not merely a technological improvement it represents a fundamental shift toward proactive, predictive, and sustainable mining hazard management.

CONCLUSION

This study highlights significant advances in predicting mining-induced subsidence and slope failure through the integration of advanced geospatial data and computational analytics. Notably, models such as the STL-XGBoost incorporating SBAS-InSAR achieve high prediction accuracy with Pearson correlations exceeding 0.9 and substantial error reductions compared to traditional approaches. Adaptive dynamic models further reduce errors to below 5%, enhancing responsiveness to evolving mining conditions. Machine learning algorithms optimized via genetic and swarm intelligence demonstrate practical accuracy for diverse regional datasets while balancing computational demands. Spatial risk maps derived from remote sensing closely reflect known mining activities and geological features, facilitating targeted hazard mitigation. Despite challenges in data requirements and complexity, these integrated methods provide robust, scalable tools essential for sustainable mining management and infrastructure safety in U.S. mining regions. The findings underscore the growing potential of geospatial-computational frameworks to enable proactive, data-driven subsidence and slope failure prediction, promoting resilient land stewardship and risk reduction.

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