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Satellite-Integrated Multi-Hazard Environmental Risk Assessment Framework for Mining-Adjacent U.S. Communities Using InSAR and GIS

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Abstract

This study examined the problem of fragmented and reactive environmental hazard monitoring in mining-adjacent communities across the United States, where ground deformation, water contamination, air quality degradation, tailings-dam instability, and legacy-site contamination are frequently assessed in isolation rather than through an integrated, satellite-enabled framework. The purpose of the study was to assess how a Satellite-Integrated Multi-Hazard Environmental Risk Assessment Framework, built on Interferometric Synthetic Aperture Radar (InSAR) and Geographic Information Systems (GIS), influences the quality and reliability of environmental risk assessment outcomes for communities located near active, inactive, and abandoned mining operations. A quantitative, cross-sectional, case-based design was adopted, and data were collected through a structured five-point Likert-scale questionnaire from 141 valid respondents out of 160 distributed questionnaires, representing an 88.1% valid response rate. The sample included geospatial analysts, environmental scientists, mining and geotechnical engineers, remote-sensing specialists, and local planning and public-health officials, with 66.7% directly involved in hazard-monitoring or risk-assessment activities. The key variables were InSAR ground-deformation monitoring, GIS multi-hazard data integration, remote-sensing data quality and validation, hazard exposure and vulnerability mapping, community and institutional engagement, framework design quality, and environmental risk assessment performance. The analysis plan included descriptive statistics, reliability testing using Cronbach's alpha, Pearson correlation, regression modeling, a framework maturity index, and a hazard risk-control priority matrix. The headline findings showed that all major constructs were rated high, with environmental risk assessment performance recording the highest mean score of 4.17, followed by InSAR ground-deformation monitoring at 4.13 and framework design quality at 4.09. Reliability was acceptable to excellent, with Cronbach's alpha values ranging from 0.79 to 0.92. Correlation results showed significant positive relationships, including $r = 0.76$ between framework design quality and environmental risk assessment performance. Regression results confirmed that the model explained 69.1% of the variance in environmental risk assessment performance, $R^2 = 0.691$, adjusted $R^2 = 0.678$, $F(6,134) = 49.87$, $p < 0.001$. Framework design quality was the strongest predictor, $\beta = 0.32$, followed by InSAR ground-deformation monitoring, $\beta = 0.25$, and GIS multi-hazard data integration, $\beta = 0.22$. The findings imply that mining-adjacent U.S. communities and their supporting agencies should strengthen InSAR time-series processing, multi-source GIS integration, validation protocols, vulnerability mapping, and community engagement to improve the reliability of multi-hazard environmental risk assessment.

Keywords

InSAR; Multi-hazard risk assessment; GIS integration; Mining-adjacent communities; Ground deformation monitoring.

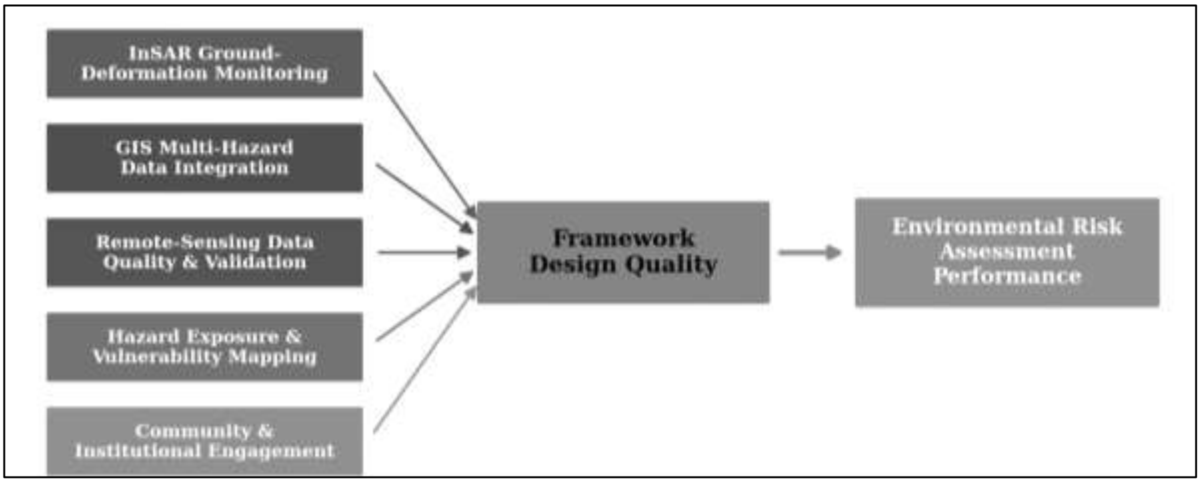
INTRODUCTION

Environmental risk assessment refers to the structured process of identifying, characterizing, and quantifying the likelihood and consequences of hazardous events that threaten human populations, ecosystems, infrastructure, and natural resources. In mining-adjacent communities across the United States, environmental risk is closely associated with a distinctive combination of hazards that arise from the extraction, processing, and long-term abandonment of mineral resources, including progressive ground deformation, subsidence, tailings-dam instability, surface-water and groundwater contamination, acid mine drainage, airborne particulate exposure, and the persistence of legacy contamination at abandoned mine lands. A satellite-integrated framework in this context means an assessment architecture in which spaceborne observations, particularly Interferometric Synthetic Aperture Radar (InSAR), are combined with Geographic Information Systems (GIS) to detect, map, and monitor these hazards continuously over large and often inaccessible areas (Ng et al., 2015). In practical terms, a satellite-integrated multi-hazard framework treats each hazard not as an isolated technical problem but as one interacting layer within a spatially referenced, temporally dynamic risk system, so that deformation signals, contamination plumes, exposure zones, and community vulnerability can be analyzed together rather than separately. This makes environmental risk assessment a technical, spatial, institutional, and lifecycle-based process rather than a single measurement or one-time survey. Research on remote-sensing-based hazard monitoring has emphasized that risk cannot be understood only through ground-based point measurements, because sampling density, site accessibility, monitoring frequency, and the spatial extent of contamination all influence how completely a hazard is captured (Osmanoğlu et al., 2016).

Within this study, the Satellite-Integrated Multi-Hazard Environmental Risk Assessment Framework is defined as the systematic development of InSAR ground-deformation monitoring workflows, multi-source GIS data integration, remote-sensing validation procedures, hazard-exposure and vulnerability mapping, and community-engagement mechanisms that together characterize environmental risk in mining-adjacent settings. Environmental risk assessment performance is defined as the assessed and measurable ability of the framework to detect emerging hazards early, characterize their spatial extent accurately, prioritize exposed populations correctly, support timely intervention, and sustain auditable, repeatable monitoring over time. InSAR provides millimeter-scale measurements of surface displacement by comparing the phase of radar signals acquired over the same area at different times, which makes it well suited to detecting slow subsidence over dewatered aquifers, the creep of unstable slopes and tailings embankments, and the deformation associated with underground void collapse (Ferretti et al., 2001). GIS provides the integrating environment in which deformation time series are combined with hydrological data, land-cover data, contamination inventories, demographic data, and infrastructure networks to produce composite risk surfaces that decision-makers can interpret (Malczewski, 2006).

The national significance of a satellite-integrated approach is connected to the scale and distribution of mining activity and its legacy across the United States, where hundreds of thousands of abandoned mine features, numerous active operations, and a large inventory of tailings storage facilities are situated near populated areas, agricultural land, and sensitive watersheds. These operations are geographically dispersed and geologically diverse, yet they share similar risk-control needs: detecting the onset of ground instability, mapping the migration of contaminants, identifying vulnerable populations, prioritizing remediation, and supporting emergency planning. Satellite observations are therefore not only local monitoring tools but also nationally consistent measurement systems that can be applied uniformly across jurisdictions with differing ground-monitoring capacity. Studies on InSAR-based subsidence monitoring show that spaceborne radar can reveal deformation patterns that would be prohibitively expensive to capture with ground instrumentation alone (Amighpey & Arabi, 2016), while also raising challenges related to atmospheric noise, decorrelation in vegetated terrain, phase unwrapping, and the need for validation against independent measurements (Przyłucka et al., 2015). Hazard-mapping research further shows that dynamic risk conditions, incomplete legacy records, and complex hazard interactions require structured spatial models that can support both diagnosis of current conditions and anticipation of emerging threats (Zhou et al., 2021).

Figure 1: Satellite-Integrated Multi-Hazard Environmental Risk Assessment Framework



InSAR and GIS provide the central methodological foundation for this research because they frame environmental risk assessment as a spatial and temporal lifecycle activity that begins with hazard and exposure analysis and continues through data acquisition, processing, integration, validation, interpretation, communication, and periodic updating (Abdur & Iftekhar, 2021). The combined approach requires analysts and decision-makers to move from qualitative hazard awareness toward quantitative and semi-quantitative risk characterization (Hasan & Uddin, 2022; Mohiul & Badrul, 2022). Academic studies have repeatedly shown that a lifecycle approach is essential because the reliability of a satellite-integrated assessment depends on both acquisition-phase assumptions, such as radar wavelength, revisit interval, and baseline geometry, and interpretation-phase follow-up, such as validation, ground-truthing, and stakeholder communication (Kanti & Rony, 2022; Sadia et al., 2022). The integration of remote-sensing engineering with spatial analysis shows that data quality, spatial resolution, temporal coverage, and analytical transparency must be coordinated across technical and institutional activities (Tohidul, 2023; Badrul & Mominul, 2023). Concerns about false positives and false negatives in deformation detection are important for mining-adjacent communities because a risk map can appear technically complete at the processing level while still being vulnerable to weak validation, poor metadata, unsuitable temporal sampling, incomplete legacy inventories, or inadequate engagement with the communities most exposed to harm.

A major technical issue in satellite-integrated risk assessment is the quantification of deformation performance through displacement rate, coherence, temporal density of acquisitions, and the reliability of persistent-scatterer or distributed-scatterer processing. InSAR observations may be affected by atmospheric delay, orbital error, vegetation-induced decorrelation, and layover in steep terrain, and each condition requires suitable processing assumptions and error models. The relationship between data-integration quality and the resulting risk assessment is therefore central to this study, which treats InSAR monitoring, GIS integration, validation, exposure mapping, and community engagement as independent variables because the degree to which an assessment applies rigorous processing, multi-source integration, validation, and stakeholder involvement may influence the quality of framework design and the resulting environmental risk assessment performance.

Background of the Study

The background of this study is rooted in the long history of mining in the United States and the environmental legacy that continues to affect communities located near extraction sites. Mining has supported industrial development and resource supply for generations, yet it has also produced enduring hazards that persist long after operations cease. Abandoned mine lands, tailings impoundments, waste-rock piles, and altered hydrology continue to threaten nearby populations through subsidence, structural failure, and the slow release of contaminants into soil, surface water, and groundwater. Many of these hazards develop gradually and are difficult to detect with conventional ground-based monitoring, particularly across the large, remote, and topographically complex terrain where mining historically occurred. The result is a monitoring gap in which hazards may progress unobserved until they reach a threshold that produces visible damage, contamination, or loss.

Remote sensing has increasingly been recognized as a means of closing this monitoring gap (Crosetto et al., 2016). The expansion of freely available radar data, particularly from missions providing regular, wide-area coverage, has made it feasible to observe ground deformation across entire mining districts with high measurement density and consistent temporal sampling (Berardino et al., 2002). When these observations are integrated within a GIS environment alongside hydrological, geological, land-cover, contamination, and demographic data, analysts can construct composite pictures of environmental risk that capture the interaction of multiple hazards (Gill & Malamud, 2014). This integration is particularly valuable in mining-adjacent settings, where a single physical process, such as the dewatering of an aquifer or the destabilization of a tailings embankment, can simultaneously drive subsidence, contamination migration, and heightened exposure for downstream communities (Kappes et al., 2012). Despite the promise of these technologies, their application in community-scale environmental risk assessment has often remained fragmented (Hossan & Adar, 2023; Risha & Khalid, 2023). Deformation monitoring, water-quality assessment, air-quality evaluation, and vulnerability analysis are frequently carried out by different agencies, using different data, at different times, without a unifying spatial framework. This fragmentation limits the ability of decision-makers to understand how hazards interact and to prioritize interventions where combined risk is greatest. The background of this study therefore reflects both the technical maturity of InSAR and GIS and the institutional need for an integrated framework that translates satellite observations into actionable, community-relevant risk assessment for mining-adjacent populations.

Problem Statement

The central problem addressed by this study is that environmental hazard monitoring in mining-adjacent U.S. communities remains fragmented, reactive, and spatially incomplete, so that satellite-observable hazards may fail to achieve early detection and effective risk reduction when InSAR deformation monitoring, GIS multi-hazard integration, remote-sensing validation, exposure and vulnerability mapping, and community engagement are weakly implemented (Hossan, 2024; Shima Ali et al., 2024). Although the technical capability to observe ground deformation and integrate multi-hazard data has advanced substantially, the translation of that capability into reliable, repeatable, community-scale risk assessment has lagged. Assessments are often conducted after damage or contamination becomes visible, cover only single hazards, rely on point measurements that miss the broader spatial pattern, or lack the validation and metadata needed to be trusted by regulators and residents (Arif Uz et al., 2025; Zaman, 2024). This problem matters because mining-adjacent communities are frequently exposed to interacting hazards that no single-hazard, ground-only assessment can adequately capture. A framework that appears technically complete at the level of individual measurements may still under-protect communities if it does not integrate hazards spatially, validate its outputs, identify vulnerable populations, or engage the people most affected. The consequences of this gap include delayed detection of subsidence and slope instability, unrecognized contamination migration, misallocated remediation resources, and reduced community trust. The study therefore investigates how a satellite-integrated, multi-hazard framework built on InSAR and GIS influences the quality and reliability of environmental risk assessment, and which technical and institutional factors most strongly shape assessment performance.

Objectives of the Study

The general objective of this study was to assess how a Satellite-Integrated Multi-Hazard Environmental Risk Assessment Framework, built on InSAR and GIS, influences environmental risk assessment performance in mining-adjacent U.S. communities. The specific objectives were: to examine the influence of InSAR ground-deformation monitoring on framework design quality; to assess the relationship between GIS multi-hazard data integration and environmental risk assessment performance; to evaluate the effect of remote-sensing data quality and validation on assessment performance; to determine the role of hazard exposure and vulnerability mapping in strengthening assessment reliability; to test the effect of framework design quality on environmental risk assessment performance; and to examine the role of community and institutional engagement in improving assessment outcomes. A further objective was to identify framework maturity levels and hazard risk-control gaps across the assessment lifecycle.

Research Hypotheses

Six hypotheses guided the study. H1 proposed that InSAR ground-deformation monitoring has significantly influenced framework design quality. H2 proposed that GIS multi-hazard data integration has a significant positive relationship with environmental risk assessment performance. H3 proposed that remote-sensing data quality and validation have significantly influenced environmental risk assessment performance. H4 proposed that hazard exposure and vulnerability mapping have significantly improved assessment reliability. H5 proposed that framework design quality has significantly predicted environmental risk assessment performance. H6 proposed that community and institutional engagement has significantly strengthened environmental risk assessment performance.

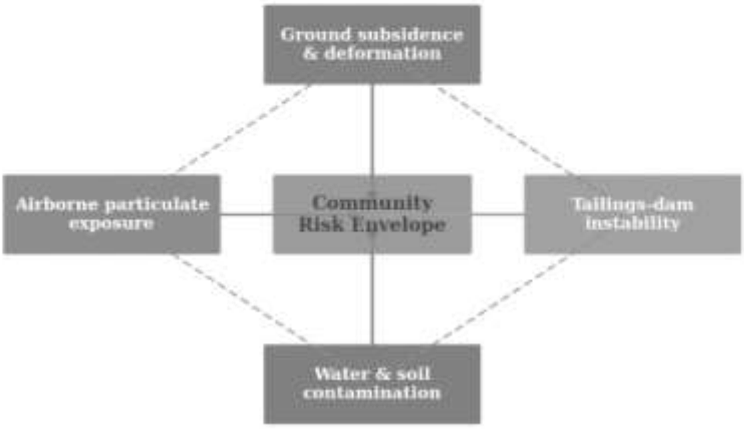
Significance of the Research

This research is significant because it addresses a practical and consequential gap between the technical maturity of satellite-based hazard observation and the institutional need for integrated, community-scale environmental risk assessment. By treating InSAR deformation monitoring and GIS integration as components of a single multi-hazard framework, the study offers a way to move beyond fragmented, single-hazard assessment toward a coordinated approach that reflects how hazards actually interact in mining-adjacent settings. The findings are relevant to environmental agencies, mining regulators, geospatial analysts, local planners, and public-health officials who must prioritize limited resources across dispersed and often abandoned sites. The study also contributes to the broader literature on remote sensing for hazard management (Ismail et al., 2022) by empirically examining which technical and institutional factors most strongly influence the reliability of satellite-integrated assessment, and by developing a framework maturity index and a hazard risk-control priority matrix that translate statistical results into actionable improvement priorities.

LITERATURE REVIEW

The literature on mining-related environmental hazards consistently emphasizes that communities located near extraction sites face a compound risk profile that differs from that of other industrial settings. Ground subsidence, which results from the collapse of underground voids or the dewatering of aquifers, can damage buildings, roads, pipelines, and drainage systems, and can develop gradually over years or suddenly as sinkholes.

Figure 2: Interacting Environmental Hazards in Mining-Adjacent Settings



Tailings storage facilities, which impound the fine-grained waste left after ore processing, represent a persistent structural hazard because their failure can release large volumes of saturated material downstream with little warning. Contamination hazards include acid mine drainage, in which sulfide minerals react with water and air to produce acidic, metal-laden runoff, as well as the leaching of heavy metals and processing chemicals into soil, surface water, and groundwater (Hudson-Edwards et al., 2011). Airborne hazards include dust from waste-rock piles and dry tailings surfaces, which can carry fine particulate matter and toxic elements into nearby settlements (Nriagu, 1988).Studies of these hazards repeatedly stress their interaction. Ground deformation can compromise the integrity of containment structures and alter drainage pathways, changing how contaminants migrate (Hossan, 2025; Mukut Kanti, 2025). Contamination can persist for decades at abandoned sites where records are incomplete and responsibility is unclear. Exposure depends not only on the physical hazard but also on the location, density, and vulnerability of nearby populations (Kanti, 2025; Shima Ali et al., 2025). The literature therefore supports a multi-hazard perspective in which subsidence, structural instability, contamination, and airborne exposure are understood as connected phenomena within a shared spatial and temporal system, rather than as separate problems to be assessed independently (Gama et al., 2019).

InSAR for Ground-Deformation Monitoring

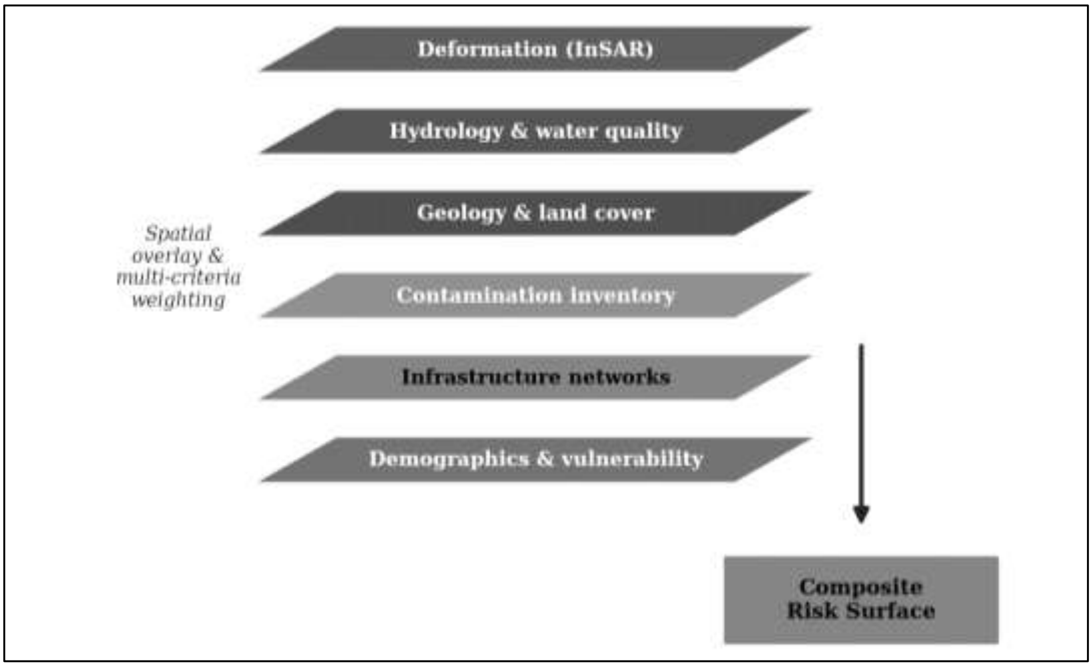
Interferometric Synthetic Aperture Radar has become a central technology for monitoring ground deformation over mining regions. By measuring the phase difference between radar acquisitions of the same scene at different times, InSAR can detect surface displacement at the millimeter to centimeter scale over wide areas, a sensitivity that has been exploited across a broad range of monitoring applications (Tapete & Cigna, 2019). Advanced time-series techniques, including persistent-scatterer (Crosetto et al., 2016) and small-baseline and distributed-scatterer approaches (Berardino et al., 2002), extend this capability by tracking the deformation of stable reflectors through long sequences of acquisitions, allowing analysts to distinguish real ground motion from atmospheric and orbital noise (Hooper et al., 2007). The literature documents successful application of these techniques to subsidence over dewatered aquifers (Hu et al., 2013), the slow creep of unstable slopes (Wasowski & Bovenga, 2014), the settlement of tailings embankments (Thomas et al., 2023), deformation of engineered structures (Jung et al., 2019), and the collapse associated with underground mining (Chen et al., 2016). At the same time, the literature is candid about the limitations of InSAR. Coherence, the measure of how well radar signals correlate between acquisitions, degrades in densely vegetated, snow-covered, or rapidly changing terrain, which is common in many mining districts. Atmospheric water vapor introduces phase delays that can mimic or mask deformation, and phase unwrapping becomes difficult where displacement gradients are steep. Steep topography produces layover and shadow that obscure parts of the scene (Amir, 2026; Mahmudul & Sadia, 2026). These limitations mean that InSAR results must be processed carefully (Ferretti et al., 2011), interpreted with attention to error, and validated against independent measurements such as leveling, GNSS, or in-situ instrumentation (Hooper et al., 2004). The reliability of an InSAR-based assessment therefore depends heavily on processing choices, acquisition geometry, temporal density, and validation, all of which the present study treats as elements of monitoring quality (Osmanoğlu et al., 2016).

GIS Integration of Multi-Hazard Data

Geographic Information Systems provide the analytical environment in which deformation observations are combined with the many other data layers needed to characterize environmental risk. The literature on GIS-based hazard assessment describes how spatial overlay, interpolation, weighted-overlay, and multi-criteria decision methods (Gigović et al., 2019) can integrate deformation, hydrology, geology, land cover, contamination inventories, infrastructure networks, and demographic data into composite risk surfaces. This integration allows analysts to identify locations where multiple hazards coincide, to trace potential pathways of contaminant migration, and to relate physical hazards to the populations and assets they threaten (Shurovi, 2026; Shima Ali et al., 2026). The quality of such integration depends on the accuracy, resolution, currency, and interoperability of the input layers, as well as on the transparency of the weighting and combination rules used to produce composite outputs (Malczewski, 2006).

Research also highlights persistent challenges in multi-hazard GIS integration. Data from different sources are often collected at different scales, in different coordinate systems, and with different levels of completeness, which complicates their combination (Syed Nurul, 2026). Legacy contamination inventories may be incomplete or outdated, particularly for abandoned sites. Weighting schemes involve judgments that can strongly influence results and that require justification and sensitivity testing (Lottermoser, 2010). The literature therefore treats GIS integration not as a mechanical overlay but as a methodological process whose reliability depends on data quality, documented assumptions, and validation, consistent with how the present study conceptualizes GIS multi-hazard data integration (Zhou et al., 2021).

Figure 4: GIS Multi-Hazard Data Integration Architecture



Hazard Exposure and Vulnerability Mapping

A recurring theme in the risk-assessment literature is that hazard alone does not determine risk; exposure and vulnerability are equally important. Exposure refers to the presence of people, property, and resources in areas subject to hazard, while vulnerability refers to the characteristics that make those people and assets more or less susceptible to harm. In mining-adjacent communities, vulnerability is shaped by factors such as population density, housing conditions, proximity to water sources, reliance on local agriculture, and the demographic and socioeconomic characteristics that affect a community's capacity to prepare for, respond to, and recover from hazardous events. The literature on social vulnerability mapping provides indices and methods for representing these characteristics spatially (Cutter et al., 2003), so that risk assessment can distinguish areas of high physical hazard from areas of high combined risk where hazard and vulnerability coincide (Birkmann et al., 2013). Integrating exposure and vulnerability with satellite-derived hazard information allows an assessment to move from mapping where the ground is moving or where contamination exists toward identifying where those hazards most threaten people. This integration is essential for prioritization (Cutter et al., 2008), because remediation and monitoring resources are limited and must be directed to where combined risk is greatest. The present study treats hazard exposure and vulnerability mapping as a distinct component of the framework precisely because its inclusion transforms technical hazard detection into community-relevant risk assessment.

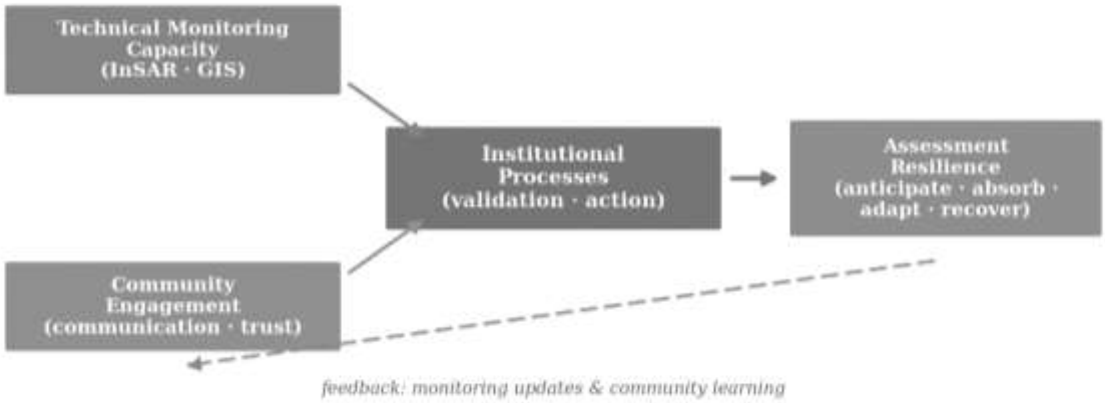
Figure 5: Risk as the Intersection of Hazard, Exposure, and Vulnerability

Theoretical Framework: Socio-Technical Systems and Resilience Theory

This study is grounded in socio-technical systems thinking and resilience theory, which together provide a lens for understanding why a satellite-integrated framework must combine technical capability with institutional and community engagement to produce reliable risk assessment (Perrow, 1984). Socio-technical systems theory holds that the performance of complex technical systems cannot be understood in isolation from the human, organizational, and institutional context in which they operate (Trist, 1981). Socio-technical systems theory holds that the performance of complex technical systems cannot be understood in isolation from the human, organizational, and institutional context in which they operate. Applied to environmental risk assessment, this perspective implies that InSAR processing and GIS integration, however sophisticated, will not translate into effective risk reduction unless they are embedded in institutions capable of validating outputs, communicating results, and acting on them, and unless the communities most affected are engaged in the process.

Resilience theory complements this view by emphasizing a system's capacity to anticipate, absorb, adapt to, and recover from disturbances (Weick & Sutcliffe, 2007). In the context of mining-adjacent communities, resilience depends on the early detection of emerging hazards (Folke, 2006), the accurate characterization of their spatial extent, the identification of vulnerable populations, and the presence of institutional arrangements that can convert information into timely action. In the context of mining-adjacent communities, resilience depends on the early detection of emerging hazards, the accurate characterization of their spatial extent, the identification of vulnerable populations, and the presence of institutional arrangements that can convert information into timely action. A satellite-integrated framework contributes to resilience by extending the temporal and spatial reach of monitoring, but its contribution is realized only when technical outputs are validated, communicated, and integrated into decision-making. Together, socio-technical and resilience perspectives justify the study's inclusion of both technical variables, such as InSAR monitoring and GIS integration, and institutional variables, such as validation and community engagement, as determinants of assessment performance.

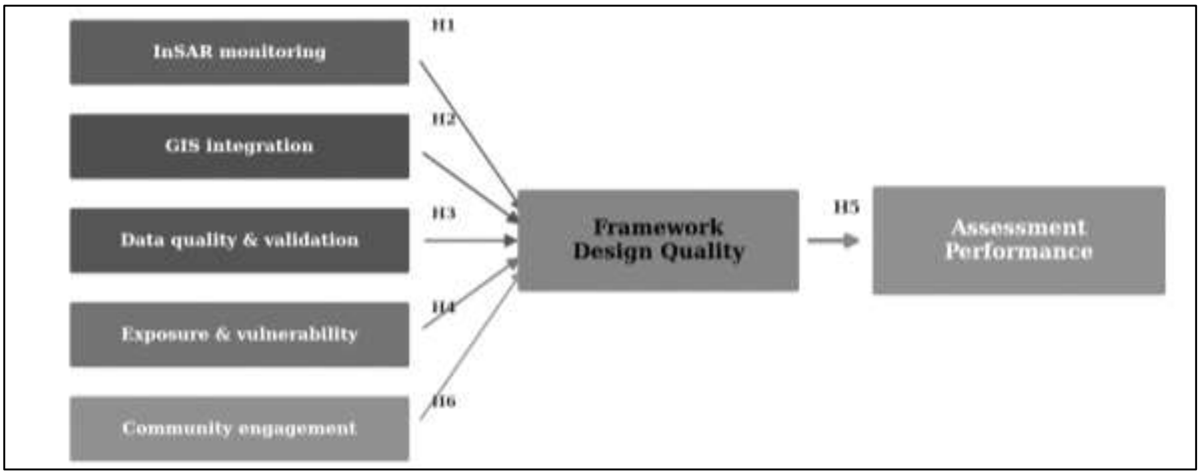
Figure 6: Socio-Technical and Resilience Framework for Environmental Risk Assessment



Conceptual Framework

Drawing on the reviewed literature and theoretical perspectives, the conceptual framework of this study positions environmental risk assessment performance as the dependent variable, influenced by six independent and mediating constructs. InSAR ground-deformation monitoring and GIS multi-hazard data integration represent the core technical capabilities of the framework. Remote-sensing data quality and validation, together with hazard exposure and vulnerability mapping, represent the methodological rigor that converts raw observation into trustworthy, community-relevant information. Community and institutional engagement represents the socio-technical context that determines whether outputs are acted upon. Framework design quality functions as an integrating construct that captures how coherently these elements are combined, and it is expected to be the strongest direct predictor of assessment performance. The framework proposes that stronger implementation of each construct, operating together as a socio-technical system, produces more reliable, timely, and actionable environmental risk assessment for mining-adjacent communities.

Figure 7: Predictive Conceptual Framework for Environmental Risk Assessment Performance

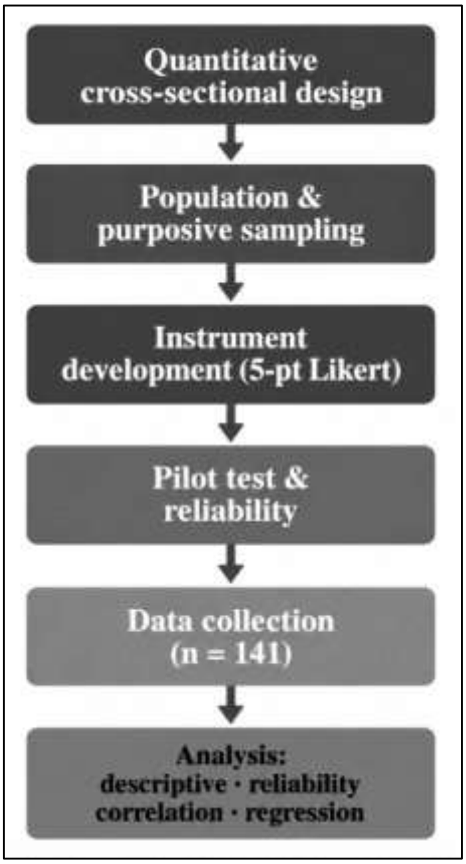


METHODS

This study adopted a quantitative, cross-sectional, case-based research design to examine how a Satellite-Integrated Multi-Hazard Environmental Risk Assessment Framework, built on InSAR and GIS, influences environmental risk assessment performance in mining-adjacent U.S. communities. The quantitative approach was selected because the study measured relationships among key variables using numerical data collected through a structured questionnaire. The cross-sectional design was appropriate because data were gathered from respondents at a single point in time, while the case-based approach enabled the research to focus on communities located near active, inactive, and abandoned mining operations where InSAR and GIS have been applied or considered relevant for environmental hazard monitoring. The case context focused on mining-adjacent environments such as districts affected by coal, hard-rock, and metal mining, tailings-storage areas, abandoned mine lands, and watersheds subject to acid mine drainage and heavy-metal contamination. These settings were selected because they depend heavily on wide-area monitoring for the detection of subsidence, slope and tailings instability, contamination migration, and airborne exposure. The study considered these environments suitable because a satellite-integrated framework is highly relevant to their monitoring, remediation-prioritization, and community-protection needs.

The population of the study consisted of professionals involved in environmental monitoring, geospatial analysis, remote sensing, mining and geotechnical engineering, hazard assessment, and local planning and public health. The unit of analysis was the individual professional respondent who possessed knowledge or experience related to InSAR, GIS, multi-hazard assessment, mining-related contamination, or community risk in mining-adjacent settings. The study used a purposive sampling strategy because respondents needed specific technical or institutional knowledge to provide valid responses. Where possible, the sample included geospatial analysts, environmental scientists, remote-sensing specialists, mining and geotechnical engineers, hydrologists, and local planning and public-health officials. The data-collection procedure involved a structured questionnaire distributed to selected respondents electronically or physically. Before data collection, respondents were informed about the academic purpose of the study, voluntary participation, confidentiality, and anonymity. The collected responses were reviewed for completeness, consistency, and suitability before analysis, and incomplete or invalid responses were excluded to maintain data quality.

Figure 8: Research Methodology



The instrument design was based on a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The questionnaire included sections on demographic profile, InSAR ground-deformation monitoring, GIS multi-hazard data integration, remote-sensing data quality and validation, hazard exposure and vulnerability mapping, community and institutional engagement, framework design quality, and environmental risk assessment performance. A pilot test was conducted before the main survey to assess the clarity, relevance, wording, and technical suitability of the questionnaire items. Feedback from the pilot test was used to improve ambiguous or repetitive items. Validity and reliability were ensured through expert review and statistical testing. Content validity was supported by aligning questionnaire items with the study objectives and risk-assessment concepts, while reliability was tested using Cronbach's alpha, with a value of 0.70 or above considered acceptable.

DATA ANALYSIS AND PRESENTATION

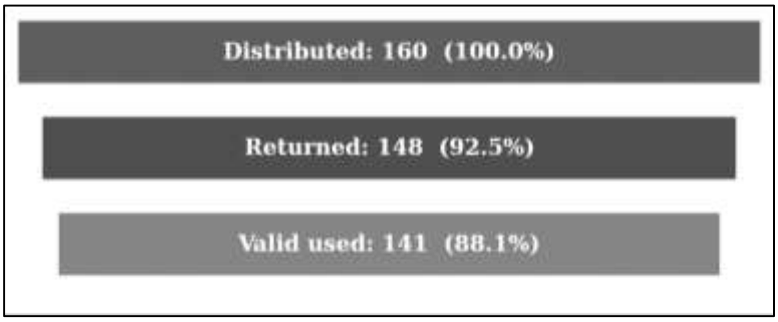
Response Rate

Table 1: Response Rate of the Survey

Survey Status	Frequency	Percentage
Questionnaires distributed	160	100.0%
Questionnaires returned	148	92.5%
Invalid/incomplete responses	7	4.4%
Valid responses used for analysis	141	88.1%

The response-rate results in Table 1 showed that the study achieved a strong and acceptable level of participation from professionals involved in mining-adjacent environmental monitoring. Out of 160 questionnaires distributed, 148 responses were returned, representing a return rate of 92.5%. After screening for completeness, consistency, and suitability for statistical analysis, 7 responses were removed because they contained missing values, incomplete Likert-scale answers, or inconsistent response patterns. As a result, 141 valid responses were retained for final analysis, producing an effective valid response rate of 88.1%.

Figure 11: Survey Response Funnel and Valid Response Rate



This response rate was considered suitable for a quantitative, cross-sectional, case-based study because it provided enough data to conduct descriptive statistics, reliability analysis, correlation analysis, and regression modeling. The response rate also strengthened the credibility of the findings because the respondents represented relevant professional groups connected to remote sensing, geospatial analysis, environmental science, mining and geotechnical engineering, hydrology, planning, and public health. From a socio-technical perspective, the strong response rate suggested that the selected professional population showed meaningful engagement with hazard-monitoring issues and provided sufficient institutional insight into technical capability, validation practices, exposure analysis, and community engagement. The valid sample of 141 respondents therefore provided a dependable foundation for examining the study objectives and hypotheses, allowing the research to test whether InSAR monitoring, GIS integration, validation, vulnerability mapping, community engagement, and framework design quality significantly contributed to environmental risk assessment performance.

Demographic and Professional Profile of Respondents

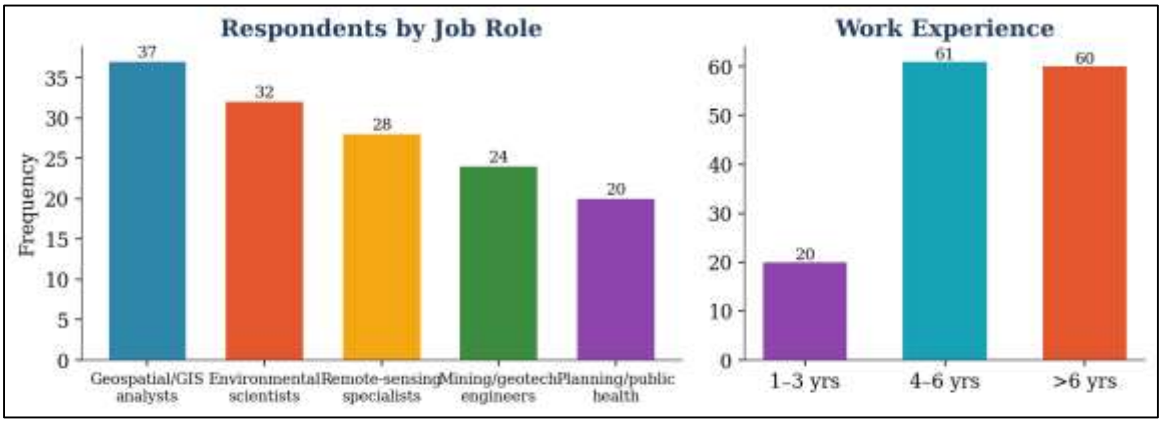
Table 2 presented the demographic and professional characteristics of the 141 respondents included in the analysis. The results indicated that the sample was technically relevant to the research topic because the largest group of respondents consisted of geospatial and GIS analysts, accounting for 26.2% of the sample. This was followed by environmental scientists at 22.7%, remote-sensing specialists at 19.9%, mining and geotechnical engineers at 17.0%, and planning and public-health officials at 14.2%. This distribution was useful because satellite-integrated risk assessment depends on multiple professional roles rather than one technical group alone. Geospatial and GIS analysts are typically involved in data integration, spatial modeling, and map production. Remote-sensing specialists contribute expertise in InSAR processing, coherence assessment, and validation. Environmental scientists support contamination assessment, water and soil analysis, and exposure evaluation. Mining and geotechnical engineers contribute knowledge of subsidence mechanisms, tailings behavior, and structural stability. Planning and public-health officials contribute knowledge of exposed populations, vulnerability, and community engagement. The experience profile also strengthened the study because 42.6% of respondents had more than six years of experience, while 43.3% had four to six years of experience. In addition, 66.7% of respondents reported direct involvement in hazard-monitoring or risk-assessment activities, while 33.3% had indirect involvement.

Table 2: Demographic and Professional Profile of Respondents

Profile Variable	Category	Frequency	Percentage
Job role	Geospatial/GIS analysts	37	26.2%
Job role	Environmental scientists	32	22.7%
Job role	Remote-sensing specialists	28	19.9%
Job role	Mining/geotechnical engineers	24	17.0%
Job role	Planning/public-health officials	20	14.2%
Work experience	1–3 years	20	14.2%
Work experience	4–6 years	61	43.3%
Work experience	Above 6 years	60	42.6%
Involvement	Direct involvement	94	66.7%
Involvement	Indirect involvement	47	33.3%

This profile supported the validity of the findings because the study depended on respondents who understood InSAR processing, GIS integration, validation, exposure mapping, and environmental risk assessment. From a socio-technical perspective, the sample reflected a cross-functional system in which reliable assessment depends on communication, expertise, spatial awareness, and coordination among different professional groups. The respondent profile was therefore appropriate for addressing the study objectives and testing the hypotheses.

Figure 12: Respondent Profile by Job Role and Work Experience



Descriptive Statistics of Study Variables

Table 3 showed the descriptive statistics for the major study variables measured through the five-point Likert scale. All variables recorded mean scores above the neutral midpoint of 3.00 and within the high interpretation range of 3.41–4.20, suggesting that respondents generally agreed that satellite-integrated practices, InSAR monitoring, GIS integration, validation, vulnerability mapping, community engagement, and assessment performance were positively present in the selected mining-adjacent context. Environmental risk assessment performance recorded the highest mean of 4.17 with a standard deviation of 0.56, indicating that respondents perceived early detection, spatial characterization, prioritization, and repeatable monitoring as relatively strong. InSAR ground-deformation monitoring recorded a mean of 4.13, showing that displacement detection, time-series processing, and coverage were perceived as well implemented.

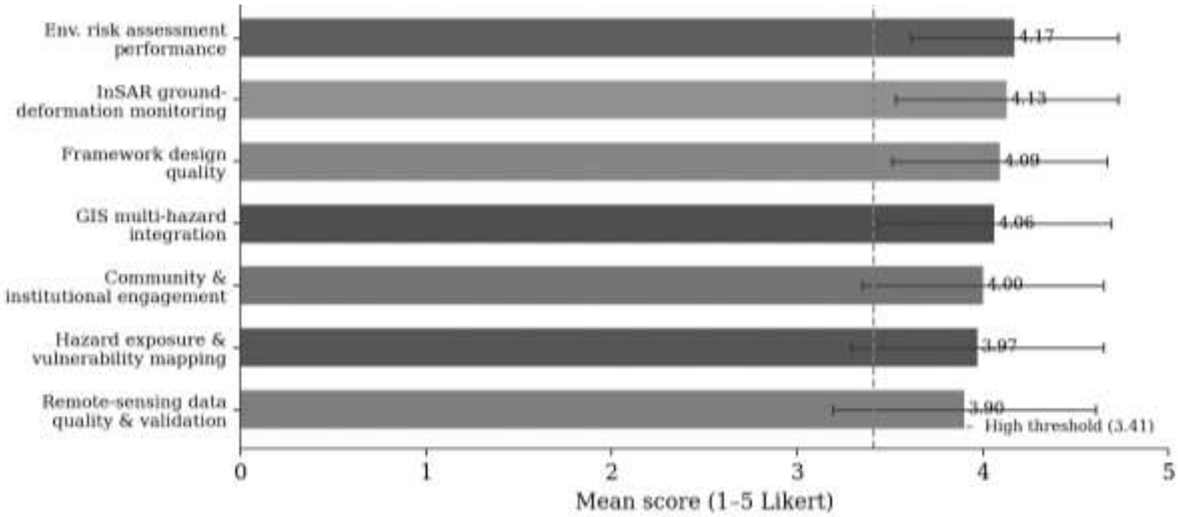
Table 3: Descriptive Statistics of Study Variables Based on Five-Point Likert Scale

Study Variable	Mean	SD	Interpretation	Rank
Environmental risk assessment performance	4.17	0.56	High	1
InSAR ground-deformation monitoring	4.13	0.60	High	2
Framework design quality	4.09	0.58	High	3
GIS multi-hazard data integration	4.06	0.63	High	4
Community and institutional engagement	4.00	0.65	High	5
Hazard exposure and vulnerability mapping	3.97	0.68	High	6
Remote-sensing data quality and validation	3.90	0.71	High	7

Likert interpretation guide: 1.00–1.80 = Very Low, 1.81–2.60 = Low, 2.61–3.40 = Moderate, 3.41–4.20 = High, 4.21–5.00 = Very High.

Framework design quality followed with a mean of 4.09, suggesting agreement that the coherent combination of technical and institutional elements supported assessment goals. GIS multi-hazard data integration recorded 4.06, community and institutional engagement recorded 4.00, and hazard exposure and vulnerability mapping recorded 3.97. Remote-sensing data quality and validation recorded the lowest mean of 3.90. Although all values remained in the high range, the lower ranking of validation and vulnerability mapping suggested that these methodological and community-facing activities may require more focused improvement. These findings aligned with socio-technical and resilience perspectives because the strongest assessment performance appeared where technical capability, methodological rigor, and community engagement operated together.

Figure 13: Mean Scores of Study Variables with Standard Deviation



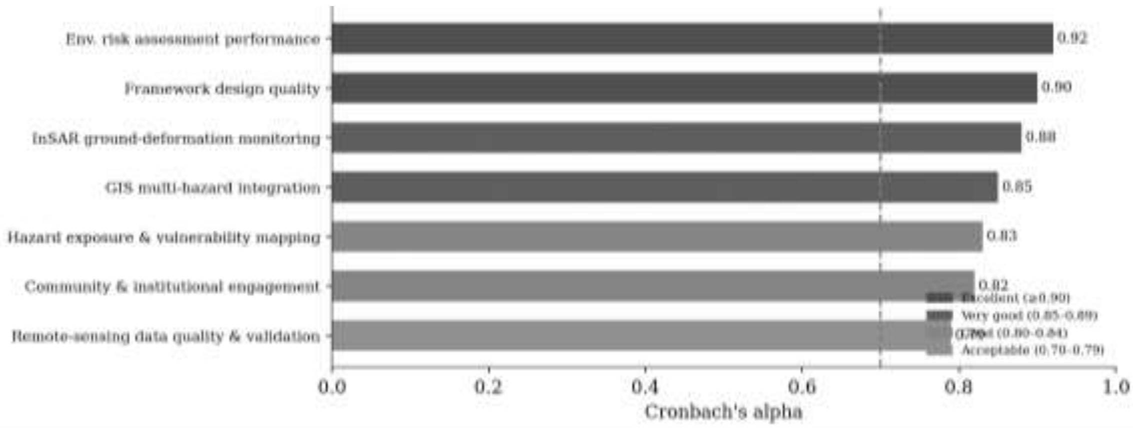
Reliability Analysis

Table 4: Reliability Analysis of Study Constructs

Construct	Items	Cronbach's Alpha	Decision
InSAR ground-deformation monitoring	6	0.88	Reliable
GIS multi-hazard data integration	6	0.85	Reliable
Remote-sensing data quality and validation	5	0.79	Reliable
Hazard exposure and vulnerability mapping	5	0.83	Reliable
Community and institutional engagement	5	0.82	Reliable
Framework design quality	6	0.90	Reliable
Environmental risk assessment performance	6	0.92	Reliable

Table 4 presented the reliability results for the major questionnaire constructs. Cronbach's alpha was used to determine whether the items measuring each construct were internally consistent. The accepted threshold was 0.70, and all constructs exceeded this minimum. Environmental risk assessment performance recorded the highest alpha of 0.92, indicating excellent internal consistency among items measuring early detection, spatial characterization, prioritization, and repeatable monitoring. Framework design quality recorded 0.90, confirming that items measuring the coherent integration of technical and institutional elements formed a reliable construct. InSAR ground-deformation monitoring recorded 0.88, GIS multi-hazard data integration recorded 0.85, and hazard exposure and vulnerability mapping recorded 0.83. Community and institutional engagement recorded 0.82, confirming that items on communication, stakeholder involvement, and institutional coordination reliably measured the socio-technical dimension. Remote-sensing data quality and validation recorded the lowest alpha of 0.79, which remained above the accepted threshold and was therefore considered reliable. These reliability results strengthened the trustworthiness of the study by showing that the questionnaire measured the intended constructs consistently, and they supported the socio-technical view that assessment performance is measurable as a combination of technical and institutional practices.

Figure 14: Internal Consistency Reliability (Cronbach's Alpha) of Study Constructs



Correlation Analysis

Table 5: Pearson Correlation Analysis among Major Study Variables

Relationship Tested	r	Significance	Interpretation	Link
InSAR monitoring and framework design quality	0.73	p < 0.01	Strong positive	H1
GIS integration and assessment performance	0.67	p < 0.01	Strong positive	H2
Data quality/validation and assessment performance	0.70	p < 0.01	Strong positive	H3
Exposure/vulnerability mapping and reliability	0.63	p < 0.01	Moderate-to-strong	H4
Community engagement and assessment performance	0.65	p < 0.01	Strong positive	H6
Framework design quality and assessment performance	0.76	p < 0.01	Strong positive	H5

Table 5 presented the Pearson correlation results used to examine the strength and direction of relationships among the major study variables. All tested relationships were positive and statistically significant at $p < 0.01$, indicating that stronger implementation of technical and institutional practices was associated with stronger environmental risk assessment performance. The relationship between InSAR ground-deformation monitoring and framework design quality recorded a strong positive correlation of $r = 0.73$, supporting H1 by showing that stronger deformation-monitoring capability accompanied stronger framework design. GIS multi-hazard data integration correlated with assessment performance at $r = 0.67$, supporting H2. Remote-sensing data quality and validation correlated with assessment performance at $r = 0.70$, supporting H3 and indicating that validation and error control contributed meaningfully to trustworthy outputs. Hazard exposure and vulnerability mapping recorded $r = 0.63$ with assessment reliability, supporting H4. Community and institutional engagement recorded r = 0.65 with assessment performance, supporting the socio-technical argument that reliable assessment depends on institutional and community behavior as well as technical systems. Framework design quality showed the strongest relationship with assessment performance at r = 0.76, supporting H5 and confirming that coherent design was highly relevant to outcomes. These findings aligned with socio-technical and resilience perspectives because assessment performance improved when technical capability, methodological rigor, and community engagement operated together as an integrated system.

Figure 15: Correlation Strength among Major Study Variables

Regression Analysis

Table 6: Multiple Regression Results Predicting Environmental Risk Assessment Performance

Predictor Variable	Std. Beta (β)	t-value	p-value	Decision
InSAR ground-deformation monitoring	0.25	3.42	0.001	Significant
GIS multi-hazard data integration	0.22	3.05	0.003	Significant
Remote-sensing data quality and validation	0.19	2.71	0.008	Significant
Hazard exposure and vulnerability mapping	0.16	2.44	0.016	Significant
Community and institutional engagement	0.17	2.60	0.010	Significant
Framework design quality	0.32	4.48	<0.001	Significant

Table 7: Model Summary for Regression Analysis

Model Indicator	Value
R	0.831
R^2	0.691
Adjusted R^2	0.678
F-statistic	49.87
df	6, 134
Significance	$p < 0.001$

Tables 6 and 7 presented the multiple regression results used to determine the predictive effect of the independent variables on environmental risk assessment performance. The regression model was statistically significant, $F(6, 134) = 49.87$, $p < 0.001$, indicating that the selected predictors collectively explained assessment performance in a meaningful way. The model recorded an R value of 0.831, showing a strong overall relationship between the predictors and the dependent variable. The R^2 value of 0.691 indicated that 69.1% of the variance in environmental risk assessment performance was explained by InSAR monitoring, GIS integration, data quality and validation, exposure and vulnerability mapping, community engagement, and framework design quality. The adjusted R^2 value of 0.678 confirmed that the model remained strong after accounting for the number of predictors. Among the predictors, framework design quality showed the strongest effect, with $\beta = 0.32$ and $p < 0.001$, indicating that coherent framework design was the most important predictor of assessment outcomes. InSAR ground-deformation monitoring showed a significant positive effect, with $\beta = 0.25$ and $p = 0.001$, confirming that strong deformation monitoring improved assessment performance. GIS multi-hazard data integration recorded $\beta = 0.22$ and $p = 0.003$, while remote-sensing data quality and validation recorded $\beta = 0.19$ and $p = 0.008$. Community and institutional engagement recorded $\beta = 0.17$ and $p = 0.010$, and hazard exposure and vulnerability mapping recorded $\beta = 0.16$ and $p = 0.016$, a smaller but still significant contribution. These results supported the socio-technical and resilience perspectives because assessment performance was explained by both technical capability and institutional engagement, and they directly supported the study objectives by proving that the selected variables significantly predicted assessment performance.

Figure 16: Predictive Strength of Factors on Assessment Performance (Standardized Beta)

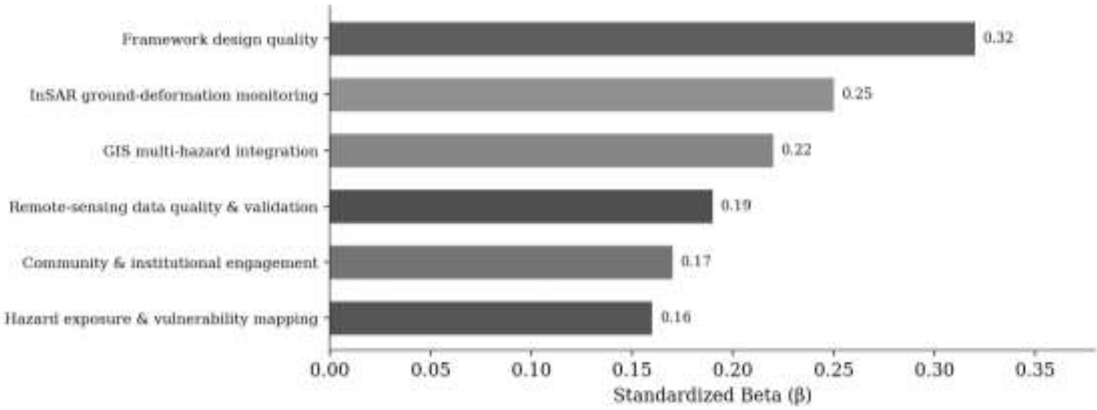
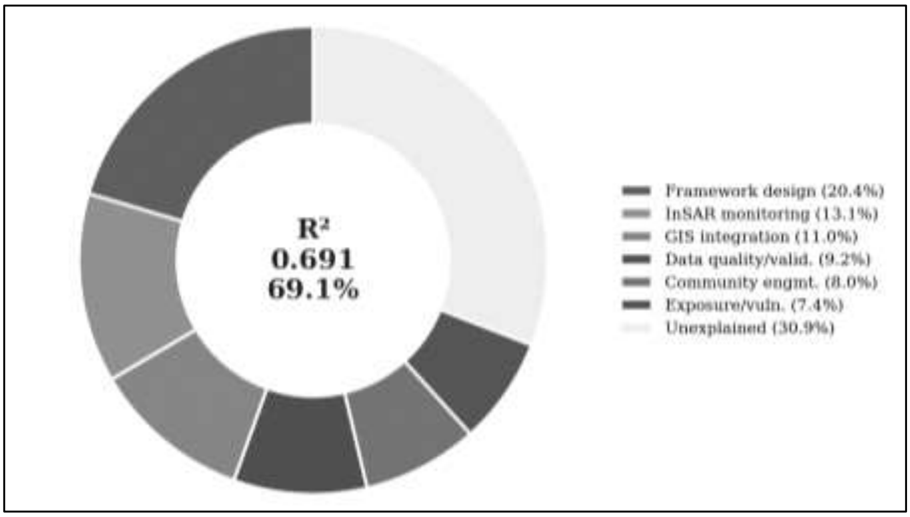


Figure 17: Proportion of Variance in Assessment Performance Explained by the Six Predictors



Hypotheses Testing

Table 8: Summary of Hypotheses Testing

Hypothesis	Statement	Statistical Evidence	Decision
H1	InSAR monitoring has significantly influenced framework design quality.	r = 0.73, β = 0.25, p = 0.001	Supported
H2	GIS integration has a significant positive relationship with assessment performance.	r = 0.67, β = 0.22, p = 0.003	Supported
H3	Data quality and validation have significantly influenced assessment performance.	r = 0.70, β = 0.19, p = 0.008	Supported
H4	Exposure and vulnerability mapping have significantly improved assessment reliability.	r = 0.63, β = 0.16, p = 0.016	Supported
H5	Framework design quality has significantly predicted assessment performance.	r = 0.76, β = 0.32, p < 0.001	Supported
H6	Community engagement has significantly strengthened assessment performance.	r = 0.65, β = 0.17, p = 0.010	Supported

Table 8 summarized the results of the hypotheses testing and showed that all six hypotheses were supported by the statistical findings. H1 was supported because InSAR ground-deformation monitoring showed a strong positive relationship with framework design quality and produced a significant regression effect, confirming that stronger deformation-monitoring capability accompanied stronger framework design. H2 was supported because GIS multi-hazard data integration showed a significant positive relationship with assessment performance, meaning that better integration of deformation, hydrological, contamination, and demographic layers was associated with stronger outcomes. H3 was supported because remote-sensing data quality and validation significantly influenced assessment performance, confirming that error control, ground-truthing, and validated outputs improved trust in results. H4 was supported because hazard exposure and vulnerability mapping showed a significant positive effect on assessment reliability, suggesting that identifying exposed and vulnerable populations strengthened the community relevance of the assessment. H5 was supported because framework design quality was the strongest predictor of assessment performance, with $\beta = 0.32$ and $p < 0.001$, directly proving the main objective of the study. H6 was supported because community and institutional engagement showed a significant positive effect, linking the findings to socio-technical and resilience perspectives, which emphasize that reliable performance in complex settings depends on communication, learning, and institutional coordination as well as technical systems. Overall, the hypotheses testing demonstrated that the study model was statistically supported and that both technical and institutional variables contributed to environmental risk assessment performance in mining-adjacent communities.

Framework Compliance Maturity Index

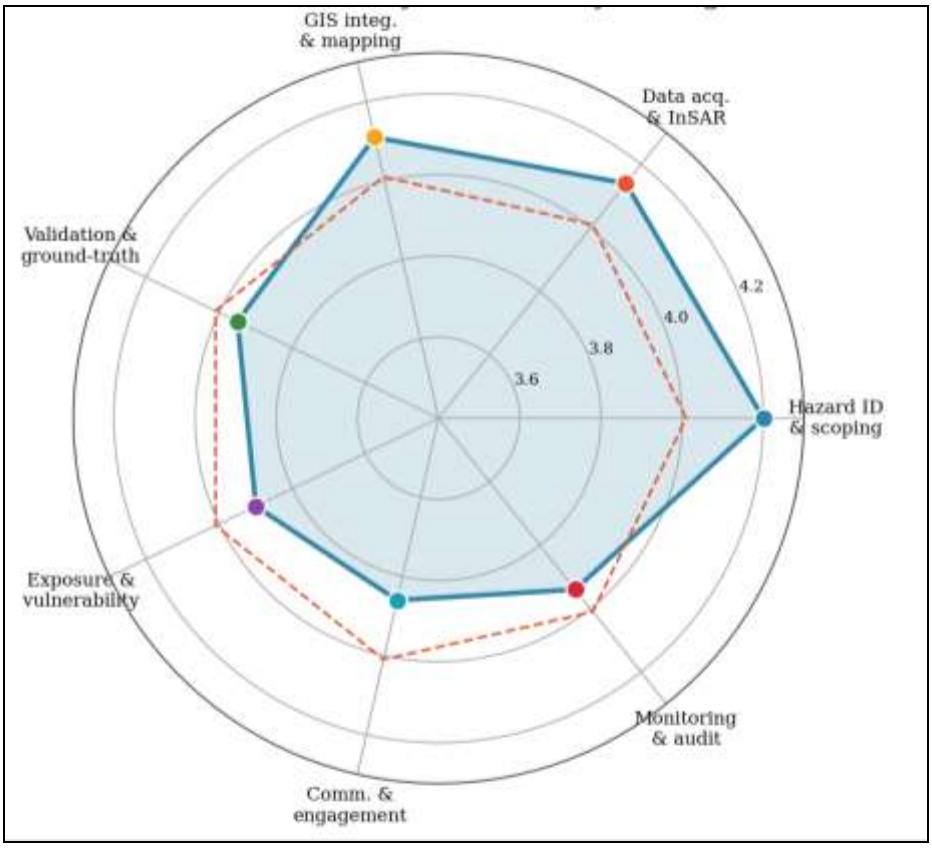
Table 9: Satellite-Integrated Framework Maturity Index

Framework Lifecycle Stage	Mean	SD	Maturity Level	Priority
Hazard identification and scoping	4.20	0.52	High maturity	Maintain and strengthen
Data acquisition and InSAR processing	4.14	0.55	High maturity	Maintain
GIS integration and composite mapping	4.11	0.57	High maturity	Maintain
Validation and ground-truthing	3.95	0.67	High maturity	Improve documentation
Exposure and vulnerability analysis	3.90	0.70	High maturity	Needs attention
Communication and community engagement	3.86	0.74	High maturity	Needs attention
Monitoring update and audit readiness	3.94	0.66	High maturity	Improve consistency
Overall framework maturity	4.01	0.63	High maturity	Strong but improvable

Maturity interpretation guide: 1.00–1.80 = Very Low Maturity, 1.81–2.60 = Low Maturity, 2.61–3.40 = Moderate Maturity, 3.41–4.20 = High Maturity, 4.21–5.00 = Very High Maturity.

Table 9 presented the Satellite-Integrated Framework Maturity Index, developed as a study-specific result to assess how mature the selected mining-adjacent settings were across major stages of the assessment lifecycle. The overall maturity score was 4.01, falling within the high-maturity range and indicating that the case context generally demonstrated strong implementation of satellite-integrated practices. Hazard identification and scoping recorded the highest maturity mean of 4.20, suggesting relatively strong capability in defining hazards, delineating study areas, and determining monitoring needs. Data acquisition and InSAR processing recorded 4.14, while GIS integration and composite mapping recorded 4.11, showing that the early technical stages were relatively strong. Validation and ground-truthing recorded 3.95, indicating high maturity but room for improvement in independent verification and documentation. Monitoring update and audit readiness recorded 3.94, suggesting that records were available but could benefit from better standardization. Exposure and vulnerability analysis recorded 3.90, while communication and community engagement recorded the lowest maturity score of 3.86. Although both values remained classified as high maturity, their lower ranking showed that community-facing and validation activities required more attention than the core technical stages. This result aligned with the descriptive findings, where validation and vulnerability mapping recorded the lowest means among the major constructs. The maturity index linked directly to socio-technical and resilience perspectives because it showed that reliable assessment depends on continuous lifecycle discipline and community engagement rather than one-time technical processing.

Figure 18: Framework Maturity Across Lifecycle Stages



Hazard Risk-Control Priority Matrix

Table 10 presented the Hazard Risk-Control Priority Matrix, developed to compare the perceived importance and current implementation effectiveness of major hazard-control areas within the framework. The gap score was calculated by subtracting the effectiveness mean from the importance mean, with a higher gap score indicating a higher improvement priority. The results showed that independent validation and ground-truthing recorded the largest gap score of 1.12, followed closely by community risk communication with a gap score of 1.08. Both areas were therefore classified as very high priority, meaning that respondents considered them highly important while rating their current effectiveness lower than desired. Vulnerability and exposure mapping was also classified as very high priority, with an importance mean of 4.60, an effectiveness mean of 3.69, and a gap score of 0.91, suggesting a need to strengthen the link between physical hazard detection and the identification of at-risk populations. Tailings-instability monitoring and legacy-contamination mapping both recorded gap scores in the high-priority range.

Table 10: Hazard Risk-Control Priority Matrix

Hazard Risk-Control Area	Importance	Effectiveness	Gap	Priority
Subsidence and ground-deformation detection	4.72	3.95	0.77	High priority
Tailings-instability monitoring	4.65	3.71	0.94	Very high priority
Independent validation and ground-truthing	4.58	3.46	1.12	Very high priority
Community risk communication	4.50	3.42	1.08	Very high priority
Vulnerability and exposure mapping	4.60	3.69	0.91	Very high priority
Legacy-contamination mapping	4.38	3.66	0.72	High priority
Water and soil monitoring integration	4.36	3.75	0.61	Medium priority
Data metadata and management of change	4.30	3.60	0.70	High priority

Water and soil monitoring integration recorded the lowest gap score of 0.61 and was classified as medium priority, suggesting that it was relatively stronger than other areas but still required continued monitoring. Legacy-contamination mapping recorded 0.72 and data metadata and management of change recorded 0.70, both classified as high priority. This priority matrix strengthened the findings by translating statistical results into practical improvement priorities. It also aligned with socio-technical and resilience perspectives, which emphasize sensitivity to weak signals, attention to community needs, and continuous improvement in high-risk environments. The matrix showed that reliable performance required attention not only to core technical detection but also to validation, community communication, and vulnerability mapping, which supported the study objectives by identifying where framework improvements should be prioritized.

Figure 19: Hazard Risk-Control Importance versus Effectiveness Gap Analysis

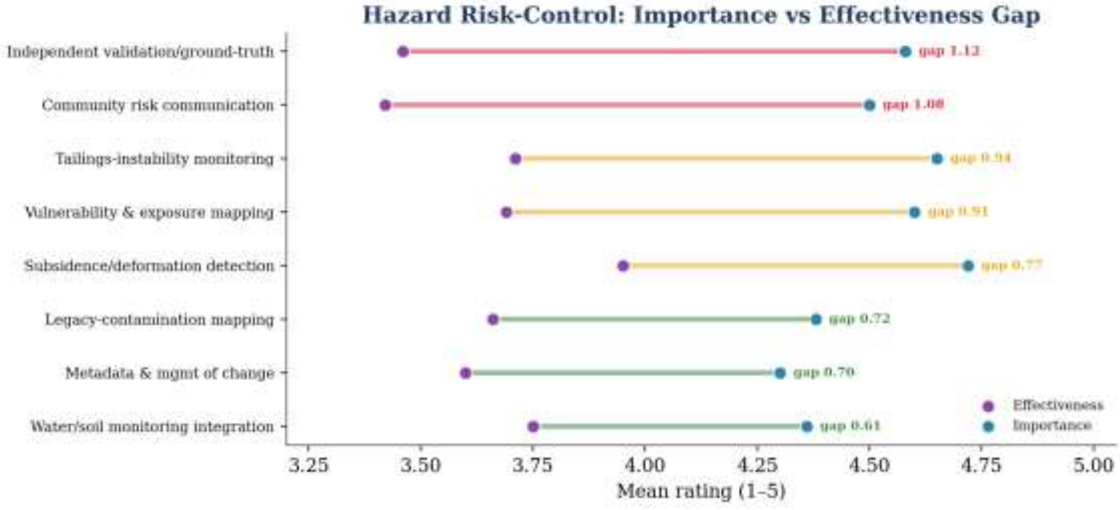


Table 11: Summary of Key Findings by Objective and Hypothesis

Study Objective	Main Result	Hypothesis	Interpretation
Examine influence of InSAR monitoring on framework design quality	InSAR monitoring strongly correlated with design quality, r = 0.73	H1	Stronger InSAR capability improved design quality
Assess relationship between GIS integration and assessment performance	GIS integration significantly related to performance, r = 0.67, β = 0.22	H2	Better multi-hazard integration improved outcomes
Evaluate effect of data quality and validation	Validation significantly predicted performance, β = 0.19	H3	Validation strengthened trust in results
Determine role of exposure and vulnerability mapping	Mapping significantly predicted reliability, β = 0.16	H4	Vulnerability mapping supported community relevance
Test effect of framework design quality on performance	Design quality was the strongest predictor, β = 0.32	H5	Design quality was central to performance
Examine role of community engagement	Engagement significantly predicted performance, β = 0.17	H6	Engagement supported resilient performance
Identify maturity and risk-control gaps	Overall maturity = 4.01; largest gaps in validation and community communication	Supports overall model	Community-facing controls required improvement

Table 11 summarized the major findings in relation to the research objectives and hypotheses, showing that all objectives were achieved and all hypotheses supported. The first objective was achieved because InSAR ground-deformation monitoring showed a strong positive relationship with framework design quality, r = 0.73, confirming that stronger deformation-monitoring capability improved the coherence of framework design. The second objective was achieved because GIS multi-hazard data integration showed a significant positive relationship with assessment performance, r = 0.67 and β = 0.22, demonstrating that integrating multiple hazard layers contributed to stronger outcomes. The third objective was achieved because remote-sensing data quality and validation significantly predicted assessment performance, β = 0.19, showing that error control and ground-truthing improved confidence in results. The fourth objective was achieved because hazard exposure and vulnerability mapping significantly predicted assessment reliability, β = 0.16, the smallest but still significant coefficient, showing that community-facing analysis contributed to assessment quality. The fifth objective was achieved because framework design quality was the strongest predictor, β = 0.32 and $p < 0.001$, confirming the central argument of the research. The sixth objective was supported because community and institutional engagement significantly predicted performance, β = 0.17, linking the results to socio-technical and resilience theory. The maturity index showed an overall score of 4.01, while the priority matrix identified independent validation, community communication, and vulnerability mapping as the highest-priority improvement areas. Overall, the results proved that environmental risk assessment performance in mining-adjacent communities depended on the combined effect of InSAR monitoring, GIS integration, validation, vulnerability mapping, community engagement, and framework design quality.

FINDINGS

This chapter presents the findings of the quantitative analysis conducted to examine how a Satellite-Integrated Multi-Hazard Environmental Risk Assessment Framework, built on InSAR and GIS, influences environmental risk assessment performance in mining-adjacent U.S. communities. The analysis was based on data collected through a structured five-point Likert-scale questionnaire, where 1 represented Strongly Disagree and 5 represented Strongly Agree. A total of 160 questionnaires were distributed to professionals involved in geospatial analysis, remote sensing, environmental science, mining and geotechnical engineering, planning, and public health, of which 141 valid responses were retained for analysis, producing a valid response rate of 88.1%.

The descriptive findings showed that all seven study variables were rated in the high range, with environmental risk assessment performance recording the highest mean of 4.17 and remote-sensing data quality and validation recording the lowest mean of 3.90. This pattern indicated broad agreement that the framework's components were positively present, while also signaling that validation and community-facing activities were perceived as comparatively weaker. The reliability findings confirmed that all constructs were internally consistent, with Cronbach's alpha values ranging from 0.79 to 0.92, allowing the study to proceed confidently to inferential analysis.

The correlation findings showed that all six hypothesized relationships were positive and statistically significant at $p < 0.01$, with framework design quality showing the strongest relationship with assessment performance, $r = 0.76$, and InSAR monitoring showing a strong relationship with framework design quality, $r = 0.73$. The regression findings showed that the six predictors together explained 69.1% of the variance in assessment performance, with framework design quality the strongest predictor, $\beta = 0.32$, followed by InSAR monitoring, $\beta = 0.25$, and GIS integration, $\beta = 0.22$. The hypotheses-testing findings confirmed that all six hypotheses were supported. The maturity index found overall high maturity, 4.01, with the strongest maturity in hazard scoping and technical processing and the weakest in validation, exposure analysis, and community engagement. The priority matrix identified independent validation, community risk communication, and vulnerability mapping as the highest-priority improvement areas. Collectively, these findings demonstrate that a satellite-integrated framework can substantially strengthen environmental risk assessment in mining-adjacent communities, and that its reliability depends jointly on technical capability, methodological validation, and community engagement.

Figure 9: Consolidated Findings Overview

DISCUSSION

The findings of this study provide strong empirical support for the proposition that a satellite-integrated, multi-hazard framework substantially strengthens environmental risk assessment in mining-adjacent U.S. communities, and that its reliability depends on the joint operation of technical capability, methodological rigor, and institutional engagement. The result that framework design quality was the strongest predictor of assessment performance, $\beta = 0.32$, is consistent with the study's conceptual argument that the value of InSAR and GIS is realized not through any single technique but through the coherent integration of monitoring, data fusion, validation, exposure analysis, and communication. This finding echoes the broader literature on remote sensing for hazard management, which has repeatedly emphasized that raw observational capability must be embedded in a well-designed workflow to produce trustworthy, actionable outputs (Raspini et al., 2018).

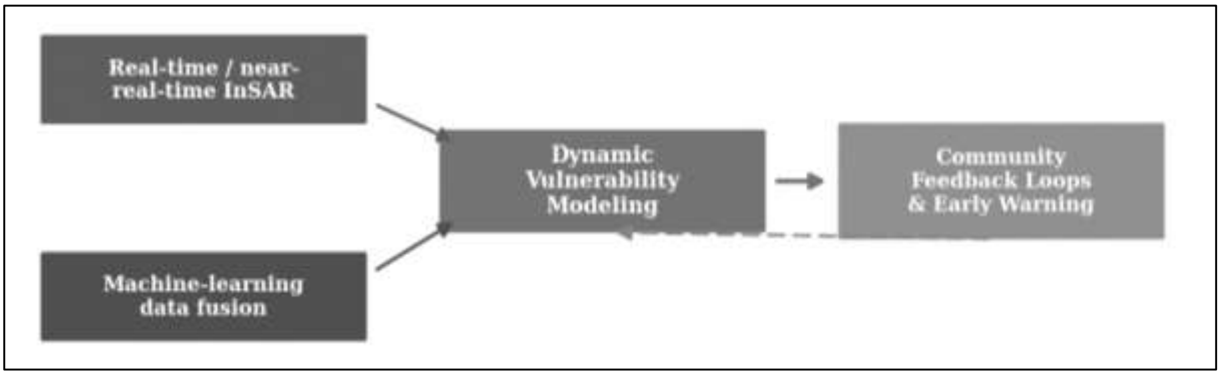
The strong relationship between InSAR ground-deformation monitoring and framework design quality, $r = 0.73$, and the significant regression effect of InSAR monitoring on assessment performance, $\beta = 0.25$, confirm the central role of spaceborne radar in this context. These results align with prior studies showing that InSAR can reveal subsidence, slope creep, and tailings settlement at spatial scales and measurement densities that ground instrumentation alone cannot match (Rott & Nagler, 2006). At the same time, the comparatively lower means and maturity scores for validation and ground-truthing suggest that respondents recognized the well-documented limitations of InSAR, including atmospheric noise, decorrelation, and phase-unwrapping error. The prominence of independent validation in the priority matrix, where it recorded the largest gap score of 1.12, reinforces the interpretation that practitioners view validation as essential yet under-implemented, a tension that the framework must resolve to be trusted by regulators and residents (Milillo et al., 2019).

The significant contribution of GIS multi-hazard data integration, β = 0.22, supports the argument that risk in mining-adjacent settings is inherently multi-hazard and cannot be adequately captured by single-hazard, ground-only assessment. By combining deformation with hydrological, contamination, infrastructure, and demographic layers, the framework enables analysts to identify where hazards coincide and interact (Bianchini et al., 2017), which is precisely where combined risk is greatest (Solari et al., 2020). This finding is consistent with resilience theory, which stresses the importance of understanding how disturbances propagate through interconnected systems. However, the moderate-to-strong correlation for exposure and vulnerability mapping, r = 0.63, and its position as the smallest significant predictor, β = 0.16, suggest that the translation of physical hazard information into community-relevant risk remains the least mature part of the framework, an interpretation reinforced by the very-high-priority classification of vulnerability mapping in the priority matrix (Cutter et al., 2003).

The significant effect of community and institutional engagement, β = 0.17, provides direct empirical support for the socio-technical perspective that underpins the study. This result indicates that even technically sophisticated assessment does not achieve its full value unless outputs are communicated to and acted upon by institutions and communities. The finding that community risk communication recorded one of the largest gaps in the priority matrix, 1.08, suggests a persistent shortfall in the socio-technical dimension: technical monitoring capacity has advanced faster than the institutional and communicative capacity needed to convert it into protective action. This pattern is consistent with resilience theory's emphasis on the human and organizational determinants of a system's capacity to anticipate and respond to hazards.

Taken together, the results describe a framework that is technically strong at its core, with high maturity in hazard scoping, InSAR processing, and GIS integration, but comparatively weaker at its methodological and community-facing margins, where validation, vulnerability mapping, and communication lag. This asymmetry has clear practical implications. It suggests that the greatest gains in assessment reliability are likely to come not from further improving already-strong technical processing but from strengthening validation protocols, deepening the integration of exposure and vulnerability, and investing in the institutional and communicative arrangements that connect satellite observations to community protection (Intrieri et al., 2019). This interpretation is robust across the descriptive, correlational, regression, maturity, and priority analyses, which consistently identify the same set of improvement areas.

Figure 10: Future Research Framework for Dynamic Multi-Hazard Assessment



CONCLUSION

This study set out to assess how a Satellite-Integrated Multi-Hazard Environmental Risk Assessment Framework, built on InSAR and GIS, influences environmental risk assessment performance in mining-adjacent U.S. communities. Using a quantitative, cross-sectional, case-based design and data from 141 valid respondents, the study found that all six hypothesized relationships were supported and that the framework's constructs together explained 69.1% of the variance in assessment performance. Framework design quality emerged as the strongest predictor, underscoring that the value of satellite observation is realized through coherent integration rather than isolated technique. InSAR ground-deformation monitoring and GIS multi-hazard integration were confirmed as central technical capabilities, while validation, exposure and vulnerability mapping, and community engagement were identified as significant but comparatively less mature contributors.

The study concludes that a satellite-integrated, multi-hazard framework offers a substantial improvement over fragmented, reactive, single-hazard assessment for mining-adjacent communities, because it extends the spatial and temporal reach of monitoring, captures hazard interactions, and links physical hazards to exposed and vulnerable populations. However, the study also concludes that the reliability of such a framework is fundamentally socio-technical: its performance depends not only on the quality of InSAR processing and GIS integration but also on the rigor of validation and the strength of the institutional and communicative arrangements that connect observation to protective action. The consistent identification of validation, vulnerability mapping, and community communication as the highest-priority improvement areas points to where future effort should be concentrated. In sum, the framework provides a promising and empirically supported basis for strengthening environmental risk assessment in mining-adjacent communities, provided that its technical strengths are matched by corresponding investment in validation, vulnerability analysis, and community engagement.

RECOMMENDATIONS

Based on the findings, several recommendations are offered for agencies, analysts, and communities engaged in mining-adjacent hazard assessment. First, organizations should strengthen independent validation and ground-truthing of InSAR outputs by systematically comparing satellite-derived displacement with GNSS, leveling, and in-situ measurements, and by documenting error models and confidence levels, since validation recorded the largest improvement gap. Second, agencies should invest in the integration of exposure and vulnerability data with satellite-derived hazard information, so that assessment outputs identify not only where hazards occur but where they most threaten people, particularly in socially vulnerable communities.

Third, institutions should develop clear community risk-communication practices that translate technical outputs into accessible, actionable information for residents and local decision-makers, addressing the persistent gap between monitoring capability and communicative capacity. Fourth, organizations should establish routine monitoring-update and audit-readiness procedures, including consistent metadata and management-of-change controls, to ensure that assessments remain current and auditable over time. Fifth, agencies should prioritize the integration of tailings-instability monitoring and legacy-contamination mapping within the framework, given their high importance and moderate effectiveness. Finally, cross-disciplinary coordination among geospatial analysts, environmental scientists, engineers, and public-health officials should be formalized, consistent with the socio-technical finding that reliable assessment depends on collaboration across professional groups.

LIMITATIONS OF THE STUDY

This study has several limitations that should be considered when interpreting its findings. First, the cross-sectional design captured perceptions at a single point in time and therefore cannot establish causal direction or track how framework performance changes as monitoring matures; a longitudinal design would allow stronger causal inference. Second, the study relied on a structured, perception-based questionnaire completed by professionals, so the results reflect informed expert assessment rather than direct measurement of hazard-detection accuracy or remediation outcomes; future work could pair perception data with technical performance metrics such as validated deformation-detection rates. Third, the purposive sampling strategy, while appropriate for reaching knowledgeable respondents, limits the generalizability of the findings to the broader population and to communities not represented in the sample. Fourth, the framework and its constructs were assessed at a general level across diverse mining-adjacent settings, and the relative importance of specific hazards may vary considerably between coal, hard-rock, and metal-mining contexts. Finally, the study did not directly evaluate the cost, data-availability, or institutional-capacity constraints that may affect real-world implementation, which represent important avenues for future research.

REFERENCES

[1]. Amighpey, M., & Arabi, S. (2016). Studying land subsidence in Yazd province, Iran, by integration of InSAR and levelling measurements. Remote Sensing Applications: Society and Environment, 4, 1–8. https://doi.org/10.1016/j.rsase.2016.06.001

[2]. Berardino, P., Fornaro, G., Lanari, R., & Sansosti, E. (2002). A new algorithm for surface deformation monitoring based on small baseline differential SAR interferograms. IEEE Transactions on Geoscience and Remote Sensing, 40(11), 2375–2383. https://doi.org/10.1109/TGRS.2002.803792

[3]. Bianchini, S., Solari, L., & Casagli, N. (2017). A GIS-based procedure for landslide intensity evaluation and specific risk analysis supported by persistent scatterers interferometry. Remote Sensing, 9(11), 1093. https://doi.org/10.3390/rs9111093

[4]. Birkmann, J., Cardona, O. D., Carreño, M. L., Barbat, A. H., Pelling, M., Schneiderbauer, S., … Welle, T. (2013). Framing vulnerability, risk and societal responses: The MOVE framework. Natural Hazards, 67(2), 193–211. https://doi.org/10.1007/s11069-013-0558-5

[5]. Chen, B., Deng, K., Fan, H., & Yu, Y. (2016). Combining SAR interferometric phase and intensity information for monitoring of large gradient deformation in coal mining areas. Engineering Geology, 208, 76–86. https://doi.org/10.1016/j.enggeo.2016.06.006

[6]. Crosetto, M., Monserrat, O., Cuevas-González, M., Devanthéry, N., & Crippa, B. (2016). Persistent scatterer interferometry: A review. ISPRS Journal of Photogrammetry and Remote Sensing, 115, 78–89. https://doi.org/10.1016/j.isprsjprs.2015.10.011

[7]. Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008). A place-based model for understanding community resilience to natural disasters. Global Environmental Change, 18(4), 598–606. https://doi.org/10.1016/j.gloenvcha.2008.07.013

[8]. Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. Social Science Quarterly, 84(2), 242–261. https://doi.org/10.1111/1540-6237.8402002

[9]. Ferretti, A., Fumagalli, A., Novali, F., Prati, C., Rocca, F., & Rucci, A. (2011). A new algorithm for processing interferometric data-stacks: SqueeSAR. IEEE Transactions on Geoscience and Remote Sensing, 49(9), 3460–3470. https://doi.org/10.1109/TGRS.2011.2124465

[10]. Ferretti, A., Prati, C., & Rocca, F. (2001). Permanent scatterers in SAR interferometry. IEEE Transactions on Geoscience and Remote Sensing, 39(1), 8–20. https://doi.org/10.1109/36.898661

[11]. Folke, C. (2006). Resilience: The emergence of a perspective for social–ecological systems analyses. Global Environmental Change, 16(3), 253–267. https://doi.org/10.1016/j.gloenvcha.2006.04.002

[12]. Gama, F. F., Mura, J. C., Paradella, W. R., & de Oliveira, C. G. (2019). Deformations prior to the Brumadinho dam collapse revealed by Sentinel-1 InSAR data. Remote Sensing, 11(21), 2521. https://doi.org/10.3390/rs11212521

[13]. Gigović, L., Pamučar, D., Bajić, Z., & Drobnjak, S. (2019). Application of GIS-interval rough AHP methodology for flood hazard mapping in urban areas. ISPRS International Journal of Geo-Information, 8(2), 79. https://doi.org/10.3390/ijgi8020079

[14]. Gill, J. C., & Malamud, B. D. (2014). Reviewing and visualizing the interactions of natural hazards. Reviews of Geophysics, 52(4), 680–722. https://doi.org/10.1002/2013RG000445

[15]. Hooper, A., Segall, P., & Zebker, H. (2007). Persistent scatterer InSAR for crustal deformation analysis, with application to Volcán Alcedo, Galápagos. Journal of Geophysical Research: Solid Earth, 112(B7), B07407. https://doi.org/10.1029/2006JB004763

[16]. Hooper, A., Zebker, H., Segall, P., & Kampes, B. (2004). A new method for measuring deformation on volcanoes and other natural terrains using InSAR persistent scatterers. Geophysical Research Letters, 31(23), L23611. https://doi.org/10.1029/2004GL021737

[17]. Hu, J., Li, Z. W., Ding, X. L., Zhu, J. J., Zhang, L., & Sun, Q. (2013). Resolving three-dimensional surface displacements from InSAR measurements: A review. Earth-Science Reviews, 133, 1–17. https://doi.org/10.1016/j.earscirev.2013.02.005

[18]. Hudson-Edwards, K. A., Jamieson, H. E., & Lottermoser, B. G. (2011). Mine wastes: Past, present, future. Elements, 7(6), 375–380. https://doi.org/10.2113/gselements.7.6.375

[19]. Intrieri, E., Carlà, T., & Gigli, G. (2019). Forecasting the time of failure of landslides at slope-scale: A literature review. Landslides, 16(8), 1523–1539. https://doi.org/10.1007/s10346-018-1101-2

[20]. Ismail, A., Safuan, A., Sa'ari, R., & Rahman, N. (2022). Application of InSAR and GIS in monitoring mining-induced ground subsidence. Environmental Earth Sciences, 81(9), 1–15. https://doi.org/10.1007/s12665-022-10312-0

[21]. Jung, J., Kim, D., & Palanisamy Vadivel, S. K. (2019). Long-term deflection monitoring for bridges using X and C-band time-series SAR interferometry. Remote Sensing, 11(11), 1258. https://doi.org/10.3390/rs11111258

[22]. Kappes, M. S., Keiler, M., von Elverfeldt, K., & Glade, T. (2012). Challenges of analyzing multi-hazard risk: A review. Natural Hazards, 64(2), 1925–1958. https://doi.org/10.1007/s11069-012-0294-2

[23]. Lottermoser, B. G. (2010). Mine wastes: Characterization, treatment and environmental impacts (3rd ed.). Springer.

https://doi.org/10.1007/978-3-642-12419-8

[24]. Malczewski, J. (2006). GIS-based multicriteria decision analysis: A survey of the literature. International Journal of Geographical Information Science, 20(7), 703–726. https://doi.org/10.1080/13658810600661508

[25]. Milillo, P., Giardina, G., Perissin, D., Milillo, G., Coletta, A., & Terranova, C. (2019). Pre-collapse space geodetic observations of critical infrastructure: The Morandi Bridge, Genoa, Italy. Remote Sensing, 11(12), 1403. https://doi.org/10.3390/rs11121403

[26]. Ng, A. H.-M., Ge, L., Li, X., & Zhang, K. (2015). Monitoring ground deformation in mining areas using InSAR technique. Journal of Geodesy, 89(5), 449–465. https://doi.org/10.1007/s00190-015-0782-8

[27]. Nriagu, J. O. (1988). A silent epidemic of environmental metal poisoning? Environmental Pollution, 50(1–2), 139–161. https://doi.org/10.1016/0269-7491(88)90189-3

[28]. Osmanoğlu, B., Sunar, F., Wdowinski, S., & Cabral-Cano, E. (2016). Time series analysis of InSAR data: Methods and trends. ISPRS Journal of Photogrammetry and Remote Sensing, 115, 90–102. https://doi.org/10.1016/j.isprsjprs.2015.10.003

[29]. Perrow, C. (1984). Normal accidents: Living with high-risk technologies. Basic Books. Publisher page

[30]. Przyłucka, M., Herrera, G., Graniczny, M., Colombo, D., & Béjar-Pizarro, M. (2015). Combination of conventional and advanced DInSAR to monitor very fast mining subsidence. Remote Sensing, 7(5), 5300–5328. https://doi.org/10.3390/rs70505300

[31]. Raspini, F., Bianchini, S., Ciampalini, A., Del Soldato, M., Solari, L., & Novali, F. (2018). Continuous, semi-automatic monitoring of ground deformation using Sentinel-1 satellites. Scientific Reports, 8, 7253. https://doi.org/10.1038/s41598-018-25369-w

[32]. Rott, H., & Nagler, T. (2006). The contribution of radar interferometry to the assessment of landslide hazards. Advances in Space Research, 37(4), 710–719. https://doi.org/10.1016/j.asr.2005.06.059

[33]. Solari, L., Del Soldato, M., Raspini, F., Barra, A., Bianchini, S., & Confuorto, P. (2020). Review of satellite interferometry for landslide detection in Italy. Remote Sensing, 12(8), 1351. https://doi.org/10.3390/rs12081351

[34]. Tapete, D., & Cigna, F. (2019). Detection of archaeological looting from space: Methods, achievements and challenges. Remote Sensing, 11(20), 2389. https://doi.org/10.3390/rs11202389

[35]. Thomas, A. C., Edwards, S. J., Engels, J., McCormack, H., Hopkins, V., & Holley, R. (2023). Earth observation and InSAR-based monitoring of tailings storage facilities. Remote Sensing of Environment, 293, 113542. https://doi.org/10.1016/j.rse.2023.113542

[36]. Trist, E. (1981). The evolution of socio-technical systems: A conceptual framework and an action research program. Ontario Quality of Working Life Centre. https://doi.org/10.4324/9781315227979

[37]. Wasowski, J., & Bovenga, F. (2014). Investigating landslides and unstable slopes with satellite multi-temporal interferometry: Current issues and future perspectives. Engineering Geology, 174, 103–138. https://doi.org/10.1016/j.enggeo.2014.01.003

[38]. Weick, K. E., & Sutcliffe, K. M. (2007). Managing the unexpected: Resilient performance in an age of uncertainty (2nd ed.). Jossey-Bass. Publisher page

[39]. Zhou, W., Chen, G., Li, H., & Luo, H. (2021). GIS-based multi-hazard risk assessment in mining areas: A review. Environmental Science and Pollution Research, 28(30), 40567–40584. https://doi.org/10.1007/s11356-021-13543-z

[40]. Amir, R. (2026). AI-Enabled Predictive Maintenance for Fire Alarm and Smoke Management Systems: A Systematic Review of Models. *American Journal of Interdisciplinary Studies*, *7*(01), 496-535. https://doi.org/10.63125/q3aw4y77

[41]. Kazi Rakib Hasan, S., & Uddin, H. M. M. (2022). Scalable AI For Project Portfolio Management: A Mixed-Methods Study Combining Distributed Computing Benchmarks. *Review of Applied Science and Technology*, *1*(04), 375–410. https://doi.org/10.63125/0kk4wf20

[42]. Mahmudul, H., & Sadia, Z. (2026). Safeguarding Financial Records: A Cybersecurity-Driven Management Framework. *International Journal of Scientific Interdisciplinary Research*, *7*(1), 493–526. https://doi.org/10.63125/zch4s169

[43]. Md Arif Uz, Z., Sharmin, S., & Md Abdur, R. (2025). Factors Influencing Behavioural Intention to Use he Innovative Open And Distance Learning Systems With The Role Of Continuance Intention. *American Journal of Scholarly Research and Innovation*, *4*(01), 202-220. https://doi.org/10.63125/pbjxp014

[44]. Md Tohidul, I. (2023). ERP-Integrated Financial Analytics Systems for Corporate Financial Reporting, Cash Flow Analysis, and Strategic Investment Planning. *American Journal of Advanced Technology and Engineering Solutions*, *3*(04), 87-128. https://doi.org/10.63125/qhk96h35

[45]. Md. Abdur, R., & Iftekhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, *1*(4), 70-102. https://doi.org/10.63125/dyrpc387

[46]. Mohammad Badrul, A., & Md. Mominul, H. (2023). Machine Learning–Based Assessment of Environmental and Public Health Risks in Sewerage Sludge Management Systems. *American Journal of Advanced Technology and Engineering Solutions*, *3*(02), 33-77. https://doi.org/10.63125/y3yfxa92

[47]. Mohammad Shoriful Hossan, S. (2024). Development of A Predictive Maintenance Model for Industrial Motor Drives and VFD Systems Using PLC/DCS Operational Telemetry. *American Journal of Scholarly Research and Innovation*, *3*(01), 198-242. https://doi.org/10.63125/pv1js496

[48]. Mohammad Shoriful Hossan, S. (2025). Development Of an ARC-Flash Hazard Mitigation Framework for Brownfield Industrial Power Distribution Retrofits in U.S. Manufacturing. *American Journal of Advanced Technology and Engineering Solutions*, *1*(02), 262-303. https://doi.org/10.63125/vhqjgm79

[49]. Mohammad Shoriful Hossan, S., & Adar, C. (2023). SIL-Compliant Safety Instrumented System Design for Oil & Gas Hazardous-Area Operations Using IEC 61508 / IEC 61511 Frameworks. *Journal of Sustainable Development and Policy*, *2*(02), 43-85. https://doi.org/10.63125/cb3d3w81

[50]. Mst Shurovi, A. (2026). AI-Driven Accounts Payable and Receivable Automation for Operational Risk Mitigation in U.S. SMEs: A Systematic Review (2018–2026). *American Journal of Interdisciplinary Studies*, *7*(01), 536-577. https://doi.org/10.63125/x1yzwc45

[51]. Muhammad Mohiul, I., & Mohammad Badrul, A. (2022). Predictive Analytics for Optimizing Sewerage Sludge Treatment Efficiency and Resource Recovery in Dhaka City. *Journal of Sustainable Development and Policy*, *1*(04), 158-200. https://doi.org/10.63125/t9zdp458

[52]. Mukut Kanti, B. (2025). Lifecycle Carbon Reduction and Net Zero Pathway Modeling Using LEED, EDGE, and SBTI Frameworks in Developing Economy Industrial Buildings. *American Journal of Interdisciplinary Studies*, *6*(3), 306-350. https://doi.org/10.63125/tnneth75

[53]. Mukut Kanti, B., & Rony, S. (2022). Quantitative Risk Assessment and Safety Performance Benchmarking for Structural Integrity Management in Retail Supply Chain Infrastructure. *American Journal of Data Science and Analytics*, *3*(12), 42-88. https://doi.org/10.63125/n88vth90

[54]. Risha, A., & Kazi Mohammad Khalid, A. (2023). A Meta-Analysis of AI-Driven Geospatial Analytics for Predictive Maintenance of Critical Infrastructure in Developing Economies. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 375–412. https://doi.org/10.63125/rayrex49

[55]. Sadia, Z., Mohammad Ariful, I., Sumyta, H., & Hosne Ara, M. (2022). A Review of AI-Powered Data Visualization in Enterprise Reporting: Dashboard Design And Interactive Analytics. *American Journal of Advanced Technology and Engineering Solutions*, *2*(01), 32-54. https://doi.org/10.63125/gabst658

[56]. Shima Ali, S., Musomi, K., & Sonya, G. (2024). Integrated Infectious Disease Preparedness: Multilingual Health Communication Strategies for Public Health Risk Mitigation, Disease Intervention and Prevention for Culturally Diverse Population in United States. *American Journal of Data Science and Analytics*, *5*(10), 01-47. https://doi.org/10.63125/ehk4mt02

[57]. Shima Ali, S., Sonya, G., & Mahbubul, I. (2025). Telemedicine And Remote Patient Monitoring for Preventing Risk and Chronic Disease Management in Underserved Communities. *American Journal of Health and Medical Sciences*, *6*(04), 01–42. https://doi.org/10.63125/y0e9dc38

[58]. Shima Ali, S., Sonya, G., & Mahbubul, I. (2026). STI and HIV Prevention Through Public Health Digital Twins: A Framework for Personalized Prevention and Adaptive Disease Intervention. *American Journal of Scholarly Research and Innovation*, *5*(01), 284–326. https://doi.org/10.63125/rjgna882

[59]. Syed Nurul, I. (2026). A Machine Learning Approach to Intelligent Streetlight Control for Sustainable Energy Management in Smart Cities. *American Journal of Advanced Technology and Engineering Solutions*, *6*(01), 650-689. https://doi.org/10.63125/gxwn1g63

[60]. Zaman, S. (2024). A Systematic Review of ERP And CRM Integration For Sustainable Business And Data Management in Logistics And Supply Chain Industry. *Frontiers in Applied Engineering and Technology*, *1*(01), 204-221. https://doi.org/10.70937/faet.v1i01.36