

Review

Research Status, Challenges and Future Perspectives of InSAR Technology for Surface Deformation Monitoring in Mining Areas

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Abstract

Surface deformation monitoring is essential for preventing geological hazards, safeguarding major engineering projects, and extracting mineral resources. Due to its all-weather, continuous, wide-coverage observation capabilities and millimeter-level accuracy, InSAR technology has emerged as an indispensable tool for monitoring surface deformation in mining regions. This paper presents a comprehensive review of recent advancements in InSAR technology for monitoring surface subsidence and horizontal displacement. It evaluates both fundamental D-InSAR techniques and advanced time-series analysis frameworks, such as PS-InSAR, SBAS-InSAR, and DS-InSAR. The review details the methodologies for extracting LOS deformation, multi-track combined horizontal displacement retrieval, and 3D deformation reconstruction. Furthermore, it provides a comprehensive overview of the causal mechanisms, correction strategies, impacts on deformation retrieval results, and developmental trends regarding major error sources such as decorrelation noise, residual orbital errors, and atmospheric delay. Drawing on typical case studies of large-gradient subsidence and landslide monitoring, this paper evaluates the efficacy and limitations of time-series InSAR in complex mining environments. Our analysis indicates that the InSAR monitoring system for mining areas is transitioning from single-dimensional deformation detection to multi-dimensional deformation analysis and intelligent dynamic monitoring. However, significant challenges remain regarding phase decorrelation in rapid deformation areas, the complete reconstruction of 3D displacements, the suppression of atmospheric errors under complex meteorological conditions, and real-time processing capabilities. Concurrently, this paper identifies multi-source data fusion, artificial intelligence-assisted retrieval, and cloud-based real-time processing as crucial future directions. These advancements will provide robust technical support for safe production and the early warning of geological hazards in mining regions.

Keywords: InSAR; monitoring technology; surface deformation; mining engineering; time-series analysis

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1. Introduction

The large-scale extraction of mineral resources, such as coal, serves as a cornerstone of modern industrial civilization and provides the primary energy source supporting national economic development [1–3]. Mining-induced disturbances disrupt the initial stress equilibrium of the overlying strata, subsequently triggering complex mechanical processes within the rock mass. These processes ultimately propagate to the surface, manifesting as significant surface subsidence and horizontal displacement [4,5]. Furthermore, the disturbances induced by coal extraction are multifaceted. While these mining activities trigger dynamic stress disasters deep underground [6,7], induce extensive ecological and environmental challenges [8–12], and elevate operational safety risks [13], their most direct and widespread physical manifestation is severe surface deformation. Although these intertwined factors collectively constitute the complex hazard environment of mining areas, acquiring high-precision, macroscopic data on ground movement remains the primary prerequisite for early warning of regional disasters. These intertwined physical, chemical, and anthropogenic factors collectively constitute the complex hazard environment of mining areas.

Subjected to the high-intensity disturbances of coal mining, the evolution of surface subsidence basins exhibits significant nonlinearity, abruptness, and heterogeneity [14]. Surface deformation in mining areas not only causes structural damage to buildings and the degradation of arable land but can also trigger secondary disasters such as landslides. In severe cases, these events pose a substantial threat to the lives and property of local residents [15–17]. Therefore, acquiring high-precision, three-dimensional deformation data with high spatiotemporal resolution in mining areas holds significant theoretical and practical value for early disaster warning, regional land-use planning, and the remediation of mined-out areas [18]. In this context, the physical principles underlying Interferometric Synthetic Aperture Radar (InSAR) satellite observations of surface subsidence can intuitively illustrate the propagation mechanism from underground mining activities to surface deformation (Figure 1).

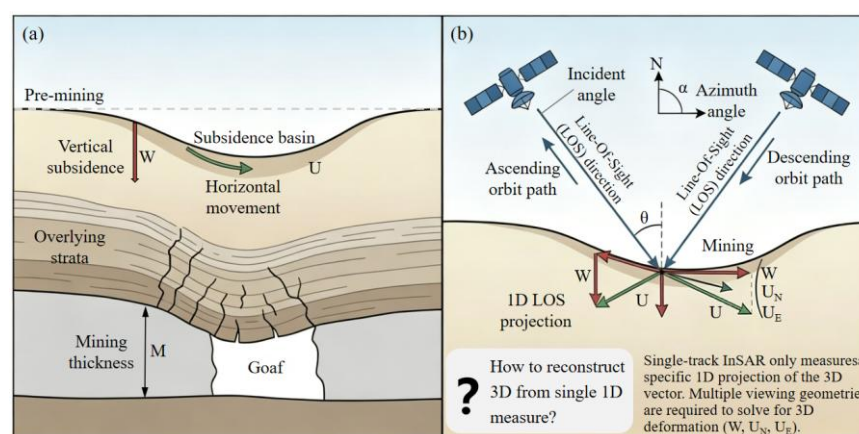


Figure 1. Surface movement basin in the mining area and geometric principle of InSAR observation. (a) Surface movement basin. (b) Principle of InSAR observation.

Although traditional monitoring methods in mining areas—such as leveling, total stations, and Global Navigation Satellite Systems (GNSS)—offer exceptional point-level precision, they are constrained by significant fieldwork demands, limited spatial coverage, and sparse sampling densities. Consequently, these methods often fail to capture the comprehensive evolutionary dynamics of subsidence basins at a macroscopic scale [19,20]. Since the 1990s, the advent of InSAR technology has revolutionized this field. In recent years, owing to its all-weather, wide-area, and high spatial resolution capabilities, along with

centimeter-or even millimeter-level deformation monitoring accuracy, InSAR has progressively emerged as the prevailing technique for monitoring mining areas. From the initial Differential InSAR (D-InSAR) to the subsequent Time-Series InSAR (TS-InSAR), this technology has demonstrated immense potential in capturing surface deformation [21,22].

To visually demonstrate the global impact of InSAR technology in monitoring mining areas, a statistical analysis was conducted using the Web of Science (WoS) Core Collection database. To accurately reflect research interest specifically in mining applications, the search encompassed literature from 1990 to the present using a combination of keywords related to InSAR and mining (e.g., “InSAR” AND “mining”) in the topic fields (Figure 2). The volume of publications in this domain exhibits an evolutionary trajectory from an initial phase to an explosive growth phase, which can be categorized into three distinct periods. The first is a “slow growth period” spanning from 1990 to 2008, which represents the exploration and foundational stage of InSAR technology [23,24]. The second is an “initial growth period” from 2009 to 2015, during which the increase in publications was primarily driven by the deployment of new-generation, high-resolution synthetic aperture radar (SAR) satellites. These technological breakthroughs facilitated the transition of InSAR from a rudimentary deformation monitoring tool to a long-term time-series monitoring instrument [25–27]. The third is an “explosive growth period” from 2016 to the present, characterized by an almost exponential growth trend. This surge has been driven by increased data accessibility, the widespread adoption of cloud computing platforms, and comprehensive interdisciplinary applications [28–30]. The exponential increase in publications not only reflects the academic community’s growing recognition of InSAR technology but also underscores the urgent demand for high-precision remote sensing data necessitated by the global green transition of the mining industry. As more radar satellites are launched into orbit in the future, it is anticipated that this growth momentum will be sustained.

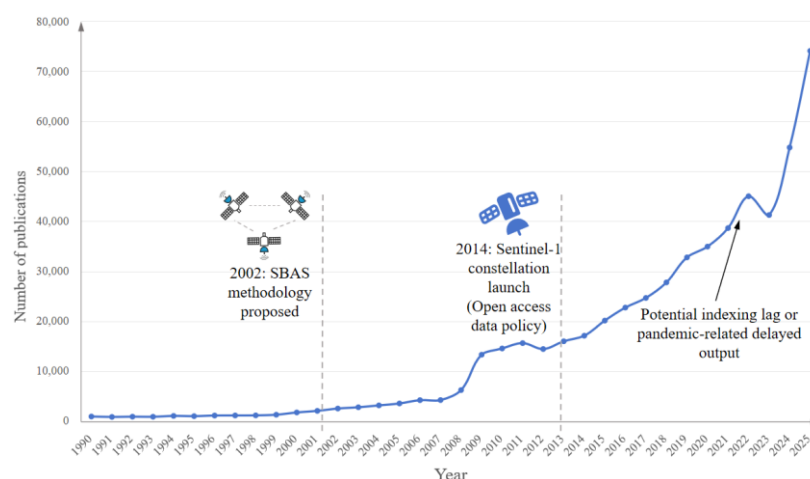


Figure 2. Trends in research interest for InSAR applications in mining areas. (Note: Data acquired from WoS Core Collection using combined keywords of InSAR and mining-related terms, spanning 1990 – the present).

Furthermore, the substantial growth in the literature not only signifies a surge in research interest but also reflects the profound evolution and interdisciplinary integration of InSAR monitoring technologies in mining regions. Undergoing a transition from quantitative accumulation to qualitative transformation, InSAR-based monitoring in mining areas has advanced from early, single-variable deformation extraction into a comprehensive multidisciplinary framework. To further elucidate the knowledge network and core

research paradigms within this field, this study constructs a knowledge graph for InSAR-based deformation monitoring in mining regions (Figure 3). Centered on this theme, this graph radially illustrates multiple dimensions ranging from underlying algorithms to high-level applications. It systematically outlines current research hotspots and the technological roadmap in this domain, aiming to provide readers with a macroscopic and clear research reference.



Figure 3. Classification system and knowledge graph for InSAR-based deformation monitoring in mining areas.

Despite recent significant advancements, the application of InSAR technology in the extreme environments of mining regions remains constrained by several bottlenecks that compromise its accuracy. These include severe decorrelation caused by vegetation coverage, large-gradient deformation induced by large-scale underground mining, and atmospheric phase delays over complex terrains [31,32]. In light of these challenges, this paper aims to comprehensively review the progress of InSAR technology in monitoring surface deformation within mining regions, thereby providing a comprehensive theoretical reference and technical guidance for future research. First, it elucidates the evolutionary trajectory of InSAR, transitioning from basic differential interferometry to multi-temporal algorithms (e.g., PS, SBAS, and DS). It then examines inversion methods, ranging from one-dimensional subsidence extraction to three-dimensional deformation reconstruction. Furthermore, targeting the specific errors inherent to mining regions, this paper summarizes cutting-edge correction strategies and highlights the necessity of multi-source data fusion to enhance monitoring robustness. Subsequently, by drawing on typical case studies involving large-gradient deformation and mining-induced landslides, the practical efficacy of this technology in complex geological environments is demonstrated. Finally, the paper outlines future development trends and anticipated challenges within this field.

2. Materials and Methods

2.1. Principles of InSAR Technology

InSAR is a spaceborne geodetic technique that utilizes microwave remote sensing. Its core mechanism employs an active synthetic aperture radar system that emits microwave signals to retrieve minute surface deformation information by capturing the phase differences of the same ground targets across distinct SAR images. The evolution of this technology is, in essence, an evolutionary struggle against “noise” and “decorrelation”; nearly every technological breakthrough has centered on suppressing noise and enhancing coherence [33].

Current research indicates that InSAR technology is not a static method, but rather has undergone a continuous evolution from “single-pair differential interferometry” to “multi-temporal time-series analysis”. This evolution is evident not only at the algorithmic level (progressing from D-InSAR to methods such as PS, SBAS, and DS) but also relies deeply on the continuous enhancements of SAR satellite systems in terms of spatial resolution, revisit cycles, and observation modes. The synergistic advancement of technology and data has enabled InSAR to transition from its initial limitation of exclusively identifying abrupt deformations into a high-precision monitoring tool capable of meticulously characterizing the entire process of mining-induced subsidence and horizontal displacement [34,35]. To more intuitively illustrate this developmental trajectory, Figure 4 presents a timeline detailing the evolution of InSAR technology alongside typical SAR satellite missions.

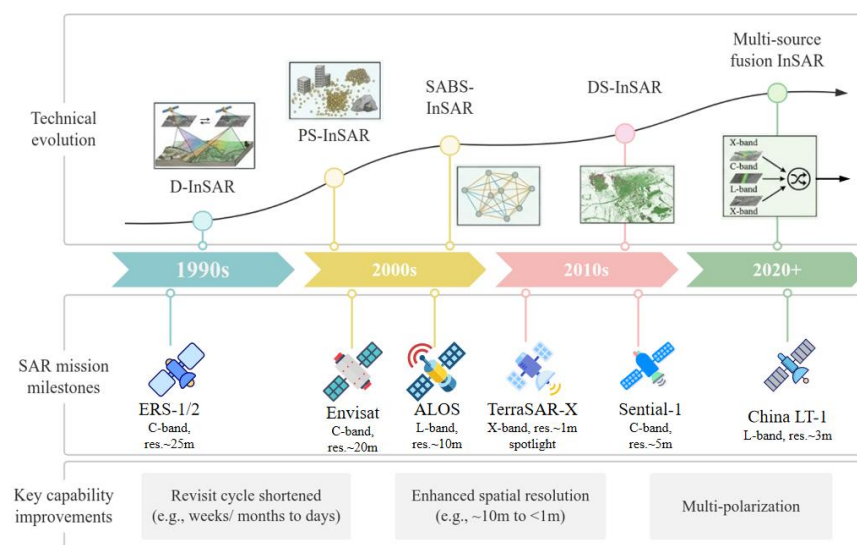


Figure 4. Timeline of InSAR technology evolution and SAR satellite mission milestones.

In the complex geographical and surface environments of mining areas, the effectiveness of InSAR monitoring depends not only on the advanced nature of the algorithms but is also heavily constrained by the physical attributes of the SAR sensors. Consequently, selecting the appropriate satellite data sources tailored to the deformation evolution patterns of specific mining areas is a crucial prerequisite for achieving high-precision monitoring [36]. To further elucidate these distinct observation capabilities, Table 1 systematically compares the key technical parameters of mainstream SAR satellite missions and evaluates their suitability for mining environments.

Table 1. Comparison of commonly used spaceborne SAR sensors and their characteristics in mining area monitoring.

Satellite Series	Band	Polarization Mode	Maximum Spatial Resolution	Revisit Period	Applicable Scenarios in Mining Areas
ALOS-1	L	Dual-polarization	10 m	46 d	Broad-area historical monitoring; vegetation penetration
ALOS-2	L	Full polarization	1–3 m	14 d	High-precision monitoring of localized deformation; complex mining geohazards
TerraSAR-X	X	Multi-polarization	0.25–1 m	11 d	Detailed monitoring of key buildings and infrastructure; high-precision inversion
Sentinel-1	C	Dual-polarization	5 × 20 m	6–12 d	Large-scale and long-time-series research on regional subsidence patterns
LuTan-1 (LT-1)	L	Full polarization	3 m	8 d	High-precision 3D reconstruction for complex deformation gradients
Gaofen-3 (GF-3)	C	Full polarization	1 m	1–15 d	Autonomous domestic data source; multi-mode monitoring

Distinct from the aforementioned time-series analysis framework, contemporary InSAR deformation monitoring methods are categorized into two primary approaches: single-pair differential interferometry and multi-temporal time-series analysis. The former, D-InSAR, serves as the fundamental differential technique for short-term deformation detection. Conversely, the latter leverages multi-temporal modeling to significantly enhance the accuracy and stability of monitoring mining-induced subsidence and horizontal displacements. The subsequent sections systematically elaborate on the principles and applicability of these methods.

2.1.1. D-InSAR

D-InSAR represents one of the earliest methods within the InSAR technological framework to achieve practical engineering applications. Its fundamental principle builds upon conventional interferometry by incorporating external topographic data to remove the topographic phase, thereby isolating the phase variation signals induced by surface deformation. This method provided a direct and effective technical approach for the initial monitoring of surface subsidence and horizontal displacements in mining areas and serves as the foundation for the subsequent development of time-series InSAR methods [37].

By employing interferometric processing and incorporating a Digital Elevation Model (DEM) to remove the topographic phase, D-InSAR isolates surface displacement along the radar line-of-sight (LOS) direction [38,39]. Notably, any residual topographic error fundamentally depends on the DEM's vertical accuracy and is directly proportional to the perpendicular baseline. The typical workflow for extracting these deformation signals is illustrated in Figure 5. In engineering practice, the critical task is to accurately filter out non-deformation components (e.g., atmospheric delay and noise) using differential techniques to quantitatively characterize the magnitude of surface subsidence [40].

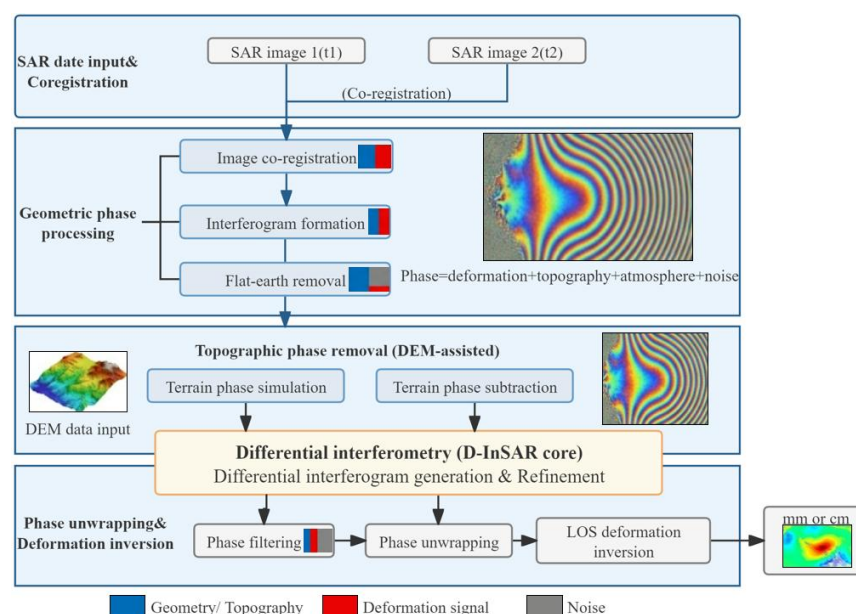


Figure 5. D-InSAR processing workflow for surface deformation inversion.

In the early identification of subsidence and rapid hazard assessment in mining areas, D-InSAR technology effectively identifies multiple subsidence basins owing to its centimeter- to millimeter-level accuracy, all-weather observation capabilities, and wide-swath, high-resolution imaging. This provides reliable data support for delineating the subsidence extent of mined-out areas and assessing the degree of hazards. However, its application within the complex environments of mining areas remains subject to certain limitations [41]. Consequently, Table 2 summarizes the advantages and limitations of employing D-InSAR for mining area monitoring. To address these issues, recent studies have frequently employed the combination of ascending and descending orbit data or incorporated physical models such as the Probability Integral Method (PIM) to enhance the monitoring accuracy of large-gradient deformations and the capability for 3D displacement retrieval [42,43]. In summary, while D-InSAR offers significant advantages in characterizing mining-induced subsidence, its inherent limitations associated with high deformation gradients and low coherence have necessitated the development of multi-source data fusion and physically constrained modeling approaches.

Table 2. Comparison of advantages and disadvantages of D-InSAR monitoring in mining areas.

Dimension	Advantages	Limitations
Spatial coverage	Achieves full coverage of the mining area, capturing the complete characteristics of the subsidence basin	Restricted by the upper limit of the deformation gradient; prone to decorrelation in areas with extremely large deformation
Accuracy and efficiency	Theoretical accuracy can reach the millimeter level, significantly reducing the cost of field-work	Highly dependent on the accuracy of the external DEM and the stability of the phase unwrapping algorithm
Observation dimension	Mature technology, serving as the preferred method for acquiring LOS displacement	Single-orbit data cannot resolve horizontal movement; insensitive to north–south deformation

2.1.2. TS-InSAR Technology

Mining-induced surface subsidence and horizontal displacements are characterized by long-term accumulation and spatially heterogeneous distributions. Traditional D-InSAR methods often prove insufficient for long-term monitoring tasks and are susceptible

to atmospheric disturbances, spatiotemporal decorrelation, and coherence variations. Consequently, TS-InSAR technology emerged; by jointly processing multi-temporal images, it effectively enhances the stability and accuracy of deformation retrieval, thereby establishing itself as an essential tool for surface deformation monitoring in mining areas [44].

Based on the differing characteristics of target scatterers, TS-InSAR technology has evolved into various technical branches, among which Persistent Scatterer InSAR (PS-InSAR), Small Baseline Subset InSAR (SBAS-InSAR), and Distributed Scatterer InSAR (DS-InSAR) are the most representative. These methods have distinct emphases in terms of monitoring density, spatial coverage, and accuracy evaluation, collectively constructing a continuous tracking system tailored to the complex geological environments of mining areas [45]. Figure 6 systematically illustrates the processing framework of time-series InSAR technology and its typical application workflow for monitoring mining-induced deformations.

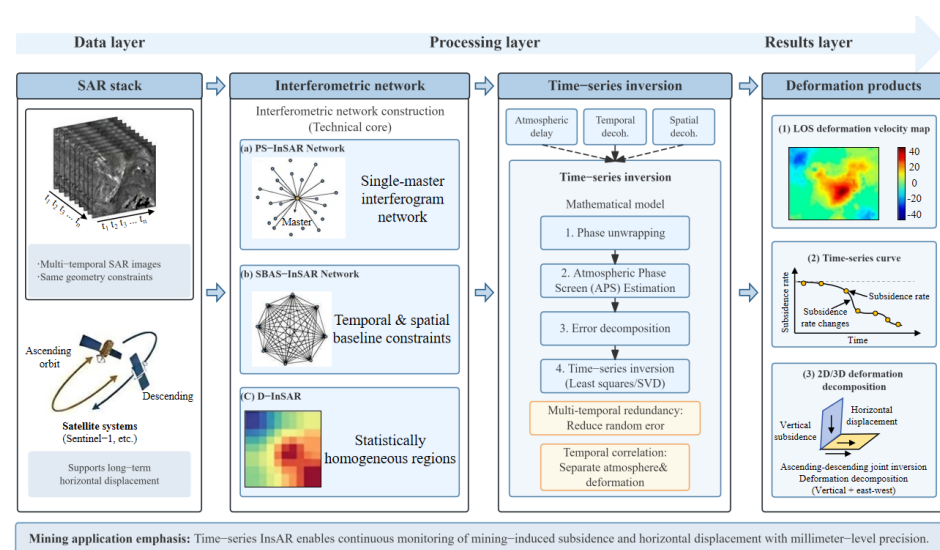


Figure 6. Time-series InSAR processing framework and its application in surface deformation monitoring in mining areas.

PS-InSAR

PS-InSAR overcomes the primary limitation of traditional D-InSAR, which is constrained by spatiotemporal decorrelation, by identifying ground pixels, known as persistent scatterers (PS), that maintain high coherence across a long time series of radar imagery. By leveraging targets with highly stable electromagnetic scattering characteristics (e.g., man-made structures and exposed rock outcrops), which are typically identified by setting an amplitude dispersion index threshold of 0.25, this technique effectively mitigates phase noise to facilitate deformation retrieval with millimeter-level accuracy [46].

In mining environments, the application value of PS-InSAR is reflected in its continuous tracking capability for surface industrial sites, infrastructure, and mine slopes. By modeling and applying spatiotemporal filtering to the unwrapped phase sequences, this technology can capture minute displacements along the radar LOS direction, providing data support for subsidence early warning in mined-out areas and infrastructure damage assessment. However, the distribution of PS points is highly dependent on surface scattering characteristics, leading to significant “spatial non-uniformity” when applying this technology to mining area monitoring: around highly urbanized mine peripheries, dense PS points can be used to construct high-density deformation fields; whereas in densely vegetated rural mining areas, the scarcity of coherent points often results in information

loss at the center of subsidence basins [47]. This monitoring characteristic, which is based on point targets, requires researchers to thoroughly understand the physical evolution and geometric imaging relationships of PS targets. Figure 7 illustrates the ground features and geometric principles of typical PS targets.

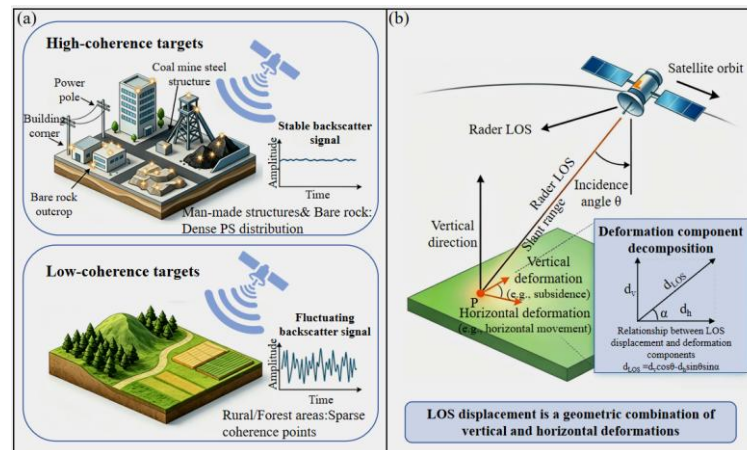


Figure 7. Ground targets and geometric principles of PS. (a) Comparison between high-coherence and low-coherence targets. (b) SAR imaging geometry and deformation components.

SBAS-InSAR

By constructing an interferometric network with short spatiotemporal baselines, the SBAS technique significantly increases the density of coherent pixels in non-urbanized areas, thereby demonstrating a superior capacity to capture the severe non-linear deformation commonly encountered in mining areas [48]. In practical mining applications, it is widely employed to characterize regional subsidence trends and model dynamic subsidence rates across different mining stages. Despite its high computational complexity, its versatile spatial coverage has established it as the primary technological approach for conducting full-lifecycle monitoring and pattern analysis of mined surfaces; the conceptual framework of its technical processing capabilities and spatiotemporal resolution is illustrated in Figure 8 [49].

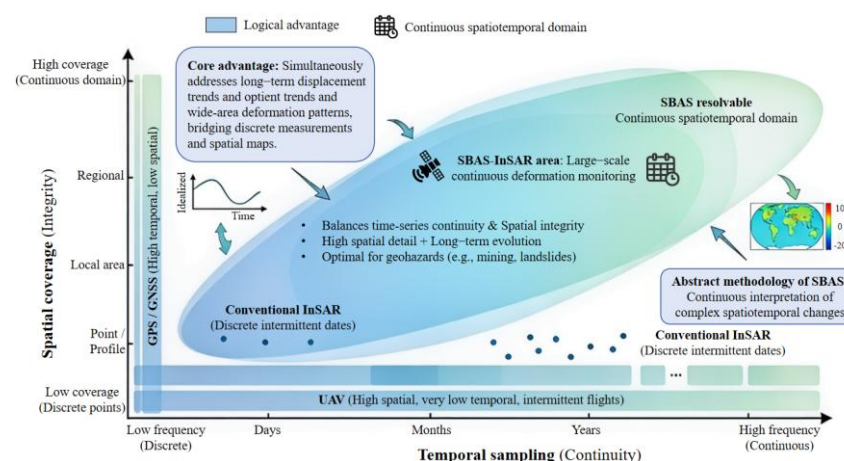


Figure 8. Conceptual framework of spatiotemporal resolution capabilities in SBAS-InSAR.

DS-InSAR

The DS-InSAR technique primarily targets regions characterized by weak scattering or sparse PS points. It extracts stable deformation signals by analyzing the coherent statistical characteristics of multiple pixels within small local patches; its core principle is

illustrated in Figure 9. By optimizing the phases of spatially adjacent pixels exhibiting similar scattering properties, this technique substantially increases the density of measurement points in natural terrain, which is pivotal for detecting subtle deformations at the margins of mining areas under complex geological conditions [50]. In mining applications, DS-InSAR is employed to characterize local anomalous subsidence, landslide margins, and boundary deformations. By integrating long-wavelength SAR data with DS algorithms, researchers can effectively attenuate noise induced by vegetation volume scattering, facilitating high-resolution characterization of surface deformation to support the green and sustainable development of coal mines [51].

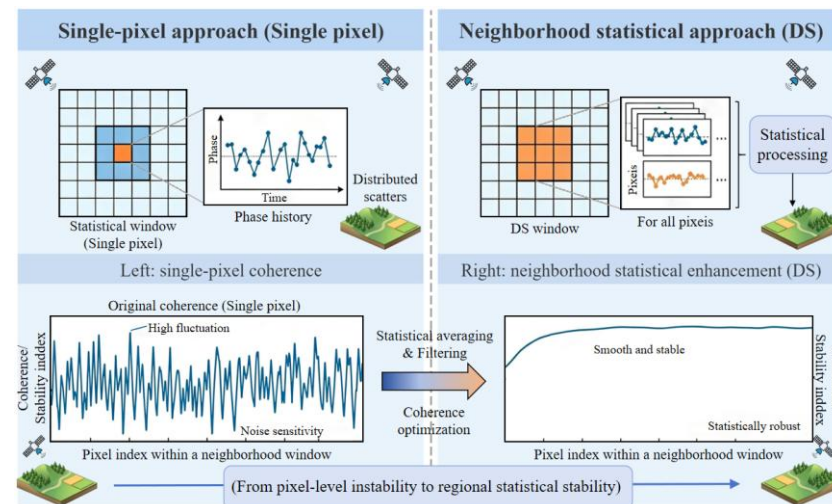


Figure 9. Core principle of statistical coherence enhancement in DS-InSAR technique.

While the aforementioned InSAR techniques each possess distinct theoretical advantages, their practical performance is significantly influenced by the complex constraints inherent to mining-induced environments. To provide a comprehensive evaluation, Table 3 systematically compares the applicability, technical limitations, and ideal monitoring scenarios of D-InSAR and the three TS-InSAR methods under typical mining conditions (e.g., large deformation gradients, dense vegetation, and dynamic surface subsidence).

Table 3. Critical comparison of mainstream InSAR techniques under complex mining conditions.

Technique	Resilience to High Deformation Gradients (Mining Centers)	Adaptability to Low-Coherence Environments (Vegetated Mines)	Data Density in Non-Urban Mining Areas	Optimal Mining Application Scenario
D-InSAR	Weak (Prone to severe phase aliasing and unwrapping failures in rapid subsidence zones)	Poor (Highly sensitive to temporal changes and mining-induced surface disruption)	Continuous spatial coverage, but high risk of information loss in goaf centers	Rapid extraction of initial subsidence basin boundaries; short-term hazard identification
PS-InSAR	Moderate (Performance relies heavily on phase unwrapping algorithms)	Moderate (Requires stable artificial structures; performs poorly in bare soil/vegetation)	Very low (Sparse distribution leads to information gaps in rural mining terrains)	High-precision continuous monitoring of mining infrastructure, shafts, and stable open-pit slopes

SBAS-InSAR	Strong (Mitigates gradient limits via multi-master short baseline combinations)	Good (Maintains coherence by restricting temporal and spatial baselines)	High regional coverage, but temporally discrete	Long-term tracking of regional subsidence basin evolution; dynamic subsidence rate mapping
DS-InSAR	Strong (Statistically recovers phase information in noisy, high-gradient zones)	Excellent (Extracts stable signals from statistically homogeneous patches)	Extremely high (Successfully recovers data in sparse/vegetated natural terrains)	Fine-grained monitoring of subtle subsidence margins and complex geohazards in vegetated open-pit mines

2.2. Surface Deformation Retrieval Methods

Surface movement induced by underground mining is a highly non-linear and complex process. However, the raw interferometric phase acquired via InSAR is essentially the geometric projection of the surface displacement vector along the radar LOS direction, resulting in one-dimensional observations. Driven by high-intensity mining operations, mine surfaces typically experience significant non-uniform subsidence and large-scale horizontal displacement. Constrained by satellite imaging geometry, single-track LOS observations cannot fully capture the spatial magnitude and direction of the true surface displacement vector. Therefore, bridging the dimensional gap between sensor observations and the physical surface deformation field to achieve an accurate mapping from scalar observations to vector field reconstruction is a prerequisite for thoroughly analyzing the deformation patterns in mining areas [52].

To accurately evaluate the damaging effects of mining-induced subsidence on surface structures and the mining environment, it is imperative to establish a three-dimensional deformation reconstruction model that conforms to geomechanical principles. By integrating multi-source observation data from ascending and descending orbits or introducing geological prior models, decomposing the LOS deformation—which is constrained by observation geometry—into vertical subsidence, as well as north–south and east–west horizontal displacements, has become crucial in the field of mining area monitoring [53]. The principle of this geometry-based deformation decomposition, along with the mapping relationship between LOS observations and the 3D surface displacement vector field, is illustrated in Figure 10.

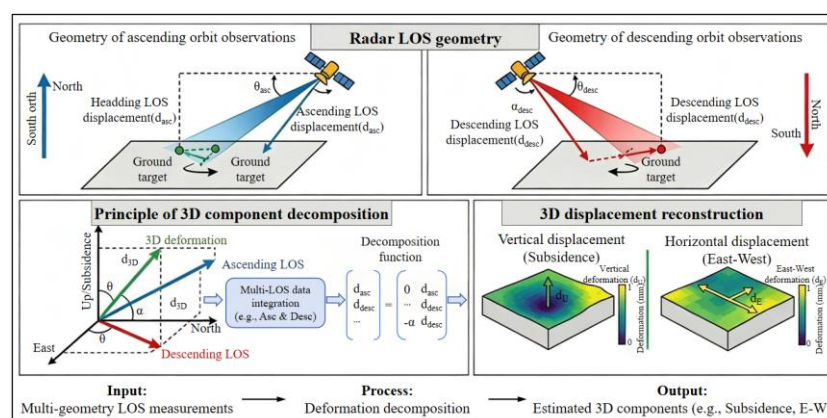


Figure 10. LOS deformation decomposition and its relationship with three-dimensional (3D) deformation.

2.2.1. Vertical Subsidence Extraction

The formation of underground mined-out areas induces progressive subsidence of the overlying strata, ultimately forming typical subsidence basins at the surface. Consequently, high-precision vertical subsidence measurements serve not only as the most intuitive parameters for characterizing surface deformation features in mining areas but also as essential indicators for hazard assessment and environmental monitoring [54].

In the context of InSAR subsidence monitoring, since mining-induced deformation is typically dominated by vertical subsidence, early studies predominantly adopted the direct LOS approximation method. This method assumes that surface movement occurs exclusively in the vertical direction, employing the radar incidence angle to directly convert LOS deformation into vertical subsidence via geometric projection. While this assumption is generally valid at the margins of subsidence basins where horizontal displacement is relatively small, facilitating the rapid extraction of preliminary subsidence distributions; however, the central zones of mining areas often exhibit “large-gradient” and “discontinuous” deformation characteristics accompanied by significant horizontal movements. Under these conditions, a simple unidirectional geometric projection is prone to introducing systematic errors [55].

To overcome these limitations and enhance extraction accuracy, modern subsidence monitoring in mining areas has largely shifted toward inversion analysis based on TS-InSAR (e.g., PS-InSAR and SBAS-InSAR). This approach not only effectively mitigates atmospheric delays and topographic phase errors but also establishes long-term deformation time series, thereby enabling the accurate extraction of surface subsidence rates, accelerations, and their nonlinear evolutionary processes. In practical mining applications, high-quality time-series subsidence data provide reliable support for precisely delineating the zone of mining influence, identifying the morphology of subsidence troughs, and categorizing the evolutionary stages of subsidence [56]. The spatial distribution of subsidence rates in typical mining areas derived from TS-InSAR technology, along with the subsidence basin structure it reveals, is illustrated in Figure 11.

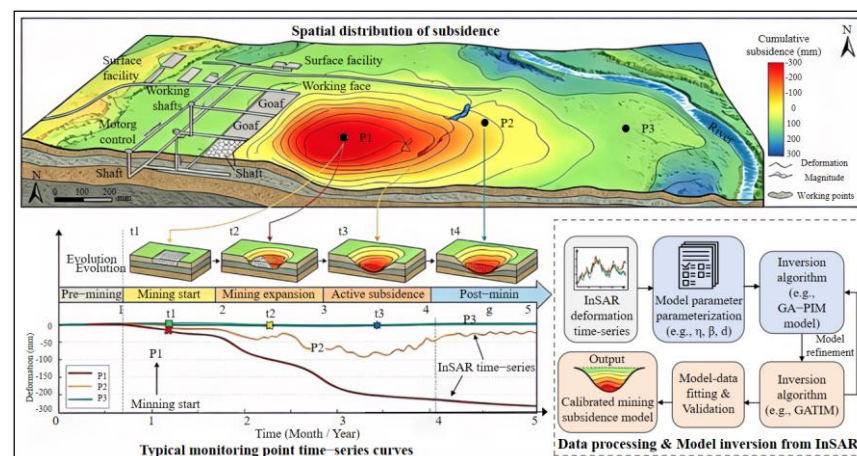


Figure 11. Subsidence rate distribution and identification of subsidence basin structures in mining areas based on time-series InSAR.

2.2.2. Horizontal Displacement Inversion

Compared to vertical subsidence extraction, the inversion of surface horizontal displacement is methodologically more complex, primarily due to the inherent constraints of InSAR observation geometry. Single-orbit SAR systems are only sensitive to LOS displacements, demonstrating a pronounced directional response to horizontal components. Notably, they are largely or completely insensitive to the north–south displacement component. Under mining-induced disturbances, surface horizontal deformation typically

manifests as a convergent displacement field directed toward the subsidence center or as tensional expansion propagating along the direction of mining advance. These characteristics directly reflect the evolution of underground goafs and the stress redistribution process. Consequently, acquiring reliable horizontal displacement information is crucial for characterizing surface dynamic behaviors in mining areas [57]. However, due to limited observational dimensions, the precise inversion of horizontal components generally relies on integrating multi-view geometric information and designing rational constraints.

In practical applications, the inversion of horizontal displacement is primarily achieved through multi-track data fusion and model constraint methods. A common strategy involves combining ascending and descending SAR observations, exploiting differences in observation geometry to decompose LOS displacements, thereby decoupling the vertical and east–west displacement components. This process can be regarded as geometric projection inversion, wherein multi-directional observations are uniformly mapped onto a ground coordinate system to reconstruct the two-dimensional deformation field. Building upon this, incorporating external observations (e.g., GNSS) or geomechanically model constraints—whose decoupling mechanism based on error ellipsoid theory is illustrated in Figure 12—can effectively mitigate the ill-posed nature of the inversion process, significantly enhancing computational stability and result reliability [58]. It should be noted that acquiring north–south displacements still necessitates supplementation via additional observation methods or assumed conditions, which remains one of the critical challenges in current research on InSAR horizontal displacement inversion.

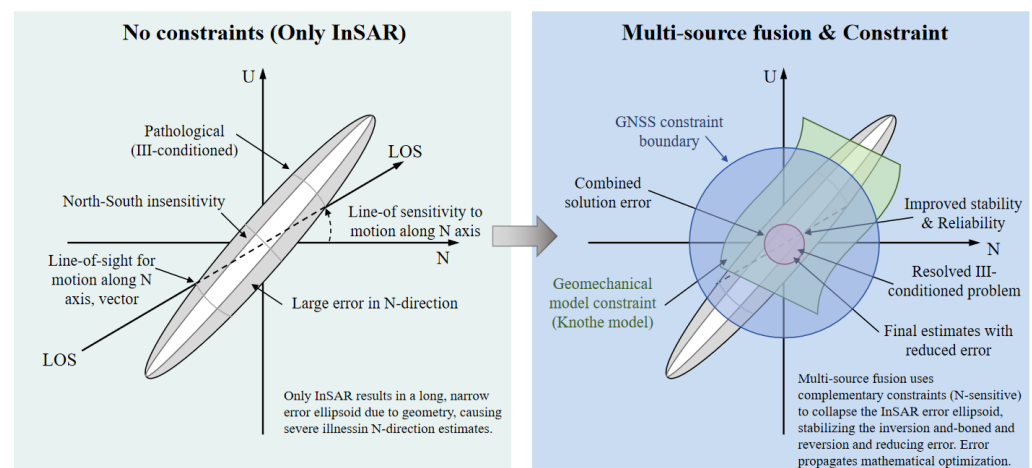


Figure 12. Decoupling mechanism of multi-source constrained deformation resolution based on error ellipsoid theory.

2.2.3. Three-Dimensional Deformation Reconstruction

Three-dimensional deformation reconstruction aims to obtain the complete surface vector field within the three-dimensional spatial coordinate system (U, E, N), serving as the core for achieving precise monitoring and mechanistic characterization of mining-induced deformation. Because conventional remote sensing techniques such as InSAR can only acquire one-dimensional projected components in the radar LOS or azimuth directions, a pronounced “dimensional deficit” exists between these single-dimensional observations and the three-dimensional parameters to be estimated. This results in typical incompatibility during the reconstruction process [59]. To resolve this inversion challenge, current research has primarily established two major technical paradigms: multi-source heterogeneous data fusion and prior physical model constraints. The former addresses the deficit in spatial geometric constraints by integrating multi-track and multi-platform observations, while the latter introduces stochastic medium theory or strata movement

models, leveraging prior mechanical mechanisms to compensate for the insufficiency of observational data [60].

Regarding their depth of application, three-dimensional deformation fields not only precisely delineate the spatial evolutionary characteristics of surface deformation but also provide crucial vector constraints for inverting the geometric parameters of underground goafs, revealing the laws of overburden movement, and evaluating the stability of shafts and roadways [61]. In recent years, driven by advancements in computational intelligence, machine learning algorithms have been integrated into three-dimensional deformation inversion frameworks. By constructing high-dimensional nonlinear feature mappings, machine learning demonstrates significant advantages in multi-source data weight optimization, nonlinear deformation modeling, and achieving regularized solutions under complex geological conditions. This trend of integrating data-driven approaches with physical mechanisms is gradually becoming an important research methodology for enhancing the reconstruction accuracy and robustness of complex mining-induced deformation (Figure 13).

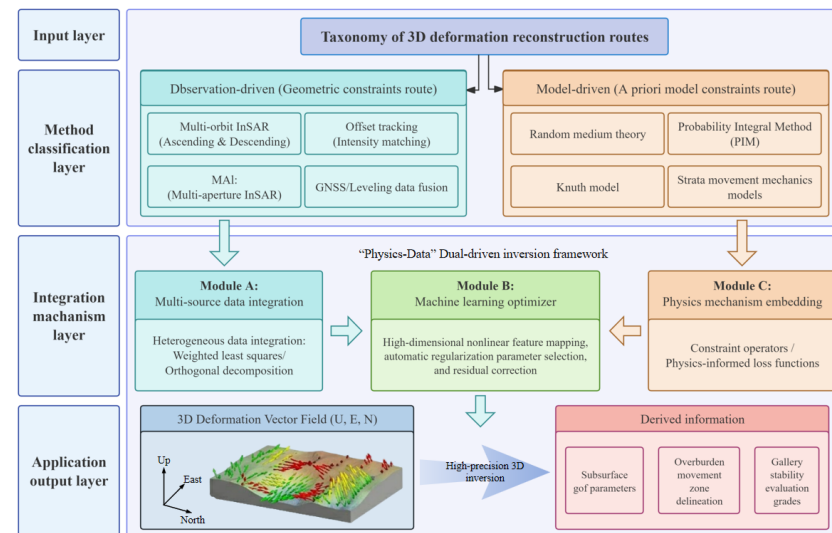


Figure 13. Classification of technical approaches for 3D surface deformation reconstruction in mining areas.

In summary, the inversion of surface deformation in mining areas has evolved from single LOS observations to complex multi-dimensional vector reconstruction. To provide a more intuitive comparison, Table 4 summarizes the differences among various inversion dimensions regarding data requirements, computational accuracy, and engineering applicability. This comparison reveals that while model-driven three-dimensional reconstruction schemes reduce reliance on multi-track data, they impose more stringent requirements on the accuracy of physical parameters. This offers a valuable reference for selecting monitoring schemes under complex mining conditions in future applications.

Table 4. Comparative analysis of deformation inversion methods in mining areas.

Inversion Dimension	Core Method	Data Requirements	Accuracy Level	Limitations
1D (LOS)	Traditional time-series InSAR	Single-orbit data	Millimeter level	Inability to distinguish between vertical and horizontal displacements

2D (Vertical + E-W)	Fusion of ascending and descending orbits	Ascending + descending orbit data pairs	Centimeter level	Insensitive to N-S displacement; larger errors when N-S deformation predominates
3D (U, E, N)	Geometric fusion method	Multi-source/multi-orbit data	Decimeter to centimeter level	High requirements for satellite revisit consistency; prominent ill-posed problems
	Model-driven method	InSAR + mining physical models	Centimeter level	Relies on the accuracy of physical models; adaptability to complex underlying strata requires improvement

2.3. Error Processing

During InSAR-based surface deformation monitoring, error processing is a critical procedure that determines both inversion accuracy and the reliability of the results. Because the SAR system operates using a side-looking imaging mechanism, its interferometric phase contains not only the true surface deformation information but is also superimposed with various non-deformation components, including orbital errors, atmospheric delays, surface scattering variations, thermal noise, and DEM errors [62]. These error sources typically exhibit distinct spatial scales and temporal characteristics. Particularly in mining environments characterized by complex topography and intense human extraction activities, the interference and masking effects of multi-source errors on the actual deformation signals are exceptionally severe (Figure 14).

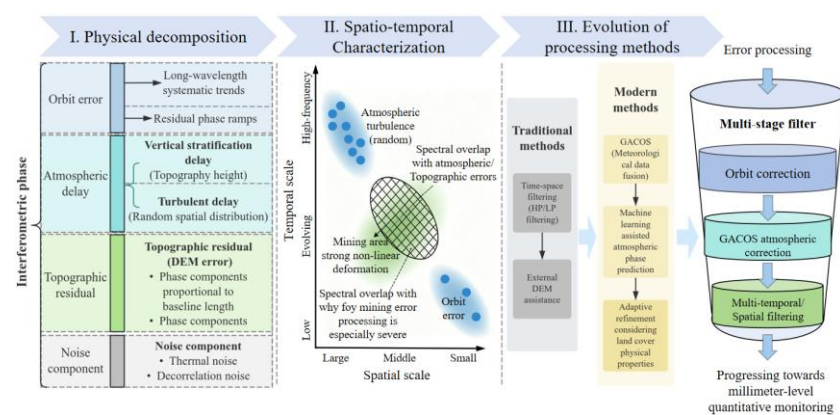


Figure 14. Framework for error source decomposition and spatiotemporal decoupling in InSAR surface deformation monitoring.

From a technological evolution perspective, enhancing error-processing capabilities has been the primary driving force propelling InSAR from qualitative identification toward millimeter-level quantitative monitoring. In recent years, with the advancement of high-precision orbital data, meteorological reanalysis products, and machine learning-assisted filtering methods, error correction has transitioned from empirical mitigation to a fusion of physical constraints and data-driven approaches. This technological advancement not only substantially enhances the measurement accuracy of vertical subsidence but also provides a robust methodological foundation for precisely capturing subtle horizontal displacements and complexly nonlinear deformation processes [37].

2.3.1. Primary Error Sources

The error sources in InSAR deformation monitoring are characterized by complex features, manifesting as multi-source coupling, multi-scale discrepancies, and spatiotemporal non-stationarity. Among these, decorrelation errors, orbital errors, and atmospheric errors are regarded as the three principal error categories affecting the accuracy of deformation inversion in mining areas. In mining environments, owing to complex land cover types, intense mining activities, and pronounced local topographic relief, these errors are frequently superimposed, thereby inducing considerable instability in the interferometric phase [63]. Consequently, a systematic analysis of the causative mechanisms and spatiotemporal characteristics of these primary error sources constitutes a vital prerequisite for constructing high-precision deformation inversion models (Table 5).

Table 5. Summary of major error sources and impact characteristics in InSAR.

Error Type	Primary Cause	Spatial Characteristics	Temporal Characteristics	Impact on Deformation Inversion	Common Correction Methods
Decorrelation error	Changes in surface scattering characteristics	Random/Local	Strong temporal variability	Increased phase noise	Optimized selection of PS/DS points
Orbital error	Orbital uncertainty/inaccuracy	Long-wavelength	Relatively stable	Regional trend distortion	Polynomial fitting
Atmospheric error	Water vapor variations	Regionally clustered	Temporally random	Obscures low-frequency/long-wavelength deformation	Atmospheric filtering

Decorrelation Errors

Decorrelation errors are among the most challenging error sources in InSAR surface deformation monitoring, fundamentally stemming from the degradation of phase coherence induced by changes in scattering characteristics between two SAR image acquisitions. Decorrelation not only introduces significant phase noise-blurring or even completely masking interferometric fringes but also drastically compromises the reliability of subsequent phase unwrapping. Based on their causative mechanisms, decorrelation is typically categorized into three primary forms: temporal decorrelation, geometric decorrelation, and volume decorrelation (Figure 15). In the context of mining-induced deformation monitoring, temporal decorrelation is particularly severe. Large-scale mining activities continuously and profoundly disrupt the surface structural integrity. Compounded by additional factors such as seasonal vegetation disturbance, surface scatterers are unable to maintain long-term coherence, thus constituting a critical bottleneck that constrains the accuracy of continuous, full-period deformation monitoring [64]. Furthermore, the severity of this temporal decorrelation is inherently modulated by the radar wavelength; longer wavelengths (e.g., L-band) exhibit deeper canopy penetration and better coherence retention over vegetated areas than shorter wavelengths (e.g., C-band or X-band).

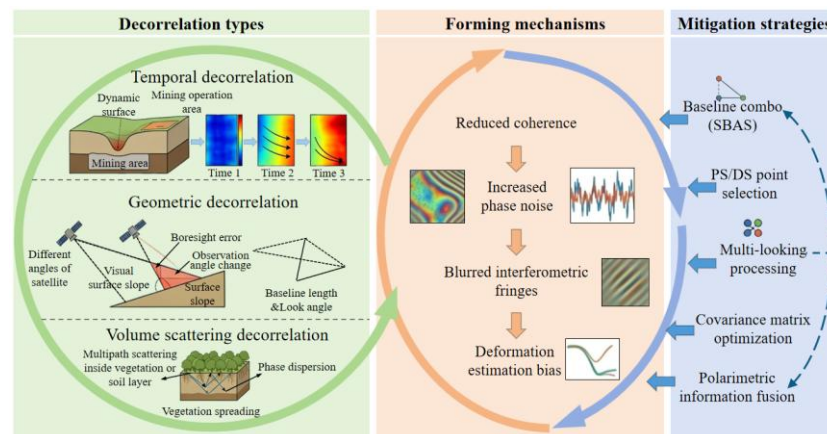


Figure 15. Schematic of types and impact mechanisms of InSAR decorrelation errors in mining areas.

In the monitoring of mining-induced subsidence and horizontal movement, decorrelation errors directly govern the effective spatial extent of deformation inversion. As the coherence coefficient decreases, phase noise substantially intensifies, subsequently leading to a marked increase in deformation estimation bias. In high-gradient mining subsidence zones, excessive deformation disparity between adjacent pixels may further trigger geometric decorrelation and phase aliasing problems. To mitigate the impact of decorrelation, researchers typically adopt combined strategies incorporating short temporal and spatial baselines, while concurrently employing methods such as PS points selection, DS statistical enhancement, and multi-look processing to improve interferometric coherence. Consequently, an understanding of the evolutionary patterns of decorrelation is not only central to error assessment but also constitutes a decisive factor in algorithm selection. In recent years, methods based on multi-temporal covariance matrix optimization and the integration of polarimetric interferometric information, specifically tailored to complex mining deformation environments, have gradually emerged as prominent research foci. These approaches exhibit superior robustness in low-coherence and large-gradient deformation zones, thereby providing crucial algorithmic support for the accurate reconstruction of mining-induced deformation processes [65].

Orbital Errors

Orbital errors primarily arise from inaccuracies in satellite orbital parameters. When orbital position deviations occur during the acquisition of a SAR image pair, additional long-wavelength trend components are superimposed onto the interferometric phase, thereby inducing large-scale spatial phase variations. These errors typically manifest as large-scale linear or bilinear phase ramps, which are particularly pronounced in wide-area monitoring of mining-induced deformation [66]. Although modern SAR satellites, such as Sentinel-1 and TerraSAR-X, currently provide highly accurate precise orbit ephemerides, residual orbital errors remain difficult to fully eliminate during long-term time-series processing, high-precision deformation inversion, and operations conducted under complex topographic conditions.

Orbital errors significantly affect the overall morphology of mining subsidence basins and are particularly prone to inducing broad-scale trend displacements. This results in spurious overall tilting, uplift, or subsidence patterns emerging in the deformation field, thereby interfering with the identification of genuine surface deformation signals. During horizontal displacement inversion and three-dimensional deformation reconstruction, these errors may further amplify the inconsistencies between ascending and descending orbit data. To mitigate the impact of orbital errors, compensation methods such as precise

orbit ephemerides correction, polynomial plane fitting, and stable-region-referenced constraints are typically employed [67]. Among these, the stable-region-based long-wavelength trend removal method is widely applied in InSAR data processing for mining areas. It effectively separates large-scale orbital phase components from localized genuine subsidence signals, thereby enhancing the spatial consistency and accuracy of deformation inversion results. Figure 16 illustrates the long-wavelength phase trends induced by orbital errors and their interference mechanisms with mining subsidence signals, further demonstrating the recovery process of localized subsidence characteristics following orbital error correction.

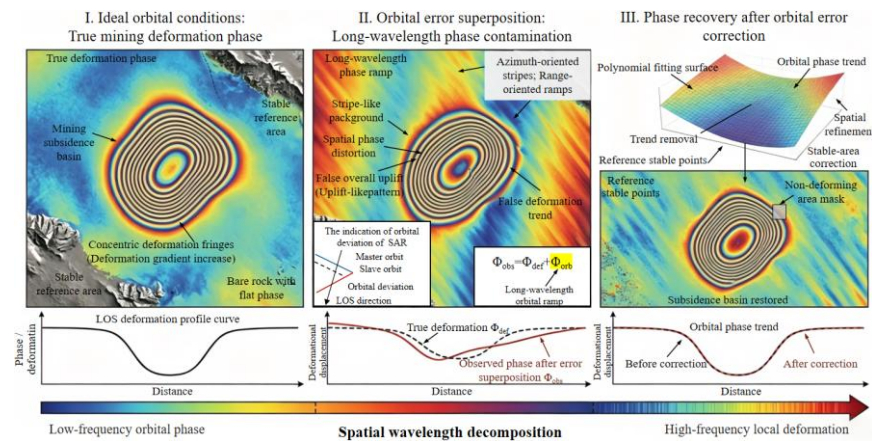


Figure 16. Long-wavelength phase trend induced by orbital errors and its interference mechanism on subsidence signals in mining areas.

Atmospheric Errors

Atmospheric errors constitute one of the primary sources of systematic errors affecting InSAR accuracy, fundamentally arising from phase delays incurred during the propagation of radar electromagnetic waves through the troposphere and ionosphere. Due to the pronounced spatiotemporal heterogeneity of the atmospheric medium in terms of temperature, pressure, and water vapor content, the propagation paths of electromagnetic waves undergo both refraction and phase delays. Among these, tropospheric delays are primarily controlled by variations in water vapor, exerting a particularly pronounced impact on C-band and X-band SAR data; in contrast, ionospheric errors are closely related to electron density perturbations, manifesting more prominently in L-band long-wavelength systems (Figure 17). Given the strong spatiotemporal randomness of atmospheric conditions, the resulting phase delays are often difficult to reliably isolate through a single observation. In mining environments, complex topographic reliefs, local thermal circulations, and variations in surface moisture further intensify atmospheric stratification effects, thereby giving rise to pronounced spatial correlation characteristics in the interferometric phase [68].

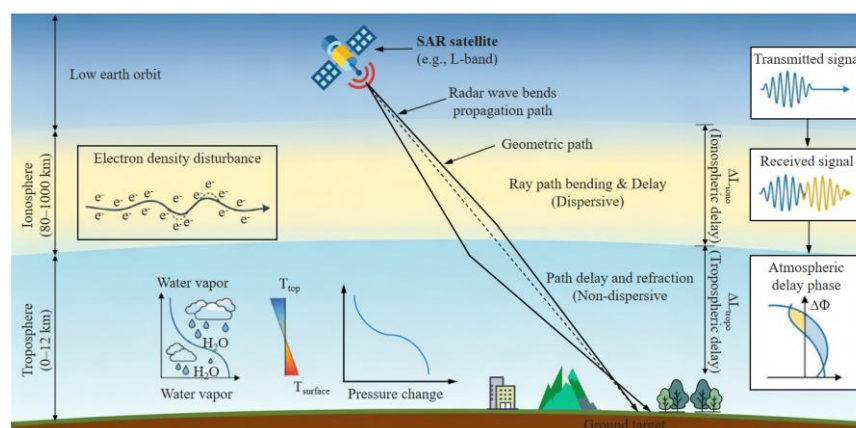


Figure 17. Multi-platform spatial-temporal monitoring framework for surface deformation.

Atmospheric errors typically mask low-amplitude deformation signals, exerting a particularly detrimental impact on the monitoring of millimeter-level, long-term gradual subsidence. In TS-InSAR analysis, the atmospheric phase is often characterized as exhibiting “temporal randomness and spatial correlation,” whereas genuine surface deformation generally demonstrates strong temporal continuity and spatial stability. Consequently, the two components can be separated based on their contrasting spatiotemporal characteristics. Currently, widely adopted atmospheric correction methods include temporal high-pass and spatial low-pass filtering, meteorological model-assisted correction, and the integration of GNSS precipitable water vapor data. With the advancement of high-resolution meteorological reanalysis data, atmospheric delay compensation methods based on external meteorological fields have achieved increasingly widespread application in InSAR data processing for mining areas, significantly enhancing the accuracy of gradual deformation monitoring [69].

2.3.2. Error Correction Methods

To address the aforementioned error sources, a multi-level and multi-scale error correction framework has been progressively established in the InSAR field. Traditional error processing primarily relied on spatial filtering and empirical models, whereas modern Multi-Temporal InSAR (MT-InSAR) approaches have shifted toward joint optimization based on the spatiotemporal statistical properties. Within the MT-InSAR framework, noise-related error components—including atmospheric delays and topographic residuals—can be effectively separated and mitigated by extracting PS with stable scattering characteristics or by constructing a SBAS baseline coherence network for weighted optimization [48,70]. This evolution from the localized processing of single interferograms to the holistic optimization of multi-dimensional time series has significantly enhanced the operational robustness of InSAR deformation monitoring under complex surface environments. The principles, advantages, limitations, and applicable scenarios of the various mainstream error correction methods are compared and summarized in Table 6.

Table 6. Comparison of different error correction methods.

Error Type	Typical Correction Methods	Basic Principles	Advantages	Limitations	Application Characteristics in Mining Areas
Decorrelation errors	PS/SBAS/DS-InSAR	Improves coherence through time-series analysis and the selection of stable scatterers	Effectively enhances deformation monitoring	Phase instability may still occur in rapid deformation areas	Widely applied in monitoring subsidence basins and

Error Type	Typical Correction Methods	Basic Principles	Advantages	Limitations	Application Characteristics in Mining Areas
			Information monitoring accuracy and spatial coverage		horizontal displacements in mining areas
Orbital errors	Precise orbit correction and trend surface removal	Eliminates orbital phase using high-precision orbital data and long-wavelength fitting	Effectively mitigates regional long-wavelength errors	May attenuate authentic large-scale deformation trends	Commonly used for correcting wide-area mining subsidence fields
Atmospheric errors	Temporal high-pass and spatial low-pass filtering; ERA5/GA-COS correction	Estimates atmospheric delays by exploiting spatiotemporal characteristic differences and meteorological data	Enhances the identification capability for slow subsidence and subtle horizontal displacements	Difficult to completely eliminate complex localized atmospheric anomalies	Demonstrates significant effectiveness in mountainous mining areas and long-term time-series monitoring
Combined errors	GNSS-InSAR joint optimization	Constrains InSAR deformation results using ground control points	Improves the stability and absolute accuracy of the results	Relies on the support of external observation data	Suitable for high-precision subsidence and three-dimensional deformation monitoring in mining areas

As research progresses, the in-depth integration of interdisciplinary multi-source data and the integration of physical constraint models have provided novel approaches for error processing in the monitoring of large-scale and high-gradient deformation in mining areas. The incorporation of external auxiliary observations (e.g., GNSS and high-resolution meteorological models) or the laws of mining-induced subsidence can effectively overcome the limitations of a single radar viewing geometry, further suppressing the nonlinear errors induced by complex environments and severe deformation [71,72]. Building upon the aforementioned technological evolution and multi-scale processing strategies, this study systematically outlines the various correction procedures from initial interferogram generation to time-series inversion. The comprehensive overall workflow for InSAR error correction is illustrated in Figure 18.

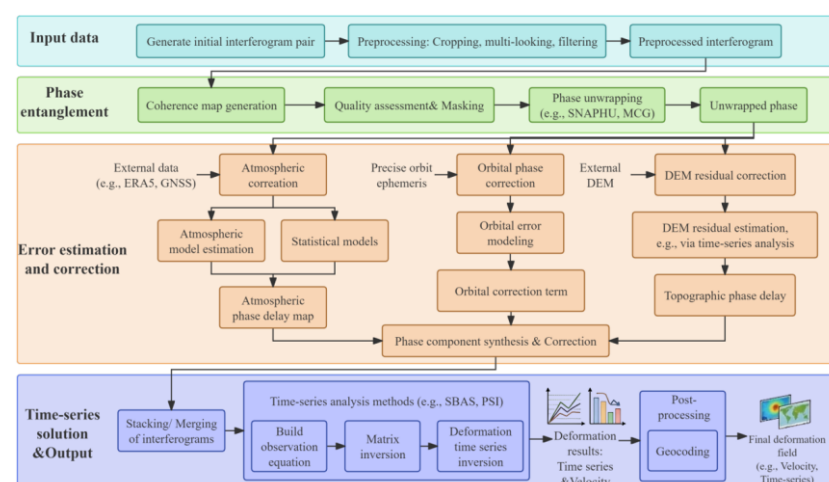


Figure 18. Overall workflow for InSAR error correction.

2.3.3. Impact of Errors on Deformation Inversion

The presence of errors constitutes a fundamental factor constraining the accuracy and reliability of deformation inversion in mining areas. In conventional LOS monitoring, errors of varying origins exhibit distinct interference mechanisms with respect to inversion results: random noise typically induces irregular fluctuations in localized deformation signals and degrades the interferometric signal-to-noise ratio (SNR), whereas systematic errors frequently distort long-wavelength signal characteristics, thereby altering large-scale subsidence trends and spatial distribution patterns. Furthermore, when the accumulation of residual errors exceeds a critical threshold, it is highly prone to inducing phase unwrapping failure, thereby introducing significant phase anomalies into the final deformation field. Particularly in characteristic high-gradient deformation zones within mining areas, intense genuine surface deformation and complex error signals often undergo significant nonlinear coupling. This consequently poses considerable challenges to the effective isolation of genuine deformation characteristics and the mechanistic interpretation of subsidence processes [73,74].

Compared to one-dimensional monitoring, the detrimental effects of residual errors on horizontal displacement inversion and three-dimensional deformation reconstruction are substantially more severe. Multi-track joint inversion models are extremely sensitive to the observational accuracy of the input data; minor errors under a single viewing geometry are often considerably amplified during the ill-posed vector decomposition process [75]. For instance, atmospheric errors may lead to the deflection of the horizontal displacement direction, whereas orbital errors may introduce an overall tilt in the three-dimensional deformation field. Therefore, in high-precision monitoring frameworks for mining areas, error analysis has been elevated from a conventional data preprocessing step to a critical constraint condition for validating the reliability of inversion results. Current research broadly indicates that error propagation theory, spatial uncertainty quantification models, and cross-validation mechanisms using multi-source heterogeneous data (such as GNSS or leveling) should be systematically introduced. This enables a credibility assessment of the inverted multi-dimensional deformation fields, thereby strengthening the application foundation of InSAR technology for the early identification of mining disasters and precision engineering monitoring (Figure 19) [76].

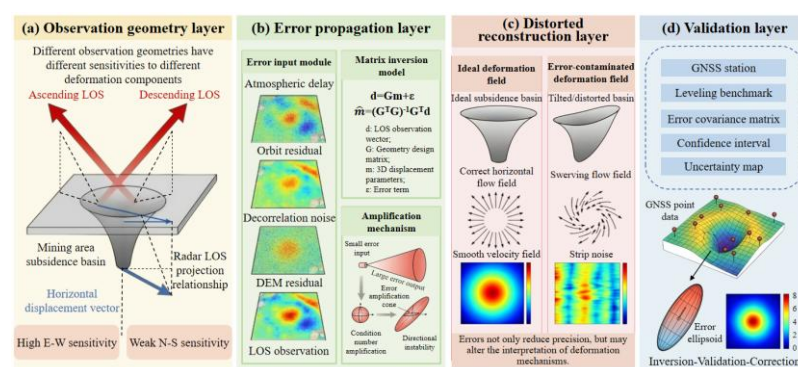


Figure 19. Framework of error propagation and uncertainty amplification mechanisms in multi-dimensional deformation inversion.

2.4. Multi-Source Data Fusion

In the monitoring of surface deformation in mining areas, although standalone InSAR technology offers the advantages of wide-area coverage and high precision, its inherent limitations have become increasingly prominent with the intensification of mining activities and the increasing complexity of deformation mechanisms, thereby giving rise

to multi-source data fusion technologies [77]. Current research indicates that these physical and technical limitations are primarily reflected in the following aspects: traditional radar LOS observations exhibit limited sensitivity to north–south surface movements; data gaps frequently occur in low-coherence regions; and atmospheric delays, along with orbital errors, significantly constrain the reliability of long-term deformation time series [78]. Consequently, sole reliance on single-source SAR data is often insufficient to comprehensively and accurately characterize the complex three-dimensional deformation patterns of mining areas. Against this backdrop, multi-source data fusion has gradually emerged as a pivotal developmental direction for enhancing both monitoring accuracy and spatiotemporal resolution.

The essence of multi-source data fusion lies in achieving complementary advantages among diverse observation techniques. Currently, common data sources for fusion include GNSS, optical remote sensing, Light Detection And Ranging (LiDAR), unmanned aerial vehicle (UAV) photogrammetry, and ground-based monitoring data [33,79]. Through the synergistic integration of multi-source data constraints, the spatial completeness, temporal continuity, and physical interpretability of mining-area deformation fields can be effectively enhanced. In recent years, with the advancement of data assimilation, machine learning, and digital twin technologies, the multi-source fusion paradigm is progressively advancing from conventional data-level overlay toward mechanism-driven and intelligent prediction approaches (Figure 20). This provides a novel methodological pathway for the precision monitoring of surface deformation and disaster risk early warning in mining areas [80]. For instance, the integration of multi-source spatial technologies has been demonstrated as an effective approach for assessing industrial waste disposal practices in complex mining sectors, underscoring the necessity of data fusion for comprehensive environmental and deformation monitoring [81].

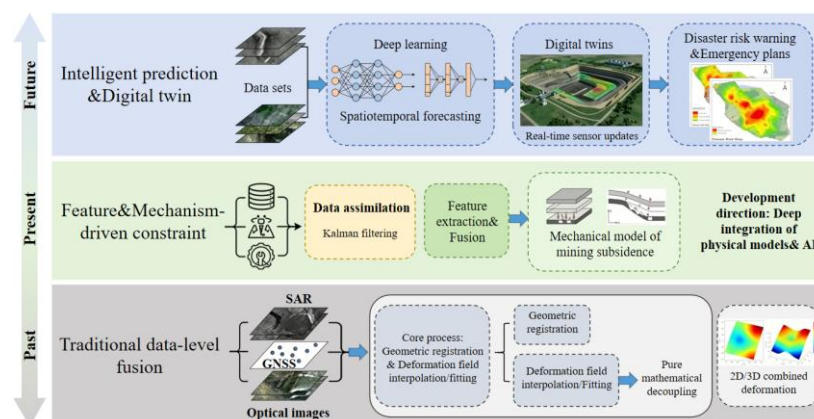


Figure 20. Evolution roadmap of multi-source fusion monitoring technologies and intelligent prediction framework for deformation in mining areas.

3. Results and Analysis

To critically evaluate the efficacy and limitations of InSAR technology in diverse mining conditions, this section presents two representative case studies. The first case, the Shangwan coal mine, demonstrates the performance of InSAR in addressing the specific challenge of high-gradient deformation. The second case, the Sukari Gold Mine, illustrates the technology’s capability in identifying potential slope stability hazards in open-pit mining environments. These cases collectively encapsulate the most prevalent and challenging deformation scenarios in contemporary mining engineering.

3.1. High-Gradient Deformation Case in Mining Areas

To address the limitations of traditional InSAR technology under high-gradient surface deformation conditions in central mining areas, our research group focused on the 12,401 working face of the Shangwan coal mine to systematically propose and validate an InSAR deformation phase restoration method based on reference phase constraints. In dealing with central mining areas exhibiting extremely large deformation gradients, the relative displacement between adjacent pixels often exceeds the maximum measurable deformation gradient limit of traditional InSAR technology. This results in excessively dense interferometric fringes or even phase jumps, thereby rendering conventional phase unwrapping algorithms ineffective. To overcome this bottleneck, this study introduced a prior deformation field-obtained from the PIM prediction model or measured data from Global Navigation Satellite System Real-Time Kinematic (GNSS-RTK)-as the reference phase. By differencing the actual InSAR wrapped phase and the reference phase, a residual interferometric phase with a significantly reduced fringe density can be extracted. This approach substantially reduces the complexity of phase unwrapping in regions with strong local noise and high gradients. Subsequently, by integrating the unwrapped residual phase with the prior reference phase, the actual three-dimensional deformation field covering the entire subsidence basin can be reconstructed with high precision [82]. The technical processing workflow and core methodological architecture of this study (Figure 21).

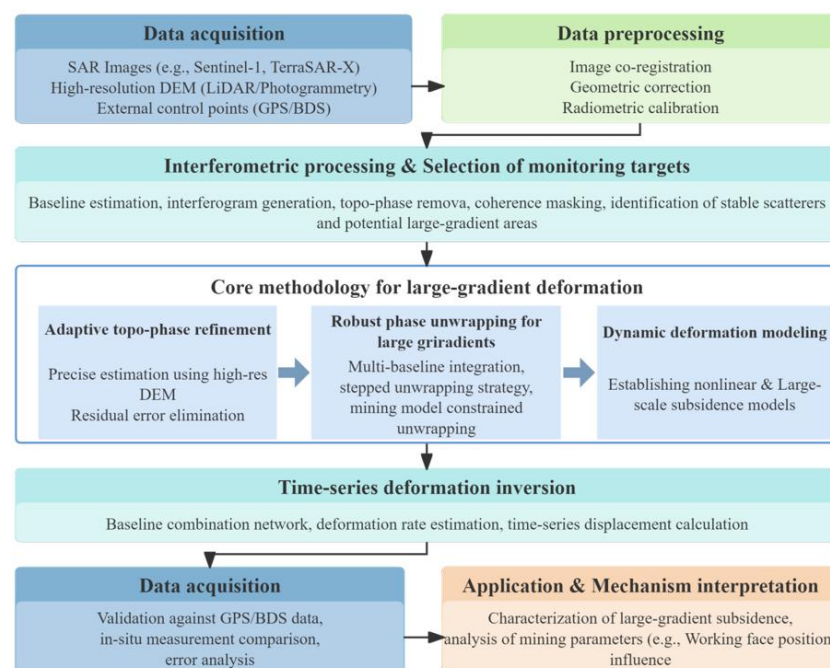


Figure 21. InSAR system processing workflow for large-gradient surface deformation monitoring in mining areas.

The results demonstrate that the phase recovery strategy based on reference phase constraints effectively overcomes the physical limitations of traditional InSAR in high-gradient deformation monitoring, significantly enhancing both the deformation inversion accuracy and spatial continuity within severe subsidence zones in central mining areas. This case further illustrates that the synergistic fusion of high-resolution SAR observation data and external high-precision prior deformation information represents a critical advancement in improving 3D surface movement monitoring capabilities in complex mining-affected areas. It provides robust technical support for analyzing subsidence evolution patterns and assessing disaster risks in mining areas [82].

While this reference-phase-constrained approach effectively restores fringes in high-gradient zones, its performance is contingent upon the accuracy of the a priori model (e.g., PIM). In scenarios where mining parameters are unknown or geomechanical models are ill-posed, this dependence on a priori information presents a significant constraint, potentially inducing systematic bias into the resultant deformation reconstruction.

3.2. Landslide Case in Mining Area

Within the complex geological environments of large-scale open-pit mining areas, slope instability is often an early precursor to catastrophic landslide events. In recent years, time-series InSAR technology has gradually emerged as a critical tool for monitoring landslides and slope stability in mining areas. Using the Sukari Gold Mine in Egypt as a case study, researchers utilized 23 scenes of Sentinel-1 ascending SAR images and applied PS-InSAR technology to systematically identify potential landslide hazards within the mining area (Figure 22). The results indicate that areas unaffected by mining activities remained largely stable, with the mean annual LOS deformation generally remaining within ± 10 mm, whereas the margins of the open pit and the tailings storage facility exhibited pronounced localized instability. The study further revealed that some slopes remained stable during the initial monitoring period but gradually displayed an accelerated sliding trend in the middle and later stages. This demonstrates that mining-induced landslides often exhibit distinct progressive evolution, and TS-InSAR can effectively reveal the dynamic process of “stability–slow creep–accelerated instability” [83].

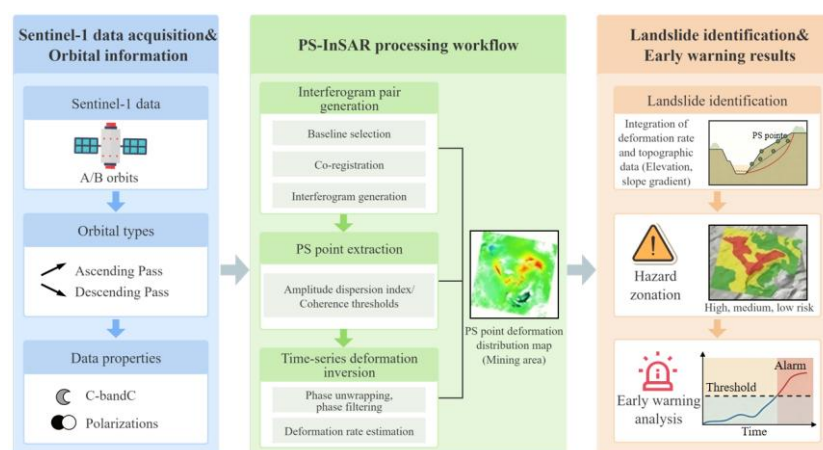


Figure 22. Overall framework of InSAR-based landslide deformation monitoring in open-pit mining areas.

From the perspective of landslide mechanisms, this case reflects a significant coupling relationship between slope deformation in mining areas and factors such as pit excavation, waste rock dumping, and tailings loading. The long-term time-series deformation information acquired via InSAR can effectively capture the critical stages of slope evolution, from subtle deformation to instability, providing a crucial basis for the early identification and risk assessment of mining-induced landslides. Current research increasingly integrates time-series methods (e.g., PS-InSAR and SBAS-InSAR) with techniques such as slope radar, numerical simulations, and engineering geological surveys. This synergistic analysis of multi-source data significantly enhances landslide identification and early warning capabilities in complex mining areas. Overall, time-series InSAR technology is no longer limited to basic deformation monitoring in mining areas. Instead, it has progressively evolved into a comprehensive geological disaster monitoring tool that integrates hazard zone identification, deformation evolution analysis, and disaster early

warning, thereby offering substantial practical value for the safety management of open-pit mine slopes [83].

Despite the established success of TS-InSAR in capturing landslide precursors, its monitoring efficacy is primarily constrained by satellite revisit cycles and the spatial density of coherent scatterers in heavily disturbed mining slopes. These limitations impede the capacity for real-time emergency response and hinder the identification of failure surfaces in rapidly evolving, low-coherence zones. To mitigate these temporal and spatial bottlenecks, point-based monitoring systems, particularly modern GNSS/CORS-RTK, serve as a critical complement. In contrast to traditional survey methods, high-frequency GNSS measurements (up to 5 Hz) provide continuous, sub-centimeter-level displacement data, as recently demonstrated by successful deployments at the Dong Cao Son mine dump site. The integration of the extensive spatial coverage of InSAR with the high temporal resolution of GNSS facilitates a multi-dimensional monitoring strategy, effectively balancing large-scale deformation trends with the immediate, mission-critical requirements of landslide early warning [84].

4. Discussion

4.1. Current Challenges

Although InSAR technology has advanced significantly in monitoring surface deformation in mining areas, current research and practice still confront several fundamental technical bottlenecks. These issues extend beyond mere accuracy improvements; rather, they involve structural limitations concerning observation mechanisms, physical models, and data processing frameworks, which significantly constrain the reliable application of this technology across a broader range of mining scenarios.

(1) The breakdown of phase continuity under high-gradient deformation conditions currently constitutes the primary challenge. High-intensity mining typically triggers widespread, large-amplitude rapid surface subsidence within a short timeframe. The deformation gradient in the central region of the subsidence basin frequently exceeds the maximum measurable deformation difference between adjacent InSAR pixels. This directly results in highly dense interferometric fringes, phase discontinuity, and even complete decorrelation. Although enhanced phase unwrapping algorithms have expanded the monitorable gradient range, their accuracy is highly dependent on the precision of prior model parameters. In scenarios with complex geological conditions or unknown mining parameters, deviations in model predictions directly amplify phase restoration errors, creating an intractable circular dependency.

(2) The inherent geometric limitations of LOS observations impose an additional fundamental constraint. Single-track SAR observations yield only one-dimensional deformation components in the LOS direction, whereas surface deformation in mining areas is fundamentally a three-dimensional movement comprising vertical subsidence and horizontal displacement. Converting one-dimensional LOS observations into a three-dimensional displacement field necessitates the integration of multi-track observations from ascending and descending tracks, or the incorporation of external auxiliary data. However, the imaging geometries of both ascending and descending tracks exhibit minimal sensitivity to the north–south horizontal displacement component (with incidence angles typically ranging between 30° and 40°). Consequently, within a pure InSAR framework, the north–south horizontal displacement component is nearly impossible to isolate accurately from LOS observations. This issue is particularly pronounced during the inversion of horizontal displacements in mining areas characterized by inclined coal seams or non-axisymmetric subsidence basins. Even when employing joint inversion of ascending and descending tracks, the normal matrix of the system of equations remains highly ill-conditioned. Minor observational errors, once amplified by this ill-conditioned matrix, can yield

significant deviations in the north–south component, severely compromising the reconstruction of the three-dimensional deformation field.

(3) The loss of useful information in low-coherence scenarios constitutes a fundamental issue that compromises the spatiotemporal completeness of InSAR monitoring in mining areas. Due to seasonal fluctuations in vegetation cover, frequent land-use changes, intense ground disturbances, and surface restructuring induced by subsidence, extensive zones of temporal decorrelation emerge across mining area surfaces. Consequently, PS-InSAR becomes nearly ineffective in western mining areas characterized by a scarcity of stable buildings or artificial targets. Although the SBAS method can partially alleviate this issue, it still faces the risk of baseline network disruption in the core zones of dynamic subsidence. Although DS-InSAR has been specifically optimized for low-coherence scenarios, the substantial computational cost of covariance matrix estimation and its reliance on surface homogeneity assumptions still constrain its practical applicability in densely vegetated or topographically complex regions. More fundamentally, when coherence is completely lost within the subsidence center, regardless of the algorithm employed, irreparable information voids persist in the spatially complete representation of the deformation basin.

(4) The coupling effects of multi-source errors significantly impact monitoring accuracy. In the heterogeneous environments of mining areas, multiple error sources—such as atmospheric delays, orbital errors, DEM errors, and thermal noise—often coexist, exhibiting pronounced spatiotemporal coupling characteristics. Among these, tropospheric water vapor variations induce spatially correlated atmospheric phase delays; orbital errors generate long-wavelength trend components over large areas; and DEM errors may further introduce coupling effects with topographic slopes in topographically complex mining areas. Because these errors overlap with genuine deformation signals in their spectral characteristics, achieving complete separation through standalone filtering or empirical models alone is considerably challenging. Particularly in long-term time-series analysis, the progressive accumulation of residual errors undermines the stability of the deformation time series and may obscure subtle subsidence signals. Therefore, the development of a more robust spatiotemporal joint error modeling framework is a critical direction for improving InSAR accuracy.

4.2. Future Perspectives

In response to the aforementioned challenges, and in light of the current developmental trajectories of remote sensing technology, artificial intelligence, and physical models, the future advancement of InSAR monitoring for mining-induced surface deformation is gradually becoming better defined, revealing several evolutionary trends that merit considerable attention.

(1) Deep fusion of artificial intelligence technologies and physically constrained models. In recent years, deep learning methods have demonstrated significant potential over traditional algorithms across various processing subtasks (e.g., interferogram filtering, phase unwrapping). However, the lack of standardized training datasets and unified benchmark results in complex mining environments remains a critical bottleneck. However, purely data-driven models still exhibit notable deficiencies with respect to cross-regional generalization capability (i.e., transferability between different mines) and physical interpretability in geological scenarios. Incorporating classical physical models for mining subsidence prediction—such as the PIM and key stratum theory—as strong physically informed prior constraints into deep learning frameworks to construct a “physics-guided machine learning” paradigm can effectively maintain constraints on the physical laws (ensuring physical consistency) of mining-induced deformation while alleviating de-

pendence on training samples. The value of this approach lies not only in enhanced accuracy but also in integrating the uncertainty quantification of model predictions into the inversion framework, thereby providing robust confidence interval estimates for the monitoring results.

(2) Evolution from deformation monitoring to disaster mechanism analysis and prediction. Currently, the majority of InSAR research remains predominantly focused on the extraction of deformation parameters, whereas future studies will increasingly pay greater attention to the dynamic mechanisms underlying surface deformation. By integrating geological structures, mining parameters, hydrological conditions, and rock mass mechanics models, the causative mechanisms of mining-induced subsidence and slope instability can be further elucidated, thereby facilitating a paradigm shift from “monitoring phenomena” to “interpreting mechanisms.” Concurrently, predictive models based on long-term time-series deformation data will progressively undergo further development. In the future, by establishing quantitative relationships between deformation evolution and geohazard occurrence, subsidence trend forecasting and landslide probability assessment will become attainable, ultimately enhancing geohazard prevention and mitigation capabilities in mining areas.

(3) Development of real-time and operational capabilities oriented toward disaster early warning. The timeliness requirements for the early warning of geohazard events—such as mining subsidence, slope instability, and goaf collapse—pose significant challenges to the near-real-time (NRT) processing capabilities of InSAR. With the deployment of cloud computing platforms, edge computing infrastructure, and 5G-integrated Internet of Things (IoT) technologies in mining areas, automated InSAR processing based on standardized workflows has laid an initial practical foundation. However, due to fundamental satellite revisit cycles, downlink data latency, and the high computational cost of SAR processing, the end-to-end processing latency remains inadequate to satisfy the demands of hourly early warning. Therefore, it is crucial to clearly separate InSAR-based Near-Real-Time (NRT) periodic monitoring from continuous ground-based early warning systems (e.g., continuous GNSS or ground-based radar). In the future, continuous research investments are required in algorithmic optimization, incremental processing strategies to minimize computational overhead, and the real-time integration of multi-source data streams. This will drive a transition of InSAR deformation monitoring from research-oriented post-event analysis to a safety-production-oriented online monitoring framework.

5. Conclusions

This paper comprehensively reviews the research progress of InSAR technology in mining-area surface deformation monitoring. The review specifically analyzes multiple aspects—including technological principles, deformation inversion methods, error processing mechanisms, and multi-source data fusion—to systematically outline and comprehensively evaluate the core research advancements in this field. Overall, driven by the continuous development of SAR remote sensing platforms and time-series InSAR methodologies, InSAR has progressively emerged as a vital technological framework for monitoring mining-induced surface deformation, demonstrating considerable application potential in geohazard identification, subsidence assessment, and slope stability analysis. Building upon the developmental trends of InSAR monitoring technology in recent years, this study draws the following principal conclusions:

(1) Time-series InSAR technology has significantly enhanced the capability of surface deformation monitoring in mining areas. Although D-InSAR-based differential interferometry has established the methodological foundation for deformation monitoring in mining areas, it remains highly susceptible to decorrelation and atmospheric errors under

conditions of long-term monitoring and high-gradient deformation. In contrast, time-series analysis frameworks—represented by PS-InSAR, SBAS-InSAR, and DS-InSAR—leverage the joint processing of multi-temporal interferograms to systematically mitigate the limitations of atmospheric errors and decorrelation noise inherent in single-scene differential interferometry. This advances the monitoring accuracy to the millimeter level and demonstrates superior robustness and improved spatiotemporal coverage in low-coherence mining environments.

(2) Three-dimensional deformation inversion and error suppression in complex mining environments remain central focuses of current research. Because InSAR is inherently limited to radar LOS observations, it exhibits limited sensitivity to horizontal movements, particularly in the north–south direction. Consequently, single-track observations are inadequate for comprehensively capturing genuine surface movement characteristics. Moreover, factors such as decorrelation errors, orbital errors, and atmospheric delays exert substantial impacts on deformation inversion accuracy. In recent years, through approaches such as ascending–descending orbit joint inversion, spatiotemporal filtering, atmospheric delay modeling, and multi-track synergistic processing, monitoring accuracy under complex deformation conditions has markedly improved; nevertheless, considerable challenges persist in dynamic subsidence zones and low-coherence regions.

(3) Intelligent processing, multi-source data fusion, and real-time monitoring will emerge as the prevailing trends in future development. A synergistic monitoring system comprising GNSS, UAV, LiDAR, and InSAR is increasingly becoming an optimal integrated framework for precision deformation monitoring in mining areas. For instance, recent research has shown that hybrid frameworks integrating traditional geodetic measurements with multi-source spatial technologies provide a robust foundation for monitoring high-risk infrastructure, specifically mine waste facilities. The complementary characteristics of diverse data sources—with respect to spatial resolution, temporal frequency, and sensitivity to deformation components—endow multi-source fusion schemes with unique advantages in overcoming the capability limitations of standalone technologies and achieving the spatially complete representation of deformation fields across the entire subsidence basin. Concurrently, the introduction of deep learning, cloud computing, and artificial intelligence (AI) will propel the transition of InSAR from conventional offline processing modes toward real-time dynamic monitoring and geohazard prediction paradigms. This will further contribute to enhancing operational safety in mining areas.

In summary, while research on InSAR technology applied to mining-area surface deformation monitoring has reached a considerable level of maturity, several fundamental challenges persist during the transition from academic achievements to practical engineering applications. These include high-gradient phase restoration, complete three-dimensional deformation reconstruction, real-time processing capabilities, and atmospheric correction under complex meteorological conditions. With the deployment of next-generation SAR satellite systems, the maturation of physically constrained deep learning methodologies, and the evolution of multi-source fusion toward mechanism-driven approaches, these limiting factors are expected to be systematically overcome in the future. Consequently, the application potential of InSAR technology in operational safety monitoring of mining areas, mining-induced damage assessment, and geohazard early warning will be further realized. This will provide more reliable spatial information support for sustainable mining and environmental protection in mining areas.

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