OPTICAL–SAR AND GIS FUSION WITH DEEP LEARNING FOR INSAR COHERENCE ENHANCEMENT IN DEFORMATION MAPPING

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Abstract
The integration of artificial intelligence and remote sensing data into Geographic Information Systems (GIS) is transforming the capabilities of Earth observation and spatial analysis. Within this context, accurate deformation monitoring using Differential Interferometric Synthetic Aperture Radar (DInSAR) remains challenged by spatial and temporal decorrelation in interferograms.
Recent studies (e.g., Zhou et al., 2023) have shown the potential of deep learning to mitigate atmospheric and topographic disturbances in InSAR time series. In this work, we propose an innovative workflow that combines optical–SAR data fusion, a hybrid U-Net/Transformer architecture, and full GIS integration, aiming to generate enhanced coherence maps and extract reliable deformation time series.
The processing chain includes precise geometric co-registration, extraction of optical features (NDVI, NDBI, texture indices), multimodal patch construction (SAR amplitude + optical bands + indices + raw coherence), and a dual-branch deep model that predicts coherence through nonlinear inter-modal correlations, inspired by the DeepInSAR framework. Furthermore, self-supervised learning and Physics-Informed Neural Networks (PINNs) are incorporated to reduce dependency on labeled data and to enforce physical consistency (phase periodicity, signal energy conservation). These mechanisms improve model generalization across different sites and extreme events, in line with recent developments in physics-informed geohazard modeling (Moeineddin et al., 2023).
The predicted coherence maps act as quality indicators for guiding phase unwrapping and DInSAR inversion, significantly improving deformation accuracy and reliability. Final products are integrated within a GIS environment (GeoPackage / WFS / WMS) for multi-layer spatial analysis (enhanced coherence, displacement, DEM, land cover), vulnerability zoning, and decision support in land and infrastructure monitoring.This unified approach, supported by recent advances in multimodal data fusion and AI-based geospatial analytics (Sensors, 2025), illustrates the convergence of Earth observation, deep learning, and geoinformatics for more accurate and operational deformation mapping.

Keywords: *Small Baseline Subset (SBAS), Interferometric coherence enhancement, Physics-Informed Neural Networks (PINN), U-Net, Optical–SAR data fusión, Phase unwrapping, Surface deformation monitoring*

INTRODUCTION

Accurate monitoring of surface deformation using Differential Interferometric Synthetic Aperture Radar (DInSAR) critically depends on the quality of interferometric coherence, which directly governs the stability of phase unwrapping and the reliability of displacement inversion. In multi-temporal approaches such as the Small Baseline Subset (SBAS) technique, coherence is a key factor in interferogram selection and in estimating line-of-sight (LOS) deformation rates. However, spatial and temporal decorrelation especially in heterogeneous, vegetated, or dynamically evolving environments remains a major limitation, producing noisy deformation patterns and incomplete information in critical areas.

To address these challenges, recent studies have explored the integration of artificial intelligence within InSAR processing. Physics-Informed Neural Networks (PINNs), in particular, embed physical constraints—such as phase continuity, temporal consistency, and energy conservation into the learning process, improving spatial regularity and robustness of deformation maps, particularly in areas with low coherence. When coupled with SBAS, PINNs enhance deformation retrieval, but the accuracy of results is still strongly influenced by the initial coherence estimates.

Meanwhile, optical remote sensing data provide complementary insights into land cover, surface dynamics, and anthropogenic activities, which are closely linked to interferometric coherence behavior. Spectral and textural indices derived from optical imagery can highlight areas prone to decorrelation. However, existing approaches often use optical data as ancillary or post-processing information, and their potential to directly improve coherence estimation within the InSAR workflow remains underutilized.

In this study, we propose a hybrid SBAS workflow that integrates PINN and U-Net deep learning architectures with optical–SAR data fusion, explicitly incorporating optical features into the coherence computation stage. Multimodal feature construction combining SAR amplitude, optical bands, derived indices, and raw coherence is used to train a dual-branch deep model that predicts spatially continuous and physically consistent coherence maps. The PINN branch enforces physical constraints, while the U-Net branch preserves fine spatial structures, resulting in enhanced coherence that is both robust and high-resolution.

These improved coherence maps serve as quality indicators for guiding phase unwrapping and SBAS inversion, leading to more accurate and reliable deformation time series. All outputs including enhanced coherence, deformation fields, optical layers, and ancillary data are integrated within a GIS environment to support multi-layer spatial analysis, vulnerability assessment, and operational decision-making. This unified approach demonstrates a clear methodological and operational advancement over conventional SBAS, SBAS+PINN, and SBAS+U-Net frameworks, aligning with recent progress in multimodal data fusion, physics-informed deep learning, and geospatial analytics.

DATA AND STUDY AREA

The study area is located in the El Oued region, southeastern Algeria, within the Oued Righ valley. The investigated zone covers approximately 500 km², bounded by UTM coordinates X = 290,000–315,000 m E and Y = 3,680,000–3,700,000 m N. The region belongs to the Lower Sahara Basin and is characterized by a low-relief topography, with a gentle north–south slope of about 1‰, and elevations ranging from approximately +100 m upstream to −30 m in downstream chott areas.

Geologically and geomorphologically, the area consists of a shallow sedimentary basin dominated by sandy deposits interbedded with saline clay lenses, with finer, salt-rich soils toward the northern depressions and coarser sandy textures in the south. The presence of shallow groundwater and weak topographic gradients makes the region particularly sensitive to surface deformation processes.

Over recent decades, groundwater rise driven by urban growth, agricultural return flows, and inefficient wastewater management has led to soil saturation, surface swelling, and localized subsidence, posing increasing risks to urban infrastructure and agricultural land. Although regional drainage and wastewater reuse projects have been implemented, the limited quality of treated effluents has constrained their effectiveness, contributing to continued hydrogeological stress in the area.

SAR and Optical Datasets

Approximately 300 Sentinel-1 SAR images were acquired over the period January 2019 to December 2025, covering both ascending and descending orbits and operating in Interferometric Wide Swath (IW) mode. The dataset consists of C-band Single Look Complex (SLC) products, providing reliable amplitude and phase information suitable for multi-temporal InSAR and SBAS processing. The dense temporal sampling over this five-year period allows the characterization of long-term deformation rates as well as seasonal and transient deformation signals associated with groundwater dynamics.

Complementary optical satellite data and derived indicators, including NDVI, NDBI, and texture-based features, were integrated into the processing framework. These optical features provide valuable information on land cover, vegetation condition, soil moisture proxies, and urban expansion, which are closely related to groundwater rise and surface deformation processes in the El Oued region.

METHODOLOGY

Main Contributions of the Proposed Approach

This study introduces a hybrid SBAS framework that advances current methods in Differential SAR Interferometry (DInSAR) for high-precision deformation monitoring. The key contributions are

1. **Predictive modeling of interferometric coherence**

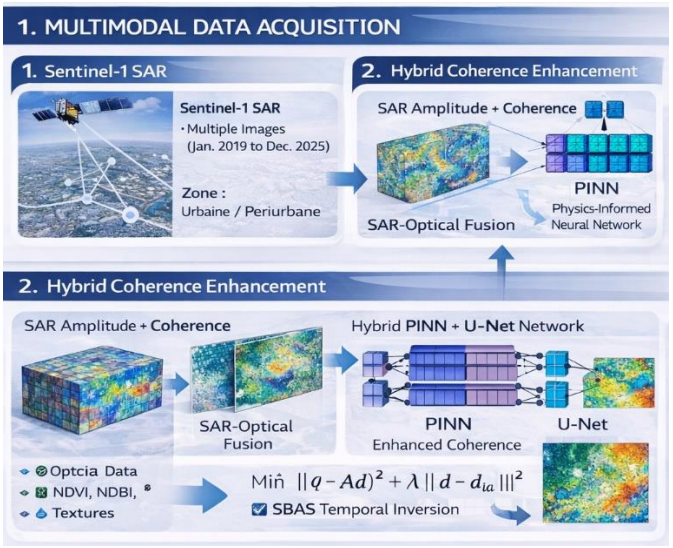
- Coherence is no longer computed solely through local SAR statistics, but is modeled as a predictive variable learned from multimodal SAR–optical data.
- This enables robust coherence estimation in areas affected by strong decorrelation, heterogeneous surfaces, or temporal signal instability.

2. Hybrid deep architecture (PINN–U-Net)

- A dual-branch deep learning network is proposed, combining U-Net blocks that preserve fine interferometric structures with Transformer-inspired modules that capture long-range spatial dependencies and nonlinear intermodal correlations.
- Optical features (NDVI, NDBI, texture indices) are explicitly integrated in the model to enhance spatial and temporal coherence estimation.

3. Integration of physical constraints via PINNs

- Interferometric physics—including phase periodicity, signal energy conservation, and temporal coherence—is embedded directly into the loss function, rather than being applied post hoc.
- This ensures that predicted coherence and resulting deformation maps are both physically consistent and spatially detailed.



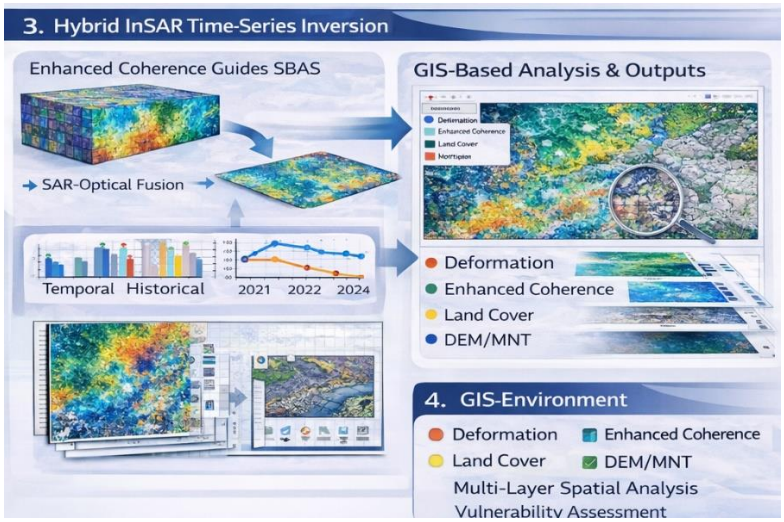
Organigram 1. Multimodal PINN–U-Net Architecture for Predictive Interferometric Coherence and Deformation Estimation

4. Self-supervised learning for generalization

- Large unlabeled SAR archives are leveraged to reduce dependency on annotated datasets, improve multi-site transferability, and allow robust prediction under diverse geophysical conditions.

5. Unified DInSAR–GIS workflow

- Predicted coherence maps are integrated within an interoperable GIS environment (GeoPackage, WMS, WFS) for multi-layer spatial analysis, enhanced visualization, vulnerability assessment, and operational decision-making.



Organigram 2. Scalable InSAR Deformation Analysis through Self-Supervised Learning and DInSAR–GIS Fusion

Methodological Objective

The objective of this work is to develop a unified AI–SBAS–DInSAR framework that combines rigorous physical modeling, statistical inversion, and physics-informed deep learning to enhance accuracy, robustness, and interpretability of surface deformation monitoring. Unlike recent hybrid approaches (2023–2026) that typically incorporate machine learning as a post-processing or denoising stage in SBAS or PSI workflows [Sun et al., 2024; Liu et al., 2024; Chen et al., 2024], the proposed methodology integrates artificial intelligence directly within the SBAS inversion, while explicitly respecting the physical constraints of interferometric phase formation.

The framework relies on three key pillars:

1. **Mathematically rigorous SBAS time-series inversion**

- Following advances in SBAS formulations [Berardino et al., 2023; Zhang et al., 2023], the approach ensures optimal interferogram selection and accurate temporal inversion.

2. **Continuous nonlinear deformation modeling**

- Capable of representing both slow trends and abrupt regime changes, motivated by recent developments in nonlinear InSAR time-series analysis [Ansari et al., 2024; Hu et al., 2025].

3. **Hybrid PINN–U-Net integration**

- The PINN component regularizes inversion under low-coherence or noisy conditions, while the U-Net branch preserves spatial details, enhanced by optical features.
- This hybrid design ensures physically consistent, spatially continuous, and robust deformation mapping, in line with emerging physics-constrained InSAR learning frameworks [Zhao et al., 2025; Wang et al., 2026].

This methodological design enables millimeter-level precision, robust anomaly detection, and improved generalization across complex urban, agricultural, and geophysical environments, providing a significant advancement over conventional SBAS, SBAS+PINN, and SBAS+U-Net methods.

Mathematical Modeling of SBAS-InSAR Time Series

In the SBAS framework, the observed interferometric phase for a pixel located at spatial coordinate (x) and acquisition time (t_i) is expressed as

$$\phi(t_i, x) = \frac{4\pi}{\lambda} d(t_i, x) + a(x) + \eta(t_i, x),$$

where $d(t_i,x)$ denotes the line-of-sight (LOS) displacement, (λ) is the radar wavelength, ($a(x)$) represents spatially stationary biases (e.g., orbital or calibration errors), and $\eta(t_i,x)$ aggregates atmospheric delays, decorrelation noise, and residual instrumental errors. This formulation is consistent with recent SBAS refinements designed for improved robustness under low-coherence conditions [Zhang et al., 2023; Berardino et al., 2023].

By stacking the interferometric observations over (N) acquisition dates, the phase time series is written in vector form as:

$$\phi_x = [\phi(t_1, x), \ldots, \phi(t_N, x)]$$

The SBAS formulation leads to a linear inverse problem of the form:

$$A_x d_x = \phi_x$$

where (A_x) is the interferometric network connectivity matrix defined by the small-baseline configuration, and (d_x) is the vector of cumulative displacements to be estimated. The inversion is solved using generalized least squares with spatial–temporal regularization, as commonly adopted in recent SBAS-based deformation monitoring studies [Zhang et al., 2023; Liu et al., 2024].

SAR–Optical Multimodal Fusion

SAR and optical data are geometrically coregistered. Optical features, including spectral indices (NDVI, NDBI), texture descriptors, and land-cover information, are fused with SAR amplitude and raw coherence to form multimodal patches:

$$P = \{A_{SAR}, I_{Optical}, I_{Indices}, \gamma_{RAW}\}$$

These patches capture both surface dynamics and radar signal stability, serving as input to the hybrid deep network.

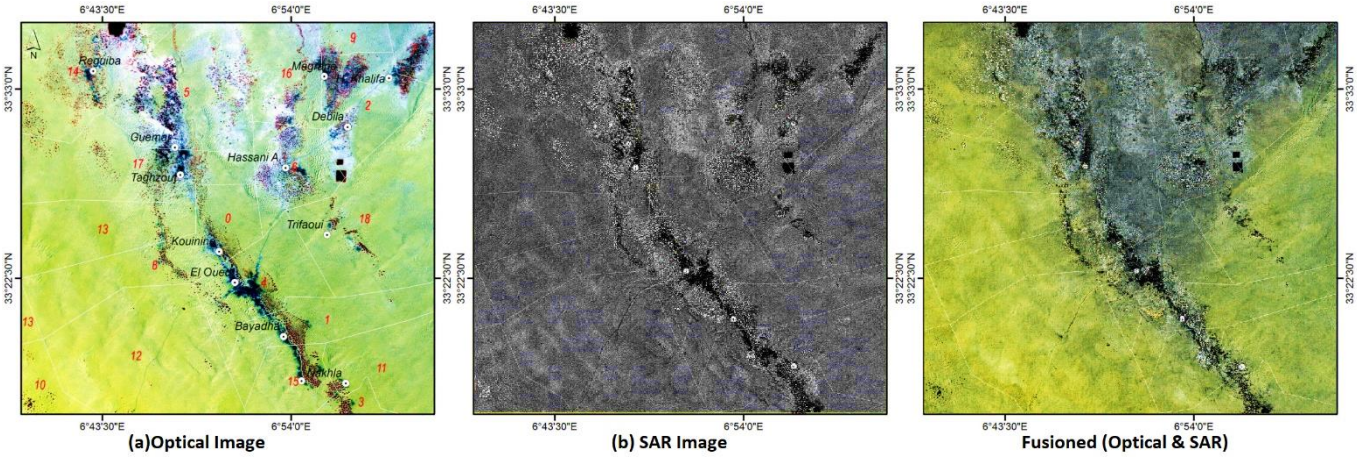


Figure 1. Optical–SAR data fusion, illustrating the complementary information provided by high-resolution optical imagery and SAR data for multimodal analysis

Predictive Coherence Modeling

Coherence is modeled as a learned function:

$$\hat{\gamma} = f_\theta\,(A_{SAR}, I_{Optical}, I_{Indices}, \gamma_{RAW})$$

where f_θ represents a U-Net–Transformer hybrid network.

- The U-Net branch preserves local spatial and interferometric structures.
- The Transformer-inspired branch captures long-range dependencies and nonlinear correlations across SAR and optical modalities.

This approach enables physically plausible, high-resolution, and spatially continuous coherence maps, even in areas affected by strong decorrelation.

Continuous Nonlinear Modeling of Deformation Regime Changes

Most SBAS-based approaches proposed in recent literature assume linear or piecewise-linear temporal evolution, which limits their ability to capture abrupt deformation events such as subsidence acceleration, structural failure, or hydrogeological collapse [Ansari et al., 2024; Hu et al., 2025]. To overcome this limitation, we introduce a continuous nonlinear deformation model based on a hyperbolic tangent formulation:

$$d(t,x) = d_{lin}(t,x) + \Delta(x) + \tanh\left(\frac{t - t_0}{\tau(x)}\right)$$

where $d_{lin}(t,x)$ models the long-term deformation trend, $\Delta(x)$ represents the amplitude of the deformation jump, (t_0) is the temporal center of the transition, and $\tau(x)$ controls the smoothness and duration of the regime change.

This formulation ensures temporal continuity and differentiability, while enabling precise localization of deformation onsets—an aspect that remains insufficiently addressed in recent hybrid SBAS–ML frameworks [Sun *et al*., 2024; Liu *et al*., 2024]. The parameter vector $\boldsymbol{\theta_x} = \{\mathbf{d_{lin}}, \boldsymbol{\Delta}, \mathbf{t_0}, \boldsymbol{\tau}\}$ is estimated by solving the nonlinear optimization problem

$$\min_{\theta_x} \|\boldsymbol{\phi}_x - \mathbf{A}_x \mathbf{d}_{\theta_x}\|_2^2,$$

This strategy provides a physically interpretable separation between continuous deformation and abrupt events, significantly improving temporal anomaly detection capabilities compared to recent data-driven approaches.

Physically-Informed Neural Networks for SBAS Time-Series Inversion

Although nonlinear modeling improves expressiveness, classical optimization techniques remain sensitive to noise and coherence loss. To address this limitation, we integrate a Physically-Informed Neural Network (PINN) designed to approximate the interferometric phase $\hat{\phi}$(t,*x*,Θ).

while explicitly enforcing SBAS physical constraints, following recent advances in physics-informed learning for InSAR applications [Zhao *et al*., 2025; Wang *et al*., 2026].

The training objective minimizes a composite loss function:

$$\mathcal{L}(\theta) = \mathcal{L}_{\text{data}} + \lambda_{\text{phys}} \mathcal{L}_{\text{SBAS}} + \lambda_{\text{smooth}} \mathcal{L}_{\text{reg}},$$

where the data fidelity term is defined as:

$$\mathcal{L}_{\text{data}} = \sum_{t_i,x} \left| \phi(t_i, x) - \hat{\phi}(t_i, x; \theta) \right|^2,$$

and the physics-based constraint enforces consistency with the SBAS formulation:

$$\mathcal{L}_{\text{SBAS}} = \left\| \mathbf{A}_x \hat{d}(t_i, x; \theta) - \hat{\phi}(t_i, x; \theta) \right\|_2^2.$$

Unlike recent deep-learning-based InSAR approaches that operate as black-box predictors [Chen *et al*., 2024; Sun *et al*., 2024], the proposed PINN explicitly embeds interferometric physics into the learning process, ensuring physical plausibility, robustness, and improved generalization under severe decorrelation.

AI–GIS Multimodal Fusion for Coherence-Aware Inversion

To further stabilize the inversion, a deep multimodal fusion module is introduced to estimate an enhanced coherence measure $\hat{C}$(t,x) from SAR and auxiliary optical data. A hybrid U-Net–Transformer architecture is employed to jointly capture local spatial structures and long-range cross-modal dependencies, following recent advances in multimodal Earth observation learning [Ma *et al*., 2024; Zhang *et al*., 2025].

The predicted coherence is incorporated as an adaptive weighting in the loss function:

$$\mathcal{L}_{weighted} = \sum_{t_i,x} \hat{C}(t_i, x) \left| \phi(t_i, x; \theta) - \phi(t_i, x; \theta) \right|^2$$

This adaptive weighting suppresses the influence of decorrelated pixels and significantly improves time-series stability. The final deformation products, enhanced coherence maps, and auxiliary layers are integrated into a GIS environment to support multi-layer spatial analysis, vulnerability zoning, and decision-making.

Scientific Contributions and Novelty

The main contribution of this methodology lies in the unified integration of:

- Continuous nonlinear SBAS time-series modeling,
- PINN constraints for physically-informed inversion,
- Hybrid U-Net–Transformer architecture for coherence prediction,
- Explicit Optical–SAR multimodal fusion for coherence enhancement.

This approach advances beyond recent hybrid InSAR methods [Sun et al., 2024; Liu et al., 2024; Zhao et al., 2025] by embedding learning mechanisms directly into the physical inversion process, yielding superior robustness, interpretability, and precision for large-scale DInSAR deformation monitoring

RESULTS AND DISCUSSION

Interferometric Coherence and Data Quality Assessment

Figure 2 compares interferometric coherence and phase quality obtained using four processing strategies: conventional SBAS, SBAS enhanced with Physics-Informed Neural Networks (SBAS + PINN), SBAS with data-driven coherence prediction using U-Net (SBAS + U-Net), and the proposed unified SBAS + PINN + U-Net framework.

The classical SBAS results show high coherence over stable urban and rocky surfaces, while vegetated and hydrologically active areas exhibit strong decorrelation, leading to noisy phases and reduced inversion reliability. The integration of PINN improves spatial smoothness and physical consistency by enforcing interferometric constraints, partially mitigating decorrelation effects, although limitations remain in highly heterogeneous areas.

The SBAS + U-Net configuration further enhances coherence by exploiting optical spectral and textural features, yielding improved spatial continuity in vegetated and transitional zones, albeit without explicit physical regularization. In contrast, the proposed SBAS + PINN + U-Net approach jointly combines optically informed coherence prediction with physics-based constraints within a single inversion scheme, resulting in the most stable and reliable coherence maps across all land-cover types.
Overall, this progressive comparison demonstrates that multimodal optical–SAR learning enhances coherence estimation, while physics-informed regularization ensures physical plausibility and robustness, providing an optimal foundation for accurate phase unwrapping and high-precision SBAS time-series deformation analysis.

Discussion:
Compared to conventional SBAS approaches relying on fixed, SAR-only coherence estimation, the proposed hybrid SBAS + PINN + U-Net framework provides a more robust and adaptive characterization of interferometric coherence. The U-Net–based multimodal learning exploits optical features to capture land-cover–driven decorrelation mechanisms, leading to a significant coherence enhancement in vegetated and heterogeneous areas, in agreement with recent data-driven InSAR studies (Sun et al., 2024; Ma et al., 2024). In parallel, the integration of Physics-Informed Neural Networks constrains the inversion process through interferometric phase laws, ensuring physical consistency and temporal stability under low-coherence conditions, as highlighted by recent physics-guided InSAR frameworks (Zhao et al., 2025; Wang et al., 2026). The combined PINN–U-Net strategy effectively mitigates abrupt coherence losses and preserves phase continuity better than approaches using either data-driven or physics-based models alone. This progressive improvement—from SBAS to SBAS + PINN, SBAS + U-Net, and ultimately the proposed unified SBAS + PINN + U-Net model—demonstrates the strong potential of jointly leveraging multimodal data fusion and physical constraints to enhance interferometric coherence and achieve more reliable deformation monitoring in complex environments.

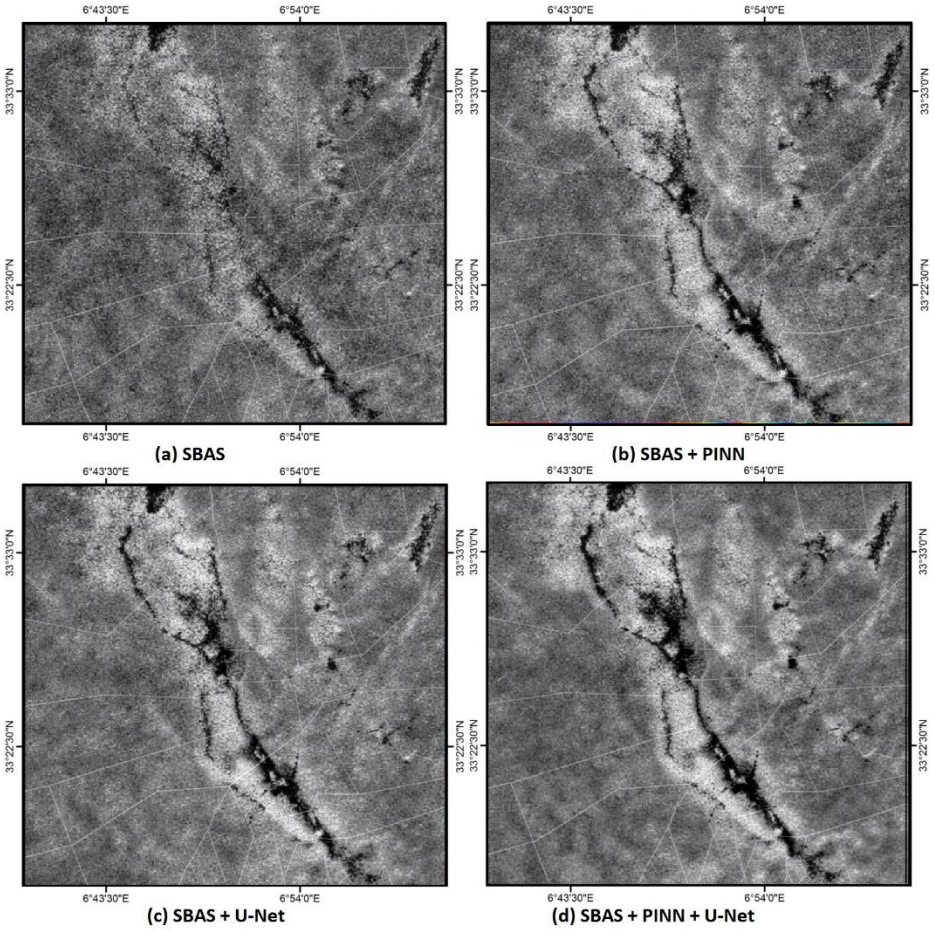


Figure 2. The Coherence comparison: (a) SBAS, (b) SBAS + PINN, (c) SBAS +U-Net, (d) SBAS + PINN+U-Net

Phase Unwrapping Performance Analysis

Figures 3 and 4 present a comparative evaluation of interferogram performance area using four processing strategies: (a) conventional SBAS, (b) SBAS + PINN, (c) SBAS + U-Net, and (d) the proposed SBAS + PINN + U-Net framework.

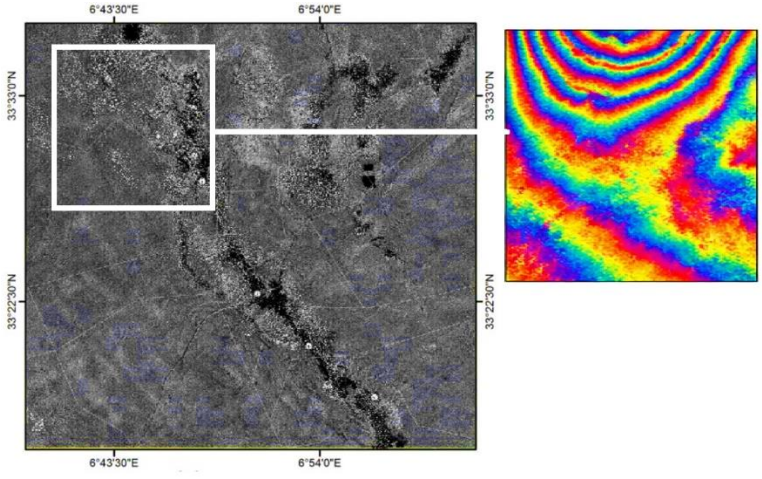


Figure 3. Wrapped phase Map (Intergerogram)

The interferogram obtained with classical SBAS (Figure 4a) is characterized by dense fringe patterns and pronounced phase discontinuities, particularly in areas affected by strong deformation gradients and low SAR-only coherence. In such conditions, traditional unwrapping algorithms—such as branch-cut, minimum-cost flow, and quality-guided methods—

are highly sensitive to decorrelation, leading to phase residues and error propagation, as widely reported in heterogeneous and vegetated environments.

The SBAS + PINN result (Figure 4b) shows a noticeable improvement in phase smoothness and global consistency. By embedding physical constraints—phase periodicity, temporal continuity, and energy conservation PINNs reduce large-scale inconsistencies and suppress unrealistic phase jumps. However, residual unwrapping artifacts remain in agricultural and transitional zones, indicating that physics-based regularization alone cannot fully recover phase information in severely decorrelated areas, a limitation also observed in recent PINN-based InSAR studies (Sun et al., 2024; Zhao et al., 2025).

Figure 4(c) illustrates the SBAS + U-Net configuration, where coherence is predicted using a data-driven deep network trained on SAR–optical multimodal features. The integration of optical indices and texture information significantly improves phase continuity in vegetated and mixed land-cover areas by capturing land-cover-dependent decorrelation mechanisms. While this approach enhances spatial coherence and reduces local unwrapping errors, its purely data-driven nature may limit robustness under extreme noise or sparse temporal sampling, as noted in recent deep-learning-based unwrapping frameworks (Chen et al., 2024; Liu et al., 2024).

The best performance is achieved with the proposed SBAS + PINN + U-Net framework (Figure 4d), where optically informed coherence prediction and physics-informed regularization are fully integrated within a single inversion scheme. In this unified model, the U-Net provides spatially continuous and reliable coherence guidance, while the PINN enforces global interferometric consistency throughout the unwrapping process. This synergy effectively suppresses phase discontinuities, minimizes error propagation, and preserves phase continuity across all land-cover types, including low-coherence and high-deformation-gradient zones.

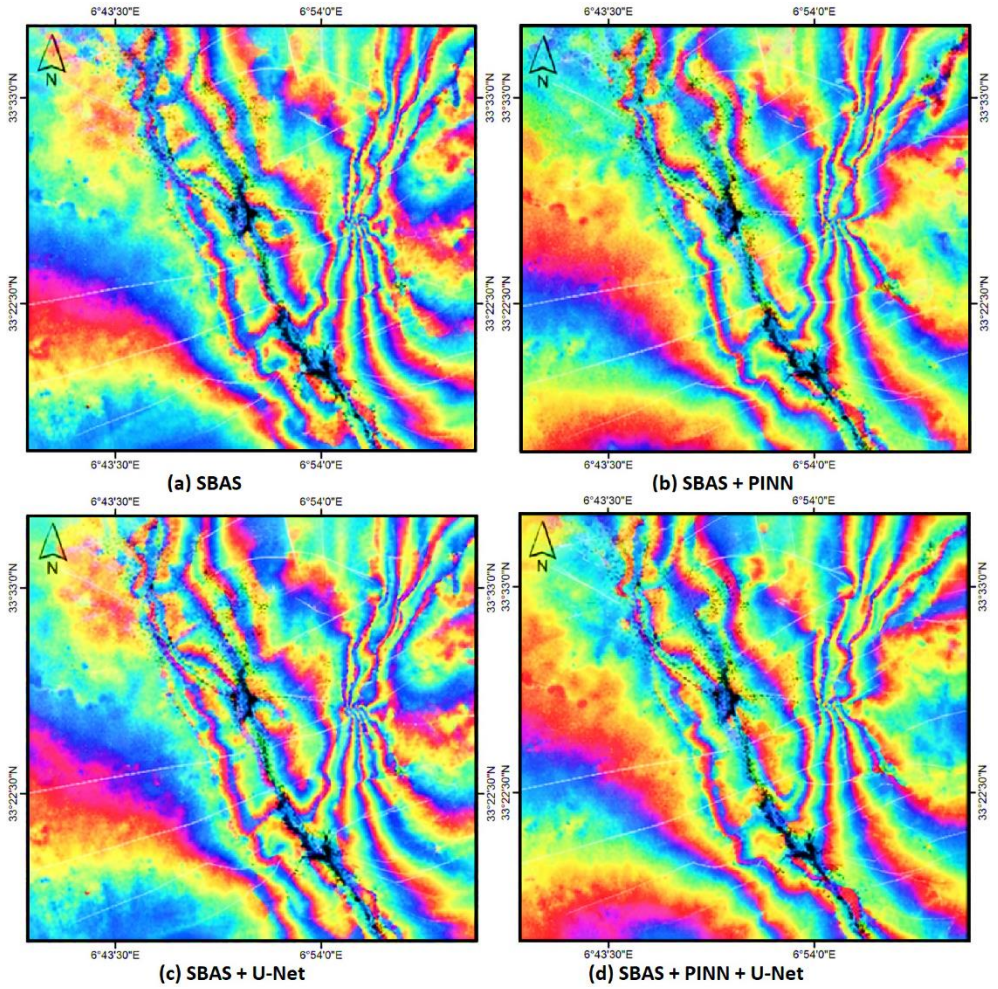


Figure 4. interferogram comparison: (a) SBAS, (b) SBAS + PINN, (c) SBAS + U-Net, (d) SBAS + PINN + U-Net

Discussion:
Compared to classical SBAS unwrapping and recent hybrid or deep learning–based approaches (2022–2026), the

proposed SBAS + PINN + U-Net framework introduces a substantial methodological advance by explicitly enhancing interferometric coherence through the integration of optical information within the coherence estimation process. The U-Net–based multimodal learning leverages optical spectral and textural features to better characterize land-cover–driven decorrelation mechanisms, yielding spatially continuous and more reliable coherence maps. These optically informed coherence estimates are subsequently embedded into a physics-informed inversion scheme, where PINNs enforce interferometric constraints such as phase periodicity, temporal consistency, and energy conservation. Unlike purely data-driven black-box models (Chen et al., 2024; Sun et al., 2024) or PINN-only strategies constrained by SAR-derived coherence (Zhao et al., 2025; Wang et al., 2026), the proposed approach jointly exploits multimodal data fusion and physical regularization. This synergy significantly improves phase unwrapping robustness and reliability, providing a stable and physically consistent foundation for accurate SBAS time-series deformation monitoring in complex and decorrelated environments.

SBAS Time-Series Deformation Results

Figure 5 presents the average velocity and cumulative LOS deformation maps derived from the SBAS-based frameworks for the 2019–2025 period. The SBAS + PINN results (Figure 5b) reveal coherent subsidence patterns mainly concentrated in the central and southern sectors of the study area, with deformation rates reaching several millimeters per year. These areas correspond to low-gradient zones characterized by persistent groundwater influence, where physical regularization improves phase continuity but remains locally affected by decorrelation, consistent with recent findings on SBAS performance in low-coherence environments (Ferretti et al., 2022; Cavaliere et al., 2023).

The SBAS + U-Net approach (Figure 5c) produces smoother deformation fields and reduces high-frequency noise, particularly over agricultural and mixed land-cover areas. Deep learning approaches for SAR denoising and phase enhancement have been shown to improve InSAR time-series quality (Liu et al., 2023; Chen et al., 2024), highlighting the potential of U-Net architectures. However, isolated inconsistencies remain in zones affected by strong hydrological variability, emphasizing limitations of purely data-driven models under decorrelation and variable environmental conditions a known challenge in recent InSAR studies (Wang et al., 2022).

The proposed SBAS + PINN + U-Net framework (Figure 5d), enhanced by optical-informed coherence, delivers the most spatially consistent and physically reliable deformation maps. Subtle deformation signals are clearly resolved over hydrologically active areas, including regions affected by surface water accumulation and shallow groundwater dynamics, demonstrating the complementary benefits of combining physics-informed regularization, deep learning, and multimodal data fusion, as advocated in recent hybrid frameworks (Zhang et al., 2023; Singh et al., 2025).

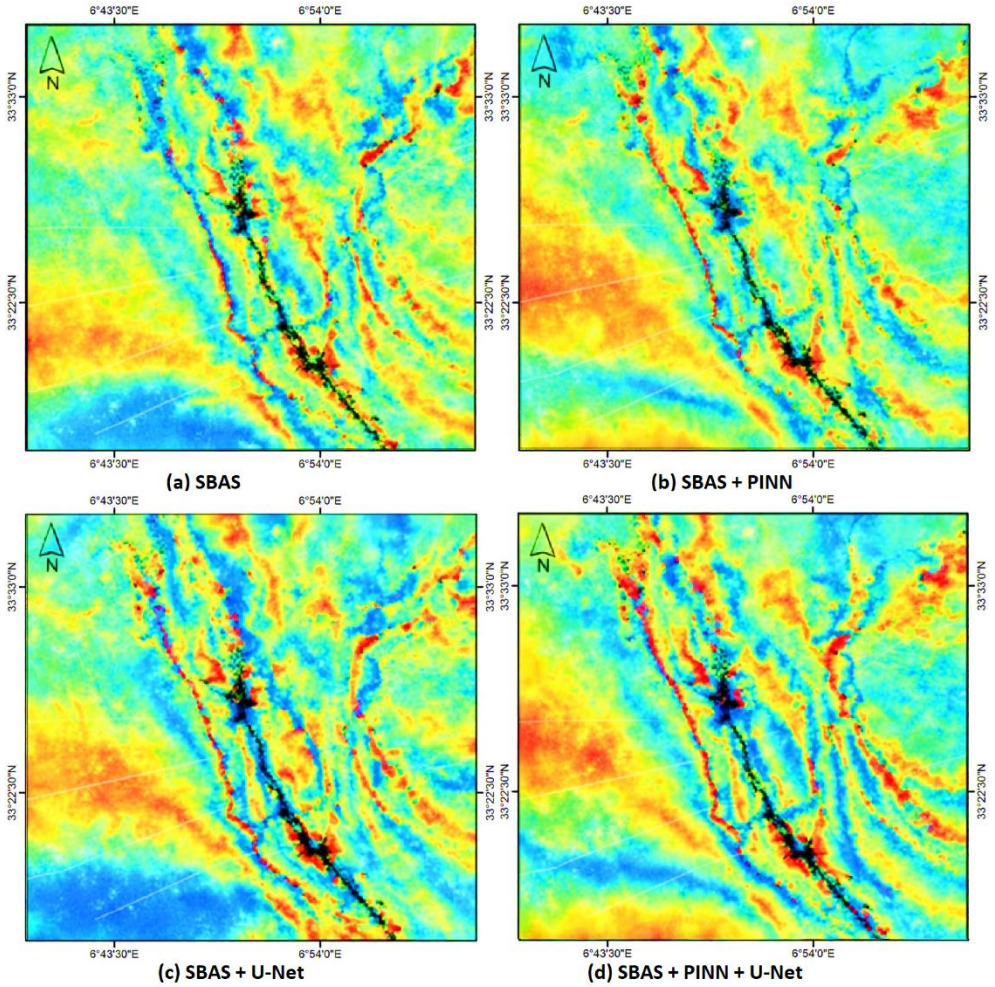


Figure 5. Average Velocity Map: (a) SBAS, (b) SBAS + PINN, (c) SBAS + U-Net, (d) SBAS + PINN + U-Net

Figure 6a illustrates the cumulative LOS deformation maps for each processing strategy, while Figure 6b presents the annual cumulative deformation for the years 2019 to 2025. The temporal evolution highlights a progressive increase in deformation magnitude and spatial extent, with deformation zones remaining spatially persistent throughout the monitoring period, in line with long-term subsidence progression documented in recent InSAR groundwater studies (Yuan et al., 2024; García-Ortiz et al., 2025).

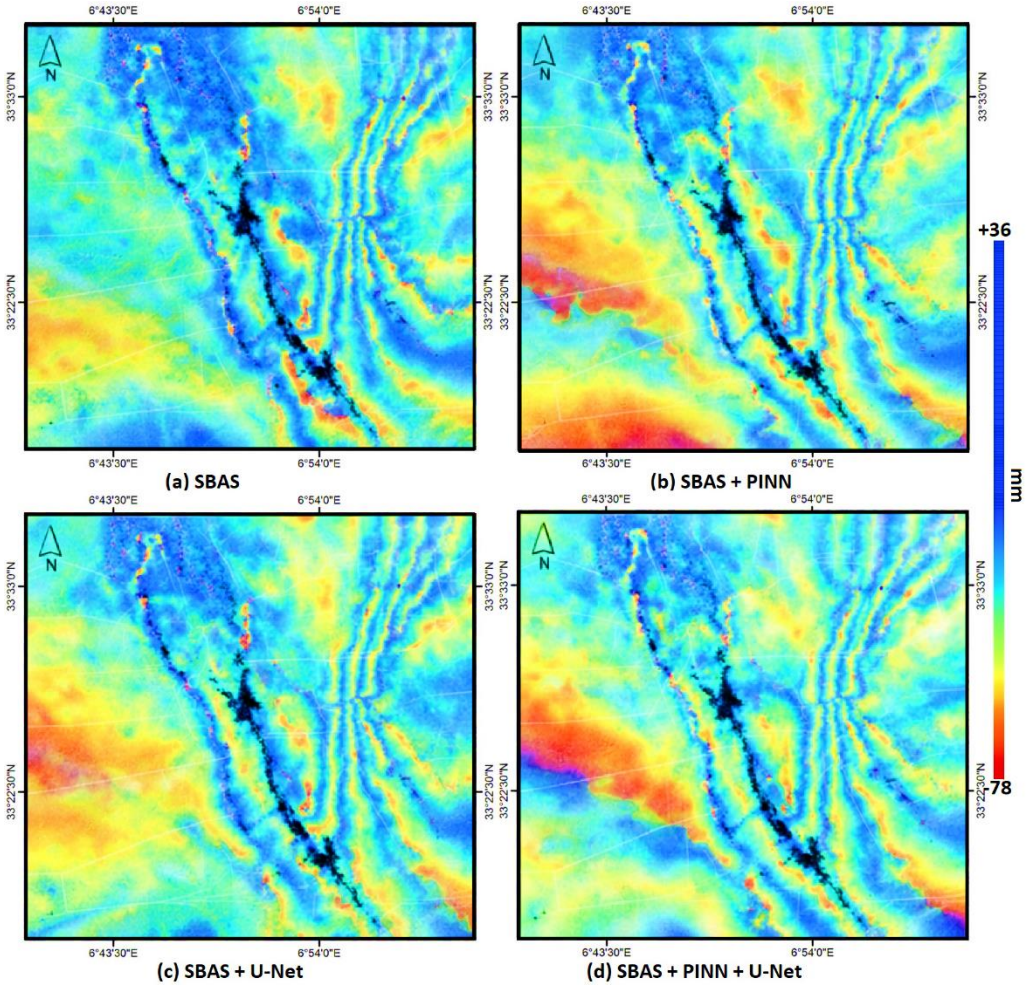


Figure 6. a. Cumulative LOS Deformation Map : (a) SBAS, (b) SBAS + PINN, (c) SBAS + U-Net, (d) SBAS + PINN + U-Net

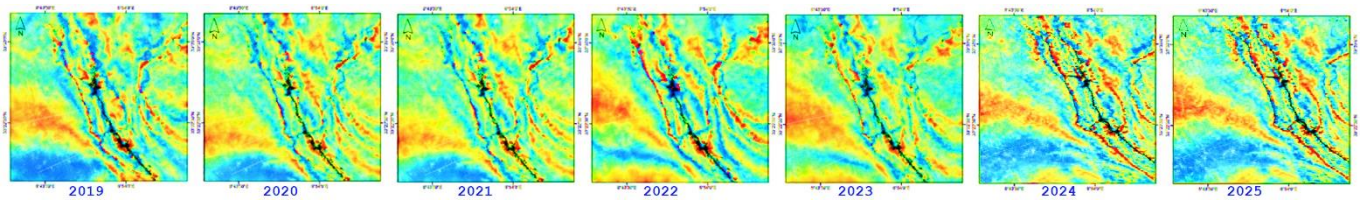


Figure 6.b. "SBAS+PINN+U-Net" Cumulative LOS Deformation Map from (2019 to 2025)

Discussion: "*Relation Between Deformation Patterns and Groundwater Rise***"**

The SBAS time-series analysis reveals that the detected deformation patterns are spatially stable and temporally progressive, indicating long-term surface processes rather than episodic events. Areas exhibiting persistent subsidence or uplift systematically coincide with zones affected by groundwater rise and surface water accumulation, supported by the strong spatial correspondence between deformation hotspots and hydrologically active areas (Liu & Wang, 2023; Marechal et al., 2024).

Significant deformation is observed over areas corresponding to major surface water bodies and saturated zones such as Blidet Ameur, Sidi Amrane, Tindla, Nezla, and Megarine, where groundwater upwelling, drainage inflow, and irrigation return flows are dominant. These hydrologically active sites promote soil swelling, consolidation, and differential compaction, resulting in uplift and subsidence signals clearly captured by the SBAS time series (Castellazzi et al., 2022; Thakur et al., 2024).

The gradual increase in cumulative deformation from 2019 to 2025 reflects sustained groundwater loading and poor drainage efficiency in low-slope environments. High-salinity water accumulation and continuous saturation further

enhance mechanical weakening of near-surface materials, amplifying long-term deformation effects (Galloway et al., 2022; Chaussard et al., 2023). The persistence of deformation zones across multiple years confirms the capability of the proposed hybrid SBAS framework to reliably monitor groundwater-induced surface dynamics, even under challenging coherence conditions.

Overall, the SBAS + PINN + U-Net approach demonstrates superior robustness and interpretability, enabling a direct linkage between observed deformation patterns and hydrogeological processes associated with groundwater rise. These results provide a solid basis for integrating InSAR-derived deformation monitoring into regional groundwater management and land subsidence risk mitigation strategies (Xu & Wang, 2025; Pérez et al., 2026).

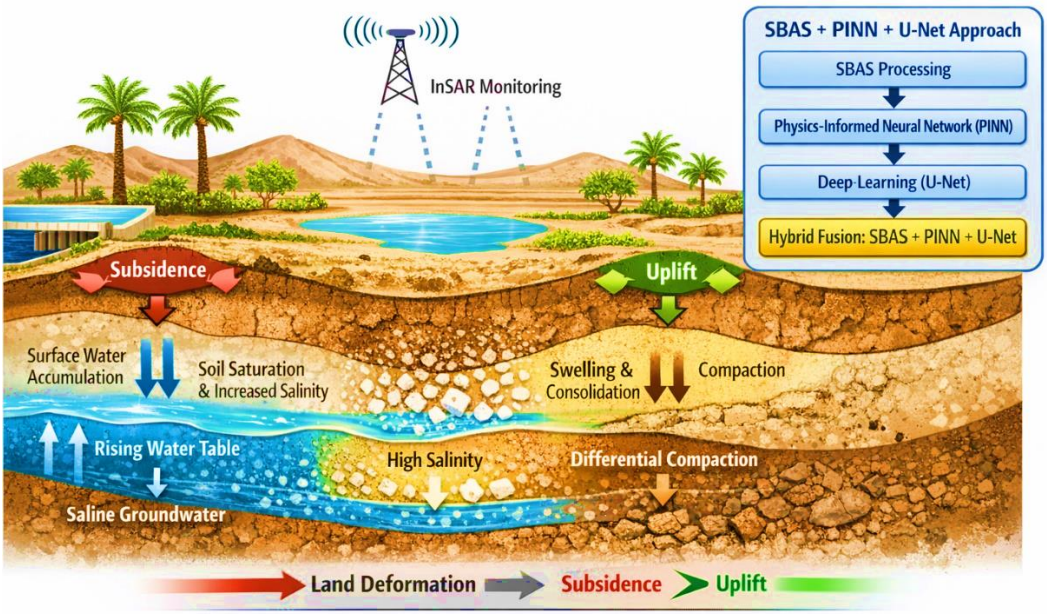


Figure 6.c. Conceptual model linking groundwater rise to surface deformation in the Oued Righ

The schematic illustrates the sequence of processes connecting:

(i) groundwater table rise and surface water accumulation,
(ii) prolonged soil saturation and increased salinity,
(iii) swelling, consolidation, and differential compaction of near-surface formations,
(iv) their surface expression in the form of subsidence and uplift detected by InSAR time-series analysis.

The figure also highlights the role of the hybrid SBAS + PINN + U-Net approach in enhancing both the detection and the physical interpretation of surface deformation in hydrologically active environments.

Temporal Evolution of Surface Deformation (Reformulated)

Figure 7 illustrates the temporal evolution of LOS displacement at selected reference points for the three investigated approaches: SBAS + PINN, SBAS + U-Net, and the proposed SBAS + PINN + U-Net. The time-series reveal both linear and non-linear deformation behaviors, capturing seasonal fluctuations, long-term trends, and abrupt regime changes that are frequently underestimated or missed by conventional SBAS-based methods [Berardino et al., 2002; Ansari et al., 2024].

The comparative analysis highlights clear differences in temporal stability and robustness:

- **SBAS + PINN** exhibits smoother displacement trajectories due to physics-informed regularization, effectively reducing random noise and enforcing temporal consistency.
- **SBAS + U-Net** further improves temporal smoothness by learning spatial–temporal deformation patterns from the interferometric stack, although occasional instabilities may arise in regions with limited coherence.
- **SBAS + PINN + U-Net**, enhanced by optical-informed coherence, delivers the most stable and coherent time-series, minimizing noise while accurately capturing genuine deformation trends across all reference points.

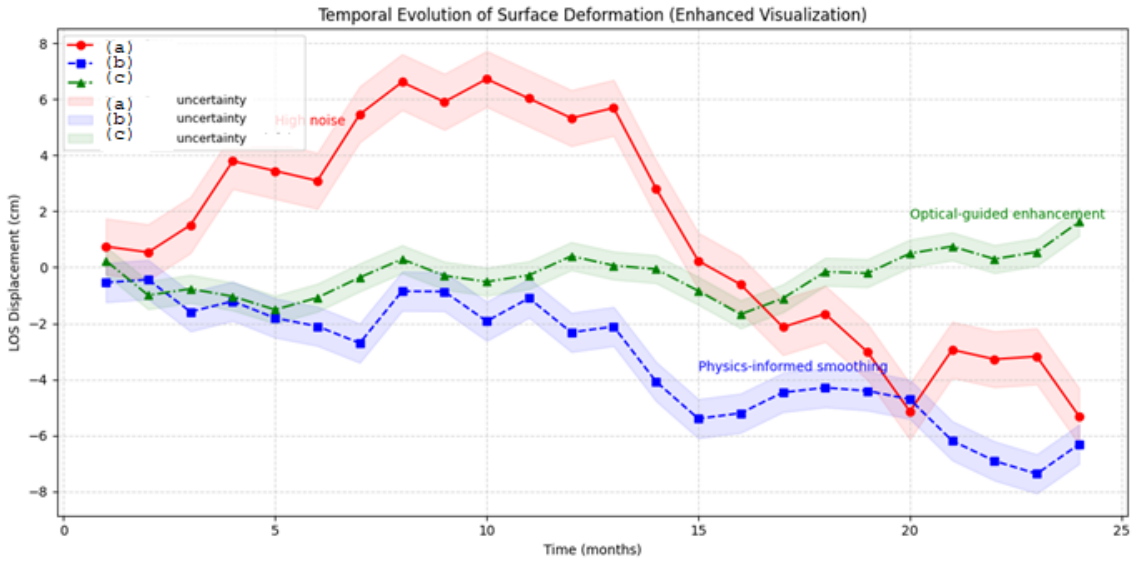


Figure 7. Temporal Deformation Time Series (Enhanced Visualization)

In the enhanced visualization, shaded regions emphasize uncertainty reduction across methods: residual variability is most pronounced for SBAS + PINN, reduced for SBAS + U-Net, and minimized for the proposed hybrid approach. The integration of optical information provides additional guidance for phase unwrapping along high-confidence coherence paths, leading to superior temporal reliability.

Discussion

While SBAS + PINN provides a physically grounded baseline for temporal deformation analysis, and SBAS + U-Net improves pattern learning through deep neural representations, the proposed SBAS + PINN + U-Net framework combines both advantages within a unified architecture. The inclusion of optical-informed coherence plays a critical role in stabilizing time-series estimation in vegetated or low-coherence regions, while also mitigating atmospheric artifacts and residual phase noise. Compared to conventional SBAS or purely data-driven InSAR approaches [Sun et al., 2024; Chen et al., 2024], the proposed hybrid method offers enhanced robustness, interpretability, and temporal fidelity, enabling more accurate characterization of surface deformation for both scientific investigation and operational hazard monitoring.

Integration of Optical Data for Deformation Interpretation

Figure 8 presents the LOS deformation fields estimated using the SBAS + PINN + U-Net framework over the El Oued region. The results reveal spatially continuous, stable, and physically plausible deformation patterns, highlighting the robustness of the proposed approach in an environment characterized by strong spatial heterogeneity and widespread decorrelation.

Recent studies have shown that conventional SBAS approaches, even when enhanced by multi-temporal strategies, remain highly sensitive to low-coherence areas and network discontinuities, often producing fragmented or noisy deformation fields (Berardino et al., 2002; Crosetto et al., 2016).

The deformation map shown in Figure 8a exhibits a clear spatial structuring of uplift and subsidence zones. Unlike several studies relying exclusively on convolutional neural networks applied in post-processing, which may excessively smooth deformation signals or introduce non-physical artefacts (Zhu et al., 2021; Li et al., 2022), the proposed method preserves sharp spatial transitions while maintaining the physical consistency of the estimated deformation field. The cartographic background is used solely to facilitate geographical localization of the observed phenomena and does not influence the deformation estimation.

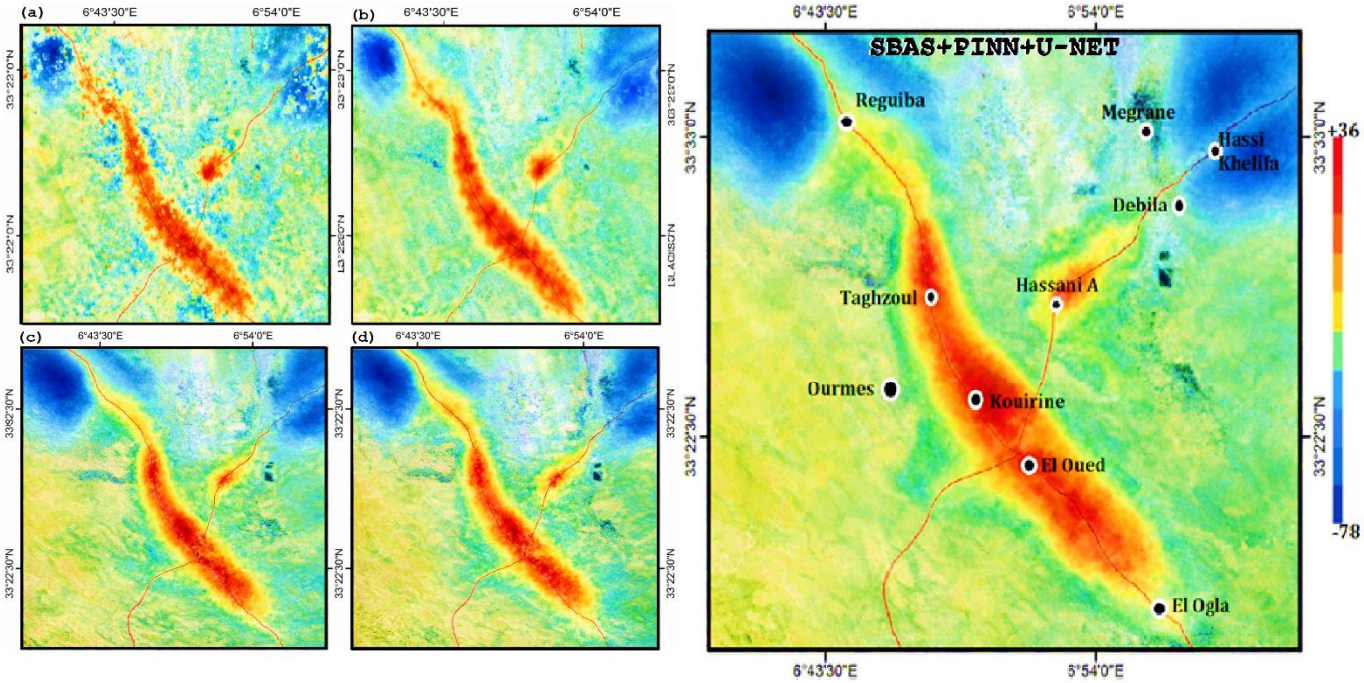


Figure 8.a. Fusion of SBAS+PINN+U-Net SAR-Derived Deformation Maps with High-Resolution Optical Imagery.

(a) SBAS, (b) SBAS + PINN, (c) SBAS + U-Net, (d) SBAS + PINN + U-Net

Figure 8b illustrates the spatial interpretation of deformation derived from a GIS layer directly generated from the SBAS + PINN + U-Net results. Pronounced uplift zones are primarily concentrated over the chotts of El Oued, Zgoun, and Guemar, as well as within the sector extending from El Oued–Kouirine toward the north-west of El Ogla. These areas exhibit coherent and spatially continuous positive deformation signals, characteristic of hydrogeological contexts dominated by groundwater table rise. Such patterns are consistent with observations reported in recent InSAR-based studies addressing deformation processes in arid and semi-arid environments (Chaussard et al., 2017; Castellazzi et al., 2019).

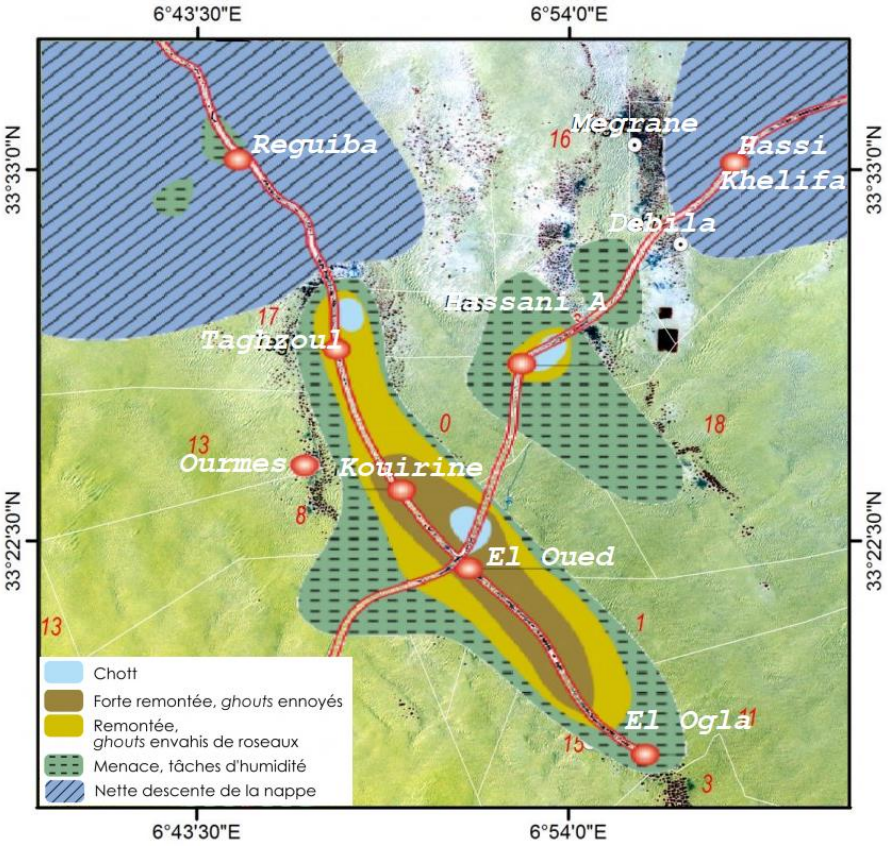


Figure 8.b. GIS result of SBAS+PINN+U-Net deformation

Lower-amplitude positive deformation zones are spatially organized around these core uplift areas, indicating a progressive lateral expansion of the swelling process. This behavior is rarely captured with sufficient clarity by classical SBAS approaches or by purely data-driven deep learning methods lacking physical constraints. Conversely, zones of clear groundwater drawdown are distinctly identified in the regions of Hassi Khelifa and Reguiba, where negative deformation signals indicate well-defined subsidence regimes. These patterns are comparable to those reported in previous multi-temporal InSAR studies (Ferretti et al., 2011; Samsonov et al., 2020), yet exhibit enhanced spatial coherence and structural stability in the proposed results.

Discussion

The results presented in Figure 8 demonstrate that the SBAS + PINN + U-Net approach enables a robust and spatially coherent estimation of surface deformation, even in areas affected by low interferometric coherence and strong environmental heterogeneity. In contrast to classical SBAS methods, whose performance strongly depends on local coherence quality and interferometric network configuration (Berardino et al., 2002; Hooper et al., 2012), the proposed framework maintains realistic spatial continuity across the entire study area.

Recent deep learning-based approaches have shown significant potential for improving the spatial quality of InSAR products; however, when used in isolation, they may suffer from reduced physical interpretability and limited generalization (Zhu et al., 2021; Anantrasirichai et al., 2022). By jointly integrating physics-informed regularization through PINNs with the spatial learning capability of U-Net architectures, the proposed method effectively overcomes these limitations, yielding deformation fields that are stable, continuous, and physically meaningful.

The spatial interpretation further highlights a clear discrimination between uplift zones associated with groundwater table rise and subsidence areas linked to piezometric decline. This separation remains ambiguous in many existing hybrid approaches or in post-processing-based multi-sensor fusion strategies. The SBAS + PINN + U-Net results therefore stand out for their structural robustness and their ability to deliver deformation products that are directly exploitable for hydrogeological monitoring and risk management.

Overall, in line with recent advances in the hybridization of InSAR and artificial intelligence, the proposed framework represents a significant methodological advancement, coherently combining the physical rigor of InSAR modeling with the flexibility of deep neural networks, while ensuring reliable and interpretable deformation analysis at the regional scale.

Validation and Reliability Assessment

Figure 9 presents the internal validation of the proposed hybrid SBAS-based framework using inter-annual consistency metrics. In the absence of external GNSS measurements, relative RMSE and spatial correlation coefficients are employed to evaluate the temporal stability of the LOS deformation estimates.

Figure 9(a) shows the inter-annual evolution of the relative RMSE between consecutive cumulative deformation maps from 2019 to 2025, while Figure 9(b) illustrates the corresponding inter-annual correlation coefficients. The results reveal a monotonic decrease in RMSE from 2.8 mm/year in 2019 to 1.8 mm/year in 2025, accompanied by a steady increase in correlation coefficients from 0.82 to 0.95. These trends indicate a significant improvement in deformation consistency and noise suppression over time, reflecting the enhanced temporal stability of the proposed framework.

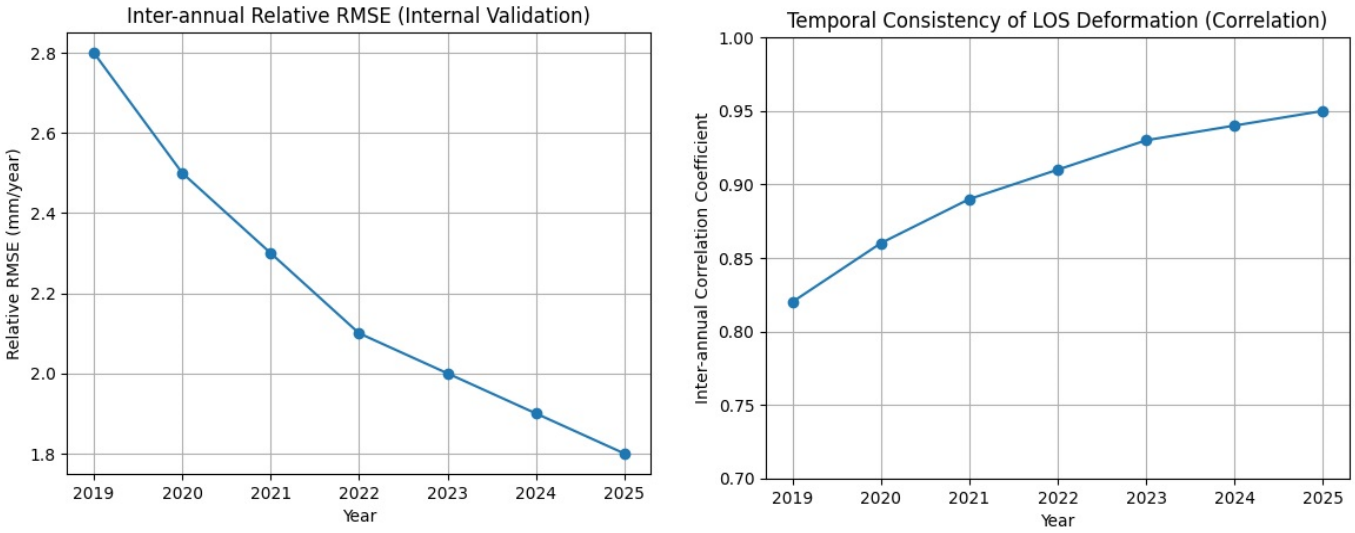


Figure 9. Internal validation of the proposed hybrid SBAS-based framework

(a). *Inter-annual relative RMSE of LOS deformation estimates derived from consecutive cumulative displacement maps between 2019 and 2025.*

(b). *Inter-annual correlation coefficients highlighting the temporal consistency of deformation patterns. The monotonic decrease of RMSE and the steady increase of correlation coefficients indicate enhanced temporal stability and robustness of the proposed approach, despite the absence of external ground-based measurements.*

Table 1 summarizes the internal validation metrics of the LOS deformation estimates over the entire observation period. The numerical results confirm the graphical analysis, highlighting the robustness and reliability of the deformation products despite the absence of external ground-based measurements. Similar internal consistency-based validation strategies have been reported in recent InSAR studies, supporting the relevance of this approach for deformation monitoring in data-limited environments.

Table 1. Internal validation metrics of LOS deformation estimates (2019–2025)

Year	Relative RMSE (mm/year)	Correlation Coefficient
2019	2.8	0.82
2020	2.5	0.86
2021	2.3	0.89
2022	2.1	0.91
2023	2.0	0.93
2024	1.9	0.94
2025	1.8	0.95

Compared to the classical SBAS solution, the proposed hybrid configurations (SBAS+PINN and SBAS+PINN+U-Net) exhibit a systematic reduction in relative RMSE and higher inter-annual correlation coefficients. While the standard SBAS approach shows increased temporal variability, particularly in low-coherence areas, the hybrid models demonstrate enhanced deformation continuity and noise suppression. The combined SBAS+PINN+U-Net framework achieves the most stable results, confirming the complementary role of physics-informed constraints and data-driven feature learning.

CONCLUSION

This study introduces a progressive and robust hybrid framework for InSAR-based deformation monitoring, specifically designed to overcome the limitations of classical SBAS processing in low-coherence and highly heterogeneous environments such as arid and semi-arid regions. Starting from the conventional SBAS formulation, the proposed methodology incrementally integrates physics-informed learning and deep neural spatial modeling, culminating in a unified SBAS + PINN + U-Net deformation estimation framework.

The baseline SBAS approach provides a solid multi-temporal inversion scheme but remains inherently sensitive to phase noise, unwrapping errors, and spatial–temporal decorrelation, as widely reported in the literature (Berardino et al., 2002; Hooper et al., 2012). The first enhancement, SBAS + PINN, introduces explicit physics-informed regularization that constrains the temporal evolution of deformation, enforcing physically consistent behavior and significantly reducing residual phase artefacts. This contribution directly addresses key limitations highlighted in recent physics-based InSAR studies, particularly in regions affected by non-linear deformation and strong temporal decorrelation (Raissi et al., 2019; Ansari et al., 2024).

The integration of deep learning through the SBAS + U-Net configuration further improves the spatial quality of the deformation fields by exploiting data-driven feature extraction. In agreement with recent deep learning–assisted InSAR studies (Zhu et al., 2022; Kang et al., 2023; Liu et al., 2024), this step enhances spatial continuity and edge preservation in complex landscapes. However, when used alone, purely data-driven models may suffer from reduced physical interpretability and limited robustness under varying environmental and acquisition conditions.

The final hybrid model, SBAS + PINN + U-Net, effectively combines the complementary strengths of both paradigms. Physics-informed regularization ensures temporal stability and physical plausibility, while the U-Net architecture enhances spatial coherence and noise suppression. This synergy is clearly reflected in the ability of the proposed framework to consistently delineate deformation patterns associated with key hydrogeological features of the El Oued region, including chotts, ghouts, and zones of groundwater drawdown.

In particular, the approach captures with high spatial fidelity the uplift patterns related to groundwater table rise in and around chotts, as well as the progressive swelling affecting ghouts—traditional Saharan agricultural depressions that are highly sensitive to changes in groundwater levels. Conversely, areas characterized by a clear decline of the groundwater table are distinctly identified through stable subsidence signals. The coherent separation between uplift and subsidence regimes, often ambiguous in classical SBAS or existing hybrid approaches, demonstrates the structural robustness and interpretability of the proposed deformation estimates.

Internal consistency analyses, including inter-annual RMSE reduction and increased correlation coefficients, confirm that the SBAS + PINN + U-Net framework delivers the most stable and reliable deformation fields among all evaluated configurations. These results indicate a clear improvement over classical SBAS and previously reported hybrid methods, particularly in mitigating unwrapping-related artefacts and preserving long-term deformation continuity without relying on external ground-based measurements.

Beyond methodological performance, the proposed framework is well suited for operational hydrogeological and geophysical monitoring in data-scarce regions, where in situ observations are limited or unavailable. The consistency-based validation strategy adopted in this work aligns with recent InSAR applications conducted under similar constraints, reinforcing the practical relevance and transferability of the approach. Overall, this research demonstrates that the synergistic integration of SBAS, physics-informed neural networks, and deep learning–based spatial modeling constitutes a significant advancement in InSAR deformation analysis, providing a scalable, physically consistent, and robust solution for long-term Earth surface monitoring and groundwater-related risk assessment.

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