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Kobid Panthi

panthik@student.unimelb.edu.au

The University of Melbourne <https://orcid.org/0000-0002-0590-4266>

Jagannath Aryal

The University of Melbourne

Yinghui Tian

The University of Melbourne

Yifa Wang

The University of Melbourne

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An approach for Reference Point Selection in SBAS-InSAR Time Series Slope Deformation Monitoring

Kobid Panthi^{1*}, Jagannath Aryal¹, Yinghui Tian¹, Yifa Wang¹

^{1*}Department of Infrastructure Engineering, The University of Melbourne, Melbourne, 3010, VIC, Australia.

*Corresponding author(s). E-mail(s): panthik@student.unimelb.edu.au;

Abstract

Slope deformation measured from Interferometric Synthetic Aperture Radar (InSAR) is inherently relative and depend entirely on the selection of a reference point. Thus, identifying a stable reference point is essential for ensuring the accuracy of displacement time-series analysis. Traditionally, reference points were selected based on high coherence zones, which may lead to subjective bias and localized errors. To overcome this limitation, this study proposes a reference point selection framework based on a hybrid threshold of multiple parameters followed by a multi-point spatial averaging algorithm. The approach was tested in the failure of the Cadia Dam in New South Wales, Australia, and validated against field measured prism data prior to failure. It resulted an average RMSE of 2.24 mm and a Pearson r of 0.85 relative to field data, representing approximately a 50% reduction in error compared to the worst case performance of the default MintPy approach. The stability of the framework was further validated through a three stage analysis: an ablation study to confirm the necessity of each threshold, a sensitivity analysis to rank the most influential parameters, and a temporal robustness test to evaluate the impact of a reduced temporal dataset on spatio-temporal consistency. The results demonstrate that the proposed approach maximizes InSAR analysis performance by identifying stable reference points and effectively removing the risk of human error or subjective bias.

Keywords: InSAR; Reference Point; Deformation Monitoring; Cadia Tailing Dam

1 Introduction

Accurate displacement time-series analysis in InSAR depends highly on the selection of a stable reference point (Yunjun et al. 2019; Liu and Larson 2018). Since InSAR measurements are fundamentally relative, all displacement time series are evaluated against the single location. Consequently, any uncorrected phase instability, localized ground movement, or atmospheric noise at the chosen reference point propagates systematic bias throughout the entire spatial network (Yunjun et al. 2019). Despite the critical sensitivity of this step, only limited research has systematically examined the impact of reference point selection on time-series displacement accuracy (Zhang et al. 2024; Yan and Wang 2021; Fan et al. 2025). Most of the commercial InSAR processing packages still rely on simplistic spatial coherence thresholds (Rana et al. 2024; NV5 Geospatial 2025) and use this metric as the primary criterion for identifying stable reference points and masking decorrelated regions (Tang et al. 2025). However, this practice is insufficient, as high coherence indicates a reliable radar return or permanent scatterer but does not guarantee the absence of actual ground deformation (Fan et al. 2025). Likewise, open-source platforms allow the manual selection of assumed stable targets but since this approach is subjective, there is a high possibility that different analysts may select distinct reference points leading to inconsistent deformation results.

Obtaining the accurate displacement has become even more critical with the rapid advancement of modern Earth observation system, which has significantly improved continuous ground monitoring capabilities. In particular, open-access radar data from the European Space Agency’s (ESA) Sentinel-1 mission has advanced

the capacity for detailed surface monitoring and topographic investigation (Ugenti et al. 2025; Bru et al. 2024; Bui et al. 2021). InSAR methodologies are particularly advantageous in challenging terrains where conventional positioning technologies, such as Global Navigation Satellite Systems (GNSS), lack sufficient spatial density or are economically unfeasible (Yeh et al. 2025). They can be used for monitoring geohazards due to their broad spatial and temporal coverage (Yip et al. 2019; Wang et al. 2024; Celik et al. 2025). By evaluating the phase differences across multiple Synthetic Aperture Radar (SAR) acquisitions over time (Zhou et al. 2016), InSAR evaluates large-scale surface deformation. Initially, topographic changes were monitored via Differential InSAR (DInSAR), which uses single interferometric pairs to detect deformation (Gabriel et al. 1989). However, DInSAR is severely limited by atmospheric variations and temporal decorrelation in rural or vegetated environments (Dai et al. 2022). To overcome the limitations of conventional interferometry, Multi Temporal InSAR (MT-InSAR) techniques such as Small Baseline Subset (SBAS) and Persistent Scatterer InSAR (PS-InSAR) approach are employed (Dai et al. 2022). While PS-InSAR targets stable point-like reflectors and is predominantly suited for urban environments with dense man-made infrastructure (Liu et al. 2025), SBAS-InSAR is specifically designed for distributed scattering environments (Dai et al. 2022; Liu et al. 2025). By forming interferograms with minimized spatial and temporal baselines, SBAS-InSAR enhances signal coherence across various terrains and can be used for carrying out deformation analysis for extraction of mean velocity and non linear displacement time series (Yang et al. 2024; Yunjun et al. 2019).

Regardless of the methods used, the displacement depends on selecting a geologically stable region as the primary reference point (Chen et al. 2020). Although traditional studies often rely on a single Ground control point, modern research is increasingly addressing these challenges by developing automated differential displacement networks that treat each pixel as a reference to optimise the accuracy of time deformation results (Han et al. 2025; Zhang et al. 2024). For example, the Dual Threshold Algorithm is used for selecting ground control points in rugged terrain to overcome the limitation of conventional SBAS-InSAR analysis (Yan and Wang 2021). Despite these algorithmic advancements, implementing these automated approaches in real world scenarios and validating them against ground truth data remains a significant challenge. For instance, a recent study confirmed that D-InSAR displacement trends were consistent with borehole inclinometers but showed significant discrepancies during wet season (Phakdimek et al. 2024). These deviations are attributed to limitations of the conventional single reference point approach that fails to account for the complex temporal decorrelation of the surface introduced by seasonal surface changes. These methods often lack contextual consistency by failing to integrate semantic stability and spatial relationships, often causing seasonal noise to be misidentified as actual displacement.

To address these limitations, this study introduces a multi criteria reference point selection framework. To isolate the contribution of reference point selection to the final displacement time series, a fixed processing workflow was implemented by keeping all interferometric parameters constant while varying the reference point selection strategy. The framework first identified multiple stable islands by utilising multi parameter threshold approach by selecting the reference points situated closest to each island adopting the approach proposed by Zhang et al. (2024). These points were then averaged to reduce spatially correlated noise and cancel localized atmospheric effects. In the final stage, a singular pixel with the minimum temporal phase variance was identified as the stable reference point. While several researchers have previously evaluated InSAR displacement accuracy by comparing satellite derived measurements against ground-truth (Gu et al. 2026), this study validates the reference selection results through a comparison with in-situ prism monitoring data. Additionally, a series of ablation, sensitivity, and temporal robustness studies were conducted to evaluate the efficacy of this approach in understanding spatio-temporal consistency across varying observation scales.

2 Methodology

2.1 Principle and Process of SBAS-InSAR

The SBAS algorithm is a multi temporal InSAR technique designed to mitigate decorrelation by utilising interferometric pairs characterised by small spatial and temporal baselines (Wang et al. 2022). The fundamental measurement in this method is interferometric phase (ϕ) which represents the difference in travel path between two SAR acquisitions. The total phase at any given pixel is a summation of several components (Rosen et al. 2000):

$$\phi = \phi_{topo} + \phi_{def} + \phi_{atm} + \phi_{orb} + \phi_{noise}$$

Where ϕ_{topo} is the topographic phase, ϕ_{def} is the ground deformation phase, ϕ_{atm} is atmospheric delay, ϕ_{orb} is the residual phase from orbital inaccuracies, and ϕ_{noise} is thermal and decorrelation noise. In this study, the processing is divided into two primary phases: interferogram stack generation using the InSAR

Scientific Computing Environment (ISCE2) and subsequent time series inversion using Miami INSAR Time series software in Python (MintPy).

2.1.1 Interferogram Stack Generation

This study utilised ISCE2 platform to process a stack of Sentinel-1 Single Look Complex (SLC) images provided by ESA (Yunjun et al. 2019; Yu et al. 2024). To ensure phase consistency, a single reference coregistration approach was adopted by integrating Geometric Coregistration and DEM to calculate offsets with Enhanced Spectral Diversity (ESD) for preventing phase jumps between bursts. To optimise computational efficiency, a parallelised Python based execution framework was implemented using multiprocessing.Pool architecture for the execution of ISCE2 across multiple CPU cores. This parallelisation significantly reduced the processing time of the workflow, particularly for computationally intensive tasks like ESD correction and phase unwrapping.

2.1.2 Time series Inversion Framework

Following the generation of the unwrapped interferogram stack, time series inversion was conducted using MintPy to obtain surface displacement by mitigating several errors. The unwrapped interferograms, spatial coherence maps, and connected components generated by ISCE2 platform were incorporated into the MintPy environment. To establish a relative baseline for displacement, the time series was anchored to a specific reference date. The small baseline network was inverted into a time series of raw phase delays using a Weighted Least Squares (WLS) estimator (Yunjun et al. 2019). To isolate the deformation signal, systematic errors were estimated and removed from the raw time series. Atmospheric delays were mitigated using ERA5 reanalysis data via the PyAPS module (Jolivet et al. 2011). Furthermore, DEM errors were corrected using a pixelwise geometry approach which was used to estimate a linear deformation velocity.

2.2 Reference Point Selection Approach

2.2.1 Threshold for possible reference point selection

The accuracy of SBAS-InSAR time series analysis relies on the quality of the spatial reference point. An ideal reference point must have stable phase over time, reliable phase unwrapping relative to the deformation area, and located close to the region of interest to minimise atmospheric delays and orbital errors (Zhang et al. 2024). To optimise this selection, a multi criteria spatial filtering algorithm was developed to evaluate every pixel in the study area, utilising the threshold baseline parameters defined in Table 1. Although the multi-criteria thresholding strategy in this study adopts the automated selection principles developed for wetland environments (Zhang et al. 2024), proposed threshold values are distinct and must be adjusted according to local land cover and coherence conditions. Therefore, a sensitivity analysis was conducted to evaluate how these parameters affect reference stability and framework generalizability (Table 2).

Table 1: Threshold parameters and filtering criteria utilised in reference point selection algorithm.

Parameter	Description	Threshold Value
Spatial Coherence (S_c)	Minimum spatial coherence	0.7
Coherence Percentage (C_p)	Frequency above coherence limit	90%
Connectivity Frequency (C_f)	Frequency sharing target's component	50%
Path Coherence (P_c)	Minimum spatial bridge coherence	0.5
Minimum Area (A_{min})	Minimum required pixels	10 pixels
Neighbourhood Density (N_d)	Valid pixel ratio in window	80%
Neighbourhood Window (N_w)	Local moving window size	5 × 5 pixels
Island Distance (I_d)	Minimum distance between two islands	10 pixels

The initial parameter set (S_c and C_p) ensures spatiotemporal stability where a pixel is only retained if its spatial coherence exceeded the defined limit in the majority of the interferograms. This guarantees that the pixel remains highly stable across the sequence of SAR acquisitions, rather than being selected by a few high coherence pairs. The second set of constraints (C_f and P_c) addresses phase unwrapping reliability to prevent errors arising from unwrapped islands. To ensure the reference point and the deformation area belong to the same unwrapped phase, a spatial bridge mask was enforced to ensure a high coherence, continuous path exists between them and they shared the same connected components.

Similarly, a morphological filter (A_{min}) was applied to eliminate isolated and noisy pixels smaller than the minimum area threshold that might pass coherence thresholds. A localised density filter (N_d and N_w) validated pixels only if its surrounding neighbourhood met the density and window size requirements specified in Table 1. Finally, known areas of active deformation were excluded to avoid the algorithm from selecting the reference point in unstable regions. An island distance threshold (I_d) was further applied to identify multiple distinct stable islands, with the final reference point selected based on its minimum Euclidean distance to the study area. While these islands are theoretically stable, local atmospheric changes and residual phase noise can still cause spatial variability. To mitigate these errors, a final optimisation process was applied, as detailed in the following section.

2.2.2 Optimised reference point from multiple zones

The spatial filtering and regional stacking technique originally developed to remove errors from Global Positioning System (GPS) coordinate time series (Wdowinski et al. 1997) has been used for estimating optimum reference point in this study. For a given radar acquisition at time t , group mean, μ_t , is calculated as the spatial average of all displacements:

$$\mu_t = \frac{1}{N} \sum_{i=1}^N y_{i,t} \quad (1)$$

where $y_{i,t}$ is the displacement of stable location i at time t . It can be estimated using a multi point spatial average to minimise the influence of site specific noise (Dong et al. 2006) and the stable candidate can be identified by subtracting a local patch mean from candidate pixel (Hooper et al. 2004). This spatial filtering ensures that the chosen reference is capable of reducing the risk of localised subsidence or atmospheric anomalies into the final time series displacement maps. The detailed methodology for the reference point selection is provided in Algorithm 1.

Algorithm 1 Multi Criteria Reference Point Selection via Regional Stacking

Require: Stack $\mathbf{I}$, Target T , Thresholds ($S_c, C_p, C_f, P_c, A_{min}, N_d, N_w, I_d$)

Ensure: Optimal Reference Point P_{ref}

```

1:  $C_{final} \leftarrow \emptyset$ 
2:
3: for each pixel  $p \in \mathbf{I}$  do
4:   if SpatialCoh  $\geq S_c$  and CohPer  $\geq C_p$  then
5:     if ConFre( $p, T$ )  $\geq C_f$  and PathCoh( $p, T$ )  $\geq P_c$  then
6:       if Area( $p$ )  $\geq A_{min}$  and Density( $p$ )  $\geq N_d$  and Window( $p$ )  $\geq N_w$  then
7:         if IslandDist( $p$ )  $\geq I_d$  then
8:           if Mask( $p$ ) = 0 then
9:              $C_{final} \leftarrow C_{final} \cup \{p\}$ 
10:          end if
11:        end if
12:      end if
13:    end if
14:  end if
15: end for
16:
17:  $N \leftarrow |C_{final}|$ 
18: for each acquisition time  $t$  do
19:    $\mu_t \leftarrow \frac{1}{N} \sum_{p \in C_{final}} y_{p,t}$ 
20: end for
21:
22: for each candidate  $p \in C_{final}$  do
23:    $\epsilon_{p,t} \leftarrow y_{p,t} - \mu_t$ 
24:    $\sigma_p \leftarrow \text{std}(\epsilon_{p,t})$ 
25: end for
26:  $P_{ref} \leftarrow \arg \min_{p \in C_{final}} (\sigma_p)$ 
27: return  $P_{ref}$ 

```

▷ Initialise reference point set
 ▷ Stage 1: Spatial and Topological Filtering
 ▷ Exclude known deformation zones
 ▷ Pixel Passes all filters
 ▷ Stage 2: Isolating Regional Noise
 ▷ Calculate group mean for time t
 ▷ Stage 3: Residual Phase Optimization
 ▷ Isolate local phase residual
 ▷ Measure temporal stability
 ▷ Select point with minimum noise

2.3 Experimental Design for Evaluation

2.3.1 Ablation Study Design

An ablation study has been performed by systematically disabling its internal components to quantify their individual impact on the final output by evaluating the internal drift between the selected reference points across various ablation scenarios. The configuration that yields the minimum drift signifies that the shortlisted reference points are in good agreement with one another, ensuring a stable reference point.

The study evaluates performance degradation across five distinct ablation scenarios (Figure 1), where specific filters are systematically disabled to isolate their contribution to reference point reliability. The first ablation disables the thresholds S_c and C_p to measure reliance on basic interferometric coherence versus advanced filters. The second ablation removes the connectivity parameters C_f and P_c to determine whether enforcing continuous, high quality unwrapping paths is necessary. The third ablation investigates spatial robustness by removing the A_{min} , N_d , and N_w filters to test if isolated, high-coherence pixels introduced localised phase noise. The fourth disables the minimum distance factor between candidates to check for localized clustering bias. Finally, the fifth run tests the algorithm’s performance by masking known unstable regions. This determines whether the topological and spatial filters can automatically identify the deforming zones or whether manual masking remains essential. The impact of each parameter has been quantified through several key metrics.

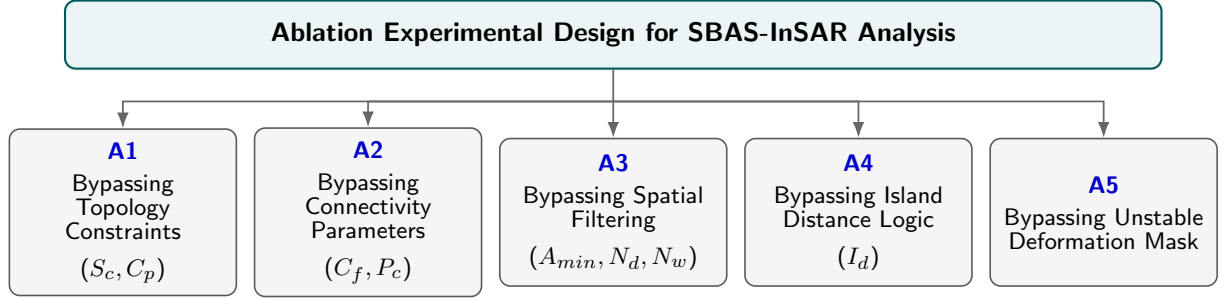


Fig. 1: Ablation experiment framework isolating individual algorithmic components (A1-A5) against the baseline workflow.

2.3.2 Sensitivity and Robustness Setup

After understanding the impact of each parameter in ablation study, a sensitivity analysis was formulated for critical parameters. The primary objective of this approach is to ensure that the proposed methodology is not overfitted to the specific threshold values presented in Table 1, and to verify that algorithm can be generalised to other scenarios. To evaluate the stability, critical parameters were varied across the ranges detailed in Table 2 and threshold was quantified using two key internal consistency metrics i.e., the Maximum Internal Spread and the Mean Pairwise Root Mean Square Error (RMSE).

Table 2: Summary of the baseline values and experimental ranges for key processing parameters utilised in the sensitivity study

	S_c	C_p	A_{min}	N_d	N_w	I_d
Baseline	0.70	90%	10 pixels	0.8	5×5	10
Sensitivity Range	0.50 - 0.80	70% - 95%	0 - 10	0.5-1	$2 \times 2 - 8 \times 8$	0-30

Additionally, a temporal robustness analysis was conducted to evaluate spatiotemporal consistency and the stability of the proposed algorithm by systematically shortening the SAR observation stack. The methodology was tested against four scenarios: the 18 month baseline (Sep 2016-Mar 2018), a 14 month stack (Jan 2017-Mar 2018), an 8 month stack (July 2017-Mar 2018), and a 2 month stack (Jan 2018-Mar 2018) for determining the impact of temporal data volume on total spatial pixel density, maximum spatial displacement spread (mm), and velocity spread (mm/yr).

3 Study Area and Dataset

The Cadia Northern Tailings Storage Facility (NTSF) was the study area for this investigation. On March 9, 2018, a localised slump occurred along the embankment wall initiating the failure (Figure 2). The failure spanned on approximately 300 m section of the wall, with a lateral displacement of about 170 m and a displaced volume exceeding 1 million cubic meters. Forensic investigations characterised the event in two phases: Phase 1 involved slow, sustained deformation in the foundation, while Phase 2 was the sudden

initiation and runout of tailings (Jefferies et al. 2019). To investigate the pre-failure behaviour of the slope, this study utilised C-band SAR dataset acquired by ESA's Sentinel-1 Mission with a spatial resolution of 20 m and temporal revisit frequency of 12 days. The temporal coverage of this study spans from September 27, 2016, to March 9, 2018 using descending orbit at a line of sight (LOS) incidence angle of 35.3° to evaluate deformation trends leading up to the failure event. The coverage was selected to maintain strict orbital and geometric consistency across the interferometric stack. Although earlier Sentinel-1 acquisitions are available, data collected before September 2016 used different satellite tracks and viewing angles that prevent direct integration into a single continuous LOS time series. Therefore, we selected the time-frame (September 27, 2016, to March 9, 2018) for experimental design and investigation.

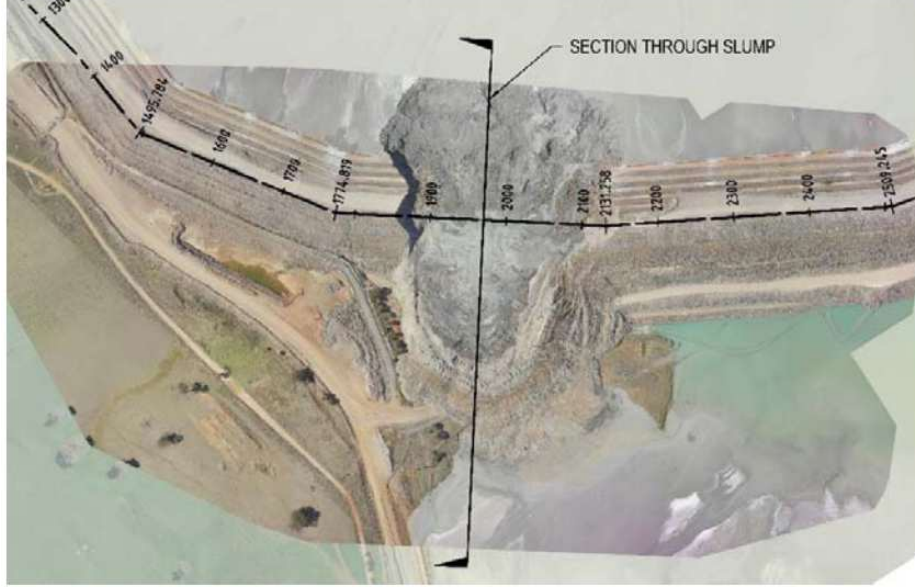


Fig. 2: Aerial View of Failure section of Cadia Dam on March 10, 2018 (Jefferies et al. 2019)

SBAS-InSAR analysis was conducted using ISCE2 for interferogram generation and MintPy for displacement inversion. A redundant network of 1,035 interferograms was generated to ensure robust time series inversion (Figure 3a). Analysis of the coherence matrix (Figure 3b) shows that while short term data shows high reliability, significant temporal decorrelation is observed over the two year period. This behaviour highlights the importance of an optimised reference point selection approach to minimise high seasonal noise. While previous studies of the Cadia failure confirm InSAR's ability to capture complex deformation (Ghorbani et al. 2022; Rana et al. 2024; Bayarara et al. 2024; Svendsen 2022; Carlà et al. 2019), the impact of reference point selection has often been overlooked. To ensure the reliability of our findings, we used precise prism measurements from the embankment crest (Figure 4) as a baseline to verify the accuracy of reference point selection algorithm.

4 Results and Discussion

4.1 Quantifying the Impact of Reference Point Selection

Following the failure of the Cadia Northern TSF, numerous research work (Rana et al. 2024; Bayarara et al. 2024; Jefferies et al. 2019; Thomas et al. 2019; Chua et al. 2019) was carried out to assess deformation prior to the movement. Theoretically, applying different multi temporal InSAR algorithms to the same Sentinel-1 orbital tracks should yield consistent displacement trajectories. However, a review of the published literature reveals discrepancies in the magnitude and temporal evolution of the dam's deformation. To understand it, spatial grid analysis was performed over the Cadia study area of approximately 60 km² with generation of 400 m uniform spatial grid spacing to extract a vast array of reference points. The deformation time series for the known dam failure zone (Lat/Lon: 33° 30' 27.18" S, 149° 0' 32.58" E) was then calculated against every point in this grid. Furthermore, time series data from five independent previous studies (Rana et al. 2024; Bayarara et al. 2024; Jefferies et al. 2019; Thomas et al. 2019; Chua et al. 2019) were aligned to a common baseline date and plotted alongside the grid based results (Figure 5). This comparison is not meant to

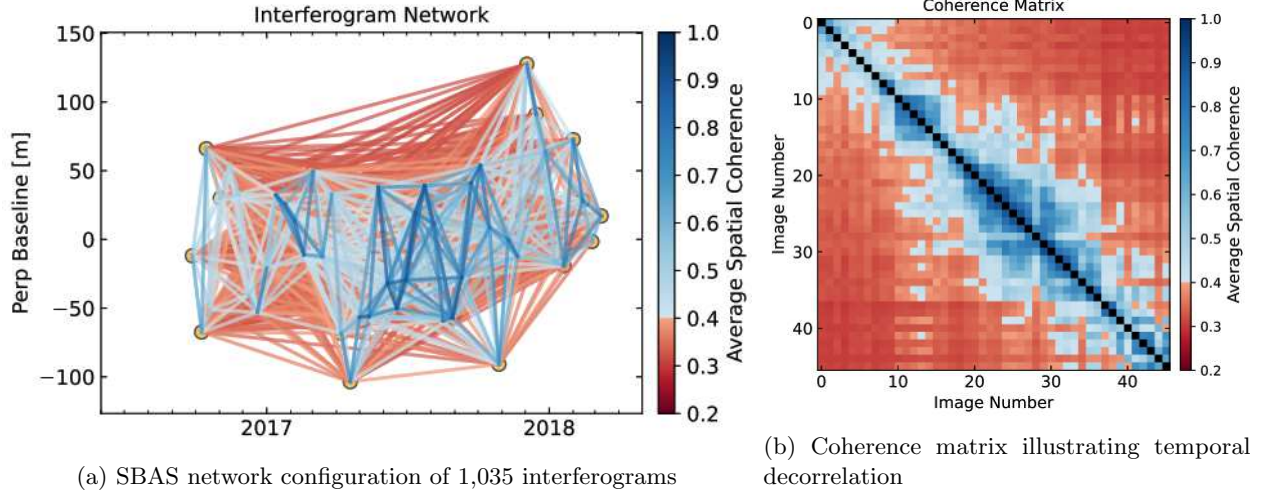


Fig. 3: Characterization of the InSAR dataset of Cadia Dam (a) The baseline network indicates high redundancy and connectivity (b) The temporal coherence matrix reveals a stable zone along the diagonal and seasonal decorrelation in other regions

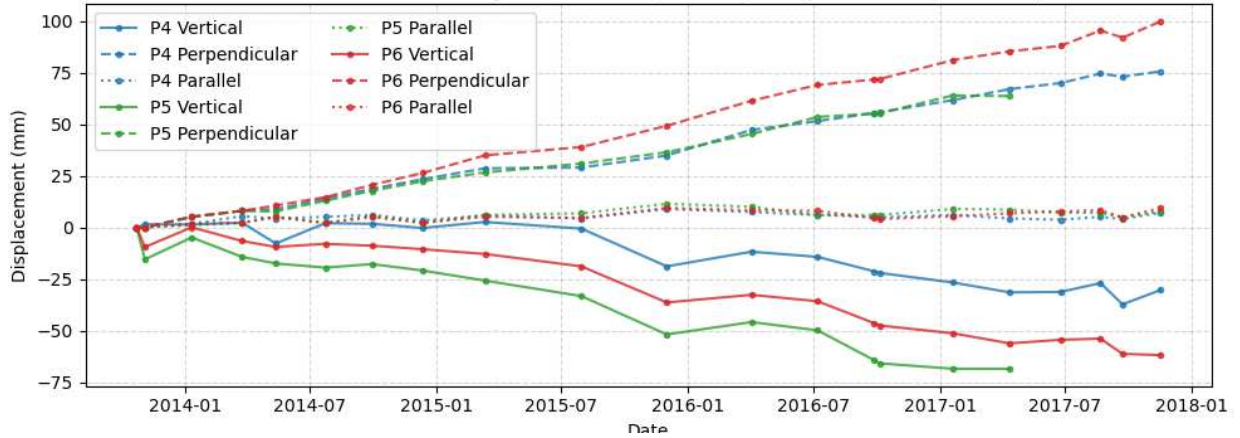


Fig. 4: Time series monitoring of dam deformation at crest along vertical, perpendicular and parallel locations from 2013 to 2018 (Jefferies et al. 2019)

measure exact dam movement because differing elevation models, unwrapping algorithms, and atmospheric corrections across these studies might also affect the final deformation. Instead it provides useful context showing that different studies report varying ground movement even under identical satellite viewing angles.

The result exhibited significant fluctuations in deformation magnitudes. In some cases, heaving was observed when a reference point subsided more than the target zone, creating a false upward trend. Since previous studies have not disclosed the precise spatial coordinates of selected reference pixels, direct comparisons of the absolute time series possess a significant challenge. This ambiguity highlights the necessity of the algorithm proposed in this study to standardise reference point selection strategy.

4.2 Determination of Reference Point from Proposed Approach

The reference point selection algorithm was applied to the Sentinel-1 interferometric stack covering the Cadia dam study area. Following multi criteria spatial and topological filtering based on Table 1, the algorithm successfully isolated several highly stable zones. The sequential refinement was carried out to filter unstable parameters before shortlisting the possible reference points. This process involved spatial and temporal coherence thresholds (Figure 6a-b), connectivity and path coherence (Figure 6c), minimum area filtering (Figure 6d), and neighbourhood density optimization (Figure 6e). Finally, spatial exclusion masks were imposed over known deformation zones, and a proximity filter was applied to enforce minimum island distance

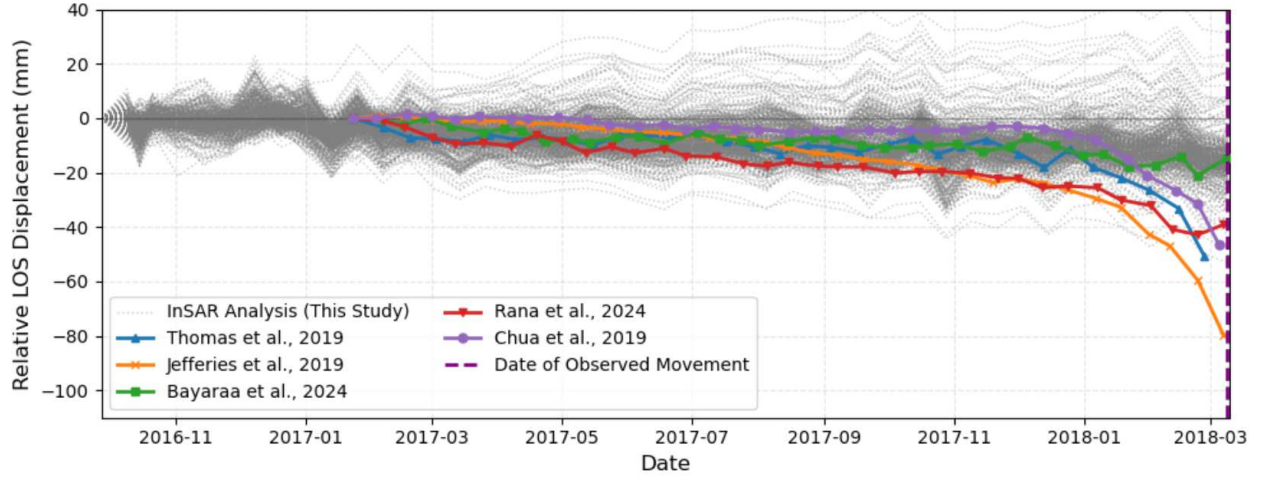


Fig. 5: Comparison of pre-failure deformation timeseries from published literature versus observed data from this study

criteria (Figure 6f). This hierarchical filtering approach identified three primary stable reference locations (Ref 1, Ref 2, and Ref 3) that met all multi parametric criteria, as shown in Figure 7a.

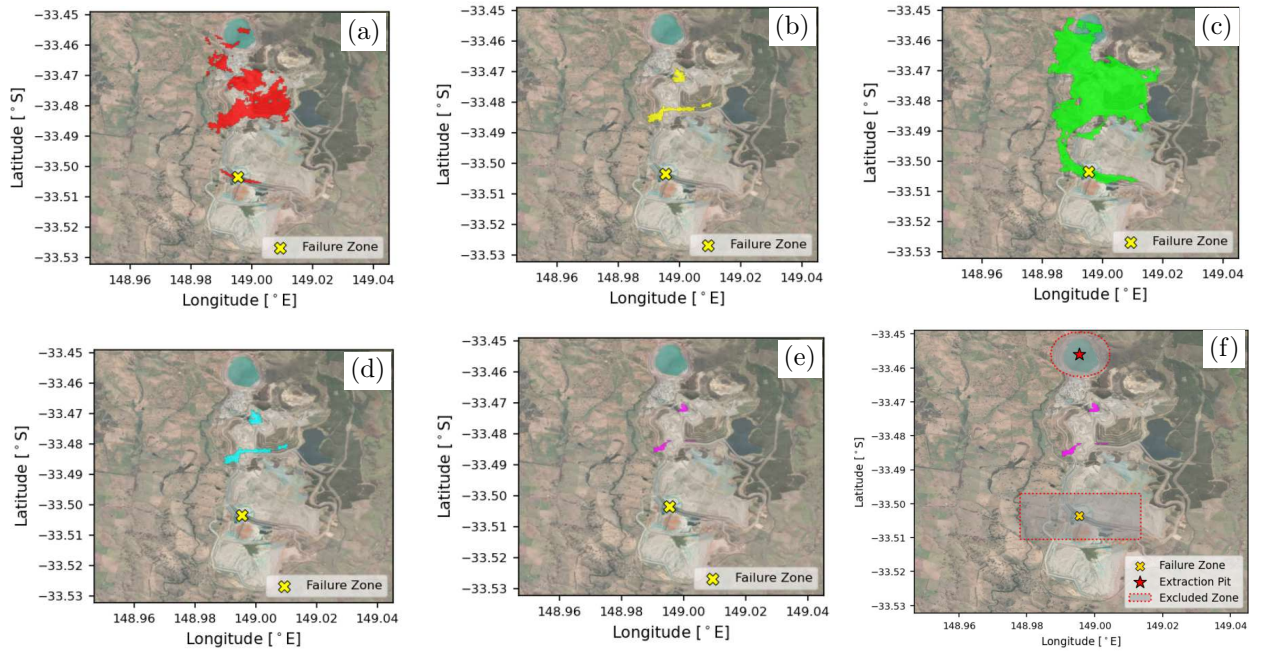
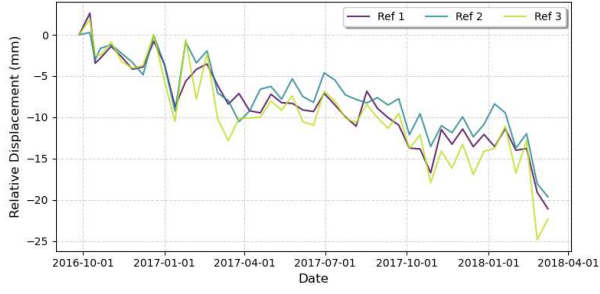
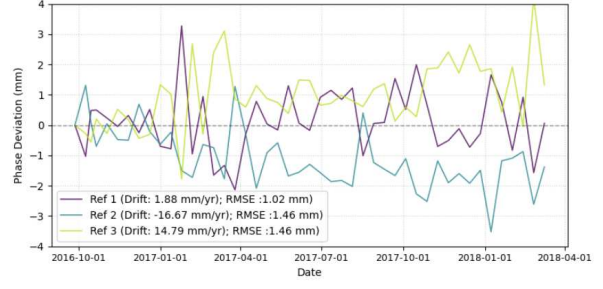


Fig. 6: Step by step spatial and topological filtering process for reference point selection: (a) spatial coherence threshold; (b) percentage threshold of coherence; (c) evaluation of connectivity frequency and path coherence; (d) minimum area threshold; (e) neighbourhood density and window optimization; (f) final selection with manually excluded unstable zones.

The individual time series analysis of the shortlisted candidates were compared against the mean value for the calculation of temporal drift and residual phase (Figure 7b). The theoretical approach identified Ref 1 as the optimal candidate. It exhibited the lowest relative drift (1.88 mm/yr) and the lowest internal noise variance (RMSE of 1.02 mm), indicating a stable location independent of the localised noise. Likewise, Ref 2 and Ref 3 demonstrated higher drift rates (-16.67 mm/yr and +14.79 mm/yr, respectively), suggesting localised instability.



(a) Phase deviation Time series.



(b) Annualised drift rate (mm/yr).

Fig. 7: Time series analysis of the proposed reference points approach using InSAR dataset of stable candidates

4.3 Comparison of Results with Field Measured Data

To access the proposed reference point selection methodology, InSAR derived deformation results were compared against field measured data. Field monitoring data from three physical prisms (P4, P5, and P6) located on the surface of the tailings dam were utilised for this evaluation. The 3D displacement obtained from prism vectors were projected into the satellite's LOS using the local incidence angle ($\theta = 35.3^\circ$) and satellite heading angle ($\alpha = -13.27^\circ$) using the following relationship (Fialko et al. 2001):

$$d_{LOS} = d_v \cos(\theta) - d_e \sin(\theta) \cos(\alpha) + d_n \sin(\theta) \sin(\alpha) \quad (2)$$

where d_{LOS} is the projected 1D displacement along the satellite line of sight; d_v , d_n , and d_e are the vertical, North/South, and East/West displacement components measured by the prisms, respectively which were temporally aligned and zeroed to a mutual baseline reference date of September 27, 2016 (Figure 8a). The observation window in the analysis was limited to this specific timeframe because all Sentinel-1 satellite images were taken from the exact same satellite path, orbit, and viewing angle. Images taken before this period used different viewing angles, which would measure ground movement in different directions and cannot be directly combined into a single time series.

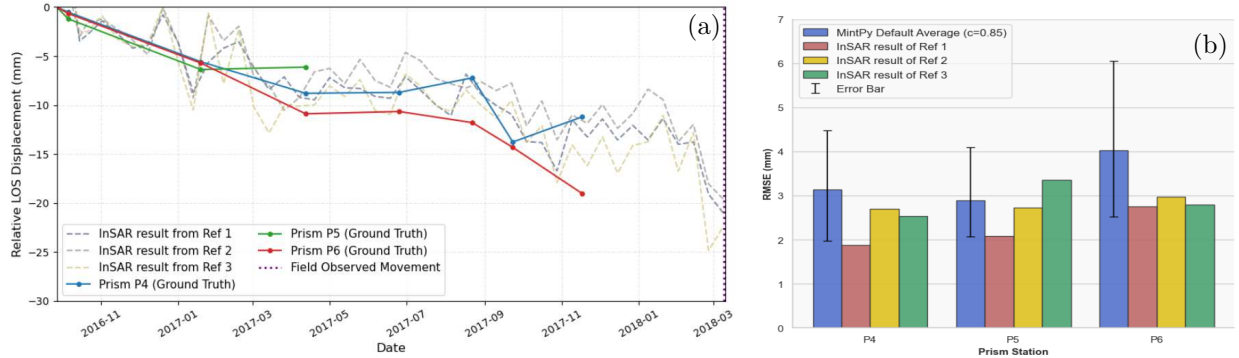


Fig. 8: (a) Time series comparison of InSAR displacement from shortlisted reference points against prism monitoring data; (b) Comparison of RMSE between default Mintpy vs. proposed reference point selection approach.

Discrepancies between InSAR and field prism observations arise primarily from geometric projection differences, where 3D field displacements is projected onto a single 1D satellite (d_{LOS}) (Chang et al. 2025). To evaluate this relationship, RMSE and the Pearson correlation coefficient (r) were used to evaluate the InSAR time series against prism data. While the default MintPy approach ($S_c=0.85$) exhibited high RMSE variability due to the random selection of reference points from high-coherence candidates (Yunjun et al. 2019), Ref 1 achieved the highest correlation with ground truth across all three prisms, corroborating the theoretical framework (Table 3, Figure 8b). While default selection algorithms are prone to stochastic error, the proposed framework identified a stable reference point, yielding an average RMSE of 2.24 mm and a Pearson r of 0.85. This represents approximately a 50% reduction in error compared to the potential worst-case default selection, effectively mitigating the risk of localised phase instability.

Table 3: Statistical performance evaluation of different reference point selection strategies against insitu prism data

Approach	RMSE (mm)				Pearson r			
	P4	P5	P6	Avg.	P4	P5	P6	Avg.
InSAR Ref 1	1.88	2.08	2.75	2.24	0.89	0.74	0.91	0.85
InSAR Ref 2	2.70	2.73	3.97	3.13	0.81	0.61	0.85	0.76
InSAR Ref 3	2.54	3.36	2.79	2.90	0.84	0.67	0.87	0.79
Mintpy Default	1.97-4.47	2.09-4.09	2.52-6.05	-	0.66-0.90	0.43-0.74	0.71-0.92	-

*MintPy default statistics represent the distribution obtained across 10 randomized single-pixel reference selections under standard coherence threshold constraints.

While recent InSAR investigations of tailings dam failures have demonstrated the capacity of time-series methods to understand pre-collapse deformation history, they lacked in-situ instrumentation to validate the workflow (Duan et al. 2023). In this study, we overcome this limitation by validating our reference point selection framework with direct in-situ field measurement results.

4.4 Ablation Study

To demonstrate the efficacy of the proposed methodology, a systematic ablation study was conducted by selectively disabling individual filters based on Figure 1. The observation of the various ablation scenarios are provided in Figure 9 and Table 4, and detailed observations from each ablation case are discussed below:

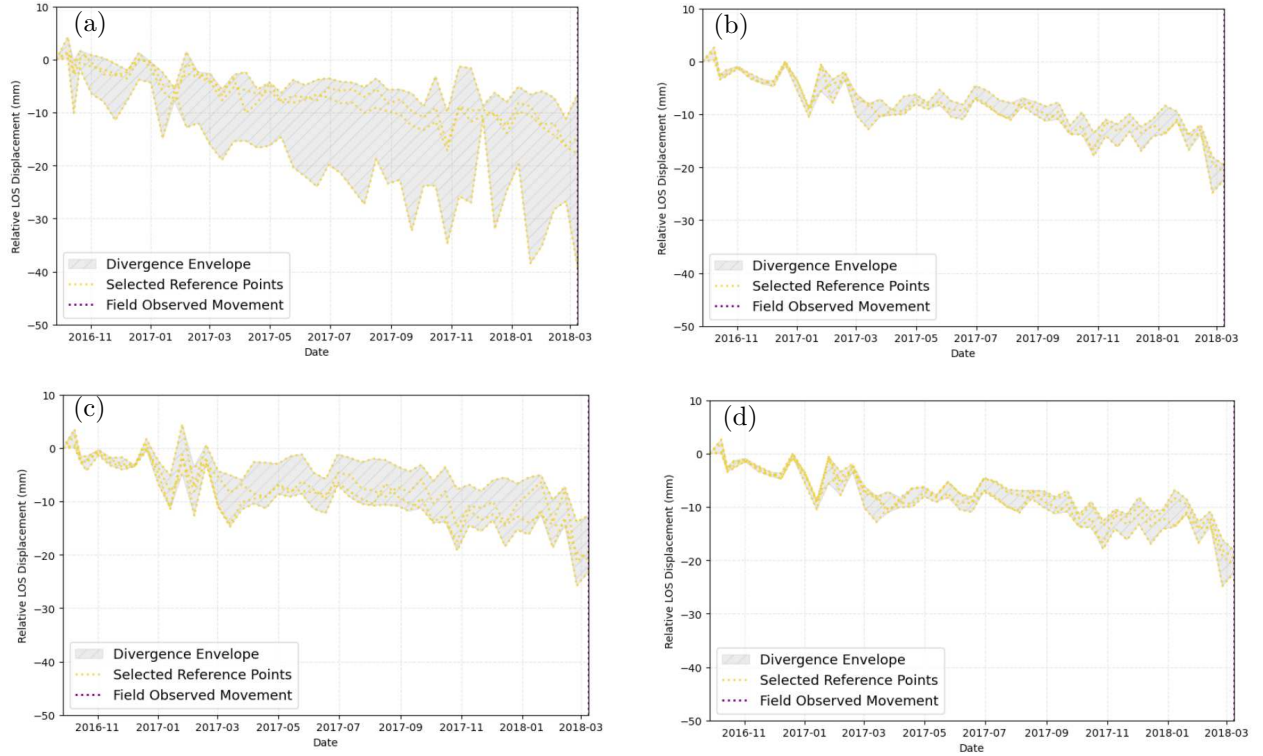


Fig. 9: Visual validation of algorithmic internal consistency across baseline and ablation scenarios: (a) A1; (b) proposed approach (also representative of A2 and A5); (c) A3; (d) A4

- i. Bypassing Topological Constraints: It had the maximum spread ranging from 6.79 mm to 33.02 mm and linear drift rates of 14.76 mm/yr (Figure 9a). Without these constraints, the algorithm is prone to selecting unstable pixels affected by phase unwrapping errors, leading to significant long term inconsistency.
- ii. Bypassing Connectivity Parameters: It yielded identical results to the baseline because coherent pixels were already clustered in continuous blocks (Figure 9b). However, these constraints remain vital in vegetated or aquatic regions (Zhang et al. 2024), where isolated pixels frequently trigger phase unwrapping errors.

Table 4: Quantitative evaluation and ablation study of reference point selection strategies across five experimental scenarios.

Scenario	Max Spread (mm)	Avg Spread (mm)	Max Drift Diff. (mm/yr)	Mean Pairwise Pearson r	Mean Pairwise RMSE (mm)
Proposed Approach (Baseline)	6.79	2.70	2.63	0.953	2.28
A1 (Without S_c & C_p)	33.02	14.93	14.76	0.833	8.92
A2 (Without C_f & P_c)	6.79	2.70	2.63	0.953	2.28
A3 (Without A_{min} , N_d & N_w)	12.92	6.76	6.60	0.879	4.39
A4 (Without I_d)	8.72	3.15	3.90	0.955	2.23
A5 (Without Masking)	6.79	2.70	2.63	0.953	2.28

- 279 iii. Bypassing Spatial Filters : It doubled the maximum spread to 12.92 mm and increased the drift rate to
280 6.60 mm/yr (Figure 9c). This was due to selection of isolated and high coherence pixels, such as unstable
281 boulders or structures with high backscatter characteristics.
- 282 iv. Bypassing Island Distance: It had negligible impact with a maximum spread of 8.72 mm and drift difference
283 of 3.90 mm/year (Figure 9d). However, its absence risks localised clustering, which may introduce spatial
284 bias into the final analysis.
- 285 v. Bypassing Unstable Zone Masking: Results were identical to the baseline, proving the algorithm’s filters can
286 independently identify deformation (Figure 9b). However, manual masking remains necessary to prevent
287 coherent, smooth deformation from being misidentified as a stable reference.

288 4.5 Sensitivity Analysis and Parameter Optimization

289 Sensitivity analysis quantified the impact of threshold parameters, identifying topological constraints (C_p and
290 S_c) as the primary determinants of stability (Figure 10). Relaxing C_p from 0.7 to 0.5 increased the maximum
291 spread by nearly 80%, while strict thresholds ($S_c=0.9$ and $C_p=1$) filtered the entire dataset conforming that
292 small decorrelation are necessary to obtain viable stable region. Conversely, I_d (tested from 0 - 30 pixels) had
293 the least severe impact among all parameters, with results remaining consistent up to 25 pixels. Similarly, N_d
294 was also found to be critical, and increasing its value to 1 might be theoretically valid but was impractical
295 in real world scenario as it led to sharp increase in RMSE. For spatial filters, increasing the N_w from 2×2
296 to 8×8 pixels had a moderate impact but 10×10 was too restrictive resulting in an empty set. Finally,
297 increasing A_{min} from 0 to 100 reduced the spread by filtering small and fragmented areas, but had minimal
298 impact on the overall result.

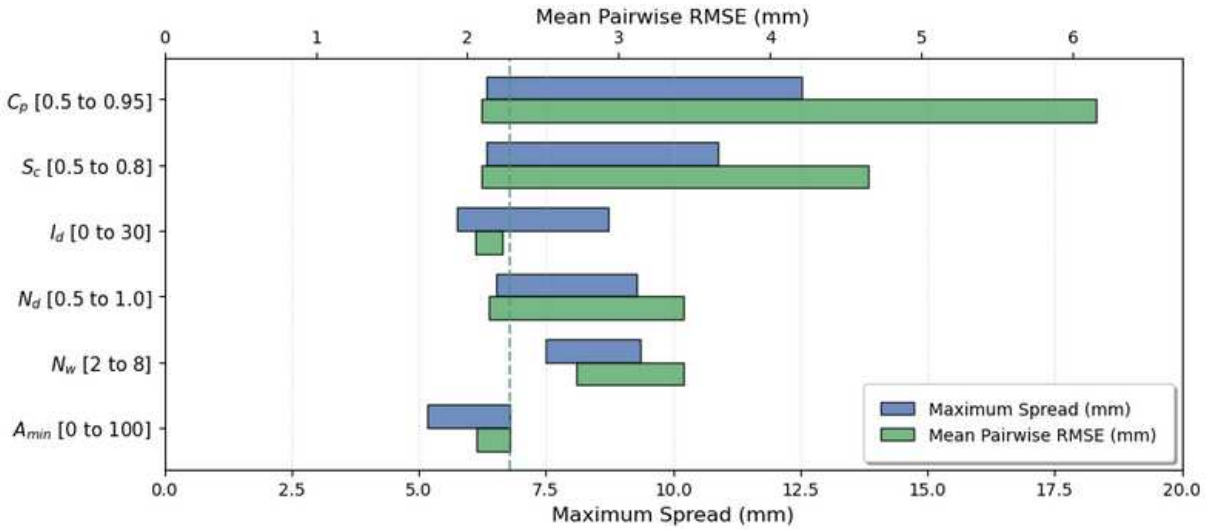


Fig. 10: Tornado diagram illustrating the sensitivity of the geodetic datum to six primary filtering parameters. The top axis tracks Maximum Internal Spread (blue) and the bottom axis tracks Mean Pairwise RMSE (green) . The dashed line represents the baseline value.

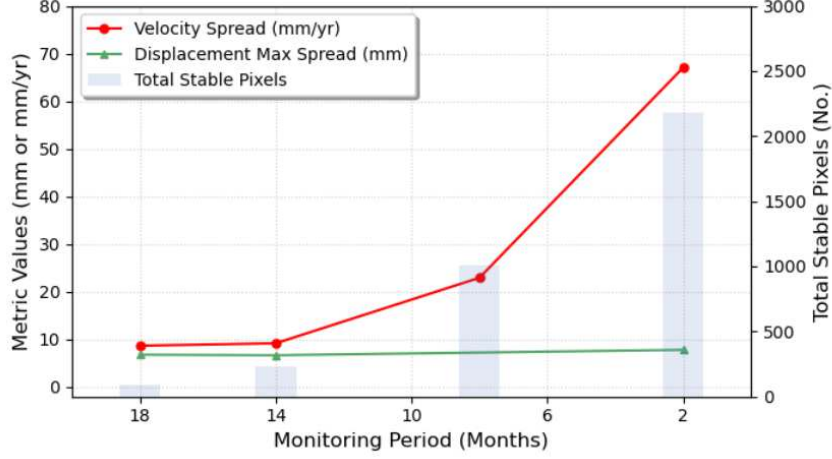


Fig. 11: Dual axis spatio-temporal robustness analysis evaluating the impact of SAR observation stack duration. The metrics include total stable pixel density, maximum spatial displacement spread, and velocity spread.

Table 5: Temporal robustness metrics comparing spatio-temporal consistency across varying observation windows

Scenario	Duration	Islands (<i>N</i>)	Total Pixels	Max Spread (mm)	Velocity Spread (mm/yr)
Baseline	18 Months	3	93	6.79	8.68
Test A	14 Months	2	229	6.68	9.19
Test B	8 Months	1	1011	-	22.94
Test C	2 Months	3	2183	7.81	67.04

4.6 Temporal Robustness and Spatio-Temporal Consistency

To validate the reliability of the proposed algorithm, a temporal robustness analysis was carried out by progressively shortening the SAR observation stack across various scenarios. This analysis evaluated the relationship between spatial pixel density and temporal velocity as detailed in Table 5 and Figure 11. The result shows that reducing the temporal window increased the number of stable pixels by over 2,200% (from 93 to 2,183 pixels). This validates the findings of Villarroya-Carpio et al. (2024), who observed that dry soil and sparse vegetation maintain high coherence over short intervals but suffer from temporal decorrelation as the baseline increases. Despite the increase in stable pixel count, the maximum spatial spread among stable islands remained highly consistent for observation periods exceeding one year, varying by only 0.11 mm between the Baseline and Test A. However, only a single stable island was obtained under intermediate temporal baselines (Test B) and in short time period the velocity error jumped to 67.04 mm/yr but decreased significantly over time. This demonstrated that that longer observation periods are essential to accurately measure displacement rates.

5 Conclusion and Recommendation

While InSAR is a powerful tool for high resolution monitoring, its adoption within civil engineering remains limited. This research bridges the gap between remote sensing observation and engineering application by demonstrating that InSAR accurately captures complex field behaviour when anchored by a stable reference point. Our study introduces Multi Criteria approach for reference point selection in temporal InSAR applications. We evaluated the effectiveness of this method by comparing InSAR deformation with the field measured deformation at Cadia Dam, Australia. The proposed method was able to find the optimum reference point for estimating the deformation with higher accuracy as compared to other approaches. The workflow is highly compatible with open source timeseries processing platforms like ISCE2 and MintPy, providing a solution for deformation studies. Crucially, it is necessary to understand that multi-parametric thresholds governing this workflow must be calibrated according to site-specific conditions (Zhang et al. 2024).

Comparison of the proposed algorithm with in-situ prism data confirms that the algorithmically selected reference points are statistically consistent with ground truth. To achieve this reliability, the regional stacking approach successfully mitigates localized atmospheric changes and spatially correlated noise by utilizing the group mean phase of stable candidates. Furthermore, a sensitivity analysis identified topological phase constraints (C_p and S_c) as the primary drivers of geodetic accuracy, while spatial constraints such as A_{min} and I_d played a vital role in suppressing localized noise. An ablation study further identified topological constraints and spatial filtering parameters as the primary factors governing reference point selection. Although connectivity and masking were non-impactful in this specific case, they remain essential for maintaining reliability in more decorrelated environments. Finally, while evaluation of temporal robustness showed low internal spread across the tested observation windows, the resulting large velocity uncertainties demonstrate that an observation period greater than one year is essential for accurate monitoring.

Author contributions

Kobid Panthi: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing-original draft, Visualization; **Jagannath Aryal:** Conceptualization, Supervision, Project administration, Funding acquisition, Writing-review & editing; **Yinghui Tian:** Supervision, Validation, Writing-review & editing; **Yifa Wang:** Supervision, Validation, Writing-review & editing.

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Declaration of Generative AI Use

During the preparation of this manuscript, the author used Gemini 3.1 to enhance the clarity and grammatical flow of the text. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the integrity and accuracy of the submitted work.

Data availability statement

The dataset and Python scripts generated in this study are publicly available in Melbourne Figshare at <https://doi.org/10.26188/31985604>. The raw Sentinel-1 SLC imagery used in this study was retrieved from the NASA Alaska Satellite Facility (ASF). The dataset was filtered for descending orbit over the Cadia region (Location: 149°E, 33.5°S) for the period September 2016 to March 2018. Data are accessible via the ASF Vertex portal <https://search.asf.alaska.edu/>.

Declarations

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