



An Optimized Method for Slope Deformation Monitoring via Parallel-Track InSAR Data Fusion

Aoyang Liu¹, Bingquan Chen¹, Fengyu Chen², Yizhuo Meng³, Lingjun Kong⁴, and Wen Zhang¹

¹School of Remote Sensing and Information Engineering, Wuhan University, 299 Bayi Road, Wuhan 430072, Hubei, China

²Water Development and Research Center, Taihu Basin Authority, Shanghai 200438, China

³Thomas Lord Department of Computer Science, University of Southern California, Los Angeles, CA 90089, USA

⁴Open Platform Product Department, China Mobile IoT Co., Ltd., Chongqing 401121, China

Correspondence: Wen Zhang (wen_zhang@whu.edu.cn)

Abstract. This study addresses geometric distortion in SAR imagery caused by complex topography in reservoir areas, which adversely affects the accuracy of InSAR monitoring. A multi-orbit data fusion technique is proposed, integrating the R-Index(im) with an improved Geometric Distortion (GD) Index. Using the study landslide mass at Danjiangkou Reservoir as a case study, the research leverages Sentinel-1A satellite data. The GD index model is optimized by incorporating a shadow effect coefficient (Sh). Combined with the R-Index(im) 's capability for distortion-region identification, an adaptive weighted fusion model is established. Empirical analysis demonstrates that this approach effectively corrects deformation monitoring biases caused by geometric distortion. Compared to single-orbit data, the fusion results reduce deformation rate errors by 0.02 mm/year and 0.36 mm/year, while expanding the monitoring coverage by 32%. Verification against GNSS ground-truth data confirms that this method significantly enhances the accuracy and reliability of InSAR monitoring in complex terrain, offering an effective technical solution for reservoir landslide early warning.

1 Introduction

As a major geological hazard threatening critical infrastructure and public safety in mountainous regions (Xu et al., 2023), landslides accounted for over half of all geological disasters in China between 2013 and 2022 (Valkaniotis et al., 2018).

Reservoir landslides, in particular, are highly susceptible to instability due to periodic water-level fluctuations, which alter the geotechnical properties of slope materials (Zhang et al., 2024). Several studies have demonstrated that reservoir impoundment can reactivate ancient landslides or trigger new ones along reservoir banks (Li et al., 2019; Zhao et al., 2018). Tu et al. (2025) employed DInSAR with overlapping Sentinel-1 SAR data to investigate landslide deformation in the Three Gorges Reservoir area, revealing significant correlation between deformation patterns and water level variations.

While traditional monitoring technologies (such as total stations and global navigation satellite systems) offer high precision, their limited spatial coverage and high implementation costs restrict widespread application (Huo et al., 2015). In contrast, Interferometric Synthetic Aperture Radar (InSAR) has emerged as a crucial technique for landslide monitoring due to its wide-area coverage and high precision (Zhu et al., 2022). In particular, time-series InSAR methods, such as Persistent Scatterer InSAR (PS-InSAR) and Small Baseline Subset (SBAS-InSAR), have been widely applied to detect and quantify slow-moving



landslides with millimeter-level accuracy (Osmanoglu et al., 2016; Perissin et al., 2012). Ground-based SAR interferometry has also demonstrated significant capability for localized deformation measurement (Monserrat et al., 2014). However, its application in complex terrain areas still faces notable limitations.

In complex terrain environments such as reservoir areas, the side-looking imaging mode characteristic of SAR satellites induces geometric distortions, including foreshortening, layover, and shadow, severely compromising the reliability of InSAR monitoring data (Hanssen, 2001). Researchers have proposed various models and mitigation strategies at different stages.

Colesanti and Wasowski (2006) developed the P-NG method to simulate imaging distortions. They assessed radar visibility based on slope aspect angle to identify slope aspect ranges prone to distortion. Notti et al. (2010) proposed the R-index model, which calculates the ratio of radar slant range to actual ground distance. Based on its numerical range, this model distinguishes between perspective shrinkage and shadow regions and analyzes geometric distortion decoherence using PS point density. In subsequent research, the team further incorporated shadow effect and layover effect parameters, enhancing its applicability in steep slopes and shadowed areas (Notti et al., 2014).

To overcome the R-index's limitations in effectively distinguishing good visibility zones from active shadow zones, Ren et al. (2021) introduced a long-range passive layover coefficient, developing an improved R-index model. This model demonstrated superior efficiency in assessing occlusion effects under complex terrain compared to traditional P-NG methods. Dai et al. (2022, 2021) quantitatively evaluated geometric distortion in the Qinghai-Tibet Plateau using Sentinel-1A ascending/descending data, further elucidating the relationship between radar line-of-sight displacement, actual slope displacement, and geometric distortion. Recently, Deng et al. (2025) proposed a robust LOS sensitivity correction framework for retrieving slope-parallel displacements from single-track InSAR observations, demonstrating that topographic parameters critically influence the conversion between LOS measurements and true landslide displacements. Wang et al. (2024a) developed a three-dimensional deformation rate calculation method incorporating quantitative geometric distortion information. They derived the relative length error between the radar and the ground in the range direction as the basis for range distortion, and solved the three-dimensional deformation rate by integrating multi-source, multi-orbit SAR data. Results indicate that this weighted strategy enhances the overall accuracy of deformation solutions. Wang et al. (2024b) proposed a two-dimensional geometric distortion quantification model based on the pixel-to-ground-area ratio and applied it to fuse parallel-orbit deformation rates, effectively mitigating distortion's impact on deformation monitoring.

Although geometric distortion assessment methods such as the R-index and GD index have been developed, systematic research on multi-orbit data fusion remains insufficient, hindering the full exploitation of complementary effects from different orbital data. Recent studies have demonstrated that combining ascending and descending orbit InSAR data can effectively compensate for geometric distortion-induced monitoring blind spots and improve deformation field reconstruction (Wang et al., 2025a; Li et al., 2025). Particularly in densely vegetated areas, signal decoherence further amplifies the impact of geometric distortion, significantly degrading monitoring data quality (Tao et al., 2025). InSAR-based landslide monitoring has been further advanced through integration with other data sources. Cernuto et al. (2025) combined InSAR monitoring with numerical modelling to analyze landslide-bridge interactions, demonstrating that integrated approaches provide more detailed deforma-



tion information than either method alone. For automated detection of deformation features, deep learning techniques have shown promising results in extracting deformation signals from satellite imagery (Anantrasirichai et al., 2019).

60 To address these technical challenges, this study developed a novel deformation monitoring method based on parallel-orbit InSAR data fusion, using the study landslide mass at Danjiangkou Reservoir as a case study. By refining the GD index model and integrating the distortion detection capability of the R-Index(im), this approach constructs an adaptive weighting fusion model. The research outcomes not only enhance the accuracy and reliability of InSAR monitoring in complex terrain but also provide robust technical support for reservoir landslide disaster early warning and prevention efforts.

65 2 Study Area and Data Sources

2.1 Study Area

The study area encompasses the study landslide within the Danjiangkou Reservoir region, located in Shiyan City, Hubei Province. As shown in Fig. 1, the study area covers approximately 100 square kilometers, including the landslide and its surrounding areas, spanning roughly 12 km east-west and 10.6 km north-south.

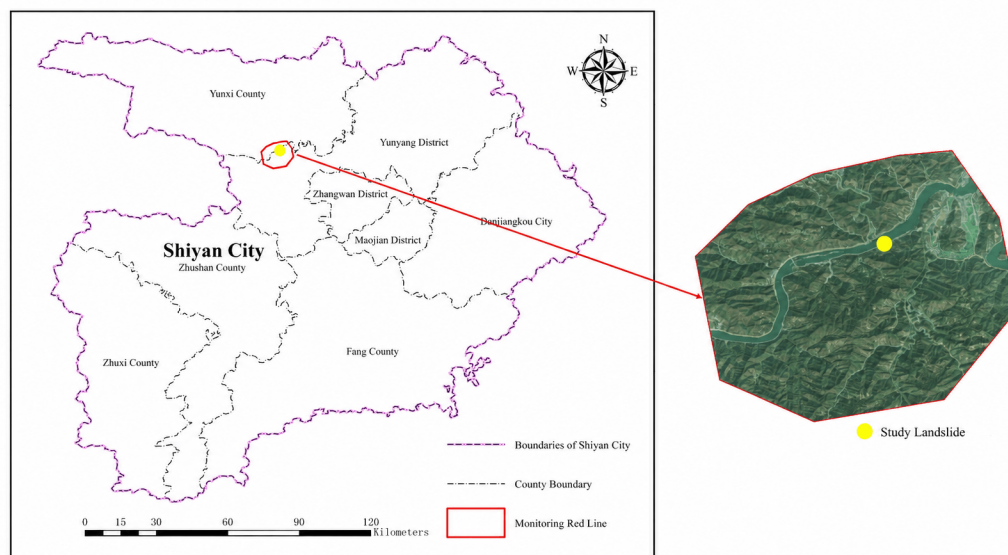


Figure 1. Schematic of study Landslide and Surrounding Area Coverage and Topography. Basemap source: Tianditu (National Platform for Common Geospatial Information Services of China).

70 The terrain and topography of this area are predominantly mountainous and hilly, with significant elevation variations reaching up to 580 meters. Vegetation coverage is high, and the terrain is complex. Regarding geological hazards, the right bank of the Han River is a high-risk landslide zone. The study landslide, a typical near-dam landslide, serves as a representative



geological hazard site in this area. Since its inclusion in the geological hazard monitoring and early warning system in May 2014, it has become one of the 30 key monitoring points for prevention and control at the Danjiangkou Reservoir. Its inclusion
 75 in the system has highlighted that reservoir high-water-level operation exacerbates landslide risks. Furthermore, the study area is situated in a critical zone of the South-to-North Water Diversion Project, adjacent to hydropower dam structures, where instability could potentially compromise dam safety.

2.2 Research Data

2.2.1 Sentinel-1A Satellite Data

- 80 This study utilizes C-band SAR data from the European Space Agency (ESA) Sentinel-1A satellite. A total of 121 SLC images were selected: 55 from an eastern ascending orbit (Path11Frame101) from October 2021 to 2023, and 66 from a western ascending orbit (Path84Frame100) from October 2021 to December 2024. The spatial relationship between the study area and adjacent orbits is shown in Fig. 2.

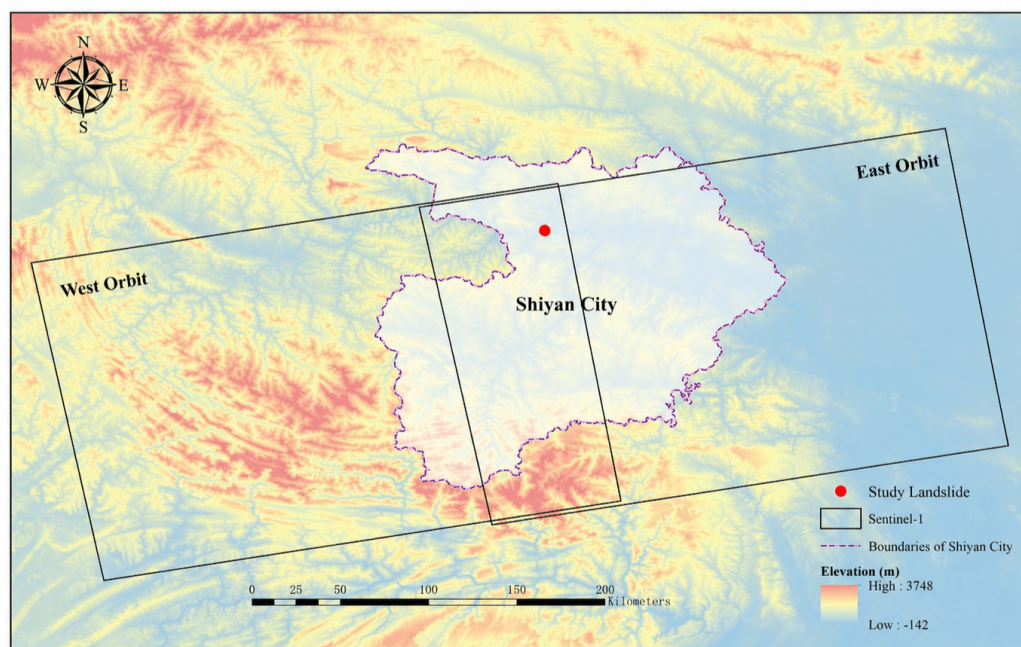


Figure 2. Spatial orientation of adjacent orbits relative to the study area

Key technical parameters are summarized in Table 1:



Table 1. Sentinel-1 Satellite System Parameters

System Parameter	East Orbit SAR Image Set	West Orbit SAR Image Set
Orbital Orientation	Ascending Orbit	Ascending Orbit
Radar Wavelength	5.6 cm	5.6 cm
Operating Band	C-band	C-band
Spatial Resolution	5 m × 20 m	5 m × 20 m
Azimuth	Approx. 347°	Approx. 347°
Average Incidence Angle	Approx. 34°	Approx. 44°

85 **2.2.2 Digital Elevation Model Data**

This paper employs two distinct digital elevation model datasets tailored to different task requirements. SRTM-1 (Shuttle Radar Topography Mission) DEM: Featuring 30-meter resolution, it is primarily used for image registration, terrain phase simulation, and other preprocessing tasks. ALOS (Advanced Land Observing Satellite) DEM: Launched by the Japan Aerospace Exploration Agency (JAXA), with a resolution of 12.5 meters. Its L-band data exhibits strong penetration capabilities and superior terrain detail representation, making it suitable for precise geometric distortion analysis.

95 **2.2.3 GACOS Atmospheric Correction Data**

GACOS (Generic Atmospheric Correction Online Service) atmospheric correction data features a spatial resolution of approximately 93 meters. Its core algorithm employs the Iterative Tropospheric Decomposition (ITD) model, which is utilized in this study to eliminate tropospheric delay phase errors. This significantly enhances monitoring reliability in complex terrain areas.

95 Tropospheric delay remains one of the primary error sources in InSAR deformation monitoring, particularly in mountainous areas where elevation-dependent atmospheric effects can be substantial (Dong et al., 2019; Wang et al., 2022). Advanced correction methods, including Tikhonov regularization-based modelling (Kirui et al., 2022) and spatially varying stratified delay correction (Liang et al., 2023), have been developed to mitigate these effects.** Additionally, recurrent neural networks have shown promise in removing atmospheric noise from InSAR time series, including handling missing values (Zhao et al., 2021).

100 Recently, Xie et al. (2026) proposed a quadtree wavelet multiresolution approach for correcting heterogeneous topography-correlated tropospheric delays in mountainous landslide monitoring, further enhancing the accuracy of deformation estimates.

2.2.4 GNSS Ground Monitoring Data

Eleven GNSS monitoring stations were deployed. Excluding TP03 due to equipment failure, data from stations TP01–TP12 (excluding TP03) were used, covering 66 monitoring periods from October 2021 to December 2024. Fig. 3 shows the spatial distribution pattern of GNSS monitoring stations in the study area. The spatial distribution of stations balances vegetation zones and road alignments, thereby validating and correcting InSAR results.

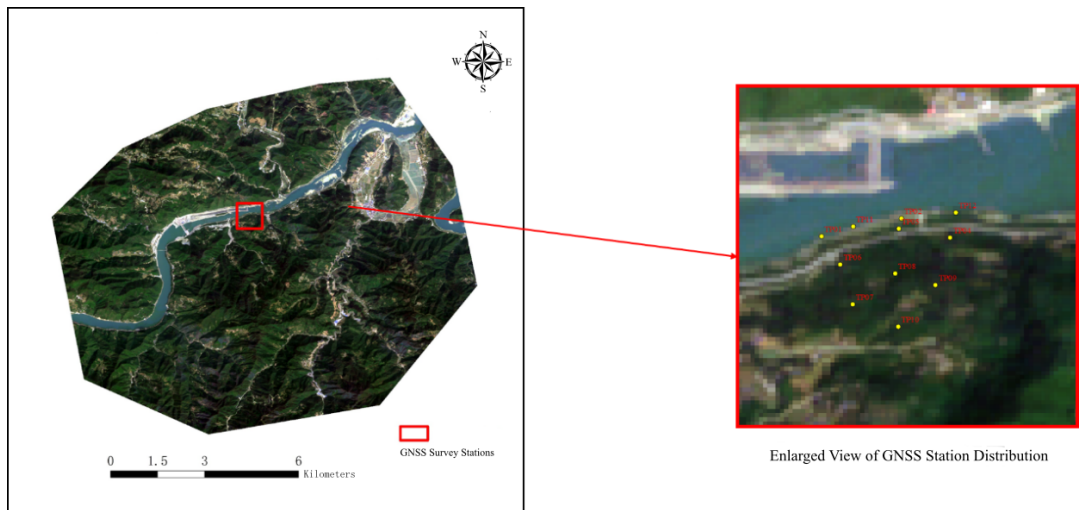


Figure 3. Distribution Map of GNSS Survey Stations. Contains modified Copernicus Sentinel-2 data 2024.

2.2.5 ERA5-Land Precipitation Data

The ERA5-Land dataset, released by the European Centre for Medium-Range Weather Forecasts (ECMWF), is a global land reanalysis dataset. This study systematically processed precipitation data for the study area using the Google Earth Engine (GEE) cloud computing platform. The data exhibit a decadal temporal resolution spanning October 2021 to December 2023. The spatiotemporal distribution characteristics of precipitation in the study area are shown in Fig. 4, with the primary feature being concentrated precipitation during the summer and autumn months (June–October), peaking at 130.4 mm.

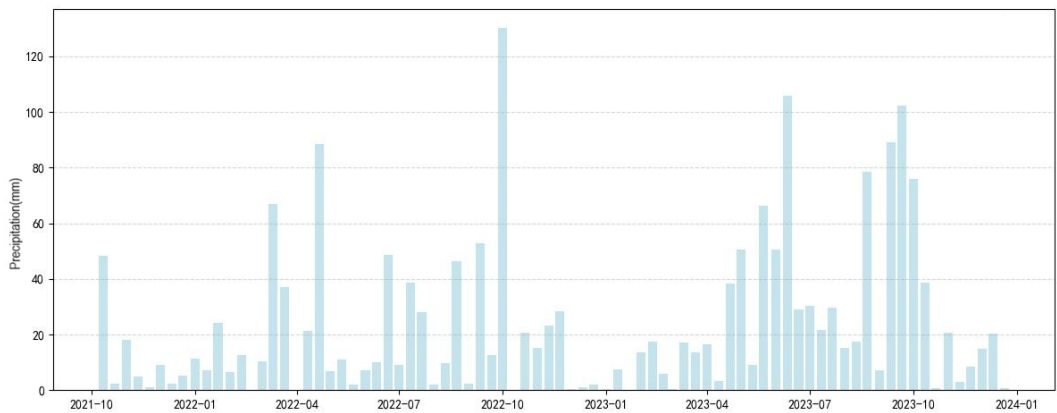


Figure 4. Bar Chart of Decadal-Scale Precipitation Distribution in the Study Area

3 Method

To address geometric distortion issues in InSAR landslide monitoring over complex terrain, this study proposes a parallel-orbit deformation fusion method based on a combined geometric distortion index. The method first utilizes high-precision DEM and satellite parameters to calculate the R-Index(im) and the improved GD index, respectively. The former effectively identifies distortion types such as shadow and layover, while the latter precisely quantifies distortion severity. Subsequently, the time-series deformation results from master-slave orbits obtained via SBAS-InSAR are unified along the radar line-of-sight direction. An adaptive fusion weighting model is constructed, with the GD index as the primary factor and the R-Index(im) as a constraint, enabling weighted fusion of parallel orbits. The experimental workflow is illustrated in Fig. 5.

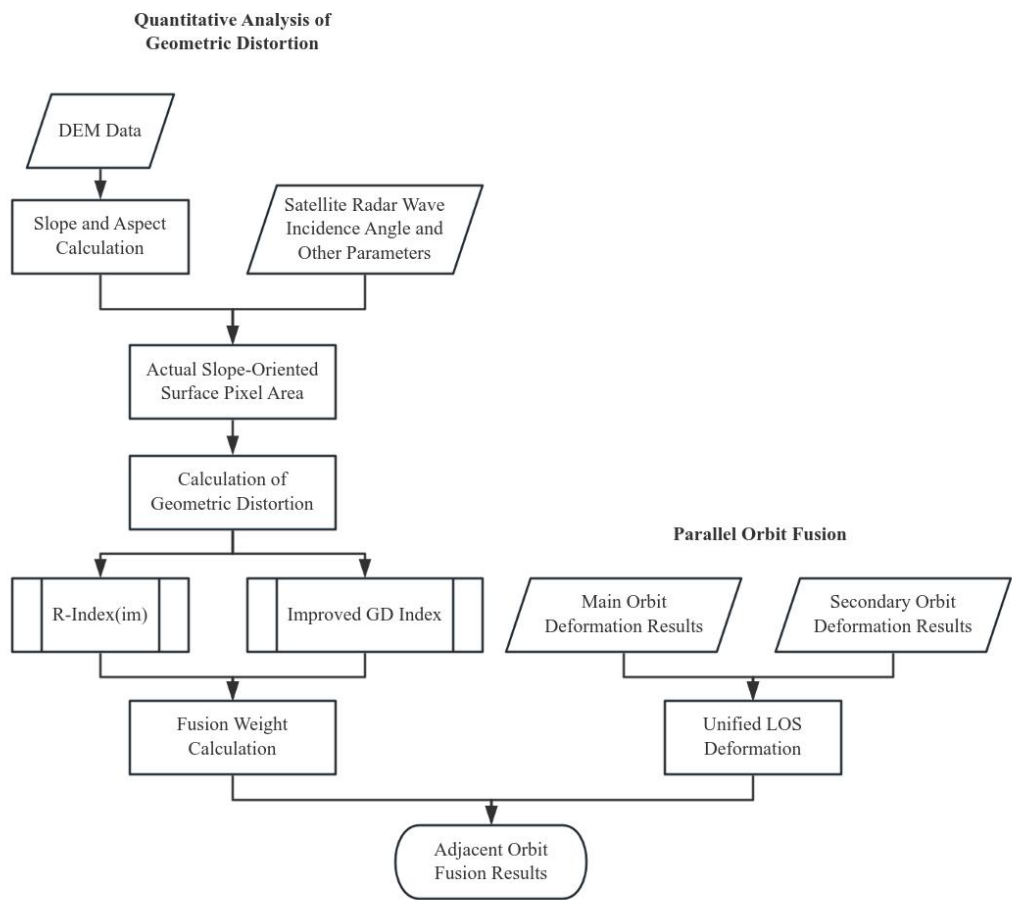


Figure 5. Technical Workflow



3.1 Analysis of Geometric Distortion Features in SAR Images

During side-looking imaging, SAR satellites produce various geometric distortions due to the relative spatial relationship between ground features and the radar. These distortions primarily fall into three categories: foreshortening, layover, and shadow. Characterizing these distortions forms the foundation for subsequent research.

125 (1) Foreshortening: When a slope faces the radar direction with an inclination angle α smaller than the incident angle θ , the angle between the radar wave's path and the ground surface decreases. Consequently, the projected distance of the same feature on the image plane also shortens. Although the signal-to-noise ratio in this region is high, allowing some bright pixels to be extracted and monitored using time-series InSAR methods, it compromises the accuracy of deformation estimation.

(2) Layover: When the slope angle α exceeds the incident angle θ , echo signals from the slope crest arrive before those from
 130 the slope foot. This causes higher-elevation features to “layover” onto lower-elevation features in the image, forming an active layover zone. Adjacent areas affected by this phenomenon constitute a passive layover zone, exhibiting signal instability and temporal phase incoherence that severely compromise subsequent deformation studies.

(3) Shadow: When slopes incline away from the radar direction and the slope angle α exceeds the complementary angle of the incident angle, the radar beam cannot illuminate this region, creating an active shadow zone. Areas beyond the shadow
 135 zone experience significantly reduced echo energy due to terrain obstruction or scattering, forming a passive shadow zone. This makes it difficult to generate deformation points in SAR imagery.

3.2 Geometric Distortion Assessment Models

3.2.1 R Index

The R index model, first proposed by Notti et al. (2010), calculates the distance-direction distortion estimate based on the ratio
 140 of the projected length of a ground feature point along the slant range to its actual distance from the ground.

The original R-index model assigns integer values to both areas with good visibility and areas with active shadows, failing to effectively distinguish between these two types of regions. Furthermore, this model cannot identify passive layover areas and passive shadow areas caused by adjacent terrain. Therefore, this paper does not analyze the original R-index model. Notti et al. (2014) improved this model by introducing shadow coefficients(Sh) and layover coefficients(La).

145 Both coefficients can be calculated using the Mountain Shade Model based on ArcGIS: Sh is computed by setting the satellite position as the “light source” and modeling using the LOS azimuth ϕ and its complementary incident angle $(\frac{\pi}{2} - \theta)$. La is computed by modeling using the reverse LOS azimuth $(\phi + \pi)$ and the original incident angle θ . In the output of the Sh model, areas where $Sh > 0$ are reclassified as 1, indicating areas with unobstructed line-of-sight; areas where $Sh = 0$ represent shaded regions.



150 3.2.2 R-Index(im)

Ren et al. (2021) improved the R-index model proposed by Rotti by incorporating the geometric mechanism of long-range passive stacking. They introduced the long-range passive stacking coefficient (Lr) to derive the R-index(im), calculated as follows:

$$R_{im} = \cos \gamma = \sin \theta + \arctan(\tan \alpha \cdot \cos \phi - \beta \cdot S_h \cdot L_a \cdot F_a) \quad (1)$$

155 In Equation(1), Lr equals 0 within passive overlay regions and 1.0 elsewhere. This coefficient can be calculated using ArcGIS's Mountain Shade Model by inputting an inverted DEM model, setting the light source elevation angle to the satellite's line-of-sight incidence angle, and setting the light source azimuth angle to the opposite direction of the satellite's line-of-sight. Ultimately, the R-index(im) takes values within the range shown in Table 2. The improved R-index model demonstrates significant advantages in identifying distant passive occlusion zones and enhancing InSAR data screening accuracy, particularly for
 160 landslide monitoring in complex mountainous terrain. However, its dependence on DEM resolution and simplified LOS parameter assumptions remains a key limitation. Future optimization may be achieved through dynamic LOS parameter modeling and multi-source data fusion.

Table 2. R-index(im) Range

R-index(im) Range	Region Type	Radar Line-of-Sight Visibility
$R\text{-index(im)} \geq \sin(\theta)$	Visibility Good Zone	High
$0 < R\text{-index(im)} < \sin(\theta)$	Perspective Contraction Zone	Medium
$R\text{-index(im)} = 0$	Overlay/Shadow Zone	Low

3.2.3 Improved GD Index

The GD index is a model proposed by Wang et al. (2024b) for two-dimensional quantitative analysis of geometric distortion. By introducing azimuthal distortion, this model extends the original one-dimensional distance distortion analysis to a
 165 two-dimensional area distortion analysis. Its core method involves calculating the ratio of pixel area in SAR imagery to the corresponding actual ground surface area, and incorporating a shadow coefficient to ultimately determine the geometric distortion value. The core advantage of the improved GD Index model lies in its effective resolution of geometric distortion challenges in InSAR monitoring of complex terrain through two-dimensional area distortion analysis and physically driven
 170 data fusion strategies. This significantly enhances the quality of deformation products and the accuracy of geological hazard identification. However, this improvement comes at the cost of increased computational complexity and higher demands on input data quality.

In the specific calculation process, for ascending SAR data, the model first determines the azimuth deviation between the terrain aspect and the satellite line-of-sight (LOS) direction based on the side-looking imaging geometry. Subsequently, the

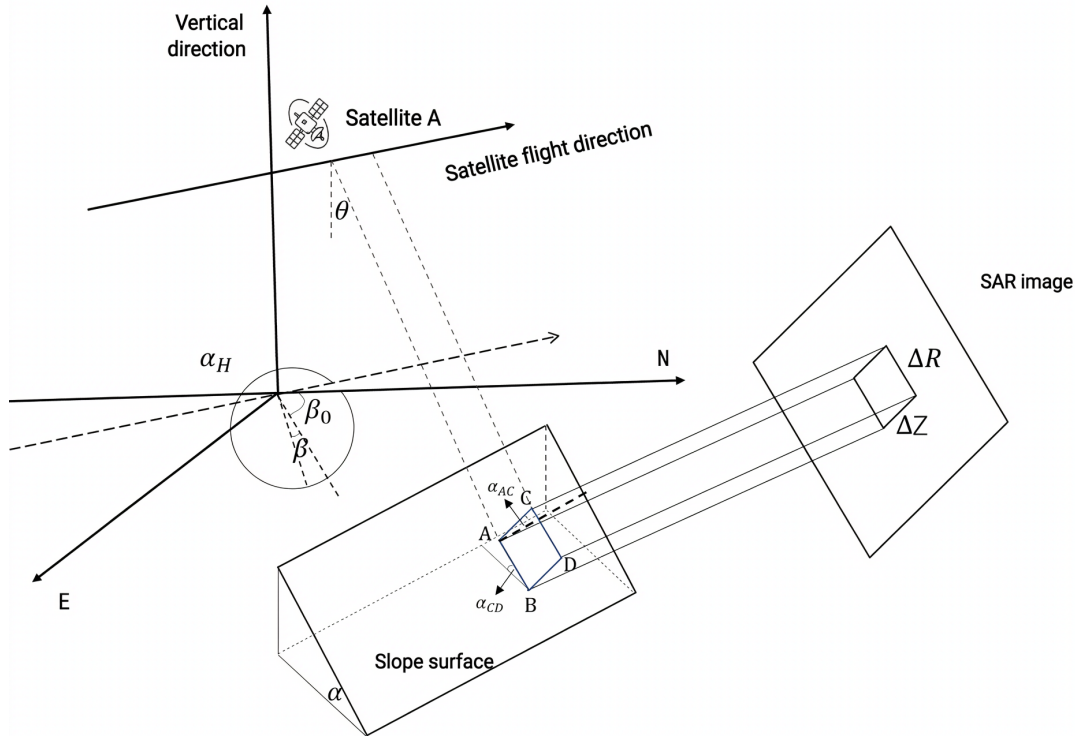


Figure 6. SAR Satellite Imaging Geometry Diagram

175 actual ground area corresponding to a single pixel in the SAR image is approximated as a rectangle. By integrating the range
 and azimuth resolutions of the SAR image, the satellite incidence angle, and the terrain slope information, the projected slope
 angles and projected lengths of the slope surface in both the range and azimuth directions are derived. After calculating the
 actual ground area corresponding to the pixel based on these geometric projection relationships, the 2D geometric distortion
 value is defined as the ratio of the SAR image pixel area to the actual ground area, and is ultimately corrected by incorporating
 180 the shadow coefficient.

3.3 Weighted Parallel Orbit Fusion Using Geometric Distortion Indices

Based on a comparative analysis of the improved R-Index(im) and GD distortion indices, this study finds that both possess com-
 plementary advantages in assessing geometric distortion in SAR imagery. The R-Index(im) demonstrates greater effectiveness
 in identifying shadowed and masked areas within images, making it more suitable for overall classification of distortion types
 185 across study regions. In contrast, the GD distortion index focuses on detailed pixel-level quantification of geometric distortion,
 enabling a more precise reflection of distortion severity across different areas.

To this end, this study proposes a weighting method that integrates two indicators and applies it to the weighted fusion of
 parallel-orbit InSAR deformation data. This approach enhances the representativeness and reliability of fusion results under



varying terrain conditions. By analyzing improvements in the spatial continuity of fused deformation data and validating results in representative regions, the effectiveness of this orbit fusion method in mitigating geometric distortion is evaluated.

The R-Index(im) comprehensively reflects changes in image visibility caused by terrain occlusion in the study area by integrating factors such as shading, layover, and perspective shrinkage. The improved GD distortion index places greater emphasis on the physical relationship between local slope, aspect, and radar incidence geometry. Combined with the Sh factor, it enhances shadow recognition accuracy and can more precisely characterize local geometric distortion features in complex terrain.

Given their complementary nature, this study employs the GD distortion index as the primary basis for weight calculation. Leveraging its capability to continuously quantify terrain distortion, it assigns differentiated weights to InSAR deformation data across varying spatio-temporal locations. Concurrently, shadow and occlusion regions identified by the R-Index(im) are introduced as spatial constraints to calibrate the GD weights. Specifically, when a pixel is identified by R-Index(im) as a potential shadow or layover area, it is excluded from the fusion calculation even if its GD value is small, thereby preventing low-quality data from influencing the results. This dual-constraint weighting model retains the continuous quantification advantage of the GD index while integrating the occlusion detection capability of R-Index(im), achieving more refined spatially adaptive fusion.

At the implementation level, the deformation rates from both orbits are first unified into the same coordinate system through geocoding and Kriging interpolation. To eliminate baseline errors and ensure consistency in deformation direction, the orbital deformation results are projected onto the primary orbital line-of-sight direction (Chaussard et al., 2015).

Based on the complementary characteristics of R-Index(im) and the improved GD distortion index, the GD distortion index serves as the primary weighting basis for calculations, while the shadow and layover regions identified by R-Index(im) are applied as constraint conditions. The specific weighting formula is as follows:

$$210 \quad \begin{cases} P_M = 1, P_S = 0, & \text{if } Rim_S = 0, Rim_M > 0 \\ P_M = 0, P_S = 1, & \text{if } Rim_S > 0, Rim_M = 0 \\ P_M = 0, P_S = 0, & \text{if } Rim_S = Rim_M = 0 \\ P_M = \frac{\sigma_S}{\sigma_M + \sigma_S}, P_S = \frac{\sigma_M}{\sigma_M + \sigma_S}, & \text{if } Rim_M > 0, Rim_S > 0 \end{cases} \quad (2)$$

Where parameters are defined as follows: P_S and P_M represent the fusion weights for the sub-orbit and main orbit, respectively; σ_S and σ_M correspond to the R-Index(im) values for the sub-orbit and main orbit, respectively; and denote the improved GD distortion index values for the sub-orbit and main orbit, respectively. To maximize monitoring data utilization, data from a single orbit is retained to expand coverage in areas with low geometric distortion. In layover regions, weighted fusion based on geometric distortion weights is applied to achieve more complete and accurate deformation distribution results.



4 Results and Analysis

Based on the theoretical framework and methodology described in the preceding sections, this section presents a comprehensive evaluation of the experimental results. The analysis is organized into two main parts: first, the geometric distortion assessment of dual-orbit SAR imagery is conducted using both the R-Index(im) and the improved GD distortion index; second, the effectiveness of the proposed weighted fusion strategy is validated through comparative analysis with single-orbit results and independent GNSS measurements. All experimental data were processed using the same parameter settings to ensure comparability across different orbits and fusion schemes.

Geometric distortion is a fundamental factor affecting the quality and interpretability of SAR imagery, particularly in mountainous reservoir areas with complex terrain. To systematically characterize the distortion patterns of the study area, two complementary metrics were employed: the R-Index(im), which categorizes visibility into discrete types (shadow, layover, and foreshortening), and the improved GD distortion index, which provides a continuous measure of distortion severity. The following subsections present the calculation results for each metric and discuss their respective advantages and limitations in describing geometric distortion.

4.1 R-Index(im) Calculation and Analysis

This study employed 12.5-meter resolution DEM data acquired from the ALOS satellite's L-band single-polarization mode for geometric distortion calculations. Experimental results indicate that shadow distribution across the east and west orbits exhibits high consistency, with most areas in the study region remaining shadow-free. Significant variations exist between the layover effects of the two orbits and the far passive layover effect, with the distortion area distribution being more extensive in the eastern orbit imagery. Among the three distortion effects, the layover effect has the most significant impact on the visibility of SAR imagery in the study area, as detailed in Fig. 7 for specific spatial distribution differences.

Based on the calculated distortion factors, combined with the topographic parameters of the study area and satellite orbital parameters, the R-Index(im) distributions for the east and west orbits were calculated using Equation(1) (see Fig. 8).

Analysis reveals that the east orbit imagery exhibits numerous non-visible areas, primarily concentrated in shadowed and layover zones with steep terrain undulations; the west orbit imagery shows relatively lighter occlusion, but due to its larger satellite line-of-sight incidence angle, a pronounced perspective compression effect occurs, manifesting as extensive mild distortion zones within the 0.5–0.7 range.

The specific visibility classification results for both orbits are detailed in Table 3. This differentiated distribution pattern provides crucial quality assessment criteria for subsequent multi-orbit data fusion.

4.2 Improved Calculation and Analysis of GD Distortion Index

This study enhances the two-dimensional geometric distortion index proposed by Zhengyang Wang. The original method employs the shadow determination coefficient B based on slope distance and projection angle, considering only the geometric relationship between local slopes and radar line-of-sight. This approach has limitations in that it fails to account for surrounding

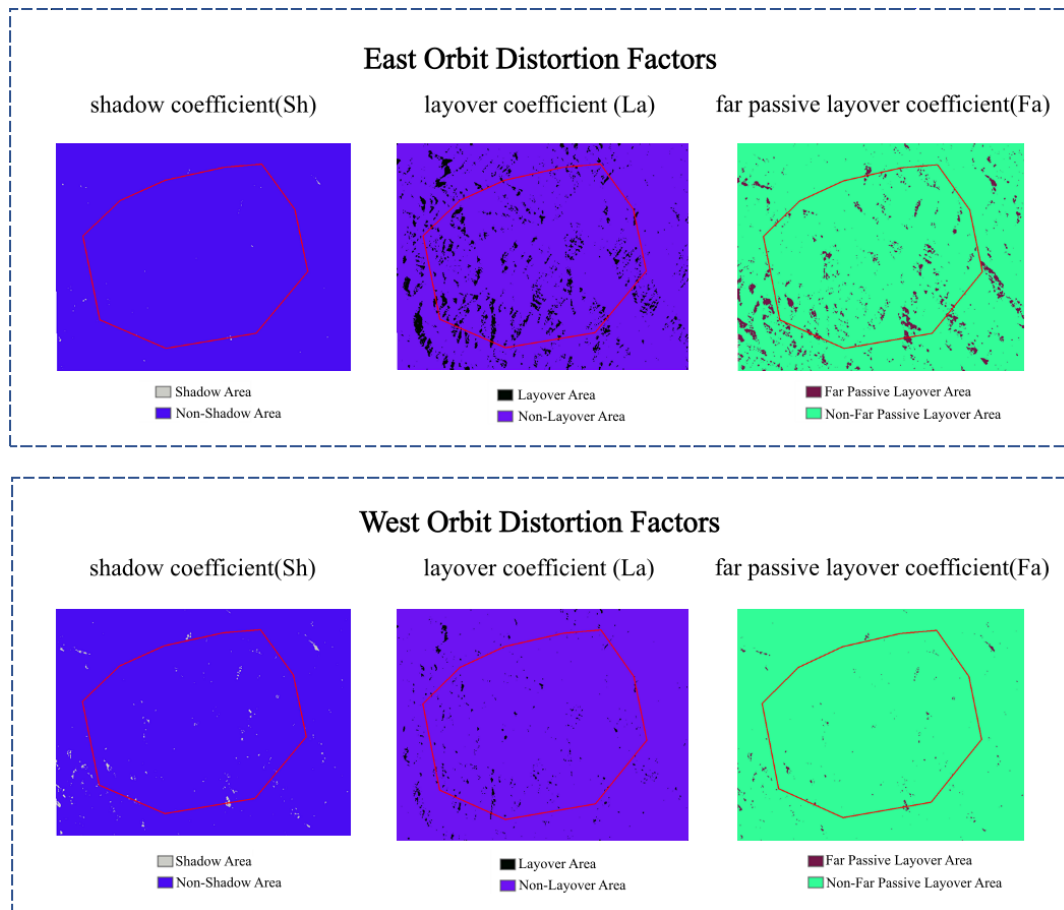


Figure 7. Schematic Diagram of Dual-Orbit Distortion Factors

Table 3. Visibility Region Types for East and West Orbits Based on R-Index(im)

Orbit	R-Index(im) Range	Area Proportion (%)	Region Type
East Orbit	$R = 0$	11.26	Shadow/layover Region
	$0 < R \leq 0.56$	17.95	Perspective-distorted area
	$0.56 < R \leq 1$	70.79	Normal observation area
West Orbit	$R = 0$	1.84	Shadow/layover Region
	$0 < R \leq 0.7$	46.33	Perspective-distorted area
	$0.7 < R \leq 1$	51.83	Normal observation area

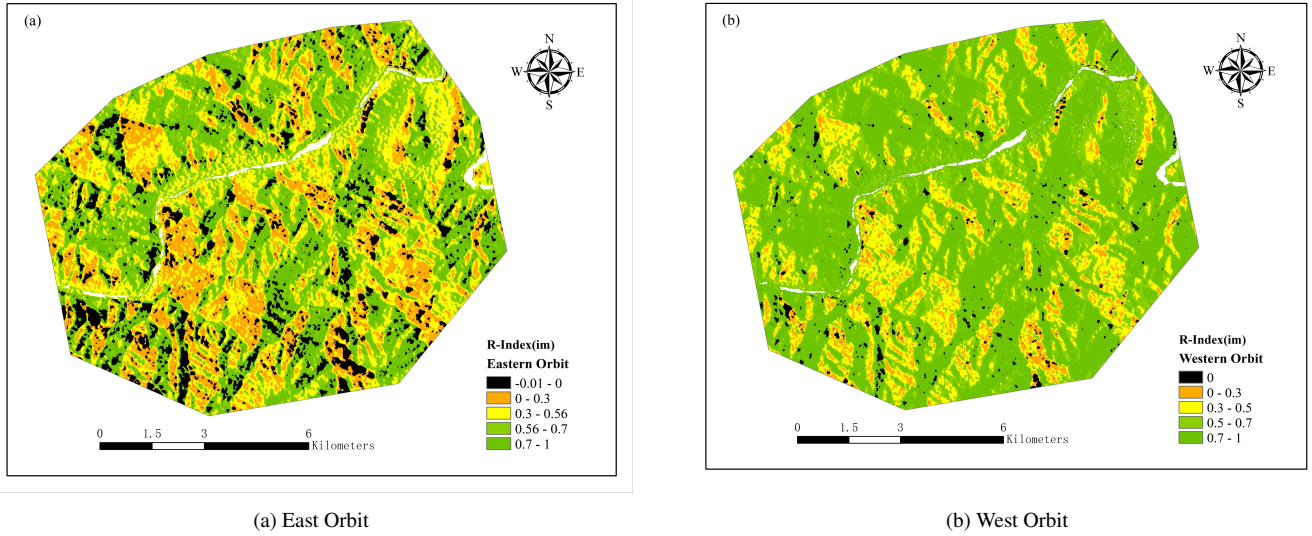


Figure 8. R-Index(im) Distribution Maps in the Experimental Area, (a) for East Orbit and (b) for West Orbit.

terrain occlusion effects, making it difficult to accurately reflect actual shadow distribution; it exhibits abrupt changes near critical thresholds, failing to match the natural transition characteristics of actual shadows; and it is prone to misclassification or missed detection in complex terrain areas.

To address this, this paper introduces the shadow effect coefficient Sh from the R-Index model for improvement. This coefficient simulates solar illumination conditions using DEM data, comprehensively considering terrain slope, surrounding elevation differences, and relative spatial relationships. Compared to the original method, it more accurately identifies mutual shading between mountains, significantly enhancing shadow detection precision in complex terrain areas. The improved GD distortion index formula is:

$$\sigma = S_h \cdot (1 - \sin(\theta + \alpha_{CD})) \cdot \cos(\alpha_{AC}) \quad (3)$$

where Sh is the shadow effect coefficient, θ is the satellite incidence angle, and α_{CD} and α_{AC} are the distance-projected and azimuth-projected slope angles, respectively. Fig. 9 displays the spatial distribution of the improved GD distortion index for the east and west orbits.

In the results, green indicates minimal distortion, yellow to red indicates increasing distortion. Black areas represent shadow regions, and blue areas indicate severe layover zones. Comparative analysis reveals:

(1) Overall distribution characteristics: both orbits exhibit similar distortion distribution patterns. Most areas experience minimal distortion, as indicated by the continuous green coloration, while higher σ values are found predominantly in regions with complex topography.

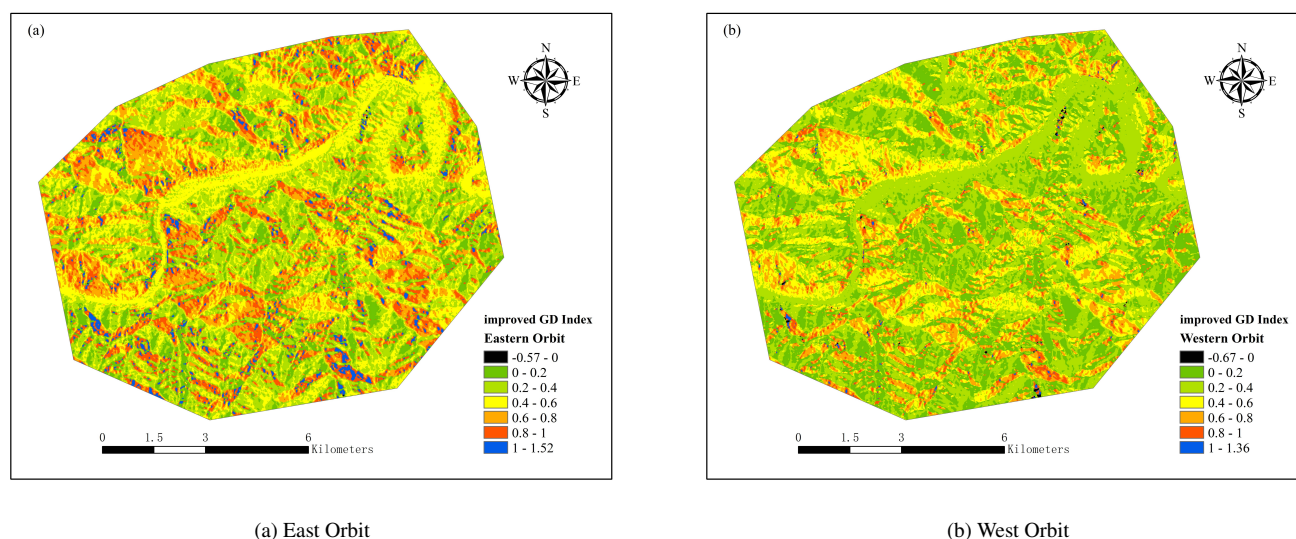


Figure 9. GD distortion index Distribution Maps in the Experimental Area, (a) for East Orbit and (b) for West Orbit.

(2) Inter-orbit differences: the western orbit (Fig. 9b) shows generally milder distortion overall. The proportion of high-quality imaging zones (0–0.2) is 28.69% for the western orbit, higher than the eastern orbit’s 13.59%. Similarly, the proportion of moderate distortion zones (0.2–0.4) is 33.93% for the western orbit, compared to 28.36% for the eastern orbit. In contrast, severe layover areas account for 2.63% in the eastern orbit, significantly higher than the 0.25% observed in the western orbit.

(3) Comparative advantages of metrics: the R-Index(im) effectively identifies shadow (11.26%) and layover (1.84%) areas, demonstrating a strong ability to differentiate between distortion types. Meanwhile, the GD Index accurately quantifies distortion severity based on differences in two-dimensional projected area. It offers high continuity and comparability, while also reflecting fine-scale distortion variations across the 0–1 range.

In summary, the two indices exhibit complementary characteristics: R-Index(im) is suitable for global distortion type identification, while GD Index excels at pixel-level distortion quantification. This complementary nature provides a reliable foundation for quality assessment in subsequent multi-orbit data fusion.

5 Discussion

Based on the aforementioned theoretical analysis and the assessment of accuracy and visibility for dual-orbit deformation monitoring, this study selected the SBAS-InSAR time-series monitoring results from the western orbit of the study landslide experimental area—corrected for tropospheric effects via GACOS—as the primary orbit data.

The capability of SBAS-InSAR for monitoring slow-moving landslides has been extensively validated in various geological settings. Dai et al. (2016) successfully monitored activity at the Daguangbao mega-landslide using Sentinel-1 TOPS time series interferometry, while Bekaert et al. (2020) developed an InSAR-based detection method specifically designed for mapping



slow-moving landslides in remote regions with steep terrain. For reservoir area applications, the combination of InSAR with flow models has enabled time and path prediction of landslide evolution (Roy et al., 2022).

285 The concurrent processing results from the eastern orbit served as the secondary orbit data. By integrating the R-Index(im) and the improved GD distortion index from both orbits through weighted fusion, the final fusion results are compared with single-orbit monitoring, as shown in Fig. 10.

Analysis indicates: (1) Improved spatial coverage: The fusion result (Fig. 10a) demonstrates significantly better spatial coverage than the eastern orbit (Fig. 10c). The effective integration of western orbit data (Fig. 10b) fills the observation blind spot of the eastern orbit, achieving coverage close to the combined monitoring area of both orbits. Only extremely severe distortion zones remain uncovered.

(2) Enhanced Data Quality: Distorted outliers in single-orbit data from landslide zones along both banks of the Han River were effectively corrected. The merged deformation field exhibits a smoother and more continuous spatial distribution.

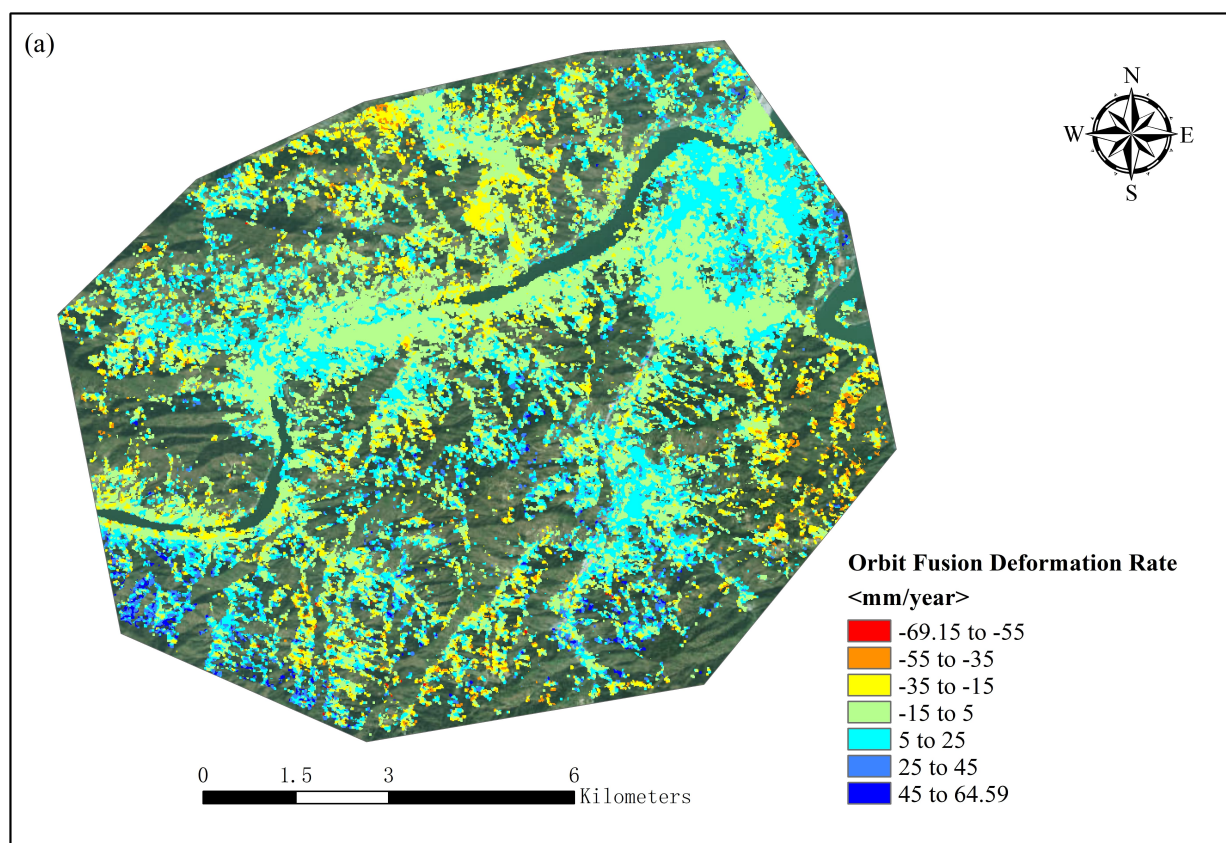
(3) Accuracy Validation: To assess the reliability of the weighted fusion results, statistical analysis was conducted on deformation rate distributions for the layover landslide area—specifically for the eastern orbit (Fig. 11a), western orbit (Fig. 11b), and merged results (Fig. 11c)—with corresponding histograms plotted. Results (see Fig. 11) show the eastern orbit's deformation rate mean of -6.1 mm/yr with a standard deviation of 18.4 mm/yr, the western orbit's mean of -0.3 mm/yr with a standard deviation of 16.9 mm/yr, and the fused mean of -0.4 mm/yr with a reduced standard deviation of 15.0 mm/yr. The near-zero mean and reduced standard deviation collectively indicate that the fusion process effectively eliminated systematic errors between different orbits, thereby enhancing monitoring accuracy.

Understanding the kinematic characteristics of landslides is essential for hazard assessment. Crippa et al. (2021) developed a semi-automated classification method for slow rock-slope deformations using PS-InSAR velocity data, while Torre et al. (2024) emphasized the importance of geomorphological assessment as a complement to InSAR analysis for understanding landslide processes. Schlögel et al. (2016) revealed through L-band InSAR observations that structural control plays a key role in governing the kinematics of deep-seated landslides.

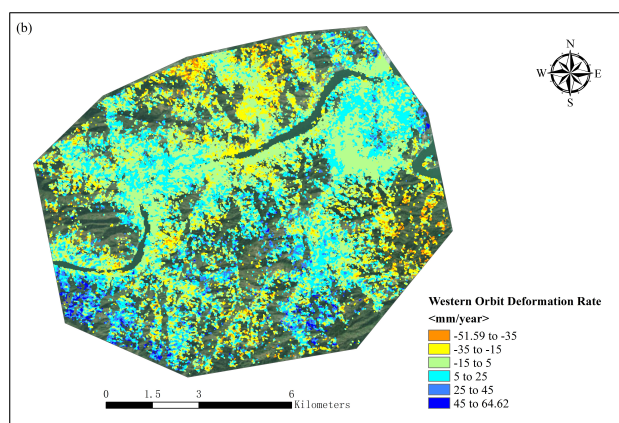
The integration of GNSS and InSAR data has become an effective approach for validating and improving deformation monitoring results. Liu et al. (2024) demonstrated the capability of combining InSAR and GNSS to derive kilometer-resolution three-dimensional crustal deformation, confirming the complementary nature of these two techniques. Additionally, corner reflectors and surface models have proven valuable for enhancing InSAR precise point positioning accuracy (Yang et al., 2019). Wang et al. (2025b) proposed an adaptive error correction method for InSAR data processing guided by deformation prior information, which could further reduce systematic errors in multi-orbit fusion.

GNSS Validation (see Fig. 12, Table 4): The fusion results show high consistency with the GNSS interpolated deformation field. Significant reductions in deviation were observed at stations TP02, TP05, and TP08, effectively filling data gaps at stations like TP04 in the eastern orbit. The mean error decreased from 4.88–5.22 mm/yr in single-orbit mode to 4.86 mm/yr.

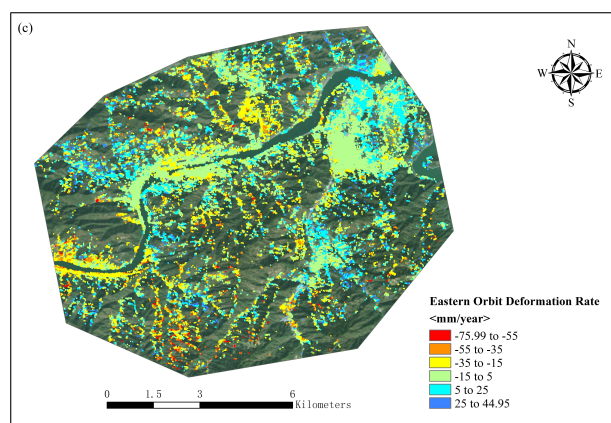
315 To validate the integrated approach proposed in this paper, the validation landslide mass was added for supplementary analysis. Its specific location is shown in Fig. 13.



(a) Fusion result



(b) East Orbit



(c) West Orbit

Figure 10. Deformation rate results, (a) for the fusion result, (b) for West Orbit, and (c) for East Orbit.

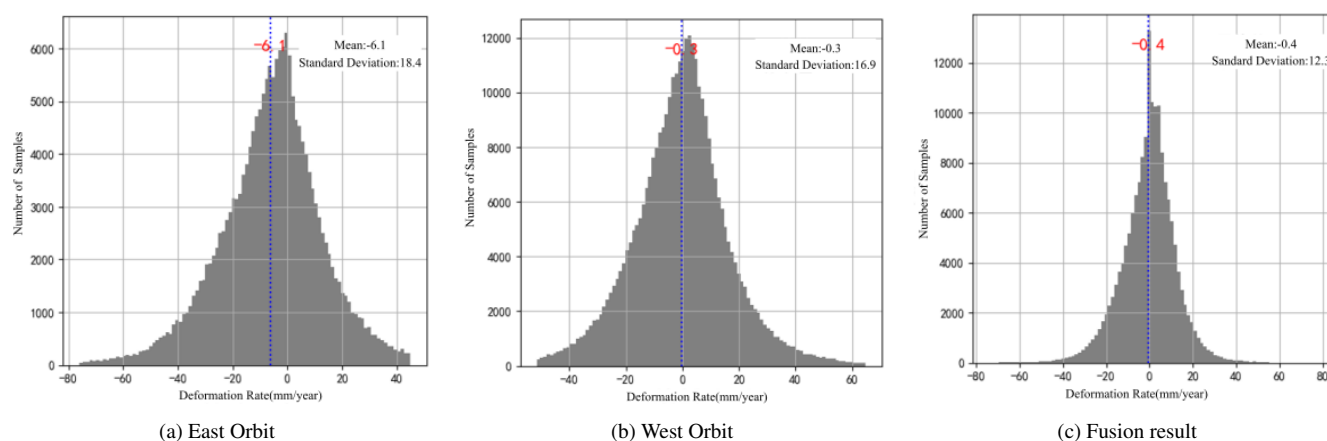
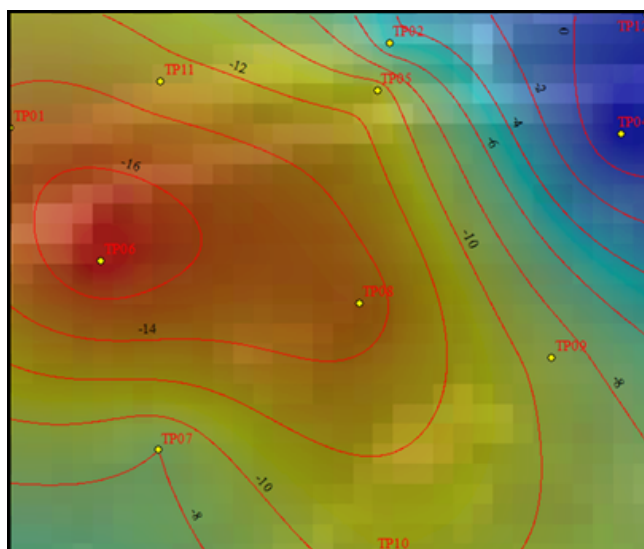


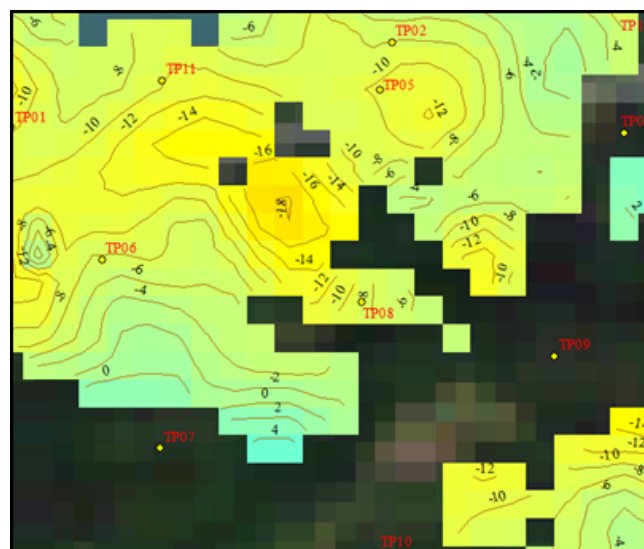
Figure 11. Histogram Statistics Before and After Orbit Fusion, (a) for East Orbit, (b) for West Orbit, and (c) for the fusion result.

Table 4. Comparison of deformation rates monitored at specific GNSS stations

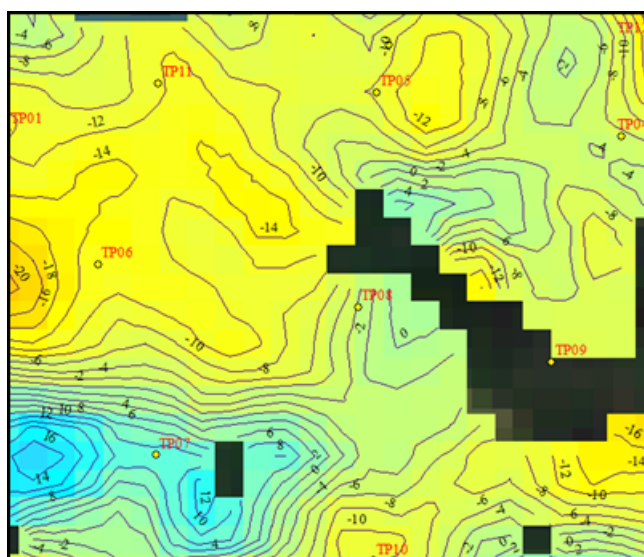
Site	GNSS Monitoring (mm y ⁻¹)	Fusion Result (mm y ⁻¹)	West orbit (mm y ⁻¹)	East orbit (mm y ⁻¹)
TP01	-15.11	-11.14	-12.40	-14.96
TP02	-3.46	-7.38	-9.98	-9.58
TP04	2.56	-4.36	-4.36	NAN
TP05	-12.28	-10.21	-10.12	-16.06
TP06	-18.21	-7.95	-13.12	-5.51
TP07	-7.45	9.23	9.23	NAN
TP08	-15.43	-9.54	-2.12	-21.66
TP09	-9.33	NAN	NAN	NAN
TP10	-10.86	-10.03	-10.03	NAN
TP11	-12.64	-9.56	-11.11	-12.35
TP12	0.75	-16.39	-16.39	NAN



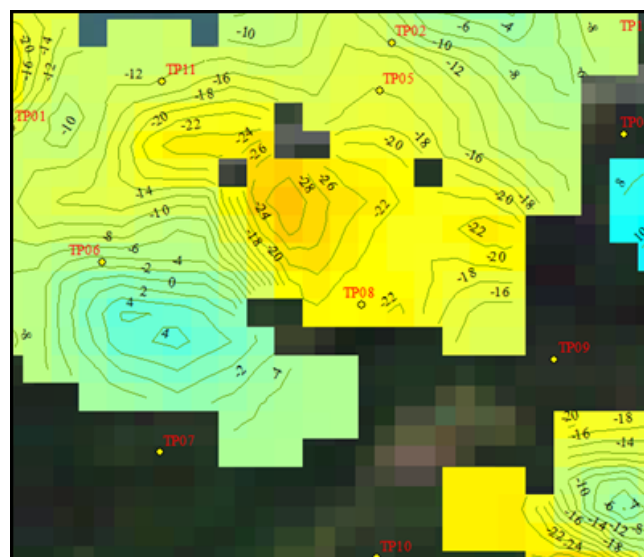
(a) GNSS monitoring annual deformation rate contour map



(b) Two-orbit fusion annual deformation rate contour map



(c) West orbit SBAS annual deformation rate contour map



(d) East orbit SBAS annual deformation rate contour map

Figure 12. Contour map series of annual deformation rates for the SBAS method and GNSS stations before and after fusion

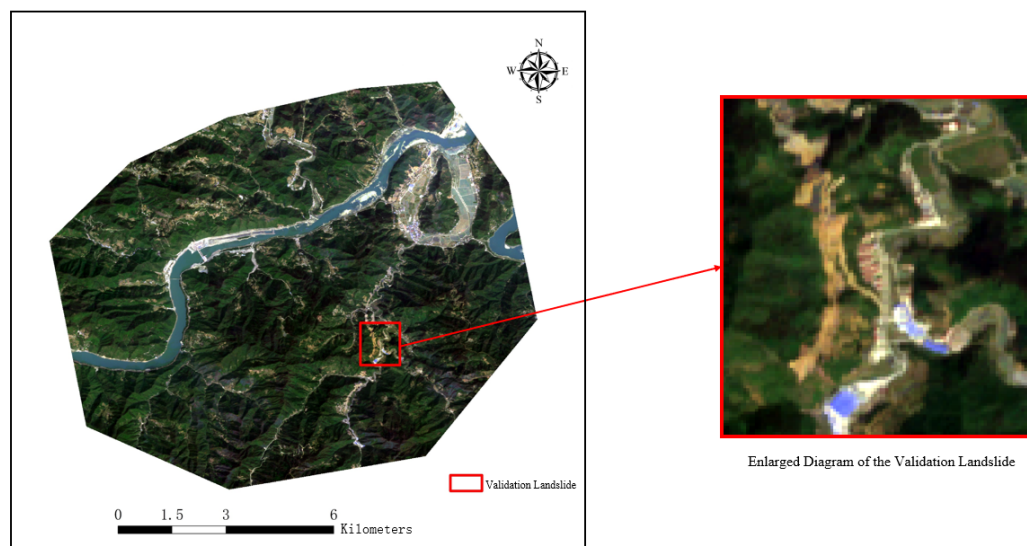


Figure 13. Relative Position Map of the Validation Landslide. Contains modified Copernicus Sentinel-2 data 2024.

Results from Fig. 14 indicate that the upper sections of the landslide mass exhibited slight subsidence between October 2021 and June 2022. By April 2023, localized uplift was observed in the lower sections, consistent with deformation patterns. The method successfully corrected anomalous uplift data in the red-framed area of the western orbit. Mask processing effectively
 320 filtered unreliable data from the severely layover region marked in blue.

In summary, the weighted fusion method based on the improved GD index and R-Index(im) significantly expands monitoring coverage, effectively corrects monitoring errors caused by geometric distortion, eliminates systematic biases between orbits, and enhances the reliability and continuity of deformation monitoring results. This provides a superior multi-source InSAR data fusion solution for landslide monitoring in reservoir areas.

325 6 Conclusions

This study addresses geometric distortion in SAR imagery caused by complex terrain in the study landslide area. It innovatively proposes a parallel-orbit weighted fusion method based on R-Index(im) and an improved GD index. This approach optimizes the GD distortion index by introducing the shadow coefficient Sh and combines it with the R-Index(im) to achieve intelligent fusion of multi-orbit deformation data. Results demonstrate that the mean deformation rate approaches zero after fusion, with
 330 significantly reduced standard deviation. The mean error decreases by 0.02 mm/yr and 0.36 mm/yr compared to single-orbit monitoring, while GNSS validation confirms enhanced deformation field consistency.

This study pioneers the joint application of R-Index(im) and the improved GD index. By enhancing geometric distortion correction accuracy through the shadow coefficient Sh , it establishes a weighted fusion model accounting for terrain visibil-

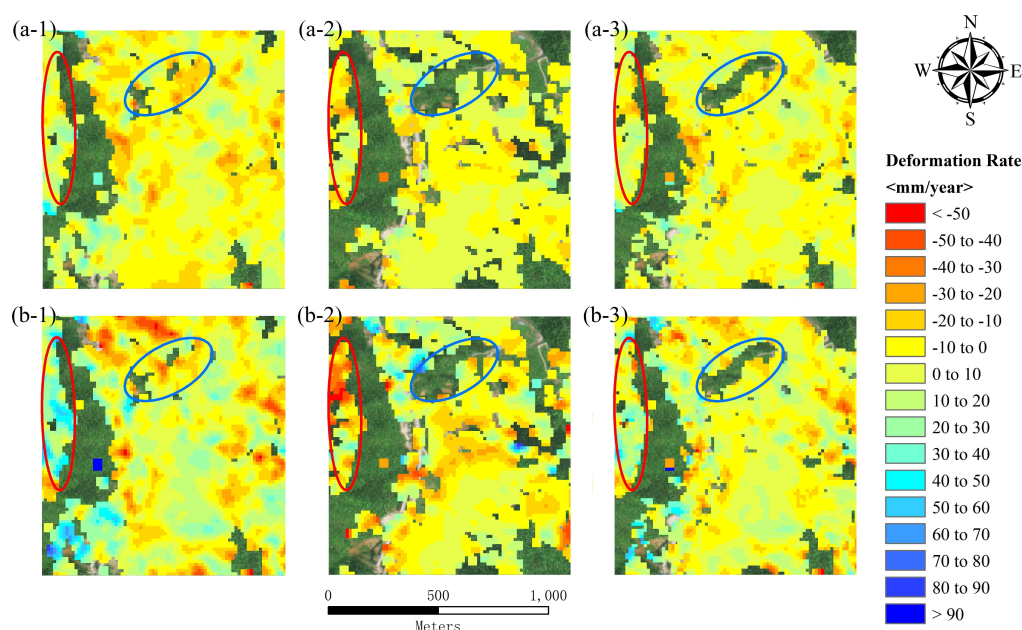


Figure 14. Deformation Monitoring Comparison Around the Validation Landslide: (a) shows the cumulative deformation from October 2021 to June 2022, while (b) covers the period from October 2021 to April 2023; (a-1)–(b-1) for the western orbit, (a-2)–(b-2) for the eastern orbit and (a-3)–(b-3) for the fusion data

ity. However, several challenges remain. Regarding data validation, the current reliance on limited GNSS station data lacks
 335 high-precision leveling verification. Future work should expand validation across diverse terrain conditions. For technical optimization, deepening DS-InSAR algorithm research targeting high vegetation coverage could enhance monitoring capabilities in complex environments.

This study offers novel technical approaches for landslide monitoring in reservoir areas. Continuous improvements can be pursued through incorporating more ground-truth data, expanding validation across diverse terrains, optimizing the DS-InSAR
 340 algorithm, and enhancing monitoring accuracy in highly vegetated areas. These enhancements will further elevate the reliability and applicability of InSAR technology for landslide monitoring in complex topographies.

Data availability. Restrictions apply to the datasets. The data partially belong to a private entity.



Author contributions. All authors contributed to the study conception and design. Liu Aoyang designed the study, developed the methodology, performed the data processing, and drafted and revised the manuscript. Chen Bingquan conducted the experiments and validated the results. Chen Fengyu and Meng Yizhuo performed the data analysis and interpretation. Kong Lingjun optimized the research idea and provided technical guidance. Zhang Wen acquired the funding, conceived the original idea, and supervised the overall research.

Competing interests. The authors declare that they have no competing interests.

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