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Dynamic fusion of displacement parallelism and mass conservation for landslide slip-surface depth inversion from SBAS-InSAR observations: a case study in the Wudongde reservoir area

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Abstract

Accurate quantification of landslide slip-surface depth and volume is a cornerstone of hazard assessment and risk management, particularly in large reservoir basins where conventional borehole and geophysical surveys are logistically challenging or economically unfeasible. This study proposes a novel dynamic fusion framework that integrates the displacement parallelism principle and mass conservation law to invert the time-varying active thickness of landslides using multi-orbit Sentinel-1 Small Baseline Subset Interferometric Synthetic Aperture Radar (SBAS-InSAR) observations. First, topography-constrained quasi-three-dimensional (quasi-3D) surface displacements are reconstructed from ascending and descending line-of-sight (LOS) measurements. Second, a spatially variable rheological coefficient is calibrated point-by-point using the static slip-surface geometry derived from the geometric method as a benchmark under quasi-steady-state conditions. This calibration enables the mass conservation equation to be solved without cumulative integration errors, yielding time-series slip-surface thickness fields anchored to the static geometric baseline. The framework is applied to active landslides along the Wudongde Hydropower Reservoir in southwestern China. The inverted slip-surface depths range from 15 to 85 m, and the volume of active Jinpingzi landslide is approximately $6.25 \times 10^7 \text{ m}^3$. Validation GNSS comparisons show root mean square errors (RMSE) values of 3D displacement is 7.8 mm, 4.2 mm and 2.4 mm in Vertical, Eastern and Northern, respectively. The proposed dynamic fusion approach mitigates the ill-posedness of pure mass-conservation inversion and the oversimplification of purely geometric methods, providing a physically consistent, spatially distributed tool for regional landslide characterization and reservoir hazard management.

Keywords: SBAS-InSAR; landslide slip-surface depth; displacement parallelism; mass conservation; dynamic fusion

1. Introduction

Landslides represent one of the most destructive geohazards worldwide, causing widespread loss of life, infrastructure damage, and economic disruption every year. The slip surface, defined as the basal weak plane along which unstable slope mass moves relative to stable bedrock, governs the kinematics, stability, and failure magnitude of a landslide [1]. Reliable characterization of slip-surface geometry underpins accurate calculation of landslide failure volume, which is among the most decisive parameters for predicting propagation range, affected zones, and potential hazard losses following slope instability [2]. The slip surface defines the extent of the landslide body, while the failure volume is fundamental to understanding the underlying mechanisms [3]. Therefore, accurate estimation of slip-surface depth (SSD) is critical for hazard assessment and risk mitigation.

Conventional approaches for SSD determination include borehole drilling, geophysical prospecting, and geological mapping. While these methods deliver high local accuracy, they are often expensive, time-consuming, and impractical for large or remote mountainous areas [4-6]. Remote sensing techniques, particularly Synthetic Aperture Radar Interferometry (InSAR), have emerged as a powerful non-contact tool for landslide monitoring, owing to its ability to provide spatially dense, millimeter-scale surface displacement measurements over large areas with all-weather, day-and-night capabilities [7]. InSAR has become a premier tool for mapping millimeter-scale surface deformation over large areas, which can be broadly categorized into geometric and physical methods [8]. Advanced multi-track and multi-sensor approaches have significantly improved three-dimensional (3D) displacement retrieval, while generic atmospheric correction models have enhanced time-series accuracy in complex terrains [9, 10]. Regional area

detection and classification of active geohazards have also been rapid advancement based on 3D displacement [11]. Several prior investigations have employed the vector inclination method to delineate slip surface geometry along a cross-section, leveraging 3D displacement measurements derived from InSAR [12]. Nevertheless, as a purely geometry-driven approach, it can only yield the two-dimensional (2D) morphological features of a slip surface confined to the profile plane.

Two main methodological paradigms have been developed to infer subsurface slip-surface geometry from InSAR-derived surface deformation: i) Geometric methods based on the displacement parallelism assumption posit that landslide movement is parallel to the underlying slip surface [13-14]. The vector inclination method can delineate 2D slip-surface profiles along landslide central axes using InSAR data [15]. Kang et al. [11] further extended this approach to map regional slip-surface geometry for creeping landslides in the Jinsha River Basin. This method is computationally efficient and requires minimal assumptions about landslide rheology, but it only yields cross-sectional morphology, is highly sensitive to displacement noise, and cannot capture temporal variations in slip-surface depth. ii) Physical methods based on mass conservation relate thickness variations to velocity divergence [16,17]. The geometric method describing the spatial configuration of the failure surface, and the mass conservation governing the driving and resisting forces. These two methods are physically sound and can handle more complex deformation scenarios, the geometric representation of the slip surface and the energy-based stability criterion are coupled through a parametric search procedure [18]. However, they require additional assumptions about the depth-averaged velocity profile and are prone to instability in the inverse problem solution, especially in regions with low deformation gradients.

While some studies have attempted to combine these two approaches, existing methods typically use fixed weighting schemes or apply them sequentially, failing to fully exploit their complementary strengths [19,20]. The performance of such combined methods thus depends sensitively on site-specific landslide characteristics and data quality, with no robust mechanism to account for spatial heterogeneity in kinematics [21]. Moreover, while recent work has demonstrated the potential of using multi-orbit SAR decomposition [22] and deep learning [23] to improve inference, a seamless integration that simultaneously honors geometric simplicity, physical rigor, and spatial heterogeneity remains elusive. The integration approaches apply static weights or single methods, failing to account for spatial heterogeneity in kinematics and data quality.

To address these gaps, this study proposes a novel dynamic fusion framework that integrates displacement parallelism and mass conservation in a spatially adaptive manner. The core innovation lies in calibrating a pointwise rheological coefficient using a quasi-steady geometric benchmark, which eliminates the need for global empirical parameters and avoids cumulative integration drift. Applied to the Wudongde Reservoir area in the Jinsha River Basin, the framework delivers time-series slip-surface depth and active volume estimates validated against GNSS. This work provides a practical, cost-effective tool for regional landslide characterization in data-scarce reservoir environments.

2. Study area and dataset

2.1 Regional geological and geomorphological setting

The Wudongde Hydropower Station is located along the lower Jinsha River at the boundary between Luquan County, Yunnan Province, and Huidong County, Sichuan Province, on the southeastern margin of the Tibetan Plateau [23]. The reservoir corridor extends for approximately 150 km and is characterized by steep V-shaped valleys, narrow valley bottoms, and intense relief, with local elevation differences commonly exceeding 1000 m, as shown in Figure 1. The terrain is deeply dissected by fluvial incision and controlled by strong tectonic uplift, making the region highly susceptible to slope instability [24]. The descending data of Sentinel-1 synthetic aperture radar (SAR) acquisition swaths cover the study domain: the red rectangular polygon delineates the footprint of the descending orbit SAR dataset. Grey lines represent active tectonic faults distributed throughout the study region.

The regional geology belongs to the Jinsha River tectonic zone and includes a combination of metamorphic and sedimentary rocks, such as phyllite, slate, schist, marble, limestone, and local basaltic units [25]. These rocks are variably weathered and structurally controlled by faults, joints, foliation, and fracture zones, which promote the development of weak horizons and slope deformation. Ancient landslide deposits are widespread along the valley sides, and many slopes show evidence of reactivation under present-day hydrological and engineering disturbances.

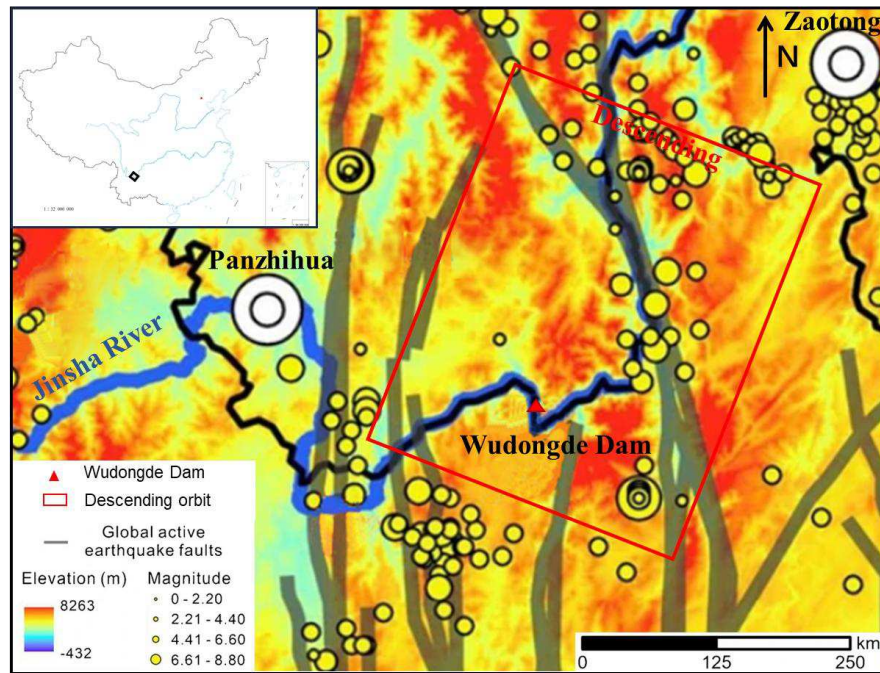


Figure 1. Map of study area

The study area is influenced by a subtropical monsoon climate with a distinct rainy season from May to October and a relatively dry season from November to April. The average annual precipitation generally ranges from 450 to 900 mm, and most rainfall is concentrated during the rainy season [26]. This seasonal rainfall pattern strongly influences infiltration, groundwater recharge, and pore-pressure evolution in slope materials. Since the reservoir impoundment began in 2020, the seasonal water-level regulation has produced repeated drawdown and impoundment cycles along the newly formed banks [27]. These fluctuations can reduce toe support, alter groundwater gradients, and induce repeated wetting-drying and loading-unloading cycles, all of which are known to destabilize reservoir-bank slopes [28].

2.2 Landslide inventory map

A landslide inventory map (LIM) provides fundamental spatial information for identifying landslide-prone areas and evaluating regional slope stability [29]. Previous studies along the Jinsha River have reported widespread ancient landslides, active creeping slopes, and rapidly deforming sectors, indicating a high level of geomorphic activity and slope instability in this region [30]. These landslides are generally controlled by lithological variations, pre-existing structural discontinuities, and the steep valley-bank morphology formed by long-term river incision [31, 32]. Considering the strategic importance of the Wudongde Hydropower Station and the dense distribution of roads, settlements, and reservoir infrastructure along the riverbanks, a systematic landslide inventory is necessary for regional landslide characterization and hazard assessment.

In this study, the LIM of the Wudongde reservoir area was compiled based on field surveys and detailed interpretation of remote sensing images. Mapped geological hazards mainly include landslides and rock collapses, as shown in Figure 2. Landslides are predominantly distributed along both banks of the Jinsha River, where steep slopes and strong fluvial incision provide favorable geomorphic conditions for failure. The compiled LIM provides the basis for subsequent deformation monitoring and landslide characterization.

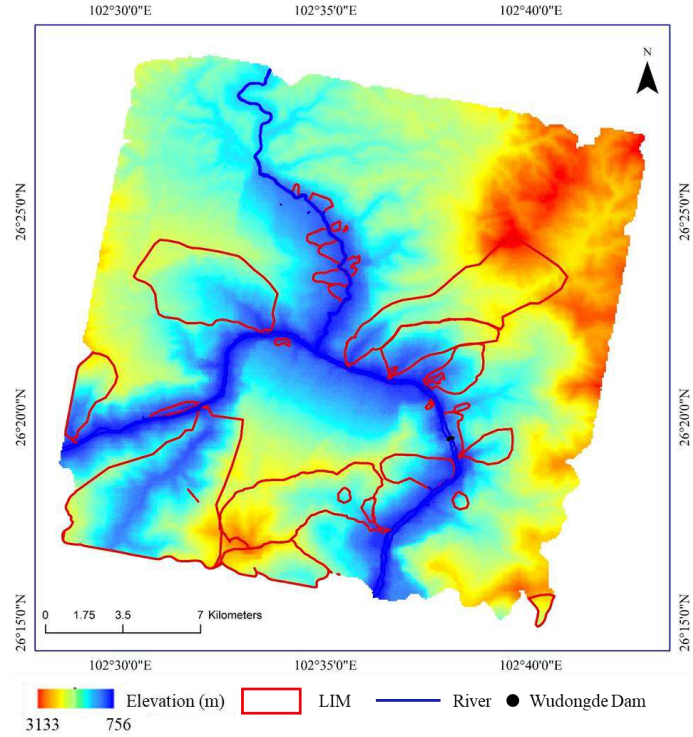


Figure 2. LIM of Wudongde area

2.3 SAR data and auxiliary datasets

A total of 86 descending and 79 ascending Sentinel-1A Interferometric Wide Swath (IW) C-band images, acquired between March 2023 and December 2025, were used for time-series InSAR analysis. Sentinel-1 data provide suitable temporal sampling, broad spatial coverage, and stable acquisition geometry for long-term deformation monitoring. Key parameters of the SAR datasets are listed in Table 1.

Table 1. The main parameter of Sentinel-1

Orbit direction	Incidence angle (°)	Azimuth angle (°)	Polarization mode	Resolution	Data Source	Number of scenes
Descending	40.39	281.47	VV	10 × 10m		86

ASTGTM2 DEM with 30 m resolution was used for topographic phase removal, geocoding, and derivation of slope and aspect parameters. Reservoir water-level records were used to analyze deformation response to impoundment and drawdown. Daily precipitation data from local meteorological stations were used to evaluate rainfall forcing. Geological maps and field observations were used to interpret landslide distribution. Global Navigation Satellite System (GNSS) measurements at 12 monitoring sites were used to validate 3D displacement results.

3. Methodology

A new approach was proposed to integrate displacement parallelism and mass conservation principles to determine landslide slip surface (SSF) and estimate landslide volume. There are four steps as follows:

Step 1: Data processing. The ascending and descending Sentinel-1 data, ASTGTM2 DEM, Small Baseline Subset- InSAR (SBAS-InSAR) products were used to obtain the LOS deformation (D_{LOS}). The active landslides in the study area were identified based on D_{LOS} and LIM.

Step 2: 3D deformation estimation. The topography-constrained model combines with D_{LOS} to invert 3D displacement in time series, yielding the horizontal velocity $\vec{D}_h$ and the vertical displacement component D_z .

Step 3: Sliding surface thickness inversion. By calibrating a pointwise rheological coefficient from a quasi-steady geometric benchmark thickness derived via 3D velocity field and DEM, the time-series thickness is obtained by superimposing mass-conservation based on dynamic thickness variations onto the benchmark, with uncertainty quantified through error propagation.

Step 4: Volume estimation. The active landslide volume at each time step is calculated by summing the inverted thickness of all pixels within the landslide boundary multiplied by the pixel area. This estimated volume represents only the currently deforming portion of the landslide and may be smaller than the total geomorphic volume of the entire landslide body.

3.1 SBAS-InSAR processing and active landslide detection

The SAR data were processed using SBASInSAR, the workflow according to [33–34]. Key processing steps included co-registration, interferogram generation with a temporal baseline threshold of 12 days, topographic phase removal using ASTGTM2 DEM, adaptive Goldstein filtering, minimum cost flow phase unwrapping, atmospheric phase correction using a combined spatial-temporal filtering approach, time-series inversion via singular value decomposition (SVD), and geocoding to geographic coordinates. For each coherent pixel, the SBAS analysis generated LOS velocity, cumulative displacement, and displacement time series. Pixels affected by low coherence (<0.3), phase-unwrapping errors, or deformation signals inconsistent with local downslope direction were excluded from subsequent analysis.

Based on the LIM of study area, the dynamic susceptibility method was used to identify the active slow-moving landslides in time series [35]. Active landslides were identified by integrating SBAS-InSAR velocity maps, time-series LOS deformation, optical remote-sensing images, DEM-derived terrain factors, and the spatial-temporal features of landslides. The detail detection method has been analyzed in our previous study [36]. Only deformation zones consistent with plausible gravitational slope movement were retained. Specifically, an active landslide was required to satisfy three criteria: spatial-temporal continuous InSAR deformation, deformation direction broadly consistent with local slope movement, and geomorphic evidence of instability, such as scarps, cracks, bulging toes, disturbed drainage, or hummocky terrain. The delineated polygons represent the active deforming portions of landslides rather than necessarily the entire geomorphic boundaries of ancient landslide deposits.

3.2 3D displacement estimation

The Sentinel-1 observation cannot independently resolve all three displacement components, as spaceborne SAR is inherently insensitive to north-south displacement. For active landslides whose motion is predominantly downslope and approximately parallel to the local slope surface, a topography-constrained quasi-3D solution is adopted [37, 38]. This is justified for active landslides whose motion is predominantly downslope and approximately parallel to the local slope surface. The geometric relationship between the LOS and the slope is shown in the Figure 3, the LOS displacement is expressed as [39]:

$$\begin{pmatrix} D_{Asc} \\ D_{Des} \end{pmatrix} = \begin{pmatrix} -\sin\theta_{Asc}\cos\alpha_{Asc} & \sin\theta_{Asc}\sin\alpha_{Asc} & \cos\theta_{Asc} \\ -\sin\theta_{Des}\cos\alpha_{Des} & \sin\theta_{Des}\sin\alpha_{Des} & \cos\theta_{Des} \end{pmatrix} \begin{bmatrix} D_N \\ D_E \\ D_v \end{bmatrix} \quad (1)$$

Where, D_N, D_E, D_v represents the north-south, east-west, and vertical displacement components, respectively. θ is the radar incidence angle; α is the satellite heading angle. Thus, the topography-constrained 3D displacement can be expressed:

$$\begin{bmatrix} D_N \\ D_E \\ D_v \end{bmatrix} = (G)^{-1} \begin{bmatrix} D_{Asc} \\ D_{Des} \\ 0 \end{bmatrix} \quad (2)$$

Where, $G = \begin{bmatrix} -\sin\theta_{Asc}\cos\alpha_{Asc} & \sin\theta_{Asc}\sin\alpha_{Asc} & \cos\theta_{Asc} \\ -\sin\theta_{Des}\cos\alpha_{Des} & \sin\theta_{Des}\sin\alpha_{Des} & \cos\theta_{Des} \\ i_E & i_N & -1 \end{bmatrix}$. The horizontal displacement vector $\vec{D}_h = (D_E, D_N)$ and vertical displacement D_v were then obtained by linear regression of the displacement time series.

In this study, a coordinate system D_x, D_y, D_z is established along the slope surface of the landslide according to the eq. (3):

$$\begin{bmatrix} D_x \\ D_y \\ D_z \end{bmatrix} = S^T \begin{bmatrix} D_N \\ D_E \\ D_v \end{bmatrix} \quad (3)$$

Where, $S = \begin{bmatrix} \cos\beta\cos\delta & \cos\beta\sin\delta & \sin\beta \\ \sin\beta\cos\delta & \sin\beta\sin\delta & -\cos\beta \\ -\sin\delta & \cos\delta & 0 \end{bmatrix}$, δ is the slope angle, β is the aspect angle. The 3D deformation in the slope surface was calculated.

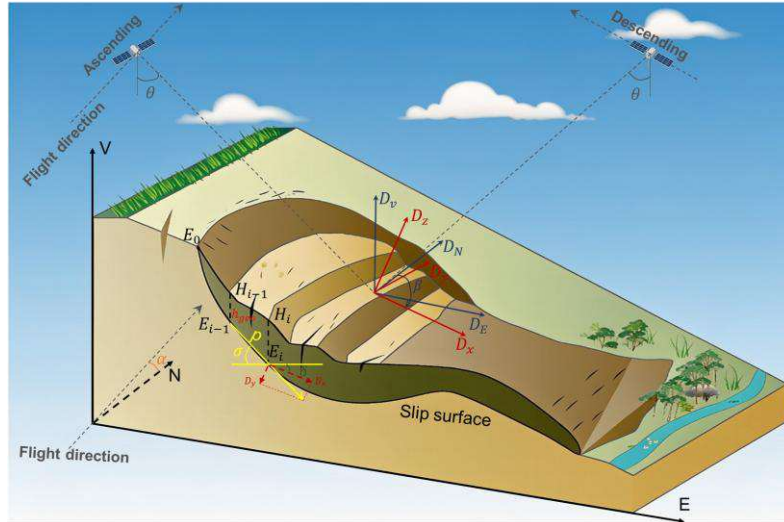


Figure 3. The geometric relationship between LOS direction and 3D displacement coordinate system

3.3 Landslide active thickness inversion method

The proposed landslide active thickness inversion method integrates two complementary physical principles: displacement parallelism and mass conservation, to invert the time-varying slip-surface depth of active landslides. The displacement parallelism method provides a static benchmark thickness under quasi-steady state conditions, while the mass conservation principle supplies the temporal evolution of thickness variations. The seamless integration of these two paradigms is achieved through a spatially variable rheological coefficient calibration strategy.

3.3.1 The displacement parallelism method for static benchmark thickness

For a landslide exhibiting uniform and stable sliding during a quasi-steady state period t_0 , the temporal variation of landslide thickness is negligible $\partial h / \partial t \approx 0$ [40]. Under this condition, the displacement vector of any surface point is assumed to be parallel to the underlying slip surface [41]. This assumption is valid for translational and rotational landslides with coherent mass movement. As shown in Figure 3, the sliding surface slope angle σ at each pixel can be derived from the 3D displacement field as:

$$\sigma = \delta \pm \arctan\left(\frac{|D_z|}{\sqrt{D_x^2 + D_y^2}}\right) \quad (4)$$

Where, σ is the sliding surface slope angle, δ is the surface slope angle, that the sign is determined by the direction of vertical movement, negative value for $D_z > 0$ and positive value for $D_z < 0$. D_x and D_y are the downslope and cross-slope displacement components.

The sliding surface elevation E_i was then calculated by recursive propagation along the main sliding direction:

$$E_i = E_{i-1} - p \tan \sigma_i, (i \geq 1) \quad (5)$$

Where, E_i is the sliding surface elevation at pixel i , E_0 is the sliding surface elevation at the landslide crown, and p is the horizontal distance corresponding to one pixel. The quasi-steady state benchmark thickness field $h_{geo}(x, y, t_0)$ was obtained by subtracting the sliding surface elevation from the digital elevation model (DEM) surface elevation, as shown in Figure 3:

$$h_{geo}(x, y, t_0) = H(x, y) - E_{geo}(x, y, t_0) \quad (6)$$

Where, $h_{geo}(x, y, t_0)$ is the landslide thickness, $H(x, y)$ represents the elevation at position (x, y) on the surface of landslide, which is extracted from DEM, and $E_{geo}(x, y, t_0)$ represents the elevation of SSF, the value is equal to E_i .

3.3.2 Mass conservation principle for thickness variation

The mass conservation principle states that the temporal change in landslide thickness is balanced by the spatial divergence of the depth-integrated mass flux [42]. For an incompressible landslide material with uniform density, the continuity equation can be written as:

$$\frac{\partial h}{\partial t} + \nabla \cdot (h \vec{v}) = 0 \quad (7)$$

Where h is the active landslide thickness, t represents time, $\vec{v} = (v_x, v_y)$ is the average depth horizontal velocity vector and $\nabla \cdot (\cdot)$ is the two-dimensional divergence operator. For shallow translational landslides, the relationship between the surface vertical deformation and the internal deformation field is given by [43]:

$$v_z = -f \cdot \nabla \cdot (h \vec{v}) \quad (8)$$

Where, f is the rheological coefficient that relates the surface and internal velocity fields. Traditional methods typically assume f as a global constant ranging from 0.5 to 1.0, which introduces significant uncertainty in thickness inversion. According to the power law landslide rheology, $f = 0.5$ for linear vertical velocity profile, $f = 1$ for a rigid sliding body [44].

Traditional approaches treat f as a globally constant empirical parameter, introducing significant uncertainty into thickness inversion. To overcome this limitation, we propose a physics-guided calibration strategy that leverages the geometric benchmark thickness to constrain f in a spatially distributed manner. Under the quasi-steady state condition $\partial h / \partial t \approx 0$, the mass conservation Eq. (6) can be simplified to:

$$\nabla \cdot (h \vec{v}) = 0 \quad (9)$$

Under the displacement parallelism assumption, the velocity field is approximately parallel to the local slope, implying that $\nabla \vec{v} \approx 0$ within the quasi-steady sliding mass. This condition holds when the landslide moves as a coherent block with negligible internal strain. The calibrated rheological coefficient $f_{cal}(x, y)$ at each valid pixel was derived by rearranging the mass conservation equation, can be solved:

$$f_{cal}(x, y) = - \frac{v_z(x, y, t_0)}{\nabla h_{geo}(x, y, t_0) \cdot v_x(x, y, t_0)} \quad (10)$$

Post-processing was applied to the initial f_{cal} field to ensure physical plausibility: (1) Outlier removal: Pixels with $f_{cal} < 0.4$ or $f_{cal} > 1.1$ are excluded, as these values fall outside the physically admissible range $0.5 < f_{cal} < 1.0$; (2) Spatial smoothing: A 5×5 Gaussian filter is applied to the retained valid pixels to suppress high-frequency noise; (3) Spatial Interpolation: Ordinary Kriging is employed to extrapolate the smoothed f_{cal} field to the frontal portion of the landslide where the geometric method is unreliable due to low deformation gradients or high uncertainty.

3.3.3 Landslide active thickness inversion

Traditional time-series thickness inversion based solely on the mass conservation principle suffers from cumulative error over time, as it requires integration from the start of the monitoring period. To overcome this limitation, we developed a static-dynamic fusion inversion framework that combines the high-precision static benchmark thickness from the geometric method with the dynamic thickness variation from the calibrated mass conservation method. The sliding active thickness is defined as the vertical distance between the topographic surface and the inferred basal surface.

Substituting the calibrated rheological coefficient $f_{cal}(x, y)$ into the mass conservation equation yields the thickness change rate without parameter uncertainty:

$$\frac{\partial h(x, y, t)}{\partial t} = \frac{v_z(x, y, t)}{f_{cal}(x, y)} \quad (11)$$

Due to the InSAR data acquisition period is a discrete time series $t_0, t_1, t_2, \dots, t_n$, the active thickness variation $\Delta h(x, y, t)$ was computed as:

$$\Delta h(x, y, t_k) = \Delta h(x, y, t_{k-1}) + \frac{v_z(x, y, t_k) + v_z(x, y, t_{k-1})}{2f_{cal}(x, y)} \cdot \Delta t_k \quad (12)$$

Where, $\Delta t_k = t_k - t_{k-1}$ is the time interval between two SAR acquisitions. Thus, the final time series landslide thickness field was synthesized by superimposing the dynamic thickness variation on the static benchmark thickness:

$$h(x, y, t_k) = h_{geo}(x, y, t_0) + \Delta h(x, y, t_k) \quad (13)$$

This landslide active thickness inversion method combines the high-precision geometric benchmark with the physically constrained mass-conservation dynamics which captures temporal evolution, ensuring both accuracy and robustness in time-varying slip-surface depth estimation.

3.4 Volume estimation

The uncertainty of the inverted thickness was quantified using the error propagation law. The total variance of the final thickness consists of two independent components:

$$m_h^2(x, y, t) = m_{h_{geo}}^2(x, y, t_0) + m_{\Delta h}^2(x, y, t) \quad (14)$$

Where, the $m_{h_{geo}}$ is the error of geometric benchmark thickness, and $m_{\Delta h}$ is the error of the thickness variation, which is determined by the measurement error of D_z and the calibration error of f_{cal} :

$$m_{\Delta h}^2 = \left(\frac{\Delta t}{f_{cal}}\right)^2 m_{V_z}^2 + \left(\frac{v_z \Delta t}{f_{cal}^2}\right)^2 m_f^2 \quad (15)$$

According to the sliding active thickness $h(x, y, t_k)$, the active landslide volume $V(t)$ in time series is estimated as:

$$V(t) = p^2 \sum_{i=1}^n h(x, y, t_k) \quad (16)$$

Where, n is the total number of pixels within the landslide boundary. Therefore, the estimated volume represents the currently deforming portion of the landslide and may be smaller than the total geomorphic volume of the entire landslide body [45-46].

4. Results

4.1 3D displacement field

The InSAR time-series analysis reveals widespread but spatially heterogeneous slope deformation in the Wudongde reservoir area. Figure 3 depict the mean velocity in the capture time, derived from descending Sentinel-1 datasets. Based on time series InSAR technique, the descending SAR images achieve a spatial monitoring density of 19354 measurement points (MPs), the range from -262 (mm/y) to +35 (mm/y). The velocity values above zero indicate movement toward from the satellite, inversely, below zero indicate movement away from satellite. During the monitoring period, the study area exhibited several active slopes in spatial distribution, predominantly on the both sides of Jinsha River, which threat to reservoir safety. The known active Jinpingzi landslide, which located on the downstream of Wudongde hydropower station has been observed due to the deformation feature of SBA-SInSAR. The LOS velocity and vertical cumulative displacement are shown in Figure. 4(a) and Figure. 4(b), reveal a distinct linear temporal pattern in landslide motion. From LOS monitoring results, the maximum velocity is 262mm/year. However, the average velocity from GNSS monitoring result in this area is 225mm/year. This difference suggests that the LOS deformation not completely reflect the true deformation characteristics of the landslide, underscoring the necessary of 3D deformation inversion.

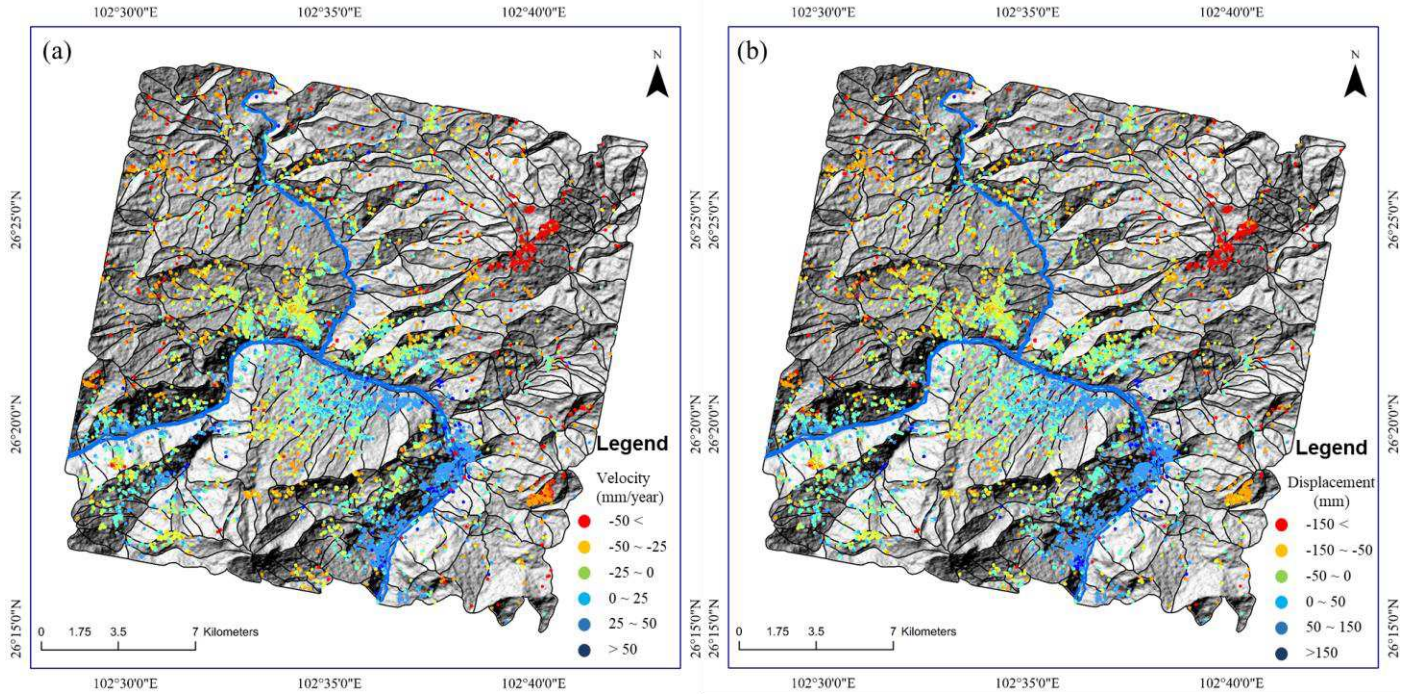
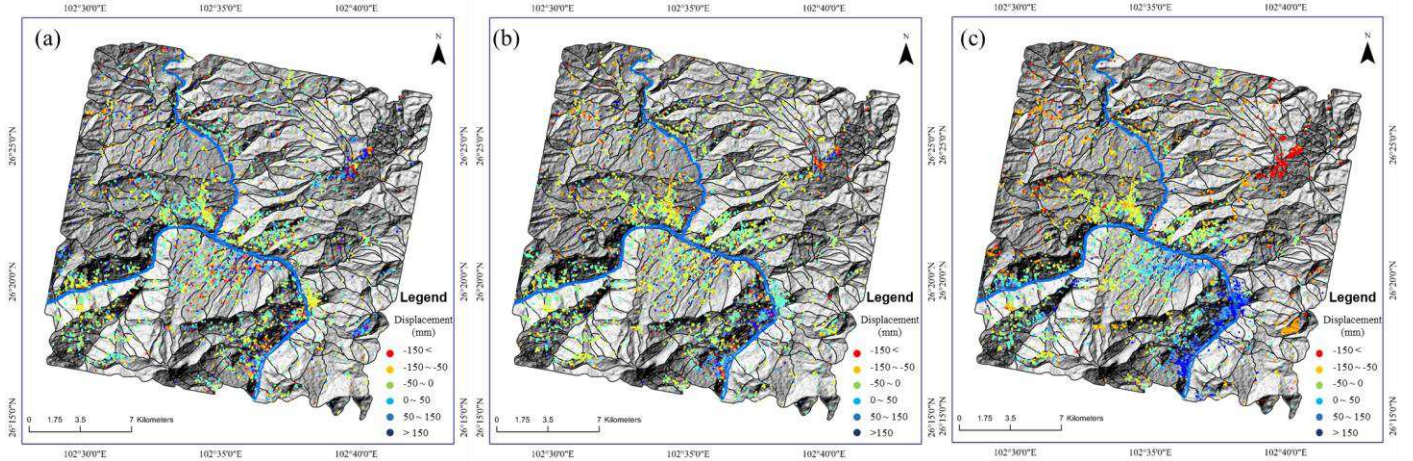


Figure 4. The monitoring results map based on SBASInSAR (a) the velocity map; (b) the cumulative displacement map

Using the method proposed in Section 3.2, time-series three-dimensional (3D) surface displacements were calculated for the study area. The spatial patterns of cumulative 3D displacements from March 2023 to December 2025 are visualized in Figure 5 under two independent coordinate systems. Specifically, Figures 5(a-c) present the displacement components in the geographic coordinate system, corresponding to the north-south (N-S), east-west (E-W), and vertical directions, respectively. Figures 5(d-f) decompose the same displacement field into a slope-aligned coordinate system, consisting of the downslope, normal to downslope, and slope-normal components. For all displacement maps, positive values represent movement consistent with the positive direction of the respective coordinate axis, while negative values indicate movement in the opposite direction.



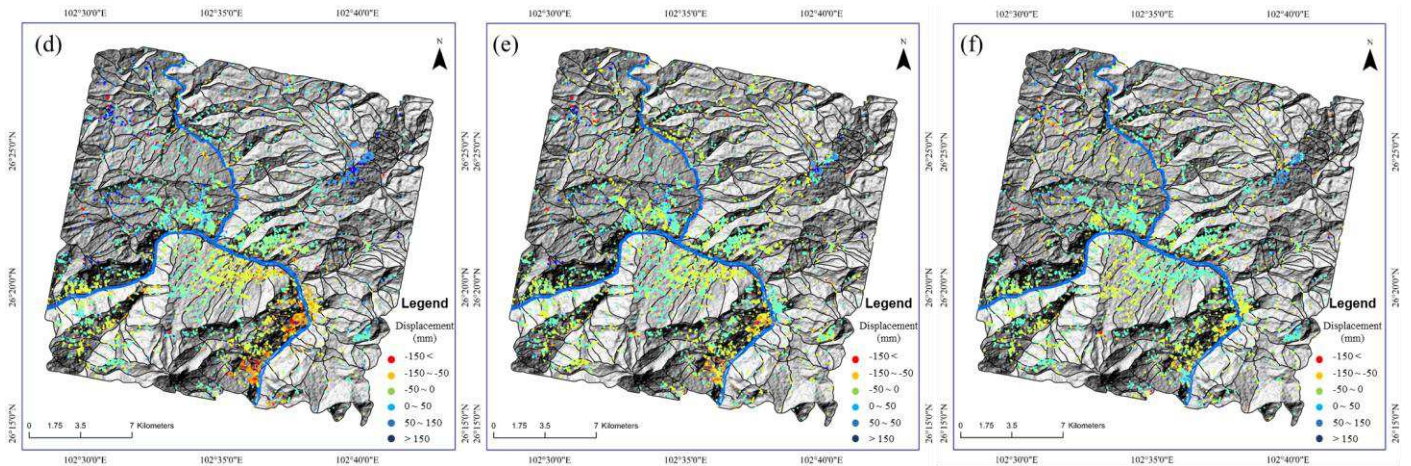


Figure 5. 3D displacement in Wudongde area: (a) N-S deformation; (b) E-W deformation; (c) vertical deformation; (d) downslope direction deformation; (e) normal to downslope direction deformation; (f) slope-normal direction deformation.

As clearly shown in the figure, deformation signals of active landslides present spatially continuous and concentrated distribution patterns, which generally coincide with the topographic boundaries of individual landslide bodies. For landslides dominated by N-S movement, noticeable E-W displacement is limited to localized segments rather than the entire landslide area. Meanwhile, the vertical component consistently exhibits subsidence across all active landslides, which conforms well to the general kinematic law of gravity-driven slope movement.

In addition, landslides with a N-S strike tend to yield a larger standard deviation in displacement estimation. This phenomenon is mainly ascribed to the relatively lower accuracy of 3D displacement retrieval along the N-S direction, an inherent limitation of InSAR-based 3D decomposition constrained by satellite orbital geometry. At Jinpingzi landslide, comparison with GNSS observations shows RMSE of approximately 7.8 mm for the vertical component, 4.2 mm for the east-west component, and 2.4 mm for the north-south component, indicating reasonable kinematic consistency.

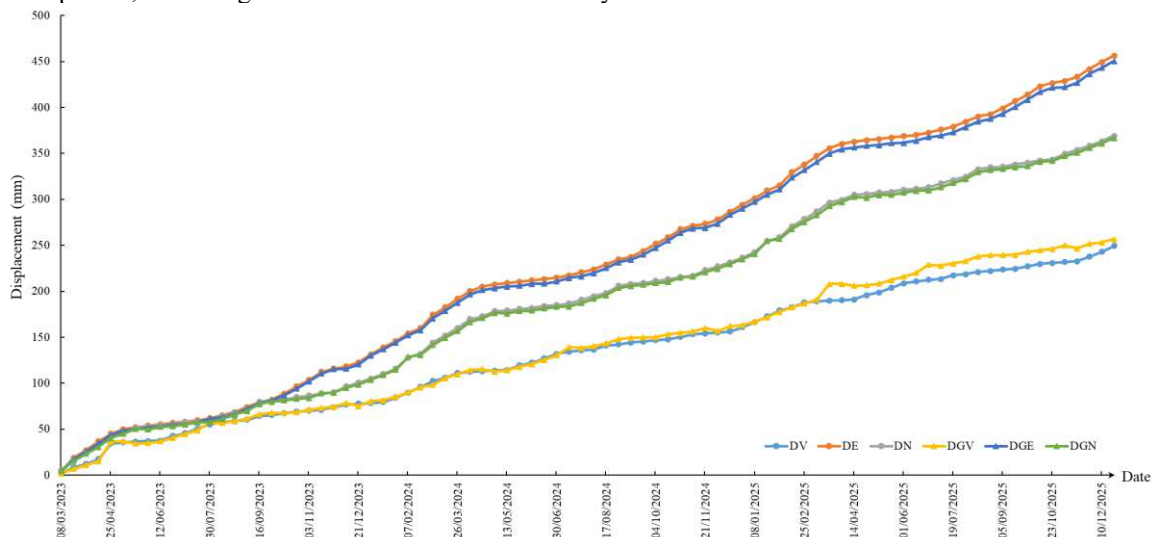


Figure 6. 3D displacement map of the Jinpingzi area in time series obtained from InSAR and GNSS monitoring methods

4.2 Slip-surface depth distribution

Figure 7 illustrates the slip surface slope angle (SSA) σ for study area in Dec 2025. This parameter is positively correlated with the thickness of the slip surface at each point, where higher values correspond to thicker slip surfaces. As an illustration in Figure 8, taking Jinpingzi landslide as example based on the complete set of in-situ monitoring data and geological information. The thickness of the slip surface exhibits distinct spatial variation along the landslide. The slip surface thickness gradually increases from the head scarp to the central section and decreases toward the toe of the landslide. The change of surface sliding thickness for Jinpinzi landslide in the period time, with the maximum value 18m. To validate the reliability of our calculated results, we compared

the InSAR-derived SSF with independent GNSS of the SSF in Jinpingzi landslide. The location of GNSS has shown in the previous research [28]. The GNSS results indicate multiple SSFs, with the InSAR-inferred SSF closely matching those shown by GNSS. The SSF depths estimated in this study are consistent with GNSS data, differing by only 8 mm to 12 mm.

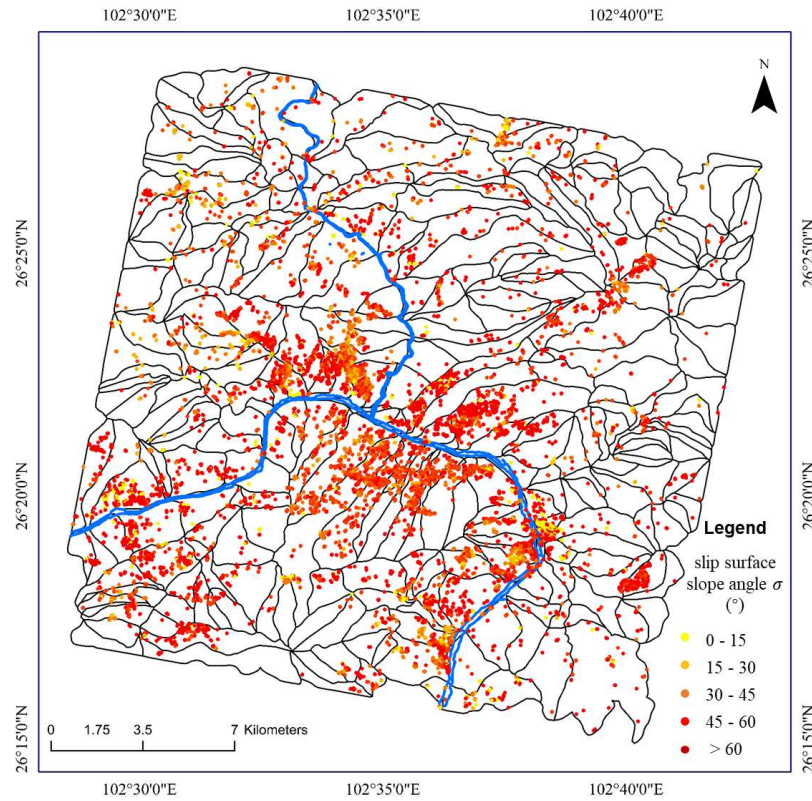


Figure 7. Distribution map of slip surface slope angle (SSA) σ

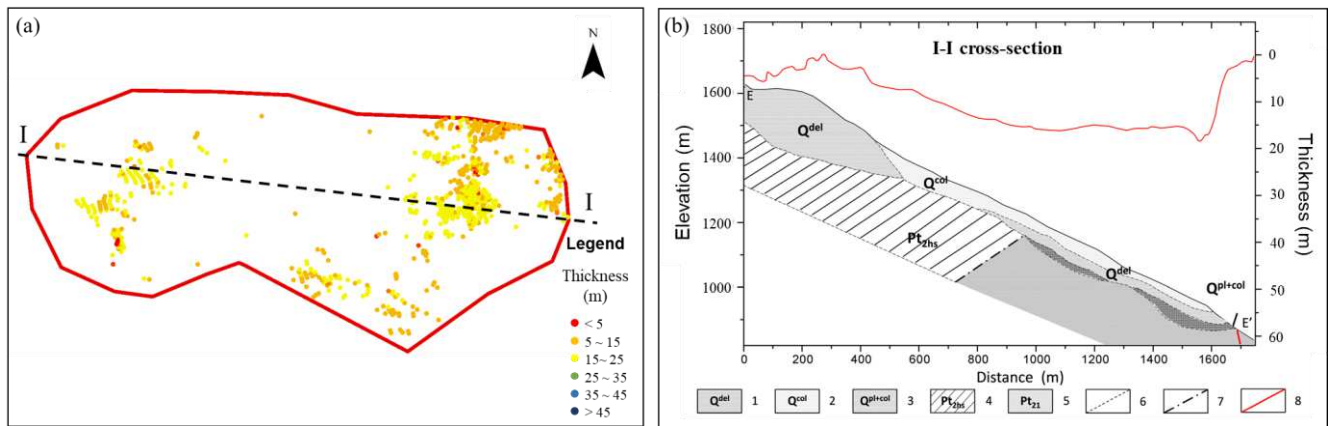


Figure 8. The surface sliding thickness map for Jinpingzi landslide: (a) Plan view (b) I-I cross section

Static methods for determining the thickness of the slip surface are inherently limited to instantaneous estimates. Because landsliding is a dynamic phenomenon and the active slip surface thickness evolves continuously during movement, a dynamic estimation framework is indispensable. To evaluate the active thickness in the Wudongde area, we used three-dimensional displacement velocities defined in a downslope coordinate system as inputs to an inversion scheme, from which the active thickness and subsurface geometry were inferred. Under a constant sliding velocity, a larger rheological coefficient f yields a thinner sliding mass, reflecting the inverse relationship between basal resistance and material mobility. A clear systematic dependence of the inferred active slip surface thickness on the rheological coefficient emerges. As shown in the active thickness distribution map (Figure 9), the landslide mass exhibits pronounced internal heterogeneity and substantial spatial variation in deformation depth. Overall, as f increases from 1/3 to 1, the slip surface migrates progressively upward toward the ground surface, and the bulk landslide thickness decreases continuously. This qualitative influence of rheological parameters on the inferred thickness agrees [41], who demonstrated

that, under analogous modeling assumptions, varying the rheological parameters primarily rescales the magnitude of the estimated thickness while largely preserving its spatial pattern.

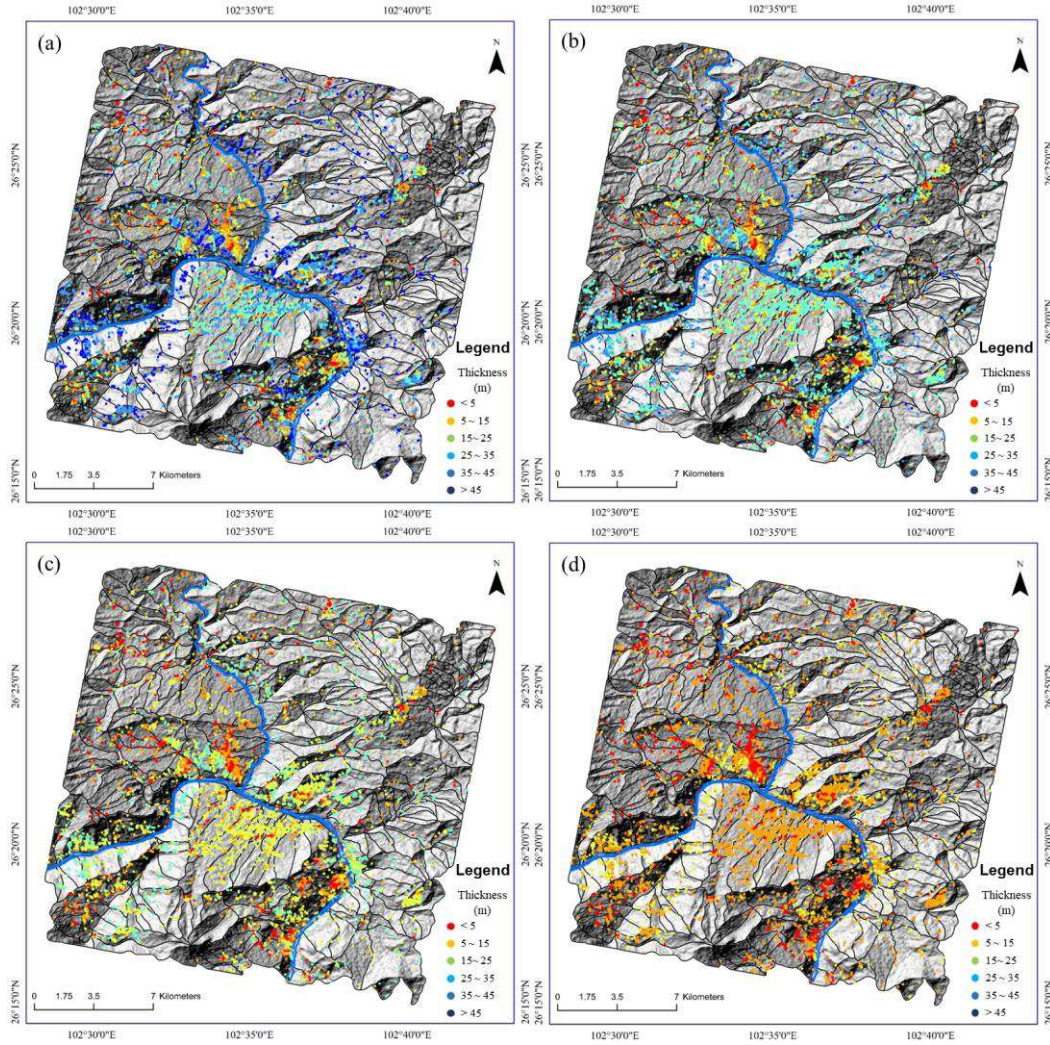


Figure 9. Landslide active thickness distributions for Jinpingzi landslide under different rheological coefficients. (a) $f = 1/3$; (b) $f = 1/2$; (c) $f = 2/3$; (d) $f = 1$

For the thickness inversion model, we adopted $f = 1/2$ based on two considerations: (i) Jinpingzi landslide is a debris-clay composite accumulation landslide, which is currently in an active creep phase, far from a rigid sliding body ($f = 1$); (ii) the displacement time series indicate that the landslide is in a steady sliding stage, with the material not in an extremely loose state prior to failure. The resulting active thickness map (Figure 7) reveals marked internal heterogeneity and considerable variability in deformation depth across the landslide. The thickness distribution is distinctly uneven: the thicker zones are located in the central part, where the maximum thickness reaches 86 m, and in the lower portion, with a maximum of 60 m. This geometry suggests that shear deformation is predominantly concentrated along a planar basal zone, consistent with a translational sliding mechanism dominated by thrust-like movement. In our case, this relationship is particularly evident at the Jinpingzi landslide, where areas of sharp velocity change correspond to pronounced basal deepening, whereas zones of peak surface velocity remain comparatively thin. Such consistency underscores that the depth-dependent shear structure of translational landslides is primarily controlled by internal velocity gradients and localized basal resistance, rather than by uniform surface displacement magnitude.

4.3 Volume estimation

Using the retrieved dynamic slip surface depth and the area of individual slope units, the volume of the Jinpingzi landslide is estimated at approximately $6.25 \times 10^8 \text{ m}^3$. We further compared our results with previously published landslide data for this region. The active landslide volumes we obtained are generally consistent in order of magnitude with those reported in the existing literature, though our estimates tend to be moderately smaller. This discrepancy is primarily attributed to the different spatial extents used in the volume calculations: our estimates are confined to the area exhibiting measurable surface displacement in the actively deforming

portion, whereas the literature values are typically derived from the entire topographic footprint of the landslide. In addition, some previously reported volumes may themselves require revision. A further source of difference lies in an inherent limitation of our inversion method, which resolves only a single dominant slip surface for each active landslide and cannot capture multi-layered sliding geometries. This constraint reflects the fundamental challenge of inferring deep-seated landslide structure solely from three-dimensional surface displacement fields.

The deformation history reveals three main stages. Prior to reservoir impoundment, most slopes moved slowly and steadily. After reservoir filling commenced in 2020, many slopes underwent notable acceleration. During the operational period, a distinct cyclic deformation pattern emerged, with acceleration phases generally coinciding with rapid drawdown events. In addition, several landslides displayed short-lived acceleration following intense rainfall, suggesting that precipitation acts as a secondary trigger superimposed on the primary, reservoir-driven forcing.

5. Discussion

5.1 Methodological advances and applicability

The proposed dynamic fusion framework integrates displacement parallelism and mass conservation in a spatially adaptive manner, overcoming key limitations of each approach when used separately. Purely geometric methods [39] rely on vector inclination and provide static 2D profiles but are sensitive to measurement noise and require dense measurement points along cross-sections. Purely physical methods based on mass conservation can estimate time-varying thickness but suffer from cumulative errors and require prior knowledge of rheological parameters. Our framework addresses these issues by: (1) calibrating a spatially variable rheological coefficient $f_{cal}(x, y)$ using a geometric benchmark under quasi-steady conditions, eliminating the need for global empirical constants; and (2) anchoring time-series thickness variations to this benchmark, avoiding integration drift. Validation against GNSS show the RMSE of 3D displacement less than 7.8 mm confirms accuracy and robustness of this method.

Compared with the IPSO-based inversion method proposed by Shen et al. [9], our approach does not require heuristic optimization or iterative computation, and the calibrated rheological coefficient has explicit physical meaning. Computational efficiency is significantly higher, making it more suitable for regional-scale screening of large numbers of landslides.

The method is most suitable for active translational or rotational landslides with a single dominant slip surface and coherent downslope movement. It is less reliable for earthflows, multi-layered sliding systems, or highly fractured slopes where internal deformation is not parallel to the basal surface. For regional-scale hazard screening in large reservoir corridors, this framework offers a practical tool that balances data availability with mechanistic constraints.

5.2 Hydrological forcing and deformation response

Time-series deformation records reveal that rapid reservoir drawdown is the dominant driver of post-impoundment landslide acceleration in the study area. This finding is consistent with observations from other large hydropower reservoirs in the Jinsha River basin [47]. Physically, rapid lowering of the reservoir level reduces hydrostatic toe support more quickly than pore pressures can dissipate within the slope mass, leading to a temporary reduction in effective stress and shear resistance [48].

The observed 2–4 months lag between water-level change and peak acceleration reflects the time required for pore-pressure transmission from the slope surface to the basal shear zone, controlled by landslide thickness, permeability structure, and fracture connectivity. Thicker landslide bodies exhibit longer lag times, consistent with our inversion results. This delayed response has important implications for early warning systems: displacement monitoring alone may not provide immediate precursors, but integrating pore-pressure diffusion models with InSAR-derived thickness fields could enhance predictive capability.

Rainfall acts as a synergistic secondary trigger. Short-lived acceleration following intense rainfall events is particularly evident during the wet season (May–October), indicating that infiltration reduces matric suction and increases positive pore pressures, further lowering shear strength along the basal surface. The combined effect of reservoir drawdown and intense rainfall is non-linear: slopes already destabilized by drawdown are more susceptible to rainfall-induced acceleration, supporting the dual-forcing mechanism widely proposed for reservoir-bank landslides [25].

5.3 Geological controls on slip-surface geometry

The inferred slip-surface geometry as shown in Figure 7 to Figure 9 exhibits distinct spatial patterns strongly correlated with lithological and structural features. At the Jinpingzi landslide, thicker zones in the central and lower portions coincide with the axis of the paleo-Jinsha River channel, where thick Quaternary deposits and deeply weathered bedrock provide favorable conditions for deep-seated sliding. In contrast, thinner zones near the crown and toe reflect shallower shear planes, consistent with the geomorphic expression of a translational slide with a relatively planar basal surface.

This geometric variability also reflects rock mass heterogeneity. Rotational slides are more common in relatively homogeneous phyllite or slate units, where internal deformation is distributed across a curved shear zone. Complex slides with multiple slip surfaces are associated with fault zones, lithological contacts, and strongly foliated metamorphic rocks [49]. Our inversion results capture these litho-structural dependencies: areas with high fracture density and weathering intensity exhibit larger thickness variations and deeper basal surfaces, indicating that pre-existing discontinuities exert first-order control on landslide kinematics.

The active volume estimates are consistent in order of magnitude with published values for the region [10], but tend to be smaller because we restrict calculations to the actively deforming portion rather than the entire geomorphic footprint. This distinction is critical for hazard assessment: the active volume represents the mass currently in motion and therefore directly contributes to potential failure consequences. Total geomorphic volume, while useful for geological characterization, may overestimate hazard potential if large portions of the deposit remain stable [51].

5.4 Limitations and future work

Several limitations should be acknowledged. First, the assumption of slope-parallel movement along a single slip surface may not hold for complex or multi-layered landslides. Second, InSAR coherence loss and geometric distortions reduce data coverage in steep, vegetated terrain, affecting both 3D deformation retrieval and thickness inversion. Third, the rheological coefficient calibration relies on a quasi-steady period; for continuously accelerating slopes, adaptive updating strategies are needed.

Future work should integrate higher-resolution SAR, optical image correlation, and UAV-based topographic surveys to improve data coverage and accuracy. Incorporating hydro-mechanical forward models would enable scenario-based prediction of landslide evolution under different reservoir operation strategies. Despite these limitations, the proposed framework provides a robust and efficient tool for regional landslide characterization and risk-informed reservoir management, complementing traditional field investigations where they are costly or impractical.

6. Conclusions

This study has developed a topography-constrained framework for reconstructing quasi-3D displacement fields and inferring time-varying slip-surface geometry of active reservoir-bank landslides, using ascending and descending Sentinel-1 InSAR observations. By integrating displacement parallelism and mass conservation principles in a spatially adaptive manner, and by introducing a locally calibrated rheological coefficient, the proposed dynamic fusion method overcomes the ill-posedness of pure mass-conservation inversion and the oversimplification of purely geometric approaches. Applied to the Wudongde reservoir area in southwestern China, the framework successfully identified 28 active landslides, predominantly distributed within and immediately above the water-level fluctuation zone. The reconstructed 3D displacement fields are predominantly downslope-oriented and show good agreement with independent GNSS measurements, with root-mean-square errors of 7.8 mm for the vertical component, 4.2 mm for the east-west component, and 2.4 mm for the north-south component, confirming the kinematic reliability of the inversion.

The inverted slip-surface depths in the study area range from 15 m to 85 m, and active Jinpingzi landslide volume approximately $6.25 \times 10^8 \text{ m}^3$, with thicker zones concentrated in the central and lower portions of landslides, reflecting lithological heterogeneity and paleo-topographic controls. Time-series deformation reveals that rapid reservoir drawdown is the dominant driver of post-impoundment landslide acceleration, while intense rainfall acts as a secondary trigger. The observed 2–4 months lag between drawdown and peak acceleration suggests delayed pore-pressure diffusion within the slope mass, a finding that has important implications for displacement-based early warning systems.

The proposed dynamic fusion framework provides a physically consistent and spatially distributed tool for regional-scale landslide characterization and hazard assessment, without requiring prior depth data, making it particularly valuable for large reservoir areas where comprehensive field investigations are costly and logistically difficult. The method is most suitable for translational and rotational landslides with a single dominant slip surface, but its applicability is limited in cases of multi-layered sliding, complex internal deformation, or earthflow-type movements. Future work should integrate higher-resolution SAR data, optical image correlation, UAV-based topography, and hydro-mechanical forward modeling to further improve inversion accuracy and predictive capability. Overall, this study transforms InSAR from a surface deformation mapping technique into a process-oriented landslide characterization system, offering a practical and cost-effective basis for hierarchical hazard screening, risk-informed reservoir operation, and safer management of large hydropower reservoirs in active tectonic and monsoonal environments.

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Huang; writing—review and editing, J.H. Huang, Jan Lueking and W.C. Du; visualization, J.H. Huang and W.C. Du; supervision, J.P. Sun; project administration, J.H. Huang; funding acquisition, J.H. Huang. All authors have read and agreed to the published version of the manuscript.

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