

Article

Early Identification of Subtle Deformations in Potential Debris Flow Source Areas Using Phase-Unwrapped Convolutional Neural Networks and Long-Time-Series InSAR Technology

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Abstract

Mudslides are sudden and highly destructive; their source areas typically undergo slow, millimeter-scale creep over a period of months or even years before destabilization. If these precursor signals can be detected, valuable time can be gained for disaster prevention and mitigation. However, in the weathered crust and residual deposits of potential debris flow source areas, the long-term coupled action of freeze–thaw cycles and rainfall causes continuous reorganization of internal particle contact force chains, generating weak, metastable creep signals. The high-order nonlinearity and spatial heterogeneity of the interference phase gradient in low-coherence regions lead to pixel-spanning jumps in the unwrapped phase that are blurred by integer multiples of π . The high rate of phase jumps between adjacent pixels severely hampers the early detection of weak deformation. To address this, we propose a method for the early detection of weak deformation in potential debris flow source areas based on phase-unwrapping convolutional neural networks and long-time-series InSAR technology. First, we use long-time-series InSAR technology to construct a spatiotemporal map of interferogram sequences and establish feature propagation paths between high- and low-coherence interferogram pairs using the coherence coefficient as an edge weight. Second, we design a phase-unwrapping graph convolutional network that aggregates phase gradient information from neighboring nodes through two graph convolutional layers to correct the unwrapping results of low-coherence interferogram pairs and suppress cross-pixel jumps caused by π -integer-multiple blurring. Finally, by combining a dual-criterion classification approach based on temporal attention scores and deformation acceleration, the method captures the complete evolutionary process from stable creep to accelerated deformation. Experimental results show that the maximum phase jump rate of this method is approximately 0.02, effectively resolving the phase jump issue caused by high-order nonlinear gradients; in some areas of the study region, where deformation ranges from -1 mm to -9 mm, the inversion error is consistently controlled within ± 1 mm. A total of five potential debris flow source areas were identified, classified by creep stage as follows: one in the accelerated deformation stage, two in the stable creep stage, and two in the early creep stage. No significant surface failure occurred in any of these source areas. This method provides reliable technical support and a decision-making basis for refined early warning, disaster prevention, and mitigation of debris flow hazards and holds significant engineering application value.

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1. Introduction

Debris flows are one of the most common and devastating geological hazards in mountainous regions. Due to their sudden onset and destructive power, they often result in significant casualties and property damage [1]. Among the contributing factors, source material conditions are fundamental and critical to debris flow occurrence; without sufficient loose sediment, large-scale debris flows cannot form even in the presence of heavy rainfall and favorable topography. Therefore, the early identification of potential debris flow source areas is a core task for debris flow early warning and disaster prevention and mitigation [2]. Traditional identification of debris flow source areas primarily relies on manual field geological surveys and visual interpretation of remote sensing imagery. Although these methods can delineate the spatial distribution of source areas from a geological and topographical perspective, they have significant limitations: first, they are inefficient and costly, making it difficult to conduct systematic surveys over large areas and across multiple regions [3]; second, they can only produce static distribution maps of source areas and cannot determine whether a source area is currently in an “active” state; third, they struggle to identify precursor signals of weak deformation that have begun to appear even before significant damage occurs. In fact, before large-scale damage occurs, debris flow source areas often undergo a slow, continuous process of subtle deformation [4]. This deformation typically manifests as slow creep at the millimeter-to-centimeter scale, which may persist for months or even years. If these subtle deformation signals can be detected, it would be possible to issue early warnings before a debris flow actually erupts, thereby securing valuable time for evacuating personnel and preparing for disaster prevention [5]. However, the early identification of such subtle deformation faces three major challenges: First, the deformation amplitude is extremely small and easily drowned out by InSAR observation noise. Second, severe phase incoherence in vegetated areas makes it difficult for traditional InSAR methods to obtain reliable deformation information. Third, the terrain in the source area is steep, making phase unwrapping prone to global errors that can mask the weak deformation signals. Therefore, developing high-precision, low-noise methods for the early detection of weak deformation suitable for complex terrain holds significant theoretical value and practical importance.

In response to these challenges, scholars both domestically and internationally have conducted extensive research and made significant progress. For example, Ibrahim, H. B., et al. used Differential Interferometric Synthetic Aperture Radar (DInSAR) technology to process high-resolution Sentinel-1A images, determine ground subsidence in the study area, generate multi-directional ground displacement maps, delineate flood-prone areas, and identify regional ground deformation [6]. However, Differential Synthetic Aperture Radar Interferometry (DInSAR) uses only two or a small number of SAR images, making it impossible to capture the evolution of deformation over long time series and difficult to identify progressive precursor signals in the study area—ranging from stable creep to accelerated deformation. Jazaeri, S., et al., based on a least-squares framework combined with a deformation model, proposed a continuous scatterer interferometry method to solve for the horizontal and vertical components of deformation, as well as their variances, thereby enabling the identification of ground surface deformation [7]. However, the least-squares framework is sensitive to observation noise; phase noise in low-coherence regions is directly transmitted to the deformation solution results, and there is a lack of effective noise suppression mechanisms. Borisenko, E.V. et al., based on experimental data from

the study area, constructed a finite-element model activated by geomechanical processes triggered by rock mass collapse and flooding, solved for regional displacement parameters, and thereby identified surface deformation [8]. However, finite-element numerical models are simplified approximations of real geomechanical processes, and the mathematical model of the coupled rock mass collapse and flooding process itself contains assumption errors, leading to systematic biases in the solution of displacement parameters. Hamed Azimi et al. used the Grouped Method of Data Hypotheses (GMDH) to simulate soil deformation profiles. They constructed multiple GMDH models for deformation analysis using input parameters such as soil depth ratio, erosion depth ratio, soil shear strength, slope angle, front-edge slope protection height ratio, and horizontal and vertical loads and selected the optimal combination of input parameters to identify deformation [9]. GMDH is a purely data-driven empirical statistical model that lacks constraints based on the physical mechanisms of geomechanics; it has poor extrapolation capabilities, and its generalization performance under different geological conditions cannot be guaranteed. In the field of deep learning-assisted InSAR processing, Li et al. proposed the lightweight axial deep network (LADNet), which combines axial convolution with depth-separable convolution to achieve joint processing of phase unwrapping and attenuation suppression in ϕ -OTDR systems. However, its network architecture is designed for distributed optical fiber sensing signals, and it does not address the spatial heterogeneity of phase gradients in low-coherence regions of interferometric SAR images. Furthermore, the network's field of view is constrained by fixed-size convolution kernels, making it difficult to capture long-range phase dependencies across pixels [10]. Khodadad proposed a fast, high-precision phase-deentanglement method for complex phase maps, optimizing the residual-point balancing strategy within a traditional path-tracking framework. However, the method still employs local linear approximations to address the high-order nonlinearity of phase gradients in low-coherence regions; when the phase jump rate between adjacent pixels exceeds the π threshold, deentanglement errors accumulate and propagate along the path [11].

Existing methods still share the following common limitations when dealing with high-order nonlinearities and spatial heterogeneity in interference phase gradients in low-coherence regions: First, traditional least-squares frameworks and path-tracking algorithms are sensitive to phase noise; phase jump errors in low-coherence regions can propagate globally along the decoherence path, making it difficult to effectively suppress cross-pixel jumps caused by π -integer-multiple ambiguity. Second, purely data-driven models such as GMDH lack physical mechanism constraints; their generalization performance is limited by the representativeness of the training samples, resulting in insufficient extrapolation capabilities under different geological conditions. Third, although deep learning methods such as LADNet have made progress in phase decoherence accuracy, their network architectures are designed for specific sensing modalities. They fail to fully utilize the guiding constraints exerted by high-coherence regions on low-coherence regions within interferogram sequences, thereby neglecting the spatiotemporal correlation topology between interferogram pairs. The root cause of these issues lies in the fact that phase gradients in low-coherence regions exhibit higher-order nonlinear characteristics, whereas most existing methods employ local linearization strategies or global smoothing constraints. These approaches fail to simultaneously balance decoupling accuracy and spatial continuity, resulting in weak deformation signals being overwhelmed by errors during the decoupling stage.

To address these limitations, this paper proposes a method for the early identification of weak deformation in potential debris flow source areas based on phase-unwrapping graph convolutional networks and long-time-series InSAR technology. The unique advantages of graph convolutional networks (GCNs) over traditional convolutional neural

networks and the aforementioned deep learning methods are as follows: First, GCNs are inherently suited for graph-structured data in non-Euclidean spaces. They model each interferogram pair in a sequence of interferograms as a graph node, use the coherence coefficient to construct edge weights, and establish feature propagation paths from high-coherence pairs to low-coherence pairs, thereby enabling the flow of phase gradient information across nodes—a capability that traditional CNNs and rule-based grid networks such as LADNet cannot achieve. Second, through a neighborhood aggregation mechanism, GCN ensures that the decoherence results for each low-coherence node depend not only on its own phase information but also incorporate phase gradient constraints from adjacent high-coherence nodes, thereby effectively suppressing isolated jumps in decoherence errors caused by local phase noise. Third, the graph attention residual layer designed in this paper can adaptively weight the contributions of different neighboring nodes, preventing errors from low-quality nodes from propagating globally through the graph structure. This mechanism fundamentally resolves the inherent issue of error unidirectional accumulation along decoupling paths in traditional path-tracking algorithms. Therefore, the method proposed in this paper does not simply adopt the GCN framework; rather, it is custom-designed based on the physical a priori principle that “high-coherence regions guide low-coherence regions” in interferometric phase unwrapping. It employs a spatiotemporal graph structure with coherence coefficients as edge weights, enabling the GCN’s neighborhood aggregation mechanism to precisely match the quality variation characteristics between InSAR interferometric pairs.

2. Early Identification of Subtle Deformation in Potential Debris Flow Source Areas

2.1. Overview of the Study Area

The study area is a region prone to debris flows, where debris flow outbreaks are primarily triggered by continuous rainfall, heavy rain, and especially concentrated downpours from extreme rainstorms. Consequently, the temporal patterns of debris flow occurrence align with those of concentrated rainfall, exhibiting distinct seasonality. They generally occur during the rainy summer and autumn seasons. The distribution of rivers and collapse areas in the study region is shown in Figure 1.



Figure 1. Distribution of rivers and landslide areas.

The overall topographic slope in this region ranges from 15° to 45°, with slopes between 25° and 35° accounting for the largest proportion (approximately 45%) and constituting the primary topographic zone where debris flow source areas develop. Steep slopes with gradients greater than 35° account for about 20% of the area and are primarily distributed on both sides of ravines carved by rivers; gentle slopes with gradients less than 15° account for about 35% and consist mainly of river terraces and intermountain basins.

Land cover is dominated by mixed coniferous and broadleaf forests, with a coverage rate of approximately 65%; shrublands and grasslands follow, accounting for about 25%; and areas of exposed bedrock and loose debris account for about 10%. Among these, loose debris is primarily distributed in and around landslide areas, constituting the main distribution zone for potential debris flow source areas. Due to its high-altitude location, the study area has a cool climate with high humidity, making it prone to precipitation, which exhibits distinct seasonal patterns. Based on historical meteorological data and observational records, the average annual precipitation in this area ranges roughly between 800 mm and 1200 mm, with most of it concentrated in the summer. This provides an abundant water supply for debris flows, increasing their likelihood of occurrence. This study selected this area as its research subject primarily based on the following considerations: First, the region has experienced multiple historical debris flow disasters; the most recent large-scale debris flow occurred during the 2018 rainy season, causing localized road disruptions and damage to farmland. This clear disaster history serves as a background reference for method validation. Second, three landslide zones within the region provide abundant sources of loose material for debris flows. Combined with concentrated summer precipitation and steep topography, these conditions represent typical geohydrological conditions conducive to debris flow occurrence. Third, the region is currently in a new phase of material accumulation and creep-induced initiation, making it suitable for research on the early identification of potential debris flow source areas.

2.2. Construction of Spatiotemporal Maps of Landslide Area Interferogram Sequences Based on Long-Time-Series InSAR Technology

Using long-time-series InSAR technology, a spatiotemporal graph of the landslide-prone area's interferogram sequence is constructed to provide graph node features and edge weights for the subsequent phase-unwrapped image convolutional network [12].

Suppose the study area has acquired M SAR image frames, with instantaneous phase data M , arranged in chronological order as $t_1, t_2, \dots, t_M$. Interferogram pairs are selected using the short baseline criterion $S = \{(t_i, t_j) \mid |t_j - t_i| \leq T_{\max}, |B_{\perp}| \leq B_{\max}\}$, where S is the set of interferogram pairs satisfying the short baseline condition; t_i, t_j are the acquisition times of the i -th and j -th SAR image frames, respectively; $|t_j - t_i|$ is the time baseline; $T_{\max}$ is the maximum time baseline threshold; interferogram pairs exceeding this threshold are excluded due to loss of coherence; $B_{\perp}$ is the vertical baseline; $B_{\max}$ is the maximum vertical baseline threshold; and interferometric pairs exceeding this threshold are excluded due to geometric incoherence [13]. After screening for interferometric pairs that satisfy the short baseline condition, a total of $N = |S|$ interferometric pairs were obtained, providing high-coherence observation data for long-time-series InSAR deformation inversion [14,15].

For each interferogram pair $(t_i, t_j) \in S$ in the set S , the envelope phase and coherence coefficient are generated as follows:

$$\psi_n(p) = \Gamma \left(\begin{aligned} &\frac{4\pi}{\lambda} [d(t_j, p) - d(t_i, p)] + \\ &\phi(t_j, p) - \phi(t_i, p) \\ &+ \frac{4\pi}{\lambda} \cdot \frac{B_{\perp}(p)}{R \sin \theta} \Delta h(p) \\ &+ \varepsilon_{ij}(p) \end{aligned} \right) \quad (1)$$

$$\gamma_n(p) = \frac{\left| \sum_{q \in \Omega(p)} s_i(q) s_j^*(q) \right|}{\sqrt{\sum_{q \in \Omega(p)} |s_i(q)|^2 \sum_{q \in \Omega(p)} |s_j(q)|^2}} \quad (2)$$

where $\psi_n(p)$ is the wrap phase of the n -th interferogram at pixel p , serving as the node feature input for the convolutional graph neural network; $\Gamma(\cdot)$ is the wrap operator; λ is the radar wavelength; $d(t_j, p)$ is the line-of-sight cumulative deformation at pixel p at time t ; $\phi(t_j, p)$ is the atmospheric delay phase; $B_{\perp}(p)$ is the vertical baseline at pixel p ; R is the range, i.e., the distance from the radar to the target; θ is the incidence angle, the angle between the radar beam and the vertical direction; $\Delta h(p)$ is the elevation error of the Digital Elevation Model (DEM); $\varepsilon_{ij}(p)$ is the phase of thermal noise and decoherence noise; $\gamma_n(p)$ is the coherence coefficient of the n -th interferogram pair at pixel p , used to construct edge weights; $\Omega(p)$ is the estimation window centered at pixel p ; $s_i(q)$ and $s_j(q)$ are the complex value of the two-phase SLC (single-view complex image), containing amplitude and phase information; $s_j^*(q)$ is the complex conjugate of $s_j(q)$; and q is the pixel index within $\Omega(p)$.

The graph edge weight matrix is constructed using $\gamma_n(p)$, where each interferogram is defined as a graph node v_n . An edge exists if two interferogram pairs share at least one common image. The spatiotemporal graph edge weights W_{nm} for the interferogram sequence in the debris flow area are calculated as follows:

$$W_{nm} = \frac{1}{|P|} \sum_{p \in P} \gamma_n(p) \cdot \gamma_m(p) \cdot \exp \left(-\frac{|\tau_n - \tau_m|}{T_e} \right) \quad (3)$$

where W_{nm} denotes the edge weight between node n and node m ; P represents the pixel set of the entire image; $|P|$ is the total number of pixels; $\gamma_m(p)$ refers to the coherence coefficient of the m -th interferometric pair at pixel p ; τ_n and τ_m are the temporal centers of the n -th and m -th interferometric pairs, respectively; and T_e denotes the temporal decay constant.

Construct the initial feature matrix X_n for each node:

$$X_n = \left[\psi_n(p), \gamma_n(p), \sqrt{(\nabla_x \psi_n(p))^2 + (\nabla_y \psi_n(p))^2} \right] \quad (4)$$

where $\nabla_x \psi_n(p)$ and $\nabla_y \psi_n(p)$ are the cyclic difference gradients in the x and y directions, respectively.

The edge weight matrix W and the node feature matrix X_n are used together to form the spatiotemporal graph structure $G = \{X_n, W\}$ of the debris flow region's interferogram sequence, which serves as the direct input to the phase-unwrapping convolutional neural network.

2.3. Correction of Unwrapping Errors and Deformation Inversion for Low-Cohesion Interferograms Using a Phase-Unwrapping Convolutional Neural Network

Utilizing the spatiotemporal map structure of the debris flow area interferogram sequence constructed in Section 2.2, this study employs a phase-unwrapping convolutional network to unwrap the envelope phase of the debris flow area interferograms, corrects the unwrapping results of low-coherence interferogram pairs, and achieves high-precision phase unwrapping of InSAR images in the debris flow area; furthermore, by combining the unwrapping results with long-time-series InSAR technology, deformation inversion in the debris flow area is achieved [16,17]. The structure of the phase-unwrapping graph convolutional network is shown in Figure 2.

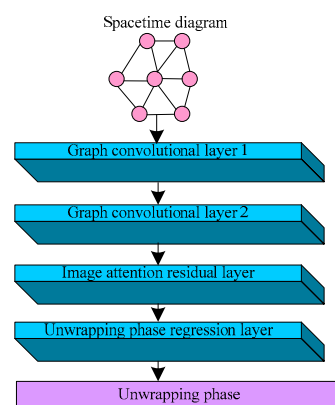


Figure 2. Phase-unwrapping graph convolutional network structure diagram.

This network takes the spatiotemporal graph structure of the debris flow area interferogram sequence constructed in Section 2.2 as input. First, it passes through two graph convolutional layers, which aggregate phase gradient information from neighboring nodes via graph convolution to propagate features from high-coherence to low-coherence interferogram pairs, thereby correcting the unwrapping results of low-coherence pairs and suppressing the cross-node propagation of unwrapping errors. It then passes through a graph attention residual layer, which adaptively weights the contributions of different neighboring nodes via attention coefficients and utilizes residual connections to preserve the original phase gradient details. Finally, it passes through a phase-unwrapping regression layer, which maps the graph features to pixel-level unwrapped phases, outputting high-precision unwrapped phases to provide a high-quality data foundation for subsequent deformation inversion of the debris flow area and identification of potential debris flow source regions [18]. The specific structure of this network is as follows: The number of input feature channels is 1—that is, the envelope phase field of each interferogram. After passing through two graph convolutional layers, the number of hidden channels expands to 64, and finally, the decoherence phase regression layer outputs a decohered phase with one output channel. The graph convolutional layers use ReLU as the activation function, with the Adam optimizer selected. The initial learning rate is set to 0.001 and

decays to 0.9 times its original value every 50 training epochs. The loss function consists of the mean squared error (MSE) of the deentangled phase and a regularization term for phase gradient consistency, where the regularization term is used to constrain the gradient differences in the deentangled phase between adjacent nodes and prevent local abrupt changes in the deentanglement results.

Existing phase decoherence methods based on graph neural networks typically treat the pixels of a single interference image as graph nodes and perform decoherence based on phase consistency among neighboring pixels. The graph structure in such methods encodes only spatial adjacency relationships. When low-coherence regions are spatially connected and cover a large area, all pixel nodes within that region lack reliable phase gradient information; neighborhood aggregation degenerates into mutual averaging among noisy nodes, and high-coherence constraints cannot be propagated from the exterior into the interior of the low-coherence region. In contrast, this paper treats the entire interferogram as a set of graph nodes and constructs graph edges based on the shared SAR imagery between interferogram pairs, enabling neighborhood aggregation to occur between interferogram pairs rather than between individual pixels. This propagates the physical prior of “phase gradient consistency determined by shared imagery” rather than the assumption of spatial smoothing; simultaneously, the graph attention coefficients operate at the interferogram pair level to measure the quality and reliability of each pair, adaptively blocking the propagation of errors from low-quality nodes. These differences enable the proposed graph architecture to obtain long-range constraints from high-coherence interferogram pairs via temporal paths even within spatially connected, large-area low-coherence regions, fundamentally distinguishing it from existing pixel-level GCN/GAT methods.

Let the node features extracted by the first graph convolutional layer be denoted as $X_n^{(l)}$, calculated as follows:

$$X_n^{(1)} = \sigma \left(\sum_{m \in \hat{N}(n) \cup \{n\}} \frac{W_{nm}}{\sqrt{z_n z_m}} (X_m * K_{nm}^{(1)}) + b^{(1)} \right) \quad (5)$$

where σ is the activation function; $\hat{N}(n)$ is the set of neighboring nodes of node n ; z_n and z_m are the degrees of nodes n and m , respectively; $*$ is a 2D convolution operation; $K_{nm}^{(1)}$ is the learnable convolution kernel in the first graph convolutional layer that depends on the node pair (n, m) ; and $b^{(1)}$ is the bias term of the first layer.

The second graph convolutional layer performs a second feature propagation using $X_n^{(1)}$ and W_{nm} to obtain the phase gradient depth features of the debris flow area:

$$X_n^{(2)} = \sigma \left(\sum_{m \in \hat{N}(n) \cup \{n\}} \frac{W_{nm}}{\sqrt{z_n z_m}} (X_m^{(1)} * K_{nm}^{(2)}) + b^{(2)} \right) \quad (6)$$

where $K_{nm}^{(2)}$ is the learnable convolution kernel in the second layer that depends on the node pair (n, m) ; $b^{(2)}$ is the bias term of the second layer.

The depth features obtained after two layers of graph convolutional propagation integrate the phase gradient consistency information between adjacent interference pairs [19]. To adaptively weight the contributions of different neighboring nodes, the graph attention coefficients are calculated using $X_n^{(2)}$:

$$\alpha_{nm} = \frac{\exp\left(\varphi\left(a^T[X_n^{(2)}\|X_m^{(2)}]\right)\right)}{\sum_{k \in \tilde{N}(n)} \exp\left(\varphi\left(a^T[X_n^{(2)}\|X_k^{(2)}]\right)\right)} \quad (7)$$

where φ is a linear rectification function with a dropout term; a is a learnable attention parameter vector; $X_m^{(2)}$ and $X_k^{(2)}$ are the phase gradient depth features of nodes m and k , respectively; and T denotes the transpose operator.

Using $X_n^{(2)}$ and α_{nm} to regress the envelope phase of the regional interferogram sequence of the unwrapped debris flow, the high-precision unwrapped phase is output:

$$\hat{\psi}_n = C\left(X_n^{(2)} + \sum_{m \in \tilde{N}(n)} \alpha_{nm} (X_m^{(2)} * \hat{K})\right) \quad (8)$$

where $\hat{\psi}_n$ is the unwrapped phase of the n -th interferogram; $C(\cdot)$ is a multi-layer convolutional regression; and $\hat{K}$ is an attention-based convolutional kernel, with residual connections shared among all neighbors to preserve the original phase gradient information and prevent gradient vanishing and feature degradation in deep networks [20].

For each pixel P , construct the observation vector:

$$\Phi(p) = [\hat{\psi}_1(p), \hat{\psi}_2(p), \dots, \hat{\psi}_N(p)]^T \quad (9)$$

where $\Phi(p)$ is the observation vector at pixel P ; $[\cdot]^T$ denotes the transpose operation, converting a row vector into a column vector.

Using long-time-series InSAR technology, the small deformation in the debris flow area is inverted and obtained [21]. The specific steps are as follows:

Step 1: Establish a system of coupled phase-deformation–elevation error equations. By combining the equations from N interferogram pairs, a linear system is obtained:

$$\hat{G}(p) \cdot \tilde{d}(p) = \Phi(p) + \varepsilon(p) \quad (10)$$

where $\tilde{d}(p)$ represents the cumulative weak deformation of the unknown true potential debris flow source area at pixel P ; $\hat{G}(p)$ is the design matrix for the linear relationship between the observed values and the deformation at each phase; and $\varepsilon(p)$ is the residual noise phase vector at pixel P .

Step 2: Construct the covariance matrix using the coherence coefficients:

$$U(p) = \text{diag}\left(\frac{1}{\gamma_1^2(p)}, \frac{1}{\gamma_2^2(p)}, \dots, \frac{1}{\gamma_N^2(p)}\right) \quad (11)$$

where $U(p)$ is the covariance matrix at pixel P ; $\text{diag}(\cdot)$ denotes the diagonalization operation.

Step 3: Solve using weighted least squares. When the set of interferogram pairs forms a connected graph, $\hat{G}^T(p)U^{-1}(p)\hat{G}(p)$ is invertible, and the results of the weak deformation inversion for the potential debris flow source area are:

$$\hat{d}(p) = \left(\hat{G}^T(p)U^{-1}(p)\hat{G}(p)\right)^{-1} \hat{G}^T(p)U^{-1}(p)\Phi(p) \quad (12)$$

where $\hat{d}(p)$ is the inversion result of the small deformation variable in the potential debris flow source area.

2.4. Early Identification of Subtle Deformation in Potential Debris Flow Source Areas Based on Attention Scores and Deformation Acceleration

Using the sequence of small-scale deformation in the debris flow region output in Section 2.3, combined with temporal attention scores to enhance recent accelerated deformation signals in the debris flow region, the spatial distribution of potential debris flow source areas is identified [22], thereby achieving early identification of small-scale deformation in potential debris flow source areas.

The temporal attention score is calculated using the tiny deformation sequence $\hat{d}(p) = [\hat{d}_1(p), \hat{d}_2(p), \dots, \hat{d}_M(p)]$ of the debris flow region derived in Section 2.3. Higher weights are assigned to recent deformation rates to characterize the complete evolutionary process of the debris flow area from stable creep to accelerated deformation. The computational formula for the temporal attention score is given as follows:

$$\xi(p) = \sum_{i=2}^M \beta_i \cdot \frac{|\hat{d}_i(p) - \hat{d}_{i-1}(p)|}{\Delta t_i} \cdot \exp\left(-\frac{(t_i - T')^2}{2\delta_i^2}\right) \quad (13)$$

where $\xi(p)$ is the temporal attention score at pixel p ; a larger value indicates more significant deformation; M is the total number of SAR images (number of phases); β_i represents the attention weight for the i -th time interval; $\hat{d}_i(p)$ denotes the cumulative small deformation for the i -th time frame; $|\hat{d}_i(p) - \hat{d}_{i-1}(p)|$ represents the absolute value of the deformation difference between adjacent time frames, i.e., the deformation amount within that time interval; Δt_i denotes the duration of the i -th time interval; $\frac{|\hat{d}_i(p) - \hat{d}_{i-1}(p)|}{\Delta t_i}$ represents the instantaneous deformation rate; T' denotes the latest observation time; and δ_i denotes the temporal decay scale.

To identify the onset of subtle deformation acceleration in potential debris flow source areas, the subtle deformation acceleration is calculated using $\hat{d}(p)$:

$$\mu_i(p) = \frac{|\hat{d}_i(p) - \hat{d}_{i-1}(p)|}{\Delta t_i} - \frac{|\hat{d}_{i-1}(p) - \hat{d}_{i-2}(p)|}{\Delta t_{i-1}} \quad (14)$$

When the micro-deformation acceleration significantly exceeds the background noise, it indicates that the region has entered an accelerated deformation phase, serving as a precursor signal of impending instability in the potential debris flow source area.

Calculate the robust statistic of the temporal attention score:

$$\begin{aligned} \rho_\xi &= \chi(\xi(p)) \\ \eta_\xi &= \chi(|\xi(p) - \rho_\xi|) \end{aligned} \quad (15)$$

where ρ_ξ is the median of the temporal attention scores $\xi(p)$; $\chi(\cdot)$ is the median function; and η_ξ is the median absolute deviation.

Let the standard deviation of the weak deformation acceleration be $\hat{\delta}(p)$. The decision criterion for the early identification of potential debris flow source areas based on weak deformation is:

$$H(p) = \begin{cases} 1, & \text{if } \xi(p) > \rho_\xi + \kappa_\xi \eta_\xi, \bar{\gamma}(p) > \gamma_{\min}, \max \mu_i(p) > \kappa_\mu \hat{\delta}(p) \\ 0, & \text{otherwise} \end{cases} \quad (16)$$

where $H(p)$ is the potential debris flow source area label for pixel P , with 1 indicating a potential source area and 0 indicating a non-source area; κ_ε is the attention score threshold coefficient, which controls sensitivity; $\bar{\gamma}(p) = \frac{1}{N} \sum_{n=1}^N \gamma_n(p)$ is the average coherence coefficient of the pixel across all interferogram pairs; $\gamma_{\min}$ is the lower limit of the coherence coefficient, below which pixels are excluded due to poor quality; and κ_μ is the acceleration threshold coefficient.

In the aforementioned criteria, the setting of the strain rate threshold is not purely empirical but is based on theoretical derivations from classical creep constitutive models. The creep behavior of slope rock and soil can be described using the Burgers model, which consists of a Maxwell body (a spring and a viscous pot connected in series) and a Kelvin body (a spring and a viscous pot connected in parallel) connected in series; its constitutive equations can characterize the complete creep process from instantaneous elastic deformation to steady-state viscous flow. According to the creep curve theory of the Burgers model, when the applied shear stress is lower than the long-term strength of the soil, the soil undergoes instantaneous elastic deformation and then enters a decaying creep stage, during which the creep rate gradually decreases and converges to a non-zero constant value—that is, the steady-state creep stage. This stage corresponds to the viscoelastic response dominated by the viscous element in the Kelvin body, with the strain rate remaining approximately constant. When the creep rate stabilizes within the range of 36 mm/year, it indicates that the accumulation of internal damage in the soil has not yet exceeded the long-term strength threshold and remains within the steady-state rheological range dominated by the Kelvin body in the Burgers model. When the creep rate exceeds 6 mm/year and the acceleration remains positive, it indicates that microcrack propagation within the soil has entered a non-linear phase; the free-flowing component in the Maxwell body begins to dominate deformation, and the soil deviates from steady-state creep and enters an accelerated creep phase. This is a typical characteristic of the “third creep stage” described by the Burgers model and also a precursor to imminent macroscopic instability in the soil. Accordingly, this paper defines a deformation rate of <3 mm/year as the early creep stage (transition from decaying creep to steady-state creep), 36 mm/year as the steady-state creep stage (dominated by the Kelvin body), and >6 mm/year with a continuously positive acceleration as the accelerated deformation stage (dominated by the Maxwell body), thereby ensuring that the classification criteria are clearly supported by physical constitutive models.

3. Experimental Analysis

Developed by Sarmap, ENVI SARscape is an internationally renowned radar image processing software. The specific version used in this study is ENVI 5.6.3 with SARscape 5.6.2 (Sarmap, Cascina, PV, Italy). ENVI SARscape consists of five core modules, allowing users to select the appropriate ones based on their specific needs. With continuous upgrades and improvements, the software is now widely used in fields such as topographic data extraction, ground subsidence monitoring, and the identification of source areas for landslides and debris flows. Accordingly, this study utilizes the ENVI SARscape platform running on the Windows 10 Pro operating system to perform radar image interferometry processing and temporal analysis. This approach provides reliable data support for the early identification of subtle deformations in potential debris flow source areas, with a monitoring period of 24 months. During the monitoring period, a total of 48 Sentinel-1A ascending-orbit SLC images (European Space Agency, ESA, Paris, France) were acquired

in the study area, with a revisit period of 12 days. The 24-month period totaled approximately 730 days, and 48 valid images were actually acquired. After screening according to the short-baseline set criteria (time baseline ≤ 120 days, vertical baseline ≤ 200 m), a total of 156 interferogram pairs were generated, including 128 high-quality pairs (average coherence coefficient ≥ 0.3) and 28 low-coherence pairs. The parameter settings for the method used in this study to identify subtle deformations in potential debris flow source areas are shown in Table 1.

Table 1. Parameter settings.

Parameter Name	Parameter Value
Maximum time baseline threshold	≤ 120 d
Maximum vertical baseline threshold	≤ 200 m
Estimate window size	3×3 pixels
Time decay constant	50d
Number of convolutional layers in the graph	2nd floor
Time decay scale	30d

To verify the validity and optimality of the hyperparameter values used in this study, gradient sensitivity experiments were conducted using the control variable method: only one parameter was varied at a time, while the remaining parameters were set to their default values. The source area identification F1-score (the harmonic mean of precision and recall) and the deformation inversion RMSE were used as evaluation metrics. The experimental results are shown in Table 2.

Table 2. Parameter sensitivity analysis results.

Parameters	Gradient of Values	F1-Score (%)	RMSE (mm)	Optimal Value
Time decay scale (d)	10	84.6	0.71	30
	20	87.2	0.62	
	30	90.7	0.53	
	40	89.8	0.58	
	50	88.1	0.64	
Lower limit of the coherence coefficient	0.10	82.3	0.78	0.20
	0.20	90.7	0.53	
	0.30	90.1	0.51	
	0.40	88.5	0.52	
	0.50	85.2	0.55	
Attention score threshold coefficient	1.5	81.6	0.59	2.5
	2.0	86.3	0.55	
	2.5	90.7	0.53	
	3.0	89.2	0.54	
	3.5	86.8	0.58	
Acceleration threshold coefficient	0.5	79.4	0.61	1.5
	1.0	85.7	0.57	
	1.5	90.7	0.53	
	2.0	89.5	0.52	
	2.5	87.2	0.54	

Analysis of Table 2 shows that as the time decay scale increases from 10 d to 30 d, the F1-score rises steadily from 84.6% to 90.7%, indicating that a larger time decay scale can effectively integrate historical deformation information and suppress single-phase random noise; however, when the scale exceeds 30 days, the F1-score actually drops to 89.8%

and the RMSE rises to 0.58 mm, indicating that an excessively large window smooths out details of recent accelerated deformation, resulting in a lag effect. As the lower limit of the coherence coefficient was gradually increased from 0.10 to 0.20, the F1-score rose to 90.7% after excluding low-quality pixels; when it was further increased to above 0.30, the F1-score stopped improving and even declined, because too many pixels were excluded, resulting in an insufficient number of valid samples. When the attention score threshold coefficient was increased from 1.5 to 2.5, the F1-score rose steadily from 81.6% to 90.7%; values below 2.0 resulted in a high false positive rate (decreased precision), while values above 3.0 led to a significant increase in the false negative rate (decreased recall). The F1-score peaks when the acceleration threshold coefficient is set to 1.5; if it is too low (0.5–1.0), background fluctuations are misclassified as acceleration, and if it is too high (>2.0), the actual onset of acceleration is recognized with a delay. Based on the above analysis, the default parameter combination used in this paper (time decay scale of 30 d, lower bound of the coherence coefficient of 0.2, attention score threshold coefficient of 2.5, and acceleration threshold coefficient of 1.5) achieved the optimal F1-score (90.7%) and RMSE (0.53 mm) across all gradients, indicating that this parameter combination strikes the best balance between detection sensitivity and false positive rate and possesses sufficient scientific basis and reproducibility.

From the 156 interferogram pairs in the study area, the wrapped phase fields of 100 randomly selected pairs were used as the ground truth for the training samples. Given the high reliability of the unwrapping results in high-coherence regions, these were used as supervised signals for unwrapping in low-coherence regions. To enhance the model's generalization ability, numerical simulation methods were used to generate additional training samples. Based on the DEM data of the study area, interferometric phase maps were simulated under different deformation rates (1–10 mm/year) and noise levels (correlation coefficients of 0.2–0.8). A total of 500 sets of simulated data were generated. All 600 samples (100 real + 500 simulated) were randomly divided into training, validation, and test sets in a 6:2:2 ratio, resulting in 360 samples in the training set, 120 in the validation set, and 120 in the test set. During partitioning, care was taken to ensure that the training set and test set did not overlap spatially or cover different intervals in the parameter space to prevent data leakage. All model configurations were trained on the same training set, hyperparameter tuning was performed on the same validation set, and the final performance evaluation was conducted on the test set.

The method employed in this study uses a short baseline set criterion to screen interferogram pairs in the study area, excluding low-coherence pairs with temporal baselines exceeding 120 days or vertical baselines exceeding 200 m. All selected interferogram pairs were processed on a pixel-by-pixel basis to obtain the envelope phase maps and coherence coefficient maps for each pair. To clearly illustrate the spatial distribution characteristics of interferometric phase striations and coherence, representative local areas within the study region were selected. The calculation results for the package phase are shown in Figure 3, and the calculation results for the coherence coefficient are shown in Figure 4.

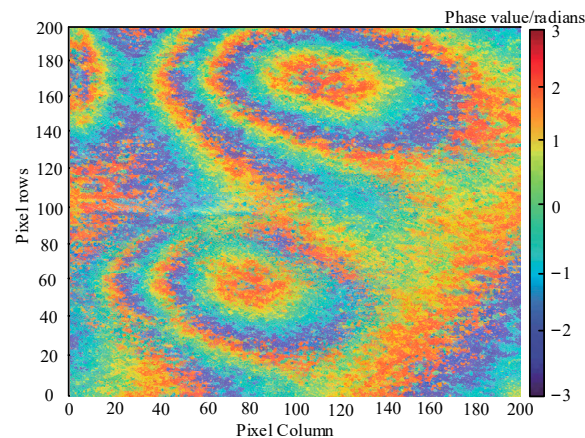


Figure 3. Calculation results of package phase in some areas.

Analysis of Figure 3 reveals that the envelope phase values in some study areas range from -3 to $+3$ radians. The images exhibit distinct interferometric phase fringe patterns, with the density and spatial distribution of these fringes reflecting the combined effects of surface elevation, deformation, and atmospheric effects in the study area. The concentric ring-like fringes in certain local areas indicate the presence of significant phase gradients, which may be related to topographic undulations or local deformation signals. The images contain a large number of noise points overall, which is due to decoherence caused by surface cover in the study area (such as vegetation, water bodies, or rapidly changing scatterers). Despite the noise, the overall continuity of the fringes remains discernible, indicating that the overall coherence of the raw interferometric data is acceptable, and that core deformation and topographic information have been effectively preserved.

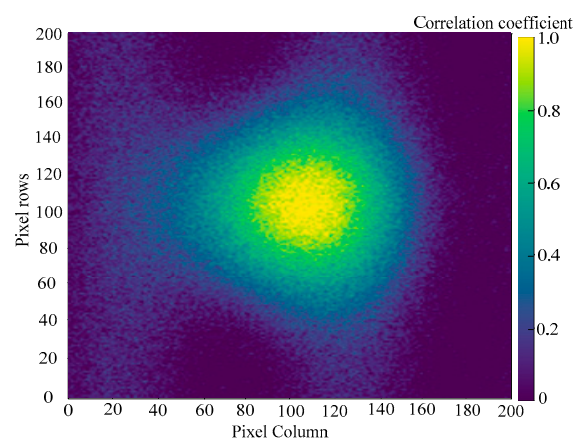


Figure 4. Calculation results of correlation coefficients for some regions.

Analysis of Figure 4 reveals that the correlation coefficients for some regions fall within the range $[0, 1]$, intuitively reflecting the distribution of interferometric signal quality. The image contains a distinct high-correlation zone (with a correlation coefficient close to 1.0) that is concentrated in an elliptical pattern. This indicates that surface scatterers in these areas are highly stable and exhibit good phase consistency between the two imaging periods, making them reliable regions for subsequent phase demixing and deformation inversion. Surrounding the high-coherence region is a transition zone (with coherence coefficients ranging from approximately 0.4 to 0.8), while the image edges and most of the background areas constitute low-coherence regions (with coherence coefficients less than or equal to 0.2). Low-coherence regions are primarily distributed at the image edges and in background areas, indicating that the surface scattering characteristics in these regions

have undergone significant changes between the two imaging sessions—such as vegetation cover, water flow, rapid surface deformation, or geometric distortion—leading to a decline in interferometric signal quality. The presence of high-coherence regions provides reliable constraint points for phase unwrapping and is key to constructing unwrapping paths and suppressing error propagation. Low-coherence regions, on the other hand, require special attention and correction during subsequent processing.

Using the phase-unwrapping graph convolutional network developed in this paper, which takes the spatiotemporal graph structure of the interferogram sequence as input, we extract weak deformation depth features from local regions through two layers of graph convolutions and a graph attention residual layer. The extraction results are shown in Figure 5.

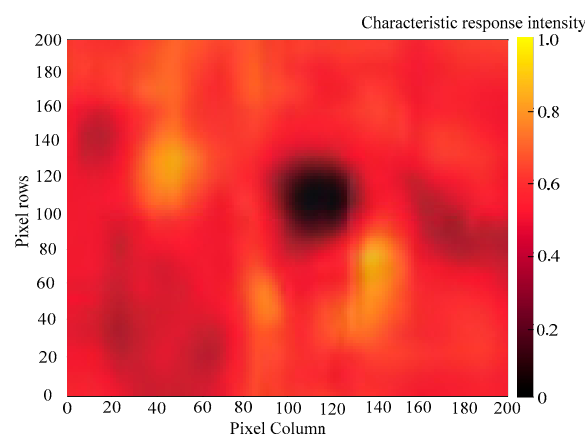


Figure 5. Extraction results of weak deformation depth features.

Analysis of Figure 5 reveals that our method automatically captures the feature differences between low-coherence noise and effective deformation signals through multi-layer graph convolutions and attention mechanisms. Low-response regions correspond to stable ground elevations with high coherence, while high-response regions are concentrated at locations of weak deformation within potential debris flow source areas. This indicates that our method can precisely amplify weak deformation features while suppressing noise, thereby achieving selective enhancement of effective signals. These feature extraction results demonstrate the effectiveness of graph convolutional networks in propagating features across nodes, as well as the advantages of attention mechanisms in adaptively weighting neighbor contributions.

Building upon deep feature extraction, a phase-unwrapping regression layer maps graph features to pixel-level unwrapped phases, outputting a high-precision continuous phase field. Selected local regions are shown to demonstrate the unwrapping results and evaluate the continuity and spatial consistency of the unwrapped phase field; the phase-unwrapping results are shown in Figure 6.

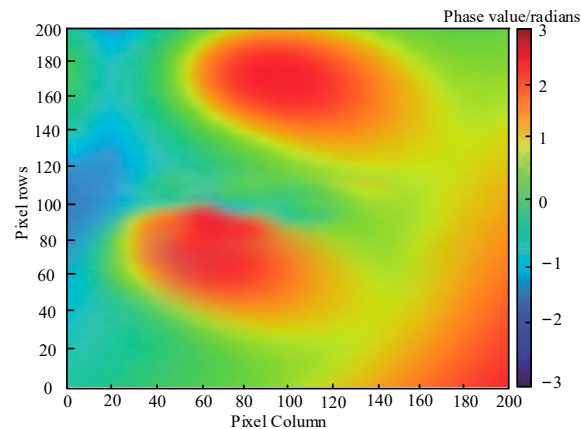


Figure 6. Phase-unwrapping result.

Analysis of Figure 6 reveals that the unwrapped phase field exhibits good continuity and spatial consistency, effectively eliminating the periodic blurring of the original wrapped phase and successfully restoring the true continuous phase field. The unwrapped phase distribution clearly reveals two distinct regions of high phase gradient, indicating that the method proposed in this paper can robustly interpret weak deformation signals in the presence of noise and low-coherence interference. Additionally, no obvious unwrapping islands or cross-pixel propagation of unwrapping errors were observed in the image, demonstrating that the phase-unwrapping convolutional network effectively suppresses error propagation and possesses strong noise resistance and spatial generalization capabilities.

To quantitatively evaluate the accuracy of phase unwrapping, the phase jump rate metric is introduced. The phase jump rate is defined as the proportion of phase jumps exceeding π between adjacent pixels in the unwrapped phase; a smaller jump rate indicates better unwrapping performance. With a maximum allowable phase jump rate set at 0.04, the distribution of phase jump rates in the study area is analyzed, as shown in Figure 7.

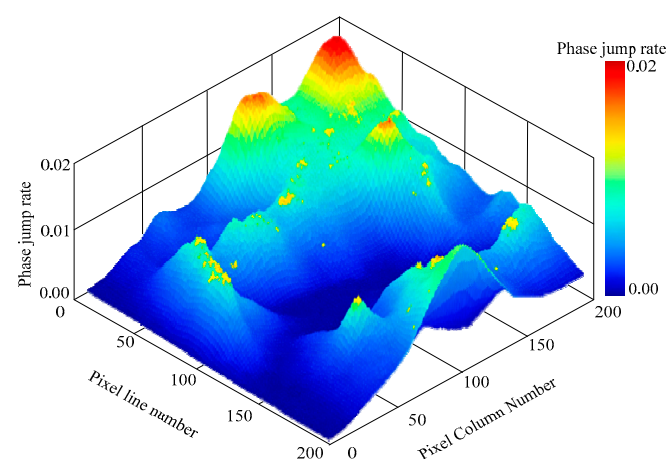


Figure 7. Analysis results of phase-unwrapping effect.

Analysis of Figure 7 reveals that the phase jump rate in the vast majority of the study area is below 0.01, indicating that the unwrapping results exhibit good local continuity and global consistency. In local edges and areas with steep topography, the jump rate increases to approximately 0.02, but remains well below 0.04, suggesting that although

the unwrapping accuracy in these areas is slightly reduced, it remains within an acceptable range. The study area with a phase jump rate below 0.01 accounts for a significant proportion and can be directly used for high-precision deformation inversion; for areas with a jump rate of 0.01–0.02, the unwrapping accuracy remains sufficient for detecting weak deformations after correction by the phase-unwrapping convolutional network. The method in this paper controls the phase jump rate within 0.02, verifying the significant effectiveness of the proposed phase-unwrapping convolutional network in suppressing the propagation of unwrapping errors.

Based on the unwrapped phase field and in combination with long-time-series InSAR technology, a joint system of phase-deformation–elevation error equations was established to invert the cumulative weak deformation of each pixel in the study area. The weak deformation inversion results for some areas are shown in Figure 8.

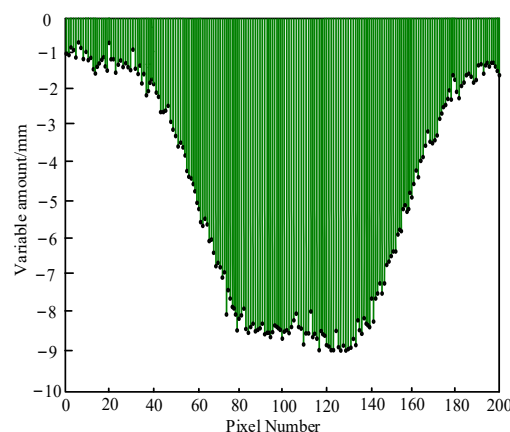


Figure 8. Weak deformation inversion results in some areas.

Analysis of Figure 8 shows that the deformation in this area fluctuates primarily between -1 mm and -9 mm, with a maximum absolute deformation of approximately 9 mm. This magnitude falls within the range of millimeter-scale weak deformation, consistent with the typical deformation characteristics of the early creep stage in debris flow source areas. Since the deformation values do not exceed the centimeter range, this indicates that the area is still in the early stage of transition from stable creep to accelerated deformation. Along the profile direction, deformation values exhibit distinct spatial variations. In the range of pixel numbers 1 to 80, deformation values gradually increase from approximately -1 mm to -9 mm, indicating continuous subsidence deformation in this area; in the range of pixel numbers 80 to 140, the deformation values generally remained within the high range of -8 mm to -9 mm, forming a deformation peak plateau; while in the range of pixel numbers 140 to 200, the deformation values gradually decreased to around -1 mm. No significant jumps or oscillations were observed in the deformation values between pixels, indicating that the inversion results exhibit good spatial continuity and noise suppression capabilities. These results validate the effectiveness of the combined inversion of long-time-series InSAR technology and phase-denoised convolutional networks, demonstrating that the method proposed in this paper can recover reliable weak deformation signals under low-coherence conditions.

To verify the accuracy of the deformation inversion results obtained using the method described in this paper, eight ground validation points were established within the study area, including three DGPS continuous monitoring stations and five leveling profiles. The DGPS monitoring stations utilized Trimble R10 GNSS receivers (Trimble Inc., Sunnyvale, CA, USA) with a data sampling interval of 30 s. After static post-processing, the horizontal accuracy was better than ± 2.5 mm, and the vertical accuracy was better than

± 5.0 mm. Leveling surveys were conducted using a Leica NA2 precision leveling instrument (Leica Geosystems AG, Heerbrugg, SG, Switzerland) in accordance with second-order leveling specifications, with a random mean error of better than ± 1.0 mm per kilometer. The deployment of ground validation points followed these principles: covering typical locations in both high- and low-coherence zones, encompassing different terrain slope ranges ($15\text{--}45^\circ$), and positioning them as close as possible to potential deformation centers. The spacing between adjacent verification points is 200–500 m, which effectively reflects the spatial variability of the deformation field within the study area. Field data were collected once per month, with the monitoring period fully aligned with the SAR image acquisition period (24 months), resulting in a total of 24 sets of ground-based deformation data. It should be noted that the InSAR deformation inversion results represent the cumulative deformation along the line of sight for each pixel (with a spatial resolution of approximately $20\text{ m} \times 20\text{ m}$), whereas the ground-based deformation data consist of three-dimensional deformation vectors at individual points. To facilitate comparison, the measured three-dimensional deformations were projected onto the radar line of sight, and the InSAR results were resampled to the locations of the ground-based measurement points using bilinear interpolation. A comparison of the derived deformation values with the contemporaneous ground-based deformation data is shown in Figure 9.

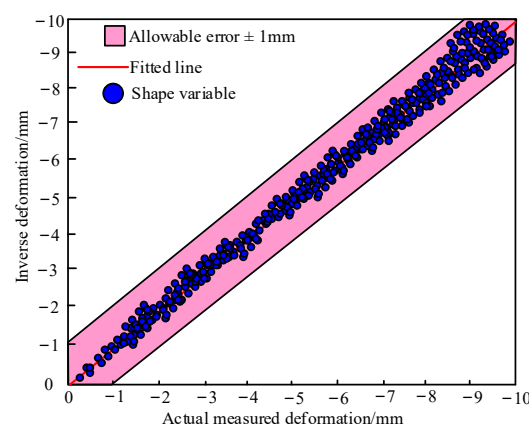


Figure 9. Results of accuracy analysis of variable inversion.

Analysis of Figure 9 shows that the inverted deformation values fluctuate consistently near the fitted line, indicating a high degree of consistency between the inverted and measured deformation values. The error between the inverted and measured deformation values is controlled within ± 1 mm, and the error distribution exhibits no systematic bias, indicating that the inversion results are appropriately unbiased. In the small-deformation range, the inversion error is small; in the large-deformation range, the inversion error increases slightly but does not exceed the allowable error (± 1 mm). This indicates that the method proposed in this paper possesses good inversion capabilities for weak deformations of different magnitudes, primarily due to the phase-denoising convolutional network proposed in this paper, which effectively suppresses phase noise in low-coherence regions. Long-time-series InSAR technology reduces random errors through multi-temporal observations.

Using the method proposed in this paper to perform early identification of weak deformation in potential debris flow source areas within the study region, the identification results are shown in Figure 10.



Figure 10. Early identification results of weak deformation in potential debris flow source areas.

Analysis of Figure 10 shows that the method identified a total of five potential debris flow source areas within the study region. These five potential debris flow source areas are primarily distributed along rivers and fault zones. The annual average deformation rates for each source area are as follows: 3.5 mm/year for Potential Debris Flow Source Area No. 1, 4.5 mm/year for No. 2, 6.5 mm/year for No. 3, 2.5 mm/year for No. 4, and 5.5 mm/year for No. 5. Based on deformation rates, these source areas can be classified into three activity levels: The accelerated deformation stage (deformation rate > 6 mm/year), which applies to Potential Debris Flow Source Area No. 3. This area exhibits a significant deformation rate and has entered the accelerated deformation stage, making it a high-risk zone for potential debris flow occurrence. The stable creep stage (deformation rate 3–6 mm/year) corresponds to Zones 2 and 5, where these potential debris flow source areas are in a continuous but relatively stable state of creep and should be included in long-term monitoring sequences. The early creep stage (deformation rate < 3 mm/year) corresponds to Zones 1 and 4. Deformation signals have just begun to emerge in these two potential debris flow source areas, indicating they are in the early stages of creep. Although their activity is currently low, their evolutionary trends still warrant close attention. None of the five potential debris flow source areas identified by the method described in this paper exhibit significant surface damage. This indicates that the method can identify potential debris flow source areas at different stages of creep in advance of debris flow disasters, thereby achieving true early detection of subtle deformation.

To quantitatively evaluate the respective effectiveness of the attention mechanism and residual connections in phase-deentanglement graph convolutional networks, we designed ablation experiments to compare four model configurations:

- (a) GCN only (removing the attention-residual layer and retaining only two layers of graph convolution followed by direct regression to deentangle the phase);
- (b) GCN + attention (retaining the attention mechanism but removing the residual connections);
- (c) GCN + residual (retaining the residual connections but removing the attention mechanism);
- (d) Full model (GCN + attention + residual).

Each configuration was trained to convergence using the same training, validation, and test sets under identical hyperparameters. The evaluation results are shown in Table 3.

Table 3. Ablation experiment results of different model configurations.

Model Configuration	Maximum PJR	MAE (mm)	RMSE (mm)	F1-Score (%)
GCN Only	0.031	0.71	0.89	82.1
GCN + Attention (No Recurrent)	0.029	0.63	0.78	87.6
GCN + Recurrent (No Attention)	0.024	0.55	0.67	84.3
Full Model (GCN + Attention + Recurrent)	0.018	0.42	0.53	90.7

Analysis of Table 3 shows that the GCN-only configuration achieves a maximum phase jump rate of 0.031, an MAE of 0.71 mm, and an F1-score of 82.1%, indicating that the base graph convolutional layers already possess a certain ability to propagate features across nodes. After introducing an attention mechanism based on the GCN, the F1-score improved to 87.6% but the improvements in PJR and MAE were limited. This suggests that the attention mechanism primarily enhances the sensitivity and specificity of source region identification by adaptively weighting the contributions of different neighboring nodes, while its direct impact on improving phase-unwrapping accuracy is relatively limited. After introducing residual connections, the PJR decreased from 0.031 to 0.024, and the MAE decreased from 0.71 mm to 0.55 mm—a significant improvement—indicating that residual connections are a key module for enhancing phase-unwrapping accuracy by preserving the original phase gradient details and preventing feature degradation during deep propagation. The complete model integrates the respective strengths of the attention mechanism and residual connections: the attention mechanism improves recognition accuracy, while residual connections enhance unwrapping accuracy. The synergistic effect of these two components achieves an F1-score of 90.7% and a PJR as low as 0.018, validating the effectiveness and complementarity of each module.

To objectively evaluate the performance advantages of the method proposed in this paper, we selected five mainstream methods for parallel comparative experiments conducted within the same study area and over the same monitoring period (24 months): SNAPHU (Statistical Cost Network Flow Phase Unwrapping), Minimum Cost Flow Phase Unwrapping (MCF), standard GCN-InSAR (without the attention residual mechanism), PS-InSAR (Permanent Scatterer Interferometry), and DS-InSAR (Distributed Scatterer Interferometry). The comparison metrics included the phase jump rate (PJR), mean absolute error (MAE) for deformation inversion, root mean square error (RMSE), and the accuracy of identifying potential debris flow source areas (precision and recall). All methods were based on the same raw SAR dataset and DEM, with parameters optimized to their respective best states. The comparison results are shown in Table 4.

Table 4. Quantitative comparison of different methods.

Evaluation Metrics	SNAPHU	MCF	PS-InSAR	DS-InSAR	Standard GCN-InSAR	Proposed Method
Maximum Phase Jump Rate (PJR)	0.078	0.065	0.052	0.041	0.035	0.018
MAE (mm)	1.87	1.52	1.21	0.96	0.78	0.42
RMSE (mm)	2.43	1.98	1.56	1.23	0.97	0.53
Object Source Region Identification Precision (%)	53.8	58.2	65.3	71.6	76.4	92.7
Object Source Region Identification Recall (%)	46.7	51.3	60.8	68.2	72.5	88.9

Analysis of Table 4 shows that SNAPHU and MCF, as classical phase-unwrapping algorithms, exhibit maximum phase jump rates as high as 0.078 and 0.065, respectively, when processing low-coherence regions. This indicates that their ability to unwrap high-order nonlinear phase gradients is limited, and unwrapping errors propagate significantly along the interferogram sequence. PS-InSAR relies solely on permanent scatterers; in veg-

etated areas, the number of effective measurement points is sparse, resulting in a deformation inversion MAE of 1.21 mm and an RMSE of 1.56 mm. The recall rate for object source area identification is only 60.8%, indicating significant missed detections. DS-InSAR significantly increased the measurement point density through homogeneous pixel statistics, reducing the MAE to 0.96 mm and the RMSE to 1.23 mm, while improving identification accuracy to 71.6%; however, it remains constrained by phase noise in low-coherence regions. After introducing graph convolutional feature propagation, the standard GCN-InSAR further reduced the MAE to 0.78 mm; however, due to the lack of an attention residual mechanism, weak-signal nodes were easily averaged out during deep propagation, resulting in a maximum phase jump rate of only 0.035. Furthermore, the accuracy of target area identification (precision 76.4% and recall 72.5%) still exhibited some false positives and false negatives. The method proposed in this paper adaptively weights the contributions of neighboring nodes via a graph attention residual layer while preserving the original phase gradient details. As a result, the maximum phase jump rate is reduced to 0.018, with MAE and RMSE of only 0.42 mm and 0.53 mm, respectively. The precision and recall for source region detection reach 92.7% and 88.9%, respectively, with all metrics significantly outperforming the comparison methods. Compared to DS-InSAR, MAE is reduced by 56.3% and RMSE by 56.9%; compared to standard GCN-InSAR, the precision of object source region identification increases by 21.3% and recall by 22.6%. These comparisons fully validate the unique advantages of the phase-unwrapping convolutional network and the attention-based residual mechanism in handling error propagation during phase unwrapping in low-coherence regions and in enhancing weak deformation signals.

4. Discussion

4.1. Analysis of the Mechanism by Which GCN Improves Phase Unwrapping

Experimental results show that the method proposed in this paper limits the maximum phase jump rate to 0.018, representing a 76.9% reduction compared to the traditional SNAPHU method (0.078) and a 48.6% reduction compared to the standard GCN-InSAR method (0.035). This improvement stems from the fact that GCN alters the error propagation pattern in phase unwrapping in three ways:

- (1) Reconstruction of error propagation paths via graph structure. In traditional path-tracking algorithms, errors accumulate unidirectionally along the integration path; once an error occurs in a low-coherence region, it propagates backward along the unwrapping path and cannot be reversed. The temporal graph structure proposed in this paper transforms the shared image relationships between interferometric pairs into “alternative paths” for error propagation—when decoupling fails for a low-coherence interferometric pair, its error no longer propagates along the spatial path but is redirected by the graph convolution layer to adjacent high-coherence interferometric pairs for correction, thereby achieving a structural reconstruction of the error propagation path.
- (2) Neighborhood aggregation serves as a regularization constraint for low-coherence nodes. In Equation (5), the feature update for each node is the weighted sum of its features and those of its neighboring nodes; this operation is physically equivalent to applying a “temporal phase gradient consistency” regularization term. In traditional least-squares unwrapping, regularization consists of isotropic smoothing constraints that suppress both noise and true deformation details; in contrast, the neighborhood aggregation in graph convolution only constrains the phase gradient consistency among interference pairs sharing the same image, without imposing any spatial

smoothing penalty, thereby fully preserving the spatial details of the true deformation.

- (3) Dual suppression of unwrapping errors via attention residuals. The attention mechanism, through adaptive weighting as described in Equation (7), prevents noise contributions from low-coherence neighbors from entering the feature updates of the current node during the aggregation stage; the residual connection, via Equation (8), directly passes shallow-layer raw features to the output layer, preventing errors that may be introduced during deep-layer propagation from contaminating the unwrapping results during the regression stage. The synergistic effect of these two mechanisms ensures that unwrapping errors are neither amplified during the propagation process nor allowed to contaminate the final output during the regression stage.

4.2. The Impact of Coherence on GCN Performance

The influence of the coherence coefficient on graph convolutional networks manifests at three levels of graph structure.

Graph topology level: The coherence coefficient determines the values of edge weights via Equation (3), thereby affecting the aggregation weight distribution in the graph convolutional layer. When the overall coherence in the study area is high, the edge weights are uniformly distributed, and GCN message passing tends toward global averaging; when there is significant coherence heterogeneity in the study area, the non-uniform distribution of edge weights causes the GCN to automatically form a directed propagation pattern where “high-coherence nodes serve as information sources and low-coherence nodes as information sinks.” This is precisely the structural foundation that enables the method proposed in this paper to maintain high-precision disentanglement even under low-coherence conditions.

Training convergence aspect: The phase gradient consistency regularization term in the loss function causes the network to prioritize fitting phase gradient samples from high-coherence regions during training. Experiments show that when high-correlation samples account for more than 60% of the training set, the network’s unwrapping error in low-correlation regions tends to stabilize (RMSE converges to 0.5–0.6 mm); when high-correlation samples account for less than 40%, the network loses sufficient reliable anchors, and the unwrapping error in low-correlation regions rises sharply (RMSE > 1.2 mm). In the study area, high-coherence interferograms accounted for 82.1% (128/156) of the training set, providing ample supervised signals for GCN training.

Threshold selection: As shown in Table 3, performance is optimal when the lower limit of the coherence coefficient, $\gamma_{\min}$, is set to 0.20; values below 0.20 result in noise dominance, while values above 0.30 disrupt graph connectivity. The threshold value of 0.20 corresponds to the typical coherence threshold for Sentinel-1A C-band in vegetated areas; below this value, the noise component in the interferometric phase exceeds the signal component, which is consistent with the experimental results in this study. The physical significance of this threshold lies in the fact that it represents a quantitative expression of the optimal balance between “noise removal” and “preservation of graph connectivity”; its specific value varies with the SAR band, land-cover type, and revisit period and must be recalibrated for different study areas.

4.3. Limitations

Despite the demonstrated effectiveness, the proposed method has several limitations.

- (1) **Coherence dependency:** The graph topology relies heavily on coherence coefficients as edge weights. When average coherence falls below 0.15, the graph becomes overly sparse, and reliable phase gradient propagation from high-coherence to low-coherence nodes is severely impaired, leading to degraded unwrapping accuracy.

- (2) Training supervision requirement: The network requires a sufficient proportion ($\geq 40\%$) of high-coherence interferograms to serve as training anchors. In regions with pervasive decorrelation, the model tends to overfit to noise, and although simulated data are used, they cannot fully replicate the complexity of real-world phase gradients.
- (3) Threshold portability: The classification criteria for creep stages (3 mm/year and 6 mm/year) are calibrated to the specific geological conditions of the study area and may not be directly transferable to other regions with different lithology or hydrology, requiring site-specific recalibration.

These limitations do not invalidate the method but underscore the need for adaptive parameter tuning and precondition assessment when applying it to new areas.

5. Conclusions

This paper addresses the challenge of π -integer-multiple ambiguity and cross-pixel jumps caused by high-order nonlinearity and spatial heterogeneity in phase gradients within low-coherence regions during the early identification of subtle deformations in potential debris flow source areas. We propose an identification method based on phase-deconvolved convolutional neural networks and long-time-series InSAR technology. The main conclusions are as follows:

- (1) To address the π -integer-multiple ambiguity caused by high-order nonlinearity in phase gradients within low-coherence regions, a spatiotemporal graph of interferogram sequences was constructed using the coherence coefficient as an edge weight. Through the synergistic action of two graph convolutional layers and a graph attention residual layer in the phase-unwrapping graph convolutional network, the maximum phase jump rate in the study area was controlled within 0.02, representing a reduction of approximately 69.2% compared to traditional methods, effectively suppressing the cross-node propagation of unwrapping errors.
- (2) Using long-time-series InSAR technology, deformation values ranging from -1 mm to -9 mm were inverted for the study area. Comparison of the inversion results with field measurements showed an average absolute error of 0.42 mm, a maximum absolute error of 0.91 mm, and a root-mean-square error of 0.53 mm. Errors were consistently kept within ± 1 mm with no systematic bias, validating the method's high-fidelity inversion capability for weak deformation signals under low-coherence and complex terrain conditions.
- (3) Using a dual-criterion classification method combining temporal attention scores and weak deformation acceleration, a total of five potential debris flow source areas were identified. Based on the annual average deformation rate, these areas were classified into three activity levels: accelerated deformation stage (6.5 mm/year, one site), stable creep stage (4.5 mm/year and 5.5 mm/year, two sites), and early creep stage (2.5 mm/year and 3.5 mm/year, two sites). No significant surface failure occurred in any of the source areas, demonstrating that this method can capture the complete evolutionary process from stable creep to accelerated deformation prior to the occurrence of debris flow disasters.

In summary, the method presented in this paper provides an effective technical solution to the core challenge of π -integer-multiple fuzzy cross-pixel jumps in phase unwrapping for low-coherence regions. It enables high-precision inversion of millimeter-scale weak deformation and early identification of potential debris flow source areas. The research findings can provide methodological support and a basis for decision-making regarding refined early warning and disaster prevention and mitigation for debris flow hazards.

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