

Article

An SBAS-InSAR Analysis and Assessment of Landslide Deformation in the Loess Plateau, China

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Highlights

What are the main findings?

- An SBAS-InSAR post-processing workflow integrating velocity direction conversion and Z-score clustering was developed for classifying the state of landslide activity across the Loess Plateau. Conversion of the LOS direction velocity vector into a slope direction is used to identify and monitor the landslides' displacement change. The Z-score clustering method is applied to group measurement points for classification, thereby enhancing efficiency, albeit with a reduction in classification completeness.
- This work combined time series displacement with precipitation to analyze the kinematic characteristics of the landslides, and used historical optical images for verification.

What are the implications of the main findings?

- The experiment shows that open and easily accessible Sentinel-1 data can be one data source for identifying and monitoring landslides. The SBAS-InSAR post-processing workflow, incorporating velocity direction conversion and Z-score clustering, is an effective method for updating landslide activity across most of the Loess Plateau, except in forested areas.
- The results suggest that the creep deformation of landslides was highly sensitive to seasonal rainfall.

Abstract

This study conducts a landslide deformation assessment in Tianshui, Gansu Province, on the Chinese Loess Plateau, utilizing the Small Baseline Subset InSAR (SBAS-InSAR) method integrated with velocity direction conversion and Z-score clustering. The Chinese Loess Plateau is one of the most landslide-prone regions in China due to frequent rains, strong topographical gradients and severe soil erosion. By constructing subsets of interferograms, SBAS-InSAR can mitigate the influence of decorrelation to a certain extent, making it a highly effective technique for monitoring regional surface deformation and identifying landslides. To overcome the limitations of the satellite's one-dimensional Line-of-Sight (LOS) measurements and the challenge of distinguishing true landslide signals from noise, two optimization strategies were implemented. First, LOS velocities were projected onto the local steepest slope direction, assuming translational movement parallel to the slope. Second, a Z-score clustering algorithm was employed to aggregate measurement points



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with consistent kinematic signatures, enhancing identification robustness, with a slight trade-off in spatial completeness. Based on 205 Sentinel-1 Single-Look Complex (SLC) images acquired from 2014 to 2024, the integrated workflow identified 69 “active, very slow” and 63 “active, extremely slow” landslides. These results were validated through high-resolution historical optical imagery. Time series analysis reveals that creep deformation in this region is highly sensitive to seasonal rainfall patterns. This study demonstrates that the SBAS-InSAR post-processing framework provides a cost-effective, millimeter-scale solution for updating landslide inventories and supporting regional risk management and early warning systems in loess-covered terrains, with the exception of densely forested areas.

Keywords: landslide; SBAS-InSAR; Loess Plateau; slope direction; Z-score clustering

1. Introduction

Landslides are a natural phenomenon in which slope materials move downward or outward along the slope under the influence of gravity and other external conditions (climate, water, earthquake, etc.) [1,2]. They play an important role in the evolution of mountainous landforms [3,4]. Landslides, as highly destructive geological hazards, pose a severe threat to numerous regions and communities worldwide [5]. Landslides are among the common geohazards in China, accounting for 68% of geological disasters. They resulted in 211 people dead, 13 people missing, 75 people injured, and economic losses of CNY 2.77 billion in 2019 in China, according to the National Geohazards Report. Therefore, how to effectively monitor and forecast the occurrence of landslides is an urgent problem that many researchers and geologists need to solve.

The Chinese Loess Plateau is highly susceptible to landslides, given its frequent heavy rainfall and steep topographic gradients, which together exacerbate severe soil erosion [6,7]. The study area (Figure 1) is situated on the Loess Plateau in southeastern Gansu Province, China. It is adjacent to the West Qinling Mountains and falls within the Weihe River Basin. It belongs to the semi-arid continental monsoon climate type. July through August is the highest-rainfall season, accounting for more than 75% of the annual rainfall. Because of strong tectonic activity in the Loess Plateau, a huge terrain elevation difference has been formed. In addition, the Chinese Loess Plateau is mainly covered by soil, and soil erosion is prone to occur during the rainy season [8]. Soil landslides account for 72% of all geological hazards in the Loess Plateau area, according to a national survey by the Ministry of Natural Resources [9]. Therefore, soil landslides on the Chinese Loess Plateau serve as representative cases and hold significant research value for geologists.

Traditional methods for monitoring regional surface deformation, such as GPS and leveling surveys, are often prohibitively time-consuming and costly. These approaches are limited to measurements at discrete points and cannot provide continuous long-term coverage. In contrast, remote sensing techniques like laser scanning and unmanned aerial vehicle (UAV) photogrammetry can acquire data more rapidly and extensively [10]. They have thus proven effective for characterizing surface displacement without incurring the high expenses associated with in situ measurements. As a newly developed technology, InSAR has become prominent for this purpose [11–13]. SAR systems operate day and night, penetrate most clouds and atmospheric haze, and, as active sensors with their own illumination sources, offer full control over imaging geometry, frequency, and polarization. With advantages including broad coverage, high measurement density, precision, and all-weather capability, InSAR has emerged as one of the most effective technical means for regional surface deformation monitoring and landslide identification.

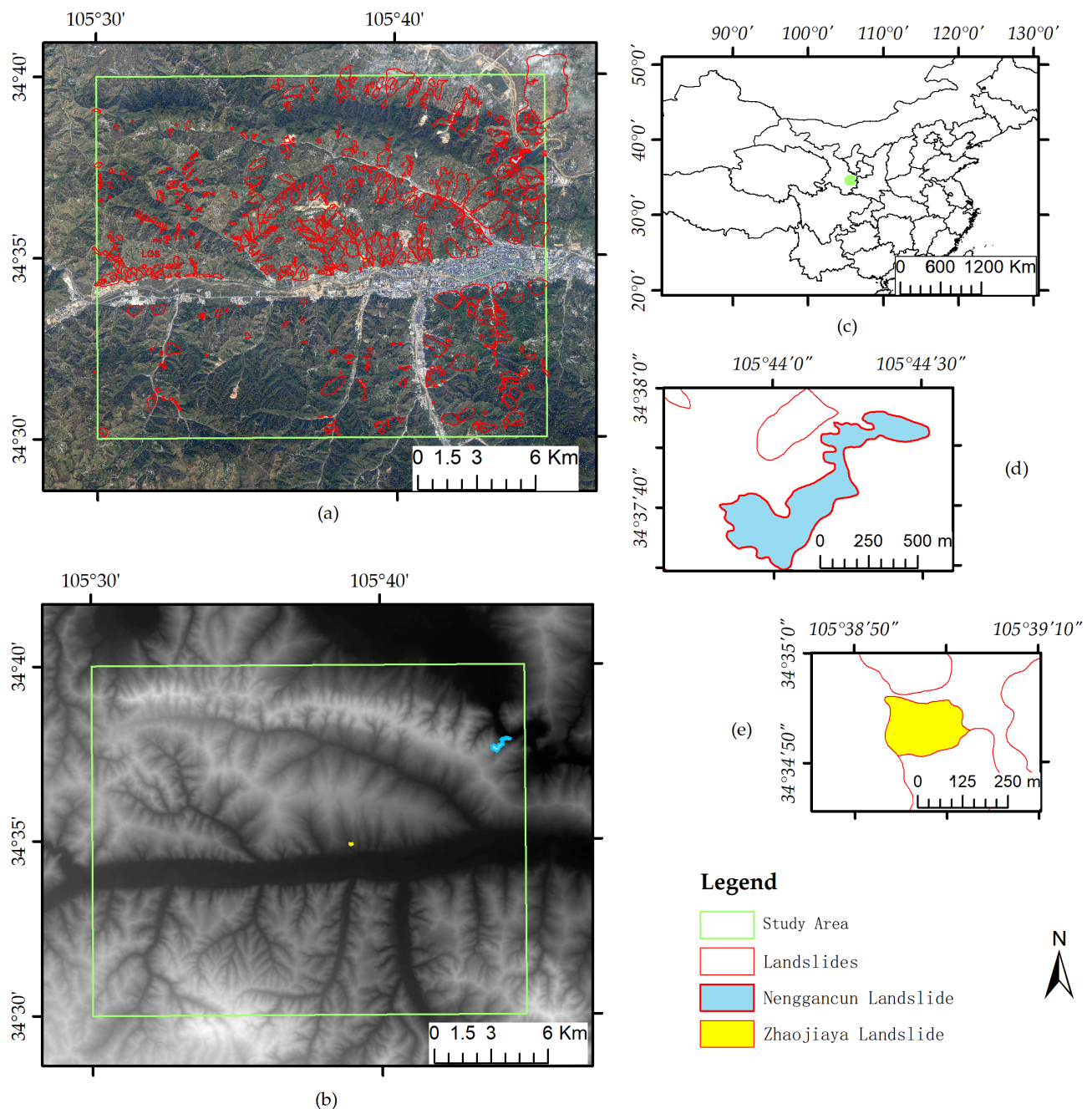


Figure 1. The study area, 1:50,000. The map sheet number is I48E004009015, and the map sheet name is Tianshuifu. The pink polygons are landslide polygons obtained by field work in 2016. (a) The background is an orthophoto obtained from GF-6, acquired on 17 October 2022. (b) The background is DEM data with a nominal resolution (pixel spacing) of 90 m. (c) The location of the study area in China. (d) The location of the Nenggancun landslide. (e) The location of the Zhaojiaya landslide.

The research on InSAR for landslide monitoring has developed rapidly [14–16]. Differential-InSAR (D-InSAR) technology has often been used to obtain interferograms of large-scale landslides [17–20]. However, the accuracy and reliability of traditional D-InSAR deformation measurements are severely affected by spatial decorrelation and atmospheric delay. Many new InSAR techniques with time series processing algorithms can be employed to acquire more precise long-term surface deformation of landslides [21,22]. In 2001, Ferretti proposed the Permanent Scatterer InSAR (PS-InSAR) technique, the basic framework of which involves selecting persistent coherent point targets and processing

them with a single master image [23–26]. Due to the limitations of PS-InSAR in areas with complex terrain or high vegetation coverage, it becomes extremely difficult to extract permanent scatterers from limited SAR data, making deformation monitoring in such terrains highly challenging. In 2002, Berardino introduced the SBAS-InSAR technique [27–29]. Its main feature lies in dividing interferograms into one or more subsets by setting temporal and spatial baseline thresholds to mitigate the impact of interferogram decorrelation [30]. The time series deformation of the target point is inverted based on algorithms such as least squares or singular value decomposition. This method does not require a large number of SAR images, and when combined with PS-InSAR technology for surface deformation monitoring, it can effectively overcome the problems of poor coherence of radar signals in complex-terrain areas and difficulty in accurately calculating surface deformation [31–33]. Based on InSAR theory, since 2001, scholars worldwide have successively developed mainstream algorithms for time series surface deformation monitoring, including the Stanford Method for Persistent Scatterers (StaMPS) [34,35], Interferometric Point Target Analysis (IPTA) [36], Coherent Pixels Technique (CPT) [37], SqueeSAR [38], and so on. These algorithms have been successfully applied to various deformation monitoring tasks and are suitable for different types of environmental conditions. Therefore, it is essential to select the appropriate algorithm for processing SAR data based on the environmental context and surface deformation characteristics of the study area to obtain more effective surface deformation results.

There are numerous challenges in the current application of SBAS-InSAR for regional landslide activity classification on the Loess Plateau. Although SBAS-InSAR can mitigate the influence of decorrelation to a certain extent by constructing subsets of interferograms, it is still ineffective against decorrelation caused by rapid surface movement or dense vegetation coverage. Moreover, the average velocity derived from SBAS-InSAR is a one-dimensional measurement along the satellite's LOS direction, which does not fully represent the true three-dimensional movement of a landslide. Once we obtain average velocity measurement points, it is difficult to distinguish genuine landslide activity from noise, especially in cases where only an isolated deformation point is detected. The resulting ambiguity poses a significant challenge for accurate hazard assessment. The scientific and quantitative conversion of the average displacement velocity obtained from SBAS-InSAR into landslide activity classifications lacks a universal-threshold standard system, particularly for loess landslides on the Loess Plateau.

To address these issues, we adopt an SBAS-InSAR-based framework that integrates the conversion of the LOS velocity into the slope direction and Z-score clustering analysis to achieve the goal of landslide activity classification. In this paper, Sentinel-1 satellite SLC data on the Loess Plateau for the 12 October 2014 to 2 January 2024 period were used. Those SLCs were resampled to coregister a stack of SLCs using the ISCE V2.6.3 software. Then, SBAS-InSAR processing was applied by the StaMPS V4.1 software with a spatial baseline threshold of 180 days, perpendicular temporal baseline threshold of 300 m to obtain velocity and time series displacement in the LOS direction. In addition, we applied atmosphere correction with TRAIN V3 software to acquire the corrected average velocity and time-series displacement. Post-processing was performed to calculate velocity in the slope direction, which is converted from the LOS velocity vector. A key assumption in this projection is that the displacement occurs entirely parallel to the local maximum slope. The conversion can reflect the real ground motion that occurs predominantly as transitional movement, parallel to the topographic slope. Z-score clustering analysis was applied to extract significant deformation clusters and remove isolated, anomalous, very stable, and non-representative points. We hypothesized that using a cluster of PS points with similar velocities would yield a more robust classification of landslide activity. This approach

ensures that the assigned “representative velocity” is based not merely on the quantity of PS points, but on the coherence of velocity within a defined cluster. Previous studies proved that a velocity threshold of 10 mm/year was frequently cited and applied to classify active landslides [39,40], particularly as it correlates with observable moderate damage to infrastructure. In line with this evidence, our study adopts the 10 mm/year threshold to define active landslides. Finally, typical landslides combined with precipitation and historical optical images were used to verify the classification results.

2. Materials and Methods

2.1. Study Area

The study area (Figure 1) was selected in the southeastern district of Gansu, China, which is located in the transition zone between the Qinling Mountains and the Loess Plateau. It is located on the Loess Plateau, adjacent to the West Qinling Mountains, and belongs to the Weihe River Basin. The altitude of the study area ranges from 1000 to 2000 m. The longitude is between 105°30'E and 105°45'E, and the latitude is between 34°30'N and 34°40'N. The 1:50,000 map sheet number is I48E004009015, and the map sheet name is Tianshuifu. The landform is mainly plateau, basin, mountain, and sandy land. It belongs to the semi-arid continental monsoon climate type. Rainfall mainly occurs in summer and autumn. July and August account for more than 75% of the annual rainfall. There is little rain in spring and winter. The average annual precipitation is between 100 mm and 800 mm. The average annual temperature is about 11 °C [41,42]. The Loess Plateau is widely covered by a thick layer of sedimentary loess, underlain by impermeable bedrock such as mudstone, schist, and gneiss. This geological combination exhibits good water barrier properties. The Chinese Loess Plateau is one of the most landslide-prone regions in China because of frequent rains, strong topographical gradients, and severe soil erosion. Statistics show that nearly 30% of landslides in China occur in loess areas [43]. Of these, soil landslides represent 72% of these landslides and are primarily medium in scale, according to the national geological hazard survey by the Ministry of Natural Resources [9].

2.2. SAR Data and Landslide Inventory

In this study, our primary objective was to conduct an identification and analysis of landslides within the Loess Plateau region, leveraging the advanced capabilities of the Sentinel-1 satellite survey in conjunction with an extensive landslide inventory.

We initiated the process by downloading Sentinel-1 satellite SLC imagery from the Alaska Satellite Facility (ASF) website. Specifically, we utilized Sentinel-1 SLC data acquired along the ascending orbit of path 55, frame 107, which provided optimal coverage of our study area. Over the period from 12 October 2014 to 2 January 2024, we amassed a total of 205 SLC images, ensuring a robust dataset for our time series analysis. The detailed parameters of SAR are summarized in Table 1.

Table 1. Parameters of SAR and optical images in the study.

Sensor	Sentinel-1	GF-6
Track	55	-
Orbit direction	Ascending	-
Incident angle	43.3°	-
Acquisition period	12 October 2014~2 January 2024	17 October 2022
Number of images	205	1
Range pixel spacing	2.33 m	-
Azimuth pixel spacing	13.95 m	-
Resolution	-	2 m

We incorporated Shuttle Radar Topography Mission (SRTM) data into our analysis workflow. Originally produced by NASA, the SRTM dataset offers a global digital elevation model with a nominal resolution (pixel spacing) of 90 m. It allowed us to accurately remove the topographic phase from the interferograms generated from the Sentinel-1 SLC images.

The precipitation data were downloaded from the China Meteorological Data Service Centre. The institution provided a historical dataset of monthly surface meteorological observations of China. Precipitation can be analyzed for its relationship to landslide displacement.

We also conducted extensive fieldwork in 2016 to compile a comprehensive landslide inventory for the study area. This inventory was created through on-site surveys, where our team of researchers visually inspected and mapped landslide boundaries, collecting valuable data on landslide morphology, size, and activity status. The outcome of this fieldwork was a detailed inventory comprising 699 landslide polygons, each representing a distinct landslide event or area within the Loess Plateau. This inventory not only served as a ground-truth reference for validating our satellite-based landslide identification results but also provided essential baseline information for understanding the spatial distribution and characteristics of landslides in the region.

2.3. Methods

In this study, we used the SBAS-InSAR technology to delve into the intricate dynamics of landslide movements in the Tianshui region, which is nestled within the geologically complex Loess Plateau. Our primary objective was to obtain the average velocity and time series displacement of landslides over an extended period, spanning October 2014 to January 2024. This timeframe was chosen to capture both short-term activity and long-term trends in landslide behavior, providing a comprehensive understanding of their evolution and potential hazards.

By processing a series of SLC images acquired by Sentinel-1 satellites over the study area, we were able to extract average velocity and time series displacement in the LOS direction caused by landslides through SBAS-InSAR methods. Then we embarked on a post-processing phase to calculate the average velocity of landslide movements in the slope direction. By projecting the three-dimensional displacement vectors onto the slope plane, we obtained a more accurate representation of the landslide's motion relative to its natural inclination. Lastly, we integrated cluster analysis into our workflow. By analyzing the spatial distribution and patterns of displacement velocities, we were able to delineate points exhibiting coherent and significant movement, indicative of ongoing landslide activity.

The entire data processing workflow is visually represented in Figure 2. This schematic diagram provides a clear and concise overview of the sequential steps involved in our analysis. Furthermore, to ensure a thorough understanding of our approach, we have provided a detailed explanation of each method employed in the subsequent sections. This includes a description of the SBAS-InSAR algorithm, the post-processing techniques used for velocity calculation in the slope direction, as well as the cluster analysis methodology for identifying active deformation areas.

2.3.1. SBAS-InSAR Processing

For the time series analysis spanning 12 October 2014 to 2 January 2024, a comprehensive dataset comprising 205 SLC images was assembled. These SLC images were resampled and coregistered into a unified stack utilizing the ISCE V2.6.3 software. Given that the landslides within our study area predominantly exhibit medium-scale characteristics, we did not apply multilook processing. This decision aimed at preserving the highest possible resolution and thereby enhancing the accuracy of our results.

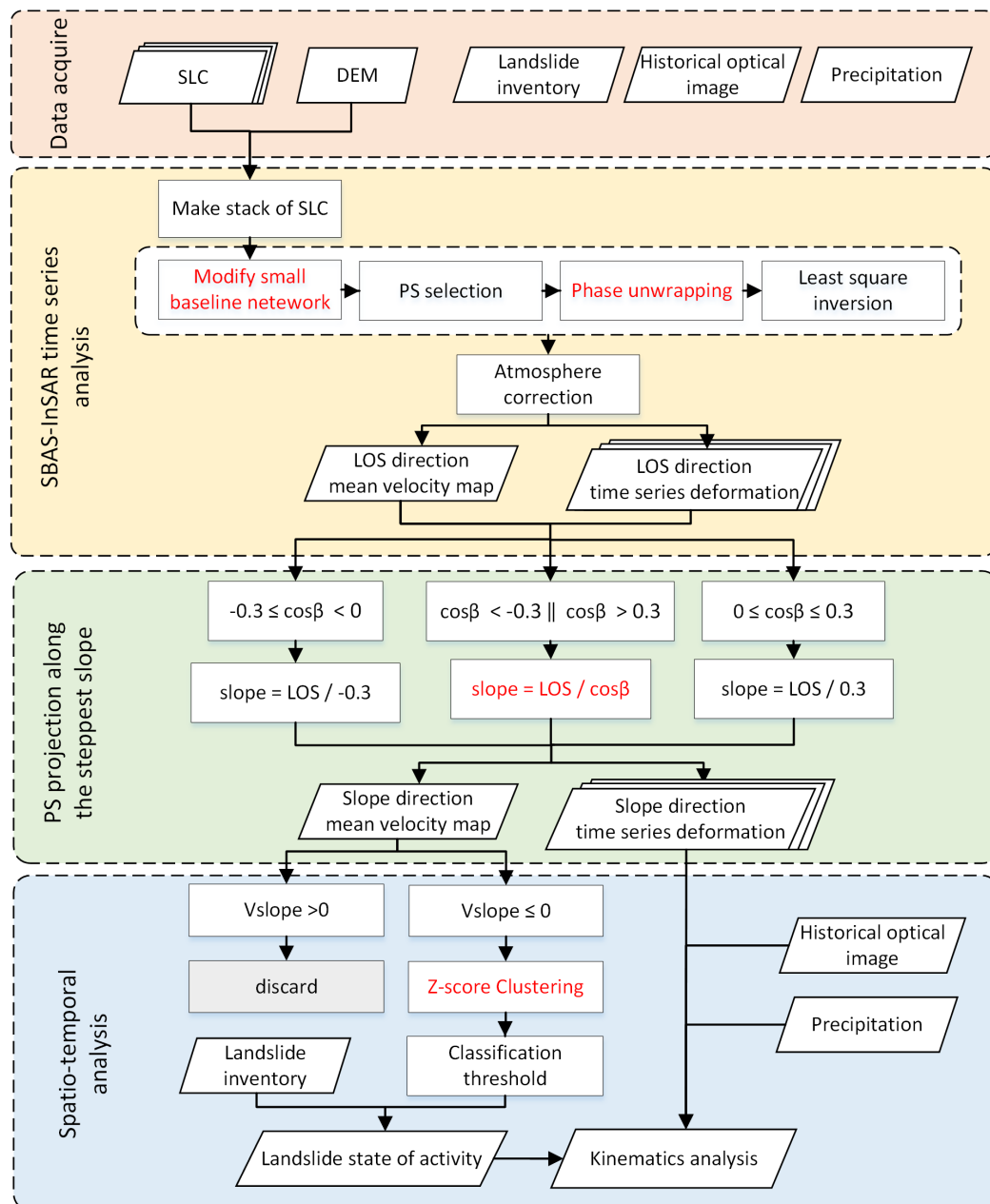


Figure 2. Flowchart. SBAS-InSAR technology is used to average velocity and time series displacement of landslide in study area. Post-processing was performed to calculate velocity in slope direction, combined with cluster analysis to identify active deformation area for hazard assessment. Historical optical image and precipitation are used for typical landslide analysis.

Then we employed the StaMPS V4.1 [44] software, modifying its small baseline network configuration to suit our specific needs. We set a spatial baseline threshold of 180 days and a perpendicular temporal baseline threshold of 300 m, along with a minimum coherence threshold of 0.6. These parameters were carefully chosen to optimize the generation of interferograms, resulting in a robust collection of 638 interferograms. Subsequently, we embarked on the task of identifying Persistent Scatterer (PS) pixels. We computed the likelihood of each pixel being a PS pixel by taking into account both its amplitude stability and estimated phase stability. This probabilistic approach allowed us to select PS pixels with high confidence, excluding those that exhibited persistence only in specific interferograms or were predominantly influenced by scatterers in neighboring PS pixels. Once the

PS pixels were identified, we isolated the deformation-induced signal within these pixels, effectively filtering out noise and other non-deformation-related signals. The next step is phase unwrapping, a critical process of recovering unambiguous phase values from phase data that are measured modulo 2π rad (wrapped data). We applied the three-dimensional-unwrapping algorithm developed by Hooper [45] to implement phase unwrapping. To derive the velocity and time series displacement from the processed interferograms, we applied a least-squares inversion method. This mathematical technique allowed us to solve for the unknown parameters (velocity and displacement) by minimizing the sum of the squared residuals between the observed and modeled data.

Finally, to correct for atmospheric effects, which can introduce significant errors in InSAR measurements, we utilized the TRAIN V3 software. This tool enabled us to estimate and remove atmospheric contributions from our displacement measurements, resulting in more accurate and reliable average velocity and time series displacement data that captured the dynamics of surface deformation over the study period.

2.3.2. Conversion of the LOS Velocity Vector into Slope Direction

The velocity and displacement time series of a Persistent Scatterer (PS) are measured along the satellite's Line-of-Sight (LOS). Positive LOS values indicate movement toward the satellite, while negative LOS values indicate movement away from it. To utilize LOS velocities for detecting landslide-induced displacements, the LOS velocity vector is converted into the slope direction. This conversion assumes that the displacement occurs entirely parallel to the direction of the maximum slope [40,46–49].

In the following, a given vector is 3 components ordered, respectively, along the east, north, and Z directions.

$\hat{r}$ represents the unit vector of the LOS direction, $\hat{\mu}$ represents the unit vector of the steepest slope direction:

$$\hat{r} = \begin{bmatrix} r_E \\ r_N \\ r_Z \end{bmatrix} = \begin{bmatrix} -\sin \theta \cos \alpha_s \\ \sin \theta \sin \alpha_s \\ \cos \theta \end{bmatrix}, \quad (1)$$

$$\hat{\mu} = \begin{bmatrix} u_E \\ u_N \\ u_Z \end{bmatrix} = \begin{bmatrix} -\sin \alpha \cos \varphi \\ -\cos \alpha \cos \varphi \\ \sin \varphi \end{bmatrix}, \quad (2)$$

where θ is the incidence angle with respect to the “flat earth”, which is the angle between the vertical direction and the radar LOS; φ is the slope angle; α is the aspect angle; and α_s is the angle between the azimuth and the north direction.

Assuming the angle between the LOS and slope is β [46],

$$C = \cos \beta = \hat{\mu}^T \hat{r}, \quad (3)$$

Then,

$$V_{slope} = \frac{V_{los}}{\cos \beta}, \quad (4)$$

The terrain aspects and the slopes in the study area can be calculated by DEM. V_{slope} tends to infinity when $\cos \beta$ tends to zero (i.e., in layover conditions when β approaches 90°). To avoid anomalous solutions, the C-value is constrained to -0.3 (if $-0.3 \leq C < 0$), and to $+0.3$ (if $0 \leq C \leq +0.3$) for this study area. As a consequence, the V_{slope} cannot exceed 3.33 times V_{LOS} . As established in [39,40], the proposed scaling factor of 3.33 times V_{LOS} has been validated as reasonable and effective.

2.3.3. Z-Score Clustering

Accurately detecting deformation areas poses significant challenges due to various factors, including geometric distortions in images arising from layover and shadow effects, unwrapping errors induced by rapidly moving landslides, temporal decorrelation resulting from vegetation cover, discontinuities in radar image time series, and unfavorable alignments between satellite LOS directions and actual terrain movements. Therefore, some statistical methods need to be used to remove outliers from the retrieved MTI results, so that more reliable deformation information can be extracted. So the Getis–Ord, G_i^* , statistical method was adapted to post-process the InSAR results [50–53] for extracting significant deformation clusters and removing isolated, anomalous, very stable, and non-representative points.

For scatter point i in the InSAR results, the G_i^* statistic is defined as

$$G_i^*(d) = \frac{\sum x_j + x_i - n_{ij}\bar{x}^*}{s^* \left\{ \left[(n \times n_{ij}) - n_{ij}^2 \right] / (n - 1) \right\}^{0.5}}, \quad (5)$$

where n represents the total number of scattering points, n_{ij} is the number of elements within the scale distance of a given i , x represents the surface displacement recorded by InSAR, $\bar{x}^*$ and s^* are the mean value and the standard deviation of displacements of all elements, respectively.

The above $G_i^*(d)$ is then used to determine the Z-score as follows:

$$Z(G_i) = \frac{G_i(d) - E[G_i(d)]}{\sqrt{\text{Var}G_i(d)}}, \quad (6)$$

where $\sqrt{\text{Var}G_i(d)}$ represents the variance of $G_i^*(d)$, and $E[G_i(d)]$ represents the expectation of $G_i^*(d)$.

The p -value is a probability. Z-scores are standard deviations. Both Z-scores and p -values are associated with the standard normal distribution. Generally, significant measurement points are those with a Z-score exceeding the 95% confidence level. A confidence level of 99% would be the most conservative threshold in this case, indicating that you are unwilling to reject the null hypothesis unless the probability that the pattern was created by random chance is very small (less than a 1% probability). To preserve a greater number of measurement points, we selected a confidence level of 99% for this study. Thus, scattering points with probability values (p -values) < 0.01 (confidence level is 99%) and Z-score $> \pm |2.58|$ were selected and considered to be highly reliable.

3. Results

Figure 3a provides a detailed visualization of average velocity in the LOS direction, while Figure 3b shows average velocity in the slope direction, both of which have been derived by the SBAS-InSAR method. This analysis covers the extensive time frame from October 2014 to January 2024, offering a comprehensive view of the ground movement patterns over nearly a decade. In these figures, a color-coding system is employed to distinguish between different types of ground movement. Specifically, the red points signify areas where there is movement toward the slope. Conversely, the blue points denote regions where the ground is moving away from the slope. The green points, on the other hand, indicate areas that are relatively stable, showing no significant signs of deformation or movement during the observed period. Upon examining the results, it becomes evident that the cities and villages in the study area were relatively stable with little deformation, but the mountainous regions had obvious deformation. In total, 82,788 measurement points

(MPs) were identified in the study area derived by the SBAS-InSAR method, so the average spatial sampling density was 195 measurement points per km². The majority of these measurement points are concentrated in urban areas and along transport infrastructure, which are typically of high importance for monitoring and safety assessments. However, it is noteworthy that there is also a sufficient number of measurement points located within landslide inventory areas. This strategic placement ensures that the SBAS-InSAR results are not only comprehensive but also reliable, providing valuable insights into the ground movement patterns and potential risks associated with landslides and slope instability.

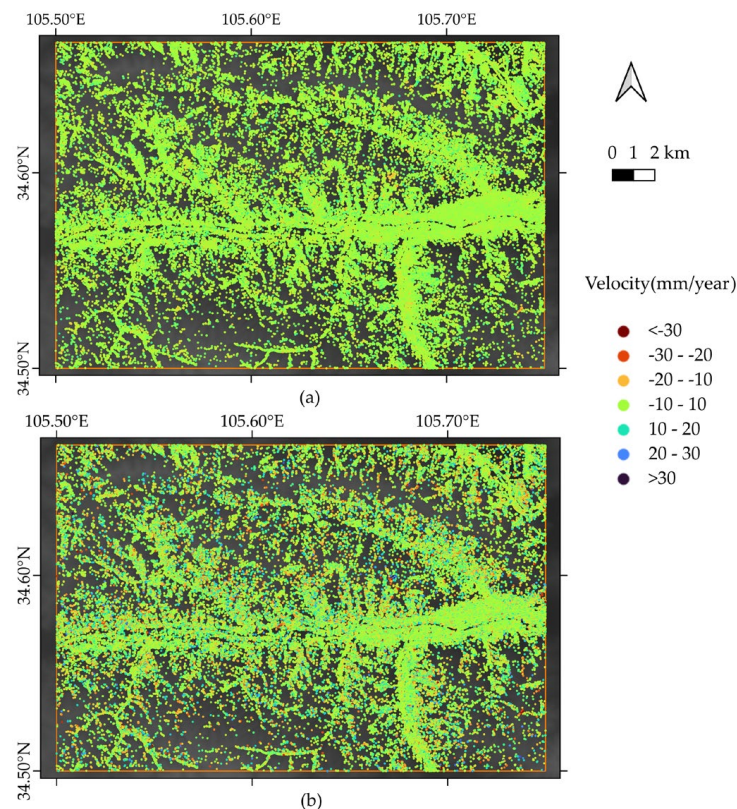


Figure 3. Average velocity maps derived by SBAS-InSAR for the October 2014–January 2024 period. (a) Average velocity in the LOS direction. (b) Average velocity in the slope direction.

All measurement points exhibiting positive average velocity values, which indicate uphill displacement or movement away from the intended direction of focus (downhill displacement), were systematically discarded. This filtering process resulted in a significant reduction in the total number of measurement points, leaving only 42,891 points for further analysis. This step accounted for the elimination of 48% of the initial dataset to improve the precision and effectiveness of the clustering method employed in the study. This focused approach minimizes the influence of extraneous factors and ensures that the results are more representative of the actual ground movement patterns occurring in the downward direction. Subsequently, after this initial filtering, the Z-score clustering technique was applied to the remaining dataset. This advanced statistical method is instrumental in identifying and extracting data points that exhibit a high degree of similarity or clustering behavior, thereby enhancing the reliability of the results. Through this process, a highly reliable subset of 22,068 measurement points, all indicating movement toward the slope direction, was successfully extracted. These points represent the most significant and consistent patterns of downhill displacement within the study area, providing valuable insights into the geological dynamics and potential hazards present.

3.1. Landslides' States of Activity

In the comprehensive analysis of landslide activity, the core methodology involved considering the maximum velocity recorded among all measurement points that intersected with the predefined landslide inventory boundaries. This maximum velocity value was then utilized as a representative metric for the entire landslide inventory, enabling a standardized classification of landslide activity states.

The classification scheme employed in this study was designed to reflect the varying degrees of landslide movement, drawing upon established criteria from the relevant literature [1,39]. The classification categories included “active, very slow;” “active, extremely slow;” “inactive;” and “not classified” (Table 2). These categories provided a nuanced understanding of landslide dynamics, distinguishing between actively moving landslides with different velocities and those that were either inactive or could not be reliably classified based on the available data.

Table 2. The landslide activity classification criteria and results.

Landslide Activity Classification	Peak Velocity (mm/Year)	Number of Landslides	Percentage of All Landslides
active, very slow	>16	69	9.9%
active, extremely slow	10–16	63	9.0%
inactive	<10	112	16.0%
not classified	/	455	65.1%

Specifically, a landslide was deemed “active, very slow” if the peak velocity of the cluster results, which intersected with the landslide polygon, exceeded 16 mm/year. This threshold was set to capture landslides that, while still active, exhibited relatively sluggish movement rates. Conversely, if the peak velocity fell within the range of 10 mm/year to 16 mm/year, the landslide was classified as “active, extremely slow”, indicating an even more gradual rate of movement. Landslides with peak velocities below 10 mm/year were considered “inactive,” suggesting that they were either stable or moving at such a slow pace that they did not pose an immediate threat. Finally, landslides whose peak velocity did not intersect with the landslide polygon were labeled as “not classified.”

Out of the 699 landslides initially mapped in the study area, 34.9% were successfully classified according to this scheme. This classification rate, while not perfect, provided a substantial subset of landslides for which activity states could be confidently determined. Figure 4 visually presents the results of this classification effort, offering a clear and intuitive overview of the distribution of landslide activity states within the study area.

According to the results (Table 2 and Figure 4), there were 69 landslides classified as “active, very slow,” indicating a significant number of landslides with slow movement rates. Additionally, 63 landslides were categorized as “active, extremely slow,” highlighting the prevalence of landslides with even more gradual movement. A larger group of 112 landslides was identified as “inactive,” suggesting that a substantial portion of the mapped landslides were not currently exhibiting significant movement. Finally, the remaining 455 landslides were either “not classified” or exhibited uphill movement, underscoring the challenges in reliably classifying all landslides based on the available data and analysis methods.

We offer a more detailed and nuanced classification of landslide activity states, taking into account the specific velocity thresholds and the intersection of measurement points with landslide polygons. This level of detail enhances the accuracy and reliability of the classification results, providing valuable insights for landslide hazard assessment and management.

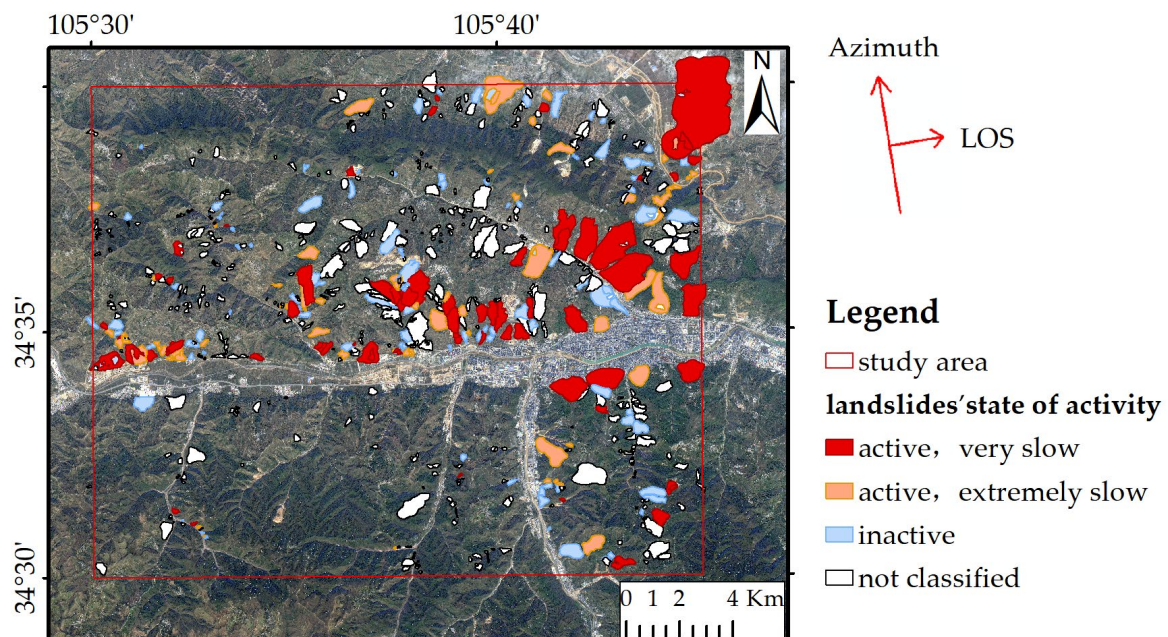


Figure 4. Landslides' states of activity for the October 2014–January 2024 period. The red polygon indicates active landslides that move very slowly; the orange polygon indicates active landslides that move extremely slowly; the blue polygon indicates inactive landslides; the white polygon indicates landslides that could not be classified.

Among the 132 active landslides that were identified, a notable pattern emerges regarding their altitude, aspect and slope distribution (Figure 5). Specifically, the majority of these landslides are situated at altitudes ranging between 1300 and 1400 m. The aspect of landslides, or the direction in which they face, was found to be centered around the range of 135° to 315° , which is nearly facing the LOS direction. We can conclude that landslides facing the LOS direction are more easily detectable by the SBAS-InSAR method compared to those facing other directions. That is because landslides facing the LOS direction present a more favorable geometry for radar signal reflection. The analysis results reveal that 114 active landslides, accounting for 86.3% of all the active landslides, fall within the slope range of 20° to 45° . In contrast, a smaller number of landslides, four in total, are found in areas with slopes less than 20° . In addition, 14 landslides are recorded on slopes ranging from 45° to 60° . All in all, the underlying reason for this distribution pattern can be traced back to the accumulation of loess deposits, which tend to build up easily in the gentle slope areas of mid-low mountains.

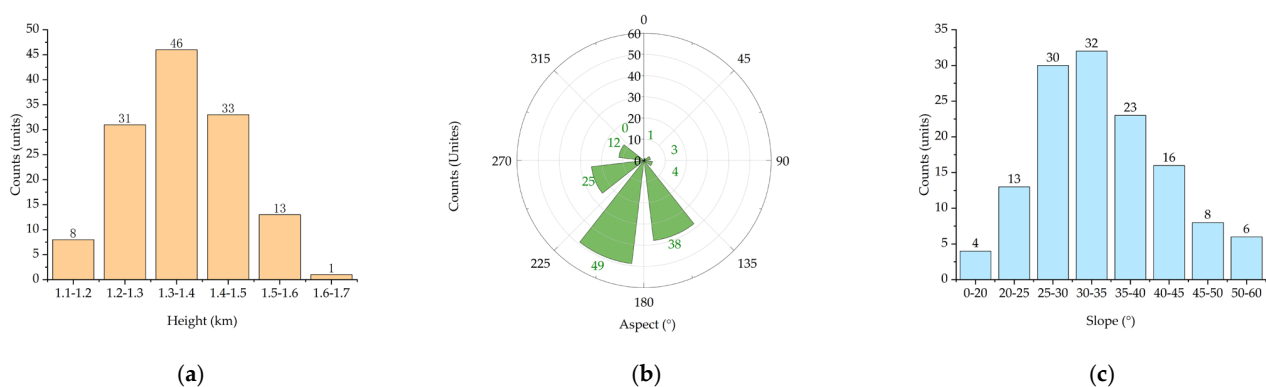


Figure 5. The analysis data on height, aspect, and slope of active landslides. (a) The height of active landslides. (b) The aspect of active landslides. (c) The slope of active landslides.

3.2. Time Series Analysis of Typical Landslides

The Nenggancun landslide and the Zhaojiaya landslide are two prominent entries within the landslide inventory that has been surveyed for the region. These two landslides are of particular concern, not only due to their size and potential for movement but also because they pose a direct and substantial threat to nearby villages and critical infrastructure. In addition, there are sufficient high-resolution optical images with long time series to verify the SBAS-InSAR displacement results. So the Nenggancun landslide and the Zhaojiaya landslide were chosen to analyze the Loess Plateau landslide kinematic characteristics.

From 9 to 11 July 2018, Gansu Province experienced the strongest precipitation since the beginning of 2018, with heavy rain falling for two days. The maximum cumulative rainfall in the southeastern part of Gansu reached 200 to 250 mm, a deluge that seeped into the ground, lubricating the underlying layers and triggering significant landslides. This extreme weather condition triggered a series of significant landslides, with the Nenggancun landslide being one of the affected areas.

The Nenggancun landslide was located in the northeastern part of the study area (Figure 1b,d). It is a medium-sized landslide and faces to the southeast, covering an area of 0.22 km². The average velocity could reach −3.4 mm/year during the period from October 2014 to January 2024, derived by SBAS-InSAR. According to the classification threshold, the landslide is considered active, although it moves extremely slowly. Figure 6a shows a Google Earth historical image acquired on 1 May 2018, before the landslide event, with a spatial resolution of 0.5 m. Figure 6b shows a Google Earth historical image acquired on 22 September 2018 after the landslide event, with a spatial resolution of 0.5 m. As shown in Figure 6, during the period, an obvious change can be found on the crown of the landslide, which results in exposed bedrock devoid of vegetation. The main eroded area, which was stripped of all surface vegetation, measured 140 m in length and 130 m in width. It featured an average slope angle of 25–38° and an aspect of approximately 90°. At the toe of the landslide, the road was blocked by sliding materials. The northeastern part of this area experienced less severe erosion than the southwestern part, but was still displaced during the main event.

The kinematic characteristics of the landslides were mapped by analyzing their time series of deformation, using satellite imagery to track changes over time. Four measurement points (P1, P2, P3, P4) were selected to analyze the change in the landslide in the study area, each point strategically placed to capture different zones of movement within the landslide body. The average velocities at the points P1, P2, P3, and P4 were −12.8 mm/yr, −13.1 mm/yr, −13.4 mm/yr, and −17.4 mm/yr during the 2014–2024 period. Obvious deformation can be seen from the linear graph (Figure 7), where the plotted points form a gentle downward trend. Especially for P3, acute displacement occurred in May 2018, which is consistent with the landslide's change in optical images in Figure 6. Figure 6b shows a distinct bare bedrock on the southwestern part of the landslide, matching the sudden increase in displacement recorded at that monitoring point. The results are a clear indicator of how rainfall can accelerate the movement of even slowly creeping landslides. This correlation between the precipitation event and the landslide's response underscores the critical role of hydrological factors in influencing landslide dynamics.

The Zhaojiaya landslide was located in the central part of the study area (Figure 1b,e). It is a medium-sized landslide and faces to the west, covering an area of 0.22 km². There is a road across the landslide. The average velocity could reach −7.2 mm/year during the period from October 2014 to January 2024, derived by SBAS-InSAR. According to the classification threshold, the landslide is considered active, although it moves very slowly. Figure 8a shows a Google Earth historical image (0.3 m spatial resolution) acquired on

8 August 2017. Figure 8b shows a Google Earth historical image (0.3 m spatial resolution) acquired on 17 December 2017. There was continuous rain from 20 August to 27 August in 2017, and the rainfall reached as high as 90 mm. Thus, the landslide first occurred in August 2017, which is consistent with Figure 8. Figure 8c shows a Google Earth historical image (0.5 m spatial resolution) acquired on 1 May 2018, before the landslide event. Figure 8d shows a Google Earth historical image (0.5 m spatial resolution) acquired on 22 September 2018, after the landslide event. During the period, obvious changes can be found in the central part of the landslide body. The primary eroded region had dimensions of 70 m (length) $\times$ 40 m (width), with an average slope of 34° and an average aspect of 250° . All surface vegetation within this region was scoured away. In the central part of the landslide body, the road was blocked by sliding debris, and its original route was altered. The crown of this landslide did not experience severe erosion during the main event, which contrasted sharply with the central slopes. The toe of this landslide appears to have surged forward, swallowing vegetation and reshaping the landscape.

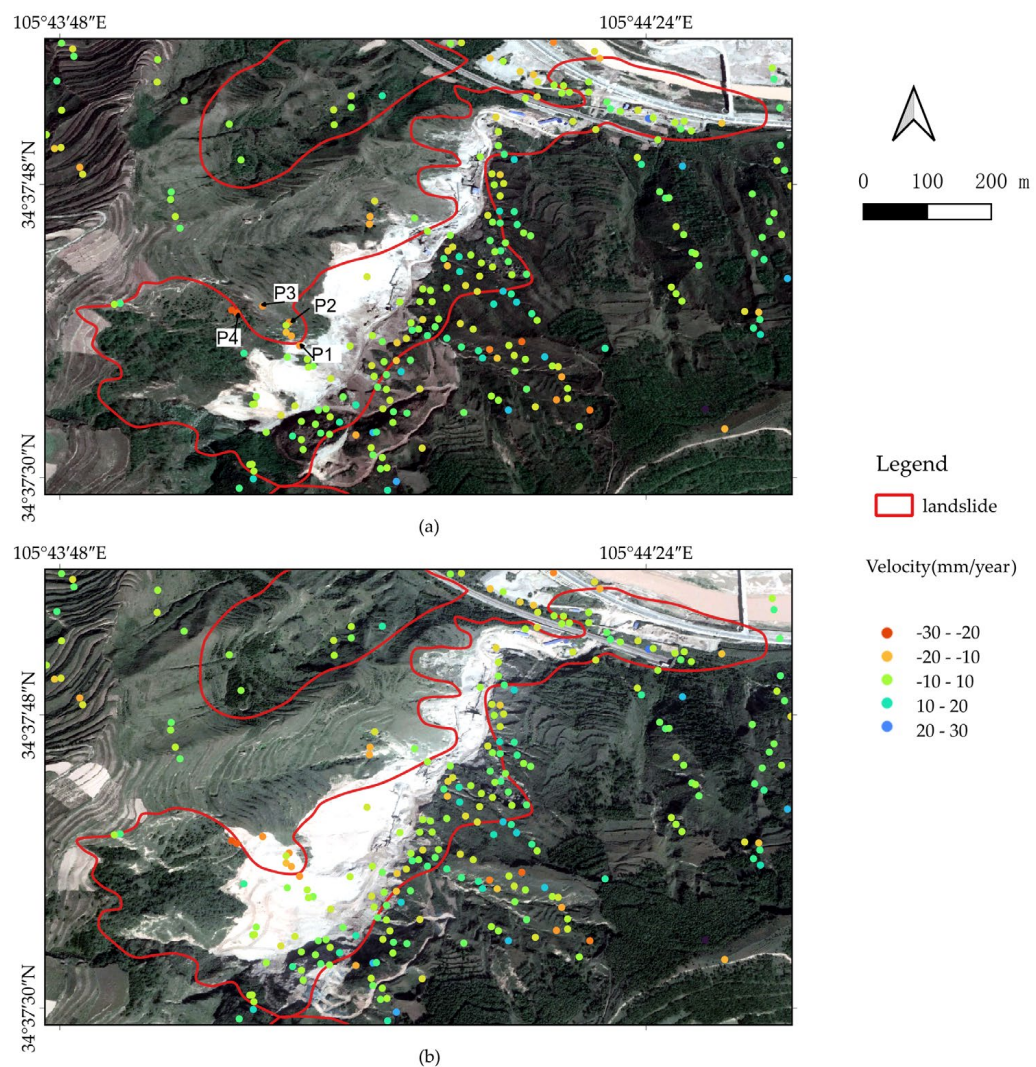


Figure 6. Average velocity of the Nenggancun landslide. Points P1, P2, P3, and P4 were the chosen MPs for time series displacement. (a) The background is a Google Earth historical image from before the landslide event on 1 May 2018. (b) The background is a Google Earth historical image from after the landslide event on 22 September 2018.

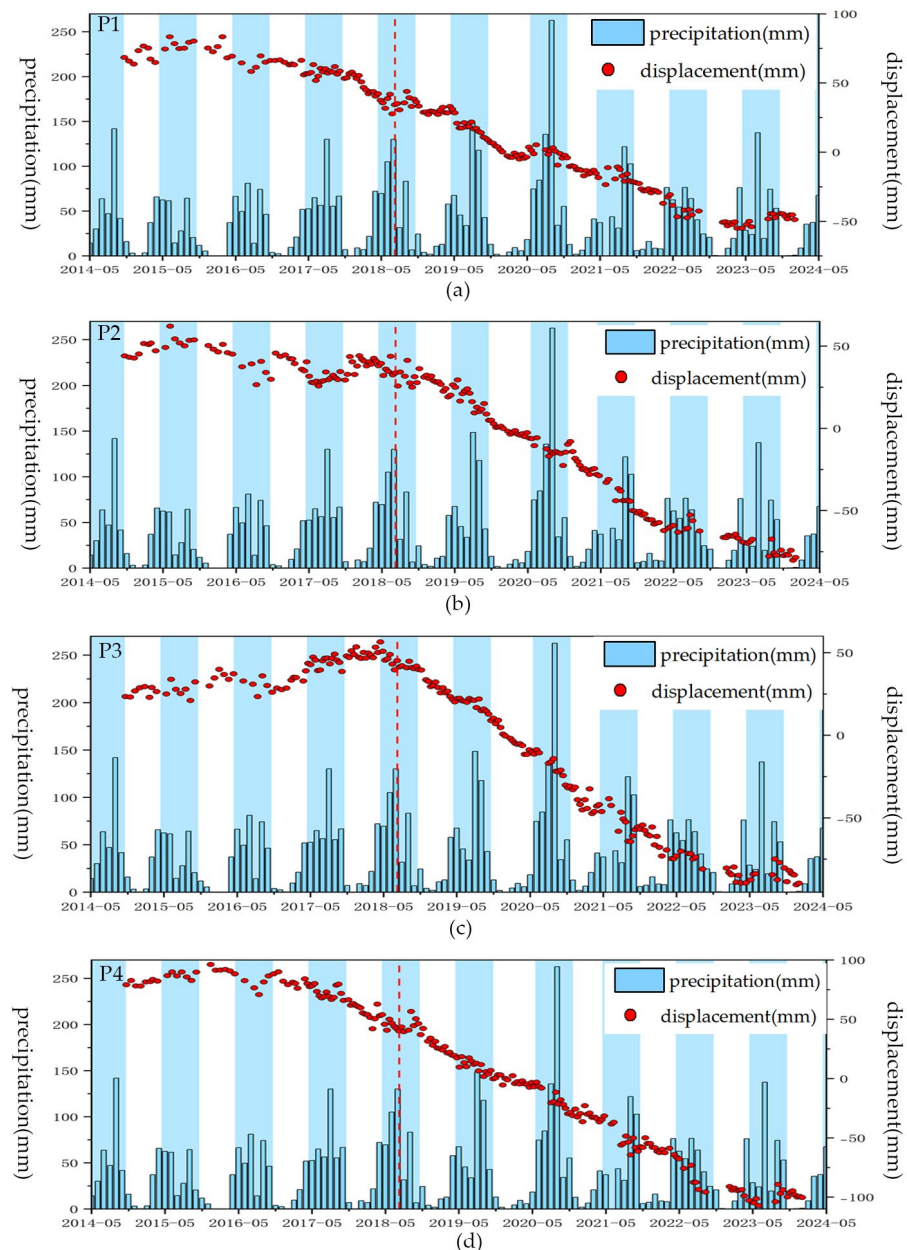


Figure 7. The relationship between displacement and precipitation. (a–d) The time series displacement in the slope direction for points P1, P2, P3, and P4, which are shown in Figure 6 for the October 2014–January 2024 period. The baby-blue interval indicates the rainy season, from May to October, and the dark blue indicates the average monthly precipitation. The red points indicate the displacement of measurement points.

The kinematic characteristics of the Zhaojiaya landslide were mapped by analyzing its time series of deformation. Four typical landslide time series displacement points (P1, P2, P3, P4) were also selected to analyze the change of the landslide in the study area; these points were placed to capture the full movement across the slope. The average velocities at points P1, P2, P3, and P4 from 2014 to 2024 were -16.4 mm/yr, -19.6 mm/yr, -12.5 mm/yr, and -5.3 mm/yr, respectively, each rate a testament to the varying degrees of instability across different sections of the landslide. The landslide exhibited continuous creep during the 2014–2024 period. Obvious deformation can also be seen from the displacement of the slope direction in the linear graph (Figure 9).

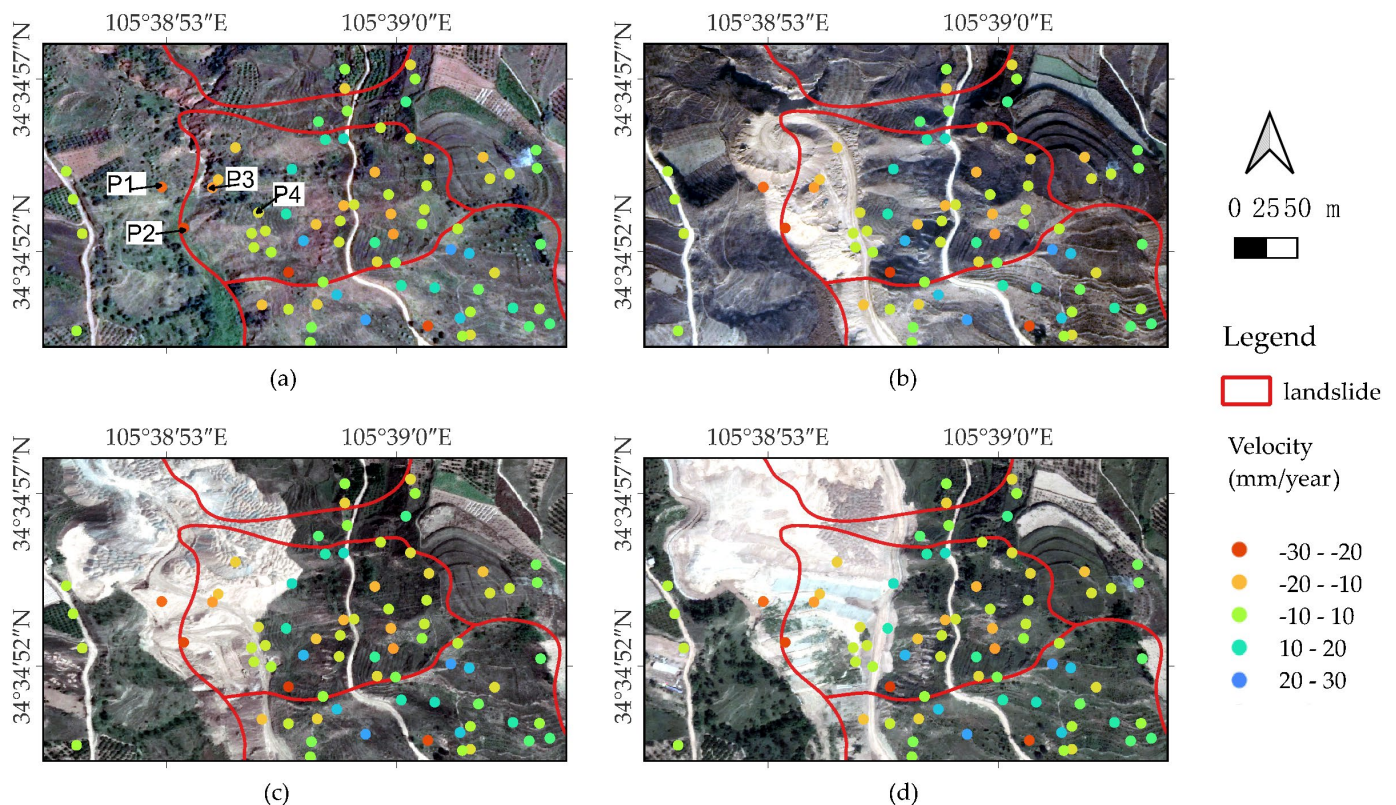


Figure 8. Average velocity of the Zhaojiaya landslide. Points P1, P2, P3, and P4 were the chosen MPs for time series displacement. (a) The background is a Google Earth historical image from 8 August 2017. (b) The background is a Google Earth historical image from 17 December 2017. (c) The background is a Google Earth historical image from 1 May 2018. (d) The background is a Google Earth historical image from 22 September 2018.

Focusing on the specific displacement patterns observed at key monitoring points within the study area, point P1 emerged as a notable example of the direct correlation between extreme precipitation events and landslide activity. In August 2017 and again in May 2018, P1 experienced acute displacement episodes. The visible changes in the landslide's morphology (Figure 8) correspond precisely to the timing of the time series displacement recorded at P1 and the concurrent rainfall events. Similarly, points P2, P3, and P4 also exhibited displacement patterns that were consistent with the landslide changes depicted in Figure 8 and the rainfall event that occurred in May 2018. Although the magnitude and timing of the time series displacements may have varied slightly among these points, the overall trend indicated a synchronized response to the heavy precipitation.

In conclusion, most of the displacement that occurred each year was concentrated during the rainy season. From May to October, the occurrence of rainfall increases soil moisture and the ground becomes saturated and heavy, substantially decreasing the shear strength of the landslide, and accelerating deformation, with the slope sliding more readily under its own weight. But there is a delay to the influence of rainfall, ranging from one to three months, a lag that reflects the complex interplay of water infiltration, soil saturation, and internal stress within the landslide mass, turning gentle rain into a delayed but powerful shove.

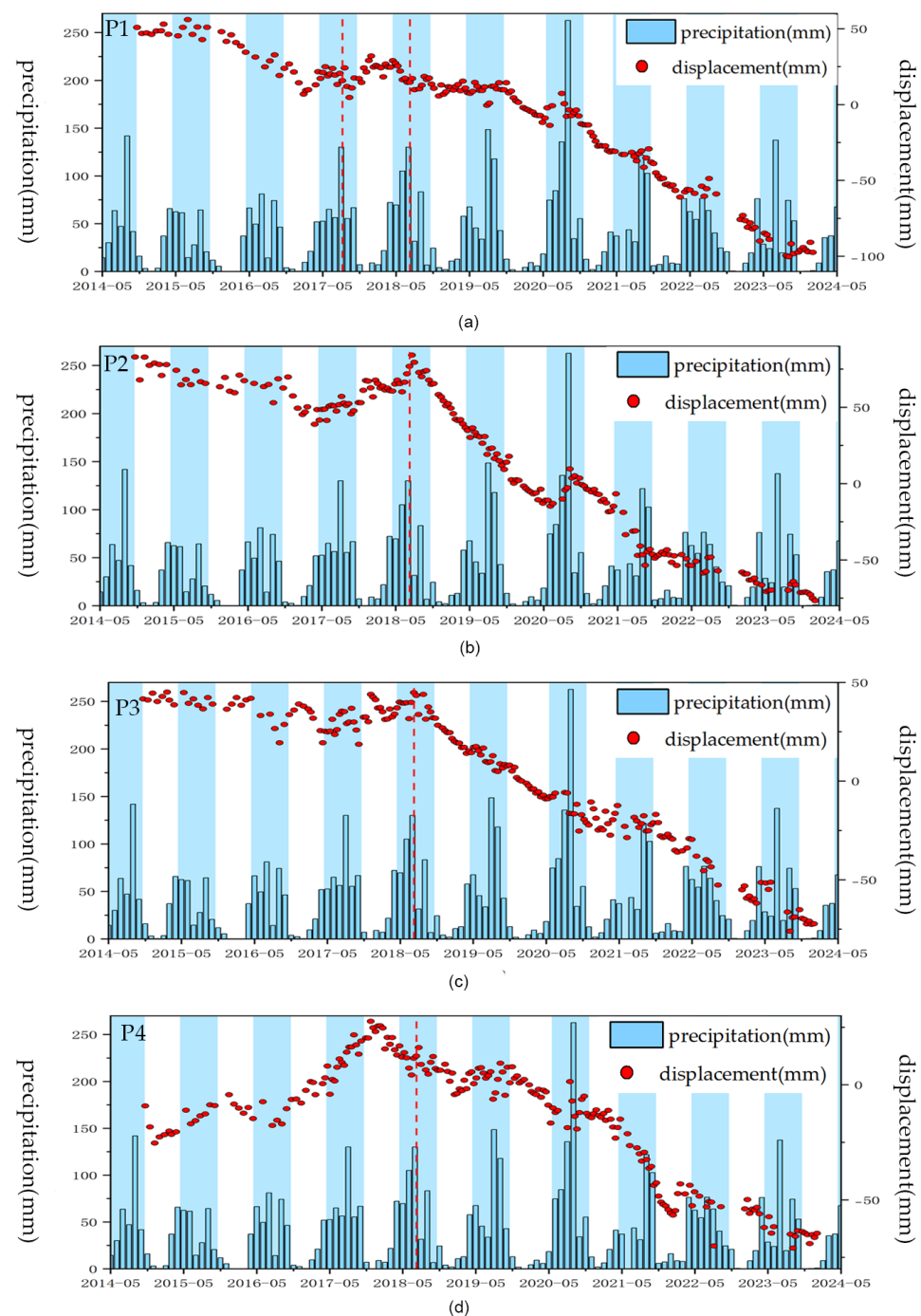


Figure 9. The relationship between displacement and precipitation. (a–d) The time series displacement in the slope direction for points P1, P2, P3, and P4, which are shown in Figure 8 for the October 2014–January 2024 period. The baby-blue interval indicates the rainy season, from May to October, and the dark blue indicates the average monthly precipitation. The red points indicate the displacement of measurement points.

4. Discussion

Based on the SBAS-InSAR results, the integration of LOS-to-slope conversion with Z-score clustering was implemented to derive slope-aligned displacement and classify landslide activity. These methods offer clear improvements in classification accuracy and efficiency; nevertheless, certain limitations should be considered.

4.1. Velocity Conversion Between LOS Direction and Slope Direction

The conversion process outlined in this study is predicated upon a fundamental assumption that ground motion predominantly manifests as translational movement, aligning with the same slope angle as the topographic surface. This assumption, while useful for simplifying the analysis of certain types of landslides, presents limitations when applied to rotational landslides. Rotational landslides involve a complex rotation of the mass around an axis, resulting in a more intricate displacement pattern. Consequently, the slope direction displacement, as captured by our methodology, may not fully encapsulate the complete change inherent in rotational landslides. However, it does offer insights, to a certain extent, into the alteration of the accumulation zone within rotational landslides, providing valuable information about their behavior. The assumption in this study is consistent with some previous studies [40,46].

Moreover, the accuracy of the DEM employed in our analysis plays a pivotal role in determining the precision of the slope and aspect calculations, which, in turn, influence the conversion results. Recognizing this, our study emphasizes the necessity for higher-accuracy DEMs to improve the overall accuracy of slope velocity estimations. This consideration is often overlooked in other studies, where the impact of the DEM accuracy on the final results is not thoroughly examined.

Another significant aspect is the influence of the inclination of the incident angle and slope direction, particularly in sensitive areas where the slope is perpendicular to the incident angle. This scenario can lead to an overestimation of the velocity in the slope direction. To counteract this, we introduce the concept of a C-value, which is constrained within specific ranges to limit the overestimation of slope direction velocity. By implementing this constraint, we ensure that the slope velocity does not exceed 3.33 times the velocity in the LOS direction, providing a more realistic and accurate representation of ground movement [39,47].

Furthermore, some studies proposed an additional method to alleviate the influence of overestimation by utilizing both ascending- and descending-orbit satellite observations. This approach allows for the calculation of vertical and horizontal vectors, enabling the isolation of the vertical velocity component. By incorporating this vertical velocity into the analysis, it can further refine and improve the accuracy of the slope velocity estimations [48,49].

4.2. Cluster Analysis for Landslide State of Activity Classification

A persistent challenge arises when attempting to distinguish genuine landslide activity from mere noise, especially in situations where only a solitary deformation point is detected. This ambiguity poses a significant obstacle, as distinguishing between actual ground movement and spurious signals is crucial for accurate hazard assessment and mitigation strategies. Previous works by various authors have grappled with this issue, often relying on manual inspection or simplistic thresholding techniques to filter out noise [2,46]. However, these methods are inherently limited, as they can either be too lenient, allowing noise to masquerade as deformation, or too stringent, inadvertently excluding legitimate deformation signals.

In contrast, our study introduces a more sophisticated approach by leveraging Z-score clustering to address this challenge. The Z-score, a statistical measure that quantifies the number of standard deviations a data point is from the mean, serves as a powerful tool for identifying outliers or anomalous values within a dataset. By applying Z-score clustering to the deformation points, we can effectively segregate those that exhibit statistically significant deviations from the norm, thereby distinguishing potential landslide-induced deformation from random noise. This method offers a marked improvement over previous

approaches, as it provides a more objective and data-driven means of noise exclusion, enhancing the efficiency of identifying potential deformation areas.

While Z-score clustering excels at filtering out noise, the completeness of classification, or the ability to correctly identify all instances of true deformation, may be compromised to some extent. This is because clustering algorithms, by their nature, seek to group similar data points together, which can sometimes result in the over-aggregation of noise or the fragmentation of genuine deformation clusters. Previous studies have also noted this challenge, highlighting the difficulty of achieving perfect classification accuracy, particularly in complex and heterogeneous landscapes [52,53].

Despite these limitations, Z-score clustering represents a significant advancement over existing methods, as it offers a more robust and automated framework for noise exclusion and potential deformation identification. Future research could further refine this method by incorporating additional data sources, such as high-resolution topographic data or multi-temporal satellite imagery, to enhance the accuracy and completeness of deformation classification. Additionally, exploring alternative clustering algorithms or hybrid approaches that combine multiple techniques could potentially yield even better results, pushing the boundaries of what is currently achievable in the field of landslide deformation analysis.

4.3. Advantages and Limitations of SBAS-InSAR

The SBAS-InSAR method, while innovative and powerful in its ability to monitor ground deformation, is not without its share of disadvantages and limitations. First and foremost, due to the side-looking imaging system, the images it produces are susceptible to geometric distortions, including foreshortening, layover, and shadow. These distortions can significantly complicate the interpretation of the data and introduce errors into the deformation analysis.

Moreover, the alignment between the LOS direction and the actual direction of terrain movement plays a crucial role in determining the accuracy of deformation results. Unfavorable alignments can lead to underestimation or overestimation of the true deformation, thereby affecting the reliability of the findings. To mitigate this issue, it is beneficial to utilize satellite observations from different incident angles as well as both ascending and descending orbits, as this provides a more comprehensive view of the terrain and helps to correct for any LOS-related biases. Many researchers have applied multi-source satellite imagery from both ascending and descending orbits to improve their results [48–50,52].

Another significant limitation of the SBAS-InSAR method is its applicability primarily to slow-moving landslides. Rapidly moving landslides can introduce phase-unwrapping errors, which are difficulties in accurately reconstructing the continuous phase information from the interferometric fringes. This limitation stems from the fact that the method relies on the assumption of gradual, continuous deformation over time, which is not valid for rapidly changing scenarios.

Furthermore, the measurement density and the maximum detectable velocity in a given area are constrained by the characteristics of the C-band Sentinel data used. Specifically, the time interval between two successive acquisitions, determined by the satellite revisit time, limits the temporal resolution of the deformation monitoring. Considering the revisit time and wavelength of Sentinel-1, for instance, the maximum detectable velocities are capped at 42.6 cm/year for 12-day image pairs (C band). To enhance the method's capability to detect rapid displacement targets, SAR data with longer wavelengths or shorter revisit periods would be required.

In addition, the SBAS-InSAR method also faces challenges in areas with dense vegetation cover. Vegetation can cause temporal decorrelation, which is a loss of coherence

between successive SAR images due to changes in the scattering properties of the surface. This decorrelation can significantly degrade the quality of the interferometric fringes and make it difficult to extract reliable deformation information. In our study, only 34.9% of landslides were successfully classified according to this scheme. One of the most important reasons is that most landslides were covered by vegetation, which induces interferogram decoherence, so that we could not extract MPs to monitor the change of landslides. Another reason that causes a low density of MPs is the resampling during the processing of SBAS-InSAR.

The land cover of the Loess Plateau is characterized by cropland, grassland, forest, shrubland, and so on. Vegetation types significantly influence radar signal interferometric coherence, primarily through their canopy structure, moisture content, and seasonal dynamics. Dense, tall arboreal forests cause severe volume decorrelation year-round, rendering C-/X-band signals nearly unusable. The impact of cropland and seasonal grassland is strongly cyclical, with coherence dropping sharply during the summer growth period and recovering significantly after autumn harvest or during winter dormancy. Low shrubs, due to their stable structure and low biomass, have a relatively weaker effect on coherence. Therefore, for areas with dense vegetation cover, specific methods can be adopted to mitigate the influence of vegetation. For single-polarization data, longer wavelengths with stronger penetration capabilities, such as L-band and P-band, can be considered. For example, we could use the L-band to penetrate forested areas, and the C-band to monitor deformation in farmlands during non-growing seasons. If multipolarized or fully polarized data are available, polarization optimization techniques may be applied. Furthermore, in the selection of interferometric pairs, data from periods when vegetation is less vigorous, such as during the defoliation season, should be chosen to minimize the impact of vegetation as much as possible. Such a seasonal and vegetation-specific assessment would not only clarify the temporal windows most suitable for InSAR monitoring but also inform optimal acquisition strategies (e.g., selecting SAR data from dry, leaf-off periods) to enhance deformation measurement reliability in this challenging environment.

Another environmental factor that can affect the accuracy of SBAS-InSAR measurements is atmospheric heterogeneity, particularly over mountainous regions. Atmospheric delays, which vary with topography, can introduce artifacts into the interferometric phase, leading to erroneous deformation estimates. To minimize the impact of atmospheric effects, various atmospheric correction methods can be applied, although their effectiveness may vary depending on the specific conditions. In this paper we use TRAIN V3 atmospheric correction to mitigate the atmospheric change.

Despite these limitations, the SBAS-InSAR method remains a highly advanced and valuable tool for identifying active landslides, offering significant advantages over traditional fieldwork methods. With the increasing number of satellites being launched by different countries, featuring longer wavelengths, shorter revisit periods, and higher resolution observations, the availability and diversity of data sources for InSAR analysis are expanding rapidly. This, coupled with ongoing improvements in methodological approaches and computational capabilities, is making it possible to derive time series displacement data more rapidly and efficiently than ever before. As a result, the SBAS-InSAR method could play an increasingly important role in landslide monitoring and hazard assessment in the years to come.

5. Conclusions

This work presents a comprehensively designed SBAS-InSAR post-processing workflow, specifically tailored for the classification of landslide states of activity within the Loess Plateau area, as well as for an in-depth analysis of the kinematic characteristics exhibited by

these landslides. One of the key innovations in this workflow is the conversion of the LOS direction velocity vector into the slope direction. This conversion is crucial as it provides a more accurate and relevant representation of the landslides' actual movement patterns, facilitating the identification and monitoring of displacement changes with greater precision. To streamline the classification process and enhance computational efficiency, we employ the Z-score clustering method to derive measurement point clusters. These clusters serve as the basis for classification, allowing us to categorize landslides based on their movement characteristics. While this approach improves efficiency, it does come at the expense of some classification completeness, as certain subtle or complex movement patterns may not be fully captured by the clustering algorithm. Nevertheless, the trade-off is deemed acceptable given the significant gains in processing speed and the overall robustness of the classification results.

In this paper we obtained the average velocity through the SBAS-InSAR method by using 205 SLC images from the Sentinel-1 satellite, ranging from October 2014 to January 2024. We identify 69 "active, very slow" landslides and 63 "active, extremely slow" landslides with a coverage area of 423 km². Two notable landslides, the Nenggancun landslide and the Zhaojiaya landslide, are further verified through the examination of optical images, confirming their active status and providing visual evidence of their movement. The experiment shows that open and easily accessible Sentinel-1 data can be one data source for identifying and monitoring landslides, and the SBAS-InSAR post-processing workflow can be used as a method to update landslide activity inventories. Furthermore, the results reveal that the creep deformation of landslides was highly sensitive to seasonal rainfall. It is of significance for the prevention and mitigation of landslides in the Loess Plateau, especially during the rainy season.

Remote sensing data analysis, as showcased in this study, offers a powerful tool for supporting landslide hazard assessments. The accuracy of InSAR-derived landslide deformation was verified through comparison with the landslide inventory surveyed by field work in 2016 and historical Google Earth images. The kinematic plausibility of the detected deformation pattern can be a crucial qualitative check. However, it is essential to incorporate quantitative comparison into this research. We plan to conduct cross-validation using different methods (e.g., PS-InSAR and CPT) in future research, and to use root mean square error (RMSE) to assess the accuracy of InSAR. In addition, it is essential to acknowledge a significant limitation associated with relying solely on InSAR technology for assessing landslide kinematics in regions with specific surface characteristics. The Loess Plateau, characterized by its vegetation cover, poses challenges for the extraction of reliable surface deformation measurements using InSAR. The presence of vegetation introduces phase noise and decorrelation effects, which can degrade the quality of InSAR-derived deformation maps. Although the use of advanced algorithms such as SBAS-InSAR can improve the performance of InSAR time series, more insights can be gained when such data are combined with high-quality geologic, geomorphologic, meteorological, and in situ measurements. This multi-disciplinary approach enables a more holistic assessment of landslide hazards, taking into account not only the surface deformation patterns but also the underlying geological structures, topographical features, climatic conditions, and triggering factors. By combining these diverse data sources, we can develop more accurate and reliable landslide prediction models, ultimately enhancing our ability to protect lives and property from the devastating impacts of landslides.

Our InSAR-based identification of active landslides contributes to practical risk management. The detected landslides and their displacement rates provide critical input for early detection systems by highlighting slopes requiring priority monitoring. Furthermore, the spatial patterns of deformation help optimize the placement of field instruments

(e.g., GNSS, crack meters) for targeted monitoring, thereby forming a cost-effective InSAR-guided surveillance framework. This process directly informs engineering decision-making by prioritizing slopes for intervention (e.g., drainage control, structural reinforcement) based on the spatial extent and severity of movement revealed by our analysis. This work establishes a basis for developing regional-scale, multi-tiered early warning systems.

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