



Technical Note

Potential Landslide Identification in Baihetan Reservoir Area Based on C-/L-Band Synthetic Aperture Radar Data and Applicability Analysis

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Abstract: The Baihetan reservoir region is characterized by complex geomorphology, significant altitude differences, and rugged terrain. Geological hazards in such areas are often characterized by high concealment, wide distribution, and difficulty in field investigation. Traditional identification techniques are unable to detect and monitor geological hazards on a large scale with high efficiency and accuracy. In recent decades, interferometric synthetic aperture radar (InSAR) techniques, such as small baseline subset InSAR (SBAS-InSAR), have been widely applied to landslide identification. However, due to factors such as vegetation and the degree of landslide deformation, single-band synthetic aperture radar (SAR) still has certain limitations in detecting landslides. In this study, SBAS-InSAR was conducted based on ALOS-2 and Sentinel-1 ascending-descending images covering the Baihetan reservoir region. Deformation identification results were utilized to conduct a statistical analysis of the SAR detection performance and landslide characteristics, and the effect of vegetation on the detection effectiveness of different SAR bands was discussed. The study revealed that when surface vegetation coverage reaches a high degree, the percentage of areas with coverage greater than 0.6 is greater than 95%, the SAR coherence is mainly affected by vegetation thickness; the comparison of the difference change in the average coherence of the C/L bands among the four vegetation types shows that the ratio of the average coherence of the L-bands to the C-bands increases by a factor of three with the increase in thickness and the transition from crops to shrubs and trees. The results showed that the L-band has better detectability than the C-band in alpine-canyon terrain with vegetation coverage and complex vegetation composition. However, considering the high temporal resolution and accessibility of Sentinel-1 SAR data, it is still the main data choice for wide-area identification of landslides in the reservoir area, while other satellite-borne SAR data with different wavelengths and resolutions, such as ALOS, can be used to assist in the identification and monitoring of landslide hazards with significant magnitude of deformations and dense vegetation coverage. Therefore, the combined utilization of multi-band SAR data has the potential to enhance the dependability of landslide identification and monitoring, resulting in more accurate detection results.

Keywords: potential landslide; time-series InSAR; multi-band; vegetation coverage

1. Introduction

The Baihetan hydropower station, as one of the nearly 20 planned and constructed hydropower stations in the Jinsha River Basin, Baihetan, plays a crucial role in the “West-to-East Power Transmission” project. The Baihetan reservoir area is a typical area of alpine-canyon terrain due to its complex landforms and significant elevation differences. Meanwhile, the extensive reservoir construction and rapid water level fluctuations have resulted in a marked increase in the frequency of landslides, avalanches and other geological disasters [1–3]. Therefore, accurate location and prevention of potential landslides are particularly important while developing and constructing hydropower projects vigorously [4].

However, traditional investigation and monitoring techniques are not efficient in mapping geological hazards in alpine-canyon terrain. Over the past several decades, interferometric synthetic aperture radar (InSAR) all-weather, all-day, large-scale, and highly accurate characteristics have made it widely applicable in geological hazard monitoring [5–10], with time-series InSAR as one of the main techniques for landslide hazards [11–18]. Subsequently, SBAS-InSAR technology has been effectively utilized in various areas at risk of landslides, such as highways [19,20], reservoir areas [21], and river basins [22], validating its applicability and accuracy in landslide monitoring. Although time-series InSAR technology is widely employed in identifying and monitoring landslides, there has also been an increased focus on investigating the impact of factors like vegetation and terrain on coherence loss during the monitoring process. Westerhoff et al. conducted studies on the influence of vegetation on InSAR coherence from both temporal and spatial perspectives [23]. Guo et al. compared the vegetation anomaly information with InSAR deformation results, concluded that utilizing abnormal vegetation information for monitoring landslides with high vegetation coverage has a certain level of reliability and practicality [24]. However, the above studies only qualitatively analyzed the impact of vegetation on InSAR deformation monitoring. Pan et al. established a second-order linear model using *NDVI* and dual-polarization Sentinel-1 data, revealing and validating the relationship between C-band InSAR decorrelation and vegetation coverage [25]. Liu et al. found the coherence with InSAR was logarithmically related to increasing *NDVI* [26]. Dai et al. conducted a comparative analysis of vegetation penetration between ALOS-2 and Sentinel-1 data; two SAR datasets with different wavelengths show significant differences in the penetration effects over different types of vegetation and different coverage areas [27]. The previous study mainly analyzed the comparative analysis of C-bands and L-bands from the perspective of the influence of vegetation density on the detectability of InSAR. However, the complex composition of vegetation structure in the alpine-canyon terrain has a greater impact on InSAR detection results. Therefore, it is necessary to further consider and comparatively analyze the impact of vegetation thickness and density on the coherence of different bands.

This study utilized L-band ALOS-2 data and C-band Sentinel-1 data, and applied the SBAS-InSAR technique to monitor the Mianshawan-Tuandigou section of the Baihetan Reservoir Area, and combined with optical images to obtain the distribution of potential landslides. Then, by combining the *NDVI* and optical images of vegetation, a further analysis was conducted on the effects of vegetation coverage, thickness and SAR wavelength on landslide identification and monitoring, and it was concluded that combining the advantages of L-band and C-band SAR further improves the detectability of InSAR in the area with extensive vegetation coverage, which provides theoretical and empirical support for landslide identification and monitoring in alpine-canyon terrain with extensive vegetation coverage.

2. Study Area and Datasets

2.1. Study Area

Jinsha River originates from the Tanggula Mountains in Qinghai Province, China. It is dominated by steep alpine banks and deep valleys and, as a result, forms a typical alpine-canyon terrain. The large elevation drop (about 3300 m), rugged terrain, and abundant water resources have resulted in the construction of more than 20 hydropower stations,

which are one of the main hubs of the “West–East Power Transmission” project. As one of them, Baihetan Hydropower Station, which is the second largest in the world in terms of power generation capacity, is located in Qiaojia County, Yunnan Province and Nanning County, Sichuan Province, in the lower reaches of the Jinsha River (as shown in Figure 1). The Baihetan reservoir region experiences a subtropical dry/warm river valley climate, with an average annual temperature that varies from 12 °C to 20 °C. The region undergoes significant rainfall between May and October, contributing to approximately 90% of the annual precipitation in contrast to the clear and dry weather prevalent from November to April with minimal rainfall [28]. The area is primarily composed of limestone and basalt rocks, with basalt being structurally fragile and prone to fracturing. Factors, including precipitation, gravity, and water level changes due to reservoir operations, contribute to the frequent occurrence of geological hazards like landslides and debris flows, which has a significant impact on reservoir water level changes and the stability of the dam.

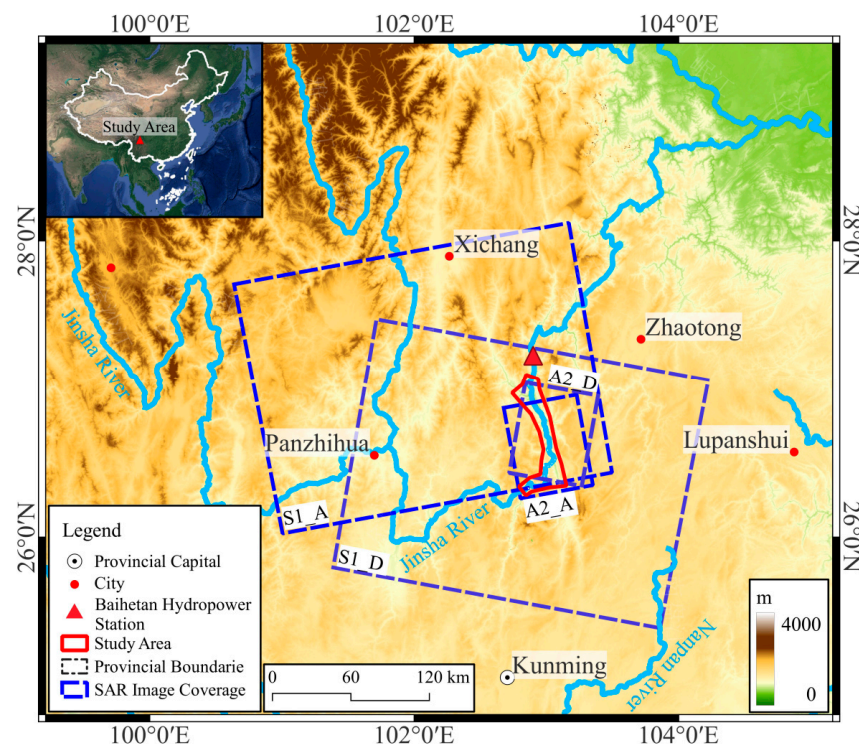


Figure 1. Study area overview.

2.2. Datasets

This study utilized SAR data from two satellite missions collected from four orbits, including L-band data from both the ascending and descending orbits of ALOS-2 and C-band data from both the ascending and descending orbits of Sentinel-1. The datasets consisted of 11 ascending images, 9 ascending images from ALOS-2, and 35 ascending images, 32 descending images from Sentinel-1. Figure 2 shows the temporal distribution of these images. Figure 1 displays the coverage area of the SAR images, while Table 1 presents the main parameters. For this study, the data on vegetation coverage originated from the Landsat 8 satellite. The Landsat panchromatic image of the study area was obtained in August 2022.

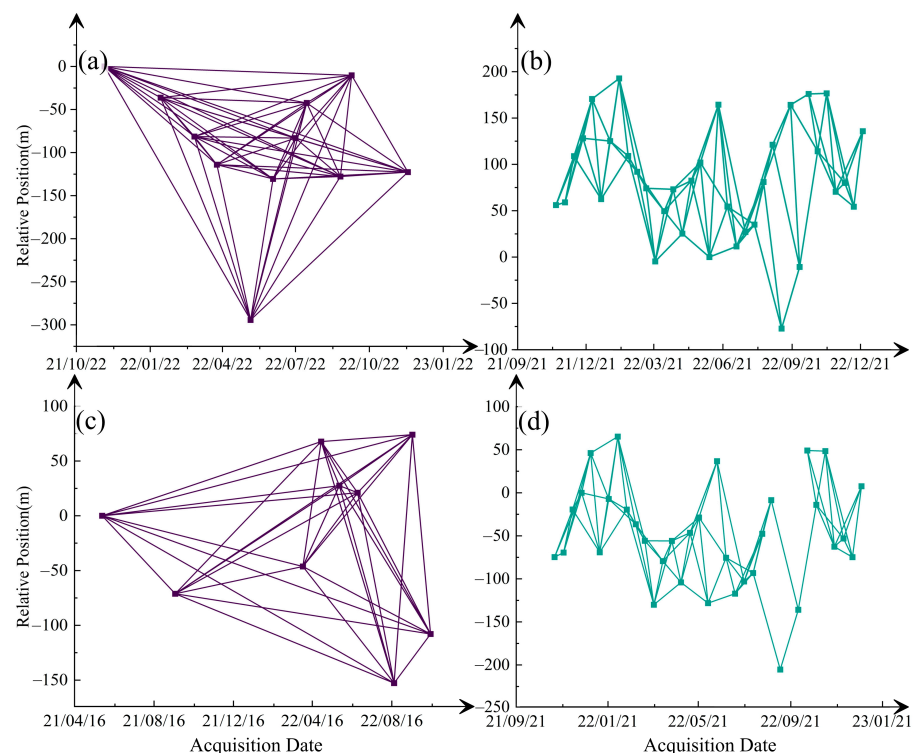


Figure 2. Time–position plots: (a) ALOS-2 ascending; (b) Sentinel-1 ascending; (c) ALOS-2 descending; (d) Sentinel-1 descending.

Table 1. Main parameters of SAR data.

Parameter	Sentinel-1		ALOS-2	
Orbit direction	Ascending	Descending	Ascending	Descending
Band	C		L	
Wavelength (cm)	5.6		23.6	
Azimuth/Range pixel spacing (m)	2.3/13.9		14/2.3	
Revisit frequency (d)	12		14	
Acquisition time	November 2021–December 2022	November 2021–December 2022	November 2021–December 2022	May 2021–October 2022
Number of data	35	32	11	9

3. Methodology

This study utilized SBAS-InSAR technique to conduct the identification and monitoring of landslide-prone areas in Baihetan reservoir region. The detection of landslide-prone areas was based on the analysis of the results of ground deformation monitoring, along with terrain information. The coherence of SAR image pairs played a significant role in evaluating the interferometric quality during InSAR processing. Additionally, vegetation coverage and vegetation types were obtained from imagery sources such as Landsat 8, which was used to evaluate the impact of different vegetation thicknesses on the coherence of SAR data at different wavelengths. The technical workflow is shown in Figure 3.

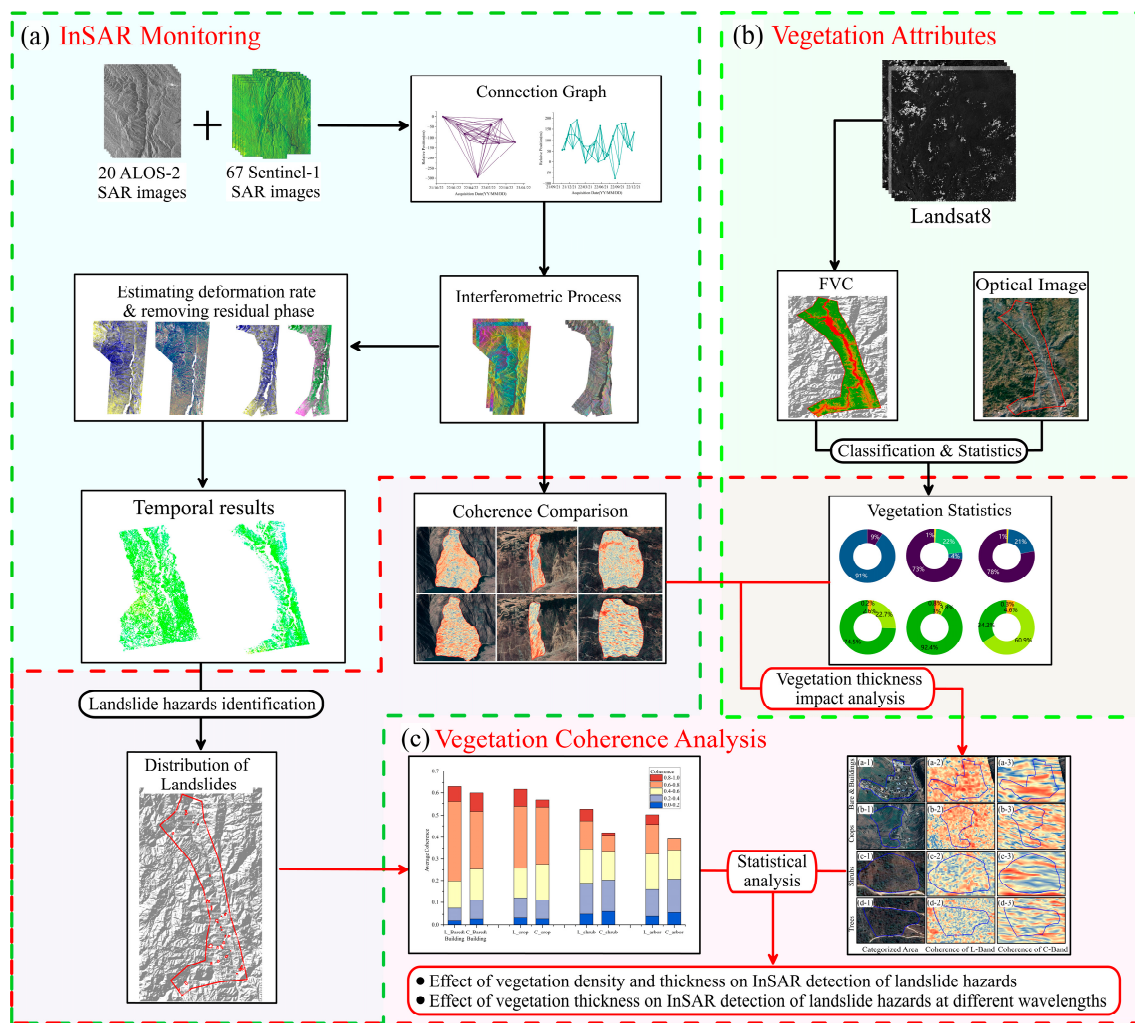


Figure 3. Technology flowchart: (a) InSAR monitoring; (b) vegetation information statistics; (c) vegetation coherence analysis.

3.1. Identification and Monitoring of Landslide-Prone Areas Using SBAS-InSAR

SBAS-InSAR is a method utilized to estimate ground deformation by constructing interferograms from a collection of short temporal and spatial baselines formed by multiple master images and extracting temporal data on the deformation by using high-coherence points with high coherence values in the images. This approach overcomes the challenges of substandard coherence in interferograms induced by a single master image. Moreover, it reduces the data prerequisites of time-series InSAR while displaying a high level of computational effectiveness [29]. The implementation of SBAS-InSAR facilitates the recognition and tracking of zones susceptible to landslides, thereby making it easier to carry out further statistical analysis of landslide hazards. The principle of SBAS-InSAR requires the computation of the temporal and spatial baselines among several image pairs in the research area. Interferometric processing is carried out by selecting image pairs that meet specific temporal and spatial threshold. Subsequently, the Singular Value Decomposition (SVD) method is used to estimate deformation parameters from the interferograms, and atmospheric filtering is applied for mitigating the effects of atmospheric delay, resulting in non-linear deformation. With combining low-frequency deformation and non-linear deformation, the overall deformation phase in the region was obtained. The processing of data and outcomes is shown in Figure 3a.

3.2. Statistical Analysis of Vegetation Information

Vegetation coverage, also known as fractional vegetation cover (*FVC*), refers to the percentage of the vertical projection area occupied by vegetation (including leaves, stems, and branches) per unit of area [30], which is a comprehensive quantitative indicator of the surface condition of vegetation communities and ecosystems. This study utilized the near-infrared (*NIR*) and red (*R*) bands from Landsat 8 panchromatic imagery to calculate the normalized difference vegetation index (*NDVI*).

$$NDVI = \frac{NIR - R}{NIR + R} \quad (1)$$

The pixel-based binary model categorizes the vegetation structure of a pixel into two categories: pure pixel and mixed pixel. A pure pixel represents a fully vegetated area with a coverage value of 1. On the other hand, a mixed pixel consists of both vegetation and non-vegetation components. The *NDVI* of a mixed pixel is a linearly weighted combination of the *NDVI* values of the vegetation and non-vegetation portions. The weights for each component are determined by their respective ratios in the pixel area.

$$NDVI = f_v \times NDVI_v + (1 - f_v) \times NDVI_0 \quad (2)$$

In the equation, *NDVI* represents the *NDVI* value of the pixel, *f_v* represents the *FVC* of the pixel, *NDVI_v* and *NDVI₀* represent the *NDVI* values of the vegetation-covered and non-vegetation-covered parts, respectively.

Therefore, the equation can be expressed as follows:

$$f_v = \frac{NDVI - NDVI_0}{NDVI_v - NDVI_0} \quad (3)$$

Taking the cumulative frequency of the histogram at 5% and 95% of the *NDVI* values as *NDVI_v* and *NDVI₀*, respectively, for pixels with *NDVI* ≤ *NDVI₀*, the vegetation coverage is set to 0, and for pixels with *NDVI* > *NDVI_v*, the vegetation coverage is set to 1. Vegetation coverage types are classified based on the *FVC* values, as shown in Table 2, and the process and results are shown in Figure 3b.

Table 2. Classification of vegetation coverage.

FVC	Vegetation Cover Type
0 ≤ H ≤ 0.45	Low Vegetation Cover
0.45 < H ≤ 0.6	Lower Vegetation Cover
0.6 < H ≤ 0.75	Medium Vegetation Cover
0.75 < H ≤ 1	High Vegetation Cover

4. Results

4.1. Overall Identification Result

Based on the SBAS-InSAR technique, the temporal deformation information of the Mianshawan-Tuandigou section in the Baihetan reservoir region is obtained from the ascending and descending SAR data of Sentinel-1 and ALOS-2 on both sides of the river. These results are shown in Figure 4.

By processing SAR data acquired from four different orbits by different satellites in two bands, a total of 35 significant potential landslides were identified and numbered sequentially from south to north, i.e., BHT01–BHT35. Among the potential landslides, 22 points were identified along the reservoir banks, while the remaining 13 points were outside the reservoir banks. The monitored points displayed significant displacement over time, with an annual deformation rate maximum of 380 mm per year.

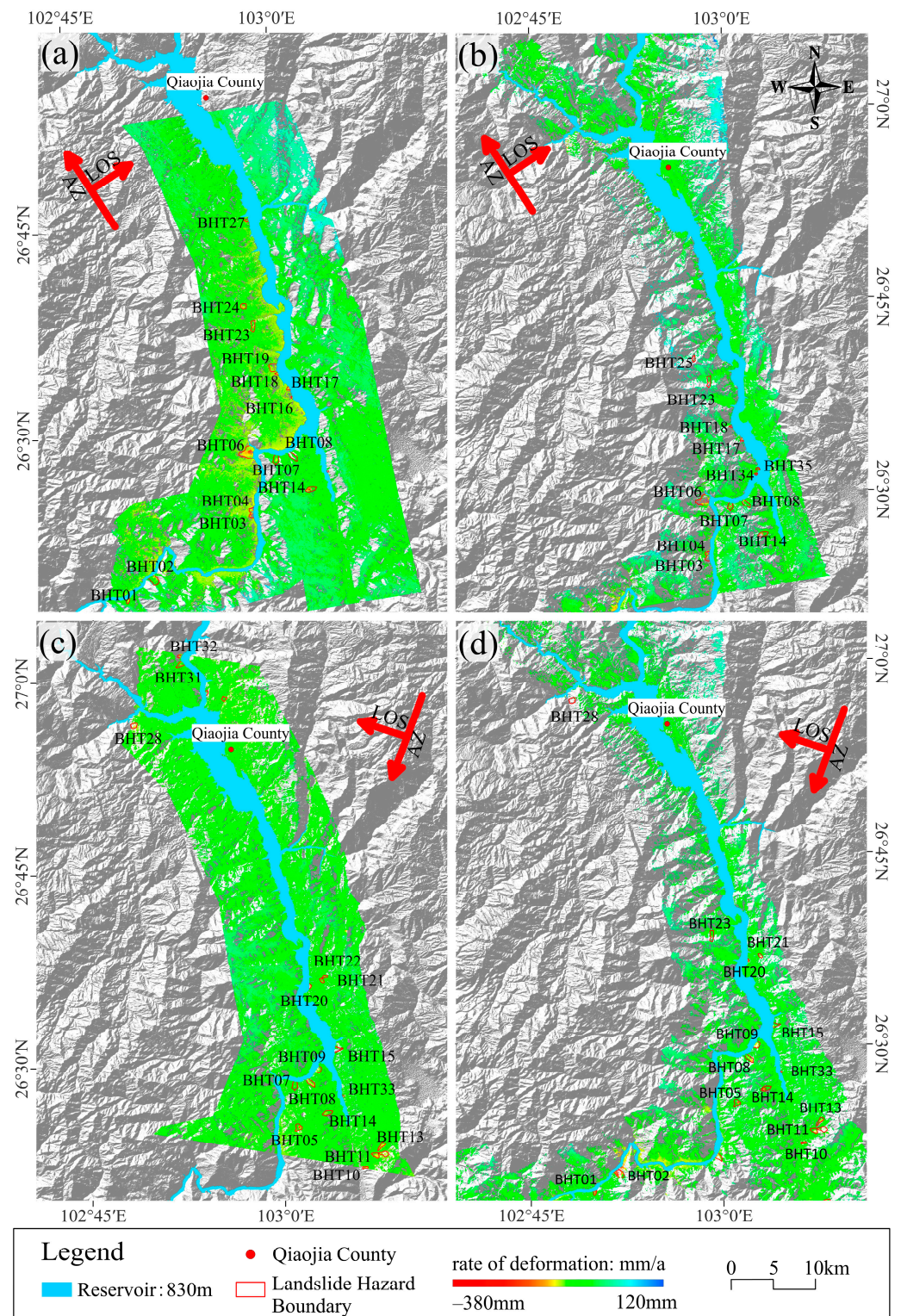


Figure 4. Displacement velocity map. (a) ALOS-2 ascending; (b) Sentinel-1 ascending; (c) ALOS-2 descending; (d) Sentinel-1 descending.

In the alpine-canyon terrain, which is affected by the rugged terrain, the SAR sensors for side view detection are severely affected by geometric distortions during the surface detection process. This study addresses the distribution of geometric distortions during SAR data acquisition for each orbit in the study area based on the local incidence angle, orbital parameters, and digital terrain model, as shown in Figure 5a–d. The statistics of

geometric distortions acquired from ALOS-2 ascending orbit SAR data indicate that the detectable area accounts for 84% of the study area. The overlapping mask and shadow are undetectable areas, accounting for 15.8% and 0.3%, respectively. The detectable areas of ALOS descending orbit, Sentinel-1 ascending orbit, and descending orbit account for 85.1%, 76.6%, and 65.7%, respectively.

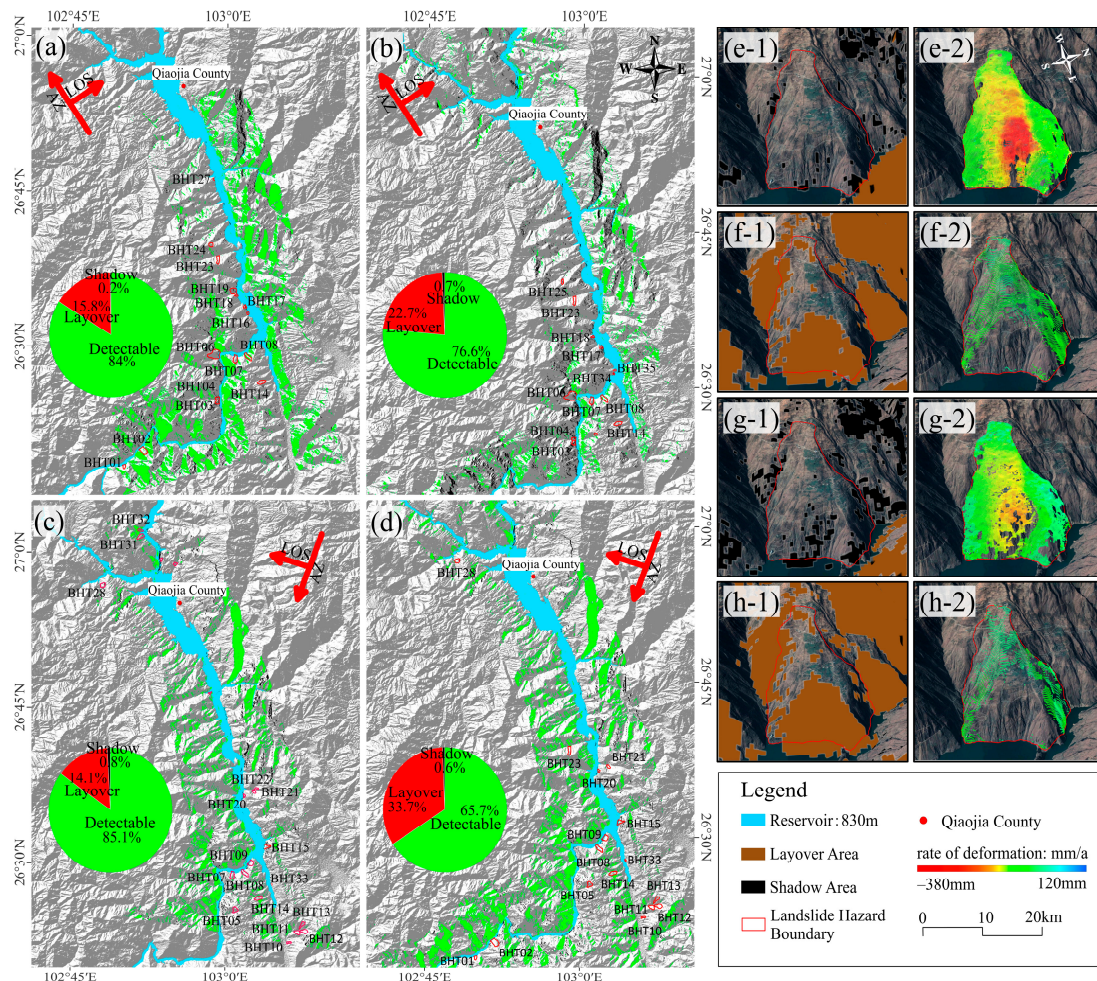


Figure 5. Geometric distortion distribution. (a) ALOS-2 ascending; (b) Sentinel-1 ascending; (c) ALOS-2 descending; (d) Sentinel-1 descending; (e-1–h-1) geometric distortion distribution of BHT06 from ALOS-2 and Sentinel-1; (e-2–h-2) effective point distribution of BHT06 from ALOS-2 and Sentinel-1.

The SAR data acquisition process is affected by geometric distortion, which is mainly related to the ground slope direction and slope gradient. This study selects the landslide point of BHT06, which has a sharp slope change and the slope is oriented to the east, and obtains the distribution of geometric distortion and the distribution of effective monitoring points of the temporal deformation of the landslide point in the four orbits, respectively, as shown in Figure 5(e-1,e-2,f-1,f-2,g-1,g-2,h-1,h-2). As shown in Figure 5(e-1), in the ALOS-2 ascending SAR data, only a very small area of the BHT06 potential hazard point is affected by the shadow, so the point coverage is high and obvious deformation is detected, as shown in Figure 5(e-2). As shown in Figure 5(f-1), in the ALOS-2 descending SAR data, due to the sharp slope change at the foot of the slope, the foot of the slope is severely affected by the layover, resulting in very few effective monitoring points in this area, and no obvious deformation is detected. Figure 6(a-3,e).

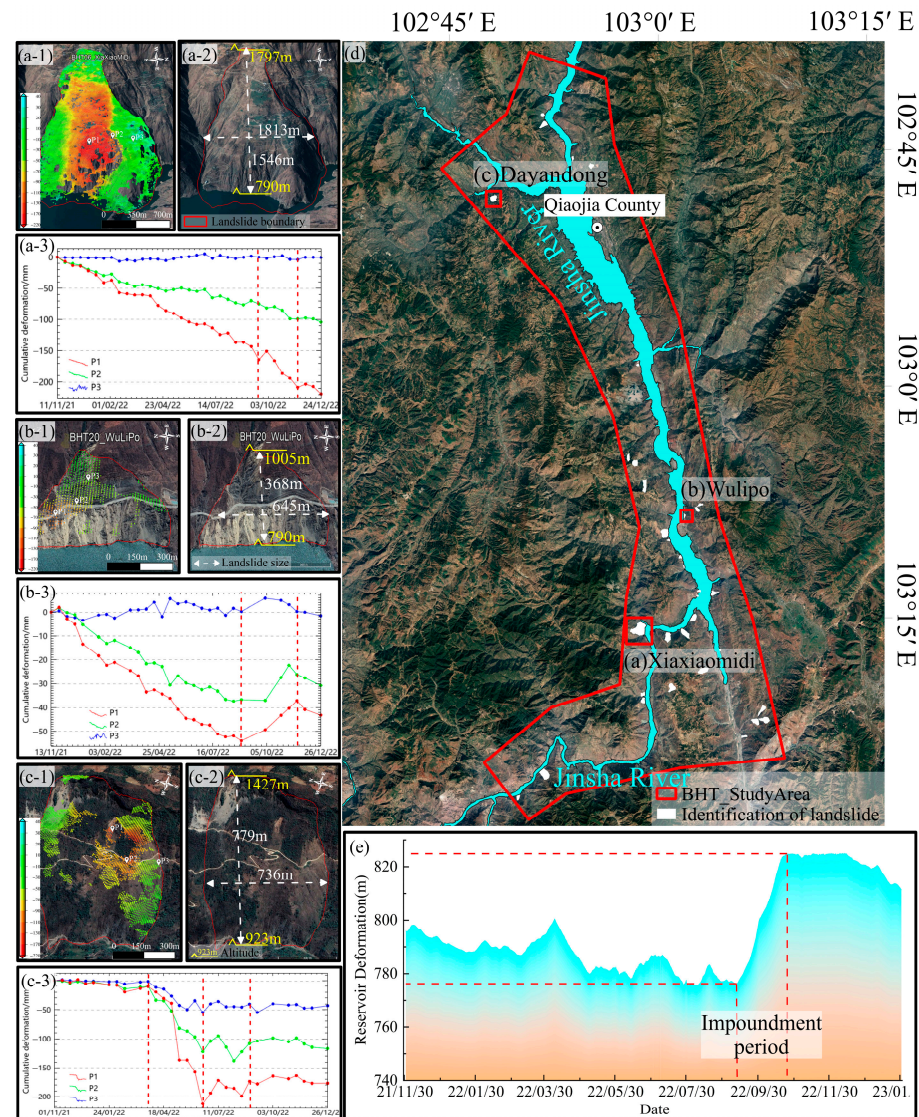


Figure 6. Typical landslide profile (a-1–c-1) effective point distribution of BHT06-Xi Xiaomidi, BHT20-Caizidi and BHT28-Dayandong; (a-2–c-2) size of BHT06-Xi Xiaomidi, BHT20-Caizidi and BHT28-Dayandong; (a-3–c-3) deformation curve of monitoring point of BHT06-Xi Xiaomidi, BHT20-Caizidi and BHT28-Dayandong; (a,d) overview of the distribution of landslide hazards; (e) reservoir deformation.

Table 3 shows the detectability of the 35 potential landslide points identified in the four orbits based on the above comparisons.

Table 3. Statistics and comparison of landslide hazards detected in different orbits.

Orbit Direction	Ascending		Descending	
Satellite platform	Sentinel-1	ALOS-2	Sentinel-1	ALOS-2
Number of identifications	12	15	16	17
Undetected due to vegetation	BHT24		BHT31, BHT32	
Undetected due to low deformation values		BHT24, BHT34, BHT35	BHT07, BHT22	BHT23
Undetected due to geometric distortion	BHT16, BHT19, BHT27			
Undetected due to uncovered area in the image	BHT01, BHT02			BHT01, BHT02

The statistics of the detected potential landslides from different platforms and orbits are shown in Table 3. The L-band SAR data identified more landslides than the C-band SAR data, both for ascending and descending orbits. In an ascending orbit, both the L-band and C-band SAR data detected 9 landslide hazards, while in a descending orbit, the two sets of data together detected 13 landslide hazards.

The statistics of landslide hazards identified by SAR data from the same orbit, but different bands showed that two landslide hazards (BHT01 and BHT02) were not identified due to lack of SAR image coverage in the area. In the ascending orbit due to geometric distortion, three landslide hazards (BHT16, BHT19, and BHT27) were identified only in ALOS-2, while landslide hazards such as BHT24 are not identified by different bands of SAR data in the same orbit, due to low detected deformation. It is worth noting that after eliminating several reasons such as geometric distortion caused by topography, three potential hazards, BHT24, BHT31, and BHT32, were not detected by different bands of SAR data in the same orbit, due to dense vegetation coverage, and all were detected only by ALOS-2.

Concerning the distribution of hazards overall, the northern section of the study area had less vegetation coverage and were generally susceptible to landslide hazards with exposed rocks or low shrub cover. On the contrary, the landslide hazards in the southern section of the study area hosted denser vegetation, consisting of shrubs or trees. Therefore, the impact of vegetation on detectability will be further explored in subsequent discussions.

4.2. Analysis of the Typical Landslides

The study used two approaches to validate the landslide hazards identified by InSAR: terrain-coupled SAR image parameter analysis to assess geometric distortion effects, geological comparison with optical imagery. The data obtained from multi-orbit detection can be used for deformation monitoring in the study area.

Considering factors such as terrain, the scale of landslide hazards, the influence of reservoir water levels, and vegetation coverage, seven representative landslide hazards were selected from the identified 35 points as typical cases. Figure 6 shows the spatial distribution of these three typical landslide hazards: Xiaoxiaomidi (BHT06), Wulipo (BHT20), and Dayandong (BHT28). Xiaxiaomidi was detected using ascending orbit data, while the rest were detected using descending orbit data.

The Xiaxiaomidi slope is situated on the western bank of the Jinsha River, approximately 90.1 km upstream of the Baihetan hydropower dam, with a difference of about 1007 m in height (as shown in Figure 6(a-2)). The slope has an eastward orientation and a conical shape that narrows at the top and widens towards the bottom. The slope's central portion has a mild gradient of under 30 degrees, and there are three settlements located throughout the slope. InSAR monitoring has shown that the middle part of the slope experiences the highest rate of deformation, with a maximum yearly deformation rate of 220 mm. During the monitored period, the slope deformation rate remained constant, and did not show any significant influence from changes in the reservoir water level (shown in Figure 6(a-3,e)).

The Wulipo slope is located on the eastern bank of the Jinsha River, around 72.9 km upstream of the Baihetan dam. Its elevation ranges from 790 m to 1005 m (shown in Figure 6(b-2)). The slope faces west, and has a cone-shaped form, with a narrower upper section and a wider lower section. However, the lower section of the slope has experienced soil layer slippage, resulting in significant exposure of rock and soil, steep slope surfaces, and a maximum slope angle of 63 degrees. Due to these factors, the effectiveness of InSAR time-series monitoring on this slope is relatively limited. The middle section of the slope is traversed by two trunk road tunnels: the Kunqiao Line and the Qiaomeng Line. The deformation of the slope poses a significant road safety hazard. The maximum cumulative deformation detected by InSAR monitoring in the observable part of this landslide is 45 mm (shown in Figure 6(b-1)). Throughout the monitoring period, the slope exhibited a clear response to changes in the reservoir water level. Since mid-September 2022, when the

water level began to rise continuously, the slope displayed an upward trend. By November, the slope slowly stabilized but still showed a deformation trend (shown in Figure 6(b-3)).

5. Discussion

Although the time-series InSAR deformation monitoring technique has the advantages of high efficiency and low cost, its monitoring effect is seriously affected by the terrain and vegetation in the high mountain valley reservoir area where landslides occur frequently [31]. In the identified landslide hazards within the study region, most of the slopes are covered by vegetation of different scales, which has different effects on landslide hazard identification and monitoring. To study the influence of vegetation on the coherence of different wavelength SAR interferograms within the landslide hazard areas, three representative landslide areas (BHT06, BHT23, BHT28) were selected for comparison between L-band and C-band interferograms using four pairs of interferometric images. The parameters for these comparisons are shown in Table 4.

Table 4. Interference pair parameters.

Data Source	Sentinel-1 A	Sentinel-1 D	ALOS-2 A	ALOS-2 D
Acquisition time	27 June–21 July 2022	29 June–23 July 2022	24 June–22 July 2022	28 May–25 June 2022
Temporal baseline (d)	24	24	28	28
Spatial baseline (m)	37	40	47	13
Landslide Area	BHT06	BHT23, BHT28	BHT06	BHT23, BHT28

To mitigate the impact of temporal and spatial baselines on coherence for different pairs of images, the experiment controlled the temporal baseline, which influences coherence, within the range of 24 to 28 days, and the spatial baseline within 50 m. To further analyze and compare the effect of vegetation on different SAR wavelengths, the experiment combined vegetation coverage and optical images to delineate the vegetation study area. The vegetation within the area was classified (as shown in Figure 7(a-1,a-2,b-1,b-2,c-1,c-2)), and the vegetation coverage and proportion of different vegetation types were calculated and shown in Figure 7d.

As shown in Figure 7(a-1,a-2,b-1,b-2,c-1,c-2), in the three mentioned regions, areas with low coherence and sparse coverage of deformation monitoring points, were mainly distributed in vegetation-covered regions. The theoretical effect of vegetation on InSAR coherence is related to spatial decorrelation, which occurs when the radar detects different ground targets with varying incidence angles. This encompasses both surface and volume scattering decorrelation [32]. The surface scattering decorrelation is mainly influenced by vegetation coverage, while the volume scattering decorrelation involves the penetration of radar waves and is highly correlated with the wavelength and size of the scattering bodies.

From the perspective of vegetation surface scatter decorrelation, in the statistics on vegetation cover in Figure 7d, the areas with vegetation coverage medium or above accounted for over 95% of the total area in the three vegetation study regions, indicating high and similar vegetation coverage. However, as shown in Figure 7e, the coherence among the three regions was significant different, with the average coherence trend of BHT06 (0.6) > BHT23 (0.48) > BHT28 (0.42). In the vegetation study area of BHT06, the proportion of areas with coherence higher than 0.6 was much higher than that of the other two regions. In addition, in the BHT23 vegetation study area, the percentage of high vegetation cover is 92.4%, which is significantly higher than the 34.2% found in the BHT28; however, in terms of the overall consistency, the image pair consistency is higher in BHT23, which has higher vegetation cover. Therefore, the effect of vegetation on InSAR coherence cannot be fully explained by vegetation surface scattering.

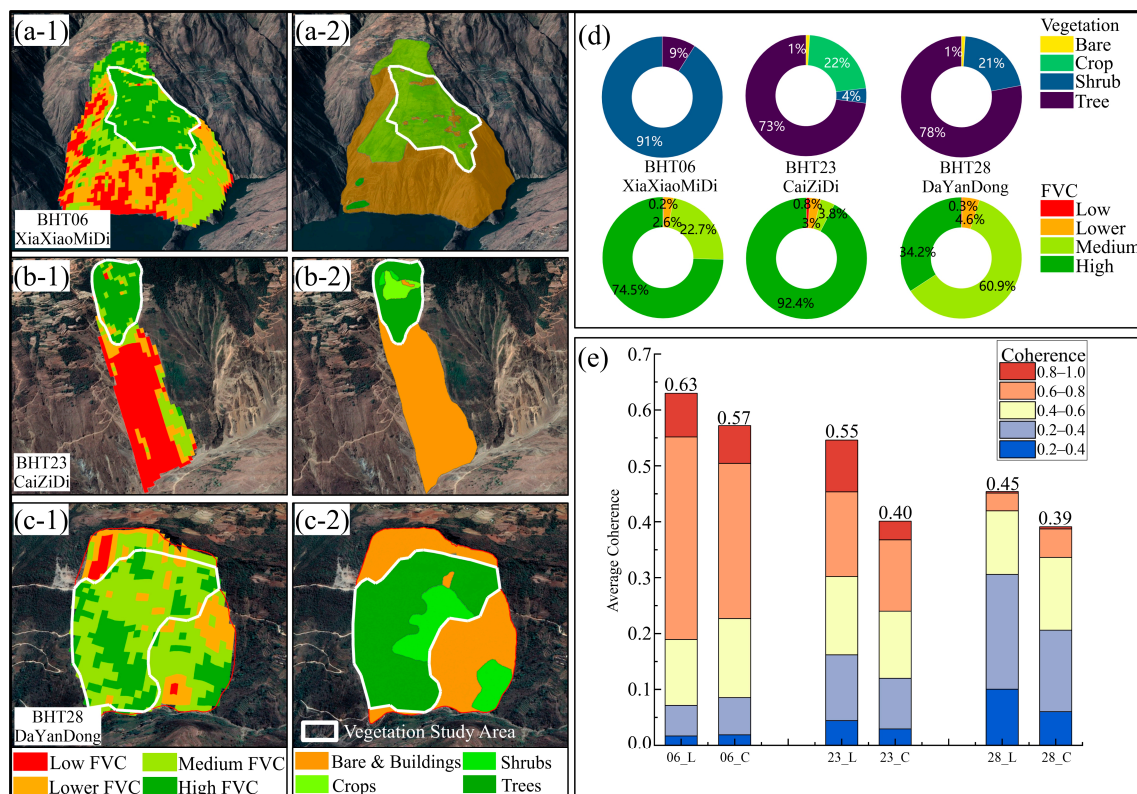


Figure 7. Coherence and vegetation cover overview: (a-1–c-1) fractional vegetation cover of BHT06-Xiaxiaomidi, BHT20-Caizidi and BHT28-Dayandong; (a-2–c-2) distribution of vegetation classification of BHT06-Xiaxiaomidi, BHT20-Caizidi and BHT28-Dayandong; (d) percentage analysis of vegetation types in the study area; (e) percentage analysis of vegetation cover classes in the study area.

Taking into account the volume scattering decorrelation caused by vegetation, and under similar vegetation surface scattering conditions, different vegetation types with varying thicknesses were compared in four typical regions, as shown in Figure 8(a-1,a-2,a-3,b-1,b-2,b-3,c-1,c-2,c-3,d-1,d-2,d-3). It can be observed from the comparison that, under similar vegetation cover, the contribution of the vegetation volume scattering decorrelation component follows the pattern of trees > shrubs > crops, reflecting the influence of vegetation thickness. The coherence of the four vegetation types in the three regions was statistically analyzed as shown in Figure 8e. The coherence of the four types followed a pattern of buildings and bare ground (0.62) > crops (0.59) > shrubs (0.53) > trees (0.45). Among the four vegetation types, L-band interferograms exhibited greater coherence compared to C-band interferograms. Figure 8e shows that the average coherence of the L-band and C-band increases with the thickness of vegetation. The pattern of the average coherence is buildings and bare ground (0.03) < crops (0.04) < shrubs (0.11) = trees (0.11). In areas bare of vegetation or with the lowest crop cover, the proportions of coherence values for both bands were similar, with mean values greater than 0.58. In areas with trees and shrub coverage, L-band interferograms showed better coherence performance, both in terms of overall coherence and the proportion of high coherence values, compared to C-band interferograms.

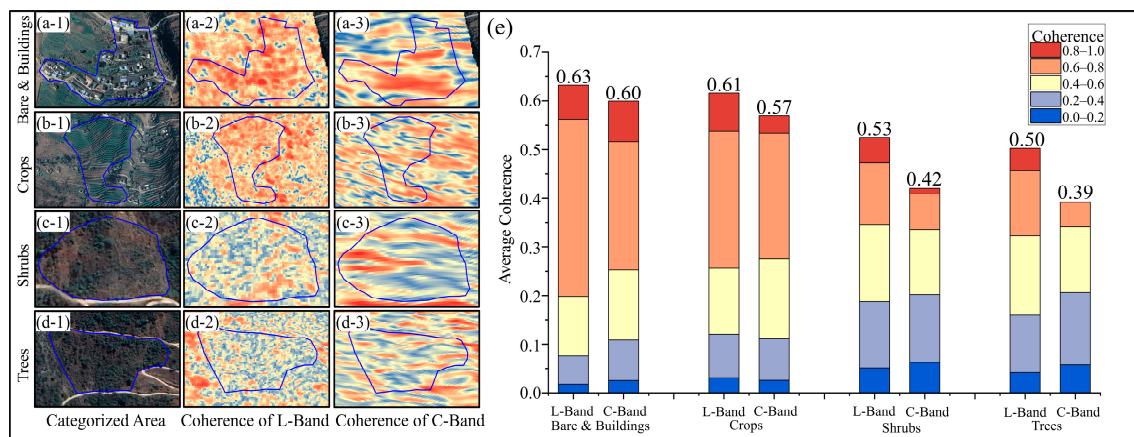


Figure 8. Effects of different thicknesses of vegetation on coherence: (a-1–d-1) visible light image of trees, shrubs, crops and bare area; (a-2–d-2) coherence of L-band of trees, shrubs, crops and bare area; (a-3–d-3) coherence of C-band of trees, shrubs, crops and bare area; (e) coherence statistics.

However, all vegetation study areas had multiple vegetation mixes. As shown in Figure 7(b1,b2), in the BHT06, characterized by low-density crops, the proportion of coherence values was similar for both L-band and C-band interferograms. However, in the BHT23 area, which is dominated by trees, L-band outperformed C-band in terms of coherence overall and the proportion of high coherence values, the coherence difference peaked at 0.15. In the BHT28 area, where shrubs were more prevalent than in BHT23, the coherence of the L-band decreased significantly from 0.55 to 0.45, whereas C-band did not significantly change in coherence. As shown in Figure 7(b1,b2), the vegetation coverage of the vegetation study areas selected for the study are all in the medium-high coverage class, areas with medium and higher vegetation coverage account for more than 95% of the total area, and the effect of wavelength on spatial incoherence in vegetated regions is mainly on vegetation thickness, the volume scattering decorrelation component. In areas with low vegetation coverage, such as those dominated by bare ground or buildings, the SAR coherence is mainly influenced by feature attributes.

As shown in Figure 8e, in areas bare of vegetation or with low vegetation coverage, both L-band and C-band showed good coherence. However, in areas with trees and shrubs, both L-band and C-band were impacted, but L-band maintained an average coherence above 0.5. The average coherence difference between the L-band and the C-band is three times greater in the area of shrubs and trees compared to the area of bare ground and crops. The difference rapidly changes due to variations in vegetation thickness and type, which greatly emphasizes the detection ability of the L-band in vegetated areas. Based on the comparative analysis, it is evident that the L-band is more suitable than the C-band for identifying and monitoring landslides in tree and shrub-covered alpine-canyon terrain. However, the stable orbit and high temporal resolution of C-band SAR data (such as Sentinel-1) are significant advantages that should not be overlooked. The complementary advantages of multi-band InSAR landslide monitoring is one of the main approaches to improve accuracy.

6. Conclusions

The study utilized ascending and descending orbit data of Sentinel-1 and ALOS-2 from November 2021 to December 2022 covering the Baihetan reservoir region. The SBAS-InSAR method was employed to process the data and then obtain the time series results from four different orbits. As a result, a total of 35 landslide hazards were identified, of which 22 were located along the reservoir banks. Analysis of slope direction, vegetation cover, and terrain characteristics at the landslide hazards was conducted to further analyze the detectability of different SAR datasets. The results showed that ALOS-2 identified more landslide hazards than Sentinel-1, and is superior to Sentinel-1 in interferometric performance. Among the

identified landslide hazards, seven typical potential landslides were selected for further analysis of slope deformation rates, cumulative deformation curves, and slope profiles. The characteristics of the slope at two typical hazards were described. The study further discussed the effect of vegetation on the detection efficiency of SAR data in different bands based on the analysis results. The main findings and conclusion are as follows:

- (1) By comparing the interferometric performance of SAR data in areas with varying vegetation coverage, the performance in vegetated areas is influenced by both vegetation surface scattering and volume scattering decorrelation components, specifically vegetation coverage and thickness. In areas with high overall vegetation coverage (i.e., where the proportion of areas with moderate vegetation coverage exceeds 95%), vegetation thickness has a more significant effect on interferometric performance.
- (2) Under the same vegetation coverage conditions, coherence is positively correlated with radar wavelength. ALOS-2 is suitable for identifying and monitoring landslide hazards in alpine-canyon terrain covered by trees, shrubs, and other vegetation. For areas with low vegetation cover and small deformations, Sentinel-1, with its high temporal resolution and shorter wavelength, offers advantages. Therefore, utilizing multi-band SAR data jointly can considerably enhance the reliability of identifying and monitoring landslide hazards, leading to better detection results.

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