Interpretation and sensitivity analysis of the InSAR line of sight displacements in landslide measurements

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ABSTRACT
Landslides are major geological hazards and frequently occur in mountainous areas with steep slopes, often causing significant loss. Interferometric Synthetic Aperture Radar (InSAR) has been widely used in landslide measurement over the last three decades. However, InSAR only can measure one-dimensional displacements (i.e. those in the radar’s line of sight (LOS) direction), resulting in the uncertainty between LOS displacement and the real slope displacement. In this paper, based on ascending and descending data from Sentinel-1 satellite, a wide-area potential landslide early identification was carried out using SBAS-InSAR in the whole of Mao County, a mountainous area in western Sichuan (China), with a total of 41 potential landslides successfully detected. Based on the quantitative analysis, the results show that the InSAR LOS measurement values are slope aspect and gradient-dependent. Finally, we innovatively derived a LOS displacement sensitivity map of InSAR in landslide measurement, revealing the relationship between LOS displacement, real displacements on slopes with arbitrary aspects and gradients, and SAR geometric distortion. This is a generalized finding useful for any slopes. It provides theoretical support to acquire and understand the real slope displacement from InSAR landslide measurement, which is vital to assist in correctly interpreting LOS displacement and carrying out subsequent quantitative geological engineering analysis.

1. Introduction
Landslide disasters frequently occur in the southwestern Sichuan Province in China, with massive casualties and economic losses (Dai et al. 2020; Dong et al. 2018; Fan et al. 2017; Intrieri et al. 2018; Tien Bui et al. 2018; Xu et al. 2018; Yin, Wang, and Sun 2009; Zhao et al. 2018). For instance, Xinmo village, in Mao County, Sichuan Province, China, was entirely buried by a sudden 13 million m\textsuperscript{3} landslide in 2017, with ten fatalities and the disappearance of 73 people (Dai et al. 2020; Meng et al. 2018; Intrieri et al. 2018). Featuring wide coverage and high accuracy (Tomás and Li 2017; Wasowski and Bovenga 2015; Cigna and Tapete 2021), Interferometric Synthetic Aperture Radar (InSAR) have been widely used to detect and monitor the landslides (Canuti et al. 2007; Dai et al. 2016; Nhu et al. 2020; Novellino et al. 2021; Mohammadi et al. 2020; Rosi et al. 2017; Schlögel et al. 2015; Shi et al. 2016; Sun et al. 2016; Tofani et al. 2013). However, in practice InSAR can only measure displacement in the radar’s line-of-sight (LOS) direction (Cigna et al. 2011; Li et al. 2015). For quantitative analysis of potential landslides and precise geological interpretation, it is important to acquire and understand actual slope displacements from InSAR-derived LOS displacements.

To investigate the relationship between InSAR-derived LOS displacements and actual slope displacements, many studies have been conducted since the 1990s. A unit vector in the north, east, and vertical directions has been used to represent the sensitivity of LOS measurement (Colesanti et al. 2003; Massonnet, Thatcher, and Vadon 1996). The method of deriving three-dimensional surface displacements from LOS displacements was originally applied to earthquake displacement field extraction (Fialko, Simons, and Agnew 2001; Hu et al. 2014; Wright...
In terms of the InSAR-related landslide measurement, Colesanti and Wasowski (2006) attempted to calculate the actual displacement along a west-facing slope from the LOS displacement. Plank et al. (2012) broke down the slide direction into the horizontal and vertical directions to calculate the percentage of measurability of InSAR. During the past ten years, many researchers have proposed direct calculations of the relationship between actual displacements along the slope and InSAR-derived LOS displacements (Cascini, Fornaro, and Peduto 2010; Cigna, Bianchini, and Casagli 2013; Greif and Vlcko 2011; Wang et al. 2021; Zhao et al. 2012) and applied the conversion to landslide measurements (Zhang et al. 2021; Zhao et al. 2020). These studies focused on converting the LOS displacements to NEU components or the displacements parallel to the slope. The quantitative relationship between LOS displacement and the real displacement on the slope with arbitrary slope aspect/gradient is still uncertain. This relationship, including the geometric distortion on slopes, directly influences InSAR landslides measurement and is therefore worthy of further research.

In this paper, we used the time series InSAR algorithm to identify active slopes (i.e. potential landslides) over the whole area of Mao County based on dual-orbit Sentinel-1 data. By quantitatively analyzing the identification differences derived from ascending/descending datasets, we find that slope aspects and gradients influence the InSAR LOS measurement value. We novelty derive a LOS displacement sensitivity map that reveals the relationship between LOS displacement, actual displacements on slopes with arbitrary aspects and gradients, and SAR geometric distortion. This extracts the real slope displacement for correctly understanding and interpreting LOS direction displacement in InSAR-related landslide measurement.

2. Study area and datasets

2.1 Study area

Mao County is located on the southeast edge of the Tibetan Plateau in the northwest of Sichuan Province, with an administrative area of 3900 km² (Figure 1a). Mao County is a typical area with alpine-canyon terrain, in which over 60% slopes are steeper than 30°, and rock, and soil consolidation fracture is relatively developed, resulting in frequent occurrences of geological hazards (Hu et al. 2018; Qiu et al. 2017) (Figure 1a). Several active faults surround this region, with several earthquakes occurring in the recorded past (Figure 1a). Three large earthquakes have struck this region in recent times, i.e. Mw7.3 Diexi Earthquake in 1933 (Wei et al. 2021); Mw6.7 Songpanpingwu Earthquake in 1976 and Mw7.9 Wenchuan Earthquake in 2008, (the epicenter is only around 60 km from Mao county, Fan et al. 2019; Huang and Li 2014); resulting in numerous landslides and widespread loose deposits. The geological condition mentioned above contributes to the high occurrence of geohazards in this area, such as landslides and debris flows.

The slope aspect and gradient maps of Mao County are shown in Figure 1b and Figure 1c, respectively. In this area, the quantity of west-facing (W) and east-facing (E) slopes is less than slopes in other aspects (NW, NE, SE, SW, N, S) and the slopes are mainly distributed with a gradient of 20°~50°.

2.2 Datasets used in this study

The Sentinel-1 series satellites (Poursanidis and Chrysoulakis 2017) are supported and funded by the European Space Agency. Carrying C-band SAR, Sentinel-1 satellites can provide continuous images in different weather conditions. One hundred and four images acquired from the ascending track from January 2017 to June 2020 and 102 from the descending track from January 2017 to June 2020 (Figure 1a, Table 1) were used in this study. Figure 2 shows the baselines of the SAR datasets, in which temporal threshold of 36 days and spatial threshold of 200 m were used to form the interferograms.

To reduce the uncertainties caused by orbital errors, ESA’s precise orbital data was used to correct the orbital information in the data processing. In addition, SRTM DEM (Shuttle Radar Topography Mission) (Farr et al. 2007) was used to eliminate the topographic effects.

3. Methodology

Figure 3 provides a flowchart describing the methodology used in this study. Firstly, the time series displacements over Mao County are acquired by the SBAS-InSAR algorithm, and the results are used to detect the
potential landslides with Google Earth optical images. Through the classification and qualitative analysis, we further obtained a qualitative LOS sensitivity value revealing that the LOS sensitivity is slope aspect and gradient-dependent. According to the parameters of ascending- and descending-track data and the slope and aspect statistics derived from the SRTM DEM, we can determine the LOS sensitivity for dual-orbit data. Finally, we combined the above information with the SAR geometric distortion to obtain the quantitative LOS sensitivity map and interpretation. The core processing is detailed as follows:

SBAS-InSAR (Berardino et al. 2002; Lanari et al. 2004; Mora, Mallorqui, and Broquetas 2003) is a developed time series InSAR algorithm which reduces the temporal and spatial decoherence of traditional differential InSAR. It is an effective tool for

![Figure 1.](image)

**Figure 1.** (a) Location of Mao County and the coverage of datasets; (b) Slope aspect distribution of Mao County; and (c) Slope gradient distribution of Mao County.

**Table 1.** Main parameters of Sentinel-1 data.

| Parameters          | Sentinel-1 (Path 128) | Sentinel-1 (Path 62) |
|---------------------|-----------------------|----------------------|
| Orbital Track       | Ascending             | Descending           |
| Heading Angle (°)   | −12.8                  | −167.2               |
| Incidence Angle (°) | 41.7                   | **42.3**             |
| Resolution (m):     | 5 × 20                 | 5 × 20               |
| Number of Scenes    | 104                    | 102                  |
| Acquisition Dates   | 20,170,107–20,200,620  | 20,170,120–20,200,627|

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detecting and tracking the evolution of surface displacement (Tizzani et al. 2007), making it widely adopted in landslide research. The core of SBAS-InSAR is the use of interferograms with a short baseline to acquire the entire time series displacement of the target and the average displacement rate. The detailed processing steps can refer to (Chaussard et al. 2014; Mora, Mallorqui, and Broquetas 2003; Zhao et al. 2019).

The SARScape software (Sahraoui et al. 2006) is utilized in this study to perform the differential interferometry and SBAS-InSAR time series analysis.

**Figure 2.** Spatial and temporal baselines of SAR datasets. (a) ascending data; (b) descending data.

**Figure 3.** Detailed flowchart concerning the methodology of this study.
A multi-look factor of 10:2 is adopted to improve the overall signal-to-noise ratio in the interferometry. A high-pass temporal filter, combined with a low-pass spatial filter is used to eliminate and mitigate atmospheric pass. ArcGIS, GMT (Generic Mapping Tools), Origin and Surfer software are used during the post-processing and plotting figures.

In terms of the InSAR displacement results, the system only measures displacement along the LOS direction (Wright 2004) and the LOS displacement is not equal to the actual displacement. The relationships between LOS displacement and real slope displacement are qualitatively and quantitatively expressed in this study.

It is assumed that the actual displacement is along the slope surface. The relationship between the real displacement \( V_{\text{slope}} \) and the LOS displacement measured using ascending- and descending-track SAR data \( V_A \) and \( V_D \) from the side view and plan view is revealed in Figure 4. Their relationship can be divided into three situations.

When the slope direction is almost facing south (Figure 4a), and vice versa for north, the LOS displacements measured from the dual-orbit SAR data are almost equal, i.e. \( V_{A1} = V_{D1} \). When the slope is facing east (Figure 4b), the LOS displacement measured from the ascending-track data is greater than that from the descending-track data, i.e. \( V_{A2} > V_{D2} \). As shown in Figure 4c, when the slope is facing west, the LOS displacement measured from the ascending-track data is less than that from the descending-track data, i.e. \( V_{A3} < V_{D3} \).

To quantitatively reveal their relationship, the LOS displacement vector \( \vec{u} \) (Cascini, Fornaro, and Peduto 2010; Greif and Vlcko 2011) (Figure 5) can be defined as:

\[
\vec{u} = \begin{bmatrix} \vec{u}_E \\ \vec{u}_N \\ \vec{u}_Z \end{bmatrix} = \begin{bmatrix} \cos \alpha \sin \theta \\ \sin \alpha \sin \theta \\ -\cos \theta \end{bmatrix}
\]  

(1)

Where \( \alpha \), denotes the angle between the satellite’s azimuth direction and the north (i.e. heading direction, approximately 12° and 168° for Sentinel-1 ascending and descending track, respectively). \( \theta \) denotes the incident angle and |\( \vec{u} \)|=1. \( \vec{V} \) denotes the unit vector of the actual displacement along the slope surface (Cigna, Bianchini, and Casagli 2013; Zhao et al. 2012) which can be expressed as:

\[
\vec{V} = \begin{bmatrix} \vec{V}_E \\ \vec{V}_N \\ \vec{V}_Z \end{bmatrix} = \begin{bmatrix} \sin \alpha \cos \varphi \\ \cos \alpha \cos \varphi \\ -\sin \varphi \end{bmatrix}
\]  

(2)

Where \( \alpha \) denotes the slope aspect angle, \( \varphi \) is slope gradient and |\( \vec{V} \)|=1.

Figure 4. Schematic diagram of changes in the LOS projection component upon aspect changes.
β is the angle between the two unit vectors, which can be derived based on Figure 5 and equation 1–2, and expressed as:

\[
\cos \beta = \frac{\vec{r} \cdot \vec{u}}{|\vec{r}| \cdot |\vec{u}|} = \vec{r} \cdot \vec{u} \\
= \cos \alpha_s \sin \theta \sin \alpha \cos \varphi \\
+ \sin \alpha_s \sin \theta \cos \alpha \cos \varphi \\
+ \cos \theta \sin \varphi 
\]

\[\text{(3)}\]

Hence, the LOS displacements and real displacement can be derived and connected as:

\[V_{\text{LOS}} = V_{\text{slope}} \times \cos \beta \]

\[\text{(4)}\]

The LOS sensitivity (LS) in this study is defined as:

\[LS = \frac{V_{\text{LOS}}}{V_{\text{slope}}} \]

\[\text{(5)}\]

This determines how large the real displacement can be measured for one unit LOS displacement detected, which can be calculated based on Eq. (3) and (4).

4. Results

The annual displacement rate maps in the LOS direction derived from ascending- and descending-track Sentinel-1 data are obtained (Figure 6a-b). The displacement shown in red (negative value) indicates that the ground moved away from the satellite along the LOS direction. In contrast, the blue (positive value) indicates that the ground moved closer to the satellite.

As a result, a total of 21 and 22 active slopes with clear displacements have been identified based on ascending and descending datasets, respectively (Figure 6a-b). The boundaries of these potential landslides were determined by combining InSAR velocity, Google Earth imagery and landslide morphology structure. These potential landslides were named A01-A21 (for ascending) and D01-D22 (for descending). Among them, only two slopes were detected both by the ascending- and descending-track data. Therefore, 41 potential landslides in total were identified in Mao County and its maximum velocity can reach up to 109 mm/year. Several potential landslides have been enlarged in a subgraph in Figure 6 as examples. Field investigations were performed to validate these potential landslides (Figure 7). As a result, clear ground displacements, fissures or gullies were found on most of the slopes, such as A08 (103°43’24.26” E, 31°48’41.53” N, Shuicaoping Village in Feihong Township), A10 (103°42’24.98”E, 31°49’59.76” N, Feihong Township), D10 (103°48’57.98” E, 31°46’21.74” N, Jiaoyanbao Village in Weimen Township). Some of the detected potential landslides are already listed as potential landslides by the government. These sites already have warning signs and/or monitoring systems installed. Examples of such sites are A04 (103°41’24.23” E, 31°44’59.53” N, Ziguan Village in Heihu Town), A05 (103°42’7.81” E, 31°45’24.03” N, Xiaoheba Village in Heihu Town), A15 (103°40’56.86” E, 31°53’21.53” N, Shuanma Village in Shidaguan Township).

The results from dual-orbit data were combined for analysis in Figure 8. Generally, the potential landslides identified from the ascending-track data (red) are mostly distributed on the left bank of the G213 road (i.e. they are east-facing slopes), while the potential landslides identified from the descending-track data (blue) are almost all on west-facing slopes (Figure 8a). As shown in Figure 8b, statistical data on the aspects of these detected slopes were derived. It can be seen that most of the potential landslides detected by the ascending-track data are distributed facing an azimuth angle between 45° and 160° azimuth, i.e. facing northeast and southeast (Figure 8b, red circle). Conversely, the potential landslides detected by the descending-track data are mostly distributed between 220° and 315° azimuth, i.e. southwest and northwest (Figure 8b, second blue circle). This is because the east-facing slopes lie in a good observational position for
ascending imaging (right-look), while the west-facing slopes are almost all located in geometrically distorted positions (in layover, foreshortening areas), and vice versa. This is a reminder of the limitations attached to detecting potential landslides using only ascending-track data or descending-track data. Geometric distortion and slope aspect both affect LOS displacement measurement.

5. Discussion

5.1. The effect of aspect on the displacement results

From the results above, there are obvious differences in the spatial distribution of the potential landslides detected by the ascending- and descending-track data. In terms of displacement rates for the same
slope, the results measured by the ascending- and descending-track data are listed in Table 2. Overall, most of the potential hazards have only one valid result from the single datasets (ascending-track data or descending-track data), e.g. A01~ A03, D04, D06. Some have an approximate displacement rate (e.g. A17, D15) from the ascending/descending datasets, while several have differing displacement rates derived from ascending/descending results (e.g. A10, A11).
Table 2. Details of detection results and classification of hidden hazards from ascending and descending tracks.

| No. of hazards from Ascending | Maximum deformation from Ascending (mm/a) | Maximum deformation from Descending (mm/a) | Classification | No. of hazards from Descending | Maximum deformation from Ascending (mm/a) | Maximum deformation from Descending (mm/a) | Classification |
|-------------------------------|------------------------------------------|-------------------------------------------|----------------|-------------------------------|------------------------------------------|-------------------------------------------|----------------|
| A01                           | −29.7                                    | N/A                                       | I              | D01                           | −37.7                                    | 0.3                                       | I              |
| A02                           | −36.3                                    | N/A                                       | I              | D02                           | −26                                       | −0.3                                       | I              |
| A03                           | −43.1                                    | N/A                                       | I              | D03                           | −43.5                                     | −12.9                                      | I              |
| A04                           | −46.9                                    | −16.1                                     | I              | D04                           | −37                                       | N/A                                       | I              |
| A05                           | −45.8                                    | −23.8                                     | I              | D05                           | −50                                       | 16.1                                       | I              |
| A06                           | −44.6                                    | N/A                                       | I              | D06                           | −36                                       | N/A                                       | I              |
| A07                           | −43.7                                    | N/A                                       | I              | D07                           | −51                                       | 9.1                                        | I              |
| A08                           | −53.4                                    | 10                                        | I              | D08                           | −51.2                                     | N/A                                       | I              |
| A09                           | −48.7                                    | 6.8                                        | I              | D09                           | −34.6                                     | N/A                                       | I              |
| A10                           | −46.4                                    | −15.6                                     | II             | D10                           | −30.4                                     | −19.8                                      | I              |
| A11                           | −36.9                                    | 0.7                                        | II             | D11                           | −58.7                                     | N/A                                       | I              |
| A12                           | −33.4                                    | N/A                                       | I              | D12                           | −26                                       | −15                                       | I              |
| A13                           | −106                                     | N/A                                       | I              | D13                           | −41.9                                     | N/A                                       | I              |
| A14                           | −45.6                                    | N/A                                       | I              | D14                           | −61.7                                     | −3.8                                       | III            |
| A15                           | −60.9                                    | N/A                                       | I              | D15                           | −56.5                                     | −42.8                                      | III            |
| A16                           | −45.0                                    | −59.9                                     | III            | D16                           | −70                                       | −15.3                                      | I              |
| A17                           | −42.8                                    | −56.5                                     | III            | D17                           | −36.4                                     | −25.2                                      | II             |
| A18                           | −48                                      | N/A                                       | I              | D18                           | −52.9                                     | N/A                                       | I              |
| A19                           | −28.5                                    | −11.9                                     | II             | D19                           | −39.2                                     | N/A                                       | I              |
| A20                           | −42                                      | N/A                                       | I              | D20                           | −91.2                                     | N/A                                       | I              |
| A21                           | −32.6                                    | −2.9                                      | II             | D21                           | −28                                       | N/A                                       | I              |

Considering the slope aspect and differences between the displacement rates from the ascending/descending tracks, an in-depth analysis was conducted. It is evident that the same slope displacements are measured differently in the LOS displacement by the ascending- and descending-track data. The potential landslides are divided into the following three categories, as shown in Table 2.

Classification I. Slopes are only observed in a single dataset. These slope types are observed in the ascending-track data but also in the geometric distortion area of the descending data, and vice versa. An example is shown in Figure 9.

Classification II. Slopes with obviously different displacement rate results. These slope types are not located within the geometric distortion in either the ascending-track or descending-track data, while the displacement results are quite different in the two datasets (one result is relatively large while the other is relatively small). An example is shown in Figure 10.

Classification III. Slopes with an approximate displacement rate. These kinds of slopes are not located within the geometric distortion, and the displacement results are relatively approximate, measured from the ascending- and descending-track data. An example is displayed in Figure 11.

Figure 9 shows that the specific details of slope D11 belong to classification I. As shown in Figure 9a, the annual displacement velocity map derived from the ascending-track data is stretched at the geocoding step as the whole area is located within the geometric distortion area for ascending observation (Figure 9c). The mean velocity map derived from the descending data is good and clear, showing that the left area of this potential landslide is unstable with annual displacement rate of 58 mm/year (Figure 9b). It displays good observation geometry for the descending data (Figure 9d). This slope is west-facing, with an average aspect of 296.5°. The SAR geometric distortion would influence the identification results.

Figure 10 shows that the specific details of slope A10 belong to classification I. The Figure 10c and Figure 10d show that this slope lies in neither the geometric distortion region of the ascending track (Figure 10c) nor the descending track (Figure 10d). The mean velocity maps derived from the ascending-track and descending-track data differ. The former shows that the central part of this potential landslide is unstable and its maximum annual deformation rate is 46 mm/year (Figure 10a), while the latter shows this potential landslide as active enough to be identified as a potential landslide (Figure 10b). Under such circumstances, the derived component V_{slope} from the ascending-track data is much larger than that from the descending-track data, i.e. V_A>V_D (situation in methodology Figure 4b). This case indicates that to measure the
Figure 9. (a)-(b) Annual displacement velocity of slope D11 from ascending- and descending-track data, respectively; (c)-(d) Geometric distortion situation for ascending- and descending-track geometry, respectively; (e) Optical image at D11; and (f) Aspect of slope D11.

Figure 10. (a)-(b) Annual displacement velocity of slope A10 from ascending- and descending-track data, respectively; (c)-(d) Geometric distortion situation for ascending- and descending-track geometry, respectively; (e) Optical image at A10; and (f) Aspect of slope A10.
same slope displacement when the slope faces north-to-east (an average aspect of 9.8°), the LOS displacement sensitivity from the ascending-track data is greater than that from the descending-track data.

The case of slope A17(D15) belongs to classification III (Figure 11). The result shows that this potential landslide has suffered severe deformation, shown in the displacement velocity map from both the ascending and descending tracks, and its maximum annual displacements are −42.8 mm/year (Figure 11a) and −56.5 mm/year (Figure 11b), respectively. Simultaneously, A17(D15) is in the geometric distortion area of neither the ascending-track data (Figure 11c) nor the descending-track data (Figure 11d). The aspect of A17(D15) is 179.6° (Figure 11f), where the projection component of ascending-track data $V_A$ is similar to that in descending-track data $V_D$ (situation in methodology Figure 4a). This reveals that, when the slope is facing south, the LOS sensitivity is similar both in the ascending-track data and the descending-track data, and the slope can be well monitored using both datasets.

5.2. Interpretation of LOS direction displacements

From Eq. (3) and the analysis presented in this paper, we summarize the relationship between the LOS displacement sensitivity and the slope displacement in the arbitrary aspect and gradient (shown in Figure 12) by using the incidence angle with 36° and heading angle with 12° in ascending track and 168° in descending track. The LOS displacement sensitivity represents the magnitude that can be measured in the LOS direction when actual displacement with 1 unit of magnitude slides down along the slope, while the positive values (colored green and red) represent the displacement move away from the satellite. Overall, the LOS sensitivity lies between −0.6 and 1, revealing that the actual displacement measured in

![Figure 11. (a)-(b) Annual displacement velocity of slope A17(D15) from ascending- and descending-track data, respectively; (c)-(d) Geometric distortion situation for ascending- and descending-track geometry, respectively; (e) Optical image at A17(D15); and (f) Aspect of slope A17(D15).](image-url)
the LOS direction is not as big as the real displacement along the slope. The negative value indicates that some of the downward displacement is measured as moving closer to the satellite, which is consistent with certain imaging geometry (Dai et al. 2016).

Specifically, in terms of the ascending-track data (Figure 12a) for slopes with the same aspect and arbitrary gradient (e.g. situation ①, with a slope aspect of 78°), the LOS sensitivity for the west-facing slope (the slope aspect between 180°~360°) is generally small. With increased slope gradient, the LOS sensitivity decreases during the early stages and then increases from negative to positive. The overall sensitivity of the east-facing slope (the slope aspect between 0° and 180°) is relatively high and increases as the slope gradient increases, but it then decreases as the slope gradient reaches a certain level (54° for Sentinel-1 data). This finding is consistent with previous studies (i.e. Colesanti and Wasowski 2006; Dai et al. 2016).

For slopes with same gradient and arbitrary aspect (e.g. situation ②, with a slope gradient of 54°), the LOS sensitivity of the east-facing slope is higher than that of the west-facing slope. When the slope gradient is 54° and the slope direction is 78° (the direction of displacement along this slope is parallel to the LOS direction of ascending-track data), the LOS sensitivity reaches the maximum value 1. The situation for the descending-track data is similar, and vice versa (Figure 12b). The sensitivity value for the east-facing slope is generally small, and as the slope gradient increases the sensitivity decreases during the early stages and then increases from negative to positive. The sensitivity of the west-facing slope is relatively high and reaches a maximum value of 1 when the slope gradient and aspect is 54° and 282°, respectively. As the slope gradient continues to increase, the sensitivity gradually decreases.

In practice, SAR geometric distortion influences the LOS displacement measurement, which was not considered in the above analysis. Figure 13 shows a combination of the LOS displacement sensitivity and the geometric distortion in the arbitrary aspect and gradient (example for the Sentinel-1 satellite). For the ascending-track data, the west-facing slope would undergo foreshortening or layover geometric distortions depending on the slope gradient and slope direction. The boundary between these two geometric distortions is the zero value of the LOS sensitivity. Therefore, the positive and negative sensitivity values have their specific meaning in the derived sensitivity map.

Regarding the east-facing slope, there are two situations: suitable for observation (high-resolution) and shadow distortion for ascending track InSAR. For any slope to the east, as the slope gradient increases, the LOS sensitivity firstly continues to increase. After exceeding a threshold, shadowing
occurs making these slopes unobservable. Therefore, determining the LOS sensitivity should not only consider the specific slope gradient and slope aspect, but also the need to combine the geometric distortions of different satellite observations.

Furthermore, regional sensitivity maps covering the entire study area of dual-orbit data are generated (Figure 14), in which the three typical slopes defined in section 5.1 (A10, A17/D15, D11) are enlarged shown and analyzed. A10 is facing north-to-east, with a LOS sensitivity of 0.65 in the ascending track (Figure 14a), bigger than the sensitivity of 0.39 in the descending track (Figure 14b). Thus, the derived LOS displacement of this slope in ascending-track data is larger than it in the descending-track data (Table 2). A17/D15 is facing south with a LOS sensitivity of 0.3 both in the ascending- and descending-track data (Figure 14). This sensitivity is relatively small, but it was detected from both ascending and descending datasets with similar LOS displacement results due to its relatively large displacement (Figure 11). D11 has a LOS sensitivity of 0.9 and ~0.3 in descending- and ascending-track data respectively. Based on the LOS displacement sensitivity map derived in Figure 13, this potential landslide can be clearly detected from descending-track data instead of being monitored in the ascending-track data due to the geometric distortion of foreshortening. All these LOS sensitivity value and interpretation are consistent with the results from Figures 9–11 and Table 2.

The LOS displacement sensitivity map combined with the SAR geometric distortions would have the following potential applications: (i) to interpret and understand the real displacement through the LOS displacement rate results; (ii) to accurately identify north-facing/south-facing potential landslides using this LOS sensitivity conversion (these kinds of slopes were easily ignored as InSAR has low sensitivity in north/south); and (iii) quantitative calculation of the real displacement in subsequent geological engineering analyses. It should be noted that, practically, the LOS displacement and real slope displacement may not be totally equal to the sensitivity value derived in this study in every adjacent pixel. This is likely due to the influence of the filter and the survey adjustment in the SAR processing, which need further study in future work. In spatial calculations and applications over wide areas, the local incidence angle variation also would influence the sensitivity.

6. Conclusion

In this paper, 41 potential landslides were identified throughout Mao County using an SBAS-InSAR algorithm. The maximum displacement rate reached up to approximately 100 mm/year. Of these, 21 and 22 potential landslides were detected using the ascending-track data and descending-track data, respectively. Through statistical analysis of detected slope aspects, it was found that most potential landslides detected using the ascending-track data are eastward facing,
and the landslides detected by the descending-track data are mostly westward facing, indicating that the LOS measurement of InSAR is aspect-dependent.

Through further quantitative analysis, it was found that the average annual LOS displacement rates were different for the same potential landslide depending on whether they were derived from ascending- or descending-track data. The detection results were divided into three classifications, revealing that the measured LOS displacement rates are influenced by slope gradient, slope aspect and geometric distortion. Finally, we derived a LOS sensitivity map encompassing LOS displacement sensitivity, arbitrary slope aspect and gradient, and geometric relationship. This finding is of great significance in terms of acquiring and

Figure 14. (a) The sensitivity of the three examples (A10, A17/D15, D11) in ascending track; (b) The sensitivity of the three examples (A10, A17/D15, D11) in descending track.
understanding the real slope displacement from the LOS displacement in landslide measurement, and in carrying out subsequent quantitative geological engineering analysis supported by InSAR measurements.

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