Detecting precursors of an imminent landslide along the Jinsha River

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Abstract. Landslides are major hazards that may pose serious threats to mountain communities. Even landslides in remote mountains could have non-negligible impacts on populated regions by blocking large rivers and forming dam-breached mega floods. Usually, there are slope deformations before major landslides occur, and detecting precursors such as slope movement before major landslides is important for preventing possible disasters. In this work, we applied multi-temporal optical remote sensing images (Landsat 7 and Sentinel-2) and an image correlation method to detect subpixel slope deformations of a slope near the town of Mindu in the Tibet Autonomous Region. This slope is located on the right bank of the Jinsha River, ~80 km downstream from the famous Baige landslide. We used a DEM-derived aspect to restrain background noise in image correlation results. We found the slope remained stable from November 2015 to November 2018 and moved significantly from November 2018. We used more data to analyse slope movement in 2019 and found retrogressive slope movements with increasingly large deformations near the riverbank. We also analysed spatial–temporal patterns of the slope deformation from October 2018 to February 2020 and found seasonal variations in slope deformations. Only the foot of the slope moved in dry seasons, whereas the entire slope was activated in rainy seasons. Until 24 August 2019, the size of the slope with displacements larger than 3 m was similar to that of the Baige landslide. However, the river width at the foot of this slope is much narrower than the river width at the foot of the Baige landslide. We speculate it may continue to slide down and threaten the Jinsha River. Further modelling works should be carried out to check if the imminent landslide could dam the Jinsha River and measures should be taken to mitigate possible dam breach flood disasters. This work illustrates the potential of using optical remote sensing to monitor slope deformations over remote mountain regions.

1 Introduction

Landslides are major natural hazards in mountain regions and cause widespread disasters every year around the globe (Petley, 2012; Zhang et al., 2020). Major landslides in remote mountain regions may pose serious threats to downstream communities by choking channels, which increases the risks of landslide-dammed-lake outburst floods (Fan et al., 2020; Liu et al., 2019). For example, a hillslope near the Baige village had two landslides, damming the Jinsha River twice in 2018. The outburst floods caused widespread damage along its route and affected areas as far as Yunnan Province, >500 km from the landslides (Fan et al., 2019). In 2000, a super-large landslide dammed the Yigong River in Tibet, and 2 months later the outburst flood caused widespread damage, including to five main bridges, to highways and to communication cables in downstream areas (Shang et al., 2003). The
is controlled by a monsoon climate with > 90 % of the rain occurring from May to October.

This area is tectonically active, and active faults run through this slope from north to south. To the west of the faults are upper Palaeozoic strata and to the east are Mesoproterozoic metamorphic rocks. Cracks and fissures on the slope are visible from a 15 m resolution pan-sharpened false-colour Landsat 7 image acquired in 2001 (Fig. 1b). These cracks and fissures may be relics of historic earthquakes or precipitation. This part of the slope has a percent slope of 45 % and a southeast aspect, with an azimuth between 112.5 and 157.5° (Fig. 1c). The slope is mainly covered by grass and sparse shrubs and less affected by anthropogenic activities. Field reconnaissance has not been carried out for this slope due to outbreak of the COVID-19 pandemic. Instead, we examined the slope via Google Earth images. Fissure cracks are clearly visible on the uppermost part of the slope, and there are widespread cracks on the lower part of the slope. Evidenced by very high spatial resolution Google Earth images, the landslide in this work is a translational type (Highland and Bobrowsky, 2013).

In this work, we mainly relied on Sentinel-2 optical images to derive slope movement. The European Space Agency’s Sentinel-2 mission has two twin satellites in orbit, with a revisit time of less than 5 d. The Sentinel-2 optical imagery has 12 optical bands with wavelengths ranging from 440 to 2200 nm (Gascon et al., 2017). There are 4 bands with a spatial resolution of 10 m: blue, green, red and near-infrared bands. To derive slope movement, we used the red band because its wavelength is longer than those of other visible bands and is less influenced by the atmosphere. Compared to the near infrared, this band is less sensitive to vegetation and is more reliable for measuring slope deformation (Yang et al., 2019). We used the Level-1C product, which is orthorectified before distribution (Gascon et al., 2017).

2 Methods

2.1 Study area

The reported slope is ~80 km downstream from the Baige landslide (Fan et al., 2019) along the Jinsha River near the town of Mindu, Tibet Autonomous Region, bordering Sichuan Province (Fig. 1a). The slope is located on the right bank of the Jinsha River. Similar to the Baige landslide, the geomorphology of this section of the Jinsha River is at the bottom of a V-shaped valley. The elevation of the study area ranges from 2660 m at the valley bottom to > 4500 m on the mountain ridge. This rough topography indicates strong fluvial incision against the rapid uplift of the Tibetan Plateau. We estimated the mean annual precipitation (MAP) by using the GPM v6 monthly precipitation (from 2001 to 2019) and found the MAP of this area to be ~665 mm. The region

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Figure 1. Topographic maps of the study area. (a) Geographic locations of the Baige landslide and the downstream landslide around the town of Mindu, Tibet Autonomous Region. (b) A 15 m resolution pan-sharpened Landsat 7 false-colour image on 18 February 2001 and (c) aspect of the study area around the Mindu landslide. The elevation data in (a) are a product of NASA’s Shuttle Radar Topography Mission (SRTM), and the aspect in (c) is a derivative of the DEM. The red polygons in (b) and (c) are the selected stable zone. Both the SRTM DEM in (a) and its derivative (c) were downloaded from the Geospatial Data Cloud website (http://www.gscloud.cn/sources, last access: 22 November 2020). The Landsat image in (b) is a joint product of the United States Geological Survey and NASA and was downloaded via the Google Earth Engine (GEE).

Table 1. List of the 19 base images in early 2018 and 9 targeted images in 2019. Base images were used to detect cumulative slope displacements in targeted images. Image pairs used in this step are no. 3–no. 97.

| 19 base images in the stable period (in early 2018) | 5 target images in the moving period (in 2019) |
|--------------------------------------------------|------------------------------------------------|
| January: 11, 13, 16, 23, 28                       | 13 Apr, 17 Jul, 24 Aug, 5 Oct, 12 Nov           |
| February: 5, 12, 17, 25                           |                                                |
| March: 4, 9, 14, 19, 29                           |                                                |
| April: 3, 16, 23                                  |                                                |
| May: 21                                           |                                                |
| June: 5                                           |                                                |

9 images to derive displacements for every 2 adjacent images (image pair no. 98–no. 105).

2.2.1 Deriving slope displacements

In the first step, we used three Sentinel-2 images (on 13 November 2015, 12 November 2018 and 12 November 2019) to compose two image pairs (no. 1 and no. 2). The first image pair (no. 1) is composed of a Sentinel-2 image on 13 November 2015 and a Sentinel-2 image on 12 November 2018. Sentinel-2 images of the second pair (no. 2) were acquired on 12 November 2018 and on 12 November 2019.

By using the first two image pairs, we found the slope was stable from 13 November 2015 to 12 November 2018 and moved significantly from 12 November 2018 to 12 November 2019. Therefore, in the second step, we used two image groups, a base image group in the stable period and a target image group in the moving period.

Figure 2. Detected slope displacements in image pair no. 1 (a) and no. 2. (b). Background Sentinel-2 images were acquired on 13 November 2015 and 12 November 2018, respectively. Both images were produced by ESA’s Sentinel-2 satellites and downloaded via the GEE.

Table 2. Eight periods (image pair no. 98–no. 105) were used to derive the Mindu slope movement.

| Image pairs | Base image   | Target image |
|-------------|--------------|--------------|
| No. 98      | 28 Oct 2018  | 24 Nov 2018  |
| No. 99      | 24 Nov 2018  | 23 Jan 2019  |
| No. 100     | 23 Jan 2019  | 14 Mar 2019  |
| No. 101     | 14 Mar 2019  | 18 May 2019  |
| No. 102     | 18 May 2019  | 17 Jul 2019  |
| No. 103     | 17 Jul 2019  | 28 Sep 2019  |
| No. 104     | 28 Sep 2019  | 29 Nov 2019  |
| No. 105     | 29 Nov 2019  | 7 Feb 2020   |
image group in the moving period, to detect cumulative slope displacements (Table 1). For the base image group, there are 19 clear images without clouds in 2018. For the target image group, we selected 5 images in 2019 (13 April, 17 July, 24 August, 5 October and 12 November) to detect cumulative displacements. In all, there are \(19 \times 5\) image pairs (no. 3–no. 97) calculated in the second step. In the third step, we used 9 images from 28 September 2018 to 7 February 2020 (Table 2) to form another 8 image pairs (no. 98–no. 105) to derive slope displacements.

### 2.2.2 Error assessment and postprocessing

Misalignments between images can be estimated by selecting a stable zone (Bontemps et al., 2018; Lacroix et al., 2018; Yang et al., 2019). In this work, the stable zone was selected on the upper part of the landslide (red rectangles in Fig. 1b and c). Mean displacements estimated within the stable zone were used to correct image shifts. SDs of the displacements within the stable zone represent uncertainties, indicating the quality of the derived results for a given image pair. We selected this area because this stable zone is on the same slope as the landslide, which can minimize the influence of illumination and orthorectification errors.

In this work, we cross-validated measured slope displacements for 5 target images in 2019 identified in the second step. Uncertainties in the slope displacements for a given target image were estimated from all 19 base images in the stable periods. Standard deviations of these 19 measurements were used to indicate their reliability. We further filtered out displacements with moving directions that did not agree with the SRTM DEM-derived aspects. If there are 15° deviations between the derived slope movement and the aspect, the derived slope movement is defined as invalid and is not used for further analysis.

### 3 Results

#### 3.1 Detected stable and unstable periods

In Table 3, the EW mean and NS mean indicate the east–west (EW) and north–south (NS) shifts in images in both image pairs calculated from the stable zone. The EW SD and NS SD are SDs of displacements in the stable zone to indicate image distortions. Low EW SD and NS SD values indicate good performances during image orthorectifications. The derived EW mean and NS mean were used to correct misalignments in image pairs. The base and target images for image pair no. 1 are from 13 November 2015 and 12 November 2018, respectively. The base and target images for image pair no. 2 are from 12 November 2018 and 12 November 2019, respectively. The slope remains stable in the first image pair, whereas detectable slope displacements can be found in the second image pair (Fig. 2). The durations of image pair no. 1 and pair no. 2 span 3 years and 1 year, respectively. In Fig. 2a, we can see that the slope displacement from 2015 to 2018 was less than 2 m, whereas there was > 6 m slope displacement from 2018 to 2019 (Fig. 2b). In image pair no. 2, larger displacements were observed near the Jinsha River and smaller displacements were farther away from the river. This increasing displacement magnitude indicates the slope may start to move from its toe.

#### 3.2 Cumulative slope displacements in 2019

As in Fig. 2, we can see that this slope remained stable from November 2015 to November 2018 and moved after November 2018. To derive time series of the Mindu slope displacements after November 2018, we used 19 base images in the stable period and 5 target images in 2019. All 19 base images are from early 2018, during which the slope was stable. Five selected target images were acquired on 13 April 2019, 17 July 2019, 24 August 2019, 5 October 2019 and 12 November 2019. For each target image in 2019, we calculated slope movement by using all base images. Therefore, there are 19 estimated slope displacements for each target image. We calculated the means and SDs of slope displacements for all target images (Fig. 3).

From Fig. 3, we can see that the mean displacements are a magnitude larger than the SDs, which indicates that the displacements derived between each target image and their base images agree with each other quite well. Minor slope displacements were detected until April 2019 (maximum 3–4 m), whereas larger slope displacements can be observed in the later four target images (> 5 m). All displacements in the five target images show a similar pattern to results in image
Figure 3. Means and standard deviations of the derived slope displacements in the five targeted images (Table 1). Detected means and SDs of slope displacement on 13 April 2019 (a1–a2), 17 July 2019 (b1–b2), 24 August 2019 (c1–c2), 5 October 2019 (d1–d2) and 12 November 2019 (e1–e2).

We further selected six points on the slope to analyse time series of the slope displacements in 2019 (Fig. 4). For most target images for the first five points (p1–p5), most base images could derive > 10 valid displacements (2-D columns). For all six points, accumulated displacements show similar growing trends from April 2019 to November 2019. Maximum displacements for all six points occurred on 24 August 2019. These unreasonably large values may be caused by a difference in solar elevation and zenith angles in target images. For example, compared to the August image there are more mountain shadows in the November images in the Northern Hemisphere. Despite abnormal displacements in August 2019, we can see that displacements from July to November 2019 are still larger than displacements in April 2019. Therefore, from the time series of these six points, we can see that major slope displacements occurred from April to August 2019.

3.3 Slope displacements in eight selected periods after November 2018

To analyse spatial deformation patterns in different periods, we selected nine Sentinel-2 images forming eight image pairs (image pair no. 98–no. 105 in Table 2, corresponding to eight periods in ~2 months). The first two image pairs (Fig. 5a and b, no. 98 and no. 99) show that the middle and lower parts of the slope deformed significantly and 4–6 m of displacement occurred at multiple locations. The study area has a monsoonal climate with most precipitation occurring from May to September (Fig. 6). There are seasonal differences in the deformation of this landslide. In the dry seasons of winter and spring, deformation occurs at the foot of the slope near the Jinsha River and the deformation rate is generally less than 1 m per month (from January to May, Fig. 5c and d and periods 3–4 in Fig. 6, image pairs no. 100–no. 101). In the rainy seasons of summer and autumn, deformation affects the entire slope with some parts at a rate of more than 3 m per month (from May to September, Fig. 5e and f and periods 5–6 in Fig. 6, image pair no. 102–no. 103).

4 Discussion

4.1 Possible impacts of this imminent landslide

Major landslides in mountains may dam river channels forming transient lakes, the breach of which can result in catastrophic floods affecting downstream communities (Dai et al., 2005; Fan et al., 2019; Liu et al., 2019). In this work, we examined a hillslope near the town of Mindu along the Jinsha River. We found the slope had significant movement from November 2018 to November 2019. Despite the area of the detected moving slope (715 757 m$^2$ for displacements larger than 3 m) being similar to the area of the Baige landslide.
(830,624 m²), the width of the Jinsha River channel below the Mindu slope (~ 50) is half that of the Baige (> 100 m, in Fig. 7). Considering the similar morphology of both river sections, the collapse of the Mindu slope could pose a threat to downstream communities by blocking the Jinsha River. We call for further frequent monitoring of the hillslope in combination with other tools, such as InSAR (Intrieri et al., 2018; Samsonov et al., 2020).

### 4.2 Comparison of image matching and InSAR methods

In this work, we used the COSI-Corr method to derive slope displacements for the Mindu slope along the Jinsha River. The principle of this method is to use a sliding window to find pattern matches to derive displacements in image pairs (Leprince et al., 2007). Compared to the InSAR methods, this method is easier to understand and implement. In addition, image correlation methods favour larger displacements than InSAR methods. Limited by the wavelength of the SAR image, InSAR methods are versed in monitoring ground deformations on a millimetre to centimetre scale (Intrieri et al., 2018), whereas the capability of image correlation methods depends on spatial resolution of images. In general, image correlation methods are more reliable for deriving large ground displacements on a metre scale (Bradley et al., 2019; Lacroix et al., 2020). In this work, it might be quite challenging for InSAR methods to detect such large displacements. Long temporal intervals of a few months could lead to incoherence in SAR images (Li et al., 2019), whereas images (taken in the same season) with long temporal intervals of a few years can be used to derive reliable displacements given a stable land cover (Yang, 2020). Both methods can be affected by the atmosphere. Clear optical images without clouds should be used in image correlation methods.

Although SAR images can penetrate thin clouds, the atmosphere could cause phase delay and lead to uncertainties in derived results (Li et al., 2019).

Both methods work well on bare land without vegetation, though dense vegetation could seriously affect InSAR methods (Intrieri et al., 2018). On the contrary, image correlation methods are less affected by vegetation cover as long as images in the pair are from the same season (Yang, 2020). As image correlation methods use pattern matches within an image pair, we speculate that vegetation density may not be a major challenge for the method. The Sentinel-2 images used in this work have four 10 m resolution optical bands (Gascon et al., 2017). In theory, any of these four bands may be used to derive slope displacements. But, an ideal band should not be sensitive to ground cover change unrelated to ground displacements, which could minimize background noise. In general, optical bands with shorter wavelengths are more prone to be affected by moisture in the atmosphere. Considering that the near-infrared band is very sensitive to vegetation, we used the red band in this work.

Both InSAR and image correlation methods can be impacted by complex terrains in mountain regions. Layover and shadow areas in SAR images should not be used in InSAR methods (Li et al., 2019). Similarly, shadows in optical images also influence derived results (Yang et al., 2020). To derive reliable results, optical images acquired during larger solar angles should be prioritized to minimize the influence of mountain shadows. Fortunately, there are algorithms that have been developed to restore information in mountain shadows in optical images (Shahtahmassebi et al., 2013), which may promote the efficacy of optical image correlation methods.
4.3 Measures taken to reduce uncertainties

Many other factors may also influence the accuracy of slope deformation from image correlation methods, which include image orthorectification errors, different viewing angles during image acquisition and different illuminations in images (Stumpf et al., 2016; Yang et al., 2020). This work used the Sentinel-2 Level-1C product, which is orthorectified before distribution (Gascon et al., 2017). To correct for possible misregistration between the base and target images, we used a stable zone to calculate and correct image shifts. To reduce errors caused by different illuminations, all images used for the first two Sentinel-2 image pairs are from similar dates of different years.

The first two image pairs (no. 1 and no. 2) we mentioned above are composed of images of very similar acquisition dates in different years. Images of similar dates have similar zenith and elevation angles, which could minimize the influence of mountain shadows (Yang et al., 2020). To assess and reduce uncertainties in the second step, we first identified a stable period. Then, we used 19 base images in this stable period to derive cumulative displacements for a given target image in the moving period. The mean displacements from these 19 image pairs are expected to be more reliable than results from a single image pair. In addition, these 19 measurements can cross-validate each other and be used to estimate uncertainties by SD (Figs. 3 and 4).

There are a few strategies to suppress background noise in derived results, including selecting results with high signal-to-noise ratios (Lacroix et al., 2018; Yang et al., 2020) and integrating redundant information in time series of images (Bontemps et al., 2018). This work introduced a simple and efficient method by using the slope aspect to filter out slope movement that is different from the aspect. This is reasonable for this translational landslide as the mass moves downhill driven by gravity. This procedure could eliminate false slope movements and reserve true slope movement of the Mindu landslide. By integrating topographic information, this new procedure is expected to work well for ground movement in other regions that is consistent with slope configurations.

4.4 Potential applications of the method in landslide monitoring

As we used orthorectified images, slope displacements derived in this work are horizontal movements. To derive ground movement along the slope, we need to consider local slope configurations. Because image correlation methods use sliding windows to detect similar patterns between the base and target images, precursors with horizontal rather than vertical ground movements can be detected. Landslides that have intact moving surfaces can be detectable by image correlation methods. For translational and rotational landslides, there are more horizontal than vertical ground movements, the former of which constitute the ideal landslide type to use in image correlation methods, whereas precursors of avalanches and rockfalls may be difficult to detect due to limited horizontal ground movement (Highland and Bobrowsky, 2013).

In addition, the smallest displacements that can be detected depend on the spatial resolution of optical images (Li et al., 2020; Stumpf et al., 2016). Although image correlation methods can detect subpixel ground movement, it is very challenging to detect moving surfaces that cover an area...
of a few pixels, as smaller window sizes could result in more background noise (Yang et al., 2020).

5 Conclusions

In this work, by using the COSI-Corr method and multi-temporal Sentinel-2 images, we found precursors of a major landslide along the Jinsha River in southwest China. Fissures on the slope probably existed before 2001, but the slope remained stable between November 2015 and November 2018. From November 2018 to August 2019, we detected significant slope displacements. The size of the activated part on the Mindu slope is similar to that of the 2018 Baige landslide, whereas the river width under the Mindu slope is half that of the Baige section. If this landslide continues to slide down and fails completely, it may block the Jinsha River leading to similar consequences to the Baige landslide.

By using an image correlation technique, we can track subpixel slope movement in optical remote sensing images. We also adopted an aspect constraint to pick out downslope movement and significantly reduced background noise. However, optical images, such as the Sentinel-2 images, can only detect slope movements of up to a few metres. To continuously monitor this slope, other data and methods (such as higher-spatial-resolution data or InSAR techniques) should be used. We also call for intensive monitoring of this slope and modelling of landslides that cause river blocking and subsequent flooding.

Data availability. All Sentinel-2 images and the Landsat 8 image in this work were downloaded from the GEE. The SRTM DEM and its derivative were downloaded from the Geospatial Data Cloud website (http://www.gscloud.cn/sources, Computer Network Information Center and Chinese Academy of Sciences, 2020).

Author contributions. LL and PS discovered the moving slope of this work. WY conducted analysis and drafted the manuscript.

Competing interests. The authors declare that they have no conflict of interest.

Figure 6. Daily precipitation of the Baiyu meteorology station from October 2018 to February 2020.

Figure 7. High-spatial-resolution images from © Google Earth. The image to the left was acquired on 30 March 2015 for the Mindu slope (a), and the right image was acquired on 18 July 2017 for the Baige slope (b).
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