The monitoring of a large ancient landslide in Sichuan Province, China, using interferometric synthetic aperture radar technology and sensitivity analysis in potential landslide mass modeling

Siyuan Ma, Chong Xu

1. Key Laboratory of Seismic and Volcanic Hazards, Institute of Geology, China Earthquake Administration, Beijing, 100029, China
2. National Institute of Natural Hazards, Ministry of Emergency Management of China, Beijing 100085, China
3. Key Laboratory of Compound and Chained Natural Hazards Dynamics, Ministry of Emergency Management, Beijing 100085, China
*Corresponding to Chong Xu (chongxu@ninhm.ac.cn); ORCID: https://orcid.org/0000-0002-3956-4925

Abstract. Using interferometric synthetic aperture radar (InSAR) technology and C-band Sentinel-1A data, this work examined the surface displacement of a large ancient landslide at Xuecheng town in Lixian County, Sichuan Province, China. Based on the MassMov2D model, the dynamic process and deposit thickness of the potentially unstable rock mass (deformation rate $< -70$ mm/yr) on this landslide body was numerically simulated. Combined with unmanned aerial vehicle data, the driving factors of this ancient landslide were analyzed. The InSAR results showed that the deformation rate in the middle part of the landslide body was the largest at $-55$ to $-80$ mm/yr on average, while that of the upper part and the toe area was small at $-5$ to $-20$ mm/yr. The simulation predicted that the unstable rock mass may collapse and form a barrier dam with a maximum thickness of approximately 16 m at Zagunao River in the future.

1. Introduction

A large ancient landslide is present at Xuecheng town in Lixian County, Sichuan Province, China (103.3206° E, 31.5673° N; hereafter referred to as the “XC” landslide). The landslide is located on the left bank of the Zagunao River. Documented evidence shows that this ancient landslide has experienced two slides, the first having been the main collapsed area of the landslide, which is assumed to have been formed by a historical earthquake; the second occurred on the ancient landslide mass. Due to the impact of river erosion, small-scale collapses have occurred on the front edges of the landslide. The factors that control the landslide and its potential instability remain unclear, and there are significant concerns as to whether it could be reactivated and the geological hazards involved in such an event. Understanding the development of these ancient landslides will thus be beneficial to engineering construction in this area [1-2].

The current study investigated the XC landslide using an unmanned aerial vehicle (UAV) and interferometric synthetic aperture radar (InSAR) technology. Based on small baseline subset (SBAS)-InSAR methods, the deformation rate of this ancient landslide was measured by C-band Sentinel-1A data, and two time-series results were compared. To derive the InSAR results, we used the MassMov2D model to simulate the possible motion process and accumulation characteristics of unstable rock on the body of the old landslide. Finally, the driving factors and hazard predictions related to the landslide’s instability were discussed. The results of this study assist in providing a better understanding of the relationship between the deformation and potential triggering factors related to the landslide. Furthermore, it also presents guiding significance for the assessment of the reactivation of other established landslides in the eastern margin of the Tibetan plateau.
2. Study area

Lixian County is located in the northwest of Sichuan Province, 200 km from Chengdu (Fig. 1a). Influenced by significant elevation differences, the study area has obvious monsoonal-mountain climate characteristics. (Fig. 1b). The slopes on both sides of the Zagunao River are steep with sparse vegetation and serious river and soil erosion. Mountain hazards, such as debris flows and landslides, occur frequently on both sides [1]. Particularly following the 2008 Wenchuan earthquake (7.9 Mw), many old landslide deposits and unstable slopes have undergone significant continuous deformation [2]. The lithology of the study area mainly includes Carboniferous and Permian basalt and conglomeratic limestone, Devonian Carbonaceous phyllite or phyllite with quartzite from the Weiguan formation (Dwg1, Dwg2), Silurian gray phyllite with limestone from the Maoqun formation (Smx4 and Smx5), and Upper Triassic feldspathic quartz sandstone from the Zhunwei formation (T3zh) (see Fig. 1).

The XC landslide is located on the left bank of the Zagunao River, where the valley is deep and narrow and exhibits a “V” shape. The landslide presents as a “U” shape in which most of the material had been displaced from the upper part and deposited to the lower part of the landslide (Fig. 2). Based on its topographical features, it is a typical large-scale ancient landslide with an area of approximately 1.4 km²; it is approximately 1,900 m long and 850 m wide. The main sliding direction is 130°. The main scarp has an armchair-like shape with a height of approximately 260 m. The elevations of the main scarp and the toe are 2,750 and 1,500 m, respectively, with an elevation difference of approximately 1,250 m. The slope angle averages 35° and reaches 50° ~ 60° in some places.

![Fig.1. The geological setting of the study area: (a) the tectonic setting and historical earthquakes in the area of Lixian County; (b) elevation, rivers, and faults within the study area; (c) the lithology distribution near the XC landslide (denoted by the yellow star).]
2.1 Multi-temporal-InSAR process

The SAR data used in this study was taken from Sentinel-1 satellites and acquired using the interferometric wide swath mode. The pixel resolution of the images is approximately 3.5 m in the range direction and 14 m in the azimuth direction; 63 ascending scenes from April 2018 to April 2020 were acquired and processed with an incidence angle of 39.45°. In addition, an Advanced Land Observing Satellite (ALOS) phased array L-band synthetic aperture radar digital elevation model (DEM) of 12.5 m resolution (https://search.asf.alaska.edu/) was used as the reference elevation dataset for removing the topographic phase and geocoding the InSAR results.

The SBAS technique is a different time-series method based on multi-master images proposed by Berardino et al. (2002) [3]. This method overcomes the drawbacks of the poor coherence of some interferograms caused as a result of using one master image. Additionally, only interferograms with small baselines are selected for the time-series analysis, which makes the deformation results denser and more reliable. In this study, the maximum normal baseline and temporal baseline were set to 2% and 60 days, respectively, and interferogram pairs were generated accordingly (Fig. 3). Disconnected blocks in the SAR images were used to construct the Sentinel-1 time series, which was necessary due to several images having been discarded because of the low coherence of the interferograms they generated [4]. The phase-unwrapping was conducted using Delaunay minimum cost flow [5] and the Goldstein filter was applied for interferometric filtering [6]. The ALOS PLASAR DEM with a 12.5 m resolution was used to remove the topographic phase and for geocoding the SAR results.
2.2 The MassMov2D model
The MassMov2D is a numerical model that allows users to simulate the expansion (runout) and deposition of mass movements over a complex topography by approximating the sliding mass to a homogeneous one-phase fluid [7]. The code is freely available and is implemented in the Geographic Resources Analysis Support System’s geographic information system. The input data includes the sliding surface topography (topographic data without the sliding body) and the initial sliding mass thickness. Other input parameters that characterize the mass material are the turbulent coefficient (m/s^2), the internal friction angle of the sliding mass (degree), and the fluid rate (m/s) [8,9]. The turbulent term summarizes all velocity-dependent factors of the flow resistance, as well as the density of the debris. The fluid rate defines the transaction velocity of the sliding mass when it passes from a solid to a fluid state. Among these values, the turbulent and internal friction coefficients had the opposite effect on the model output, whereas the variation of fluid rate had little influence on the simulation results [9].

3. Results
3.1 The InSAR time series analysis
Figure 4 shows the temporal evolution of the line-of-sight (LOS) displacement for different points throughout the observation period. Based on the InSAR results and the UAV data, the area of deformation rate (<−10 mm/yr) was delineated as the presumed landslide boundary. The yellow color (negative value) indicates motion away from the satellite in the LOS (black solid arrow), and the blue color (positive value) indicates motion toward the satellite. The deformation rate in the middle part of the slope is the largest with an average of −55 ~ −80 mm/yr, while that of the upper part and toe area of the slope is relatively small and ranges from −5 ~ −20 mm/yr. The displacement of point 1 (Figure 4) outside the presumed landslide area is almost 0. Point 6 shows the largest cumulative displacement at −136 mm. However, point 2 (the upper part of the slope) and points 3, 4, and 5 (the toe area) show roughly the same displacement ranging between −50 and −70 mm.
3.2 Prediction of the potentially unstable rock mass

Combined with the UAV images, we selected the above-noted potential unstable rock mass (motion rate $\leq -70$ mm/yr) to simulate the kinematic and accumulation characteristics of the landslide. The area of this rock mass is 46,000 m$^2$ (Fig. 11a). Based on the “volume-area” power law (Xu et al., 2016), the volume was estimated as being 550,000 m$^3$ with an average thickness of approximately 12 m. To derive the material properties and the movement characteristics, we conducted a sensitivity analysis [9-12]. Table 1 shows the ranges of the input parameters.

| Parameter                        | Value  |
|----------------------------------|--------|
| Chezy (Turbulent) coefficient (m/s$^2$) | 200, 400, 600, 800, 1000 |
| Internal friction angle (°)      | 25     |
| Fluid rate (m/s)                 | 5, 10, 15, 20 |

The sensitivity analysis was performed for different simulations sets, and in each set, a single parameter was varied while others adopted the fixed value of the defined variation range. The settings for the defined variation range of the rheological parameters were estimated by previous studies. The simulation aimed to predict the potential landslide mass. We were unable to conduct the sensitivity analysis to assess the variability of our results, based on the actual deposit thickness; as such, we only observed the changes that these values caused related to the deposit depth, sliding velocity, and impacted area. Table 1 shows the ranges of input parameters, while Figs. 5, 6, 7, and 8 show the simulation results in different Chezy coefficients (the fluid rate is 10 m/s). Figure 9 shows the simulation results for different fluid rates (the Chezy coefficient is 200 m/s$^2$), while Fig. 5 illustrates the collapse body thickness for different Chezy coefficients, which indicates that the depositing characteristics including morphological characteristics and thickness distribution are essentially consistent. Figure 6 presents the cross-section of the depositing thickness in the accumulation area; the figure illustrates how the deposit thickness in this area gradually decreases from the center to both sides. Figure 7 shows the variation in maximum sliding velocity and indicates that this velocity increased with a rise in the Chezy coefficients. Overall,
the Chezy coefficients influenced the sliding velocity of the unstable rock mass; the predicted landslide boundaries and depositing characteristics of the landslide were similar (Fig. 8).

In addition, we also compared the simulation results under different fluid rates (using a Chezy coefficient of 200 m/s²). Figure 9 shows the maximum velocity and deposit thickness under different fluid rates, respectively. These results indicated that with the increase in fluid rate, the maximum velocity gradually increased from 33.7 to 36.0 m/s, while the maximum thickness of the accumulation area slightly decreased. Overall, this parameter had a modest effect on the accumulation distribution and movement characteristics when the value of the fluid rate was within a reasonable range.

Fig. 5. Distribution of the collapsed body thickness based on different Chezy coefficients: (a) 400 m/s²; (b) 600 m/s²; (c) 800 m/s²; (d) 1,000 m/s².
Fig. 6. The deposit thickness along a longitudinal profile (A-A’) for different Chezy coefficients: (a) 400 m/s²; (b) 600 m/s²; (c) 800 m/s²; (d) 1,000 m/s².

Fig. 7. The maximum sliding velocity of different Chezy coefficients: (a) 400 m/s²; (b) 600 m/s²; (c) 800 m/s²; (d) 1,000 m/s².

Fig. 8. The simulated sliding velocity of the unstable rock mass with Chezy coefficients and a fluid rate of 800 m/s² and 10 m/s: (a) t = 10 s; (b) t = 30 s; (c) t = 40 s; (d) t = 60 s; (e) t = 80 s; (f) t = 100 s.

Figure 9 shows the simulated velocity of the potentially unstable rock mass. The entire sliding process lasted approximately 100 s. At 10 s, the material in the source area began to slide in a downward
direction from the shear outlet. At 30 s, the mass rushed downstream at a high velocity of more than 30 m/s. At 40 s, a small number of materials began reaching the foot of the slope, and the remaining materials extended downward at a high speed. At 60 s, the landslide materials gradually accumulated on the riverbed, and the sliding velocity decreased rapidly. At 80 s, most of the mass had been deposited at the foot of the slope, blocking the river channel and forming a barrier dam. Only a small amount of material remained on the slope’s surface. At 100 s, the accumulation process ended.

Fig. 9. The simulated sliding velocity of the unstable rock mass at (a) t = 10 s; (b) t = 30 s; (c) t = 40 s; (d) t = 60 s; (e) t = 80 s; (f) t = 100 s.

4. Conclusion

The InSAR results of the present study showed that the two applied techniques were able to provide useful information about the landslide, while SBAS produced a smoother and more abundant displacement time series. The entire landslide body has shown obvious displacement since September 2018. The deformation in the middle of the slope is the most obvious, with an average LOS deformation rate of −70 mm/yr and cumulative displacement of approximately −120 mm. The sensitivity analysis was performed using different simulation sets and in each set, a single parameter was varied while others retained the fixed values of the defined variation range. The rheological parameter settings were estimated in previous studies. Based on the simulation results, the Chezy coefficients and fluid rate influenced the model output including the sliding velocity and movement process of the unstable rock mass; however, the predicted landslide boundaries and deposit characteristics of the landslide were similar. Compared with the Chezy efficiency, the fluid rate had less of an effect on the accumulation distribution and movement characteristics. Overall, in terms of the Chezy coefficients and fluid rates, the reasonable parameters based on previous studies could guarantee the accuracy of the simulation results. Our results indicated the application of Sentinel-1 images and InSAR techniques to landslide monitoring as an effective and low-cost method. The combination of using UAV and InSAR techniques can be beneficial for the investigation of inaccessible landslide areas. In future research, more monitoring information from different sources, such as Global Navigation Satellite System data, can be
added as supplementary data to InSAR results to verify the long-term deformation characteristics of ancient landslides.

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