Time to enter the era of Earth-Observation based landslide warning system

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Abstract. Landslide early warning remains a grand challenge due to the high human cost of catastrophic landslides globally and the difficulty of identifying a diverse range of landslide triggering factors. There have been only a very limited number of success stories to date. However, recent advances in earth observation (EO) from ground, aircraft and space have dramatically improved our ability to detect and monitor active

landslides and a growing body of geotechnical theory suggests that pre-failure behavior can provide clues to the location and timing of impending catastrophic failures. In this paper, we use two recent landslides in China as case studies, to demonstrate that (i) satellite radar observations can be used to detect deformation precursors to catastrophic landslide occurrence, and (ii) early warning can be achieved with real-time in-situ observations. A novel and exciting framework is then proposed to employ EO technologies to build an operational landslide early warning system.

INTRODUCTION

Landslides (where soil or rock moves down a slope) have been shaping mountainous regions for millennia, but today they pose a destructive hazard to people and infrastructure resulting in hundreds of deaths and billions of dollars of damage every year [1]. The combination of a rapidly increasing global population and intensifying weather extremes associated with recent climate change suggests that landslide risk will dramatically increase over the next decade. Landslide deformation can be extremely slow (few mm per year) or involve sudden extremely rapid failure [2], and thus their hazards include both enduring damage to manmade structures and catastrophic destructive events. While small landslides make up the vast majority of landslide 'events' in any given year, it is large landslides that tend to be responsible for most of the damage and loss of life [3]. Current landslide risk mitigation strategies tend to reduce exposure - the likelihood that someone or something is impacted by a landslide - primarily by moving to, or locating infrastructure in, less hazardous locations; but for many people and assets relocation is not feasible. In these situations, short-term evacuation is often the most attractive or only option. Therefore, improved landslide forecasting and the development of early warning capabilities are expected to play crucial roles in managing landslide risk for many individuals and communities.

The major landslide triggering factors (e.g., rainfall and seismic shaking) and the basic physics governing landslide initiation are well known. Yet predicting where and when landslides will occur remains a grand challenge primarily due to the difficulty in forecasting the triggering factors themselves, and the spatial variations in earth materials and slope conditions. Existing forecasting methods generally involve functional relationships between trigger-factor intensity (e.g. precipitation history and peak seismic ground acceleration) and landslide probability. However, the connection between triggers and landslides is complex, with some landslides occurring in the absence of an identifiable trigger and others occurring with significant delay. For example, the 2006 Leyte landslide that killed over 1100 people in the Philippines, occurred five days after a large rainstorm, so that although the population were initially evacuated they had returned to their homes [4]. Displacements recorded over time could provide critical additional information for predicting the possible timing of impending slope failure [5].

Based on conventional in-situ survey methods, the concept of 'landslide early warning systems' has been proposed for several years, e.g. [6-12]. The outcomes of these works are often suggested warning criteria for specific locations. Successful early warning cases, where a clear warning was given prior to catastrophic slope failure, have been very limited due to the inadequate temporal and spatial precision of ground observations [13]. Building trustworthy real-time early warning systems (capable of identifying the 'very high-risk time' to prompt short-term evacuation) with suitable spatial and temporal precision is an important but difficult challenge.

Spaceborne Synthetic Aperture Radar (SAR) sensors emit radar signals and record the amplitude of the backscattered signal as well as the phase (from which the changes in range between satellite and Earth's surface can be inferred) [14]. Interferometric SAR (InSAR) is a powerful tool for measuring the Earth's surface motion over large regions (e.g. [15-17]) in all weather conditions, at metre-resolution and offers the capability to remotely monitor unstable slopes, e.g. [18-21]. Recent studies have demonstrated that conventional InSAR and related time series techniques (e.g. Persistent Scatterer InSAR and small baseline InSAR) can identify, map and monitor active landslides [22-26] and even to detect precursory deformation signals prior to their eventual failure, e.g. [27-29]. Note that spaceborne InSAR currently has a minimum repeat cycle of 6 days for Sentinel-1, 1 day for COSMO-SkyMed [30], 11 days for TerraSAR-X and longer for other satellites, which represents a major limitation of spaceborne InSAR for early warning systems.

In-situ global navigation satellite system (GNSS) monitoring is capable of measuring three-dimensional landslide motion at very high temporal frequency (e.g. 20 Hz) and spatial accuracy (2-4 mm in plan and 4-8 mm in vertical) [31]. Other in-situ monitoring methods include extensometers, inclinometers, and pore water pressure sensors. However, these methods only provide point-based measurements at sensors that are costly to install and maintain. Thus in-situ observations are limited by the number of sensors that can be deployed at the key locations and may not capture the spatial variations in landslide motion prior to failure. There are two obvious hurdles to the deployment of ground-based monitoring techniques: (i) the sites with potential landslides should be detected prior to their failure; and (ii) the key monitoring locations in the landslide bodies should be identified.

Spaceborne InSAR and in-situ sensors are complementary tools to monitor surface displacements given InSAR's high spatial resolution (metres to 10s metres) over a wide region (e.g. 250 km x 250 km for Sentinel-1) but limited temporal resolution (constrained by the frequency of satellite overpasses) and in-situ sensors' fine temporal resolution at their locations. We suggest that it is now both feasible and timely to combine these EO technologies to build an integrated landslide early warning system. In this paper, the 2017 Xinmo (Sichuan, China) landslide is used to demonstrate the ability of spaceborne InSAR to identify precursory landslide deformation, while the 2017 Dangchuan #4 landslide in Heifangtai (Gansu, China) is used to demonstrate the successful application of timely early warning for landslides by in-situ measurements [32]. Based on the advantages, limitations and complementarity of different EO methods, a landslide early warning framework is proposed to increase the resilience of local communities to landslide hazards by informing short-term evacuations.

Our paper makes the case that landslide early warning from earth observation (EO) is now within our grasp. We believe that this is a message that is both important and timely. It is important because landslides kill thousands of people every year, predominantly in those parts of the world that are poorest and thus least able to protect themselves. It is timely because, though early warning has long been touted as a 'golden bullet' in landslide risk mitigation, it requires accurate predictions that have generally been out of reach until now.

METHODOLOGY

The InSAR dataset for the time series displacement extraction of Xinmo landslides includes 29 descending SAR images acquired by Sentinel-1A/1B satellites from 09 November 2015 to 19 June 2017 SAR on every 6-24 days. ESA's Sentinel-1A/1B satellites operate day and night performing C-band microwave SAR imaging, providing radar imagery with a wide coverage (e.g. 250 × 250 km) and a short repeat cycle (6-24 days). The SAR data in this study were interferometrically processed with GAMMA software. Shuttle Radar Topography Mission (SRTM) with 30 m horizontal resolution was used to simulate and eliminate the topographic phase. Interferograms were filtered by the adaptive filtering method to reduce the noise. Coherent pixels were detected using the full-rank matrix approach demonstrated in [33] and their time series analysis was performed following the InSAR time series integrated atmospheric estimation model (InSAR TS+AEM) described in [34]. Both the coherent pixel detection approach and the InSAR TS+AEM method have been successfully used in previous InSAR studies. The mean velocity map and time series displacements results were finally geocoded into WGS84 coordinate system.

The Heifangtai area has been monitored with a range of in-situ sensors including 7 GNSS receivers, 34 crackmeters, 2 range gauges and 13 piezometers since 2017 by researchers from the State Key Laboratory of Geohazard Prevention and Geoenviroment Protection (SKLGP) at Chengdu University of Technology. The data collected by all the sensors was transmitted to SKLGP in real time with GPRS (General Packet Radio Service). Note that the crackmeter was a real-time adaptive one developed by SKLGP [35], which acquired one sampling per hour in normal conditions but automatically increased its samples when a displacement acceleration was detected.

RESULTS

Pre-failure movement signals revealed with spaceborne InSAR

On 24 June 2017, a landslide of 13 million cubed meters suddenly buried Xinmo village, Sichuan province, China, causing 10 deaths, with 73 persons still missing. Xinmo village is located on the left bank of the Songping River, a first-order tributary of the upper reaches of Minjiang River [36]. The surrounding steep slopes are prone to rock falls, landslides, and debris flows [37]. The region is tectonically active with several active faults nearby that have generated three Mw >=6.7 earthquakes since the 1930s (Fig. 1A). Xinmo village itself was built on the deposits of an old landslide triggered by the 1933 Mw 7.3 Diexi earthquake [36, 38] (Fig. 1A).

To explore the pre-failure displacement history of the Xinmo landslide, InSAR analysis was performed on Sentinel-1 data to determine a mean velocity map and a time series of landslide motion for a ~1.5-year period prior to failure (Fig. 2). The accumulative displacement map during the period from November 2015 to June 2017 (Fig. 2A) shows that the area near the head scarp of the landslide exhibited clearly detectable displacements with a maximum of 3 cm preceding failure. Figs 2C, 2D and 2E, show the displacement times series results for three selected points P1, P2 and P3 whose locations are shown in Fig. 2B. The last three acquisition dates are 26 May 2017, 07 June 2017 and 19 June 2017 (5 days before the failure), respectively. A dramatic acceleration can be observed during the period from 07 June 2017 to 19 June 2017 (from 17 days before the failure). It should also be noted that all the interferograms were carefully checked to avoid phase unwrapping errors and the InSAR time series was performed pixel by pixel. We did NOT apply strong spatial filtering, and hence our InSAR mean velocity map is not as smooth as those in previous studies. However, the overall pattern of our InSAR mean velocity map is consistent with those in previous results (e.g. [28], [29]).

This clearly demonstrates that quantitative time series analysis from satellite radar observations can detect accelerated movements prior to catastrophic failure, occurring 5-17 days before the landslide. It should be noted that the source area of the Xinmo landslide is located on a steep slope at an altitude of ~3400 m a.s.l. where in-situ sensors would be difficult to install. This highlights one notable advantage of InSAR over in-situ monitoring sensors.

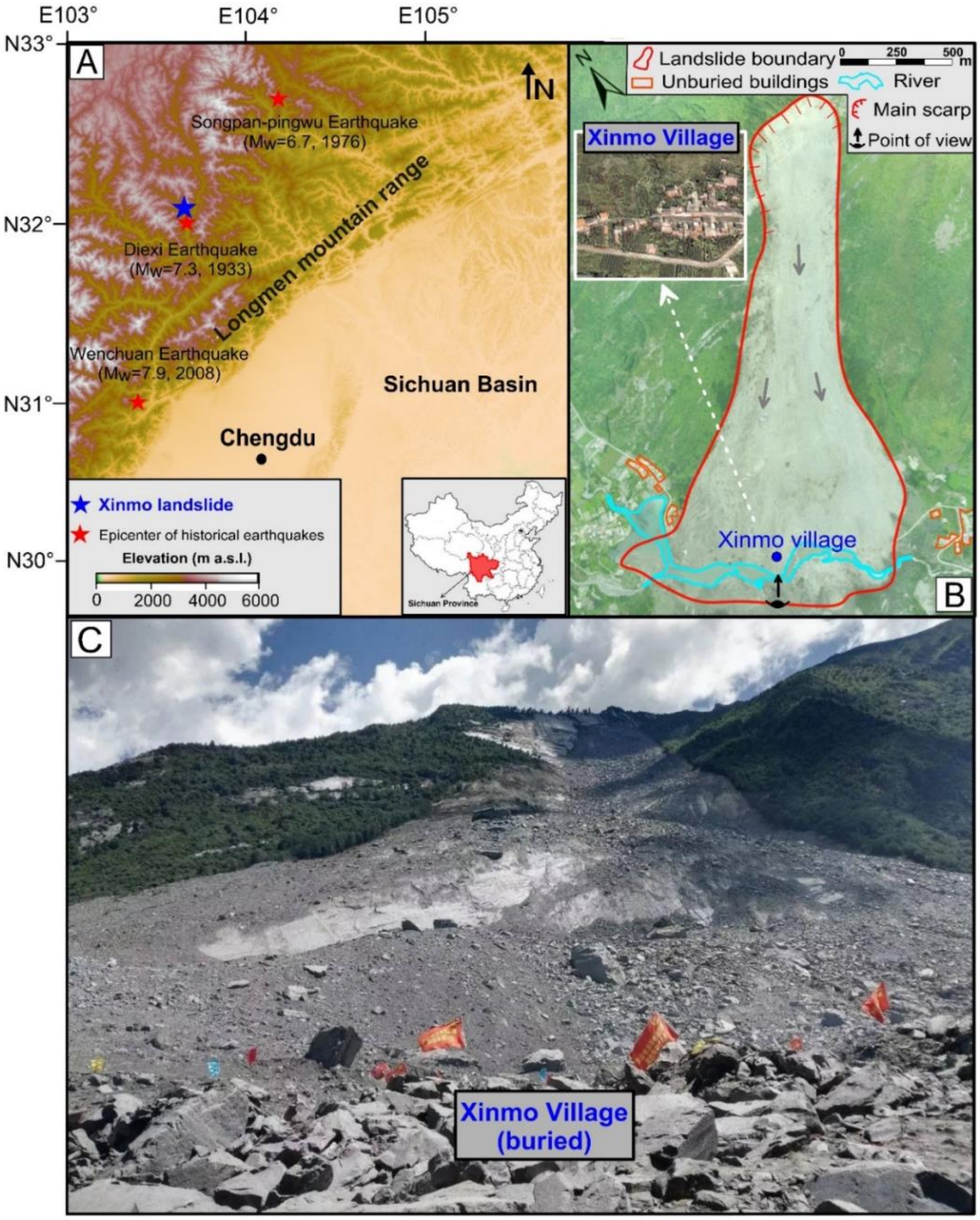


Fig. 1. The location, pre-event and post-event photos of the 24 June 2017 Xinmo landslide. (**A**) Location of the Xinmo landslide and the epicenters of three large historical earthquakes. (**B**) Unmanned aerial vehicle (UAV) aerial photo of the Xinmo landslide with an inset photo of Xinmo village taken before the event. (**C**) Post-failure photo of the Xinmo landslide (the whole village was buried under the accumulated debris).

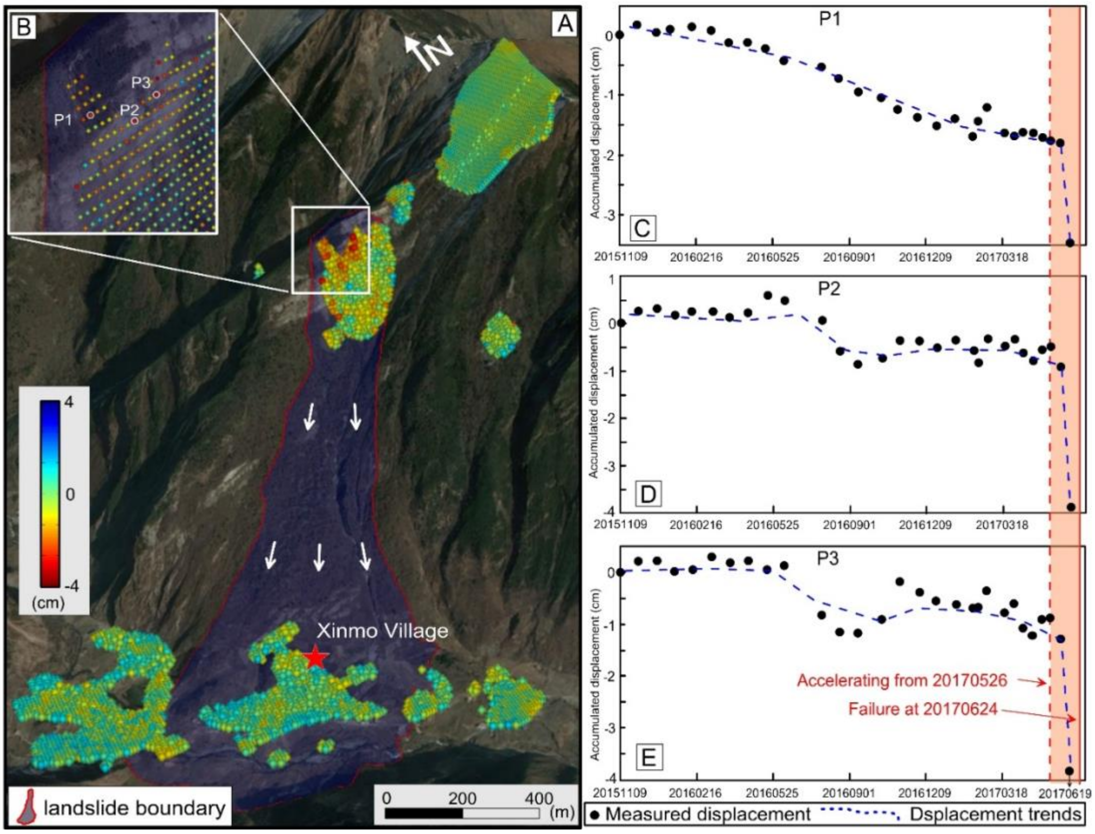


Fig. 2. Pre-failure movement signals and source area revealed by InSAR. (**A**) Cumulative displacements for coherent pixels from time series InSAR analysis. (**B**) Enlarged active displacement area and the location of points P1, P2 and P3; (**C**)(**D**)(**E**) Displacement time series for points P1, P2 and P3, respectively.

Early warning for the Dangchuan 4# landslide using in-situ sensors

The Heifangtai loess terrace, located in Yongjing County, Gansu Province, China (Fig. 3B) with an area of 13.7 squared km, is formed from a terrace of Quaternary aeolian loess deposits [39]. Since the Yellow River pumping irrigation project was kicked-off in 1966, frequent landslides have occurred on the terrace margins. The Dangchuan 4# landslide lies in southwest-central Heifangtai near Guoxia town, Yongjing County. Among all the in-situ sensors, a crackmeter installed across the trailing head scarp edge of Dangchuan 4# (Fig. 3A) provided critical displacement measurements in real time which were used in a successful 8-hour early warning in 2017.

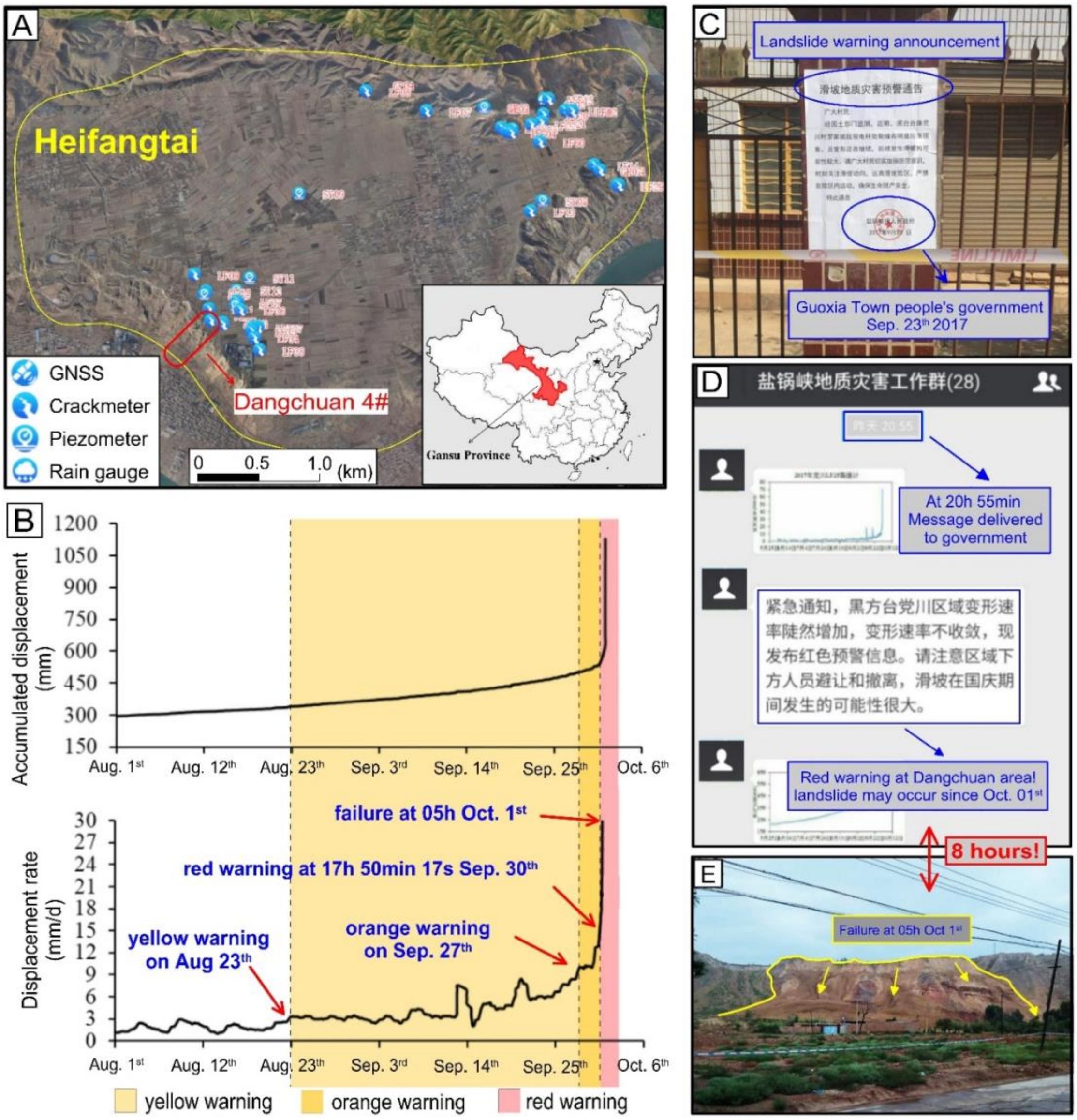


Fig. 3. landslide warning at Dangchuan 4# landslide in Heifangtai. (**A**) The location of Dangchuan 4# landslide with various in-situ sensors; (**B**) cumulative displacement and displacement rates from a crackmeter installed across the trailing head scarp edge during the period from 1 August 2017 to 1 October 2017; (**C**) On 23 September 2017 a photo of Heifangtai landslide warning announcement which was posted on a pillar in Guoxia town by the local government; (**D**) At 20:55 on 30 September 2017, a red warning message was delivered to the local government through WeChat app; (**E**) The post-failure photo of the Heifangtai landslide (Dangchuan 4# slope) which failed at 05:00 on 1 October 2017.

The crackmeter observations showed a clear acceleration in the displacement rate at Dangchuan 4# on 23 August 2017 (Fig. 3B), and hence a yellow warning was issued to the village head and local government by text message, informing them to: ‘pay close attention to this slope and prepare for disaster prevention’.

After a detailed field investigation, the local government confirmed the warning and released an official landslide warning announcement to local communities on 23 September 2017 with several alert boards posted around the landslide area (Fig. 3C). On 27 September 2017 the yellow warning was upgraded to an orange warning due to the accelerating displacement rate measured at the crackmeter. At 17:50 on 30 September 2017, a red warning was released automatically by the system (Geohazard Real-time Monitoring and Early Warning System [40]) developed by SKLGP, which was confirmed by a panel of experts. Three hours later (at 20:55 on 30 September 2017), an official red warning was issued to the local government (Fig. 3D), prompting a government led emergency response and evacuation. The local government immediately started their emergency response, and more than 20 villagers in the landslide hazard zone were evacuated. At 05:00 on 1 October 2017, a landslide occurred (Fig. 3E), damaging several buildings but with no casualties thanks to the early warning [32].

This successful case clearly demonstrates the potential importance of real-time displacement measurements and the role that in-situ sensors could play in early warning systems. A preliminary retrospective InSAR study showed that InSAR with L-band ALOS-2 images was able to capture the accelerated movements prior to failure, occurring 15 days before the landslide (Fig. 4).

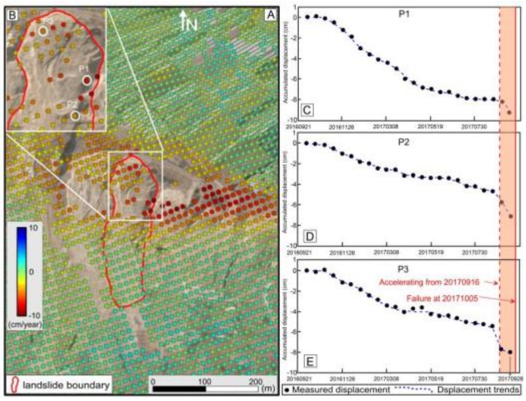


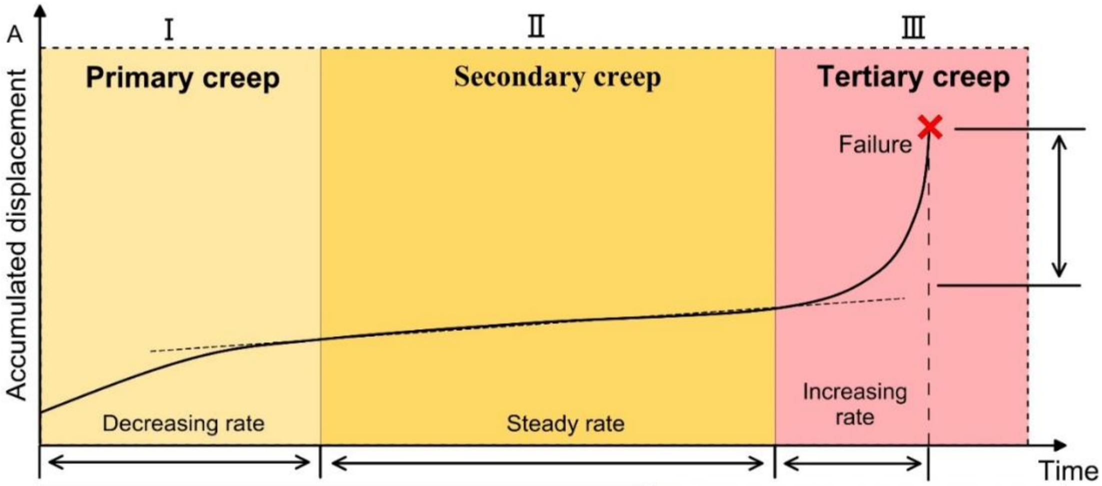
Fig. 4. Pre-event displacements of the Dangchuan 4# landslide revealed by L-band observations. (**A**) The mean velocity map from time series InSAR analysis. (**B**) Enlarged active displacement area and the location of points P1, P2 and P3; (**C**)(**D**)(**E**) Displacement time series for points P1, P2 and P3, respectively.

DISCUSSION

The feasibility and complementarity of EO for landslide early warning

A range of laboratory, field and theoretical studies have identified pre-failure creep acceleration of landslides and suggest that it can be divided into three phases [41-44]: (i) Primary creep, (ii) Secondary creep, and (iii) Tertiary creep (Fig.A). Primary creep is characterised by a decreasing strain rate over time, which often lasts for a short period or can be even absent in some cases [42]. Secondary creep is characterised by slow movement at near constant rate (but with fluctuations in real slopes due to the influence of external factors, such as rainfall). The duration of the secondary creep is difficult to estimate and can last for months, years or even decades [42, 45], despite continuous displacement during this phase. Tertiary creep is characterized by a rapid acceleration of displacement until final failure [46]. Although such speed-ups may be common prior to catastrophic failure events [45], the number of actual observations of such speed-up behavior remains limited due to the absence of the right EO technologies in the right locations at the right times. Therefore, there are two primary challenges for landslide early warning: (i) monitoring surface displacements over a wide region with sufficient resolution and accuracy to identify areas undergoing secondary creep; and (ii) identifying when or under what circumstances a slow-moving landslide (i.e. in secondary creep phase) enters the accelerated displacement tertiary creep phase leading to rapid failure.

Advances in EO offer the potential to address these two challenges. In the primary and secondary phases, weekly to monthly observations would be sufficient to distinguish areas undergoing more rapid creep. In the tertiary creep phase, sub-daily sampling intervals are needed to capture the acceleration in creep (Fig. 5B). InSAR currently has a shortest repeat cycle of 1-11 days while GNSS and some other in-situ sensors can provide high-rate (e.g. 1-20 Hz) measurements. Only slow tertiary creep displacements (e.g. <0.012 m/day over a distance of 100 m for Sentinel-1 [47]) could potentially be captured by InSAR because its measuring capability is limited by the spatial displacement gradients. This limitation can be overcome by SAR pixel offset tracking (e.g. [19]) and/or Range Split Spectrum Interferometry assisted Phase Unwrapping (R-SSIaPU) method [47]; in-situ sensors generally do not have such limitations (Fig. 5C). On the other hand, InSAR offers extensive spatial coverage enabling detection of potential landslides in the primary and secondary creep phases. To monitor a single slope in its tertiary phase InSAR and in-situ sensors can provide complementary coverage in space and time.



B — Typical sampling intervals

Phase	Temporal requirement	Satellite InSAR	GNSS + in-situ sensors
primary	Weekly→Monthly	Yes	Yes
secondary	Weekly→Monthly	Yes	Yes
tertiary	Daily→hourly	Partly	Yes

C — Velocity scale

Phase	Speed	Satellite InSAR	GNSS + in-situ sensors
primary	extremely slow to very slow	Yes	Yes
secondary	very slow to slow	Yes	Yes
tertiary	slow	Yes	Yes
	moderate	No	Yes
	rapid	No	No

Fig. 5. EO feasibility analysis on the three stages of landslide. (**A**) Idealized displacement-time curves for the three stages of creep [6, 41, 42]. (**B**)-(**C**) Typical sampling intervals and velocity scale analysis for satellite InSAR and in-situ sensors in three creep phases. The landslide speeds in (c) are defined according to [48, 49], i.e. extremely slow (<16 mm/year), very slow (1.6 m/year), slow (13 m/month) and moderate (1.8 m/h).

EO based landslide early warning system

Fig. 5 illustrates that EO can provide us with unprecedented and encouraging opportunities for pre-failure creep monitoring. However, the different technologies have their own advantages and limitations as illustrated by the Xinmo and Dangchuan case studies. A single EO method is insufficient to capture all the signals in the different creep stages, and hence multiple EO technologies should be combined to develop landslide EWS. Fig. 6 shows the framework of an operational landslide early warning system relying on an optimal combination of these EO technologies.

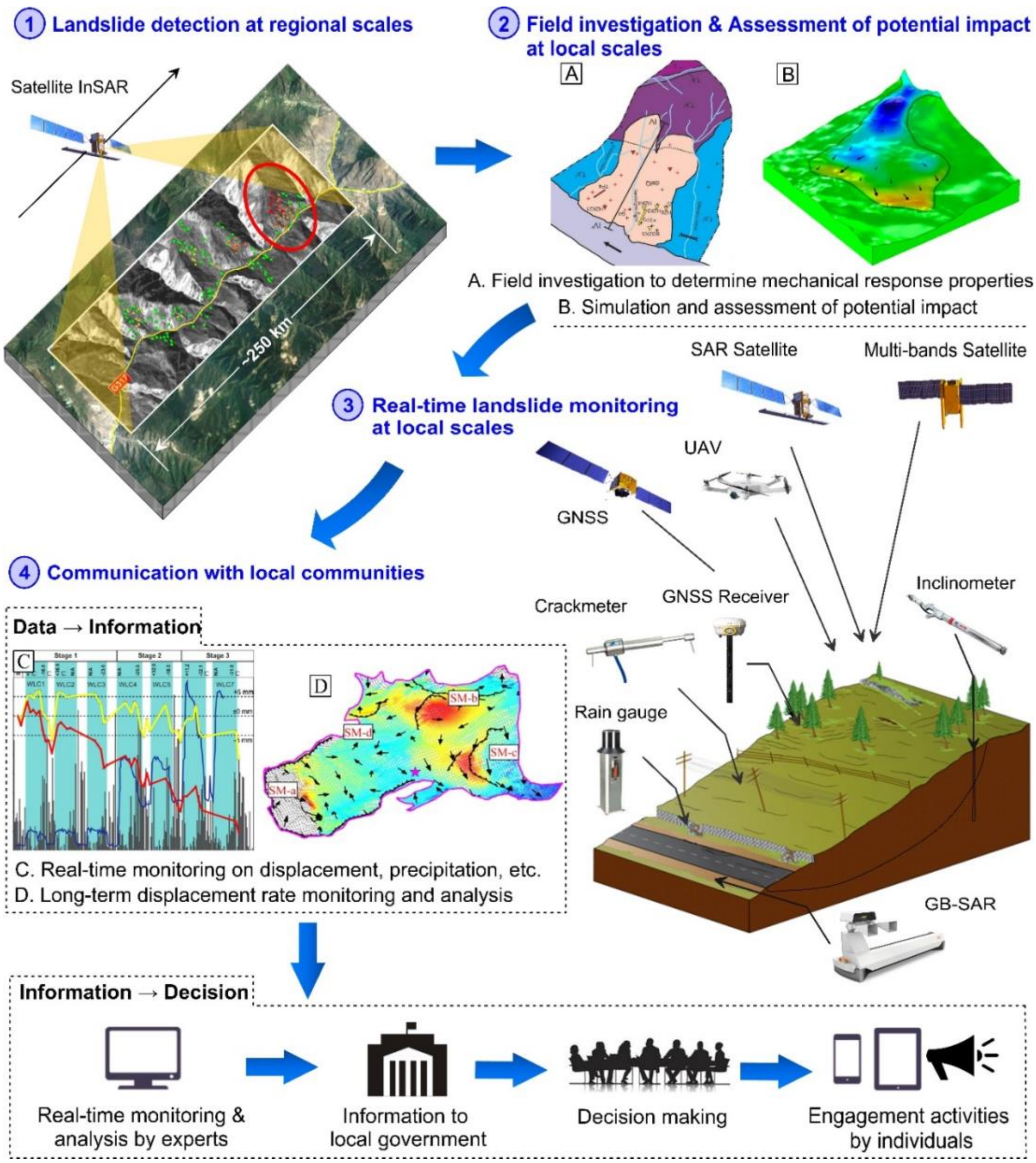


Fig. 6. EO based landslide early warning system. (**A**) Field investigation to determine geomechanical response properties. (**B**) Simulation and assessment of potential impact. (**C**) Real-time monitoring on displacement, precipitation etc. (**D**) Long-term displacement rate monitoring and analysis.

Step 1. Spaceborne InSAR is employed to comprehensively detect active slopes (i.e. clusters of points that exhibit certain deformational activity [50]) to find potential landslides at a regional scale. The archived and newly acquired SAR images (e.g. ESA's Sentinel-1) are interferometrically processed and then analysed in time series. An automatic feature detection algorithm (possibly relying on machine learning approaches, e.g. [51, 52]) should be developed to detect potential landslides based on the regional deformation rate maps and displacement time series. Time series analysis can be used to determine the sensitivity of landslide motion to external factors such as seasonal precipitation and seismic shaking (e.g. [23, 53]). First-order geomechanical modeling of landslide behavior based on critical-state soil mechanics or rate-and-state friction can provide important insights on the stability conditions of landslides (e.g. [54-56]). Eventually, such geomechanical analysis may allow us to anticipate failure conditions prior to the pronounced accelerations of the tertiary phase (e.g. [57]).

Step 2. Assessment of potential impacts of the active landslides at a local scale. After the potential landslide initiation hazard is identified for specific locations, field investigations help assess the geological setting of the landslide. A landslide dynamics model (e.g. [58, 59]) can be applied to predict the speed and run-out extent of potential landslide events. Potential landslide sites identified in Step 1 can be simulated to determine the likely impact on human settlements for each landslide. Topographic and socio-spatial data can be collated for landslide modelling and impact assessment. A detailed local land property map, including key infrastructures such as buildings, roads, power lines, and a population-distribution map could be generated based on existing open source data and community participation. These will support the impact assessment as well as early warning communication with the local community. This step also identifies the sites for which real-time landslide monitoring (RTLM) is required.

Step 3. A multi-sensor integrated system is installed combining remote sensing methods and in-situ sensors for the specific sites where the RTLM is needed. In-situ sensors can be carefully located according to the landslide motion information provided by InSAR so that an accurate continuous monitoring in time and space for all hazardous landslides in a region can be achieved by integrating these two systems whilst minimizing the associated costs by limiting the number of in-situ sensors. High-rate (e.g. 1 Hz) raw in-situ observations (e.g. GNSS and crackmeters) can be transmitted to a data centre via wireless communication infrastructure, and real-time processed with short baselines in a kinematic mode. Recent experiments with GNSS suggest ~2-4 mm horizontal and 4-8 mm vertical accuracy are possible at 1 Hz [60, 61]. Real-time monitoring is particularly important since existing observations on tertiary creep suggest that the timescale for this phase ranges from minutes to months [44, 62, 63]. Thus the data should be transmitted back to the data centre in real time and processed automatically. However, these in-situ observations are not only useful for identifying the onset of tertiary creep but can be used in the secondary phase to determine the sensitivity of landslide motion to external factors at a higher resolution and precision than was possible in stage 1 [23, 53]. The mechanical models introduced at stage 1 can be refined and calibrated through monitoring of environmental factors and geological-geotechnical parameters such as the pore pressure in soils (Table 1) [13, 64].

Table 1. Commonly used technologies for landslides monitoring. Note that UAV and TDR represent unmanned aerial vehicle and time domain reflectometry, respectively.

Observation Types	Technology	Precision	Examples
Displacement	Spaceborne InSAR	mm-cm [65]	[21, 66, 67]
	Airborne InSAR	mm-cm [68]	[68, 69]
	Ground-based InSAR	mm-cm [70]	[63, 70, 71]
	UAV photogrammetry	~ 6cm [72]	[72, 73]
	GNSS	mm-cm [74]	[80, 81]
	Optical image matching	cm-m [75]	[75, 76]
	Crackmeter	mm-cm [77]	[78, 79]
	Extensometer	~3 mm [80]	[81, 82]
	In-place inclinometer	~8 mm [65]	[10, 83, 84]
	Tiltmeter	~0.1°[13]	[13, 79, 87]
	Total station	~±1 ppm [77]	[77, 85]
	Terrestrial Lidar	~0.2-0.5 m [80]	[80, 86]
	Shape acceleration array	±1.5 mm/30 m [87]	[13, 81, 87]
	Active waveguides	Mm [88]	[13, 88]
	Seismometer	\	[89, 90]
Pore pressure	Piezometer	\	[13, 91, 92]
	TDR	\	[93, 94]
	Tensiometer (Soil hygrometer)	\	[54, 94]
Precipitation	Rain gauge	\	[79, 95]

Step 4. Communication with local communities. Providing timely and useful warnings to people exposed to landslide hazard is the ultimate objective of an early warning system. Thus

engagement and communication with local communities should be a key feature of an effective landslide EWS. A large body of work already exists on the social science of early warning, providing useful insights, explanations for unexpected EWS failure, potential secondary disasters and examples of good practice. Experience from past disasters worldwide suggests that emergency preparedness, planning and response are some of the weakest elements in many existing EWSs [96]. In particular, the link between the technical capacity to issue a warning and the public's capacity and commitment to respond effectively to the warning is often weak, limiting the capacity of the warning to trigger an appropriate and effective response from the community. Warning systems that mainly focus on technical aspects and ignore social factors generally do not work effectively because the warnings do not prompt effective action due to lack of community buy-in, which results in poor engagement and operation. There appears to be fairly widespread consensus among both academics and practitioners that EWSs are most effective when they are built in collaboration with those at risk rather than imposed from outside.

OUTLOOK

The remaining three Big Questions for landslide forecasting and early warning are as follows: (Big Question 1) where are potential landslides, (Big Question 2) when will landslides occur, and (Big Question 3) how to best reduce landslide disaster risk.

Big Question 1 - where are potential landslides: We are entering an exciting new era of Earth Observation data, and recent advances in satellite radar and in-situ sensors (e.g. GNSS) have allowed us to collect high-quality measurements to quantify the Earth's surface displacements and then address Big Question 1 over entire mountain ranges at space and time scales that are finer than ever before and at relatively low cost. In the EO based landslide early warning system, the relatively short repeat cycles of current SAR missions still represent a limitation of InSAR to detect potential landslides, but the Geosynchronous - Continental Land-Atmosphere Sensing System (G-CLASS), one of the three Earth Explorer ideas that have been accepted by ESA's Programme Board for Earth Observation to compete as the tenth Earth Explorer mission, might provide a solution. Considerable work has been done to interferometrically process massive SAR data sets in an automatic way (e.g. [97]), but more should be done to investigate how to detect potential landslides from big SAR data in a consistent, reliable and smart manner. Machine learning technologies have been widely implemented in the field of computer science and remote sensing

[98-99], where statistical techniques are employed to learn specific and complex tasks from given data. Recent studies report that machine learning has the capability to identify signals associated with geohazards from large data sets (e.g. [100]), suggesting that the integration of machine learning with EO technologies might be one encouraging solution to automatic landslide detection. To address Big Question 1, there is an urgent need to answer the following: (i) at what percentage are the detected landslides true positives? (ii) what is the percentage of the missing landslides (false negatives)? and (iii) in which scenarios are the landslides more likely be successfully detected?

Big Question 2 - when will landslides occur: A range of state-of-the-art landslide initiation and runout models have enabled us not only to estimate the location and geometry of potential landslides, but also to assess their potential impacts.

It remains a grand challenge to predict when landslides will occur. There have been a limited number of successful case studies including the 2017 Heifangtai landslide. In these cases, deformation anomalies (acceleration and/or change in pattern) observed prior to failure have been recongnised as ‘precursors’. However, accurate EWSs require the identification of a diagnostic signature that can be somewhat uniquely related to impending failure. The degree to which this signature is unique, defines the confidence with which a warning can be issued, which represents a much stricter definition of ‘precursor’. Further research is required to constrain the relationship between accelerated displacement and landslide failure and thus to establish these diagnostic signatures with more confidence. We suggest that widespread and long-term deformation monitoring combined with landslide observations will enable considerable progress on this problem.

Big Question 3 - how to best reduce landslide disaster risk: The experience of the cooperation between experts and local communities in Dangchuan 4# landslide has improved our understanding of best practices for Community-Based Disaster Risk Management (CBDRM). How to best coproduce a site specific warning system with both local experts and with members of at-risk communities to reduce landslide disaster risk remains an open challenge for the whole community.

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