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Entering the Era of Earth Observation-Based Landslide Warning Systems

A novel and exciting framework

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Early warning systems (EWSs) to detect and monitor landslides are a great challenge. They are important due to the high cost of catastrophic landslides and are challenging because of the difficulty in identifying a diverse range of landslide-triggering factors. While there has been a very limited number of successes, recent advances in Earth observation (EO) from the ground, aircraft, and space have dramatically improved our ability to detect and monitor active landslides. A growing body of geotechnical theory suggests that prefailure behavior can offer clues to the location and timing of impending catastrophic failures. In this article, we use two recent landslides in China as case studies to demonstrate that satellite radar observations can be used to detect deformation precursors to catastrophic landslides and that early warnings can be achieved with real-time, in situ observations. We propose a novel and exciting framework that employs EO technologies to build an operational landslide EWS.

INTRODUCTION

Landslides, when 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 that results in hundreds of deaths and billions of dollars in damages every year [1]. The combination of a rapidly increasing global population and the 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 (a few millimeters per year) or involve sudden failure [2], so 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, large landslides tend to be responsible for most 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. However, asset relocation is not feasible for most people. In these situations, short-term evacuation is often the most attractive or only option. Therefore, improved landslide forecasts and early warning capabilities are expected to be crucial in managing landslide risk for many individuals and communities.

Although major landslide triggers (e.g., rainfall and seismic shaking) and the basic physics governing landslide initiation are well known, predicting where and when landslides will occur remains a challenge, primarily due to the difficulty in forecasting the triggering factors themselves as well as 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; some landslides occur without an identifiable trigger and others with significant delay. For example, the 2006 Leyte landslide, which killed more than 1,100 people in the Philippines, occurred five days after a large rainstorm. Although the population was

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initially evacuated, they had returned to their homes before the landslide occurred [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 EWSs has been proposed for several years [6]–[12]. These works often result in suggested warning criteria for specific locations. Successful early warning cases, in which 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 EWSs that can identify when to prompt short-term evacuations with suitable spatial and temporal precision is important but difficult.

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 the satellite and Earth's surface can be inferred [14]. Interferometric SAR (InSAR) is a powerful tool for measuring Earth's surface motion over large regions [15]–[17], in all weather conditions, at meter resolution. InSAR also offers the capability to remotely monitor unstable slopes [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 detect precursory deformation signals prior to their eventual failure [27]–[29]. Note that spaceborne InSAR currently has a minimum repeat cycle of six days for *Sentinel-1*, one day for *COSMO-SkyMed* [30], 11 days for *TerraSAR-X*, and longer for other satellites, which represents a major limitation of spaceborne InSAR for EWSs.

In situ global navigation satellite system (GNSS) monitoring can measure 3D landslide motion at a 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 provide point-based measurements only at sensors, which are costly to install and maintain. Thus, in situ observations are limited by the number of sensors that can be deployed at key locations and may not capture the spatial variations in landslide motion prior to failure. There are two obvious hurdles to deploying ground-based monitoring techniques: sites with potential landslides should be detected prior to their failure, and 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 (meters to tens of meters) over a wide region (e.g., 250 km × 250 km for *Sentinel-1*) but are limited by 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 EWS. In this article, the 2017 Xinmo landslide in Sichuan, China, 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 a 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 populations of when to leave for short-term evacuations.

This article makes the case that obtaining a landslide early warning from EO is now within our grasp. We believe that this message is both important and timely. It is significant because landslides kill thousands of people every year, predominantly in parts of the world that are poorest and thus least able to protect themselves. It is well-timed because, although 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 data set for the time series displacement extraction of Xinmo landslides includes 29 descending SAR images acquired by *Sentinel-1A/1B* satellites from 9 November 2015 to 19 June 2017. The European Space Agency's (ESA's) *Sentinel-1A/1B* satellites operate day and night, performing C-band microwave SAR imaging and providing radar imagery with 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. A 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 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 the WGS84 coordinate system.

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

RESULTS

PREFAILURE MOVEMENT SIGNALS REVEALED WITH SPACEBORNE INTERFEROMETRIC SYNTHETIC APERTURE RADAR

On 24 June 2017, a 13 million-m^3 landslide suddenly buried Xinmo, Sichuan, China, causing 10 deaths; 73 people are still missing. Xinmo is a village on the left bank of the Songping River, a first-order tributary of the upper reaches of the Minjiang River [36]. The surrounding steep slopes are prone to rock falls, landslides, and debris flows [37]. The region is tectonically active: several active faults nearby have generated three ≥6.7-magnitude (M_w) earthquakes since the 1930s [Figure 1(a)]. Xinmo itself was built on the deposits of an old landslide triggered by the 1933 7.3-M_w Diexi earthquake [36], [38] [Figure 1(a)].

To explore the prefailure 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 an approximately 1.5-year period prior to failure (Figure 2). The accumulative displacement map during the period from November 2015 to June 2017 [Figure 2(a)] shows that the area near the head scarp of the landslide exhibited clearly detectable displacements, with a maximum of 3 cm preceding failure. Figure 2(c)–(e) shows the displacement times series results for three selected points (P1, P2, and P3), whose locations are shown in Figure 2(b). The last three acquisition dates are 26 May 2017, 7 June 2017, and 19 June 2017 (five days before the failure), respectively. A dramatic acceleration can be observed during the period from 7 June 2017 to 19 June 2017 (from 17 days before the failure). It should also be noted that all 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; 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] and [29]).

These findings clearly demonstrate 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 ~3,400 m above sea level, where in situ sensors would be difficult to install, highlighting one notable advantage of InSAR over in situ monitoring sensors.

EARLY WARNING FOR THE DANGCHUAN 4# LANDSLIDE USING IN SITU SENSORS

The Heifangtai loess terrace, located in Yongjing County, Gansu, China [Figure 3(b)], with an area of 13.7 km^2, is formed from a terrace of quaternary aeolian loess deposits [39]. Since the Yellow River pumping irrigation project began in 1966, frequent landslides have occurred on the terrace margins. The Dangchuan 4# landslide is in southwest-central Heifangtai near Guoxia, Yongjing County. Among the in situ sensors, a crackmeter installed across the trailing head scarp edge of Dangchuan 4# [Figure 3(a)] provided critical displacement measurements in real time, which were used in a successful 8-h early warning in 2017.

The crackmeter observations showed a clearly accelerated displacement rate at Dangchuan 4# on 23 August 2017 [Figure 3(b)]; hence, a yellow warning was issued to the village leader 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 [Figure 3(c)]. 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, the system (a geohazard real-time monitoring and EWS [40] developed by SKLGP) automatically released a red warning, 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 [Figure 3(d)], prompting a government-led emergency response and evacuation. The local government immediately started its emergency response, and more than 20 villagers in the landslide hazard zone were evacuated. At 05:00 on 1 October 2017, a landslide occurred [Figure 3(e)], damaging several buildings, but there were no casualties owing 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 EWSs. A preliminary retrospective InSAR study showed that InSAR with L-band Advanced Land Observing *Satellite-2* images were able to capture the accelerated movements that occurred 15 days before the landslide (Figure 4).

DISCUSSION

FEASIBILITY AND COMPLEMENTARITY OF EARTH OBSERVATION FOR LANDSLIDE EARLY WARNING

A range of laboratory, field, and theoretical studies have identified prefailure creep acceleration of landslides and suggest that it can be divided into three phases [41]–[47]: primary creep, secondary creep, and tertiary creep [Figure 5(a)]. Primary creep is characterized 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 characterized by slow movement at a nearly 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; it can last for months, years, or even decades [42], [48] despite continuous displacement during this phase. Tertiary creep is characterized by a rapid acceleration of displacement until final failure [49]. Although such speedups may be common prior

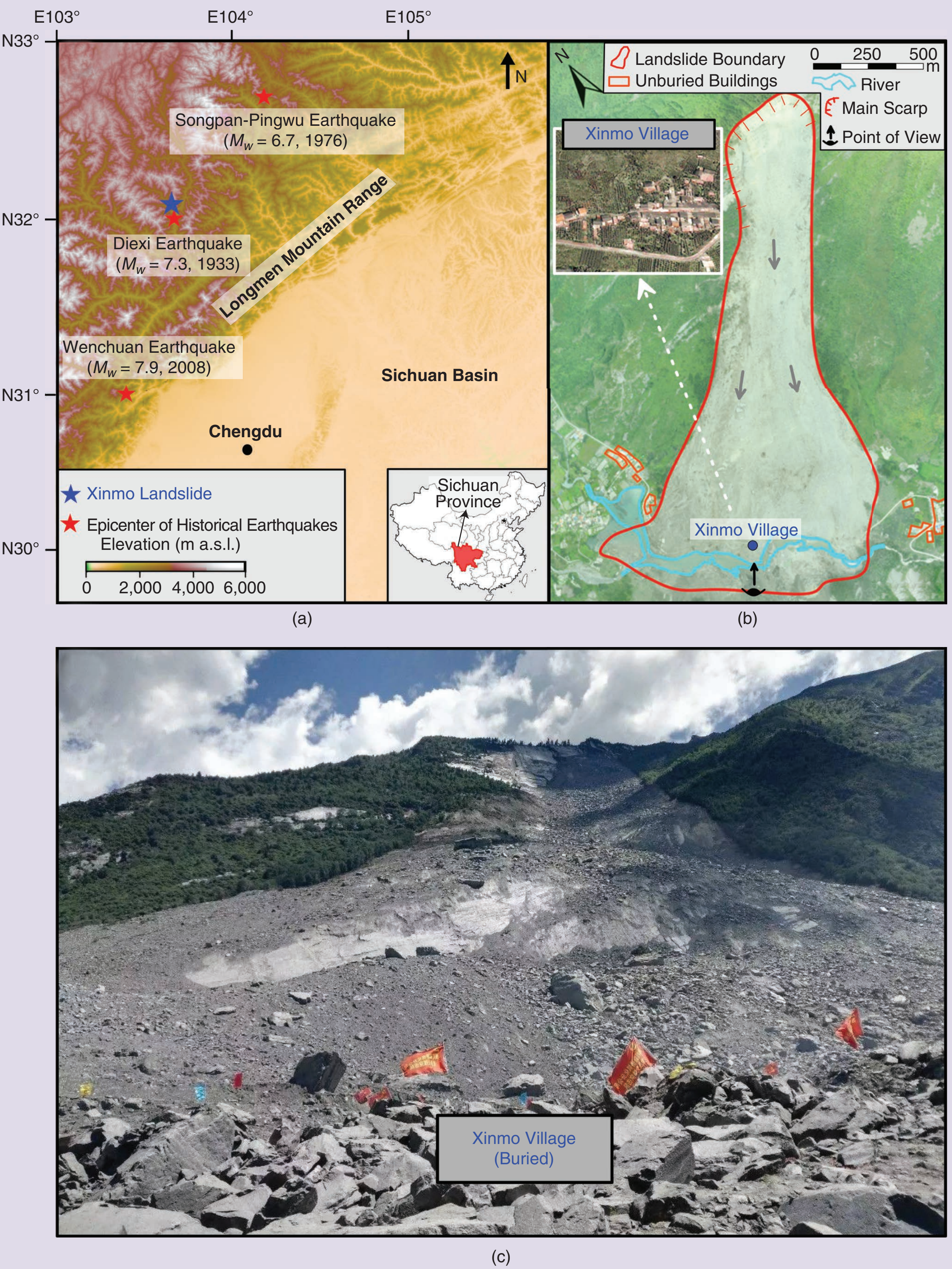


FIGURE 1. Pre- and post-event photos of the location of the 24 June 2017 Xinmo landslide. (a) The location of the Xinmo landslide and the epicenters of three large historical earthquakes. (b) An unmanned aerial vehicle (UAV) photo of the Xinmo landslide with an inset photo of Xinmo village taken before the event. (c) A postfailure photo of the Xinmo landslide. The entire village was buried under the accumulated debris. m a.s.l.: meters above sea level. [Source: State Key Laboratory of Geohazard Prevention and Geoenvironment Protection (SKLGP); used with permission.]

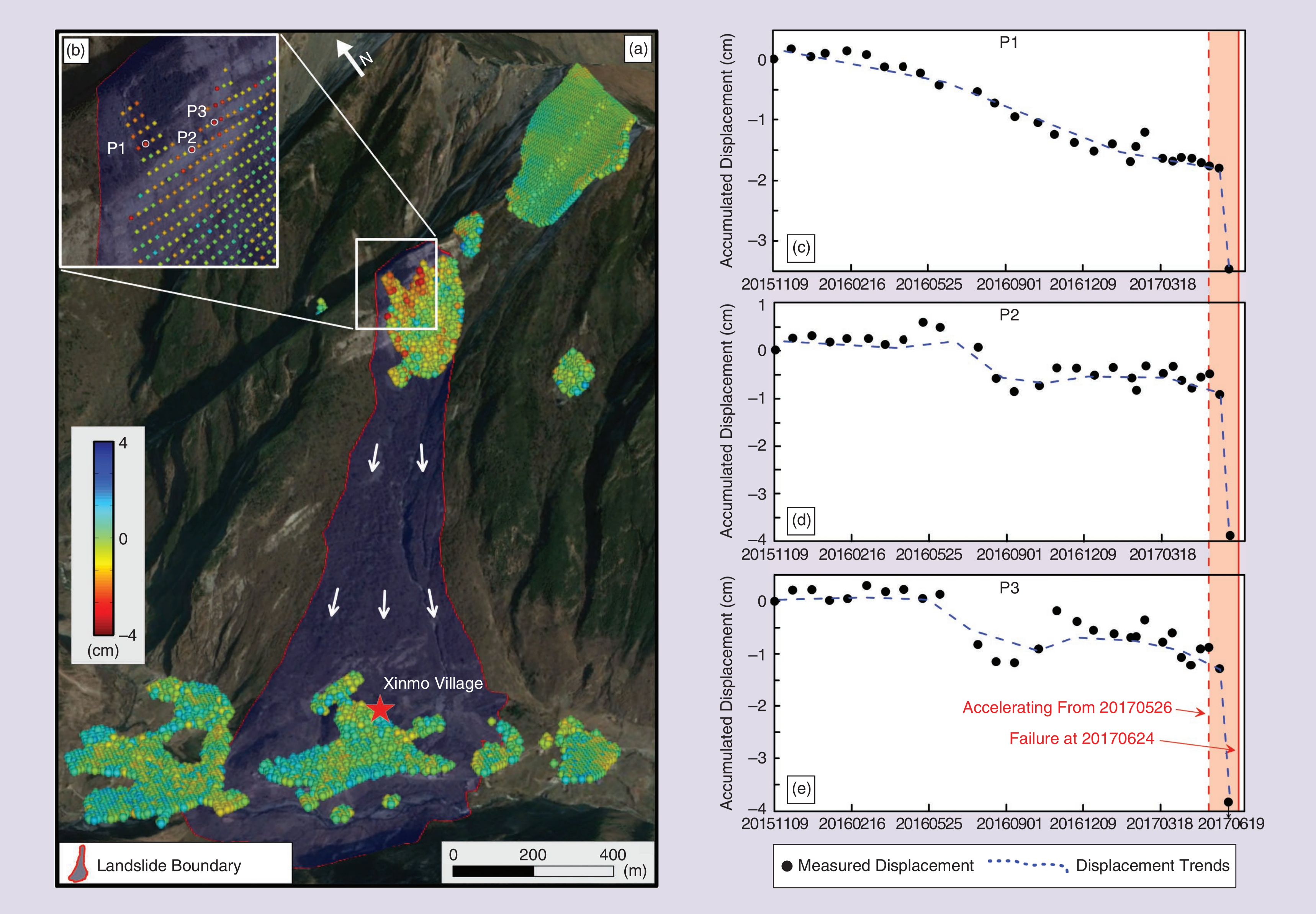


FIGURE 2. The prefailure movement signals and source area revealed by InSAR. (a) The cumulative displacements for coherent pixels from time-series InSAR analysis. (Source: Google Earth; used with permission.) (b) The enlarged active displacement area and the location of points P1, P2, and P3 are presented. The displacement time series for points (c) P1, (d) P2, and (e) P3, respectively, are shown.

to catastrophic failure events [48], the number of actual observations of such speedup 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: 1) monitoring surface displacements over a wide region with sufficient resolution and accuracy to identify areas undergoing secondary creep and 2) identifying when or under what circumstances

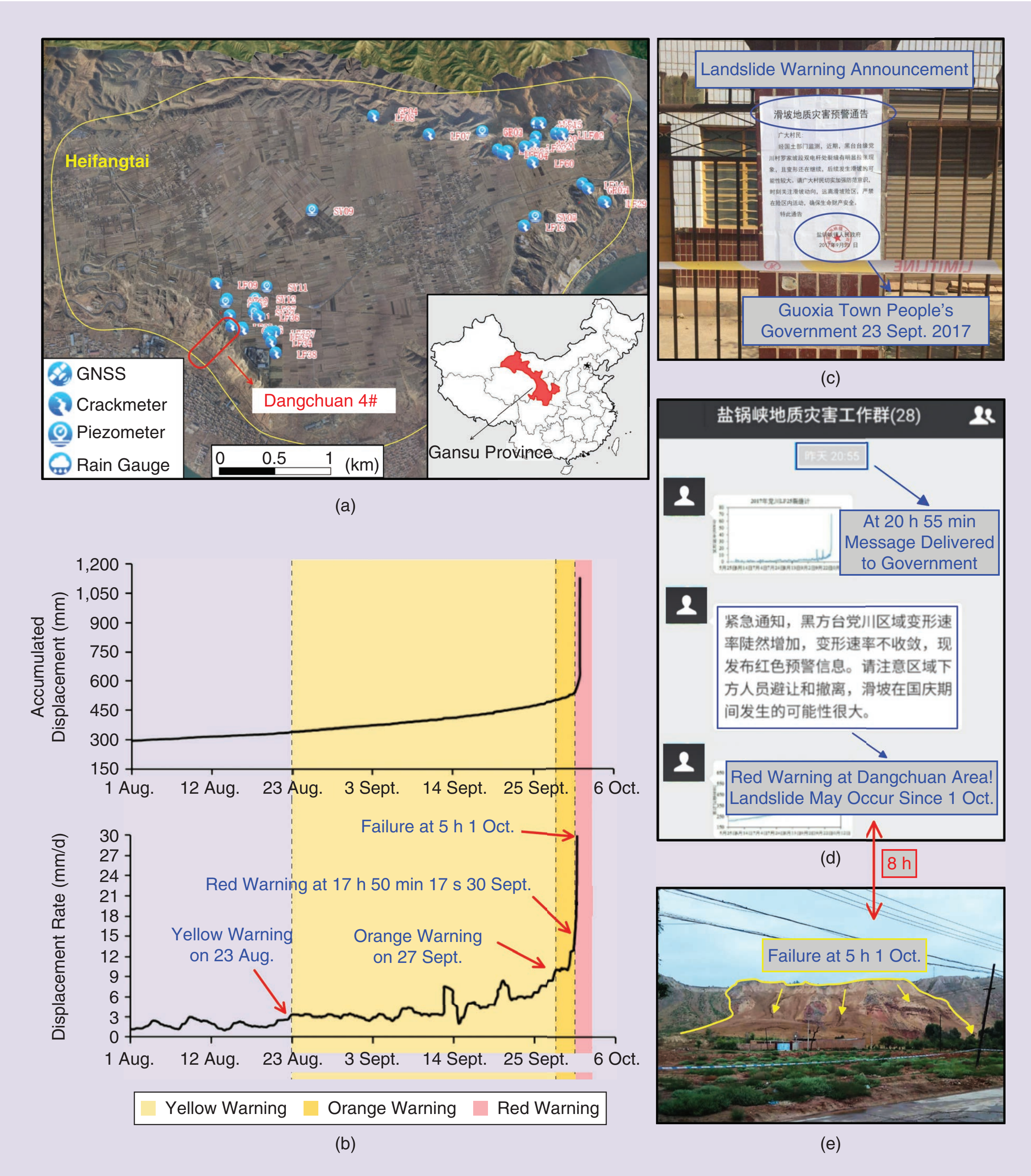


FIGURE 3. The landslide warning at Dangchuan 4# landslide in Heifangtai, China. (a) The location of Dangchuan 4# landslide with various in situ sensors. (Source: Google Earth; used with permission.) (b) The cumulative displacement and displacement rates from a crackmeter installed across the trailing head scarp edge during the period from 1 August 2017 to 1 October 2017. (c) A photo of the Heifangtai landslide warning announcement from 23 September 2017, which was posted on a pillar in Guoxia town by the local government. (d) The red warning message delivered to the local government through the WeChat app at 20:55 on 30 September 2017. (e) The postfailure photo of the Heifangtai landslide (Dangchuan 4# slope), which failed at 05:00 on 1 October 2017. (Source: SKLGP; used with permission.)

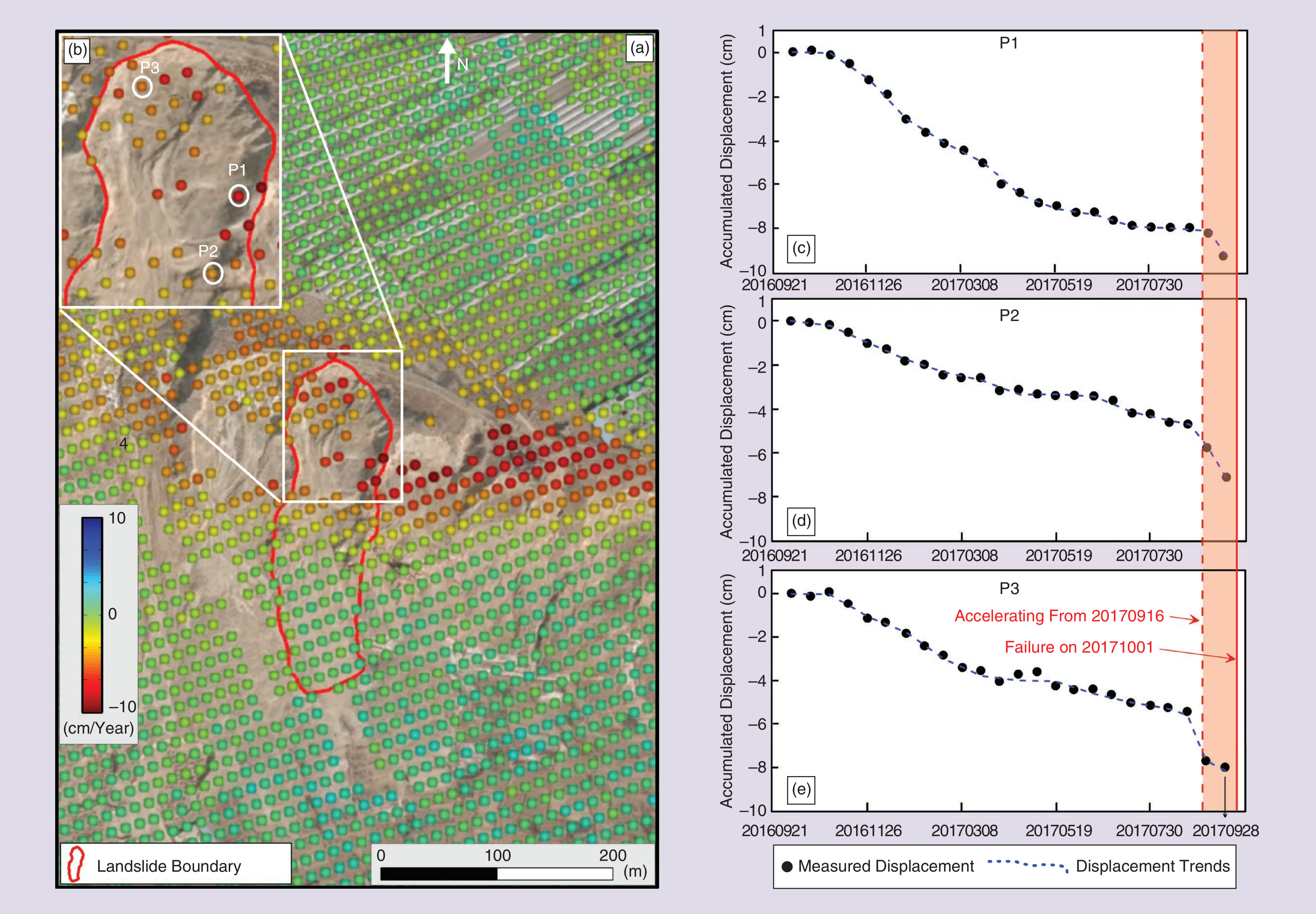


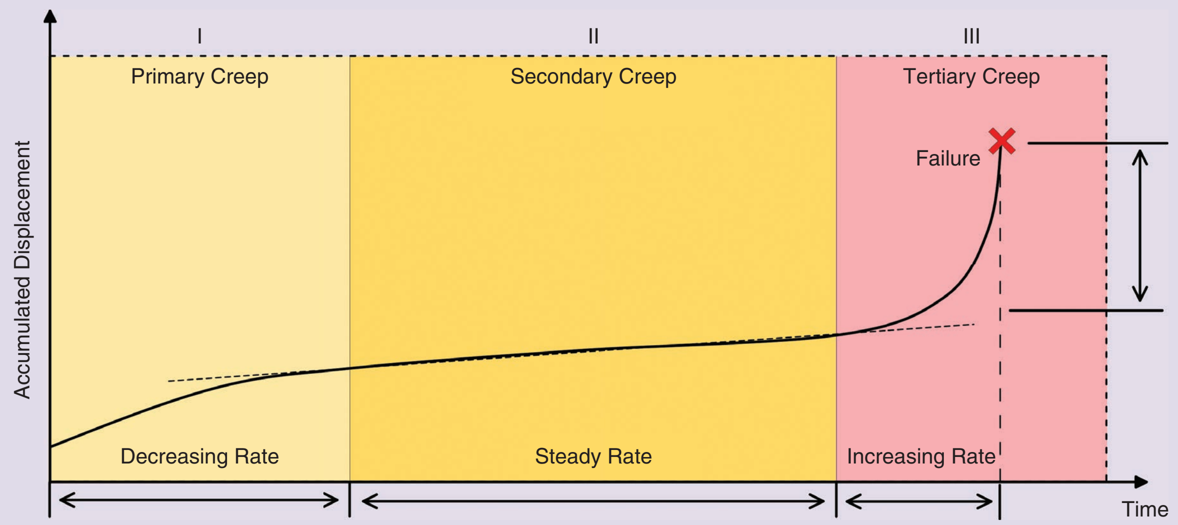
FIGURE 4. The pre-event displacements of the Dangchuan 4# landslide revealed by L-band observations. (a) The mean velocity map from time-series InSAR analysis. (Source: Google Earth; used with permission.) (b) The enlarged active displacement area and the location of points P1, P2, and P3. The displacement time series for points (c) P1, (d) P2, and (e) P3, respectively.

a slow-moving landslide (i.e., in secondary creep phase) enters the accelerated displacement of a 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 enough to distinguish areas undergoing more rapid creep. In the tertiary creep phase, subdaily sampling intervals are needed to capture the accelerated creep [Figure 5(b)]. 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*[50]) could potentially be captured by InSAR because its measuring capability is limited by the spatial displacement gradients. This limitation can be overcome using SAR pixel offset tracking [19] or the range split-spectrum interferometry-assisted phase unwrapping method [50]; in situ sensors generally do not have such limitations [Figure 5(c)]. On the other hand, InSAR offers extensive spatial coverage that enables the 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.

EARTH OBSERVATION-BASED LANDSLIDE EWS

Figure 5 illustrates EO's ability to provide unprecedented and encouraging opportunities for prefailure creep monitoring. However, the different technologies have their own advantages and limitations, as illustrated by Xinmo and Dangchuan's case studies. A single EO method is insufficient to capture all the signals in the different creep stages, so multiple EO technologies should be combined to



(a)

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

(b)

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

(c)

FIGURE 5. An EO feasibility analysis of the three stages of a landslide. (a) The idealized displacement-time curves for the three stages of creep [6], [41], [42]. (b) and (c) The 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 [51] and [52], i.e., extremely slow (<16 mm/year), very slow (1.6 m/year), slow (13 m/month), and moderate (1.8 m/h).

develop a landslide EWS. Figure 6 shows the framework of an operational landslide EWS that relies on an optimal combination of these EO technologies, detailed as follows.

- *Step 1*: Spaceborne InSAR is employed to comprehensively detect active slopes (i.e., clusters of points that exhibit certain deformational activity [53]) 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 analyzed in time series. An automatic feature-detection algorithm (possibly relying on machine learning approaches, e.g., [54] and [55]) should be developed to detect potential land-

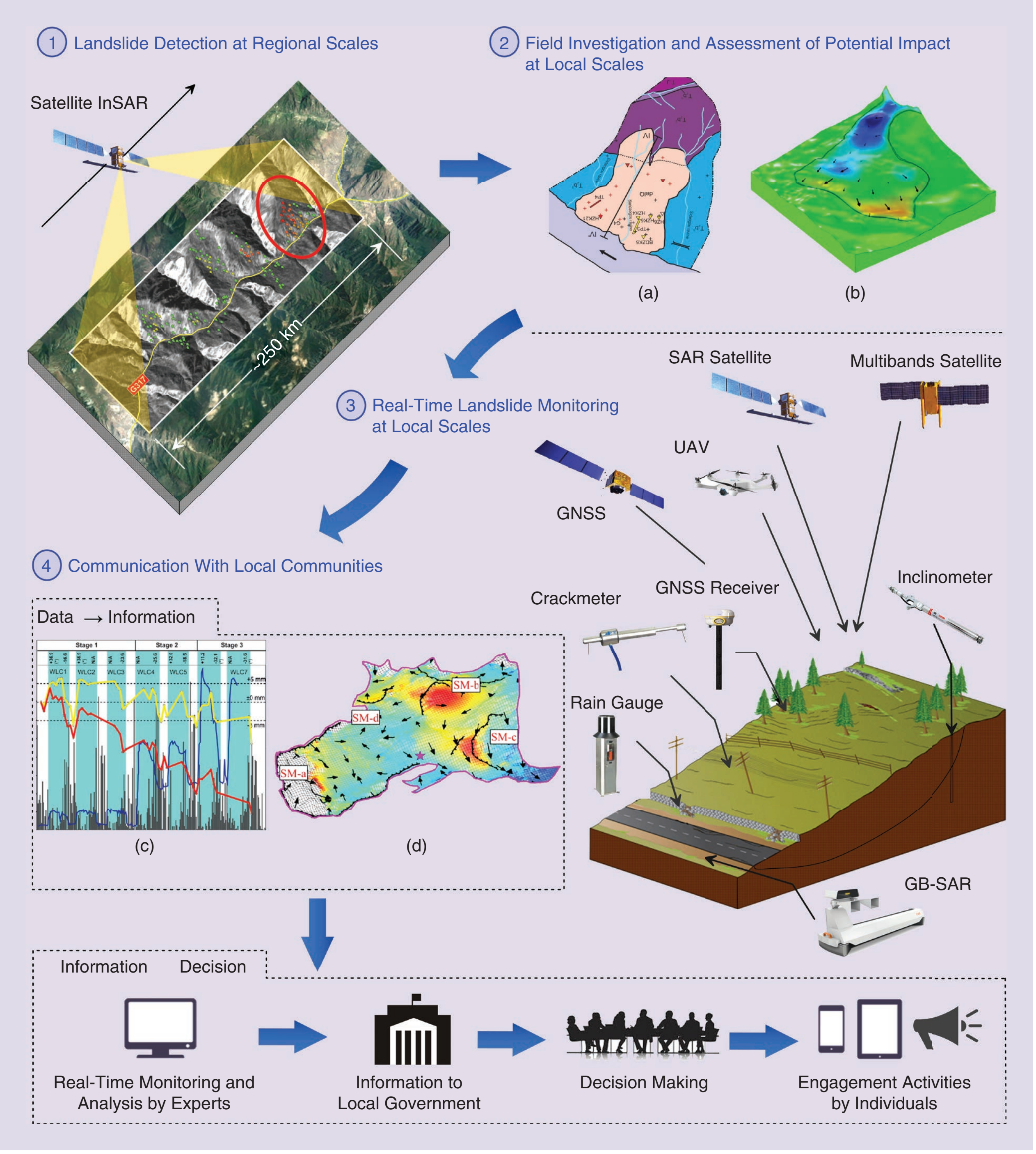


FIGURE 6. The EO-based landslide EWS. (a) The field investigation to determine geomechanical response properties; (b) the simulation and assessment of potential impact; (c) real-time monitoring on displacement, precipitation, and so on; and (d) long-term displacement rate monitoring and analysis. GB-SAR: ground-based SAR.

slides 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 [23], [56]. First-order geomechanical modeling of landslide behavior based on critical-state soil mechanics or rate-and-state friction can provide important insights into the stability conditions of landslides [57]–[59]. Eventually, such geomechanical analysis may allow us to anticipate failure conditions prior to the pronounced accelerations of the tertiary phase [60].

- *Step 2*: The potential impacts of active landslides are assessed 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 [61], [62] can be applied to predict the speed and run-out extent of potential landslide events. The potential landslide sites identified in Step 1 can be simulated to determine the likely impact on human settlements for each landslide. Topographic and sociospatial data can be collated to model landslides and assess their impact. A detailed local land property map that includes key infrastructures such as buildings, roads, and 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 multisensor integrated system is installed that combines remote sensing methods and in situ sensors for the specific sites where RTLM is needed. In situ sensors can be carefully located according to the landslide motion information provided by InSAR to achieve accurate continuous monitoring in time and space for all hazardous landslides in a region, integrating these two systems while 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 center via wireless communication infrastructure and are processed in real time with short baselines in a kinematic mode. Recent experiments with GNSS suggest that ~2–4 mm horizontal and 4–8 mm vertical accuracy is possible at 1 Hz [63], [65]. 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], [65], [66]. Thus, the data should be transmitted back to the data center in real time and processed automatically. However, these in situ observations are not only useful for identifying the onset of tertiary creep; they can also 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], [56]. The mechanical models introduced in Stage 1 can be refined and calibrated by monitoring environmental factors and geological–geotechnical parameters such as pore pressure in soils (Table 1) [13], [67].
- *Step 4*: The ultimate objective of an EWS is to communicate through timely and useful warnings to the people in local communities who are exposed to a landslide hazard. Thus, engagement and communication with local communities should be a key feature of an effective landslide EWS. A large body of work on the social science of early warning already exists that provides useful insights, explanations for unexpected EWS failure and 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 [99]. 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, which limits the warning's ability 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 a lack of community buy-in and to poor engagement and operation results. Both academics and practitioners widely agree that EWSs are

TABLE 1. COMMONLY USED TECHNOLOGIES FOR LANDSLIDE MONITORING.

OBSERVATION TYPES	TECHNOLOGY	PRECISION	EXAMPLES
Displacement	Spaceborne InSAR	mm-cm [68]	[21], [25], [69], [70]
	Airborne InSAR	mm-cm [71]	[71], [72]
	Ground-based InSAR	mm-cm [73]	[66], [73], [74]
	UAV photogrammetry	~6cm [75]	[75], [76]
	GNSS	mm-cm [77]	[70], [84]
	Optical image matching	cm-m [78]	[78], [79]
	Crackmeter	mm-cm [80]	[81], [82]
	Extensometer	~3 mm [84]	[84], [85]
	In-place inclinometer	~8 mm [68]	[10], [86], [87]
	Tiltmeter	~0.1° [13]	[13], [82], [90]
	Total station	~±1 ppm [80]	[80], [88]
	Terrestrial Lidar	~0.2–0.5 m [83]	[83], [89]
	Shape acceleration array	±1.5 mm/ 30 m [90]	[13], [83], [90]
	Active waveguides	mm [91]	[13], [91]
	Seismometer	–	[92], [93]
Pore pressure	Piezometer	–	[13], [94], [95]
	TDR	–	[96], [97]
	Tensiometer (soil hygrometer)	–	[57], [97]
Precipitation	Rain gauge	–	[82], [98]

TDR: time domain reflectometry.

most effective when they are built in collaboration with those at risk, rather than imposed from outside.

OUTLOOK

There are three big questions for landslide forecasting and early warning to address:

Big question 1: Where are potential landslides? We are entering an exciting new era of EO data. Recent advances in satellite radar and in situ sensors (e.g., GNSS) have allowed us to collect high-quality measurements to quantify Earth's surface displacements and then address this question over entire mountain ranges, at space and time scales that are finer than ever before and at a relatively low cost. In an EO-based landslide EWS, the relatively short repeat cycles of current SAR missions still represent InSAR's limitation to detect potential landslides. However, the Geosynchronous Continental Land-Atmosphere Sensing System, one of three ideas for *Earth Explorer* accepted by ESA's Program Board for EO 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 [100], 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 [101], [102], where statistical techniques are employed to learn specific and complex tasks from given data. Recent studies report that machine learning can identify signals associated with geohazards from large data sets [103], which suggests that integrating machine learning with EO technologies could be one encouraging solution to automatic landslide detection. To address this first big question, there is an urgent need to answer the following additional questions: 1) At what percentage are the detected landslides true positives? 2) What is the percentage of the missing landslides (false negatives)? 3) In which scenarios are 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. Predicting when landslides will occur remains a grand challenge. There have been a limited number of successful case studies, including those for the 2017 Heifangtai landslide. In these cases, deformation anomalies (acceleration or a change in pattern) were observed prior to failure and have been recognized 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 in addressing this problem.

Big question 3: What is the best way to reduce landslide disaster risk? The experience of the cooperation between experts and local communities in the Dangchuan 4# landslide has improved our understanding of best practices for community-based disaster risk management. How to best coproduce a site-specific warning system with both local experts and members of at-risk communities to reduce landslide disaster risk remains an open challenge for the entire community.

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Keren Dai, Zhenhong Li, Bürgmann, David G. Milledge, and Roberto Tomás contributed to writing this article. Dai, Li, Zheng Wang, Tengteng Qu, Chaoying Zhao, and Jingnan Liu carried out the SAR data processing and related experiments and analysis. Qiang Xu, Xuanmei Fan, and Tomás contributed to the geological analysis and result interpretation. Chaoyang He and Xu collected and analyzed the crackmeter data for landslide warning in the Heifangtai loess landslide. Li, Xu, Dai, and Jianbing Peng developed the concept of the Earth observation-based landslide EWS proposed in this article with contributions from Milledge, Bürgmann, Qin Zhang, Li, and Liu. All relevant data are available from the authors upon reasonable request.

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