Landslides (2020) 17:2409–2419
 DOI 10.1007/s10346-020-01402-w
 Received: 26 November 2019
 Accepted: 20 March 2020
 Published online: 3 April 2020
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Zongji Yang · Liyong Wang · Jianping Qiao · Taro Uchimura · Lin Wang

Application and verification of a multivariate real-time early warning method for rainfall-induced landslides: implication for evolution of landslide-generated debris flows

Abstract Rainfall-induced landslides are a frequent and often catastrophic geological disaster, and the development of accurate early warning systems for such events is a primary challenge in the field of risk reduction. Understanding of the physical mechanisms of rainfall-induced landslides is key for early warning and prediction. In this study, a real-time multivariate early warning method based on hydro-mechanical analysis and a long-term sequence of real-time monitoring data was proposed and verified by applying the method to predict successive debris flow events that occurred in 2017 and 2018 in Yindongzi Gully, which is in Wenchuan earthquake region, China. Specifically, long-term sequence slope stability analysis of the in situ datasets for the landslide deposit as a benchmark was conducted, and a multivariate indicator early warning method that included the rainfall intensity-probability (I - P), saturation (S_i), and inclination (I_r) was then proposed. The measurements and analysis in the two early warning scenarios not only verified the reliability and practicality of the multivariate early warning method but also revealed the evolution processes and mechanism of the landslide-generated debris flow in response to rainfall. Thus, these findings provide a new strategy and guideline for accurately producing early warnings of rainfall-induced landslides.

Keywords Early warning · Multivariate · Rainfall-induced landslide · Debris flows

Introduction

Rainfall-induced landslides and the subsequent debris flows pose a great threat to the safety of people and their properties in mountainous areas and are one of the most common types of geological disasters worldwide (Iverson 2000; Hong et al. 2006). After the Wenchuan earthquake (7.9 M_w) struck China on May 12, 2008, the widespread earthquake landslide deposits posed a high disaster risk to the earthquake-stricken regions. A significant outbreak of sudden landslides triggered by heavy rainfall and their frequent conversion into debris flows greatly affected the restoration and reconstruction of these disaster-stricken areas (Guzzetti et al. 2008; Feng et al. 2016). Many studies have demonstrated that landslide early warning system (LEWS) is among the most effective non-structural mitigation measures (Damiano et al. 2012; Thiebes et al. 2014; Pumo et al. 2016; Uhlemann et al. 2016). The rainfall intensity-duration model (I - D) is the main rainfall-induced landslide early warning model currently in use, and it directly applies real-time rainfall data to forecasting landslide initiations. A reliable rainfall threshold is crucial for establishing an accurate early warning system for landslide disasters. Numerous studies have been conducted worldwide utilizing rainfall intensity and duration data to correlate with the slope failures in

order to determine the critical rainfall and rainfall thresholds for the early warning of rainfall-induced landslides (Caine 1980; Aleotti 2004; Zhang et al. 2005; Guo et al. 2016). However, there is a lack of long-term and accurate landslide event statistics and corresponding rainfall data. As such, it is difficult to effectively analyze the correlation between an independent landslide event and corresponding rainfall event (Shao et al. 2017). Furthermore, the rainfall threshold obtained from statistical data often ignores the triggering mechanisms of the landslide and the influences of physical rainfall infiltration process on the landslide stability, causing early warning methods with a single rainfall threshold to be unreliable (Sidle and Bogaard 2016; Chae et al. 2017). To resolve the deficiencies of single rainfall threshold methods, numerous studies using multiple early warning indicators, such as rainfall, slope displacement, and their physical properties, have been conducted for landslide monitoring and early warning worldwide (He 2009; Xu and Zeng 2009; Intrieri et al. 2012; Palis et al. 2016; Ma et al. 2016; Fan et al. 2016; He et al. 2017). The correlation and contribution of rainfall infiltration to the dynamic evolution of slopes and proposed rainfall threshold values were established in recent years, and the coupling of multivariate indicators in rainfall-induced landslide early warning systems has gradually become more common (Chae et al. 2017; Yang et al. 2019). However, the construction of a multivariate LEWS for rainfall-induced landslides should consider the physical mechanisms of landslide initiation and be based on a unified scale. Owing to the limitations of measured information, there is still insufficient comprehensive understanding of the evolutionary process of rainfall-induced landslides and its relationship with hydro-mechanical parameters. This is likely the reason for the limited successful early warning cases that have combined long-term real-time monitoring data and multiple LEWS.

Understanding the hydro-mechanical coupling process and mechanism of rainfall-induced landslides is key for accurate early warnings (Godt et al. 2009; Baum et al. 2010; Song et al. 2016; Yang et al. 2017a, b). Therefore, combining the on-site monitoring big data relating to rainfall-induced landslides and the hydro-mechanical coupling mechanism is essential for developing a more accurate rainfall-induced LEWS (Berti and Simoni 2010; Ponziani et al. 2012; Greco et al. 2013). In this study, a typical post-earthquake landslide in the Wenchuan earthquake-stricken area is selected for real-time monitoring. By combining long-term real-time observed data with hydro-mechanical coupling analysis and landslide stability calculation and calibration, we set the classification criteria for landslide stability states as a uniform scale and re-establish multiple indicators. The multivariate LEWS includes a rainfall-induced landslide probability (I - P) model, the saturation indicator (S_i), and surface inclination (I_r), as well as the

benchmark of real-time slope stability calculated according to the observed data. Data measured over 5 years were used to continuously verify and revise the early warning system to improve its accuracy and reliability. By verifying the method using two successful disaster early warning scenarios, it was demonstrated that the proposed method for developing the multivariate system by coupling hydro-mechanical analysis with long-term measured data can provide a framework for efficient and accurate early warnings of rainfall-induced landslides.

Methods

Based on previous studies by the authors (Yang et al. 2017a; Shao et al. 2018; Cai et al. 2019; Yang, et al. 2019), and through on-site monitoring of the landslide in Yindongzi Gully (Yang et al. 2017b), the hydro-mechanical parameters based on 5 years of monitoring were calculated and analyzed to construct a multivariate early warning system for rainfall-induced landslides. This method was based on the unsaturated hydro-mechanical coupling analysis of the measured data.

On-site monitoring

The real-time monitoring system used in this study is presented in Fig. 1a and can monitor the process, deformation characteristics, and related hydraulic parameters of landslides, thereby providing data for the analysis of landslide processes and the development of early warning systems. The self-developed micro-electro-mechanical systems (MEMS)-based wireless real-time monitoring system can collect parameters such as precipitation, surface displacement, and soil moisture data in real time (Yang et al. 2017b). The data collected in real time are wirelessly sent to the data logger, which is convenient for the remote analysis and management of data from various monitoring sites. The Yindongzi landslide triggered by the Wenchuan earthquake is located in the Yindongzi Gully of the Baisha River in Dujiangyan County, Sichuan Province, China. The volume of the landslide is approximately $50 \times 10^4 \text{ m}^3$, and the length and area of the Yindongzi Gully is about 2.5 km and 2 km^2 , respectively (Fig. 1). The surface layers in the landslide area are composed of Proterozoic medium-grained biotite potassium feldspar granite ($\text{Pt}_2\text{K}\gamma$) and medium-fine-grained potassium feldspar granite ($\text{Pt}_2\gamma$). The Yindongzi landslide is a post-earthquake landslide, and its deposits remobilize and trough under rainfall-triggering conditions and may evolve into debris flows. According to the field investigation, large-scale landslides and debris flows occurred in the Yindongzi Gully on August 13, 2009, July 17, 2010, July 9, 2013, and August 28, 2017, under strong rainfall conditions after the Wenchuan earthquake.

Multivariate early warning system

We established the thresholds for various parameters and the stability of the landslide deposits using hydro-mechanical coupling analysis techniques. Based on the 5 years of real-time monitoring data and corresponding slope stability analysis, the thresholds for various parameters can be established by correlating the safety factors with these indicators (Fig. 2). The multivariate LEWS for rainfall-induced landslides was then statistically re-established and benchmarked by slope stability stages (Fig. S1). The multivariate LEWS includes *I-P* (Yang et al. 2019), S_i , and I_r

indicators. Using the long-term measured field data and real-time calculations of slope stability based on the hydro-mechanical behavior, we continuously verified and revised the LEWS in order to improve the accuracy of early warnings.

The safety factor of the hydro-mechanical infinite-slope stability analysis for unsaturated slopes at depth Z below the ground surface at time t is given by the following equation (Godt et al. 2009; Baum et al. 2010; Yang et al. 2019):

$$F_s(Z, t) = \frac{\tan \phi'}{\tan \beta} + \frac{c' - \sigma^s(Z, t) \tan \phi'}{(\gamma_d + \gamma_w \cdot \theta(Z, t)) Z \sin \beta \cos \beta} \quad (1)$$

where ϕ' is the angle of internal friction for effective stress, c' is the soil cohesion for effective stress, γ_d is the dry soil unit weight, γ_w is the water unit weight, β is the slope angle, θ is the measured volumetric water content, Z is the depth below the ground surface, and σ^s is the suction stress calculated by $\sigma^s = S_e \times \psi$ (Lu and Godt 2013), where ψ is the matric suction, and S_e is the effective saturation.

The *I-P* model is developed based on the ratio of landslide to rainfall events recorded within each rainfall amount category, and the threshold is defined as the corresponding minimum amount of rainfall in each category that would trigger a landslide (Supplementary material). Considering the great heterogeneity of the landslide deposit, a unified standard for the early warning practice could not be established by using the original soil water content index (Yang et al. 2017b, 2019). Hence, in this study the saturation index S_i was updated as a uniform parameter for real-time soil moisture and is calculated as follows:

$$S_i = \frac{\theta - \theta_r}{\theta_p - \theta_r} \quad (2)$$

where θ_r is the residual water content and θ_p is defined as the peak value of the monitored historical volumetric water content. As a result, the value of S_i may exceed 1 and should be adapted to a new θ_p after the historical peak value was exceeded in practice.

Furthermore, based on the classification criteria for landslide stability states, the early warning criteria were divided into the following warning levels: green (no warning), yellow (caution warning), orange (preparative warning), and red (evacuation warning). Each warning level also corresponds to a different slope stability stage, i.e., stable, moderately stable, quasi-stable, and unstable, respectively (Table 1). During the application of the early warning system, two among the three observed indicators (*I-P*, S_i , and I_r) reaching a certain early warning stage were set as the standard for the release of the corresponding early warning. A certain level is set when at least two indicators reach their corresponding early warning levels. The warning level for landslides will be further upgraded when at least two indicators reach a higher warning level.

Successful early warning scenarios

The multivariate LEWS described in the “Multivariate early warning system” section was applied and verified, and successful early warnings were issued for two events occurring in Yindongzi Gully

Fig. 1 a Scale of the natural landslide in Yindongzi Gully, Dujiangyan County, Chengdu, Sichuan Province, China, and the distribution of monitoring sites. b Shallow landslides induced by rainfall in Yindongzi Gully on August 28, 2017, which then evolved into a debris flow. c Shallow landslides induced by rainfall that evolved into a debris flow in Yindongzi Gully on June 26, 2018

on August 28, 2017, and June 26, 2018, respectively. During these events, 56 families from the village at the entrance of the ravine were urgently evacuated after the early warning was issued, and the warnings generally remained for 24 h before the local residents were allowed to return to their homes. This effectively compensated for the original manual observation and preparedness early warning system involving local residents in China. At the same time, the real-time observed data and slope stability analysis revealed the initiation and evolution process of the post-earthquake landslide and subsequent debris flows.

Event on August 28, 2017

The study area experienced up to 140 mm of rainfall within 6 h duration, and six shallow landslides were triggered and then evolved into a moderate-volume debris flow with a total deposit of $7.8 \times 10^4 \text{ m}^3$ in Yindongzi Gully. The real-time monitoring and early warning system issued an orange warning level at approximately 03:30 on August 28, and the debris flow occurred at approximately 05:40. Therefore, the early warning was issued 2 h

prior to the disaster. A total of 56 families from the village at the ravine entrance were urgently evacuated to a safety zone during the early warning period; thus, casualties were avoided. The timing of the debris flows was determined by the local observations, while the timing of the landslides was assumed based on the monitored inclination changes.

As shown in Fig. 3, at 22:00 on August 27, the rainfall intensity was 1.8 mm h^{-1} , reaching a maximum of 51.2 mm h^{-1} at 04:00 on August 28. The rainfall *I-P* model revealed the following landslide probability (*I-P*) evolution in response to 24 h of cumulative rainfall (R_{24}): R_{24} increased to 45 mm at approximately 01:45 on August 28, and the *I-P* was 40%; thus, the warning level was yellow at that time. Similarly, R_{24} reached 70.4 mm and *I-P* reached 60% by 2:30. By 03:30, R_{24} reached 110 mm and the *I-P* was 80%, which correspond to the orange and red warning levels of the *I-P* indicator, respectively.

The saturation indicator (S_i) based on soil moisture of the landslide deposits measured in real-time changed significantly due to rainfall infiltration (Fig. 4). When the rainfall intensity suddenly increased from 4.6 to 23.1 mm h^{-1} , the volumetric water

Fig. 2 a Daily cumulated rainfall was recorded by the rain gauge from May 21, 2014, to March 11, 2019. b Variations in saturation based on the volumetric water content recorded by soil moisture sensors 9 and 10 at the monitored landslide area from May 21, 2014, to March 11, 2019. c Variations in the surface tilting rate recorded by the tilt sensors from May 21, 2014, to March 11, 2019. d Modeled safety factors based on the volumetric water content recorded by soil moisture sensors 9 and 10 at the monitored landslide area from May 21, 2014, to March 11, 2019

content of the landslide deposits increased by 2.8–12.9%, and S_i increased to 0.6 at 01:30 on August 28, reaching the yellow warning level. S_i exceeded 0.8 by 02:40 and eventually exceeded 1 by 05:00, indicating that the soil moisture content exceeded the historical extreme value, meeting the orange and red warning levels, respectively.

The MEMS tilt sensors began to observe inclination at 01:30, and the maximum cumulative variation in the surface inclinations

reached 9.7°, corresponding to the yellow warning level. At 02:40, the tilt sensor observed significant acceleration. The x -axis tilt angle of tilt sensors 6, 7, and 8 changed by 23.74°, 6.93°, and 12.81°, respectively, and the y -axis of the sensors also changed with a maximum of 12.81° for sensor 8 (Fig. 5). Thus, the red warning level was reached.

An early warning level was set when two indicators reached that level. Therefore, a yellow warning was issued at 01:45, when all

Table 1 Multi-parameter early warning system

Warning level	Stability stage	Safety factor	Inclination rate ($^{\circ}$ 10 min $^{-1}$)	Saturation indicator	$R_{24}/I-P$ (mm/–)
Green (no warning)	Stable	$F_s \geq 1.15$	$I_r < 0.1$	$S_i < 0.6$	$R_{24} < 45$ (40%)
Yellow (cautionary warning)	Moderately stable	$1.05 \leq F_s < 1.15$	$0.1 \leq I_r < 2$	$0.6 \leq S_i < 0.8$	$45 \leq R_{24} < 70$ (60%)
Orange (preparative warning)	Quasi-stable	$1.00 \leq F_s < 1.05$	$2 \leq I_r < 4$	$0.8 \leq S_i < 1$	$70 \leq R_{24} < 110$ (80%)
Red (evacuation warning)	Unstable	$F_s < 1.00$	$I_r \geq 4$	$S_i \geq 1$	$R_{24} \geq 110$ (> 80%)

Fig. 3 Early warning development process based on the rainfall intensity-probability (I - P) model threshold from 0:00 on August 27, 2017, to 16:00 on August 28, 2017. DF indicates the occurrence of the debris flow

three indicators had reached the yellow warning level; i.e., S_i exceeded 0.6, I - P reached 40%, and inclination was observed. By 02:30, I - P had increased further to 60%, and S_i exceeded 0.8 by 02:40. Furthermore, a strong change was observed by the surface inclinometer; therefore, the warning level was upgraded to orange at 02:40. By 3:30, the red warning level was reached, with I - P further increasing to 80%, and the inclination change reaching its maximum value of 28.3° , which indicated that the landslide mass had entered the accelerative trend phase. Therefore, the early warning level was upgraded to red before the debris flow occurred at 05:40. That is, the yellow warning was released 4 h in advance of the landslide-generated debris flow, the orange warning was

released 3 h in advance, and the red warning was released 2 h in advance.

The safety factor of the landslide during the event varied from 0.911 to 1.102, reflecting significant variations and slope instability with increasing rainfall, as shown in Fig. 5. The safety factors at measuring sites 6, 7, and 8 decreased to a critical value of approximately 1.0 at 00:50 and subsequently fell below 1.0 at 02:40 (F_s values of 0.99, 0.93, and 0.99, respectively), and the debris flow was observed at 05:40. The calculated safety factor indicated the time of instability, and the successive slope failure was consistent with the times at which variations and accelerations in inclination were recorded by the tilt sensors (Fig. 5).

Fig. 4 Variations in soil water content and saturation in the monitored landslide from 0:00 on August 27, 2017, to 16:00 on August 28, 2017. DF indicates the occurrence of a debris flow

Fig. 5 Changes in the slope stability, daily cumulated rainfall, and surface inclinations from 0:00 on August 27, 2017, to 16:00 on August 28, 2017. The surface inclination changes were recorded by the tilt sensors 06, 07, 08, 11, and 12 at the monitored landslide. DF indicates the occurrence of a debris flow

Event on June 26, 2018

The monitored landslide experienced heavy rainfall and exhibited several shallow sliding behaviors, which subsequently evolved into a debris flow at 02:30 on June 26, 2018 (Fig. 6). A landslide-generated debris flow with a deposit of $5.0 \times 10^4 \text{ m}^3$ was initiated after the rainstorm on June 26, 2018 (see the [supplementary material](#)). The multivariate LEWS measured the parameters crucial for predicting the instability of the landslide body and successfully issued an early warning for the disaster. A red warning was successfully issued at approximately 00:30 on June 26, and all 56 families were evacuated 2 h in advance of the disaster event.

As shown in Fig. 6, the landslide began to experience rainfall at 14:00 on June 25. The maximum rainfall intensity and R_{24} were 46 mm h^{-1} and 224.4 mm, respectively. R_{24} reached 45 mm at 15:30 on June 25, and the $I-P$ was 40%; thus, the yellow warning level was reached. At approximately 21:00, R_{24} reached 70 mm and $I-P$ updated to 60%; thus, the orange warning level was reached. At 00:30 on June 26, R_{24} reached 110 mm, and the $I-P$ was 80%, indicating that the red warning level was reached. The $I-P$ then suddenly increased to its maximum level of 91% at 02:00 and the debris flow occurred 30 min later.

The volumetric water content varied greatly between the different monitoring sites (Fig. 7), but, overall, it increased with the infiltration of rainwater. Under precipitation, S_i increased with increases in the soil moisture content. At 15:00 on June 25, at each

monitoring site, S_i increased to 0.6, which is a yellow warning value. At 21:00, S_i exceeded the orange warning level of 0.8 at some sites. On June 26, at approximately 02:10, S_i exceeded 1.0, thus reaching the red warning level.

The real-time acquisition and variation of inclination are shown in Fig. 8. Before 18:00 on June 25, the inclinometer was recording a cumulative inclination of 2.1° and a maximum I_r of 1.03° per 10 min, thus reaching the yellow warning level. At 18:00, acceleration was observed, and the maximum I_r was 2.27° per 10 min, indicating that the orange warning level had been exceeded. At 21:00, the inclinometer observed a strong change, with the maximum I_r reaching 4.01° per 10 min, thus demonstrating that the indicator had reached a red warning level and an accelerative trend (Fig. 8).

According to the criteria of the multivariate LEWS, all three indicators, i.e., the $I-P$, S_i , and I_r , reached the yellow warning level at approximately 15:00 on June 25. At 21:00, all three indicators reached the orange early warning level, and the red warning was issued at 00:30 on June 26 ($I-P$ and I_r had reached the red warning level). At 02:30, a debris flow occurred in Yindongzi Gully. The yellow warning was released 11 h in advance of the debris flow, the orange warning was released 5 h in advance, and the red warning was released 2 h in advance.

The variations in the safety factors during this period are shown in Fig. 8. The safety factors of the landslide deposits decreased as

Fig. 6 Early warning model based on the rainfall intensity-probability (I - P) model threshold from 0:00 on June 25, 2018, to 23:00 on June 27, 2018. DF indicates the occurrence of a debris flow

the soil moisture increased during rainfall. At 21:00 on June 25, the safety factors of each measuring point decreased to close to the critical value of 1.0, indicating that the landslide began to destabilize. By 02:00 on June 26, all safety factors were below 1.0, thus indicating large-scale slope instability. The measured inclination value was consistent with the simulated instability time (Fig. 8).

In both events, the reliability and practicality of the proposed multivariate LEWS were verified, and the measured data and slope stability analysis further revealed the evolution of the stability of the rainfall-induced landslide and its transformation into a debris flow. Furthermore, the field investigation demonstrated that shallow landslides occurred on the steep slopes at the lower part of the

Fig. 7 Measured soil water content and saturation changes in the Yindongzi landslide from 0:00 on June 25, 2018, to 23:00 on June 27, 2018. DF indicates the occurrence of a debris flow

Fig. 8 Changes in the slope stability, daily accumulated rainfall, and surface inclinations in the monitored landslide from 0:00 on June 25, 2018, to 23:00 on June 27, 2018. The surface inclination changes were recorded by tilt sensor 7 at the monitored landslide. DF indicates the occurrence of a debris flow

corresponding monitoring sites during both events (Figs. S2 and S3).

Discussion

This study emphasizes the importance of long-term monitoring data analysis for establishing early warning criteria. The durability and sustainability of the monitoring system are essential for long-term data acquisition (Godt et al. 2009; Song et al. 2016; Chae et al. 2017; Yang et al. 2017b). This study established the criteria and calibrated the effectiveness of a multivariate LEWS for rainfall-induced landslides based on 5 years of long-term monitoring data. However, the long-term functionality and maintenance of the monitoring system remains challenging, particularly for the long-term monitoring of matric suction. Monitoring devices inevitably broke and had to be replaced, which increases the time required for the long-term monitoring of landslides and long-term monitoring is particularly problematic without continuous support and a sufficient budget. Moreover, the maintenance-free measurement of matric suction of unsaturated coarse soil is still difficult and must be resolved in the future. To facilitate long-term monitoring, periodic maintenance was conducted every 3 months, and all devices in the monitoring system were completely replaced and upgraded on December 1, 2016. Additionally, timely information transmission and publication are essential for early warning of landslides. Therefore, the temporal delay of a real-time early warning system should be discussed. The sampling frequency of the monitored parameters during the rainy season is 10 min, and the latency of the system is approximately 40 s, which is mainly

attributed to the 3-s time interval for each sensor transmitting a signal to the data logger on the same radio band. The subsequent data transmission by GPRS (general packet radio service) networks, data analysis, and the warning issued by SMS (short message service) can technically take approximately 5 s throughout the procedure. Therefore, the proposed system is qualified for the real-time early warning of rainfall-induced landslides.

Owing to the uncertainties and heterogeneous nature of rainfall-induced landslides, successful early warning is always hindered by false alarms (Martelloni et al. 2012; Intrieri et al. 2012). Currently, successful warnings only account for 9.8% of the forecasts in China (Liu et al. 2006; Tang et al. 2012) based on critical rainfall thresholds for the early warning of rainfall-induced landslides (Caine 1980; Aleotti 2004; Zhang et al. 2005). To evaluate the performance of LEWS, a review of statistics of the times at which the indicators $I-P$, S_i , and I_r reached the proposed multivariate early warning criteria during the 5-year period was carried out (Table 2). According to the results, 14 early warnings in total were reached, including the two red warnings (evacuation warnings) observed and discussed above, which were verified by two debris flows. Three orange warnings and nine yellow warnings were reached without any debris flows. However, designating these warnings as false alarms is debatable, since no actions are required after preparative warnings (orange) and cautionary warnings (yellow) are issued. The statistical analysis indicates the advantage of the proposed multivariate criteria, even though the S_i indicator reached its warning level threshold 113 times, of which only 14 early warnings

Table 2 Statistics of early warnings and indicators reached the multivariate criteria of LEWS during the 5-year period

Date	Cumulated rainfall (mm)	$I-P$ Probability	Warning level	Saturation	S_t Warning level	Tilting rate ($^{\circ}$ 10 min $^{-1}$)	Warning level	Early warning
2014/06/04	48	0.439	Yellow warning	0.624	Yellow warning	0	No warning	Yellow warning
2014/07/10	93.4	0.725	Orange warning	0.877	Orange warning	0	No warning	Orange warning
2014/07/19	53.4	0.485	Yellow warning	0.699	Yellow warning	0	No warning	Yellow warning
2015/07/08	48.4	0.443	Yellow warning	0.616	Yellow warning	0	No warning	Yellow warning
2016/7/5	74.8	0.629	Orange warning	0.639	Yellow warning	0	No warning	Yellow warning
2016/07/14	46	0.421	Yellow warning	0.637	Yellow warning	0	No warning	Yellow warning
2016/07/22	51.4	0.469	Yellow warning	0.839	Orange warning	0	No warning	Yellow warning
2017/8/18	81.3	0.665	Orange warning	0.661	Yellow warning	0	No warning	Yellow warning
2017/8/28	157.8	0.949	Red warning	1	Red warning	23.7	Red warning	Red warning
2018/6/26	152.4	0.934	Red warning	1	Red warning	4.0	Red warning	Red warning
2018/7/9	81.2	0.665	Orange warning	0.875	Orange warning	0	No warning	Orange warning
2018/7/16	59.8	0.533	Yellow warning	0.751	Yellow warning	0	No warning	Yellow warning
2018/7/19	102.6	0.765	Orange warning	0.871	Orange warning	0	No warning	Orange warning
2018/9/24	65.5	0.572	Yellow warning	0.794	Yellow warning	0	No warning	Yellow warning

were determined when other indicators also reached their early warning threshold. Statistical analysis also shows that despite the two red warning events discussed above, in which all three indicators responded, only two indicators (I - P and S_i) responded and reached their respective warning levels in other early warnings, which indicates that the inclination indicator I_r may be essential for evacuation warnings and emergency actions. However, the importance of the S_i and I - P indicator in LEWS was emphasized here; the former is highly correlated with the hydro-mechanical behavior of unsaturated soil layers, while the latter gives both the threshold and degree of hazard for LEWS; i.e., the uncertainty is treated as the probability proposed by the I - P method. Rather than predicting the initiation of disasters, this method is focused on the early warning of the risk or hazards of landslides, by emphasizing the probability of landslides occurring at different warning levels. Specifically, even for the red warning level (80% probability of a landslide occurring) proposed in this study, there is still a 20% uncertainty, which can be inferred from a new viewpoint on “false alarms.” Recent studies demonstrated that evaluating the performance of an early warning system could greatly benefit from rigorous statistical analysis, such as compiling a contingency matrix (Sarlin 2013; Holopainen and Sarlin 2017). These methods require a sufficient number of samples to be statistically robust and will be of great value in future studies with increasing numbers of samples.

Conclusions

The unsaturated hydro-mechanical coupling theory and infiltration characteristics provide a basis for understanding the mechanism of rainfall-induced landslides, and the slope stability stages are important benchmarks for developing a multivariate early warning method for these events. A multivariate LEWS for rainfall-induced landslides based on hydro-mechanical coupling analysis was developed, and the analysis involved the calibration of landslide stability from 5 years of long-term monitoring data. The multivariate LEWS, which includes a rainfall-induced landslide probability (I - P) model, saturation (S_i), and surface inclination (I_r) indicators, was evaluated and applied to the Yindongzi landslide. This approach provides a new strategy for offering more accurate early warnings of rainfall-induced landslides.

Successful real-time early warning and scientifically supported emergency decisions were achieved in two disaster events that occurred in August 2017 and in June 2018. Based on the multivariate LEWS, early warnings were disseminated 3 to 5 h ahead of the landslide-generated debris flows, and technical support was provided for the early warning decisions and evacuation of the 56 families in the village from the hazard zone. Thus, casualties were avoided and the reliability of the multivariate LEWS proposed in this study was verified. Moreover, the measured data also enabled us to identify and reveal the mechanism of the initiation of rainfall-induced landslides and their transformation into debris flows. However, the proposed LEWS is limited to rainfall-induced landslides and subsequent landslide-generated debris flows adjacent to the drainage network and may not be applicable to other types of landslides, such as co-seismic landslides, which require further study.

Funding information This work was financially supported by the National Natural Science Foundation of China (Grant No. 41771021; 41471012) and the Scientific Foundation of the Chinese Academy of Sciences (Grant No.KFZD-SW-425; KFJ-STS-QYZD-172).

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Electronic supplementary material The online version of this article (<https://doi.org/10.1007/s10346-020-01402-w>) contains supplementary material, which is available to authorized users.

Z. Yang (✉) · L. Wang · J. Qiao

Key Laboratory of Mountain Hazards and Surface Process, Institute of Mountain Hazards and Environment,
Chinese Academy of Sciences,
Chengdu, 610041, Sichuan, China
Email: yzj@imde.ac.cn

L. Wang

University of Chinese Academy of Sciences,
Beijing, 100049, China

T. Uchimura

Department of Civil & Environmental Engineering,
Saitama University,
Saitama, 338-8570, Japan

L. Wang

Chuo Kaihatsu Corporation,
Shinjuku-ku, Tokyo, 169-8612, Japan