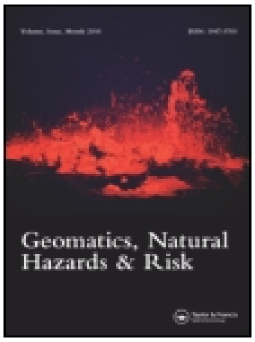

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Landslide failure forecast in near-real-time

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We present a new method to achieve failure forecast of landslide phenomena by considering near-real-time monitoring data. Starting from the inverse velocity theory, we jointly analyse landslide surface displacements on different time windows, and apply straightforward statistical methods to obtain confidence intervals on the forecasted time of failure. Our results can be relevant to support the management of early warning systems during landslide emergency conditions, also when the predefined displacement and/or velocity thresholds are exceeded. In addition, our statistical approach for the definition of confidence interval and forecast reliability can be applied also to different failure forecast methods. We applied for the first time the herein presented approach in near-real-time during the emergency scenario relevant to the reactivation of the La Saxe rockslide, a large mass wasting menacing the population of Courmayeur, northern Italy, and the important European route E25. Our results show how the application of simplified but robust forecast models can be a convenient method to manage and support early warning systems during critical situations.

1. Introduction

Landslides are one of the most frequent among geohazards, causing every year high economic losses and several fatalities (Petley 2012). For this reason, forecasting the occurrence of landslide phenomena in space and time is a major scientific challenge. The approaches used to forecast landslides mainly depend on the spatial scale analysed (regional vs. local), the temporal range of forecast (long- vs. short-term), as well as the triggering factor and the landslide typology considered (Soeters & van Westen 1996; Guzzetti et al. 1999).

By focusing on short-term forecast methods for large, deep-seated slope instabilities, the potential time of failure (ToF) can be estimated by studying the evolution of the landslide deformation over time (i.e., strain rate). This approach can be applied when landslide materials follow the creep mechanism before reaching rupture. In the last decades, different procedures have been proposed to estimate ToF, mainly by considering simplified empirical and/or graphical methods applied to time series of deformation data. The first recognized successful ToF forecast was described by Saito (1965), which used an empirical formula to infer ToF by analysing displacement data acquired in a continuous manner during the secondary creep stage. Instead, Fukuzono (1985) proposed a failure forecast method (FFM) based on the experience performed during large-scale laboratory experiments, which were aimed at observing the kinematic evolution of a landslide induced by rain. This

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approach, known also as the inverse-velocity method, considers the evolution over time of the inverse value of the surface velocity (v) as an indicator of the ToF, by assuming that failure approaches while v^{-1} tends to zero. Following these two examples, in the last decades many other authors dealt with the problem of landslide ToF, and several attempts of prediction on natural and man-made slopes have been presented (Federico et al. 2012).

In general, most of the ToF forecast approaches are based on the availability of direct measurements of surface and/or deep-seated displacements. Large slope instabilities can be nowadays monitored through *in situ* instruments, which provide accurate displacement time series with high temporal sampling. Moreover, when landslide hazard menaces the safety of people and/or infrastructure, surface displacements are usually measured, processed and interpreted in near-real-time, and early warning system (EWS) based on predefined displacement's threshold are eventually implemented to manage potential accelerations phases (Intrieri et al. 2012). However, straightforward procedures to provide reliable and near-real-time objective projections of the short-term landslide's evolution to manage emergency scenarios are yet lacking. Indeed, many of the approaches found in literature for ToF forecast consider a unique time-window for the calculations, and in general are not updated with the same temporal frequency of the data sampling. Moreover, these methods rarely provide an estimate of the reliability of the forecast.

In this work, we present an extension of the inverse-velocity method, to provide landslide ToF forecast based on surface displacement monitoring performed in near-real-time. We first describe the rationale behind the proposed methodology, and then show an example where our procedure has been successfully tested in a real scenario.

2. Method

Nowadays, through *in situ* monitoring techniques, it is possible to provide high resolution and near-real-time time series of surface displacements at specific points (targets and/or benchmarks), with processing times ranging from few minutes to maximum one hour. The time series measurements need usually a pre-processing step, which consist of procedures dedicated to noise filtering, smoothing spikes, and eventually resampling or interpolation by considering uniform time-steps, to avoid missing values and have homogenous sampling over a pre-defined reference time window (W). The choice of W analysed depends on several factors, such as the monitoring sampling rate, the landslide typology, as well as its current status.

By considering the most recent measurement of a near-real-time monitoring network at a point target d_{ti}, displacement values of the time series can be selected according to the time window analysed:

$$D_W = \{d_{ti-W}, \ldots, d_{ti}\} \tag{1}$$

and the inverse value of its first derivative with respect to time computed, obtaining the time series of the inverse velocities I_v as follows:

$$I_v = \frac{1}{\dot{D}_W} \tag{2}$$

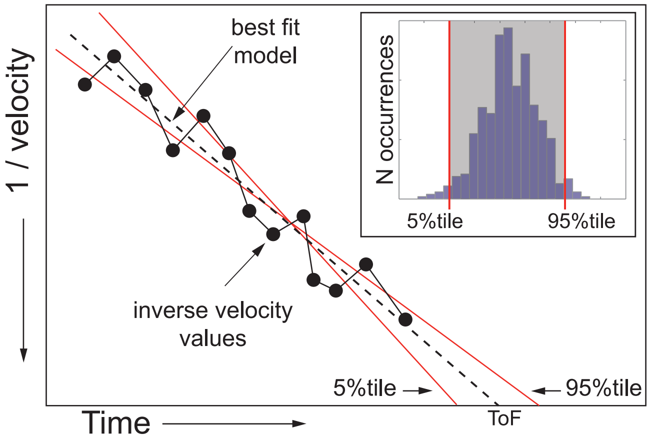

Figure 1. Schematic representation of the method presented in this work to forecast landslide failure. Time series of inverse velocity values (black dots) on a defined time window are fit through regression analysis. Bootstrap procedure is used to define confidence intervals (red lines), considering 5% and 95% tiles among the $N = 1000$ ToF estimations (inset). In addition, among bootstrap population the selected best fit (dashed line) entails minimum RMS of the residual between model and data. To view this figure in colour, please see the online version of the journal.

At this stage, we applied linear regression analysis to model I_v, in order to find the coefficients providing the best fitting of data in the least square sense (e.g., Hamming & Hamming 1973). According to the Fukuzono's inverse-velocity method, the roots of the linear model found with the regression analysis provide an estimate of ToF. The latter procedure is repeated for $N = 1000$ iterations by applying a bootstrap resampling strategy (Efron 1979), which is aimed at deriving robust assessments of errors associated to the estimated regression coefficients. The model vs. data fitness is evaluated by calculating both the Pearson's correlation coefficient (CCORR) and the root mean square (RMS) of the residuals of the difference between data and model. Thus, 5th and 95th percentiles of the bootstrap distribution are used to define of confidence intervals for the ToF estimations, and provide a time range where the failure occurrence is most likely (see figure 1). In addition, the best-fit model of the population generated via bootstrapping is considered as the most representative ToF.

The method above explained was applied in near-real-time for the first time to the surface displacement time series relevant to the La Saxe rockslide, a large slope instability located in northern Italy.

3. La Saxe rockslide: the April 2013 emergency scenario

A large and complex active mass movement (Cruden & Varnes 1996) is located in the north-western part of Aosta Valley, northern Italy (see figure 2). The rockslide, hereafter referred to as La Saxe, involves a large sector of the southern flank of the Mount de la Saxe, located in the Ferret valley just in front of the Mont Blanc massif Italian's side. La Saxe rockslide involves a total instable volume estimated in ca. 8 × 10^6 m^3 (Crosta et al. 2012). The mass wasting menaces both Éntreves and La Palud villages, which are part of the Courmayeur municipality (one of the most prominent touristic areas of the Italian western alps). Moreover, the landslide threats also a

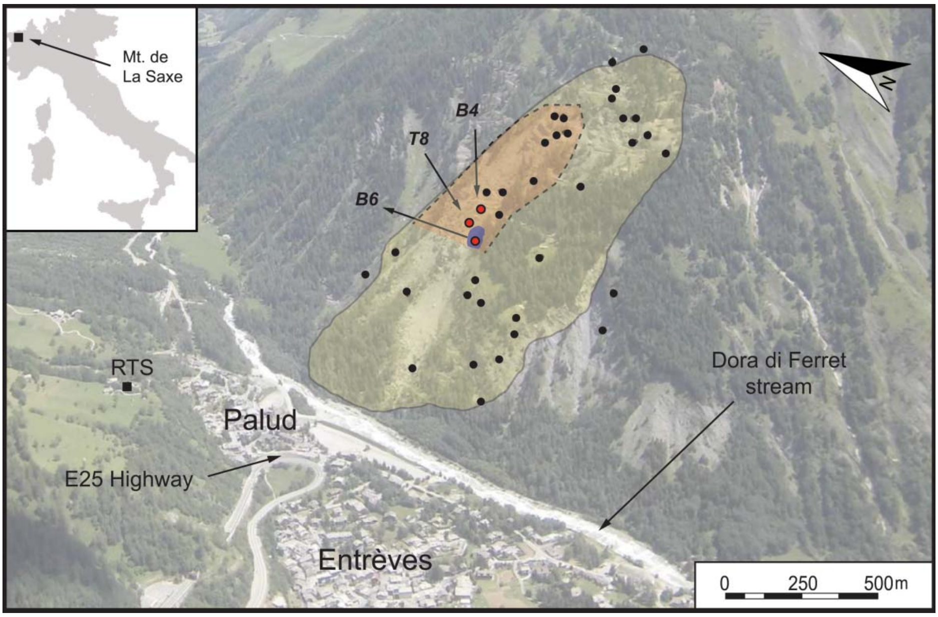

Figure 2. Aerial view of the La Saxe landslide area (N 45.81, E 6.97). Yellow shading is relevant to the whole instable area, while red shading constraints the sector showing larger displacements during the April 2013 emergency. Black dots represent the targets of the RTS monitoring network, while the black square shows the location of the measuring station. Blue shading around the B6 point identifies the area of the sector collapsed on 21 April 2013. Entrèves and Palud belong to the Courmayeur Municipality. To view this figure in colour, please see the online version of the journal.

crucial point of the route E25, an important highway connection crossing Europe from north to south.

Since 2002, *in situ* monitoring has been performed in order to follow the landslide evolution, and an EWS aimed at ensuring safety of the population has been set up starting from 2009. The current monitoring network includes several instruments to monitor surface and subsurface deformation in near-real-time (Crosta et al. 2012); however, the EWS is mainly based on surface velocity thresholds set on measurements performed hourly via a robotized total station (Leica TCA^{TM}, RTS, see location on figure 2). A first pre-alarm is issued when RTS line-of-sight (LOS) mean surface velocities measured in the last 24 hours overcome the 1-mm/hour threshold, while alarm starts for values larger than 2 mm/hour. These thresholds were defined by the Geological Survey of Regione Valle d'Aosta after careful geological and geomorphological considerations, as well as by considering the approach described in (Crosta & Agliardi 2002). When pre-alarm and alarm levels are overcome, specific civil protection actions are performed by authorities, with a pre-defined order and time scheduling. These procedures include interruption of roads traffic, and eventually evacuation of edifices located in areas at higher risk. Since 2013, the RTS measurements and EWS thresholds are processed by considering the ADVICE procedure (Allasia et al. 2013), a recently developed methodology which allows for a rapid and effective data analysis, as well as divulgation and dissemination of the current displacement status to the different users involved in the landslide monitoring activities.

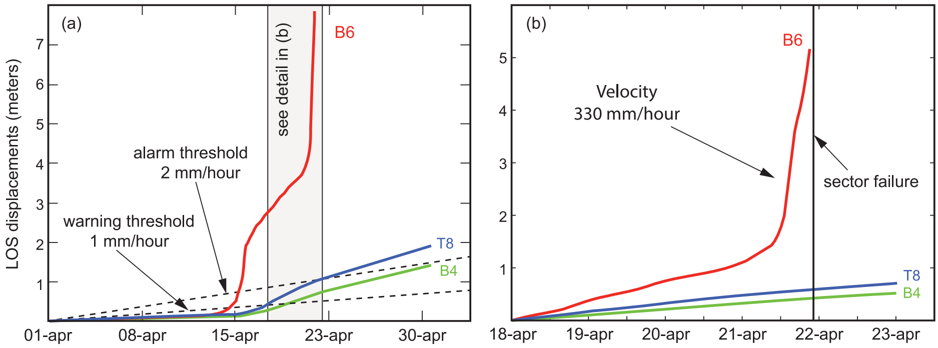

Figure 3. (*a*) Displacement time series relevant to the measurements performed via RTS in April 2013 (see Figure 2 for the locations of targets B4, B6, T8). (*b*) Zoom on the period 18–23 April, when displacements at the target B6 evolved exponentially and finally lead to a sector collapse (see also Section 3 and figure 4 for details).

At the end of March 2013, the surface displacements of the right sector side of La Saxe evolved rapidly. Indeed, since 2009 it has been observed that snow melting during spring seasons causes progressive acceleration of the surface displacements, which can potentially evolve and lead to a partial (or complete) failure of the landslide body (Crosta et al. 2012, and references therein). Pre-alarm and then alarm thresholds were both overcome on April 15 by the B6 optical prism (see figure 3), which was installed to monitor the frontal portion of the most unstable sector of the La Saxe rockslide. Although acceleration was recorded at other neighbour locations, surface velocity values measured at the point B6 were of about one order of magnitude larger, reaching values of about 330 mm/hour on 21 April 2013. Under these circumstances, an emergency status was issued, including the evacuation of several buildings located in the most risky areas.

Figure 4 shows the results of the application of the our experimental FFM procedure (outlined in Section 2) to the time series of the displacements measured by the prism B6 during the April 2013 emergency phase, by focusing on the time period 18–22 April. To test the method and check its performances on a real case scenario, the procedure was activated for the B6 point target and for the others prisms installed in the most active sector of the landslide on 15 April 2013. We considered different time windows, i.e., 24, 48, 72, and 168 hours (one week), respectively; however, due to the rapid evolution of the surface displacements, the most representative time window of interest was $W = 24$ hours. On 19 April in the afternoon, and in the morning of 20 April, the CCORR values between inverse velocity data and the best-fit model were estimated as higher than 50%, thus we started to evaluate the ToF forecast obtained; however, these values could be not yet considered reliable enough to gather robust estimations. Starting from the night between 20 and 21 April, CCORR values started to increase exponentially, reaching the 90%–95% values on 21 April 2013 at Central European Time (CET) 06:00 am, and remaining stable on that values in the period between CET 06:00 and 12:00 am. At this stage, we noticed a high probability of an imminent failure within the following 24 hours on the sector monitored by the B6 prism, which finally collapsed on 21 April 2013 at CET 11:00 pm. The rock-fall was limited to a small portion of the moving sector of the La Saxe rockslide, with an estimated volume in the range of 0.5–1 × 10^3 m^3.

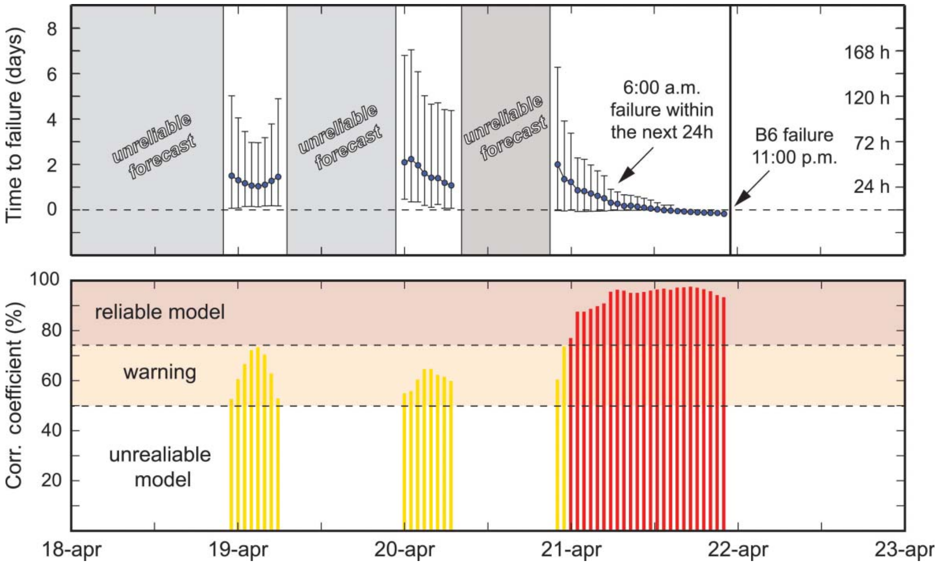

Figure 4. Top: Range of ToF calculated in near-real-time by considering the RTS measurements for the target B6. Bottom: CCORR calculated between the inverse velocity data and the best-fit linear model estimated within the bootstrap procedure. For CCORR values larger than 75% (red bars), the reliability of the regression model increases as well as the ToF forecast. On the contrary, CCORR values smaller than 50% are associated with unreliable failure forecast, and thus the results discarded. Time is expressed as CET.

4. Discussion and conclusions

Recent advances have been performed on real-time and near-real-time displacement monitoring strategies to survey a wide range of geohazards (Allen & Ziv 2011; Ji et al. 2013; Tu et al. 2013; Xiao & He 2013). In general, the principal aim of this kind of monitoring approaches is to accurately understand the temporal evolution of the investigated phenomenon, as well as to eventually provide early warning in the case of recognized risk scenarios. EWS linked to displacement monitoring is usually based on the definition of two or three different states associated with the overcoming of predefined thresholds (Medina-Cetina & Nadim 2008). One of the main limitations of this approach is that, when the last defined threshold is exceeded, the monitoring network and consequently the EWS end their efficacy although this is the most critical stage of the landslide emergency. Indeed, decision-makers have to be fully supported in their activities so that civil protection measures can start timely and be effective in reducing risk exposure. To this aim, "physics-based" numerical models can be used to evaluate slope's stability, as well as to build up and/or update landslide hazard scenarios (Crosta et al. 1999; Thiebes et al. 2013). However, the reliability of such numerical models strictly depends on the accuracy geological and rheological interpretation of the phenomenon, and in several cases, the time needed to achieve updated results is not compatible with the evolution of an emergency situation. On the other hand, in that period decision-makers and civil protection operators would benefit of straightforward tools and robust procedures associated with real-time and/or near-real-time monitoring data providing short-term indications of an imminent failure (Xu et al. 2011).

In this work, we proposed a new approach to cope with continuous monitoring data of displacements in order to obtain ToF in landslide scenarios. We combined the inverse-velocity method and bootstrap statistics in order to provide ToF confidence intervals in near-real-time. In April 2013, the method has been applied for the first time during the emergency relevant to the La Saxe rockslide. The area surrounding the point B6 collapsed on 21 April at 11:00 pm, as indicated with a high reliability level. Our approach allowed to issue a "failure warning" to the responsible authorities about 10 hours prior to the sector failure. By considering nearby point measurements (showing also acceleration in the same time period), CCORR values between data and ToF models were never as larger as evidenced for the B6 point target, thus the forecast were considered not reliable (see figure 5).

We are aware of the constraints, as well as of the several limitations, that have to be carefully considered while using "data-driven" models to infer ToF in landslide scenarios. The use of this method assumes that a continuous increasing of acceleration occurs until failure. Short-term changes in the boundary conditions, as well as variations in the driving forces of slope instability, might cause rapid changes in the acceleration trends, and thus also strongly affect ToF estimations. Also, acceleration decrease observed before failure and not consistent with existing theoretical creep models may correspond to a delay on the failure time predicted with the inverse-velocity methods (Mazzanti et al. 2014).

We also point out that information on the probability of a failure during emergency scenarios is very critical, thus the divulgation of forecast results obtained with automatic procedures has to be limited (Popescu & Zoghi 2005). Our method has been developed to obtain reliable short-term failure forecast at the scale of the single measurement point, and is not intended for medium- and long-term predictions of the ToF for the whole instable slope. On the contrary, we aim at providing a new toolbox to manage EWS in critical situations, whose final interpretation is still provided by experienced users, which are conscious of the limitations of these methods and can take into account not only displacement data, but also additional evidence from other data sources depending on the specific context. By considering the herein presented method, new thresholds based on the ToF short-term forecast might be implemented within an EWS. For example, when the forecast confidence level is sufficiently high (CCORR $>$ 75%), automatic alerts to expert operators can be supplied. This would increase the added-value of an EWS to support the management of an emergency condition also when pre-defined displacement and/or velocity thresholds are exceeded, providing an estimate of the time lasting before a failure updated at each new measurement cycle, for different observation time-windows. In addition, our statistical approach for the definition of confidence interval and forecast reliability can be applied also to other "phenomenological" methods that provide short-term predictions within the tertiary creep phase (Federico et al. 2012). Similar methods can be applied also to indirect strain measurements, as for example real-time monitoring of strain energy retrieved from seismic monitoring at active volcanoes and/or in other geohazard scenarios (Bell et al. 2011; López et al. 2012). The herein presented results seem to confirm the robustness of the methodology; however, further experiments have to be performed, as well as an accurate evaluation of the method's forecast accuracy, in order to verify the potential application in operative civil protection contexts.

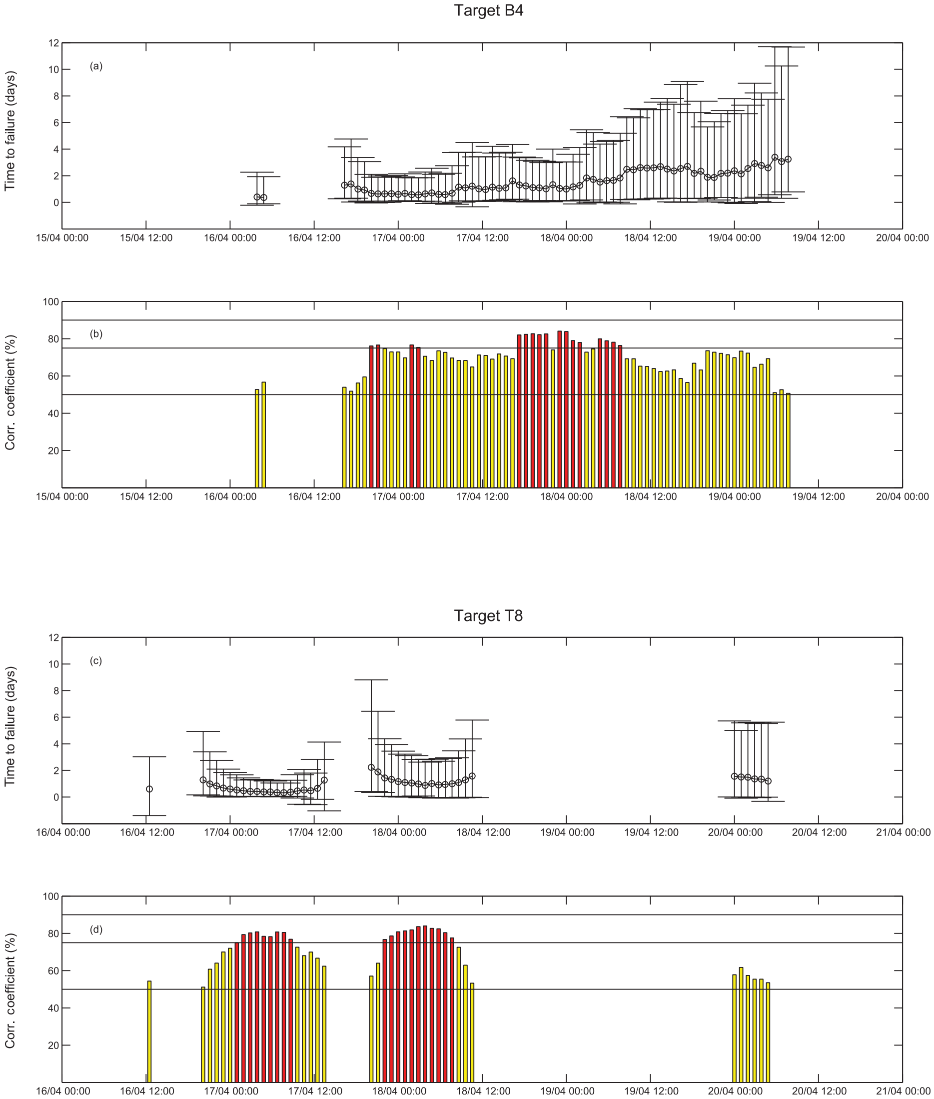

Figure 5. (*a*) Range of ToF calculated in near-real-time by considering the RTS measurements for the target B4 in the period 12–23 April, 2013. (*b*) CCORR calculated between the inverse velocity data and the best-fit linear model estimated within the bootstrap procedure for the target B4. For CCORR values larger than 75% (red bars), the reliability of the regression model increases as well as the ToF forecast. On the contrary, CCORR values smaller than 50% are associated with unreliable failure forecast, and thus the results discarded. (*c* and *d*) Same as (*a*) and (*b*) but for the T8 target in the period 12–23 April 2013. Time is expressed as CET.

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References

Allasia P, Manconi A, Giordan D, Baldo M, Lollino G. 2013. ADVICE: a new approach for near-real-time monitoring of surface displacements in landslide hazard scenarios. Sensors. 13:8285–8302.

Allen RM, Ziv A. 2011. Application of real-time GPS to earthquake early warning. Geophys Res Lett. 38:1–7.

Bell AF, Naylor M, Heap MJ, Main IG. 2011. Forecasting volcanic eruptions and other material failure phenomena: an evaluation of the failure forecast method. Geophys Res Lett. 38:1–5.

Crosta G, Agliardi F. 2002. How to obtain alert velocity thresholds for large rockslides. Phys Chem Earth Parts ABC. 27:1557–1565.

Crosta GB, Cancelli P, Tamburini A, Alberto W, Broccolato M, Castellanza R, Frattini P, Agliardi F, Rivolta C, Leva D. 2012. Chasing a complete understanding of a rapid moving rock slide: the La Saxe landslide. [Internet]. Vienna, Austria: EGU General Assembly 2012; [cited 2013 Oct 16]; 14. p. 11813. Available from: http://adsabs.harvard.edu/abs/2012EGUGA.1411813C

Crosta GB, Imposimato S, Roddeman DG. 1999. Numerical modelling of large landslides stability and runout. Nat Hazards Earth Syst Sci. 3:523–538.

Cruden DM, Varnes DJ. 1996. Landslide types and processes. In: Turner AK, Shuster RL, editors. Landslides investigation and mitigation. Transportation Research Board, Special Report 247. Washington, DC: National Academy Press; p. 36–75.

Efron B. 1979. Bootstrap methods: another look at the jackknife. Ann Stat. 7:1–26.

Federico A, Popescu M, Elia G, Fidelibus C, Internò G, Murianni A. 2012. Prediction of time to slope failure: a general framework. Environ Earth Sci. 66:245–256.

Fukuzono T. 1985. A new method for predicting the failure time of a slope. In: Proceedings of 4th International Conference and Field Workshop on Landslides; Tokyo, Tokyo University Press, p. 145–150.

Guzzetti F, Carrara A, Cardinali M, Reichenbach P. 1999. Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, Central Italy. Geomorphology. 31:181–216.

Hamming RW, Hamming RW. 1973. Numerical methods for scientists and engineers. New York: Dover Publications.

Intrieri E, Gigli G, Mugnai F, Fanti R, Casagli N. 2012. Design and implementation of a landslide early warning system. Eng Geol. 147–148:124–136.

Ji KH, Herring TA, Llenos AL. 2013. Near real-time monitoring of volcanic surface deformation from GPS measurements at Long Valley Caldera, California. Geophys Res Lett. 40:1054–1058.

López C, Blanco MJ, Abella R, Brenes B, Cabrera Rodríguez VM, Casas B, Domínguez Cerdeña I, Felpeto A, de Villalta MF, del Fresno C, et al. 2012. Monitoring the volcanic unrest of El Hierro (Canary Islands) before the onset of the 2011–2012 submarine eruption. Geophys Res Lett. 39:1–7.

Mazzanti P, Bozzano F, Cipriani I, Prestininzi A. 2014. New insights into the temporal prediction of landslides by a terrestrial SAR interferometry monitoring case study. Landslides. 1–14. Available from: http://link.springer.com/article/10.1007%2Fs10346-014-0469-x

Medina-Cetina Z, Nadim F. 2008. Stochastic design of an early warning system. Georisk Assess Manag Risk Eng Syst Geohazards. 2:223–236.

Petley D. 2012. Global patterns of loss of life from landslides. Geology. 40:927–930.

Popescu ME, Zoghi M. 2005. Landslides risk assessment and remediation. In: Taylor C, VanMarke E, editors. Monograph on natural, accidentale and deliberate hazards, Council on Disaster Risk Management, Monograph 1. Reston, VA: ASCE Publications; p. 161–193.

Rose ND, Hungr O. 2007. Forecasting potential rock slope failure in open pit mines using the inverse-velocity method. Int J Rock Mech Min Sci. 44:308–320.

Saito, M. 1965. Forecasting the time of occurrence of a slope failure. In: Proceedings of the 6th International Conference on Soil Mechanics and Foundation Engineering; Toronto, Toronto University Press, p. 537–541.

Soeters R, van Westen, JC. 1996. Landslides: investigation and mitigation. Chapter 8 – slope instability recognition, analysis, and zonation. Transp Res Board Spec Rep. [Internet]. [cited 2013 Dec 2]. Available from: http://trid.trb.org/view.aspx?id=462506

Thiebes B, Bell R, Glade T, Jäger S, Mayer J, Anderson M, Holcombe L. 2013. Integration of a limit-equilibrium model into a landslide early warning system. Landslides. [Internet]. [cited 2013 Jul 17]. Available from: http://link.springer.com/10.1007/s10346-013-0416-2

Tu R, Wang R, Ge M, Walter TR, Ramatschi M, Milkereit C, Bindi D, Dahm T. 2013. Cost-effective monitoring of ground motion related to earthquakes, landslides, or volcanic activity by joint use of a single-frequency GPS and a MEMS accelerometer. Geophys Res Lett. 40:3825–3829.

Xiao R, He X. 2013. Real-time landslide monitoring of Pubugou hydropower resettlement zone using continuous GPS. Nat Hazards. [Internet]. [cited 2013 Jul 26]. Available from: http://link.springer.com/10.1007/s11069-013-0768-x

Xu Q, Yuan Y, Zeng Y, Hack R. 2011. Some new pre-warning criteria for creep slope failure. Sci China Technol Sci. 54:210–220.