Abstract

~~We investigate the~~The validity of ~~use~~ using of landslide failure forecast models by exploiting near-real-time monitoring data is investigated. Starting from the inverse velocity theory, ~~we analyze~~ landslide surface displacements were analyzed on different temporal windows, and ~~apply~~ a straightforward statistical methods was applied to obtain confidence intervals on the estimated time of failure. ~~Here we~~This paper describes the main concepts of ~~our~~ the method, and ~~show~~ gives an example of a real world application to an ~~real~~ emergency scenario at ~~,~~ the La Saxe rockslide, Aosta Valley region, northern Italy. Based on the ~~herein presented~~ case study, ~~we identify~~ operational thresholds were identified based on the reliability of the forecast models, in order to support the management of early warning systems in the most critical phases of the landslide emergency.

Comment [SJ1]: Do you mean validity?

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1 Introduction

The use of analytical and numerical models to determine the occurrence of natural hazards ~~is a major scientific subject. For landslides, this topic~~ has great relevance in the landslide scientific community, but can lead~~s~~ to strong ~~effects~~ biases~~also~~ for the~~on~~ best practices of the ~~for an~~ efficient management of a~~the~~ territory. The approaches used to forecast landslide occurrence mainly depend on the scale of the spatial data~~scale~~ analyzed (regional vs. local), the temporal range of forecast (long- vs. short-term), as well as the triggering factor and the landslide typology considered. A consistent portion of landslide phenomena is triggered by intense and prolonged rainfall events, thus, a large number of studies have focused on the relationship between intensity/duration of the rainfalls, and the consequent activation (or re-activation) of landslides (Wieczorek and Guzzetti, 1999). In general, the main inputs for these analyses are retrieved from rain gauges data and historical landslide catalogues. Models are used to identify and calibrate the intensity/duration thresholds that, if overcome during a rainfall event, may lead to the occurrence of landslides in a specific area. Early Warning Systems (EWS) based on this approach rely on the acquisition of near real time rain gauges data, and consider both the precipitation measured as well as rain forecasts based on meteorological models (Rossi et al., 2012). EWS of this kind are used worldwide and usually applied at regional scales, and can be well considered as a suitable solution in areas where the combination of peculiar climatic conditions, landslide susceptibility, and dense population generate high-risk exposure. By considering large slope instabilities at the scale of a single phenomenon, event forecast attempts are generally approached in a different manner. Large instable slopes include a wide range of landslide mechanisms, from slow slope deformations to rapid and catastrophic rockslides. One of the most critical issues related to these phenomena is their attitude to evolve into gravitational events of impulsive nature, involving a partial or total portion of the instable mass (e.g. rock falls and/or rock avalanches). In this context, surface displacements and/or deep-seated deformation represent often the key information for a proper understanding and interpretation of the phenomenon (Wieczorek and Snyder, 2009). When instable slopes menace population and/or important infrastructures, complex monitoring networks are set up as the base of EWS. In such situations, EWS may rely on thresholds defined on direct measurements of physical parameters describing the landslide evolution over time, i.e. surface and/or sub-surface displacements data (Michoud et al., 2013). If thresholds are exceeded, specific actions are typically predisposed to reduce the consequences of a potential landslide failure on the population and/or exposed infrastructures (Medina-Cetina and Nadim,

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2008). Problems on the identification of these thresholds are well known, and are mainly caused by the complexity of the phenomena analyzed, as well as by the large number of variables to consider (Crosta and Agliardi, 2002). Moreover, an additional limitation of this approach is that, when the last threshold is exceeded, EWS end their efficacy. This is usually the most critical stage of the landslide emergency; indeed, the time lasting before a (partial or total) landslide failure occurrence is still unknown, and thus the critical situation can be protracted for long periods. In the last decades, several modeling procedures have been proposed for the estimation of the Time of Failure (ToF) for landslide phenomena. These approaches, hereafter cited as Failure Forecast Methods (FFMs), analyze the evolution of the landslide deformation over time (i.e. the strain rate), and are based on the assumption that under constant stress conditions landslide materials follow the creep mechanism. After the pioneeristic work of Saito (1965) a number of authors have attempted the estimation of ToF using different approaches, including simplified empirical and/or graphical solutions, analytical models known as "regression-only" methods, as well as physically consistent methods (see Federico et al., 2012, and references therein). The "inversevelocity" method proposed by Fukuzono (1985) has been widely considered, and has lead to successful applications both in large-scale laboratory experiments as well as in real landslide scenarios (Dick et al., 2014; Mazzanti et al., 2015; Rose and Hungr, 2007).This approach exploits the evolution over time of the inverse value of the surface velocity (v), by assuming that failure approaches while v −1 tends to zero. Recently, starting from the Fukuzono's method, Manconi and Giordan (2014) proposed a new approach to achieve landslide ToF forecast by considering near-real-time monitoring data. In this paper, ~~we start from~~ the method proposed by Manconi and Giordan (2014) is expanded by aiming at a more efficient management of landslide EWS. ~~Our~~ The objective~~goal~~ is to contribute filling an important gap, i.e. support authorities and decision makers during the time frame lasting from when the predefined thresholds set on displacements (or its derivatives) have exceeded, up to the occurrence of a (partial or total) landslide failure. In the following, we outline the main principles of the method, and we show an application to a real world landslide emergency scenario.

2 Method

Figure 1 depicts an example of the temporal evolution usually observed on landslide surface velocity prior to failure. ~~Let us assume a~~An active monitoring network deployed on the landslide area, ~~and that~~ the information on the deformation field ~~is~~ would be delivered in near real time. Under these conditions, the monitoring network is usually coupled to a EWS based on three stages, each one associated to the overcome of predefined velocity (v) thresholds: (i) v < thr1 = landslide velocity is below values considered critical, (ii) v > thr1 = warning conditions, and (iii) v > thr2 = alarm. When thr1 or thr2 are exceeded at a specific measurement point (or area), the EWS can be set to send alert messages (e.g. via SMS and/or email) to the responsible authorities. The ~~latter~~ authorities then have to evaluate the situation and eventually activate specific civil protection procedures (Allasia et al., 2013; Intrieri et al., 2012). EWS ~~using~~ that use~~as~~ thresholds ~~only~~ values based on the actual deformation measured ~~do not~~ provide ~~any~~ limited information about the possible evolution of the landslide towards failure.~~ Thus, t~~To overcome this issue, ~~when thr2 has been exceeded~~ an automatic procedure is activated to provide a failure forecast when thr2 has been exceeded. More specifically, the Fukuzono's inverse-velocity method is applied by considering several Calculation Time Windows (CTW, e.g. data acquired over the

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last 12, 24, 48 h, 1 week, etc.), and iterating the procedure several times (e.g. N = 1000 iterations) within a bootstrap resampling strategy (~~readers are referred to~~ Manconi and Giordan (2014) ~~for more details~~). This approach is aimed at evaluating the evolution of the landslide status considering data over different periods, as well as to derive robust assessments of errors associated to the estimated ToF. In addition, the fitness of the forecast vs. observations is evaluated by calculating the Pearson's correlation coefficient (CC) between the model and the data. Normalized CC values, when statistically significant, can be interpreted as a measure of the Reliability (R) of the computed forecast model. At this stage, we consider a number of model reliability ranges as follows: (i) 50 %< R < 60% = model reliability is low, failure is unlikely but the situation has to be surveyed, (ii) 60 %< R < 75% = model reliability is higher, a failure within the estimated ToF range starts to be more likely, (iii) 75 %< R < 90% = model reliability is high, a failure within the estimated ToF range is likely, (iv) R > 90% = model reliability is very high, a failure within the estimated ToF range is highly probable. In general, the results of the failure forecast procedure herein presented have to be read as follows: "if the landslide velocity continues to increase as in the last CTW, the probability to observe a failure within the estimated ToF range is R%".

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Additional information to take into account when interpreting the FFM results is the consistency of the forecast among different CTW, as well as the evolution of R tendency. For example, if R progressively increases and/or remains stable over high values (e.g. R > 75 %), the probability to observe a failure is higher. In order to facilitate the exploitation of the information based on failure forecast, as well as to provide a straightforward understanding of the modeling results also to people without detailed knowledge on the inverse-velocity theory, we designed specific representations aimed at summarizing the obtained results (see Fig. 2). We have implemented this procedure within the ADVICE system (Allasia et al., 2013), and "Failure Forecast plots" are generated automatically when a monitored target velocities overcome v > thr2 .

3 Application to Mont de La Saxe rockslide

Active mass movement affects a large portion of the southern flank of the Mount de la Saxe, northwestern part of Aosta Valley, northern Italy. The rockslide, ~~hereafter~~ referred to as La Saxe, involves an instable volume of ca. 8×106 m 3 (Crosta et al., 2013, 2015) ~~and menaces~~which poses a hazard to part of the Courmayeur municipality, i.e. Entreves and La Palud villages. In addition, the landslide threats also a crucial point of the route E25, an important highway connection crossing Europe from north to south, and ensuring commercial activities between Italy and transalpine countries. Continuous monitoring of surface modifications started from 2009, and evidenced that snow melting during spring seasons causes progressive acceleration of the surface displacements, which may locally reach up ~~to several decimeters (or even~~centimeters to meters~~)~~ per day. Over the years, these acceleration phases have ~~lead~~led to failures of portions of the landslide body, with volumes ranging from minor rock falls up to relatively larger mass wasting (> 1 × 104 m 3). The monitoring network deployed includes ~~several~~ a variety of instruments, which ~~allow following~~follow the evolution ~~surface~~of surface and subsurface ~~evolution~~ displacement of the landslide over time (Crosta et al., 2013); however, the EWS is based mainly on thresholds set on measurements performed via a Robotized Total Station (RTS). When one or more RTS point targets overcome predefined warning and/or alarm levels (1 and 2 mmh−1 , respectively, considered in a 24 h observation window), specific civil protection procedures are

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activated, including the interruption of roads traffic, and evacuation of inhabitants from edifices located in areas potentially involved by a failure event.

Comment [SJ10]: So this is an overly conservative approach?

Starting from the end of March 2014, a specific sector of the La Saxe rockslide started again to accelerate (see Fig. 3). This acceleration phase lead to a large number of minor rock falls, ~~but also to~~as well as two main failure events: (i) 17 April 2014, 20:00 CET, ca. 5×103 m 3 , (ii) 21 April 2014, 23:00 CET, ca. 3×104 m 3 . Figure 4 shows examples of the failure forecast plots generated in near real time from RTS measurements on target "B4" during this particular phase. The target B4 was installed close to the zone characterized by the larger displacements, and at that moment considered as one of the most representative for understanding the evolution of the most active kinematic domain. We notice that from 31 March to 15 April the reliability of the FFM has progressively increased for all the considered CTWs. At this stage, landslide material reached surface displacement rates larger than several centimeters per hour, and a failure was considered highly probable.

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4 Discussion and conclusions

We presented an approach aimed at updating operational EWS thresholds by including a values based on the results of the Failure Forecast Method. Our approach has been applied to forecast landslide events associated to the evolution of the La Saxe rockslide during the 2014 emergency scenario. Our results show that reliability threshold applied to FFM results can be used to help the interpretation of the evolution of the landslide body towards a failure, and to provide an additional support for early warning purposes. Despite the number of events observed is yet very limited, we evaluated the performance of the proposed methodology by building contingency tables (Jolliffe and Stephenson, 2012). For this purpose, we have taken into account the failure forecast results for the la Saxe failure event occurred in 21 April 2013 (see Manconi and Giordan, 2014) and the two major events occurred on 2014. In particular, the analysis was performed by assuming as "event forecast" only those models with Reliability (R) higher than a predefined value. Among them, models predicting a ToF range that included the time of the real events observed have been considered as "true positive", "false alarms" are models predicting a ToF range antecedent the real event occurrence, while "missed alarms" are models predicting a ToF range successive to the real event occurrence. Despite, models with R below the predefined reliability threshold have been considered as "non-event forecast", and thus as "true negatives". The analysis was performed on forecast models obtaining reliability thresholds R > 75 % and R > 90 % in the week preceding the failure (see Supplement). We note that the model hit-rate for the 2013 event is in the order of 0.8 (see Table S7), and highly depends on the considered computational time windows. Despite, the modeling procedure yields to a consistent number of false alarms, although among them the mean distance between the predicted and the real event is in the order of 2.5–3 days. Moreover, we note that by considering only the forecast models with R > 90 %, the number of missed alarms tends towards zero. For the 2014 events, the evaluation of the model performance with standard contingency estimators is of difficult interpretation. Indeed, on 21 April 2013, the event occurred after a straightforward evolution towards failure, and the target analyzed was installed right on the top of the collapsed landslide sector (see Fig. 3). On the contrary, the 2014 emergency scenario was characterized by a different evolution. In particular, in the period starting from 15 April 2014 up to 21 April 2014, a progressively large number of rock falls and minor collapses was observed (Bertolo and Arrighetti, 2014), and the landslide acceleration was highly non-linear. In addition, while the landslide acceleration trend was recorded by several RTS targets, none of them was located right on the sectors that finally collapsed (see Fig. 3). This is a main limitation of using this typology of failure forecast models on data acquired on a punctual basis: if the point is not representative of the collapsing sector, the forecasted time of failure can be inaccurate. For the above-discussed reasons, it is difficult to identify proper failure events for cases as encountered in the La Saxe 2014 emergency phase. Instead of failure events, it is more appropriate to define a “critical time range” where failure may occur. Based on the modeling results obtained for the La Saxe case study, we can consider thr3 = R > 75 % as a good compromise to catch in advance the occurrence of the critical time range (see Fig. 1). We remind that as for forecast models relevant to other natural phenomena (e.g. meteorological events), our results are based on a statistical inference, and they have to be always considered in terms of probability. Moreover, unpredictable changes of the boundary conditions, as well as deviations of the material behavior from the classical creep theory may deeply affect the results of the forecast model (Mazzanti et al., 2015). It is worth to mention that our method has been developed to achieve reliable short-term failure forecast, but is not intended for medium- and long-term predictions of the ToF. On the contrary, we aim at providing a supporting toolbox to manage EWS in critical situations, especially when predefined early warning thresholds are overcome. EWS managers can benefit of the additional information provided by the FFM, because when the reliability of the forecast is high and thus a landslide failure more likely, authorities can be informed in advance (in automatic and/or semi-automatic manner), and thus have the time to take eventual countermeasures. The final interpretation on landslide failure potential has to be provided by experienced users, which have a deep knowledge of landslide phenomena, have access to additional data on the landslide status, and are conscious of the limitations of FFM. Thus, the FFM information can be better interpreted by taking carefully into account additional evidence from other data sources, depending on the specific context. Further investigation will be performed on the reliability and accuracy of the herein presented method, mainly by considering different data sources, as well as performing tests larger number of case studies

General Comments

1. Figures are not clear or very strong. They do not overly help the reader understand your discussion
2. Your conclusions are not overly strong (Strongly stated). They should be more clear
3. How local is the method? What would be the challenges to another site?
4. Can Radar alleviate some of the concerns? Or help your technique?
5. Please avoid using pronouns.

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