Definition and application of a multi-criteria algorithm to identify landslide acceleration phases

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Abstract

Landslides represent a serious hazard in many areas around the world, potentially leading to human losses and significant damages to structures and buildings. For this reason, over the years a consistent number of studies and researches have been carried out to analyse these natural phenomena and their evolution. This study presents the application of an automatic procedure specifically developed to identify the onset of landslide acceleration by analysing monitoring displacement data with a multi-criteria approach. The proposed procedure aims to identify this point by applying a four-level validation process on a pre-determined dataset. Once the analysis returns a positive result for a certain number of monitoring data, it is possible to state that the landslide reached the accelerating phase of its evolution, thus allowing to define a specific point representing the onset of acceleration. The method was applied to several historical case studies taken from scientific literature, in order to test its practicability and effectiveness. This procedure could be especially useful in Early Warning Systems where time of failure forecasting models are implemented, allowing to improve their performances by providing an automated and reliable procedure to define the beginning of potentially critical landslide events.

Keywords: Landslide, Displacement rate, Failure forecasting, Onset-of-acceleration, Early Warning System

Introduction

Landslides are natural phenomena characterized by a significant degree of complexity and variability. Risk and hazard assessment activities, together with adequate understanding of landslide behaviour (Carlà et al. 2018), are a significant step towards the reduction of damages and prevention of human victims caused by these events. The correct identification of the problem before its critical evolution could theoretically allow to avoid at least 90% of losses caused by landslide phenomena (Brabb 1993).

The identification of pre-failure conditions in areas presenting instability signs can be performed through in-situ observations and monitoring (Brunner et al. 2000, Borgatti et al. 2008, Cascini et al 2019, Segalini et al. 2019), by exploiting satellite-based technologies such as Interferometric Synthetic Aperture Radar (InSAR) (Intrieri et al. 2018, Lacroix et al. 2018, Reyes-Carmona et al 2020), optical image data (Desrues et al. 2019), or a combination of different sensors (Clarkson et al. 2020). The parameters controlling the landslides effect in term of hazard and landscape change include the landslide occurrence time, size, duration, speed, and total amount of their movement (Schulz et al. 2018). According to Salt (1993), it is also possible to take some specific actions to improve the probability to provide an adequate forewarning, in particular for what concern rapid movements:

- Consideration of the slide geometry, with particular attention to the curvature of the failure surface;
- Definition of pre-set alarm criteria and alert thresholds. If a specified alarm level is reached, it must be taken as an indication that the slide is evolving towards its collapse and it is necessary to activate, as quickly as possible, all measures required to mitigate damage;

- Ensuring that the monitoring sampling rate is appropriate with respect to the slide development rate. In fact, the possibility that a slide may accelerate suddenly and unexpectedly between surveys must always be considered in order not to lose essential data.

Assessing the time of failure is another topic of major concern in the field of geological risk management, and several different methods have been proposed to achieve this goal (Intrieri et al. 2019). One of the most diffused approaches aimed to forecast a landslide collapse exploits the accelerating creep theory, which has been studied and applied by different authors over the years (e.g. Saito 1969, Fukuzono 1985, Voight 1989, Crosta and Agliardi 2003, Xue et al. 2014). This theory generated mainly empirical and semi-empirical methodologies, all based on the assumption that the time of slope failure can be forecasted by extrapolating the trend towards zero of the inverse-velocity vs time plot. In particular, collapse predictions obtained through the applications of the Inverse Velocity Method (IVM) firstly introduced by Fukuzono (1985) can be found in literature, displaying generally positive results (Petley 2004, Rose and Hungr 2007, Segalini et al. 2019).

Despite in-depth studies and research activities performed during several decades, the ability to predict the future behaviour of a landslide remains a challenging task. One of the most crucial and complex aspects of forecasting methods is the definition of the dataset to be used to determine the phenomenon evolution. The importance of this task derives from the assumption that the pre-failure stage can be explained by applying a tertiary creep model (Siddle et al. 2007). It follows that a correct definition of the beginning of the actual acceleration phase could be fundamental to apply these methods correctly and, consequently, provide meaningful evaluations regarding the most probable event behaviour (Dick et al. 2014). According to this consideration, the definition of the landslide acceleration phase acquires a particularly relevant position among the several components forming an Early Warning System (EWS), that typically include a field monitoring system, forecasting and data analysis methods, alert messages dissemination, and emergency planning (Intrieri et al. 2012, Calvello and Piciullo 2016). Traditionally, the identification of the landslide onset-of-acceleration (OOA) and the following application of failure forecasting methods have been performed manually (e.g. Voight and Kennedy 1979, Rose and Hungr 2007, Mazzanti et al. 2015). While this approach could provide highly accurate results due to the first-hand evaluation of an expert, it is definitely not an optimal solution when a timely warning is needed, specifically due to the lack of automation, which is a key component for an effective real-time EWS (Allasia et al. 2013). Carlà et al. (2017b) proposed an interesting approach to solve this problem, relying on the crossover between short-term and long-term moving averages (SMA and LMA, respectively) to identify a trend change in the raw data. According to the authors, when the SMA line crosses above the LMA, the beginning of an uptrend can be signalled and, therefore, the OOA point can be defined. On the opposite, a downtrend occurs when the SMA line lies below the corresponding LMA line, thus representing the end of the acceleration phase. However, it should be noted that, to this day, a standard procedure to identify the beginning of the tertiary creep phase has yet to be defined (Bozzano et al. 2018).

As explained in the previous paragraph, the applicability of failure forecasting methods has been successfully demonstrated under the hypothesis of a tertiary creep behaviour. For this reason, the dataset should contain only accelerating displacement data in order to provide reliable predictions. This assumption highly influences the forecasting analysis outcomes and increases the necessity to apply innovative monitoring tools, featuring high sampling rates and automatic acquisition procedures. In fact, a traditional monitoring approach with manual acquisition is not suitable for early warning purposes since the sampling rate is often too low to guarantee an adequate description of the acceleration phase, which can take place in a time interval up to some hours (e.g. Bozzano et al. 2011, Carlà et al. 2017a).

In general, the identification of the acceleration phase is not a difficult task when performed through a manual check by an expert operator. The issue become quite harder when a software has to recognize automatically the starting and progression of an accelerating phase in real time or near-real time. Another context that should be considered is the simultaneous monitoring activity of several different landslides, which nowadays is becoming more and more common thanks to the application of automatic instrumentation. In the latter case, the integration of highly detailed models would be hardly sustainable in terms of economical and computational resources. All these aspects were taken into consideration during the development of the proposed approach, addressing the advantages of an automated procedure and the possibility to apply it consistently to a large number of monitored sites.

Methodology

This paper presents a new algorithm aimed to identify an increasing stage in displacement rate values by analysing the dataset trend according to four different criteria, applied in a “drop-down” approach. This choice provides some relevant advantages when implementing the procedure automatically. Mainly, the possibility to stop the algorithm when a single condition is not fulfilled allows to shorten the time analysis. While the impact of this choice on a single dataset analysis could be almost negligible, it becomes more and more relevant when dealing with several devices featuring high sampling rates, often resulting in an extremely large database of monitoring values to be elaborated at the same time. This aspect heavily influenced the design of the proposed approach, which has been developed trying to balance results reliability and computational complexity. Additionally, a multi-criteria approach permits to introduce a tolerance component for each sub-routine.

Since its development, the algorithm has been tested on a large number of automatic monitoring devices featuring different sampling frequencies. However, from a conceptual point of view, the proposed methodology could be applied to any device intended to monitor slope displacements. The method is based on the hypothesis that the monitored landslide would displays a transition from a linear to a non-linear behaviour, corresponding respectively to a constant and increasing displacement rate. Moreover, the displacement rate should be increasing and positive between two consecutive readings, i.e. an increasing negative displacement rate is not considered (Carri 2019).

Displacement rate values can be computed starting from monitored data according to the following equation:

$$v_j = \frac{S_j - S_{j-1}}{t_j - t_{j-1}} \tag{1}$$

where v is the displacement rate recorded between j and $j-1$ readings, S is the displacement recorded at reading j, and t_j is the date, expressed as a number, corresponding to reading j. Each single sub-condition is detailed below, while the complete structure of the algorithm is summarized in the flowchart reported in Figure 1.

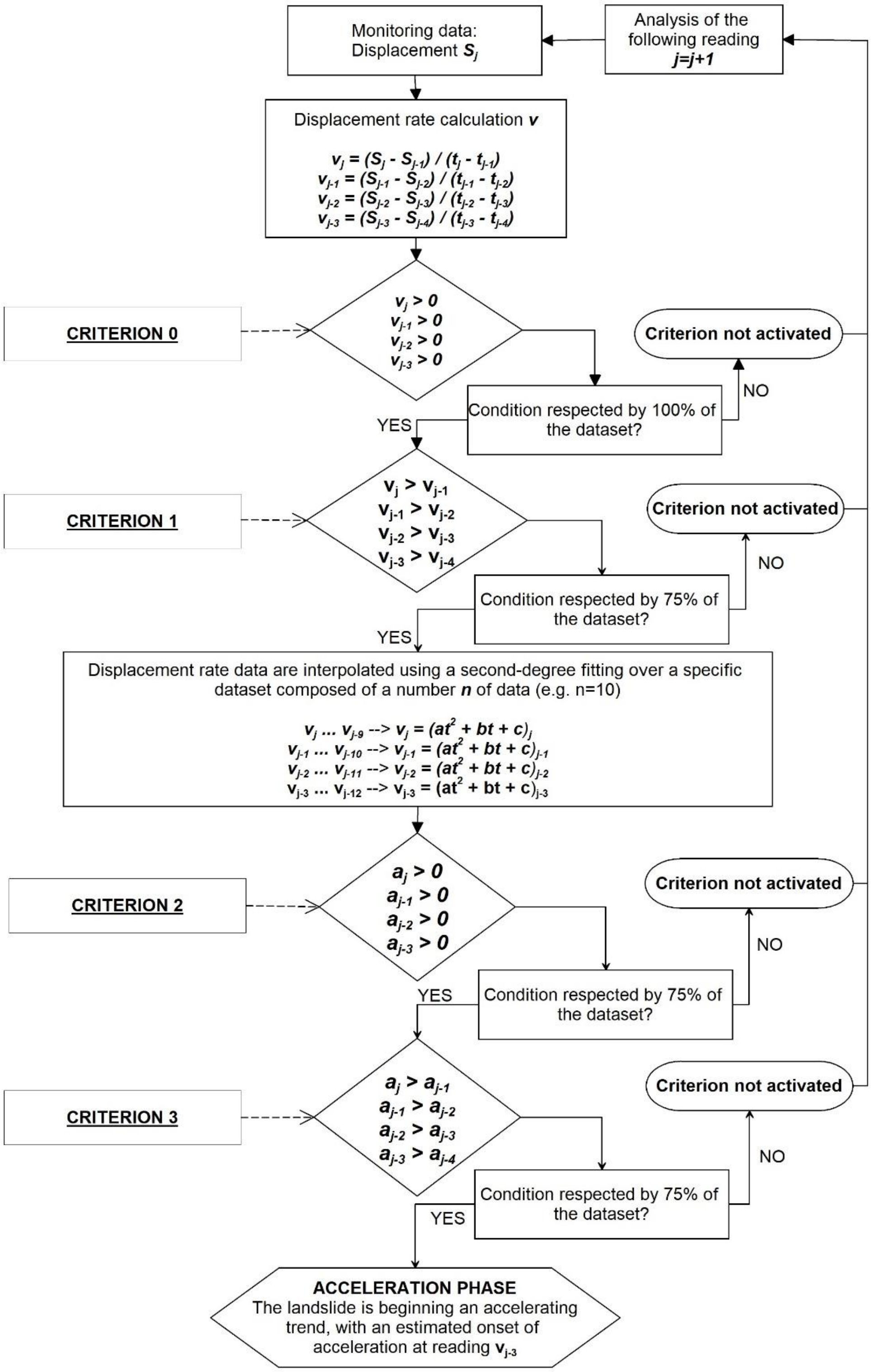

Figure 1: Flow chart of the multi-criteria algorithm, displaying each passage and the corresponding conditions

Criterion 0: positive displacement rate

Criterion 0 was introduced in the algorithm as a preliminary check on displacement rates. This condition requires four consecutive positive velocities (referred to reading j) to proceed with the following tasks, as in Eq. (2). This means that a dataset composed of at least four displacement rate values (i.e. five displacement records) is necessary in order to begin the analysis. The introduction of this first step is particularly important to obtain meaningful results from the application of forecasting models, like IVM, to the selected dataset (a negative velocity would be meaningless in this context, effectively invalidating the forecasting analysis).

$$\begin{cases} v_j > 0 \\ v_{j-1} > 0 \\ v_{j-2} > 0 \\ v_{j-3} > 0 \end{cases} \tag{2}$$

Criterion 1: increasing displacement rate

If Criterion 0 gives a positive result, the following step investigates the variation between two consecutive values in order to check if the displacement rate is displaying an accelerating trend. To verify this condition, the velocity difference Δv_j is computed by considering data referred to readings j and $j-1$. The criterion is fulfilled if the $\Delta v > 0$ condition applies to at least three out of four consecutive displacement rate values of the considered dataset.

$$\Delta v_j = v_j - v_{j-1} > 0 \tag{3}$$

The main objective of this step is to prevent errors deriving from anomalies in monitoring data, e.g. outliers or spike noises. In fact, a too strict condition could interpret a single negative result in this phase as an actual deceleration, thus stopping the procedure. On the other hand, by introducing this tolerance margin it is possible to carry on the analysis even if an anomalous value is recorded. Additionally, this approach could be helpful when dealing with high sampling frequencies, which could be able to detect a temporary deceleration within a more consistent accelerating trend. It follows that a 100% validation condition of the dataset would interpret this behaviour as an actual deceleration, while its duration could be minimal when compared to the general trend of the landslide evolution.

Criterion 2: parabolic trend

The following condition relies on the hypothesis that displacement rates will follow a nonlinear behaviour during the acceleration phase. According to this assumption, this specific step aims to define a curve fitting the selected dataset, with the purpose to identify an increasing trend. Taking as a reference the creep theory (as presented by Varnes 1982), criteria 1 and 2 are intended to highlight the initial transition from a linear trend, typically associated with a secondary creep, to a non-linear behaviour. When dealing with the evolution of potentially critical landslide events, several studies apply a power law equation to displacement rate data in order to describe the tertiary creep phase, which usually leads to the landslide collapse (e.g. Cruden and Masoumzadeh 1987, Voight 1989, Crosta and Agliardi 2003, Helmstetter et al. 2004). However, the model calibration and testing evidenced how this type of function would not be suitable in an algorithm intended to interpolate a generic trend, since it gives reliable outcomes only when applied to the last phase of the phenomenon evolution. To avoid this problem, the authors tested a fitting procedure involving a second-degree polynomial function to identify upward or downward trends in different datasets by analysing the concavity direction. Figure 2 presents four different examples obtained from the testing process, displaying a comparison between two fitting approaches, namely power law and second-degree polynomial equation (Table 1) , performed on displacement rate data (obtained from a digitizing process of time series reported in Ryan and Call 1992) It is possible to observe the accurate fitting obtained with a parabolic equation, displaying a concavity that correctly represents both an increasing (Datasets #1 and #2) and decreasing (Datasets #3 and #4) displacement rate trend.

Table 1: Equations used for the parabolic and power law fitting procedures, together with the parameters resulting from their application to datasets reported in Figure 1

Dataset	**Parabolic fitting** $y = ax^2 + bx + c$			**Power law fitting** $y = ax^b$	
	a	**b**	**c**	**a**	**b**
#1	4.9507	-775.5021	30391.6446	8.8988E-049	26.0745
#2	1.2344	-181.1658	6658.9467	2.6346E-019	10.5431
#3	-0.3178	45.8235	-1639.4291	6.7969E-012	6.5973
#4	- 0.3631	43.9043	-1318.2098	1.0399E-017	10.039

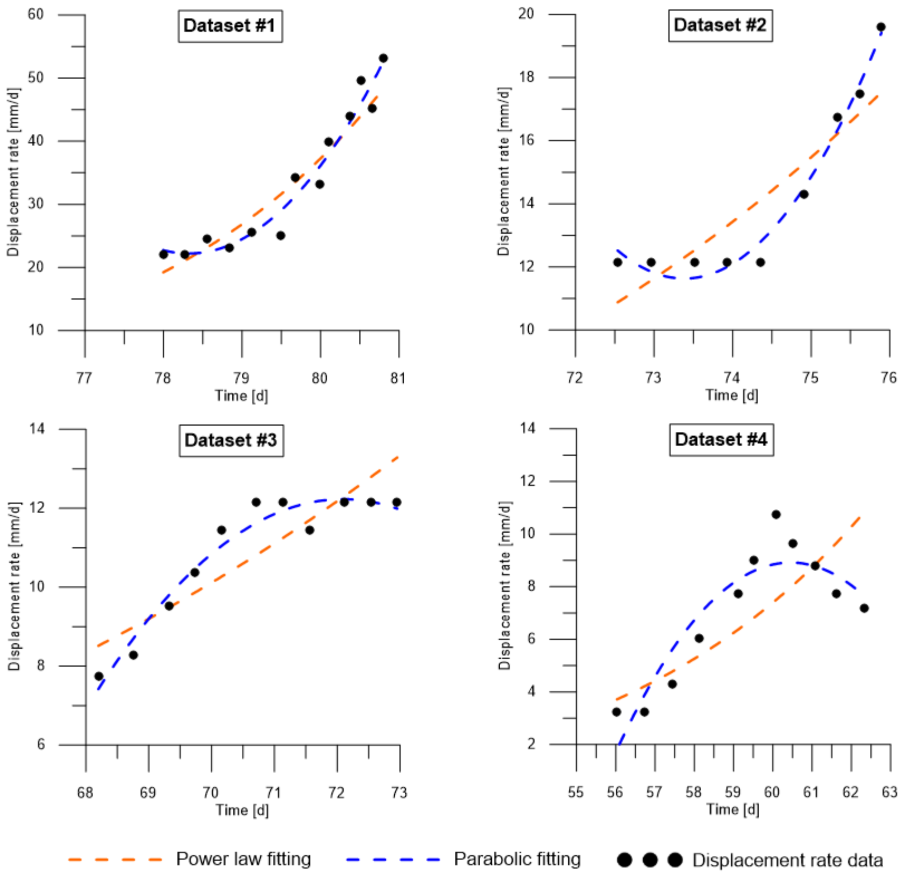

Figure 2: Comparison between two different fitting approaches, based on power law and parabolic equation, applied to four different displacement rate datasets

Based on the results obtained in the testing phase, if the Criterion 1 is activated, displacement rate data are interpolated using a parabolic fitting (Eq. 4) in order to obtain the value of the a

parameter that describes the concavity orientation:

$$y = ax^2 + bx + c \tag{4}$$

where y refers to displacement rates and x represents time, expressed as a number.

It should be specified that the most appropriate number of data to perform this operation may vary according to the specific case study, depending on parameters like sampling frequency, smoothing procedures and filters applied on monitoring data. The example in Table 2 refers to a case study concerning a fitting operation performed on a dataset composed of 10 displacement rate values.

As previously assessed, the objective of this phase is to evaluate the a coefficient of the interpolating curve, since this parameter holds information regarding the curve concavity. Specifically, a positive value identifies an upward concavity (i.e. an accelerating phase), while a downwards concavity features a value of $a < 0$. In the proposed procedure, a positive value should be observed in order to assess that an acceleration is taking place. If the condition is verified for at least the 75% of the dataset represented by j, $j-1, j-2$ and $j-3$ readings, Criterion 2 is fulfilled, and the analysis can proceed to the following step.

Table 2: Dataset considered for the Criterion 2, under the hypothesis of n=10 data for the nonlinear interpolation (modified after Carri 2019).

Referring dataset	**First reading considered in the dataset**	**Last reading considered in the dataset**	**Concavity parameter**
j	v_{j-9}	v_j	$\boldsymbol{a_j}$
j-1	v_{j-10}	v_{j-1}	$\boldsymbol{a_{j-1}}$
j-2	v_{j-11}	v_{j-2}	$\boldsymbol{a_{j-2}}$
j-3	$\boldsymbol{v_{j-12}}$	$\boldsymbol{v_{j-3}}$	$\boldsymbol{a_{j-3}}$

Criterion 3: increasing concavity

The last criterion takes into account the variation of the a coefficient between two consecutive readings. Specifically, in this step the sign of Δa is studied to assess if the curve approximating the monitoring data displays a more pronounced upward concavity (i.e. the acceleration is increasing). While the previous criteria were intended to evidence a transition between two different behaviours, this particular condition aims to analyse a non-linear trend featuring increasing values. According to the classical interpretation of creep theory, this specific trend can be observed in the tertiary phase (Varnes, 1982). This condition is represented by a positive result obtained from the application of Eq. 5. On the opposite, $\Delta a < 0$ means that the curve is experiencing a transition towards a more linear trend, thus approaching a downwards concavity that represents a deceleration of slope movements.

$$\Delta a_j = a_j - a_{j-1} \tag{5}$$

If Criterion 2 is activated at reading j, the process considers a dataset composed of four parameters and evaluates the variation of a starting from $j - 3$ reading. The Criterion 3 is activated if the corresponding condition is verified for at least three out of four consecutive data, similarly to the two previous stages. If this last step returns a positive outcome, it could be assumed that an accelerating phase is taking place, and the $j - 3$ reading could be taken as the OOA of the monitored landslide.

The validation of the proposed approach involved a parametric analysis performed on several displacement datasets, in order to evaluate the model performances under the variation of the main parameters implemented in the algorithm. In particular, the number of data points (d), the percentage limit, and the number of data (n) used in the model fitting procedure were considered during the process analysis.

Results and Discussion

Parametric study

Figure 3 displays an example of the results obtained by the parametric analysis focused on the number of monitoring data to consider in the OOA identification process. Moreover, the study included different rate limit values (i.e. the percentage of positive data points required to fulfil a specific criterion) to highlight their influence on the acceleration phase assessment, as well as the generation of possible false positives.

In particular, Figure 3a compares the reference dataset of $d = 4$ monitoring data, featuring a 3/4 rate limit (i.e. 75%), with a 5-point dataset characterized by two different rates, namely 3/5 (60%) and 4/5 (80%). Figure 3b presents the same reference case compared to a 6-point dataset with a rate of 4/6 (67%) and 5/6 (83%). Reported results derive from the elaboration of the New Tredegar landslide dataset (Bentley and Siddle 2000) and are obtained by considering 10 monitoring data for the parabolic model fitting.

By studying the outcomes of this analysis, it is possible to make the following considerations:

- All configurations provided the same OOA estimation at $t = 59$ days, except for the $d = 6$, 4/6 model that placed the OOA one day earlier.
- An increment of the data points number resulted in a delayed fulfilment of the Criterion 3 conditions, ultimately leading to a postponed identification of the onset of acceleration. This is a relevant drawback in a methodology that aims to provide timely evaluations for early warning purposes.
- Percentage limits higher than the reference value did not evidence a significant improvement in avoiding false positives. The only exception is the 83% rate in the $d = 6$ configuration, which however provided a significantly delayed OOA estimation. On

the other hand, values lower than 75% led to an increment of false positives for both $d = 5$ and $d = 6$.

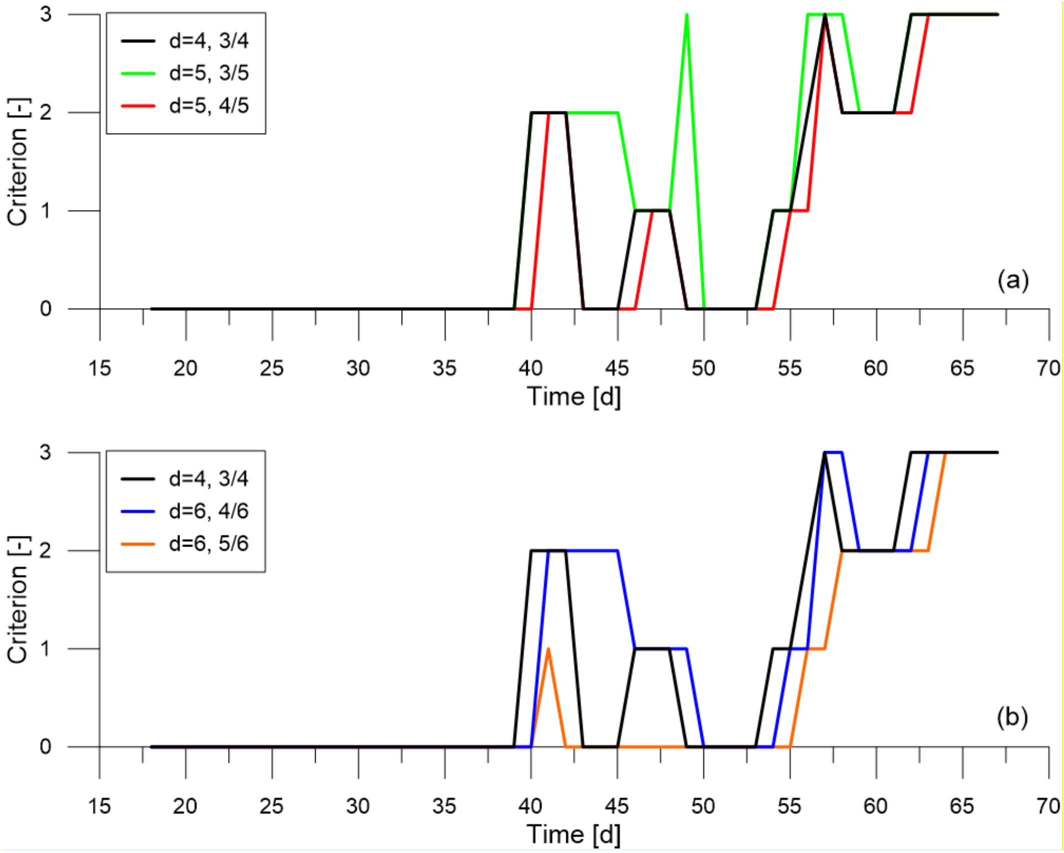

Figure 3: Parametric analysis of the New Tredegar landslide dataset, comparing the $d = 4$, 3/4 reference configuration with (a) $d = 5$, and (b) $d = 6$ configurations, including also different values for the percentage level parameter

Figure 4a and Figure 4b provide two examples of the parametric study performed on the number of monitoring data used in the parabolic model fitting, deriving respectively from the analysis of the New Tredegar landslide (Bentley and Siddle 2000) and Ohto landslide (Suwa et al. 2010) datasets. Both these cases were processed by considering a $d = 4$, 3/4 configuration.

By observing the results of these elaborations, it is possible to notice the influence of the n parameter for what concern the occurrence of false positives. In particular, values of $n > 10$ evidenced a higher number of data points fulfilling the Criterion 3 conditions, generating a series of false positives before the actual onset of acceleration. Moreover, datasets including less data points displayed a lower reliability in the assessment of the critical acceleration phase. An example of this behaviour can be observed in Figure 4b, where the analyses performed with datasets ranging from 10 to 12 points consistently fulfilled the Criterion 3 conditions after the OOA identification. On the other hand, $n = 8$ and $n = 9$ configurations were unable to provide a reliable assessment of the onset of acceleration, since the analyses did not reach the higher level of the algorithm during the critical acceleration phase, thus leading to an inaccurate OOA definition.

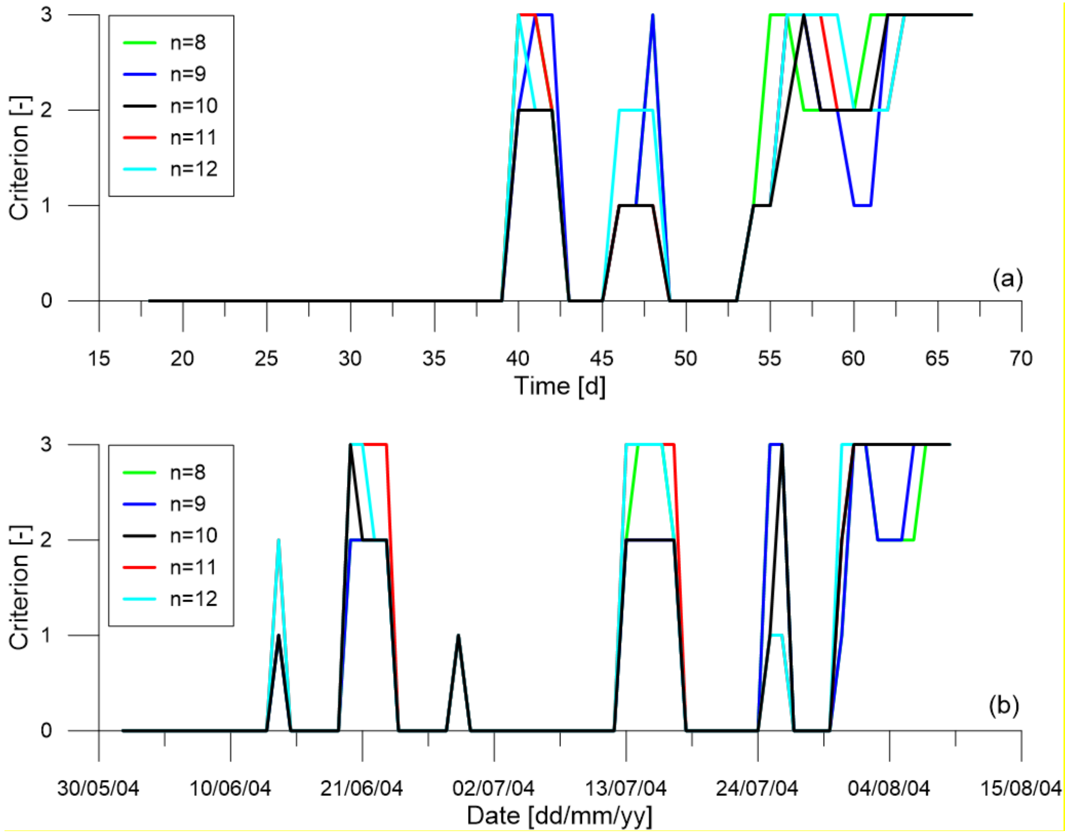

Figure 4: Parametric analysis of the (a) New Tredegar landslide and (b) Ohto landslide datasets, focusing on the number of monitoring data used for the parabolic fitting model

Case studies application

As detailed in the previous section, the proposed multi-level procedure is intended to be applied in real-time monitoring scenarios to identify potentially critical acceleration trends starting from displacement data. In this paragraph, an application to three real case scenarios is presented as an example of the algorithm implementation. The analysis was performed with the drop-down approach described in previous paragraphs, creating a new dataset for each single monitoring data. Even if all monitoring data here presented derive from historical events, the procedure is intended as a simulation of a real-time acquisition, since the algorithm provides a new result each time a sampled value is elaborated by the automatic software.

Regarding the algorithm application to these case studies, it is important to underline the following considerations:

- Displacement rate datasets were digitized from data reported in scientific literature considering a daily sampling rate;
- In order to perform the Criterion 2 procedure, a dataset composed of 10 displacement rate values (n=10) was selected for all following case studies. This implies that the minimum number of monitoring data to perform the complete analysis is 12 displacement values. In fact, the first displacement rate can be evaluated starting from the second reading and the Criterion 3 needs two nonlinear interpolation to check the concavity behaviour. Additionally, according to the results obtained in the parametric analyses, a 4-point dataset and a percentage limit of 75% were used for these elaborations.

Case Study #1: Ohto Landslide

This case study refers to a landslide occurred in Nara Prefecture, Japan on August 10, 2004 (Suwa et al. 2010). The collapse took place during a particularly critical year due to the high number of typhoons and prolonged rainfalls that interested the country, damaging structures and triggering several landslides (Fujisawa et al. 2010). The event presented in this case study was first identified in January 2004, when a series of cracks appeared on a retaining wall along National Highway 168, close to Otomura village. Due to the importance of this route, several monitoring tools were installed on site, including extensometers to observe the displacement of the unstable slope. Additionally, the system was able to send an automatic notification message at the overcoming of predefined thresholds. The National Highway was closed at 5.10 AM on August 8 when the displacement velocity reached 4 mm over 2 hours. The landslide collapsed 43 hours later, without claiming any victims (Suwa et al. 2010).

The displacement dataset obtained from the monitoring activity was used in this study to check the ability of the proposed method to identify correctly the tertiary phase of the landslide evolution (Figure 5). As reported by Suwa et al. (2010), displacement data recorded by extensometers showed a constant creep until July 31 when an acceleration was observed, meaning that the creep mode transitioned from a secondary to a tertiary phase. According to this observation, it is possible to consider this date as reference value for the landslide OOA, since it marked the beginning of the accelerating phase that ultimately led to the slope collapse.

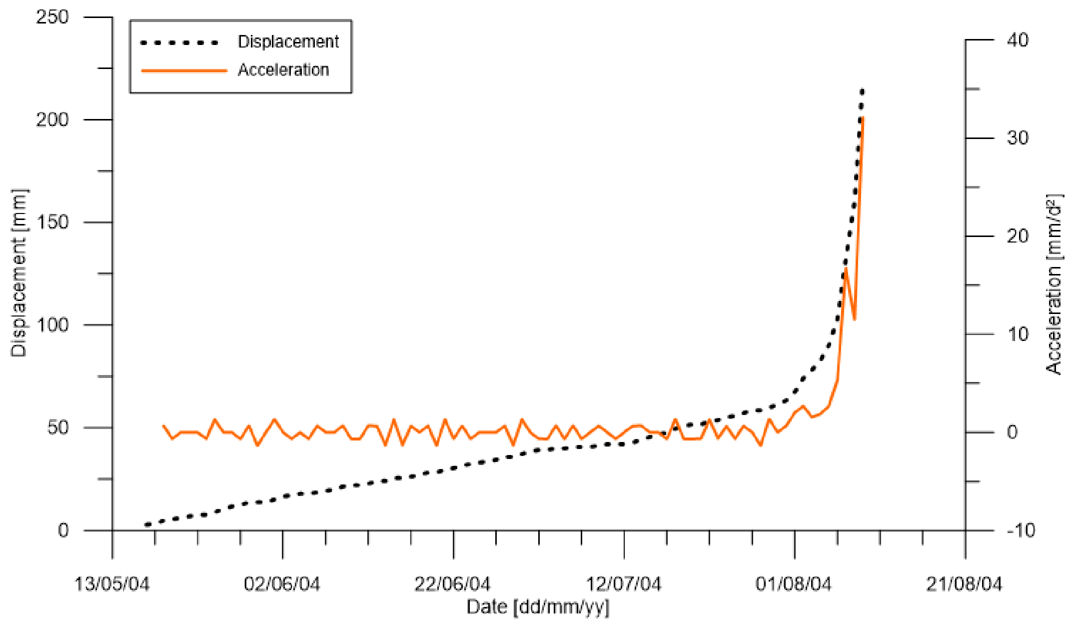

Figure 5: Displacement and acceleration curves for the Ohto landslide – dataset digitized from Suwa et al. (2010)

A graphical representation of the results obtained from the algorithm application is presented in Figure 6, displaying the outcome of the procedure applied to each single monitoring data. In particular, the chart represents the landslide displacement trend and the corresponding verified sub-criteria as the monitoring activity progresses. As can be observed, even if some early activations were detected, the algorithm identified accurately the acceleration phase. In particular, the first point of the dataset that fulfils all the conditions of the algorithm is the measure recorded on August 1st and, starting from that point, the procedure gives a positive result for all the following elaborated data. Hence, it could be assessed that the onset of acceleration point corresponds to the displacement measured on July 29th, which is in good agreement with the OOA defined in literature for this landslide.

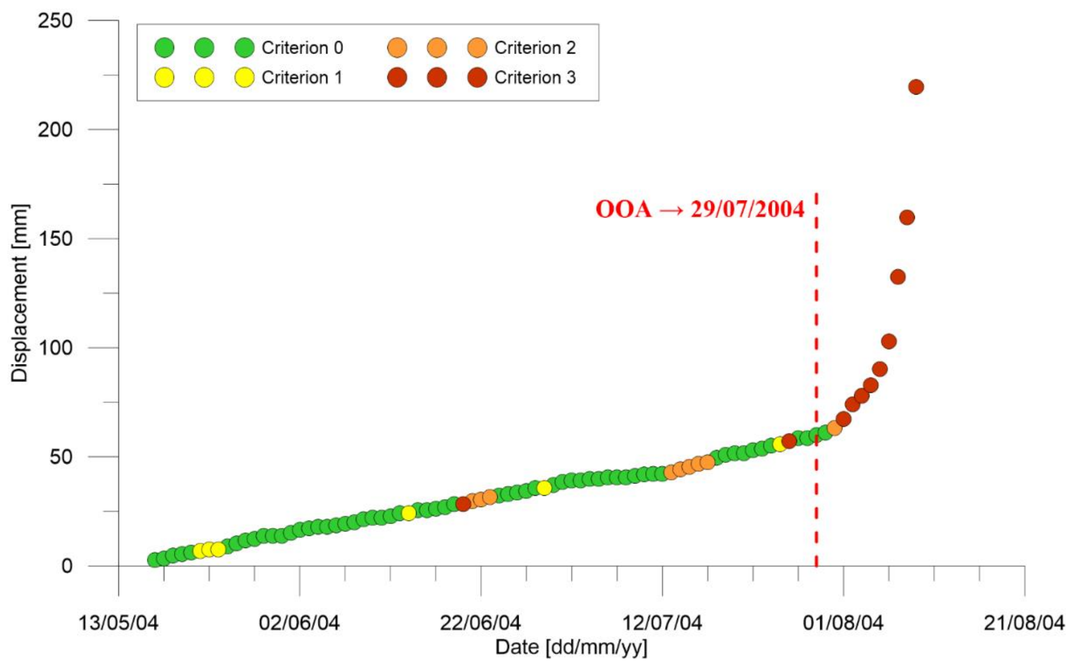

Figure 6: Results obtained from the application of the algorithm to the Ohto Landslide dataset (displacement data recorded during the monitoring period from May to August 2004)

Moreover, a more in-depth analysis of each single condition makes it possible to note that monitoring value measured on July 29th fulfilled only the Criterion 0 condition, and it was included in the accelerating dataset thanks to the tolerance factor introduced in the algorithm.

In fact, starting from July 30th, each single point verified all the conditions included in the proposed method. Therefore, this date could be taken as a more reliable OOA point, resulting in a date even closer to what Suwa et al. (2010) reported in their study.

Case Study #2: Agoyama Landslide

The second case study presented in this paper deals with a collapse occurred in December 1972 about 5 km to the northwest of Fukui City, Japan (Saito 1979). As reported by the author, the triggering factor may be attributed to excavation works as borrow-pit at the foot of the slope. First signs of instability were observed starting from October 4th, when a long-continued crack was found on a hillside of Agoyama. It was then decided to set up measuring instruments in order to sample landslide displacements. Additionally, a failure forecasting analysis was performed, and the person in charge of the site was informed concerning the phenomenon evolution. The analysis met some difficulties related to irregular movements in the final stage and partial failures of the landslide body, resulting in a slightly anticipated forecasting of the collapse, which happened on December 2nd at 1:30 AM (Saito 1979).

As reported by the author, displacement recorded by the instrumentation installed on-site (Figure 7) amounted to 10 mm per day in the first phase of the monitoring activity, reaching 20 mm/d at the end of October and escalated up to 100 mm/day after November 20th (Saito 1979). On the basis of these information, the OOA date that will serve as a comparison for the algorithm application for this case study could be placed on the moment where displacement increased significantly, i.e. November 20th, 1972.

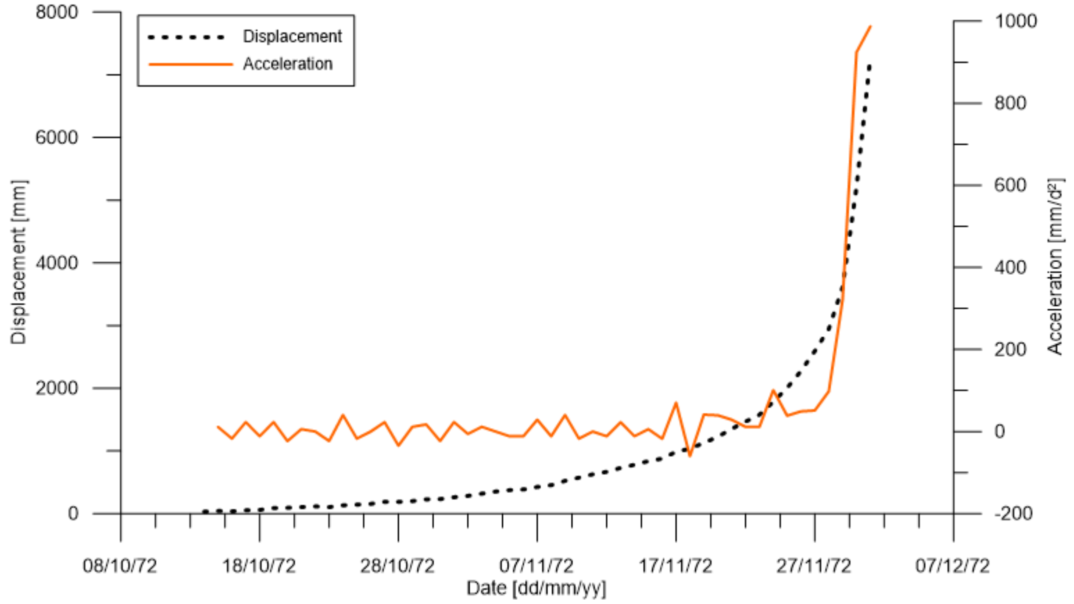

Figure 7: Displacement and acceleration curves for the Agoyama landslide – dataset digitized from Hayashi and Yamamori (1991)

Results reported in Figure 8 highlight once again the good performances of the proposed methodology, which correctly identified the accelerating trend starting from the displacement measured on November 23rd. According to this outcome, it is possible to place the OOA for this case study on November 20th, which corresponds to the reference value previously defined. Another possible interpretation of the outcome could take into account the displacement measured on November 21st, which does not satisfy the Criterion 3, as part of the accelerating trend together with the previous data that is instead classified as an accelerating point. This choice would place the onset of acceleration on November 18th, some days before the previous estimation. Even if this prevision is slightly anticipated if compared to the OOA reference value, it could be still considered a good result in terms of definition of the accelerating trend.

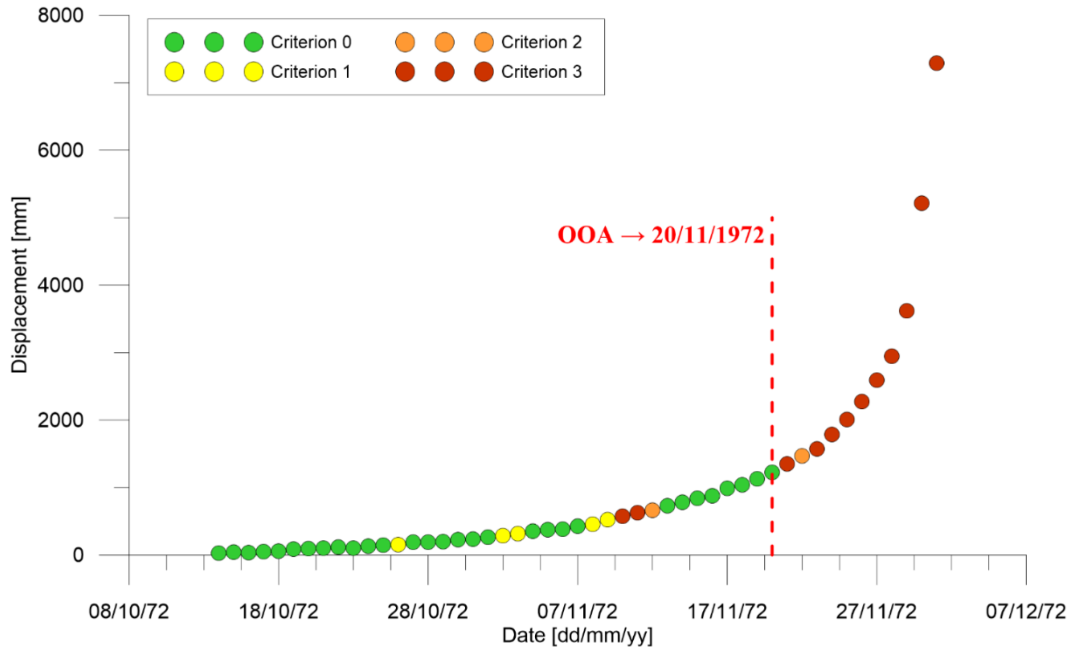

Figure 8: Results obtained from the application of the algorithm to the Agoyama Landslide dataset (displacement data recorded during the monitoring period from October to December 1972)

Case Study #3: Tuckabianna West Landslide

The third case study reported to outline the algorithm application regards a translational planar rockslide occurred in Tuckabianna West open pit mine, Australia. The collapse involved $1.2\text{x}10^5$ m^3 of material and was likely triggered by excavation works (Glastonbury and Fell, 2002). Pre-collapse rockfall events were observed in the area 10 days before the main collapse. It should be noted that these phenomena occurred before the beginning of the tertiary creep phase, which lasted approximately 6 days (Moretto et al., 2017). Monitoring activities involving surface surveys were issued after the identification of a tension crack in the upper part of the slope. However, as reported by Glastonbury and Fell (2002), mining activities continued even during the acceleration phase.

The onset of acceleration reference value for this case study was defined by taking into consideration all information reported on the phenomenon evolution by authors mentioned in the previous paragraph. In particular, displacement data trend (Figure 9) and considerations regarding the acceleration evolution over time allow to identify the beginning of the accelerating phase between March 4th and 5th.

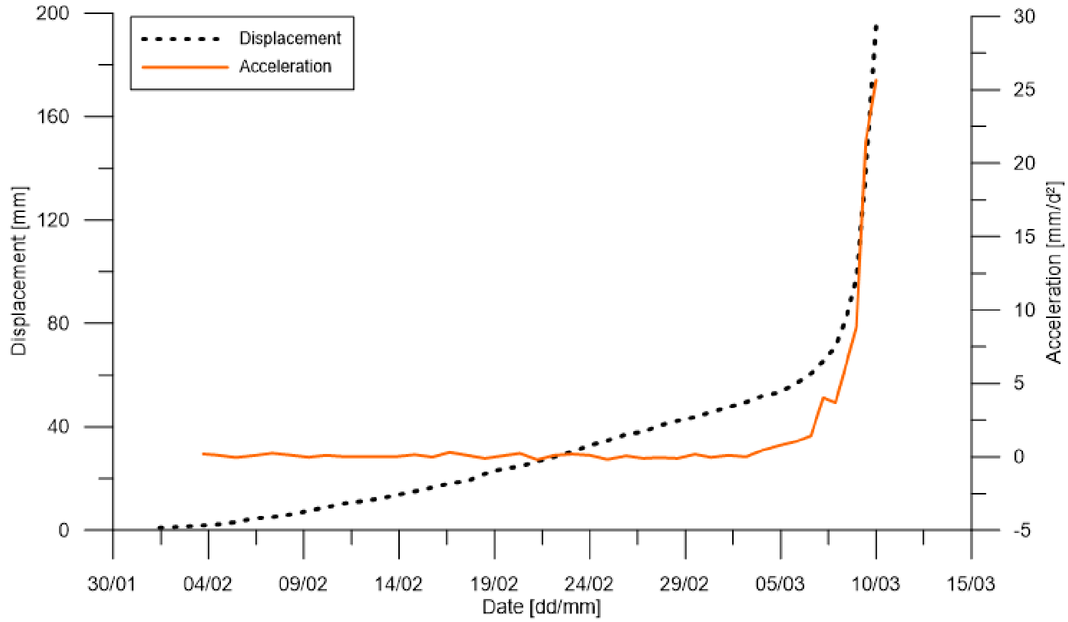

Figure 9: Displacement and acceleration curves for the Tuckabianna West landslide – dataset digitized from Glastonbury and Fell (2002)

Following the same process presented in previous case studies, the displacement dataset was elaborated by applying the algorithm to each monitoring data simulating a real-time acquisition. As evidenced by results reported in Figure 10, it is possible to observe a clear distinction between the constant velocity phase, characterized by a linear displacement trend, and the subsequent accelerating stage that ultimately led to the slope collapse. According to the outcomes provided by the software, the monitoring data sampled on March 4th was the first one to fulfil all conditions to achieve Criterion 3 requirements, while the following value managed to satisfy Criterion 1 only. However, starting from March 7th, the displacement trend highlighted an evident accelerating behaviour, and every monitoring measure from this point on reached the level defined by Criterion 3. According to these outcomes, the OOA date for this case study could be placed approximately on March 4th, which is in good agreement with the reference value retrieved from available literature.

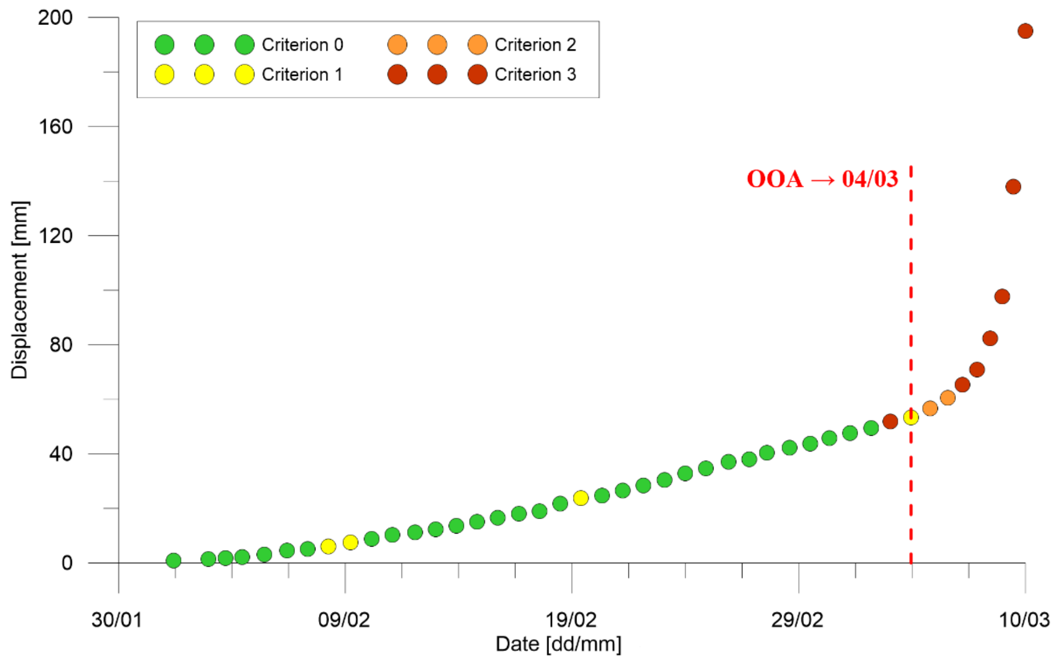

Figure 10: Results obtained from the application of the algorithm to the Tuckabianna West Landslide dataset (displacement data available starting from 1st February)

It is possible to identify a consistent behaviour in all three case studies reported in this study. In particular, the first part of each dataset is characterized by a linear trend (i.e. constant displacement rate) and is mostly limited by the Criterion 1 condition, which requires an increasing displacement rate. On the other hand, the second part presents an upward trend that consistently fulfil all conditions imposed by the methodology, effectively representing the accelerating stage of the landslide. However, it is possible to observe the occurrence of some false positives in the analysis, represented by monitoring points that fulfilled all the conditions despite not being part of the acceleration phase. These inaccuracies could be attributed to local fluctuations in the displacement dataset (e.g. small displacement increase, slight upward trend, etc.) and to the digitized dataset quality, which cannot be considered as accurate as the original monitoring dataset. From a general point of view, possible solutions could involve the application of filters and smoothing procedures on raw monitoring data. Either way, it should be underlined that in both cases the false alarm phase lasted no more than two consecutive measures, thereby resulting easily detectable when following datasets did not activate one of the algorithm sub-criteria.

Conclusions

The application of technological innovations to the geotechnical field has led, in recent years, to the development of new monitoring tools featuring improved efficiency, reliability and accuracy. These innovative devices could significantly improve the performances of an Early Warning System, by exploiting automatic processes for data acquisition, elaboration, and dissemination of alarm messages. In this context, a methodology dedicated to the identification of critical events, represented by increasing displacement rates, could be extremely useful in terms of risk management and prevention. However, despite the detailed analyses performed on failure forecasting models, studies focused on the identification of a landslide Onset-Of-Acceleration (OOA) are far less common in literature.

In this paper a newly developed methodology is presented, intended to provide a multi-criteria algorithm able to identify automatically an accelerating trend starting from displacement monitoring data. In particular, the proposed approach relies on a drop-down procedure composed of four steps that are applied to each single data sample, in order to identify specific variations in the landslide behaviour. The methodology was designed for the integration into innovative monitoring systems, featuring automatic procedures and high sampling frequencies. Additionally, the model development involved a series of parametric analyses, aimed to calibrate the main parameters included in the algorithm.

Three case studies are reported in this paper, to present a practical application by simulating a real-time acquisition in a scenario where a collapse was observed. Outcomes of the analyses performed on available displacement datasets evidenced how the algorithm allowed to identify two separate stages of the phenomenon evolution over time. The comparison of the onset-of-acceleration date estimated by the proposed procedure with the acceleration curves reported for each case study underlined the positive result of the multi-criteria methodology in locating the beginning of the critical acceleration phase. It should be however noted the presence of some isolated false positives, likely attributable to the quality of the displacement datasets.

The algorithm is currently being tested in synergy with another multi-level early warning routine, analysing data sampled from automatic monitored devices installed in different sites. Specifically, the authors are working on the development of an integrated system that includes the proposed methodology to identify critical events and describe their evolution over time (Valletta et al. 2020). This approach should allow to characterize different typologies of accelerating trends with higher accuracy, and to reduce the occurrence of false alarms caused by minor acceleration events.

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