Of reliable landslide forecasting and factors influencing predictability

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ABSTRACT
Forecasting a catastrophic collapse is a key element in landslide risk reduction, but also a very
difficult task, owing to the scientific difficulties in predicting a complex natural event and also to
the severe social repercussions caused by a false or a missed alarm. A prediction is always
affected by a certain error, however when this error can imply evacuations or other severe
consequences a high reliability in the forecast is, at least, desirable.
In order to increase the confidence of predictions, a new methodology is here presented.
Differently from traditional approaches, it iteratively applies several forecasting methods based
on displacement data and, also thanks to an innovative data representation, gives a valuation of
how the prediction is reliable. This approach has been employed to back-analyse 15 landslide
collapses. By introducing a predictability index, this study also contributes to the understanding
of how geology and other factors influence the possibility to forecast a slope failure. The results
showed how kinematics, and all the factors influencing it such as geomechanics, rainfall and
other external agents, is the key feature when concerning landslide predictability.

Keywords: landslides; forecasting; geomechanics; early warning; time of failure; slope failure

INTRODUCTION
Natural disaster forecasting for early warning purposes is a field of study that drew the media
attention after events such as the 26th December 2004 tsunami of Sumatra. Predicting landslides,
with respect to other natural hazards, is a complex task due to the influence of many factors like
geomechanical properties, rainfall, ground saturation, topography, earthquakes and many others.
So far, few empirical landslide forecasting methods exist (Azimi et al., 1988; Fukuzono, 1985a;
Mufundirwa et al., 2010; Saito, 1969; Voight et al., 1988) and none furnishes a reliability degree
about the prediction, making them unsuitable for decision making. In particular when mentioning
géomechanics we particularly refer to the study of the behaviour of a landslide concerning its
deformation with relation to the applied stress, with particular reference to its post-rupture
conditions.
In our research we present an approach to perform probabilistic forecasting of landslides
collapse. This has been achieved by reiterating several predictions using more forecasting
methods at the same time on multiple time series. This approach may have important
applications to civil protection purposes as it provides the decision makers with a level of
confidence about the prediction. Furthermore, this study, performed on 15 different case studies,
shows how the possibility or not to forecast the time of collapse of a landslide is affected by
géomechanical or geomorphological features as much as by circumstantial conditions.
The inverse velocity forecasting method
Forecasting activity can be considered the fulcrum of early warning systems (Intieri et al.,
2013), i.e. cost-effective tools for mitigating risks by moving the elements at risk away. For
many natural phenomena forecasting is common practice (for example for hurricanes;
Willoughby et al., 2007), while for others is, at present, impossible (earthquakes; Jordan et al.,
2011). Landslides lie in between. Their prediction can be performed through rainfall thresholds
(Baum and Godt, 2010), but a more reliable approach should make use of direct measures of
potential instability, such as displacements (Lacasse and Nadim, 2010; Blikra, 2008). A first
issue is that only a small percentage of landslides in the world is appropriately monitored, that
often monitoring is carried out for short periods not encompassing the final pre-failure stages, or
may have been carried out with a too low temporal frequency that does not permit to follow the
displacement trend. This also causes an insufficient knowledge of the geomechanical processes
leading to failure, which is another responsible for our deficiencies in predicting landslides.
In spite of this, few empirical methods for predicting the time of failure based on movement
monitoring data have been developed (Azimi et al., 1988; Fukuzono, 1985a; Mufundirwa et al.,
2010; Saito, 1969) and further investigated on a physical basis (Voight et al., 1988). They are all
based on the hypothesis that if a landslide follows a peculiar time-dependant geomechanical
behaviour (called creep; Dusseault and Fordham, 1994), it will display a hyperbolic acceleration
of displacements before failure; by extrapolating this trend from a displacement time series
through empirical arguments, it is possible to obtain the predicted time of failure. However such
methods do not always produce good results. In fact, other than the limitation of working only
with creep behaviours, sometimes the tertiary creep can evolve such rapidly that a sufficient lead
time is simply not possible (IEEIRP, 2015). In other cases natural or instrumental noise can
hamper the predictions and require further data treatment to allow for effective warnings (Carlà
et al., 2016). Other authors also contributed to methodologies to exploit such methods (Crosta
and Agliardi, 2003; Dick et al., 2015; Manconi and Giordan, 2015).
One of the most famous methods is Fukuzono’s (1985a), which derives from Saito’s (1969),
from here on simply called F and S method, respectively. It requires that during the acceleration
typical of the final stage of the creep (tertiary creep), the inverse of displacement velocity \( \frac{1}{v} \) decreases with time. The collapse is forecasted to occur when the extrapolated line reaches the
abscissa axis (corresponding to a theoretical infinite velocity). Such line may either be convex,
straight or concave (Fukuzono, 1985a). When it is straight this phenomenon is sometimes
referred to as Saito effect (Petley et al., 2008).
The possibility to find landslides showing the Saito effect has been related to the mechanical
properties of the sliding mass. However there is no general consensus on this issue.
According to some authors (Petley, 2004; Petley et al., 2002), in order to display the Saito effect,
landslides need to display a brittle behaviour (which indicates a drop from peak strength to
residual strength value, deformation which is concentrated along a well defined shear surface,
sudden movements and catastrophic failure, usually associated with crack formation in strong
rocks); furthermore only brittle, intact rocks evolve in catastrophic landslides and therefore can
be predicted; for others (Rose and Hungr, 2007), on the opposite, landslides displaying the Saito
effect must have ductile failures in order to be forecasted (i.e. slower, indefinite deformation
along a shear zone and under a constant stress, typical of sliding on pre-existing surfaces of soft
rocks), as brittleness is characterized by sudden, impossible to anticipate, ruptures.
This complex subject is made even more difficult due to the influence of external factors
(rainfall, earthquakes, excavations), structural constraints (joints, faults, contacts with different
lithologies) and sometimes unknown elements within the mass (the conditions of the shear
surface, the history of the landslide, the presence of rock bridges). Therefore it is often hard to
establish the mechanical behaviour and even more to find an exact correlation between the
mechanical behaviour of a landslide and the possibility to predict its failure.

The concept of predictability
Before assessing the influence of geomechanics on the predictability of a landslide it is first
necessary to address the concept of predictability.
In literature (Azimi et al., 1988; Hutchinson, 2001; Mufundirwa et al., 2010; Rose and Hungr,
2007) there are papers that deal with “predictions” made in retrospect, that is thorough post-
event analyses showing the signs of a critical pre-collapse acceleration; however whether such
signs would have been unambiguous or would have granted a sufficient lead time is often neglected.

On the other hand in our research we consider an operational definition of predictability (integrating the one of early warning system; UNISDR, 2009) as the feature possessed by a landslide which allows one to forecast its collapse with reasonable confidence and sufficiently in advance, permitting the dispatch of meaningful warning information to enable individuals, communities and organizations threatened by the hazard to prepare and to act appropriately and in sufficient time to reduce the possibility of harm or loss. Therefore, displaying the Saito effect is not the only prerequisite for an operational prediction, there is also the need for repeated time of failure forecasts fluctuating around a constant time value placed not too close in the future.

This has been achieved through the reiterative approach and the graphical representation described in the following paragraph.

METHODS

The usual way to apply landslide forecasting methods based on displacements, is to obtain a single predicted time of failure \( t_f \) and to update such prediction as soon as new data are gathered (Rose and Hungr, 2007). This is a deterministic approach, since the real time of failure \( T_f \) is predicted through a single inference. At most more predictions can be made in the future but usually only one (the most recent) is used.

On the other hand, in order to account for the uncertainty of the methods and complexity of the phenomena, predictions should have a certain confidence (for example given by the standard deviation of \( t_f \)). This is especially important for operative early warning systems. We achieved this probabilistic approach by reiterating the equations from Saito (1969), Fukuzono (1985a) and Mufundirwa et al. (2010) (the latter method will be called M method from here on) for finding \( t_f \), using continuously new data and enabling the calculation of the standard deviation.

The predictions are plotted versus the time when they have been made (time of prediction, \( t_p \)). We call these diagrams prediction plots (Figure 1). A prediction is considered reliable when the inferences oscillate around the same \( t_f \). Figure 1 also shows that since reliable predictions usually display an oscillatory trend, the most updated one is not necessarily the most accurate, contrarily to what is usually believed (Rose and Hungr, 2007) in fact, the length of the dataset is more important, from which \( T_f \) can be estimated through simple statistical analyses (like mean and standard deviation).

Since in some cases a single forecasting method can fail to give satisfactory results, in order to improve even more the confidence in the predictions, a multi-model approach is adopted together with the probabilistic approach. In fact, according to the Diversity Prediction Theorem (Page, 2007; Hong and Page, 2008), diversity in predictive models reduces collective error. The highest confidence, of course, is reached when all the employed method independently converge towards the same result. For this research we confronted the results from S and F methods and from the method by Mufundirwa et al. (2010). The equations used for the iteration are obtained from the respective authors and are:

\[
\frac{t_r^2 - (t_1 \cdot t_3)}{2t_2 - (t_1 + t_3)},
\]

for S method, where \( t_1, t_2, t_3 \) are times taken so that the displacement occurred between \( t_1 \) and \( t_2 \) is the same as between \( t_2 \) and \( t_3 \).
\[ t_r = \frac{t_2}{v_1} - \frac{t_1}{v_2} \]

for F method, where \( v_1 \) and \( v_2 \) are the velocities at arbitrary times \( t_1 \) and \( t_2 \).

\[ t \frac{dD}{dt} = t_r \frac{dD}{dt} - B, \]

for M method, where \( D \) is the displacement and \( t_r \) is the angular coefficient of the line represented in a \( t \frac{dD}{dt} = f \left( \frac{dD}{dt} \right) \) space having \( B \) as the intercept.

Figure 1. This graph represents probabilistic predictions performed with 3 different forecasting methods (Fukuzono, 1985a; Mufundirwa et al., 2010; Saito, 1969) applied to the MB34-35’ displacement time series of Mount Beni landslide (Gigli et al., 2011). The horizontal dashed line indicates the observed time of failure \( (T_f) \) and the grey diagonal line the equality between \( t_f \) and \( t_p \). Therefore the vertical distance between a point and the dashed line indicates the prediction error. The vertical distance between the diagonal line and a prediction above it is the life expectancy of the landslide at the time of prediction. In this case the predictions obtained through S and F methods give a good estimation of \( T_f \), while the one from Mufundirwa et al. (2010) consistently forecasts the collapse few days ahead.

TIME OF FAILURE PREDICTION
In order to find a relation between the predictability of a failure and the geological features of the landslide, S, F and M methods have been applied to a number of different real case studies. Some geological features of interest relative to such cases are reported in TABLE 1, when they were known or applicable. Concerning brittleness, since it was rarely explicitly stated in the referenced articles, it was assessed based on information such as the type of material, the presence of a reactivated landslide, the weathering and the shape of the displacement time series. Since this lead to approximations, brittleness has been evaluated using broad and qualitative definitions.

Since \( T_f \) must be known in order to assess the quality of predictions, all the case studies are from past landslides that have already failed. Therefore the respective time of failures are all a posteriori known.

A few representative examples of prediction plots are showed in Figure 1 and Figure 2. Mount Beni landslide is a 500,000 m\(^3\) topple that evolved as a rockslide (Gigli et al., 2011). It developed on a slope object of quarrying activity. The predictions oscillate quite regularly around the observed time of failure (\( T_f \), dashed line in Figure 2). It is this convergence that permits to correctly forecast the collapse a priori at least since late November, i.e. a month before the failure. The three methods are similar to the point that S and F previsions can be partially overlapped. M previsions overlap as well but only in the final part. The M method alone would not be sufficient for spreading a reliable alarm as the single forecasts do not converge but move forward to a different time of failure as the time passes by.

Similar behaviours can be observed also for the cases of Figure 2 that display landslides with a different array of geological features (as seen in TABLE 1). The best results are obtained when the forecasts oscillate around \( T_f \) with sufficient time in advance (as for Vajont and, limited to F method, for Liberty Pit) or when they consistently give the similar \( t_f \) (as for the artificial landslide E, where the terms “artificial landslide” indicate a landslide recreated in laboratory with an artificial slope). In other cases (Avran valley and, limited to S and M method, for Liberty Pit) the predictions are too scattered or simply never converge toward a single result, thus making it impossible to foresee a reliable time of failure.

The results of the prediction plots can be roughly summarized reporting the mean and standard deviation of the forecasts for each method (Figure 3).

### TABLE 1. LANDSLIDE CASE HISTORIES

<table>
<thead>
<tr>
<th>Name</th>
<th>Material</th>
<th>Type</th>
<th>Britleness</th>
<th>Volume (m(^3))</th>
<th>Predisposing factor</th>
<th>Trigger</th>
<th>History</th>
<th>Basal geometry</th>
<th>Ref. *</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liberty Pit</td>
<td>Weathered quartz monzonite</td>
<td>Rockslide?</td>
<td>Medium/high</td>
<td>6x10(^6)</td>
<td>N.D.</td>
<td>Blasts, pore water pressure</td>
<td>First time failure</td>
<td>Planar?</td>
<td>1, 2</td>
</tr>
<tr>
<td>Landslide in mine</td>
<td>Consolidated alluvial sediments, weathered bedrock</td>
<td>Deep-seated toppling in bedrock</td>
<td>Medium</td>
<td>10(^6)</td>
<td>Blasts, pore water pressure</td>
<td>N.D.</td>
<td>First time failure?</td>
<td>N.D.</td>
<td>1</td>
</tr>
<tr>
<td>Betze-Post</td>
<td>Weathered granodiorite</td>
<td>Rockslide?</td>
<td>Medium/high</td>
<td>2x10(^6)</td>
<td>N.D.</td>
<td>Rainfall</td>
<td>First time failure?</td>
<td>Wedge intersections?</td>
<td>1</td>
</tr>
<tr>
<td>Vajont</td>
<td>limestone and clay</td>
<td>Rock slide</td>
<td>High</td>
<td>2.7x10(^5)</td>
<td>N.D.</td>
<td>Pore water pressure</td>
<td>Reactivated</td>
<td>Concave</td>
<td>1, 3</td>
</tr>
<tr>
<td>Stromboli †</td>
<td>Shoshonitic basalts</td>
<td>Bulging (not a landslide)</td>
<td>Medium/high</td>
<td>N.D.</td>
<td>N.D.</td>
<td>Sill intrusion</td>
<td>First time failure</td>
<td>N.D.</td>
<td>4</td>
</tr>
</tbody>
</table>

\* Ref. indicates references.
<table>
<thead>
<tr>
<th>Location</th>
<th>Rock Type</th>
<th>Failure Type</th>
<th>High/Low</th>
<th>Rainfall, Structure, Basal Excavation</th>
<th>Pore Water Pressure</th>
<th>First Time Failure</th>
<th>Stepped/Planar</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monte Beni</td>
<td>Ophiolitic breccias</td>
<td>Topple/rock slide</td>
<td>High</td>
<td>$5 \times 10^5$</td>
<td>N.D.</td>
<td>N.D.</td>
<td>Stepped</td>
<td>First time failure, Stepped, High</td>
</tr>
<tr>
<td>Cerzeto</td>
<td>Weathered metamorphic rocks on top, cataclastic zone and Pliocene clays</td>
<td>Debris slide-earth flow</td>
<td>Medium/low</td>
<td>$5 \times 10^6$</td>
<td>Prolonged rainfalls</td>
<td>Reactivated</td>
<td>Compound</td>
<td>First time failure, Stepped, High</td>
</tr>
<tr>
<td>Rock mass failure</td>
<td>Clayey limestone</td>
<td>Rockslide?</td>
<td>High (within limestone)?</td>
<td>$10^5$</td>
<td>“Structural complexity” (?)</td>
<td>Intense rainfall</td>
<td>First time failure</td>
<td>Planar</td>
</tr>
<tr>
<td>Asamushi</td>
<td>Liparitic tuff, jointed and weathered. Clay in the joints</td>
<td>Medium/low</td>
<td>$8 \times 10^5$</td>
<td>N.D.</td>
<td>N.D.</td>
<td>N.D.</td>
<td>First time failure</td>
<td>Convex, First time failure</td>
</tr>
<tr>
<td>Avran valley</td>
<td>Chalk</td>
<td>Rockslide</td>
<td>Medium/low</td>
<td>$10^5$</td>
<td>N.D.</td>
<td>N.D.</td>
<td>Convex</td>
<td></td>
</tr>
<tr>
<td>Giau Pass</td>
<td>Morainic material</td>
<td>Complex slide</td>
<td>Medium/low</td>
<td>$5 \times 10^5$</td>
<td>N.D.</td>
<td>N.D.</td>
<td>Composite</td>
<td>First time failure, Composite, Planar</td>
</tr>
<tr>
<td>Artificial landslide A</td>
<td>Loam</td>
<td>Earth slide</td>
<td>Low</td>
<td>N.D.</td>
<td>N.D.</td>
<td>N.D.</td>
<td>Prolonged rainfall</td>
<td>First time failure, Planar</td>
</tr>
<tr>
<td>Artificial landslide B</td>
<td>Sand</td>
<td>Earth slide</td>
<td>Low</td>
<td>N.D.</td>
<td>N.D.</td>
<td>N.D.</td>
<td>Prolonged rainfall</td>
<td>First time failure, Planar</td>
</tr>
<tr>
<td>Artificial landslide C</td>
<td>Sand</td>
<td>Earth slide</td>
<td>Low</td>
<td>N.D.</td>
<td>N.D.</td>
<td>N.D.</td>
<td>Prolonged rainfall</td>
<td>First time failure, Planar</td>
</tr>
<tr>
<td>Artificial landslide D</td>
<td>Sand</td>
<td>Earth slide</td>
<td>Low</td>
<td>N.D.</td>
<td>N.D.</td>
<td>N.D.</td>
<td>First time failure, Planar</td>
<td></td>
</tr>
</tbody>
</table>

*The references used are numbered as follows: 1: Rose and Hungr, 2007; 2: Zavodni and Broadbent, 1980; 3: Semenza and Melidoro, 1992; 4: Casagli et al., 2009; 5: Gigli et al., 2011; 6: Iovine et al., 2006; 7: Mufundirwa et al., 2010; 8: Saito, 1969; 9: Azimi et al., 1988; 10: Petley et al., 2002; 11: Angeli et al., 1989; 12: Fukuzono, 1985b.† The case of Stromboli is not relative to a landslide, rather to a volcanic bulging preceding a vent opening that was forecasted in a similar fashion of a landslide and therefore here included.
Figure 2. These graphs show how iterating forecasts performed through multiple forecasting methods increases the confidence when estimating the actual time of failure ($T_f$, dashed line). The crosses represent forecasts performed with S method, the triangles with F method and the diamonds with M method. Note that F forecasts for Avran valley landslide include other less accurate values not showed in the graph as they are out of scale.
This graph represents for each method the differential between the mean of the forecasts ($\bar{T}_f$) and the actual time of failure ($T_f$). Negative values are safe predictions as anticipate the time of failure. The dashed line represents exact predictions ($T_f - \bar{T}_f = 0$). The standard deviations of the forecasts are represented as error bars. For Betze-Post and Mount Beni landslides, time series from different measuring points are reported. The rock mass failure, Asamushi landslide and the artificial landslides are not shown as were monitored in a different time scale (hours or minutes).

**Figure 3.**

**PREDICTABILITY INDEX**

In order to evaluate the performance of S, F and M methods and to relate it to the characteristics of the reported examples, an arbitrary scoring system has been implemented and attributed to each prediction plot (considering that every time series has a prediction plot for each forecasting method and that for some case studies more than one time series was available). This permits to quantify the predictability of a collapse based on the prediction plot. A score from 1 to 5 has been assigned according to the following criteria:

- 1 point: the prediction plot never converges on a single $t_f$ (typically $t_f$ increases at every new datum available).
- 2 points: the predictions vary considerably at every new iteration. An average time of failure ($\bar{T}_f$) can be extracted but with high uncertainty.
- 3 points: the predictions oscillate around $T_f$, although with a certain variance.
- 4 points: the predictions have a low variance although $\bar{T}_f$ is slightly different than $T_f$. Note that when the variance was low, $\bar{T}_f$ and $T_f$ never differed greatly.
5 points: the prediction plot is clearly centred on $T_f$ therefore the reliability of $\bar{T}_f$ is high.

By summing the scores obtained from S, F and M prediction for each time series, what we call the Predictability Index ($PI$) is obtained (TABLE 2). Since PI is a means to evaluate the overall quality of a set of predictions (it requires to observe the time series of $T_f$ and confront it with $T_f$, it is the predictability index) and also to compare the performance of different forecasting methods with different case studies, naturally it can only be estimated after the collapse.

By using 3 forecasting methods, $PI$ ranges from 3 (impossible to predict the time of failure) to 15 (the time of failure can be predicted in advance and with a high reliability). Though a certain degree of subjectivity is unavoidable when assigning the scores, what matters here is the relative difference of $PI$ between the case studies. In such a way it is possible to understand in which conditions a landslide is more or less predictable.

**TABLE 2. PREDICTABILITY INDEX**

<table>
<thead>
<tr>
<th>Name</th>
<th>S</th>
<th>F</th>
<th>M</th>
<th>$PI$</th>
<th>Inverse velocity trend</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liberty Pit</td>
<td>1</td>
<td>5</td>
<td>1</td>
<td>7</td>
<td>Asymptotic (linear at the end)</td>
<td>Open pit mine, structural control of 2 intersecting faults</td>
</tr>
<tr>
<td>Landslide in mine</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>15</td>
<td>Linear</td>
<td>Open pit mine</td>
</tr>
<tr>
<td>Betze-Post 1</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>7</td>
<td>Linear</td>
<td>Open pit mine</td>
</tr>
<tr>
<td>Betze-Post 2</td>
<td>4</td>
<td>5</td>
<td>4</td>
<td>13</td>
<td>Linear</td>
<td>Open pit mine</td>
</tr>
<tr>
<td>Betze-Post 3</td>
<td>5</td>
<td>4</td>
<td>1</td>
<td>10</td>
<td>Linear</td>
<td>Open pit mine</td>
</tr>
<tr>
<td>Vajont benchmark 63</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>15</td>
<td>Linear</td>
<td>Air pressure and cementation caused catastrophic collapse</td>
</tr>
<tr>
<td>Stromboli</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>5</td>
<td>Asymptotic</td>
<td>Volcanic context</td>
</tr>
<tr>
<td>Mount Beni 12-9</td>
<td>4</td>
<td>5</td>
<td>1</td>
<td>10</td>
<td>Concave</td>
<td>Back fracture</td>
</tr>
<tr>
<td>Mount Beni a'b'</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>5</td>
<td>Linear</td>
<td>Short time series</td>
</tr>
<tr>
<td>Mount Beni 15-13</td>
<td>5</td>
<td>3</td>
<td>1</td>
<td>9</td>
<td>Linear</td>
<td>Internal fracture</td>
</tr>
<tr>
<td>Mount Beni 34-35'</td>
<td>5</td>
<td>3</td>
<td>1</td>
<td>9</td>
<td>Linear</td>
<td>Lateral fracture, short time series</td>
</tr>
<tr>
<td>Mount Beni 45-47</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>6</td>
<td>Linear</td>
<td>Back fracture, short time series</td>
</tr>
<tr>
<td>Mount Beni 3-2</td>
<td>5</td>
<td>2</td>
<td>1</td>
<td>8</td>
<td>Concave</td>
<td>Back fracture</td>
</tr>
<tr>
<td>Mount Beni 4-6</td>
<td>1</td>
<td>4</td>
<td>1</td>
<td>6</td>
<td>Linear</td>
<td>Back fracture, short time series</td>
</tr>
<tr>
<td>Mount Beni 24-23</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>7</td>
<td>Linear</td>
<td>Lateral fracture</td>
</tr>
<tr>
<td>Mount Beni 49-24</td>
<td>5</td>
<td>1</td>
<td>1</td>
<td>7</td>
<td>Linear</td>
<td>Lateral fracture, short time series</td>
</tr>
<tr>
<td>Mount Beni 35'-36</td>
<td>2</td>
<td>5</td>
<td>1</td>
<td>8</td>
<td>Linear</td>
<td>Lateral fracture, short time series</td>
</tr>
<tr>
<td>Mount Beni 33-35'</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>7</td>
<td>Linear</td>
<td>Lateral fracture, short time series</td>
</tr>
<tr>
<td>Mount Beni 36-37</td>
<td>4</td>
<td>3</td>
<td>1</td>
<td>8</td>
<td>Linear</td>
<td>Lateral fracture</td>
</tr>
<tr>
<td>Mount Beni 19-16</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>5</td>
<td>Linear</td>
<td>Lateral fracture</td>
</tr>
<tr>
<td>Mount Beni 19-17</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>4</td>
<td>Linear</td>
<td>Lateral fracture, short time series</td>
</tr>
<tr>
<td>Mount Beni 33-34</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>7</td>
<td>Linear</td>
<td>Internal fracture</td>
</tr>
<tr>
<td>Mount Beni 43-44</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>6</td>
<td>Asymptotic (constant velocity at the end)</td>
<td>Internal fracture, short time series</td>
</tr>
<tr>
<td>Mount Beni 40-41</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>6</td>
<td>Asymptotic (constant velocity at the end)</td>
<td>Internal fracture, short time series</td>
</tr>
<tr>
<td>Mount Beni 40-42</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>7</td>
<td>Linear</td>
<td>Internal fracture, short time series</td>
</tr>
<tr>
<td>Mount Beni 45-46</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>7</td>
<td>Linear</td>
<td>Back fracture, short time series</td>
</tr>
<tr>
<td>Mount Beni 1-2</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>7</td>
<td>Linear</td>
<td>Back fracture</td>
</tr>
<tr>
<td>Cerzeto</td>
<td>5</td>
<td>5</td>
<td>1</td>
<td>11</td>
<td>Linear</td>
<td>N.A.</td>
</tr>
</tbody>
</table>
DISCUSSION

TABLE 2 shows how the most predictable events ($PI > 8$) can display very different features and are quite irrespective of the shape of the inverse velocity plot, the volume, the brittleness of the material, the history of the landslide and so on (see also TABLE 1).

A comparison between Figure 3 and TABLE 2 illustrates how the mean and standard deviation of the forecasts alone are not enough to represent the quality of predictions and, consequently, the predictability of a landslide. In fact the importance of a single forecast strongly depends on the time when it is made; for example, given the same set of forecasts ($t_{f,i}$), a higher $PI$ is obtained if the first predictions done are the farthest from $T_f$ while the final ones tend to converge to it; in this way the prediction plot assumes an oscillatory shape (as for S and F forecasts in Figure 1). Conversely, if the same forecasts are made with a different order so that they get closer and closer to $T_f$ as time passes by (that is $|t_{f,i} - T_f| < |t_{f,i-1} - T_f|$), then there is no $t_{f,i}$ prevailing on the others and it is not possible to define a more probable time of collapse (as for M forecasts in Figure 1). However the average and standard deviation of $t_{f,i}$ are the same for both cases and this explains why these two statistics alone are not as informative as a prediction plot. From TABLE 2 it is also possible to assess which method gives the best results. The sum of the scores for S, F and M is 119, 115 and 63 respectively. Overall S and F perform similarly, but for a specific case study their effectiveness can be very different, therefore their result are independent and not redundant; there is no indisputable clue suggesting when F method is more performing than S and vice versa; nonetheless it appears that S is negatively influenced when the displacement curve is not regularly accelerating (Liberty Pit, Stromboli), whereas for F a few aligned points in the final tract in the inverse velocity plot are sufficient for predicting the failure; however F forecasts are more disturbed when displacement data are noisy, since they use their derivative (velocity) as input. Eventually M forecasts generally perform more poorly and rarely (i.e. artificial landslides B and C) surpass those obtained from S and F methods. Interestingly, different displacement time series belonging to the same landslide can display different behaviours. This is a strong evidence that, even though the geological features do influence the predictability of a landslide, assuming that they keep the same for the whole landslide, other factors must determine the quality of the predictions. The last column of TABLE 2 shows for each time series what such factors could be, such as lithology (the asymptotic trends of the cases of Avran valley and Giau Pass can be explained as consequences of a lowly brittle material according to Petley’s experiments; Petley, 2004), external forces (excavation in open pit mines, volcanic activity, rainfall), local effects (structural constraints, displacement measured relative to internal or lateral fractures not representing the general instability of the landslide),
quality of data (length of the time series, frequency of the observations, level of noise, representativeness of the monitored point) etc.

All these case histories show that the main responsible for the predictability of a landslide, and secondary also for the presence or not of the “Saito effect”, is connected to geology but not simply and directly. Instead both depend on the kinematics of the landslide, which in turn depends on the geological conditions. In the complex relation between geology and kinematics the aforementioned factors may intervene and asymptotic trends in the inverse velocity plot have been encountered also for first failure ruptures (as found in some time series of Mount Beni landslide).

In other words, even though geomechanics is unquestionably a key factor, it is sometimes difficult to have a deep knowledge of the geomechanical features of a landslide, especially in the field and in emergency situations, although some safe assumptions can always be done by observation and a broad knowledge of the area. What it may be known about them is in part thanks to what is derived from displacement data. Like in a black box model, even if the real properties of a phenomenon are not known, we can draw conclusions from the output of those properties (i.e. the kinematics). In this case, importance has been done to kinematics because what is generally measured by monitoring are displacement data and because many other unknown factors (rainfall, ground saturation, earthquakes, anthropic disturbance) are included in the black box together with the geomechanics; this makes it virtually impossible to know in advance what may be the degree of influence of geomechanics alone with respect to other factors, thus leading to focusing on kinematics instead. Moreover, even though geomechanics is a key element (for example because it is responsible for the creep behaviour), we showed that landslide prediction can be carried out with a variety of different geomechanical settings.

Finally, the prediction plots clearly show that, contrarily to what is generally believed (Rose and Hungr, 2007), the last forecasts are not necessarily the most accurate and that past ones (starting from the initiation of the tertiary creep) are essential to estimate the correct time of failure. In fact older forecasts can be more accurate and in any case furnish precious information about the general reliability of the final prediction, as explained above. Therefore the present study highlights the importance of considering the whole set of predictions made with time. The integration of more forecasting methods further raises reliability of the predictions, which is of great importance for early warning systems, in particular when evacuations are envisaged.

Limitations of the proposed approach are those related to the intrinsic limitations of the forecasting methods that have been integrated. In fact, since S, F and M methods are all based on the creep theory, the occurrence of a tertiary creep phase slow enough to allow to monitor and take action is necessary. Voight (1988) also assumes that there must be no external force acting on the landslide, but the examples shown in this paper demonstrate that this may not represent a limitation.

Resuming, the proposed methodology can be summarized as in Figure 4.
CONCLUSIONS

In conclusion, the results of the study are the following:

- Prediction plots are introduced as graphs showing the evolution of collapse forecasts with time. Such plots provide more information than simple average and standard deviation of the forecasts and improve the reliability of the final prediction.

- A predictability index (PI) has been introduced as a scoring system based on the description of the prediction plot, in order to evaluate the quality of a set of predictions.

- The predictability of a landslide depends firstly on its kinematics and then on what determines it (geology, external forces, local effects etc.).

- Landslide collapses can be forecasted whether they are in highly or lowly brittle materials, in rock or in earth material, of different types, with different sliding surface geometries, volumes and triggers.

- Contrarily to what is generally assumed (Voight, 1988; Rose and Hungr, 2007), landslides can be forecasted also with external forces acting.

- The asymptotic behaviour of the inverse velocity curve does not imply that the landslide cannot be correctly forecasted, even though it can hinder the prediction.

- The asymptotic behaviour may be induced by external factors, lithology and local effects, rather than only by crack propagation. In fact asymptotic trends have been found in first time failures and in both brittle and lowly brittle materials. The crack propagation explanation is not neglected, but it may not represent the general rule.
Most recent displacement monitoring data increase the confidence when estimating the
time of failure but do not necessarily provide more accurate predictions than the older ones
(provided that they start from after the initiation of the tertiary creep).

The developed approach integrates more forecasting methods to further improve the
reliability of the prediction.

AUTHOR CONTRIBUTION
E. Intrieri developed the idea and performed the analyses. G. Gigli supervised and improved the
manuscript.

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REFERENCES
Angeli, M-G., Gasparetto, P., Pasuto, A. and Silvano, S.: Examples of landslide instrumentation
(Italy). In: Proceedings of 12th International Conference on Soil Mechanics and Foundation
In: Bonnard C, Balkema AA (eds) Proceedings of 5th International Symposium on Landslides,
Baum, R. L. and Godt, J. W.: Early warning of rainfall-induced shallow landslides and debris
Blikra, L.H.: The Åknes rockslide: Monitoring, threshold values and early-warning. 10th
International Symposium on Landslides and Engineered Slopes, 30th Jun - 4th Jul, Xian, China,
1089-1094, 2008.
Carlà, T., Intrieri, E., Di Traglia, F., Nolesini, T., Gigli, G., Casagli, N.: Guidelines on the use of
inverse velocity method as a tool for setting alarm thresholds and forecasting landslides and
Casagli, N., Tibaldi, A., Merri, A., Del Ventisette, C., Apuani, T., Guerri, L., Tarchi, D.,
Fortuny-Guasch, J., Leva, D. and Nico, G.: Deformation of Stromboli Volcano (Italy) during the
2007 crisis by radar interferometry, numerical modeling and field structural data, Journal of
Crosta, G.B. and Agliardi, F.: Failure forecast for large rock slides by surface displacement
early-warning time-of-failure analysis methodology for open-pit mine slopes utilizing ground-based


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