~~Operative and~~ Of reliable landslide forecasting and factors influencing~~e of geology to~~ predictability

Emanuele Intrieri[1]*, Giovanni Gigli[1]
[1] *Department of Earth Sciences, University of Studies of Firenze, via La Pira 4, 50121 Firenze, Italy.*
**Corresponding author*

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 ~~that, contrarily to what is generally believed, geomechanics plays an indirect role~~ when concerning ~~in~~ landslide predictability~~; instead kinematics, and all the factors influencing it, is the key feature~~.

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 geomechanics 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 ~~not~~ affected by geomechanical or geomorphological features~~, like usually believed,~~ as much as by circumstantial conditions.

The inverse velocity forecasting method

Forecasting activity can be considered the fulcrum of early warning systems (Intrieri 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 ~~is usually~~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~~0~~), 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 (v^{-1}) 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 latter method will be called M method from here on.~~

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:

$$t_r = \frac{t_2^2 - (t_1 \cdot t_3)}{2t_2 - (t_1 + t_3)}, \quad (1)$$

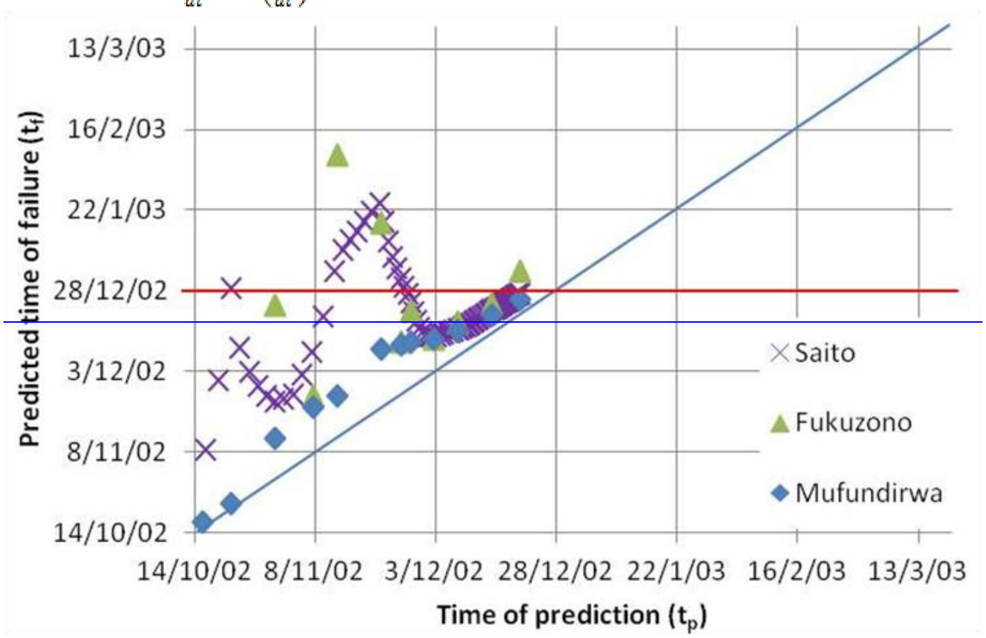
for S method, where t_1, t_2, t_3 are times taken so that the displacement occurred between t_1 and t_2 is the same as between t_2 and t_3.

$$t_r = \frac{t_2 \frac{1}{v_1} - t_1 \frac{1}{v_2}}{\frac{1}{v_1} - \frac{1}{v_2}}, \quad (2)$$

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

$$t\frac{dD}{dt} = t_r\frac{dD}{dt} - B, \quad (3)$$

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.



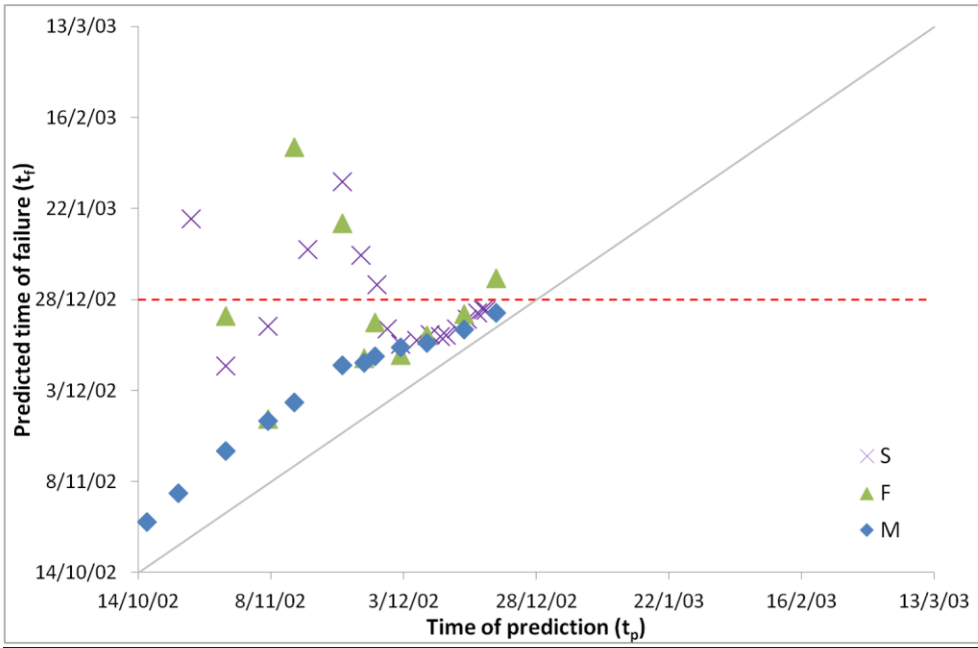


Figure 1. This graph represents probabilistic predictions performed with 3 different forecasting methods (Fukuzono, 1985a; Mufundirwa et al., 2010; Saito, 1969) applied to the MB34-35' displacement time series of Mount Beni landslide (Gigli et al., 2011). The ~~black~~ horizontal dashed line indicates 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 ~~black~~ dashed line indicates the prediction error. The vertical distance between the ~~blue~~ 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

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on a slope object of quarrying activity. The predictions oscillate quite regularly around the observed time of failure (T_f, ~~black~~ 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).

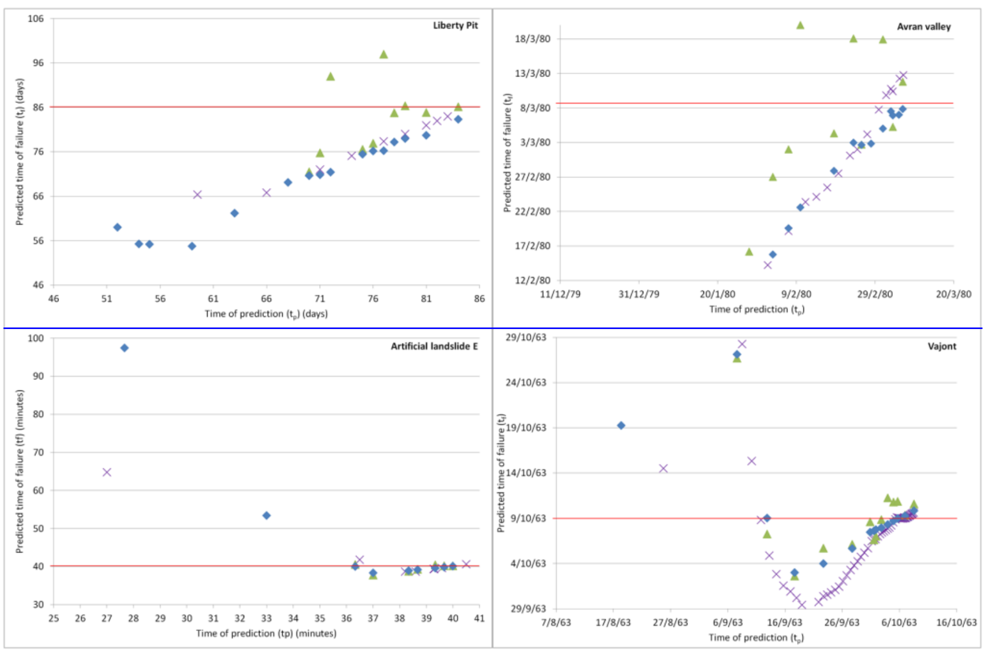
TABLE 1. LANDSLIDE CASE HISTORIES

Name	Material	Type	Brittleness	Volume (m^3)	Predisposing factor	Trigger	History	Basal geometry	Ref. *
Liberty Pit	Weathered quartz monzonite	Rockslide?	Medium/high	$6x10^6$	N.D.	Blasts, pore water pressure	First time failure	Planar?	1, 2
Landslide in mine	Consolidated alluvial sediments, weathered bedrock	Deep-seated toppling in bedrock	Medium	10^6	Blasts, pore water pressure	N.D.	First time failure?	N.D.	1
Betze-Post	Weathered granodiorite	Rockslide?	Medium/high	$2x10^6$	N.D.	Rainfall	First time failure?	Wedge intersections?	1
Vajont	limestone and clay	Rock ~~avalanche~~slide	High	$2.7x10^8$	N.D.	Pore water pressure	Reactivated	Concave	1, 3
Stromboli †	Shoshonitic basalts	Bulging (not a landslide)	Medium/high	N.D.	N.D.	Sill intrusion	First time failure	N.D.	4
Monte Beni	Ophiolitic breccias	Topple/rock slide	High	$5x10^5$	Rainfall, structure, basal excavation	N.D.	First time failure	Stepped	5
Cerzeto	Weathered metamorphic rocks on top, cataclastic zone and Pliocene clays	Debris slide-earth flow	Medium/low	$5x10^6$	Tectonized area, permeability differences	Prolonged rainfalls	Reactivated ?	Compound (steeper and irregular in the upper zone and gentler in the clays	6
Rock mass failure Japan	Clayey limestone	Rockslide?	High (within limestone)?	$5x10^2$	"Structural complexity" (?)	Intense rainfall	First time failure?	Planar?	7
Asamushi	Liparitic tuff, jointed and weathered. Clay in the joints		Medium/low	10^5	N.D.	N.D.	N.D.	Concave?	7, 8

Avran valley	Chalk	Rockslide	Medium/low	8x10^4	N.D.	N.D.	First time failure?	Convex	9
Giau Pass	Morainic material	Complex slide	Medium/low	5x10^5	N.D.	Pore water pressure	Preexisting shear surface	Composite	10, 11
Artificial landslide A	Loam	Earth slide	Low	N.D.	N.D.	Prolonged rainfall	First time failure	Planar	12
Artificial landslide B	Sand	Earth slide	Low	N.D.	N.D.	Prolonged rainfall	First time failure	Planar	12
Artificial landslide C	Sand	Earth slide	Low	N.D.	N.D.	Prolonged rainfall	First time failure	Convex	12
Artificial landslide D	Sand	Earth slide	Low	N.D.	N.D.	Prolonged rainfall	First time failure	Planar	12

*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.



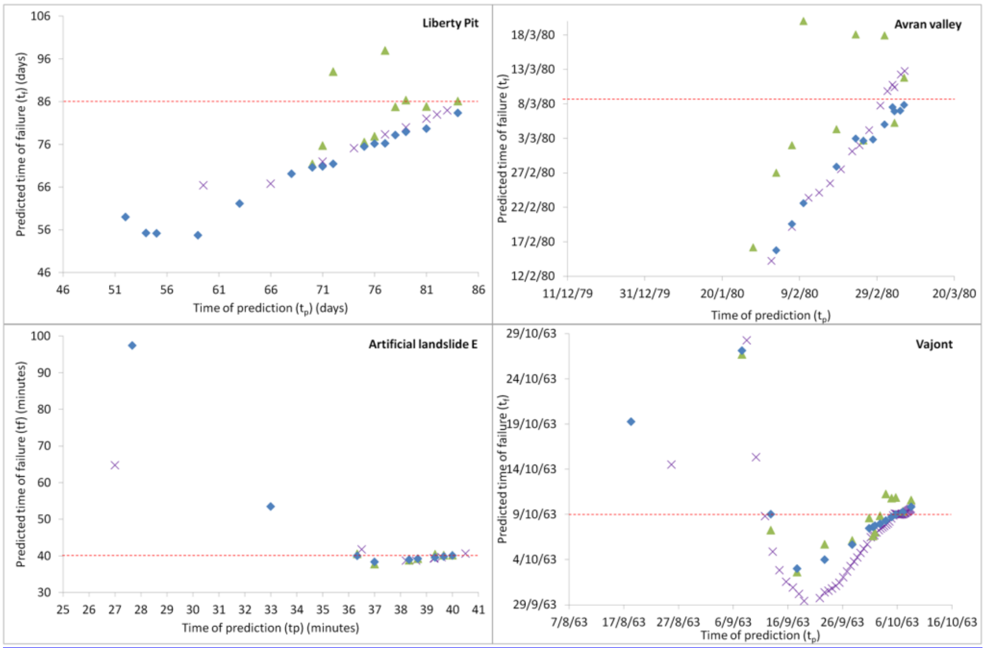
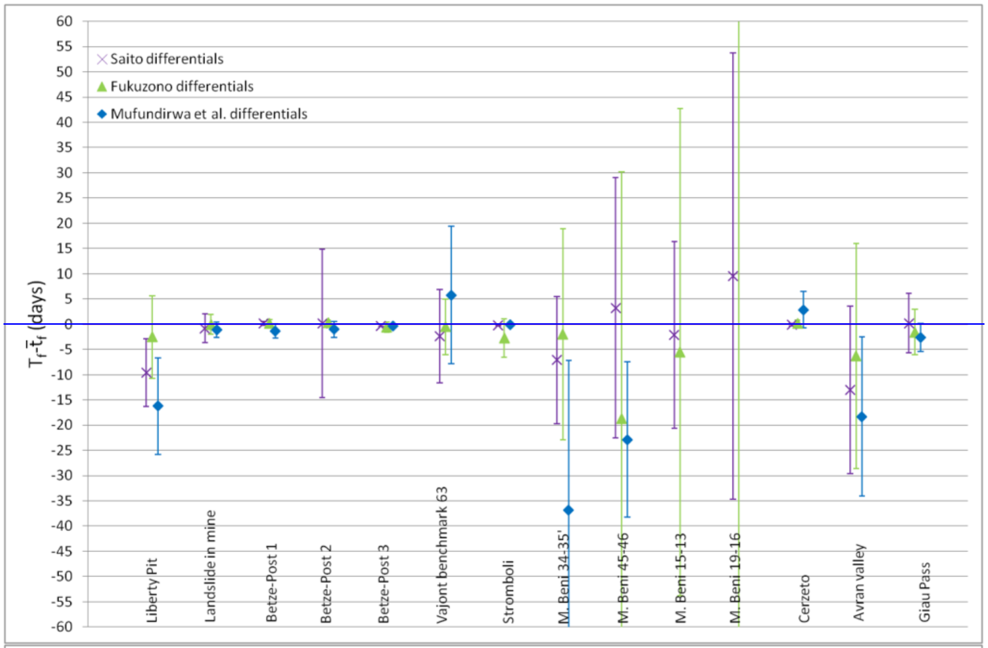


Figure 2. These graphs show how iterating forecasts performed through multiple forecasting methods increases the confidence when estimating the actual time of failure (T_f, ~~black~~ dashed line). The ~~purple~~ crosses represent forecasts performed with S method, the ~~green~~ triangles with F method and the ~~blue squares~~ 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.



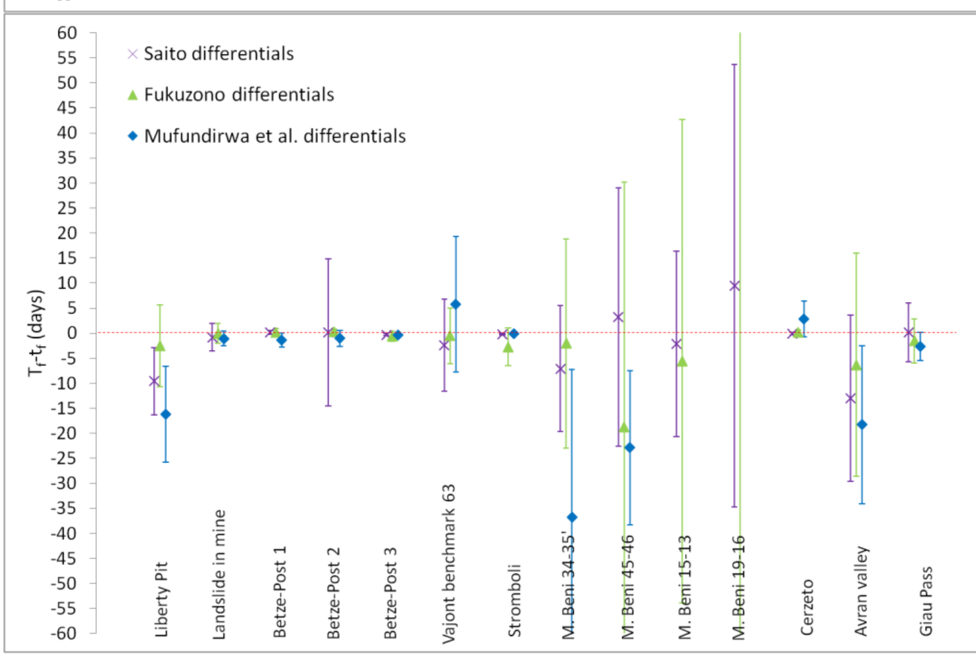


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Figure 3. This graph represents for each method the differential between the mean of the forecasts ($\bar{t}_f$) and the actual time of failure (T_f). Negative values are safe predictions as anticipate

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).

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_i) 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_i 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_i 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

Name	S	F	M	PI_i	Inverse velocity trend	Notes
Liberty Pit	1	5	1	7	Asymptotic (linear at the end)	Open pit mine, structural control of 2 intersecting faults
Landslide in mine	5	5	5	15	Linear	Open pit mine
Betze-Post 1	3	3	1	7	Linear	Open pit mine
Betze-Post 2	4	5	4	13	Linear	Open pit mine
Betze-Post 3	5	4	1	10	Linear	Open pit mine
Vajont benchmark 63	5	5	5	15	Linear	Air pressure and cementation caused catastrophic collapse
Stromboli	1	2	2	5	Asymptotic	Volcanic context
Mount Beni 12-9	4	5	1	10	Concave	Back fracture

Mount Beni a'b'	1	3	1	5	Linear	Short time series
Mount Beni 15-13	5	3	1	9	Linear	Internal fracture
Mount Beni 34-35'	5	3	1	9	Linear	Lateral fracture, short time series
Mount Beni 45-47	2	3	1	6	Linear	Back fracture, short time series
Mount Beni 3-2	5	2	1	8	Concave	Back fracture
Mount Beni 4'-6	1	4	1	6	Linear	Back fracture, short time series
Mount Beni 24-23	4	2	1	7	Linear	lateral fracture
Mount Beni 49-24	5	1	1	7	Linear	Lateral fracture, short time series
Mount Beni 35'-36	2	5	1	8	Linear	Lateral fracture, short time series
Mount Beni 33-35'	3	3	1	7	Linear	Lateral fracture, short time series
Mount Beni 36-37	4	3	1	8	Linear	Lateral fracture
Mount Beni 19-16	2	2	1	5	Linear	Lateral fracture
Mount Beni 19-17	1	2	1	4	Linear	Lateral fracture, short time series
Mount Beni 33-34	4	2	1	7	Linear	Internal fracture
Mount Beni 43-44	3	2	1	6	Asymptotic (constant velocity at the end)	Internal fracture, short time series
Mount Beni 40-41	3	2	1	6	Asymptotic (constant velocity at the end)	Internal fracture, short time series
Mount Beni 40-42	3	3	1	7	Linear	Internal fracture, short time series
Mount Beni 45-46	3	2	2	7	Linear	Back fracture, short time series
Mount Beni 1-2	4	2	1	7	Linear	Back fracture
Cerzeto	5	5	1	11	Linear	N.A.
Rock mass failure Japan	2	2	1	5	Convex	Open pit mine, very small landslide
Asamushi	5	3	1	9	Linear	N.A.
Avran valley 5	1	2	1	4	Concave	N.A.
Avran valley 6	1	1	1	3	Asymptotic	N.A.
Avran valley 7	1	2	1	4	Concave	N.A.
Giau Pass	3	3	1	7	Asymptotic /concave	N.A.
Artificial landslide A	5	5	5	15	Convex	40° artificial slope
Artificial landslide B	2	2	3	7	Concave	40° artificial slope
Artificial landslide C	1	2	3	6	Linear (slightly convex)	40° artificial slope
Artificial landslide D	5	5	5	15	Linear	30° artificial slope

DISCUSSION

TABLE 2 shows how the most predictable events (*PI*~~*i*~~ > 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 ~~P_i~~*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 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 been 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.

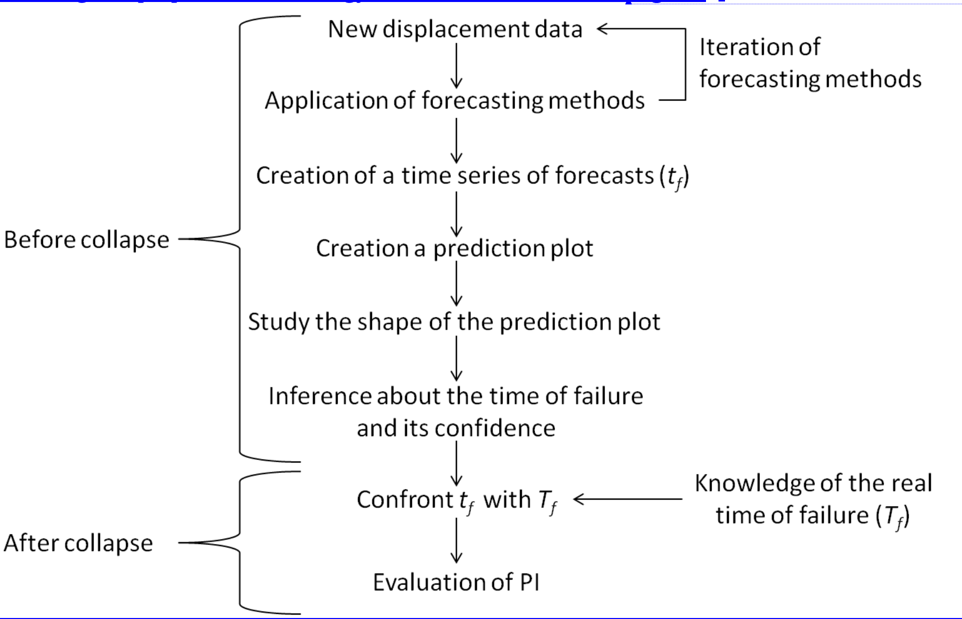

Figure 4. Flow-chart that synthesises the proposed procedure.

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~~*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.

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- 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 necessary 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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Answers to reviewers

Reviewer 1

Reviewer: I appreciate the effort by the authors on pursuing a landslide prediction tool that accounts for the reliability in its predictions. The proposed methodology is based on careful consideration of the work done by others and supported by its implementation on several case studies. This is important work that should be encouraged in landslide research for risk management purposes. I do have some general comments and discussion.

The authors state the importance of kinematics over geomechanics, based on their interpretation of results. I would suggest that not only does geomechanics play a major role in the kinematics of some of their case studies, but also that predictability of other landslide types not included in the database in this paper are likely controlled by the geomechanics. Clear examples are landslides in sensitive clays and other materials prone to collapse.

Authors: The authors did not mean to diminish the obvious importance of geomechanics to predictability. However, since this point has been unclear for all the reviewers, it is evident that we failed in our explanation.

What we mean is that 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 been 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, landslide prediction can be carried out with a variety of different geomechanical settings. This explanation can be added in the conclusions, while in the rest of the text every misleading comment that may have reduced the importance of geomechanics will be changed or removed.

R: The authors should also discuss the issue of timely predictability. Methods used to predict landslides that are based on displacement monitoring assume that slope collapse will be preceded by accelerations, sufficiently in advance to make adequate predictions followed by emergency measures. Again, landslides in sensitive clays and other collapsible materials are examples where this assumption might not be valid. Moreover, the recent failure of the Mount Polley Dam (IEEIRP, 2015) suggest that, under certain conditions, undrained responses leading to failure might not provide enough warning time for emergency plans to be in place. It is suggested the authors state such limitations of the methods proposed.

A: Indeed this is an important issue. Our test sites are all cases where timely predictions were possible. However these limitations are not addressable to the method proposed rather than to all the forecasting methods currently available to the scientific community,

since some types of landslide still do not allow for a timely prediction. This issue has been commented on in the text.

R: The methodology presented addresses the variability of the forecasting methods used. The reliability index, based on this variability, the convergence and non convergence of forecasts; appears to be a measure of data scatter and trend variation, rooted in the behavioural nature of the landslide in its pre-failure stage. To assess the reliability of any forecasting method, the range of forecasts for a number of case studies needs to be compared against observed time of failure. This requires, in my opinion, to subdivide the case dataset in groups of same landslide type, kinematics, materials, triggers, etc., and compare the forecasts with the observed times of failure.

A: The variability, convergence and non convergence of forecasts are already compared with the observed time of failure. In fact, as stated in the text, during the evaluation of the predictability index the time of failure (Tf) is always considered:

- **"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."**

Predictions that oscillate far from Tf are already addressed.

Concerning the suggestion of clustering the landslides according to type, kinematics, materials, triggers, etc., we think that, due to the not so large number of landslides, every group would be represented by only few examples and therefore would not be meaningful. However comparisons of behaviours between landslides of the same or different type, kinematics, material, trigger, etc. can easily be done by readers using tables 1 and 2. In any case, as we stated in the text, we already studied such comparisons and did not make interesting findings.

R: For particular comments:

1.- How was brittleness assigned for the cases in Table 1?

A: It was assigned based on information derived from the reference articles. Since it was rarely explicitly stated, we assumed a qualitative level of brittleness based on the type of material, the presence of a reactivated landslide, the weathering and the shape of the displacement curve. Since this leads to approximations we decided to evaluate the brittleness with broad and qualitative definitions. This is now specified in the text.

R: 2.- In Table 1, the event at Vaiont is classified as a "Rock Avalanche". This term refers to the material (rock) and its post-failure behaviour. I suggest it should be classified following its detachment process, as this is what we are monitoring prior to failure and would give more insight into the role of landslide kinematics vs. predictability.

A: We agree with your observation. Rock slide is more appropriate.

R: 3.- What are the artificial landslides?

A: We mean landslides recreated in laboratory. Although from the original paper there is not mention of the dimensions of the artificial slope, a photograph shows that it is big enough not to be called a scale model. We specified this in the paper.

R: For editorial comments:

1.- I suggest the improvement of the excel figures. fonts are too small, and layout is not technical. The text refers to dashed black and grey lines that appear continuous red and blue in the figures.

A: Thank you for your observation. The fonts have been increased. The layout has been changed. Now the symbols are coherent with the text.

R: 2.- Should the title read "...influence of geology on predictability" rather than "...influence of geology to predictability"?

A: The title has been changed as suggested by all the reviewers. It is now "Of reliable landslide forecasting and factors influencing predictability".

R: References:

Independent Expert Engineering Investigation and Review Panel (IEEIRP) (2015) Report on Mount Polley Tailings Storage Facility Breach. Province of British Columbia. https://www.mountpolleyreviewpanel.ca

A: Added.

Reviewer 2

Reviewer: Dear Editor, Please find here below my review of the paper nhess-2016-221: Operative and reliable landslide forecasting and influence of geology to predictability By Emanuele Intrieri, Giovanni Gigli This paper is related to new ways of forecasting the time of failure of landslides. It is based on the displacements interpretation by three time to failure existing approaches. The used of the variability of the three methods is proposed to assess the time of failure. The method is applied to several case study. In addition, more general consideration are made about the processes involved.

General comments

The method presented is innovative and interesting, but it seems that too much conclusions are from this research. First the title, is probably to pretentious, I do not see that this method is more operative than others, despite the fact it is interesting and deserves to be published. It is the same for the term used geology, I do not see how it is possible to extract the impact on forecasts.

Authors: The title has been changed as suggested by all the reviewers. It is now "Of reliable landslide forecasting and factors influencing predictability".

R: It is also unclear to know to understand in the paper, what is an a priori or an a posteriori information. The way the variability is presented appears to be estimated a posteriori knowing Tf. Maybe I am wrong, but then it means that it is not well explained in the text.

A: All the case studies are from past landslides that have already failed. Therefore the time of failures are all a posteriori known. In fact, as explained in the method section, the real a posteriori know time of failure is indicated with Tf, while the prediction with tf. This has been clarified in the text.

R: My proposal it to remove the interpretation part and the argument stating that the geomechanics is not the main controlling parameter. But this is obvious from the usual confusion made about creep which is related to a materials, and the landslide failure which is related to a complex body that is controlled by several variables. The creeping does not apply to landslide except in particular cases, this is a general mistake. That is why you can say something about geomechanics, it does not comes from your results, and it can be criticized on fundamental aspects. Then, if you would keep this point, you need to expand the discussion.

A: As stated concerning a similar comment of Reviewer 1, the authors did not mean to diminish the obvious importance of geomechanics to predictability. However, since this point has been unclear for all the reviewers, it is evident that we failed in our explanation. What we mean is that 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 been 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, landslide prediction can be carried out with a variety of different geomechanical settings. This has been clarified in the text, while in the rest of the text every misleading comment that may have reduced the importance of geomechanics have been changed or removed.

R: The oscillation of the values are interesting, but how do you know that you converge to Tf. In the probability index in the criterion include Tf, which you do not know a priori. Please clarify. You need also to discuss the limitations of the method. Your work deserves to be published because it is an interesting study, but please clarify the points above and avoid over interpretations. I propose that you present a figure that explain synthetically your process.

A: the predictability index in fact can only be estimated after the collapse. It has been introduced here as a means to evaluate the performance of the different forecasting methods with different case studies and to allow us to draw conclusions. This has been clarified in the text.

Thank you for your suggestion of adding a figure to show the process. It has been added.

Specific comments

R: Line 21: define what you means by geomechanics? In the text also.

A: we mean 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. We are interested in geomechanics especially concerning the issue relative to ductility and brittleness. Now we explained in the text.

R: Line 46: instead of “is usually” use “can be”

Line 48: you can add reference to the work of Blikra on Aknes rock slide

A: all have been corrected in the text.

Line 49: what do you mean appropriately monitored. In fact, displacements are usually points that often do not represent the global landslide behaviour: : :

A: Exactly. Moreover monitoring may be carried out for short periods not encompassing the final pre-failure stages, or may have been carried out with too low temporal frequency that do not allow to follow the displacement trend. This has been now explained in the text.

R: Line 56: 1994 and not 19940

Lines 67-83: references to the works of Dick et al., 2014 (Can Geotech. J., 52, 515–529) and Crosta and Agliardi Can. Geotech. J. 40: 176–191 (2003) and Manconi and Giordan 2015 NHESS.

A: these has been changed in the text.

R: Line 108: I do not see any probabilistic approach in the paper: : : There is only stdev of the forecast figure 3.

A: the standard deviation would not be possible with a deterministic approach which is the standard way of applying these forecasting methods, that is every method gives a single prediction. At most more predictions can be made in the future but usually only one (the most recent) is used. With our approach we show not only that the most recent prediction is not necessarily the most accurate, but also that the iteration of the forecasting methods (that is the probabilistic approach) enables to have a standard deviation, that is basically a confidence and a probability distribution.

R: Line 111-113: this is the heart of the paper. I think you need to develop this and make a small flow chart with graphs to explain you procedure.

A: thank you for the suggestion. The figure has been added.

R: Line124- 133: you need to give more information about the assumption of these three equations, which will be helpful for the discussion.

A: as stated in the text, the assumptions of these equations are the presence of the tertiary creep and the absence of external influencing factors such as rainfall (as stated by Voight 1988, 1989) although we showed that even in the presence of external factors reliable predictions may still be made. More details can be found in the referenced papers.

R: Table 1: for the mechanisms, you must probably refer to a classification Hungr et al., 2015 or Varnes and Cruden (1996).

Figure 2: improve the quality of graphs not simply from excel: : :

Figure 3: improve quality remove the second box.

A: these have been changed in the text.

R: Lines 190-197: unclear f Tf must be known?

A: Yes. See one of our previous comments.

R: Line 199: use PI for predictable Index instead of Pi which give the impression of a probability.

A: Agreed.

R: Lines 249-251: this is not an argument because with an oscillating process it will always have something very close to the Tf which can be better before collapse.

A: this conclusion seems obvious only after that we have demonstrated that predictions often oscillate around the actual time of failure. On the other hand, Rose and Hungr state that only more recent forecasts should be considered, without acknowledging the whole trend. This is one of the main differences between a probabilistic and a deterministic approach.

R: Line 262-263: as it is presented the predictability index need the knowledge of Tf (see lines 190-197)

A: Yes, as explained above.

Reviewer 3

Reviewer: Dear Editor of the NHESSD and authors of the paper nhess-2016-221, here is my review of the paper: The manuscript entitled "Operative and reliable landslide forecasting and influence of geology to predictability" by E. Intrieri and G. Gigli is very interesting and well structured absolutely suitable for the NHSSD. The proposed methodology is innovative and will be appreciated by the landslide prediction researchers. The paper is suitable for publication. Since I m the third reviewer and I have seen the reviews of the two other colleagues I have to say that I agree with most of the issues mentioned by the other Reviewers and I don't need to repeat some of their comments, suggestions and corrections.
I just want to repeat that it is not totally correct for the authors to state that "the geomechanics is not the main controlling parameter and that plays an indirect role in landslide predictability". Many more case studies should be investigated to come to this conclusion.
Authors: see our answers to the previous reviewers.

R: I do not see the "involvement" of the geology to the predictability. Maybe further explanation shuld be provided since it is mentioned in the title of the paper.
A: thank you for your observation. The title has been changed into "Of reliable landslide forecasting and factors influencing predictability".

R: In my opinion the authors should enrich the discussion about "the limitations of the proposed method".
A: we added a part in the discussion including all the comments made by the reviewers concerning this issue.

R: Is it possible to add a map with the locations of the landslides cases used in this study (the events of Table 1).
A: unfortunately in the references papers the location is not specified for every landslide therefore the map would be only partial and not meaningful. However in some cases more detailed information can be retrieved from the relative papers.

R: The authors should explain what they mean by the term "artificial landslides".
A: We mean landslides recreated in laboratory. Although from the original paper there is not mention of the dimensions of the artificial slope, a photograph shows that it is big enough not to be called a scale model. We specified this in the paper.

R: The quality of the diagrams should be improved.
A: as suggested by reviewer 1, the writings have been increased and the symbols are now coherent with the text. Graphics also changed.

R: A flow diagram of the proposed method would be appreciated by the readers.
A: as suggested also by reviewer 2, this has been added in the discussion.