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Session NH3.11
Towards Reliable Landslide Early Warning Systems

Definition of a new multi-level early warning procedure for landslide risk management

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INTRODUCTION

The approach proposed in this study represents a new procedure aimed to assess the hazard level posed by a potentially critical event, previously identified by analysing displacement monitoring data. The process is implemented in a near-real time Early Warning System (EWS) and defines a total of **five different activity levels**, on the basis of the results provided by two models. The first one consists of an accelerating trend identification criterion, while the second one is a failure forecasting model based on the Inverse Velocity Method (IVM). The main advantage of this approach is the possibility to classify alarms automatically detected by the software, in order to provide an adequate dissemination of information related to the ongoing phenomenon.

The main objective of this approach is to provide a methodology intended to **work simultaneously with several monitoring systems** installed in different sites, featuring high sampling frequencies and automatic processes for data acquisition and elaboration. These characteristics are typically connected with the necessity to manage large numbers of data, while pursuing at the same time a near-real time approach in order to provide timely and reliable information for early warning purposes.
The model described in this presentation was developed taking into account all these points to find a **balance between results reliability and performance efficiency.**

EARLY WARNING SYSTEM COMPONENTS

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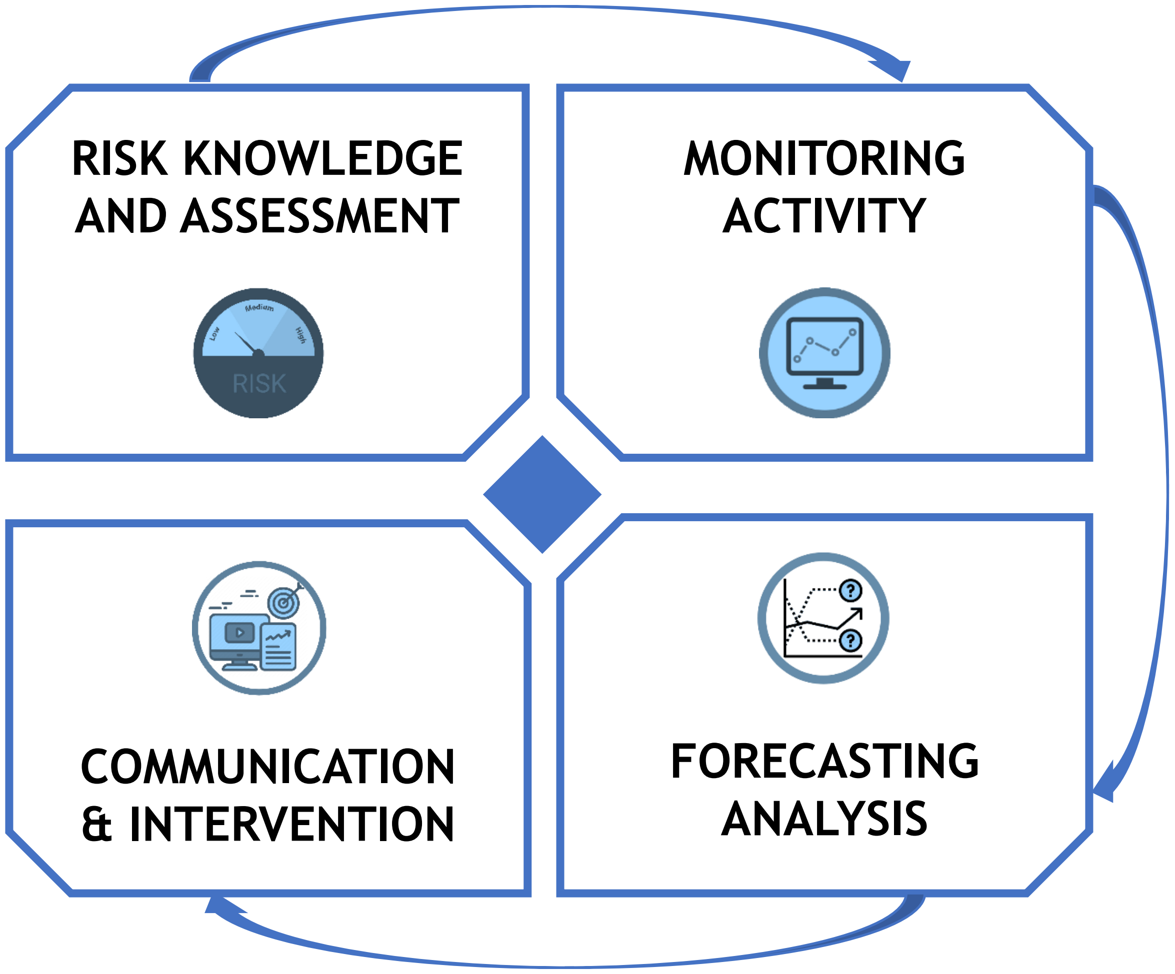

"The set of capacities needed to generate and disseminate **timely and meaningful warning information** to enable individuals, communities and organizations threatened by a hazard **to prepare and to act appropriately and in sufficient time** to reduce the possibility of harm or loss."

UN-ISDR, 2009

The methodology described in this presentation takes place after the monitoring activity, and includes components related to the application of failure forecasting models and dissemination of alert messages according to the results obtained by the analysis.

MONITORING SYSTEM – MUMS

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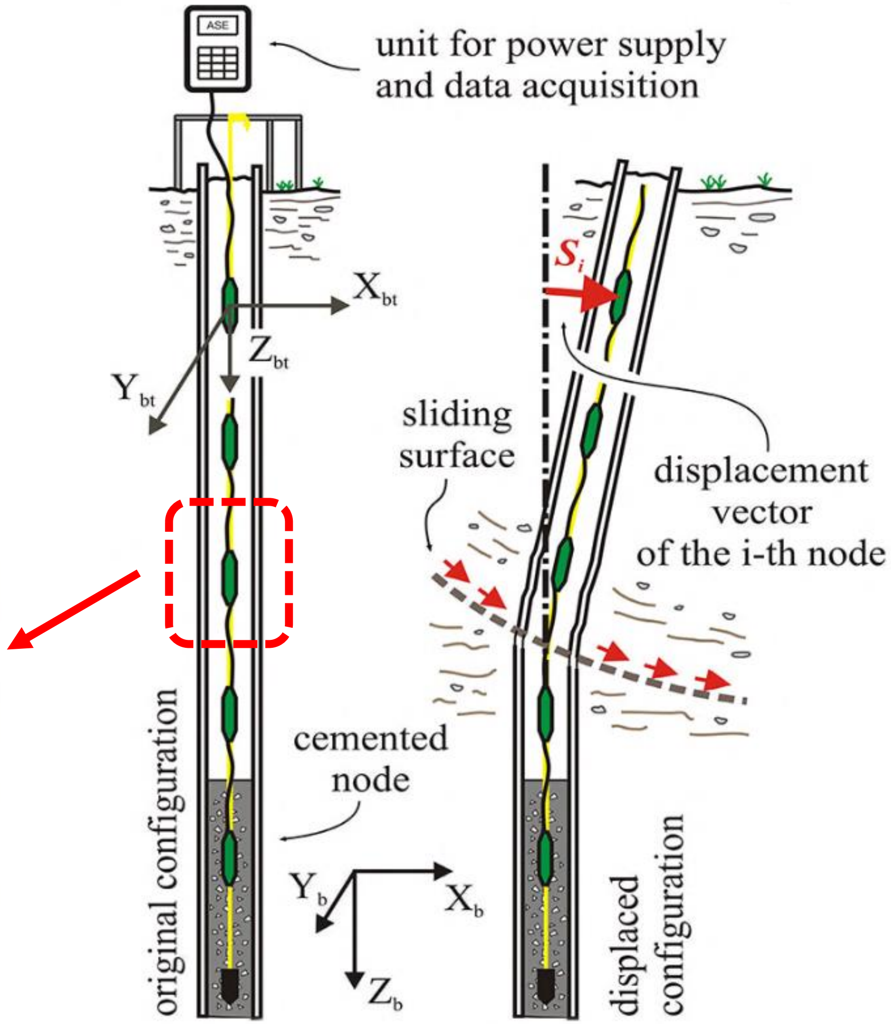
Modular Underground Monitoring System (MUMS) is a patented automatic inclinometer composed by several nodes (defined as Links) located at custom distances along a single chain, thus forming an array of sensors.
The instrumentation has been developed since 2011 with the idea to overcome the "traditional approach" to geotechnical monitoring, providing **an integrate system featuring fully automated processes for data acquisition, storage, elaboration and representation** (Segalini et al., 2014).

MUMS-based monitoring tools provide some essential features for the application of the proposed methodology, including the presence of several sensors along the same vertical and the high sampling frequency that allow to follow a near-real time approach.



ase ADVANCED SLOPE ENGINEERING

mums MODULAR UNDERGROUND MONITORING SYSTEM

FORECASTING ANALYSIS – IVM

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Inverse Velocity Method (Fukuzono, 1985)

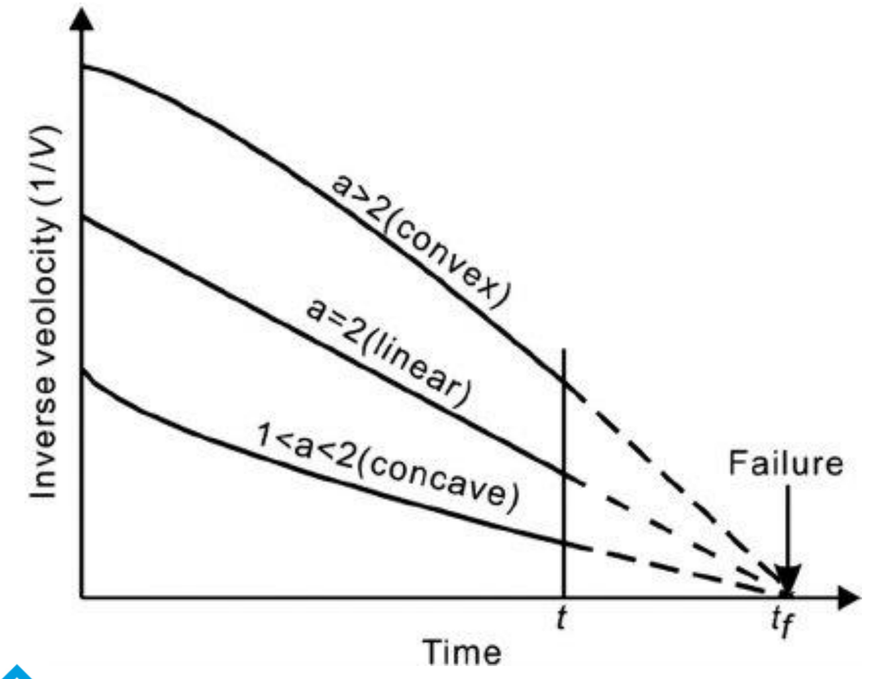
Forecasting method based on the assumption that the inverse of displacement rate decreases with time during the tertiary creep phase, characterized by an **acceleration of slope deformation**.

$$\frac{1}{v} = \left(A(\alpha - 1)(t_f - t)\right)^{\frac{1}{\alpha - 1}}$$

v: displacements rate [mm/d]
t: time [d]
t_f: time of failure [d]
A [mm^{-1}] and *α* [-]: constant parameters

The hypothesis of linearity, corresponding to **α = 2**, is generally a good assumption to estimate the time of failure, allowing to derive t_f thanks to a **linear interpolation** applied to the dataset.

It is important to remember that results obtained from IVM application should not be considered as an exact prediction of the landslide collapse, since **the method generally indicates that the failure is likely in proximity of the intersection point**.



The choice of IVM derives from its good balance between ease of application and results reliability. In this specific case, the multi-level methodology exploits IVM parameters more than the actual forecasting outcome, which is considered as an additional information.

TEST PHASE – SOME NUMBERS

The authors have worked on this topic with the objective to define a multi-level methodology that could be integrated in an automatic routine for monitoring data elaboration. The very first version consisted of a two-level structure based on the identification of accelerating trends and activation of forecasting analyses. The model was further investigated and improved starting from February 2018, increasing the number of alert levels and parameters considered in the elaboration in order to provide a more detailed analysis of real-time monitoring outcomes.

The last version (here presented) was completed and integrated in the automatic elaboration software on October 2019.

Starting from this date, the model has been continuously tested on **29 monitoring tools** installed in several different sites of interest, for a total number of **1'048 sensors** elaborated by the automatic software. By taking into account the sampling frequency of each device involved in the process (varying from 4 to 24 measures per day), it results that every day the algorithm elaborates roughly **19'000 new datasets** in order to identify potentially critical trends.

The selection of the model parameters and their reference values derive both from observations carried out by the authors on monitoring datasets collected from several sites, and other studies reported in scientific literature concerning forecasting analyses and landslides early warning systems.

MULTI-LEVEL MODEL STRUCTURE

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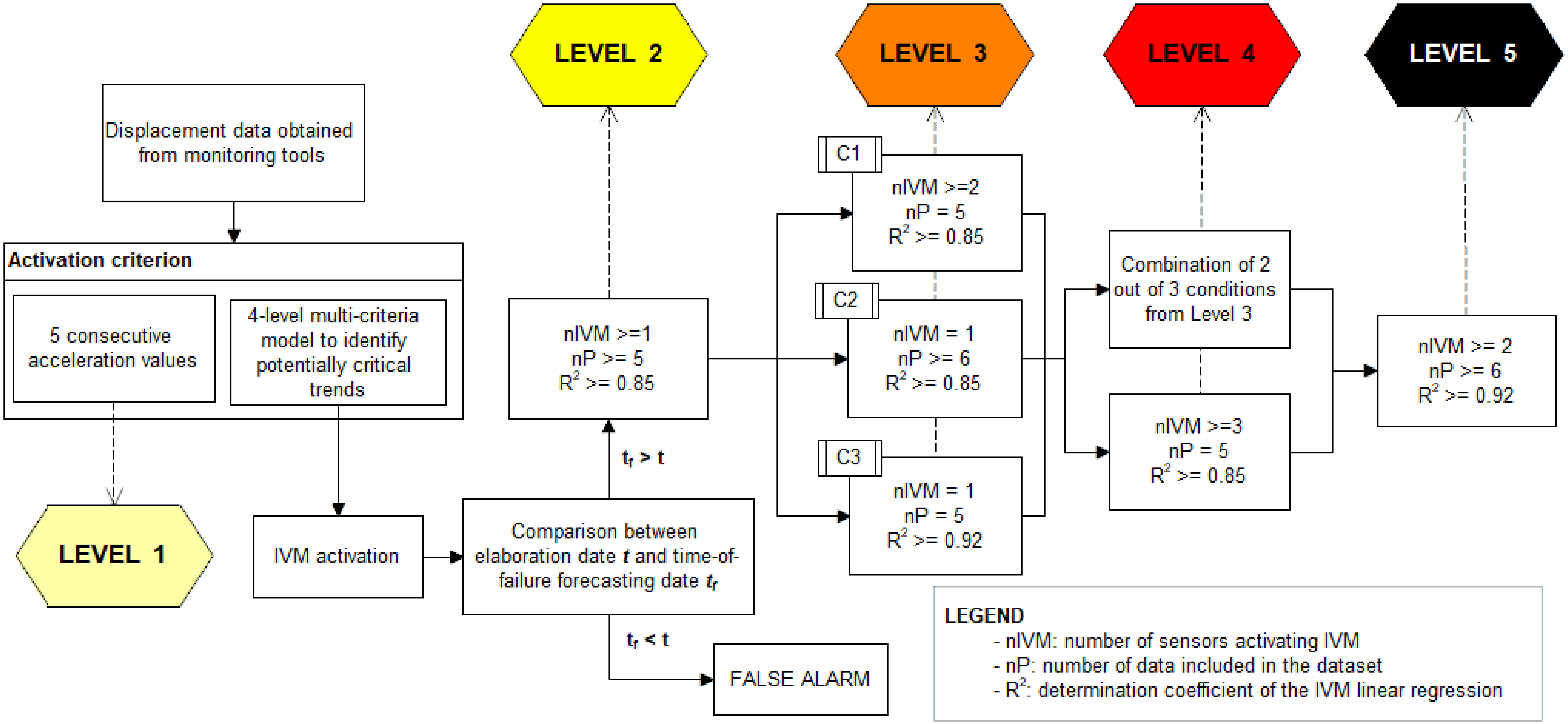
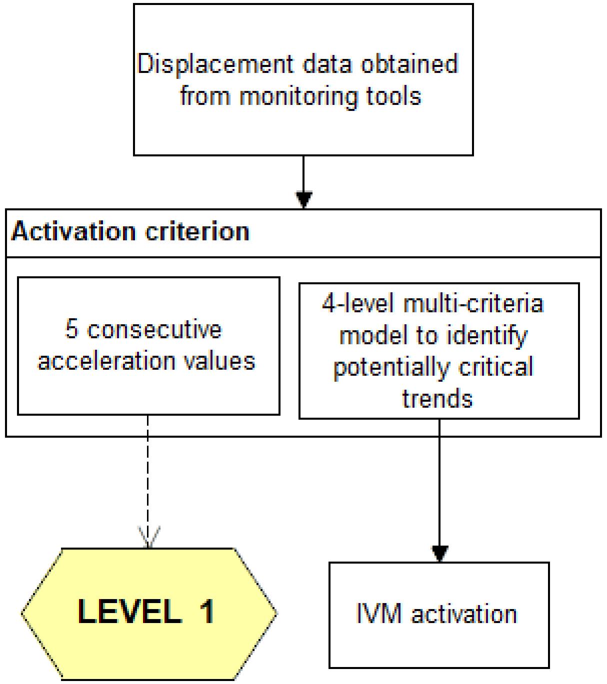


LEVEL 1



Each time a new displacement value reaches the elaboration center, the automatic software activates a routine defined "Activation criterion". This algorithm relies on a 4-level model structured in a drop-down approach in order to verify if the displacement rate and acceleration data display potentially critical trends, thus activating the IVM elaboration in the following step.

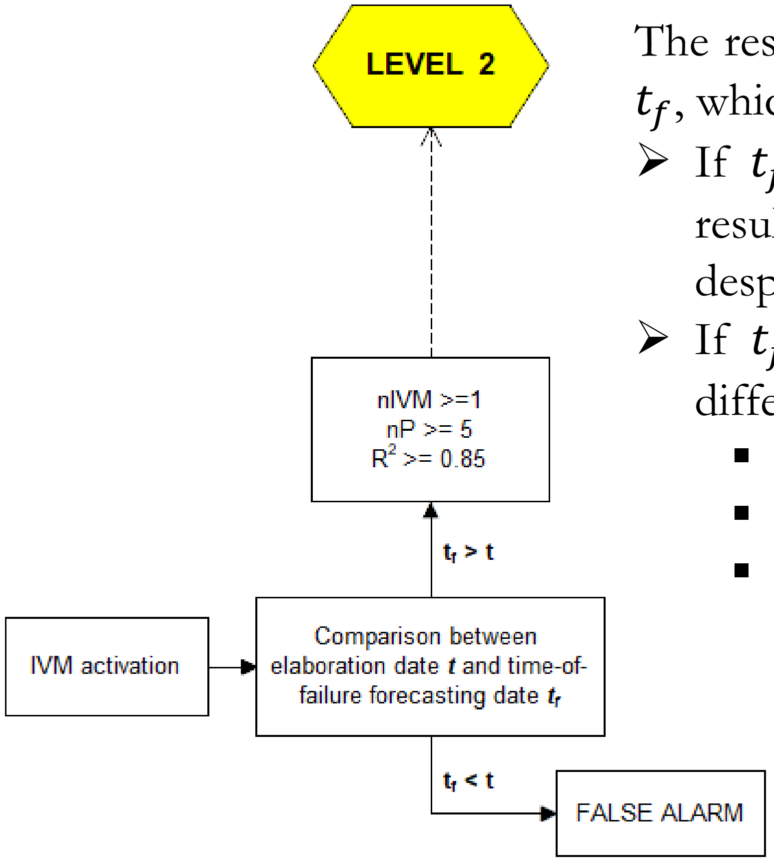
In this phase, Level 1 is reached when the software successfully identifies a continuous positive acceleration trend, represented by 5 consecutive acceleration values starting from the last monitoring data available.

The condition needed to achieve this level depends only on the acceleration trend, therefore the main information resulting from this step is an indication that the monitoring site is displaying some type of activity. At this stage, information are not sufficient to give any detail on the phenomenon evolution.

If no higher levels are achieved, a Level 1 should be seen simply as an "activity note" form the monitored site.

In its current version, the software takes into account two different dataset typologies: one is composed of monitoring data sampled immediately before the last one available, while in the other case it consists of daily values obtained by averaging all data recorded in each single day by the sensor.

LEVEL 2



LEGEND

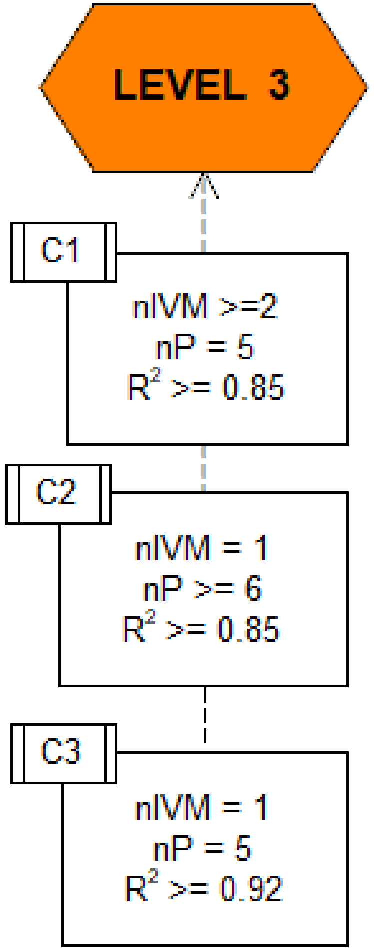
- nIVM: number of sensors activating IVM
- nP: number of data included in the dataset
- R^2: determination coefficient of the IVM linear regression

The result of the failure forecasting analysis performed with IVM is a date defined time-of- failure t_f, which is compared to the elaboration date t:

- If $t_f < t$, the estimated date is already passed, so the analysis classifies it as a false alarm; this result could be generated due to the implementation of statistical processes (e.g. moving average, despiking, etc.) involving possible re-computations based on following data acquisition;
- If $t_f > t$, the software checks if the dataset fulfills all Level 2 conditions, which rely on three different parameters related to IVM analysis results:
  - At least one IVM activation;
  - The dataset used to perform the forecasting analysis includes at least 5 monitoring data
  - The determination coefficient resulting from the IVM linear interpolation should be at least 0.85

The IVM integrated in the automatic software includes an experimental algorithm to calculate a failure "time window" instead of a single date. The applied method relies on a variation of monitoring data according to the R^2 value resulting from the IVM analysis: an higher value represents a more reliable result, therefore it will generate a smaller time window.

LEVEL 3

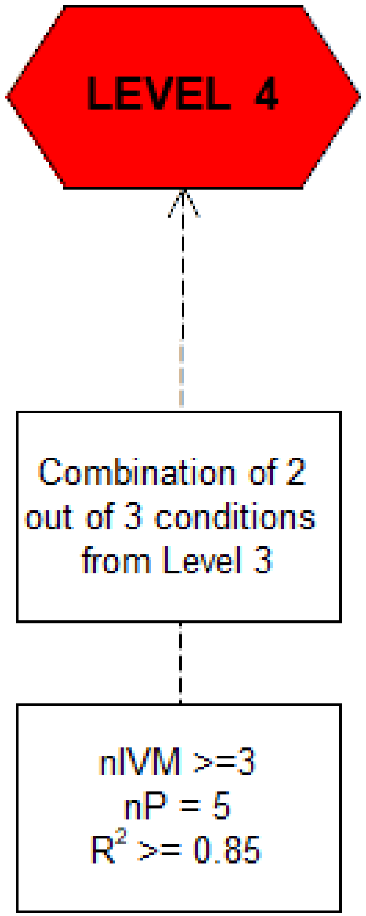


Level 3 exploits the same three parameters introduced in the previous step, namely the number of IVM activations, the dataset dimension, and the forecasting analysis reliability represented by the determination coefficient. In particular, this phase takes as a starting point the Level 2 conditions and imposes more strict requirements on each single parameter, thus generating three different combinations:

- C1 → the minimum number of IVM activations is increased to 2, representing a condition where different depths of the same landslide are displaying potentially critical trends in the same time interval;
- C2 → the dataset which fulfil all conditions imposed by the Activation Criterion is composed of 6 monitoring points, indicating a more consistent accelerating trend;
- C3 → the linear interpolation performed by the IVM analysis features a determination coefficient of 0.92 or higher, which corresponds to a more reliable forecasting analysis.

The structure of the software analysis permits to take into account displacements data recorded by different sensors along the same vertical, thus giving the possibility to apply the Inverse Velocity Method to monitoring values recorded at different depths.

LEVEL 4



The determination of Level 4 conditions follows the same approach introduced in the previous step. In particular, the level assessment depends on the fulfilment of a combination of two conditions defined for Level 3. All these requirements are intended to reflect a situation where the monitored phenomenon is showing different signs of unusual activity at the same time.

- C1 + C2 → a minimum of two IVM activations, including at least one dataset composed of 6 or more monitoring data
- C1 + C3 → a minimum of two IVM activations featuring a determination coefficient equal or higher than 0.92 for at least one of the considered datasets
- C2 + C3 → a single IVM activation with $R^2 \geq 0.92$ triggered by a monitoring dataset composed of 6 or more displacement values
- Another condition which causes the achievement of Level 4 is the presence of 3 or more IVM activations from different sensors in the same time period

Taking into account both back-analyses and real-time elaborations, Level 4 achievements were observed in correspondence of substantial displacements recorded by monitoring tools installed on-site, even if the phenomenon evolution didn't lead to an actual collapse.

LEVEL 5

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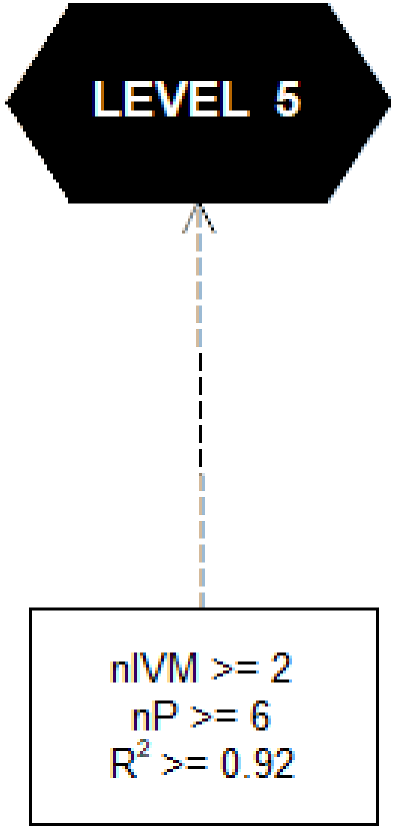

Level 5 is the highest level achievable by the analysis, and it represents a situation where monitoring datasets are highlighting an extremely active phenomenon, which should be closely investigated and observed in order to identify further signals of potential instabilities.

Level 5 activation relies on the same parameters introduced in previous phases, in particular its achievement is based on the simultaneous fulfilment of all three combinations defined for Level 3: at least two successful activations of IVM forecasting analysis on 6-point datasets featuring high R^2 values.

Up to this day (April 2020), Level 5 has never been reached in a near-real time monitoring context. Moreover, no evidence of any collapse or instability has been observed so far on any site monitored with this specific approach. Therefore, back-analysis tests have been performed during the model calibration phase, starting from previously acquired monitoring datasets. In this phase, results evidenced a 1:1 rate between Level 5 activations and slope failures.

SOME EXAMPLES – CASE STUDY #1 (LV3)

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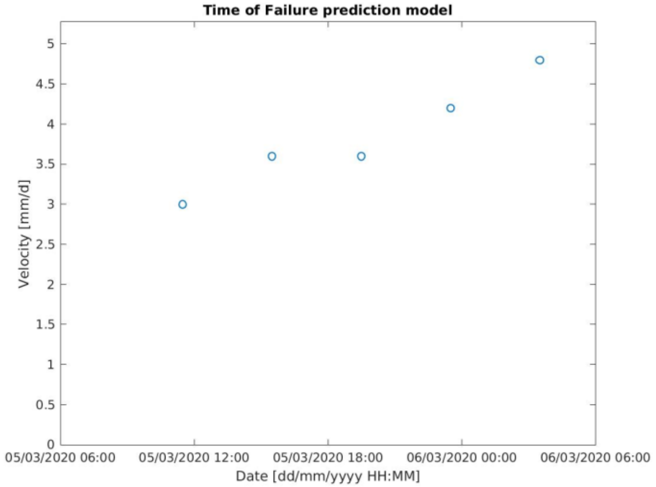
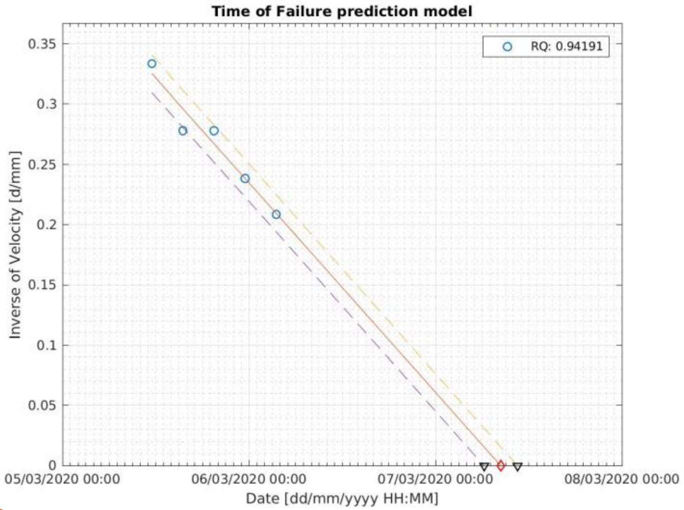




nIVM = 1

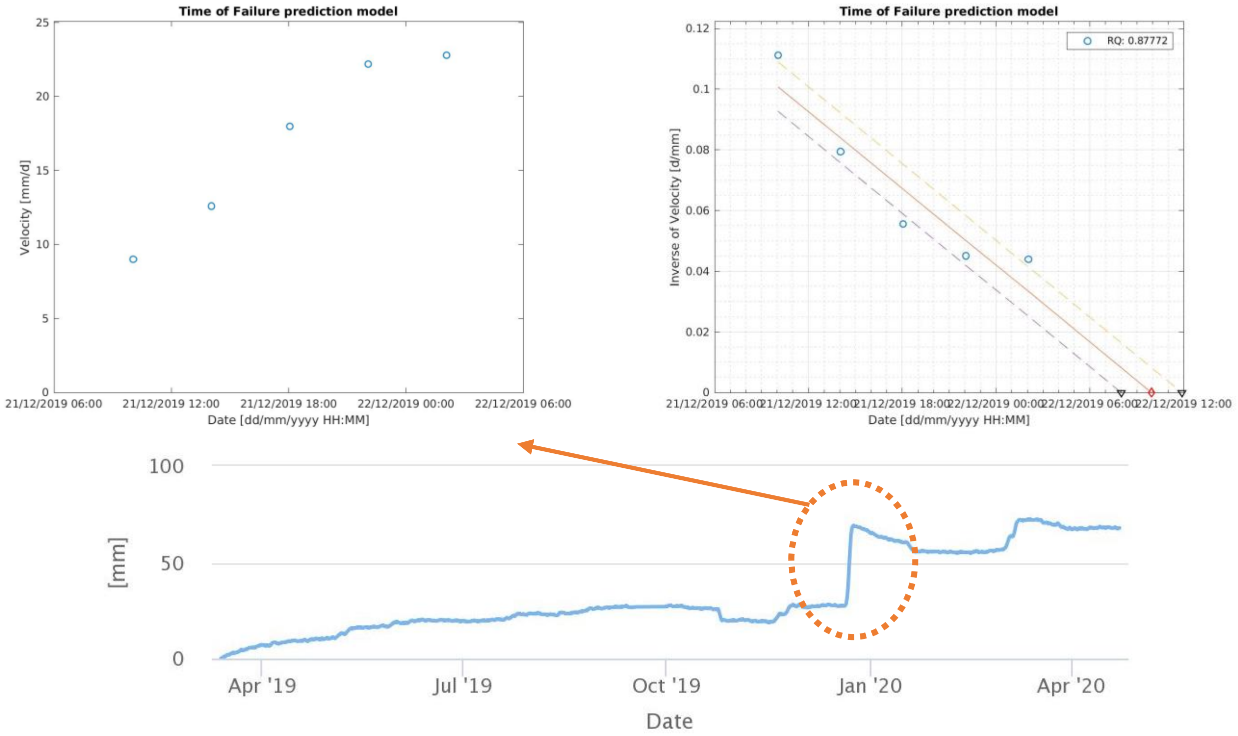
nP = 5

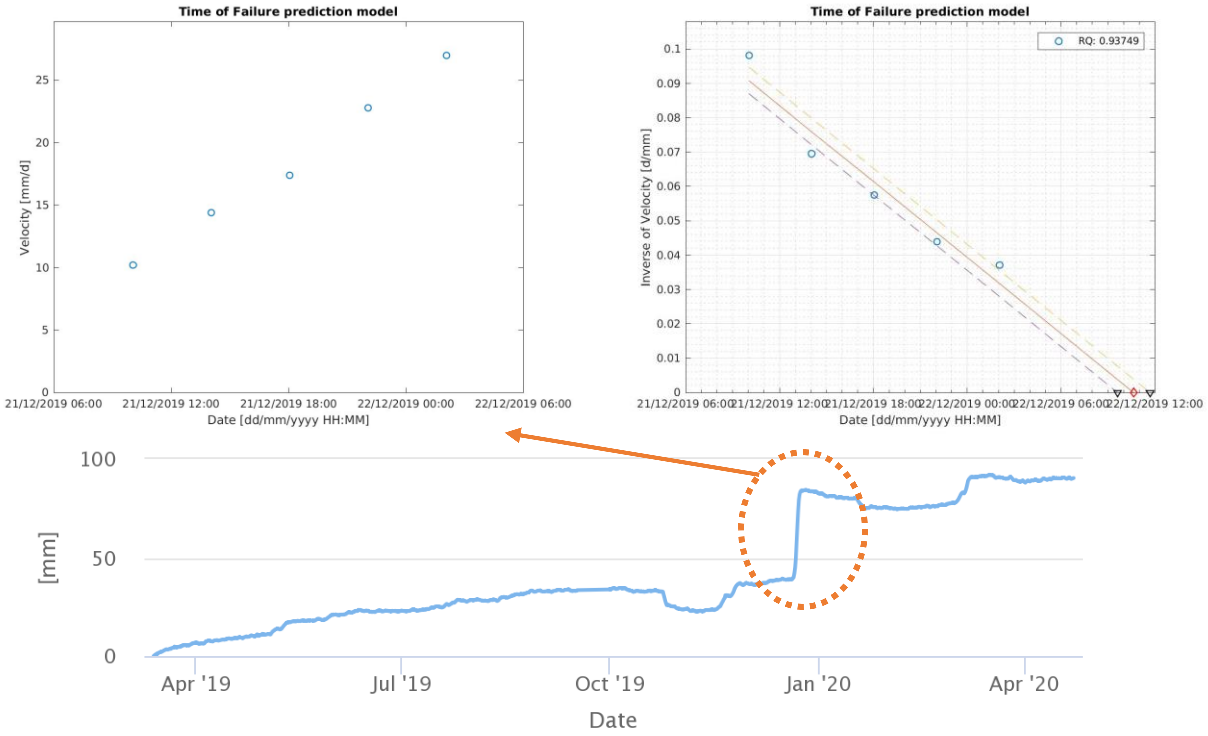
$R^2 \geq 0.92$

LEVEL 3

Monitoring data highlight an increase of displacement values in correspondence of Level 3 activation, caused by a good linear interpolation of the dataset and consequent high R^2 value. However, both displacement and velocity trends did not show a particularly alarming pattern, and following data evidenced a stable configuration.

SOME EXAMPLES – CASE STUDY #1 (LV4)





nIVM = 2

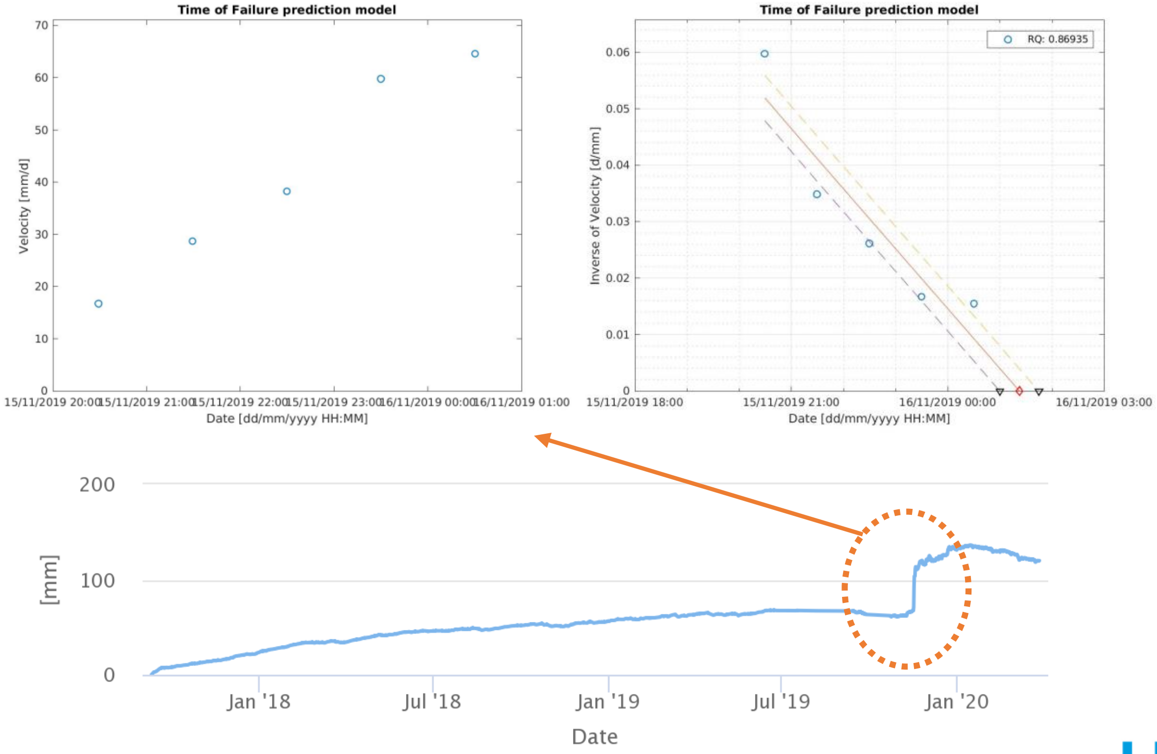
nP = 5

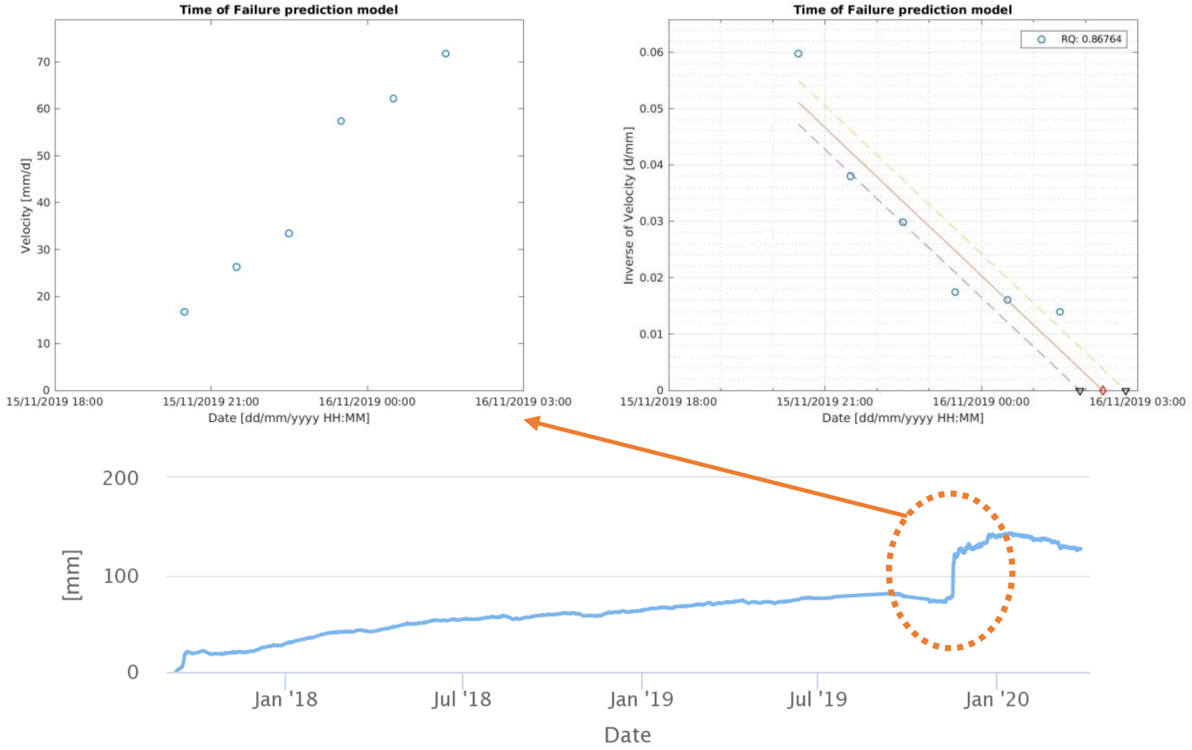
$R^2 \geq 0.92$

LEVEL 4

In this case, the achievement of Level 4 derives from a double IVM activation with at least one determination coefficient higher than 0.92. Displacement data show a sudden increase recorded at two different depths.

SOME EXAMPLES – CASE STUDY #2





nIVM = 4

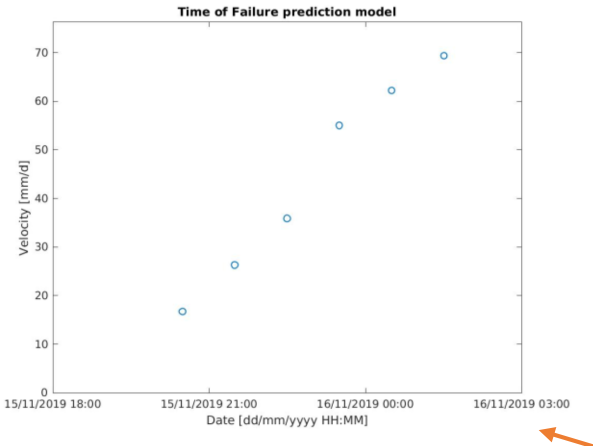
nP = 5-6

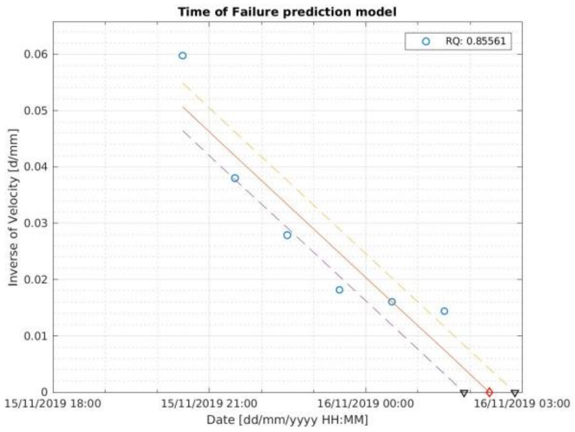
$R^2 \geq 0.85$

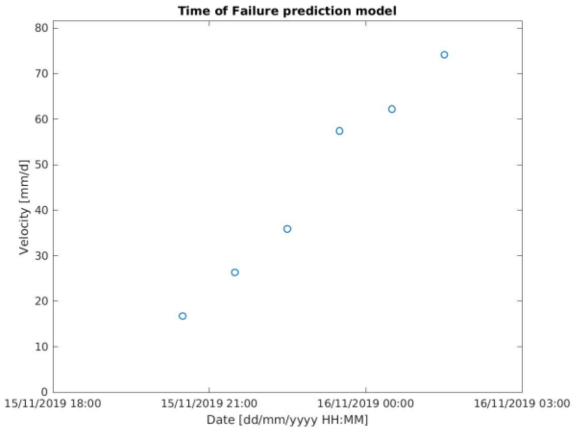
LEVEL 4

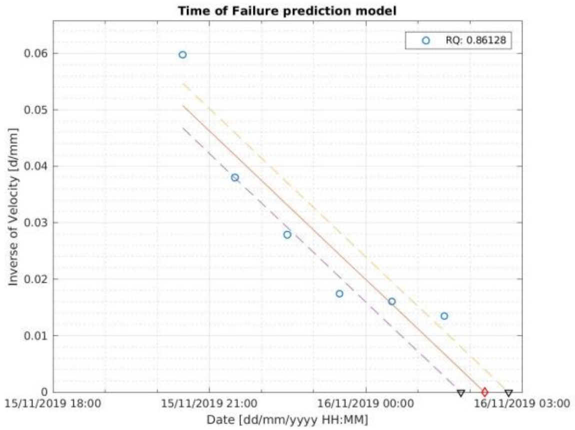
This case study presents an event which fulfils two different Level 4 conditions, i.e. number of IVM analyses performed and dataset dimension.

SOME EXAMPLES – CASE STUDY #2



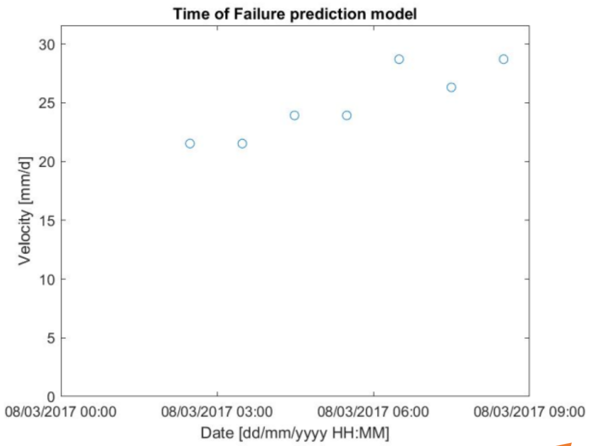


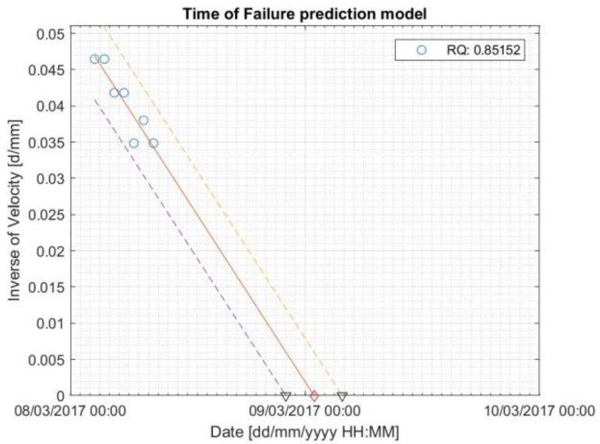


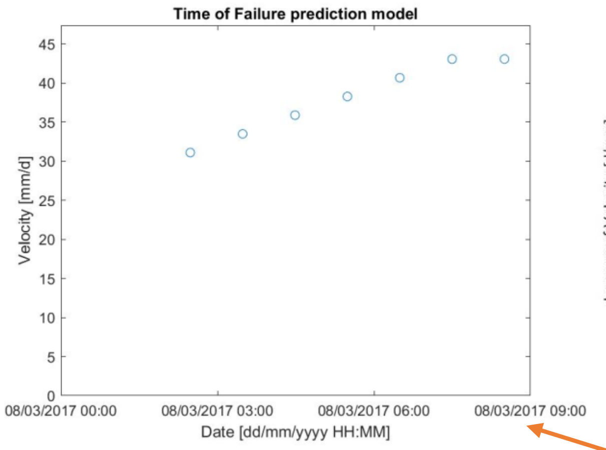


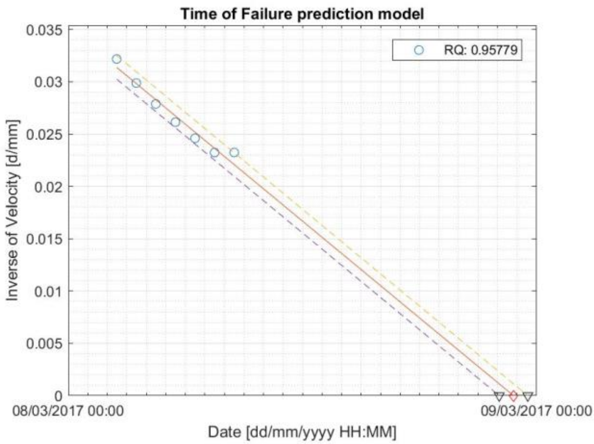
Monitoring data highlight a rapid movement in correspondence of this particular time interval. Displacement plots show a very similar trend at different depths, which could be attributed to an extremely localized movement that propagated along the vertical direction. Moreover, IVM patterns present a non-linear concave trend usually associated with stabilizing phenomena.

SOME EXAMPLES – CASE STUDY #3









nIVM = 3

nP = 6-7 → **LEVEL 5**

$R^2 \geq 0.92$

This example refers to a case study where displacement data showed several indications of potential instabilities, which ultimately led to the slope collapse and progressive damaging of monitoring tools installed on-site (Segalini et al., 2019).

SOME EXAMPLES – CASE STUDY #3

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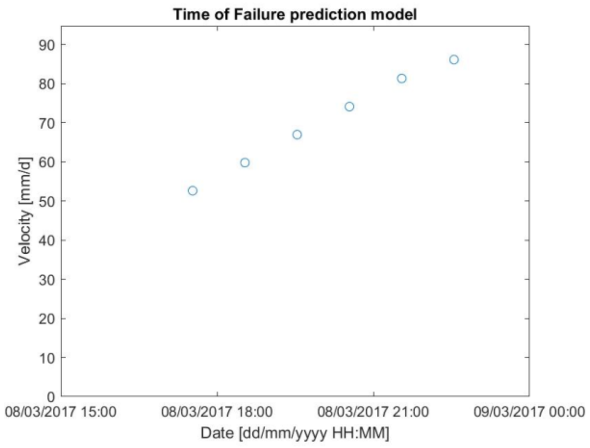

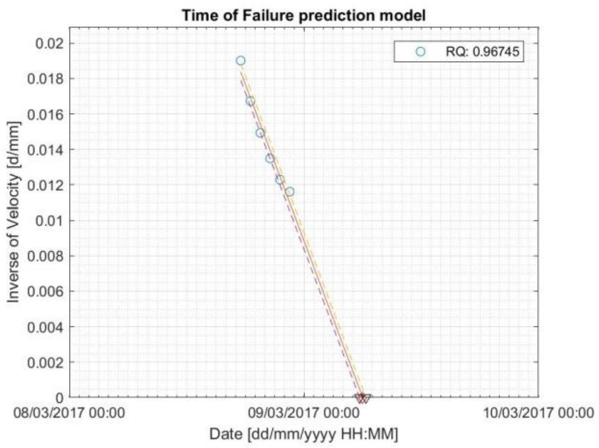

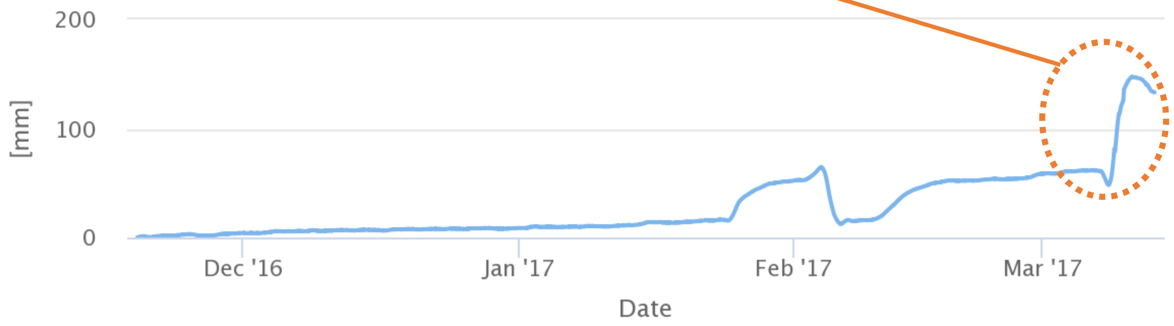

Since this event was originally analysed with a previous version of the multi-level approach, results reported here were obtained by performing a back-analysis on available datasets simulating a real-time acquisition.

In this case, the sudden displacement increase which preceded the slope collapse was identified by the software, resulting in multiple IVM activations. In particular, three of these datasets fulfilled every condition for Level 5, presenting large datasets with high determination coefficient values.

Additionally, the automatic software reported several other minor activations both before and after the main event, further highlighting the activity of the monitored landslide.

FINAL REMARKS AND FUTURE DEVELOPMENTS

It should be always taken into account that this method is mainly conceived as a **support tool for decision makers**, providing useful information on the landslide evolution with particular focus on potentially critical behaviors. Therefore, due to the phenomenon complexity, **the proposed methodology should not be used in isolation, and expert judgement is strongly recommended for a correct data interpretation.**

WORK IN PROGRESS:

- **Filter false positive patterns** → Particular attention will be devoted to the identification of datasets composed of small displacements that are not indicative of impending instabilities, but manage to fulfill some conditions due to their geometric layout resembling an accelerating trend;
- **Site-oriented approach** → While currently the model elaborates each monitoring tool singularly, another element that will be considered is the presence of several monitoring devices in the same site of interest. This could allow to expand the methodology in order to follow a "site-oriented" approach, by integrating new algorithms for datasets comparison and results correlation;
- **Temporal interval influence** → As previously mentioned, the present version of the model consider two different dataset typologies for the elaboration process, i.e. real-time and daily-average. The high sampling frequency that characterize innovative monitoring tools could give the possibility to further investigate the influence of dataset composition on the model effectiveness and its ability to identify different trends.

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THANK YOU

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