TXT-tool 2.039-4.1 FLaIR Model (Forecasting of Landslides Induced by Rainfalls)

Pasquale Versace, Giovanna Capparelli and Davide Luciano De Luca

Abstract

Mathematical models for landslide forecasting constitute an important component for Early Warning Systems. This teaching tool focuses on the empirical model named FLaIR (Forecasting of Landslides Induced by Rainfalls), developed at Laboratory of Environmental Carthography and Hydraulic and Geological Modelling (CAMILab) of University of Calabria (Italy). FLaIR is a general framework for many empirical models proposed in technical literature: in particular, it reproduces as particular cases all the ID (Intensity-Duration) schemes (Capparelli and Versace 2011). From the website www.camilab.unical.it it is possible to download the software FLaIR.exe, together with a user guide.

Keywords

Landslide forecasting · Early warning systems · Empirical models

Contents

1 Introduction

Prediction of landslides induced by rainfall constitutes an important topic for the development of Early Warning Systems (EWS), and the most adopted models are based on empirical approaches. Although they are not so adequate to model hydraulic and geotechnical aspects of landslide triggering, empirical models are preferred for EWS because of their simplicity: in fact, they can easily be calibrated on the basis of only information about historical movements, and can be

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straightforwardly used in real time as only knowledge about rainfall time series (predicted or observed in real time) is required to evaluate the exceedance of critical conditions.

Several empirical models were proposed in technical literature, and the most adopted belong to the class of Intensity-Duration (ID) schemes (Caine 1980; Cannon and Gartner 2005; Corominas et al. 2005; Crosta and Frattini 2001; Godt et al. 2006; Guzzetti et al. 2007, 2008; Nadim et al. 2009).

This teaching tool focuses on the model named FLaIR (Forecasting of Landslides Induced by Rainfalls, Sirangelo and Versace 1996; Capparelli et al. 2009; Capparelli and Versace 2011), which was developed at Laboratory of Environmental Carthography and Hydraulic and Geological Modelling (CAMILab) of University of Calabria (Italy). FLaIR has many advantages compared with other empirical schemes; in particular (i) it considers the real pattern of rainfall input and not average values along assigned durations, and thus it is possible to discriminate the influence of rainfall heights, on the basis of their lag-time from the current instant; (ii) it provides an unique threshold value and not a reference function like an ID scheme, and consequently it allows for a simpler check about exceedance or not of critical conditions for landslide forecasting, (iii) it is more flexible as it is suitable for both shallow landslides, induced by recent rainfall events, and deep movements, triggered by precipitation aggregated on longer durations. Moreover, FLaIR constitutes a general framework for many empirical models, as it reproduces as particular cases all the ID schemes proposed in technical literature (Capparelli and Versace 2011).

A short description of FLaIR mathematical background is reported in Sect. 2; parameter estimation is discussed in Sect. 3, while the use for real-time forecasting is shown in Sect. 4.

From the website www.camilab.unical.it it is possible to download the software FLaIR.exe, together with a user guide.

2 Mathematical Background of FLaIR Model

In empirical models it is possible to identify a **mobility function** $Y(t)$, which is a generic function of the rainfall that can be correlated with landslide occurrence. In details, if $P[E_t]$ is the occurrence probability of a landslide at time t, and assuming that it depends only on $Y(t)$, then $P[E_t]$ can be expressed as:

$$P[E_t] = \begin{cases} 0 & if \quad Y(t) < Y_1 \\ g[Y(t)] & if \quad Y_1 \leq Y(t) \leq Y_2 \\ 1 & if \quad Y(t) > Y_2 \end{cases} \tag{1}$$

where $g[\cdot]$ is a non-decreasing generic function that can take values between [0;1] in the interval $[Y_1;Y_2]$;Y_1 is the value of $Y(t)$ for which mobilization is impossible; and Y_2 is the value of $Y(t)$ for which mobilization is certain (Fig. 1).

A simple version of Eq. (1) is obtained by assuming $Y_1 = Y_2 = Y_{cr}$, where Y_{cr} represents a threshold value of $Y(t)$ which separates the condition "impossible mobilization" from "certain mobilization"; that is (see also Fig. 2):

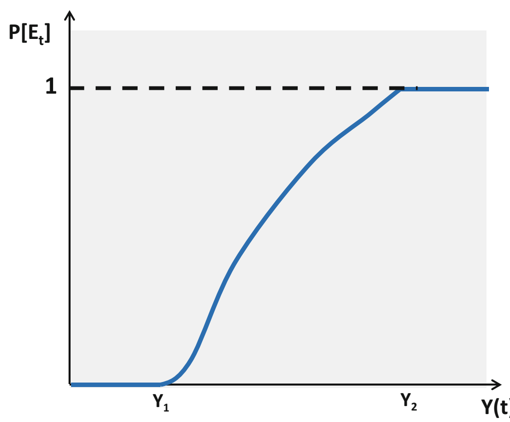

Fig. 1 Relationship between the occurrence probability $P[E_t]$ of a landslide at time t and the mobility function $Y(t)$, on the basis of Eq. (1)

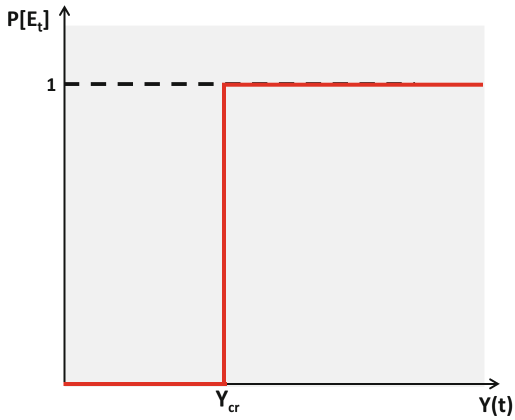

Fig. 2 Relationship between the occurrence probability $P[E_t]$ of a landslide at time t and the mobility function $Y(t)$, on the basis of Eq. (2)

$$\begin{cases} P[E_t] = 0 & \text{if } Y(t) < Y_{cr} \\ P[E_t] = 1 & \text{if } Y(t) \geq Y_{cr} \end{cases} \tag{2}$$

The choice of criteria adopted by different authors for defining threshold values is different: e.g., Cannon and Ellen (1985) assume that the threshold corresponds to "abundant landslides", while for Wieczorek (1987), the threshold corresponds to "one or more than one landslides." Nevertheless, the threshold approach remains the most widely used in rainfall–landslide studies, because of the difficulty in function identification and parameter calibration in Eq. (1) owing to the lack of experimental data.

In FLaIR model (Forecasting of Landslides Induced by Rainfall, Capparelli and Versace 2011), the mobility function $Y(t)$ is computed as a convolution between the rainfall infiltration rate $I(\cdot)$ and a filter function $\psi(\cdot)$:

$$Y(t) = \int_0^t \psi(t-\tau) I(\tau) d\tau \tag{3}$$

and a landslide trigger is predicted by the model when $Y(t)$ exceeds a critical threshold Y_{cr}, which is a parameter to be estimated (see Sect. 3).

The infiltration rate $I(\tau)$ is assumed proportional to the rainfall intensity $P(\tau)$, according to the following simple relationship:

$$I(\tau) = \begin{cases} P(\tau) & when \quad P(\tau) \leq P_0 \\ P_0 & when \quad P(\tau) > P_0 \end{cases} \tag{4}$$

where P_0 depends on soil characteristic, and it is a parameter to be estimated. In the simplest version, P_0 is set equal to $+\infty$, and then:

$$Y(t) = \int_0^t \psi(t-\tau) P(\tau) d\tau \tag{5}$$

The function $\psi(\cdot)$ is typical for each case study and it plays a central role in mobility function evaluation. It can assume different expressions (Iiritano et al. 1998), like rectangular:

$$\psi(t) = \begin{cases} 1/t_0 & \text{if } 0 < t \leq t_0 \\ 0 & \text{elsewhere} \end{cases} \tag{6}$$

exponential:

$$\psi(t) = \frac{1}{k} e^{-\frac{t}{k}} \quad t \geq 0, \ k > 0 \tag{7}$$

gamma:

$$\psi(t) = \frac{1}{\beta^\alpha \Gamma(\alpha)} t^{\alpha-1} e^{-\frac{t}{\beta}} \quad t \geq 0, \ \alpha > 0, \ \beta > 0 \tag{8}$$

power:

$$\psi(t) = m t^{-q} \quad 0 < t < T, \ m > 0, \ 0 < q < 1 \tag{9}$$

mixture of two exponential functions:

$$\psi(t) = \omega \beta_1 \exp(-\beta_1 t) + (1-\omega) \exp(-\beta_2 t) \quad t \geq 0, \ \beta_1 \geq \beta_2 > 0, \ 0 \leq \omega \leq 1 \tag{10}$$

In particular, Eq. (10) is very flexible: the first addendum reproduces the effect of the most recent rainfall (short-term component) while the second addendum is referred to the influence of antecedent precipitation (long-term component). The terms ω and $(1 - \omega)$ are the weights of the two components.

Figure 3 shows the differences in mobility function when different filter functions are adopted to transform rainfall time series.

3 Parameter Estimation

FLaIR calibration is carried out by: (i) parameter estimation referred to the chosen filter function $\psi(\cdot)$; (ii) assessment of the critical threshold Y_{cr}. With this goal, dates of historical landslide occurrences and rainfall database are used.

The estimated parameters for $\psi(\cdot)$ must ensure the condition for which the mobility function $Y(t)$ attains its highest values just in correspondence with historical movements. FLaIR applications to real cases, usually characterized by a small number of historical movements (typically one or two), often show that several parameter sets allow for this condition.

Consequently, in order to define the "best" parameter set, several techniques can be used. In the following Sect. 3.1 the *ranking method* is only discussed.

3.1 Ranking Method

Concerning a specific filter $\psi(\cdot)$, application of ranking method consists of the identification of the admissibility region, defined as the ensemble

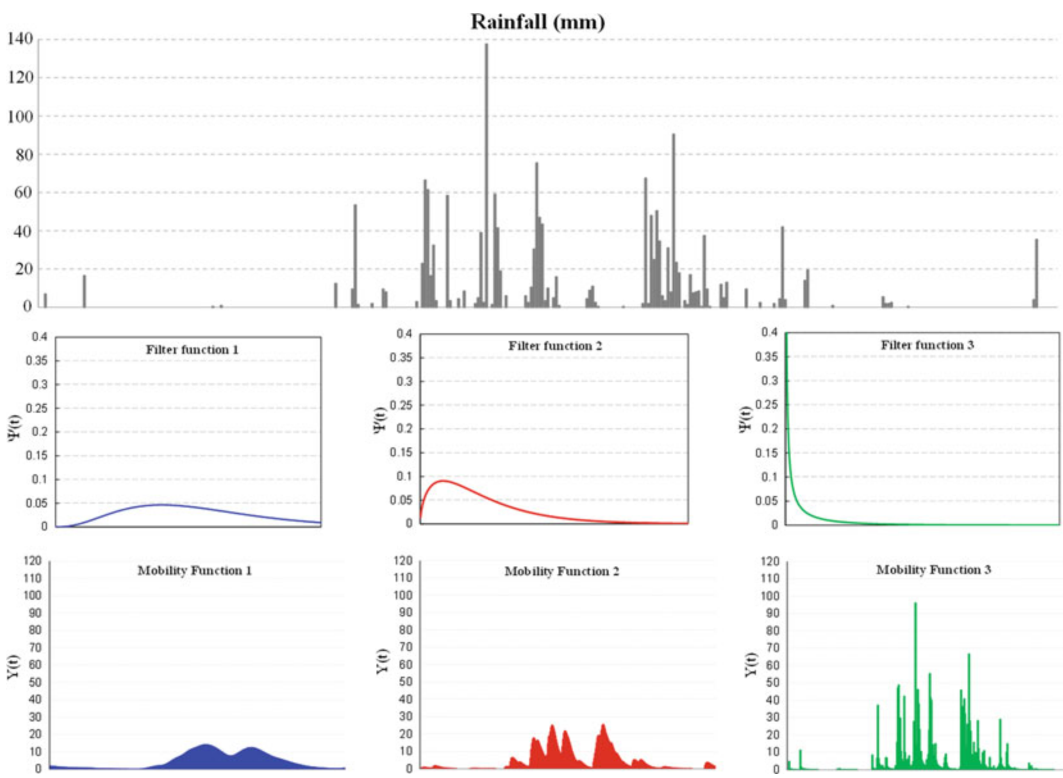

Fig. 3 Example of differences in mobility function when different filter functions are adopted to transform rainfall time series. Adapted from Capparelli and Versace (2011)

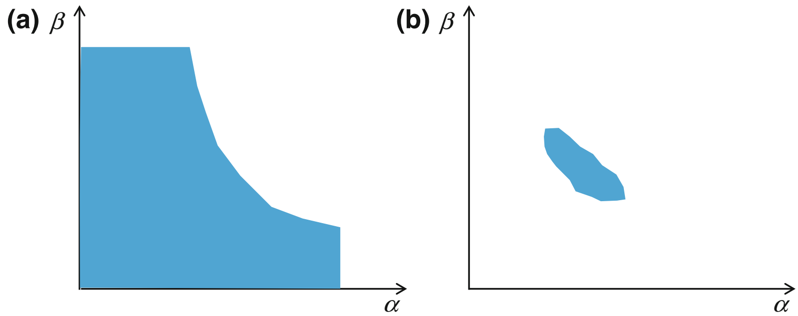

Fig. 4 **a** Example of large admissibility region; **b** example of small admissibility region

of all the parameter sets $\underline{\theta} = (\theta_1, \theta_2, \ldots, \theta_n)$ for which the mobility function $Y(t;\underline{\theta})$ assumes its k highest values in correspondence with the k known historical movements of the landslide.

Depending on the size of admissibility region, the *informative content* of landslide events can be defined. Figure 4 shows examples of two different admissibility region, related to gamma filter (Eq. 8):

- in the former (Fig. 4a), a lot of parameter sets allow for the highest values of $Y(t;\underline{\theta})$ when historical landslides occurred. This situation is typical when historical movements are triggered by only heavy rain events. In this case the informative content is very low, and then using the rainfall histogram (and not FLaIR model) produces the same results in terms of forecasting of landslide triggering;
- in the latter (Fig. 4b), $Y(t;\underline{\theta})$ presents its highest values in correspondence with historical landslides only for few parameter sets. In this case the informative content is high.

For each admissible parameter set $\underline{\theta}$ it is possible to define a lower limit function (indicated as f_L) and an upper limit function (indicated as f_U) for $Y(t;\underline{\theta})$; they represent, respectively, the highest value that did not produce any movement and the lowest value for which movement occurred. Figure 5 refers to a simple case with only one historical movement, but it can be straightforwardly generalized to multiple movements. It represents the mobility function, evaluated on the basis of a rain data sample with a time resolution equal to Δt. A tolerance interval of length $(u_1 + u_2)\Delta t$ is considered, in order to take into account the uncertainty in the information about the date of landslide movement. Finally, to avoid the possibility of estimating the lower limit function in the same rainfall event that caused the landslide, a disjunction interval, of length equal to $(v_1 + v_2)\Delta t$, is introduced.

Starting from the ensemble of all the admissible parameter sets $\underline{\theta}$, the best set is chosen by maximizing the difference:

$$r = f_U - f_L \qquad (11)$$

that means to allow for the largest possible gap between the mobility function $Y(\cdot)$ values related to no movement and those related to a movement.

Finally, estimation of Y_{cr} has to be carried out, and this requires particular care, especially in the frequent case of only one historical movement:

- if $Y_{cr} = f_L$ then the model could forecast very frequently a landslide occurrence;
- if $Y_{cr} = f_U$ then the model could not be able to identify situations of real hazard, because only events larger than the one that induced the historical occurrence would be believed able to trigger a second movement.

On the basis of the above aspects, it could be preferable to use a critical threshold equal to the lower limit function.

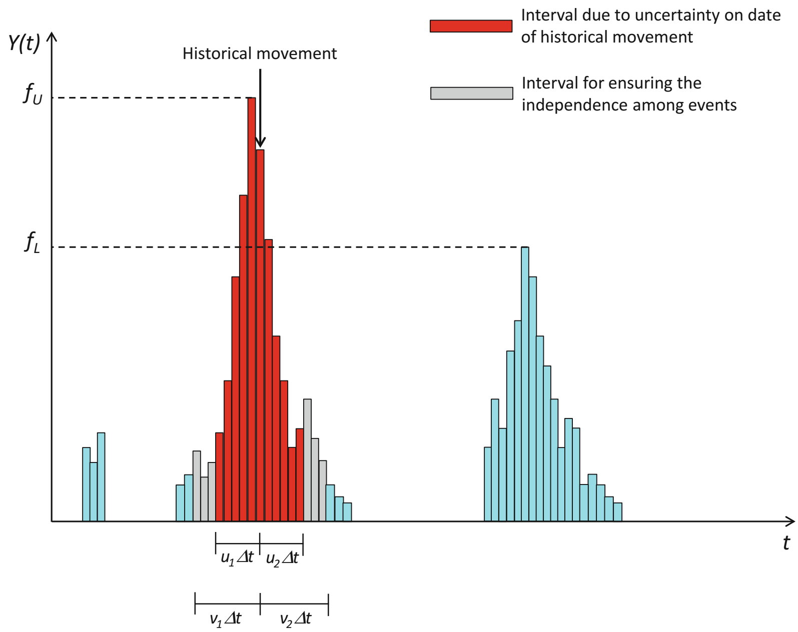

Fig. 5 Evaluation of upper limit function f_U and lower limit function f_L

4 Real-Time Forecasting

Use of FLaIR model for real-time forecasting consists in evaluating, with suitable early time, the probability that at time t, the mobility function $Y(t)$ exceeds the critical value Y_{cr}, estimated on the basis of historical information (Sect. 3), or its percentages which are indicated as Levels of Criticality (LC) and are defined in the following way:

$$LC_1 = \xi_1 Y_{cr} \tag{12}$$

$$LC_2 = \xi_2 Y_{cr} \tag{13}$$

$$LC_3 = \xi_3 Y_{cr} \tag{14}$$

with $\xi_1 < \xi_2 < \xi_3 < 1$. LC_1, LC_2 and LC_3 are also named ordinary, moderate and high criticality, respectively.

In details, setting τ as the current time, the mobility function evaluated at τ and related to the future time t (with clearly $\tau < t$) is indicated as $Y_\tau(t)$, which can be written as sum of two terms:

$$Y_\tau(t) = \int_0^\tau \psi(t-u)P(u)du + \int_\tau^t \psi(t-u)P(u)du \tag{15}$$

The first term is evaluated on the basis of observed rainfall depth until time τ and it can be considered as the ***deterministic*** component of $Y_\tau(t)$.

The second term is valuable by considering rainfall nowcasting for $P(\cdot)$ in the interval $[\tau; t]$, which is usually carried out with a Probabilistic Quantitative Precipitation Forecast (**PQPF**), that means a large number N of future rainfall scenarios (Fig. 6a). PQPF can be obtained by using stochastic or meteorological models, and the second addendum of Eq. (15) is indicated as the ***probabilistic*** component. From N predicted rainfall scenarios it is possible to obtain N realizations of $Y_\tau(t)$ (Fig. 6b).

For each predicted scenario of $Y_\tau(t)$, the dimensionless index $\xi(t) = Y_\tau(t)/Y_{cr}$ can be defined, and the maximum value $\xi_{\max}$ in the

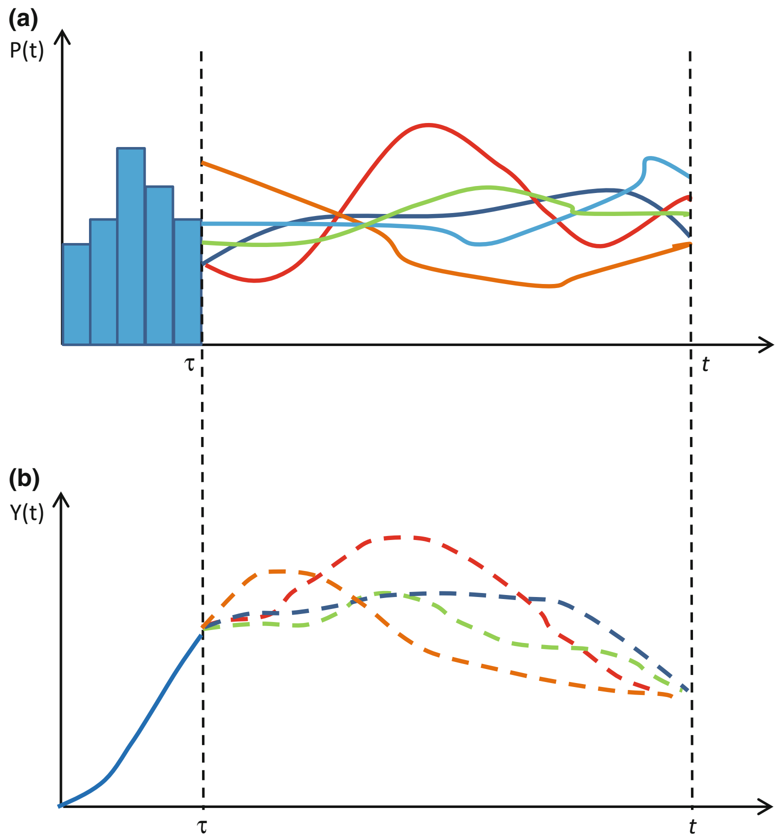

Fig. 6 Real-time forecasting in the interval [τ; t]: **a** rainfall nowcasting; **b** FLaIR scenarios

interval [τ; t] is evaluated: consequently, the exceedance probabilities can be computed in the following way:

$$P[\xi(t) > \xi_1] = \frac{N_{[\xi_{\max} > \xi_1]}}{N} \tag{16}$$

$$P[\xi(t) > \xi_2] = \frac{N_{[\xi_{\max} > \xi_2]}}{N} \tag{17}$$

$$P[\xi(t) > \xi_3] = \frac{N_{[\xi_{\max} > \xi_3]}}{N} \tag{18}$$

where $N_{[\xi_{\max} > \xi_1]}, N_{[\xi_{\max} > \xi_2]}$ and $N_{[\xi_{\max} > \xi_3]}$ indicate the number of predicted scenarios for which $\xi_{\max}$ is greater than ξ_1, ξ_2 and ξ_3, respectively.

4.1 Example of Application

FLaIR model was applied in several areas of Italy, in the context of agreements with Italian National Department of Civil Protection and with Regional Administrations.

As an example, the case study of Montenero di Bisaccia, located in Molise region (southern Italy), is shown, where a landslide occurred on 1st March 2006.

The stochastic model named PRAISE (Prediction of Rainfall Amount Inside Storm Events, Sirangelo et al. 2007) was used for rainfall prediction in real time. PRAISE model was calibrated by considering the hourly time series of Palata raingauge (close to Campobasso city).

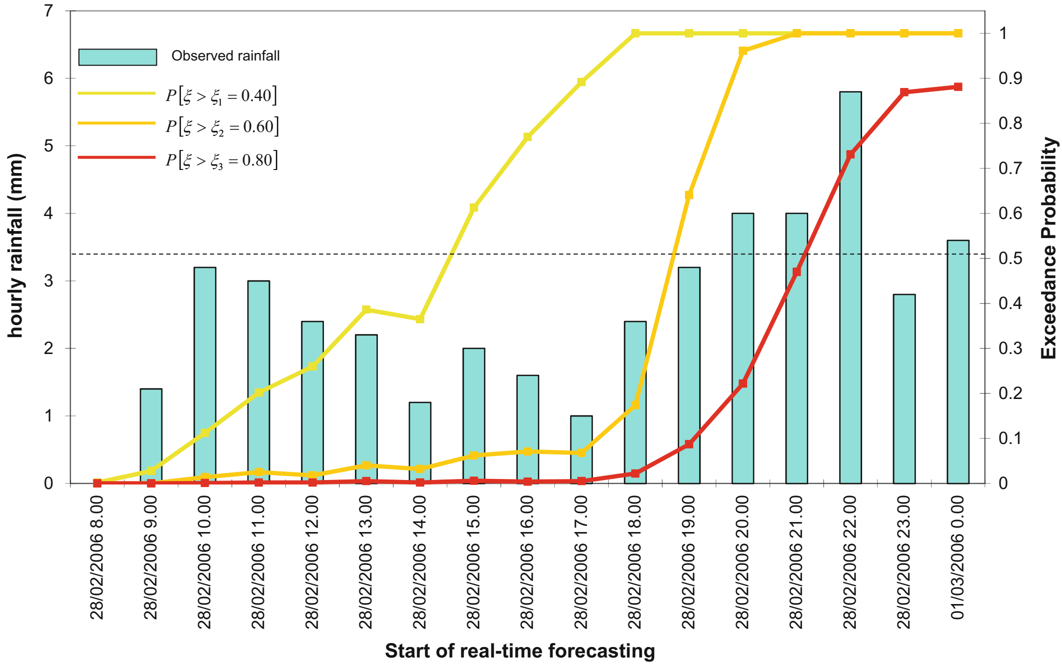

Fig. 7 Case study of Montenero di Bisaccia (southern Italy). Temporal behavior of exceedance probability referred to the thresholds ξ_1, ξ_2 and ξ_3 for a lapse time equal to 6 h successive to the beginning of the forecast

Gamma function (Eq. 8) was used as filter $\psi(\cdot)$, and parameter estimation provided $\alpha[-] = 0.9, \beta[\text{days}] = 20$ and $Y_{cr}[\text{mm/day}] = 5$.

The following threshold values for the dimensionless index were considered: $\xi_1 = 0.4, \xi_2 = 0.6$ and $\xi_3 = 0.8$.

Figure 7 represents on horizontal axis the time in which rainfall occurred and mobility function forecasting is performed; hourly rainfall heights measured by raingauge are represented on the left vertical axis, while in the right vertical axis there is the probability evaluation that the mobility function could exceed threshold values in the successive six hours. From the figure it is clear that approaching to the landslide date, $P[\xi(t) > \xi_3]$ also increases; consequently, using FLaIR coupled with a rainfall predictor allows to provide, with sufficient advance, the exceedance of the several thresholds.

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