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ScienceDirect
Procedia Earth and Planetary Science 16 (2016) 195 – 203
Procedia
Earth and Planetary Science

The Fourth Italian Workshop on Landslides

Is there predictive power in hydrological catchment information for regional landslide hazard assessment?

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Abstract

Regional landslide hazard assessment is often carried out by means of empirical meteorological thresholds, which reliability is sometimes limited by the lack of information about the hydrological processes which lead to landslide triggering in slopes. Hence, in this paper the inclusion of hydrological information at catchment scale in the definition of landslide triggering thresholds is applied to a catchment in the northern Apennines (Italy). In particular, an hydro-meteorological threshold based on event precipitation and catchment specific storage (*H-S* threshold) is proposed. The performance of the proposed threshold is compared with the one of the usually adopted precipitation Intensity-Duration (*I-D*) threshold. Although most of the landslide recorded in the observed period (2002-2013) were triggered by short and intense precipitation events with little influence of the slope conditions prior the precipitation, the *H-S*threshold performs slightly better than the *I-D* threshold.

Peer-review under responsibility of the organizing committee of IWL 2015
Keywords: Hydrological slope response; monitoring; unsaturated granular soils.

1. Introduction

Rainfall-triggered landslides are among the most widespread natural hazards, and early warning systems are an important way to reduce the deriving socio-economic risk. In this respect, regional hazard assessment is a useful tool for preliminary forecasts. Several approaches have been proposed for assessing the probability of landslide occurrenceatregional scale (see Chacon et al.[1] for a review): heuristic through susceptibility modeling; empirical,

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Peer-review under responsibility of the organizing committee of IWL 2015
doi:10.1016/j.proeps.2016.10.021

lumped-statistical, by relating meteorological information to the observed occurrence of landslides; by means of spatially distributed physically-based modeling. However, one of the mostusedapproaches is the regional hazard assessment based on meteorological information[2].

The precipitation-intensity-duration (PID) thresholds, indeed, see widespread applicationfor local, regional or global landslide hazard assessment. The basis of such a methodology is the availability of high quality spatiotemporal landslide inventory database and rainfall time series. The rainfall thresholds are then empirically derived by plotting two variables related to the characteristics of rainfall which have or have not resulted in landslides in a given area. The separation between rain events inducing landslides and events without hazard, which can be a deterministic threshold curve or a probabilistic transition zone, ismade visually or by separator techniques. Due to the spread of rainfall characteristics over several orders of magnitude, the plot is usuallyin bi-logarithmic scale.

Various PID thresholds for landslide initiation have been proposed and applied[2,3,4]. While local thresholds often refer to relatively homogeneous conditions and specific mass movement types, regional and global thresholds encompass landslides with different geo-morphological, environmental and hydrological features, such as lithology, sliding soil depth, slope inclination, land use, and boundary conditions. Hence, to accommodate the latter, which, due to the large heterogeneity in spatiotemporal scales, mass movement types and environmental factors, lack explicit hydrological information, more detailed analysis of PID thresholds was proposed: splitting the records, e.g. for rainfall duration longer/shorter than 48 hours[4], or for winter and summer conditions[5,6];introducing 1D water balance in a slope[7,8,9]; combining an Antecedent Wetness Index withthe PID curve in a decision tree model for a possible early warning system[10]; defining non-dimensional rainfall intensity and duration, accounting for the hydraulic characteristics of a particular slope[11].

The objective of this studyis testing if combining meteorological information with lumped hydrological information at catchment scale will improve the performance of empirical landslide initiation thresholds. To this aim, we studied a small catchment in Emilia Romagna (Italy), for which meteorological and landslide data are available for the period 2003-2013, and applied and compared several possible empirical thresholds. The results indicate that the inclusion of catchment storage can improve the performance of regional landslide hazard assessment.

2. Methods and data

2.1. Description of case study area

The presented application makes use of meteorological and landslide data of the catchment of the river Scoltenna at Pievepelago(Fig. 1). The river is a tributary of river Panaro, in turn flowing into river Po. The catchment area is 130.8km^2 and the mean altitude is around 1450ma.s.l. The concentration time of the catchment is estimated between 2 hours (Kirpich’s formula) and 3.5 hours (Giandotti’s relationship), The prevailing lithology, covering about 80% of the catchment, consists of clay shales (Flysch). Only in the north-western part of the catchment limestone and sandstone emerge. The discharge monitoring station of Pievepelago provides daily discharge data for the period 2003-2013. During the same period, two weather stations operated within the catchment, providing, at hourly time resolution, precipitation, air temperature and relative humidity, mean wind speed and direction. During the considered period, 61rainfall-induced landslides were recorded.

During the monitoring period, the average yearly precipitation was about 1500mm, while the yearly average specific runoff was about 1140mm, corresponding to high mean runoff coefficient of 0.76. Fig. 2 shows the mean monthly precipitation and specific discharge, which exhibit a similar pattern, confirming the direct relationship between precipitation and runoff. The only bias between the distribution of monthly precipitation and runoff can be ascribed to snow accumulation and melting in the highest part of the catchment, which causes a shift of the maximum discharge to the early spring, while the precipitation is maximum in late autumn and early winter. The third panel of Fig. 2 reports the scatter plot of cumulative specific discharge and cumulative precipitation for the monitored ten years, which indicates that the hydrological behavior of the catchment remained fairly stable during the whole considered period.

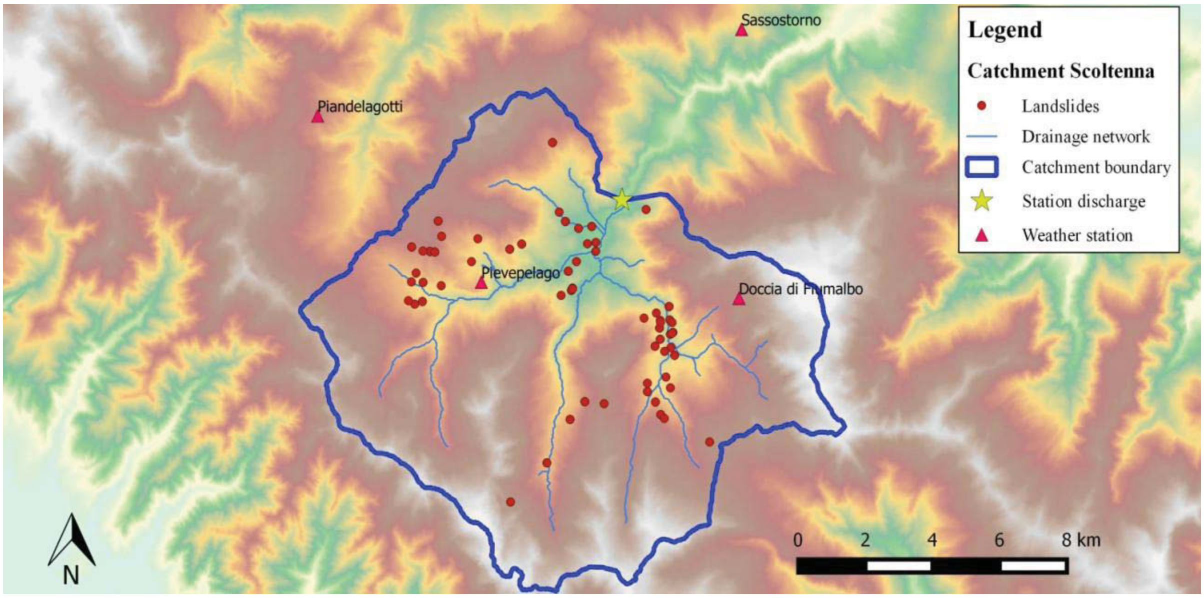

Fig. 1. Plan view and orography of the catchment of Scoltenna at Pievepelago.

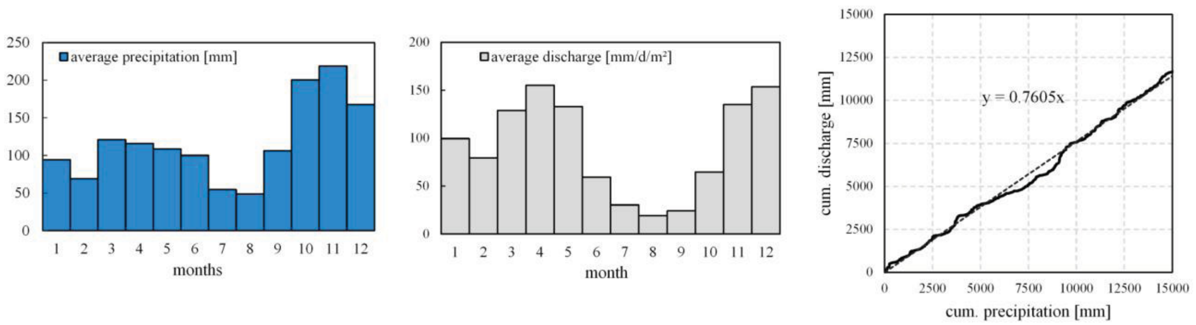

Fig. 2. Hydrological regime of the catchment of Scoltenna at Pievepelago. From left to right: average monthly precipitation; average monthly specific runoff; scatter plot of cumulative specific runoff vs. cumulative precipitation.

2.2. Modeling catchment storage

In order to introduce hydrological information into the empirical precipitation thresholds for landslide initiation, the concept of effective antecedent precipitation has been proposed[7,12]. In such a way, as soon as a rainfall event occurs, it is possible to indirectly account for the initial wetness state of the potentially unstable slope by 'adding' antecedent rainfall. However, the wetness state of an area depends not only on the antecedent precipitation itself, but also on storing and draining hydrological processes[13]. This is probably the main reason why several different time intervals and expressions have been considered for the definition of the effective antecedent precipitation[2,3,4].

Here, aiming at highlighting the role played by the hydrological processes affecting the slopes, a simple lumped model of catchment daily water balance is considered (all the quantities are specific volumes, so can be measured in mm):

$$S_t = S_{t-1} + P_d - P_s + M - Q - E \tag{1}$$

In equation (1), S_t and $S_{t-1}$are catchmentspecific water storage respectively at day t and t-1; P_d is the daily precipitation;P_S isdaily snow accumulation; $M$is daily snow melting; Q is the daily specific runoff; E the total daily evaporation and transpiration. Conceptually, it is assumed here that it is possible to identify wetness conditions predisposing to slope instability on the basis of the water stored in the catchment, regardless of what is the storing hydrological system (e.g. unsaturated regolith, perched aquifers, groundwater), as different types of rainfall-induced landslides (e.g. shallow or deep-seated) are sensitive to different predisposing factors.

The process of snow accumulation has been modeled by a degree-day model. We use a critical temperature, T_C=2°C, below which the precipitation is accumulated as snow, S_A [mm]:

$$T \le T_C \Rightarrow \begin{cases} P_s = P_d \\ S_{At} = S_{At-1} + P_s \end{cases} \tag{2}$$

The accumulated snow then melts at $T>T_C$:

$$\begin{matrix} T > T_C \\ S_{At-1} > 0 \end{matrix} \Rightarrow \begin{cases} M = C_M \cdot (T - T_C) & S_{At-1} \ge M \\ M = S_{At-1} & S_{At-1} < M \end{cases} \tag{3}$$

in which C_M is the melting coefficient[14], here assumed equal to 2.74mm°C^{-1}.

The actual daily evapotranspiration was calculated by multiplying the daily reference evapotranspiration, in turn calculated with the FAO Penman-Monteith equation[15], by a crop coefficient,k_c., which was estimated by calibration, under the assumption that in the long run (namely, the considered ten years) the catchment water storage was in equilibrium. Such an objective was achieved by imposing that the linear regression line of the storage series calculated over the 10 years was horizontal, so to exclude that a trend was observed in the storage series, and at the same time minimizing the standard deviation of the same series,aiming at not emphasizing the annual storage fluctuations. Such a calibration led to a crop coefficient k_c=0.419.

2.3. Definition and analysis of landslide initiation thresholds

The definition of empirical landslide initiation thresholds has been carried out with a univariate Bayesian approach. In particular, aiming at checking the suitability of a generic variable $B$to contain useful information for assessing landslide initiation, the probability of landslide occurrence, conditional to the probability of the tested variable, was calculated:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \quad \begin{cases} P(A) & \text{prior probability of landslide occurrence} \\ P(B) & \text{marginal probability of } B \\ P(B|A) & \text{conditional probability of } B \text{ given landslide occurrence} \end{cases} \tag{4}$$

In equation (4), $P(A)$ can be estimated as the fraction of days with landslides in the available time series; $P(B)$ as the fraction of days in which the value of the tested variable B fell within a given interval; $P(B|A)$ as the fraction of days with landslides in which B fell within a given interval.

If $P(B|A)$ is significantly larger than $P(B)$, it results $P(A|B)>P(A)$, indicating that B adds significant information for evaluating the probability of a landslide. Once two variables B_1 and B_2 are considered significant, all the registered rainfall events are plotted in the plane (B_1,B_2), and a threshold line, separating events which triggered a landslide from those which did not, is plotted by maximizing the True Skill Statistic[16]:

$$TSS = \frac{T_A}{N_L} - \frac{F_A}{N_{NL}} \tag{5}$$

In equation (5) N_L and N_{NL} represent the total numbers of events triggering and not triggering landslides, respectively; T_A (True Alarms), the number of correctly predicted landslides;F_A (False Alarms) the number of events for which the threshold predicted the triggering of a landslide which actually did not occur.A perfectly working threshold would lead to *TSS*=+1, while *TSS*=-1 indicates that the threshold always fails.

3. Results and discussion

Fig. 3 shows the daily hyetograph during the observation period (2003-2013) and the corresponding modelled catchment specific storage. In the same graph, the days in which landslides were recorded within the catchment are also plotted. A first visual interpretation shows that landslides occur more frequently when the water storage in the catchment is higher than the mean (the mean storage along the modelled period is null, as a result of the adopted calibration strategy), regardless of their type. In fact, 41 of the 61 landslides (67%) occurred when S>0 (about 47% of the observation period), and 28 (46%) when S>100mm (less than 30% of the time).

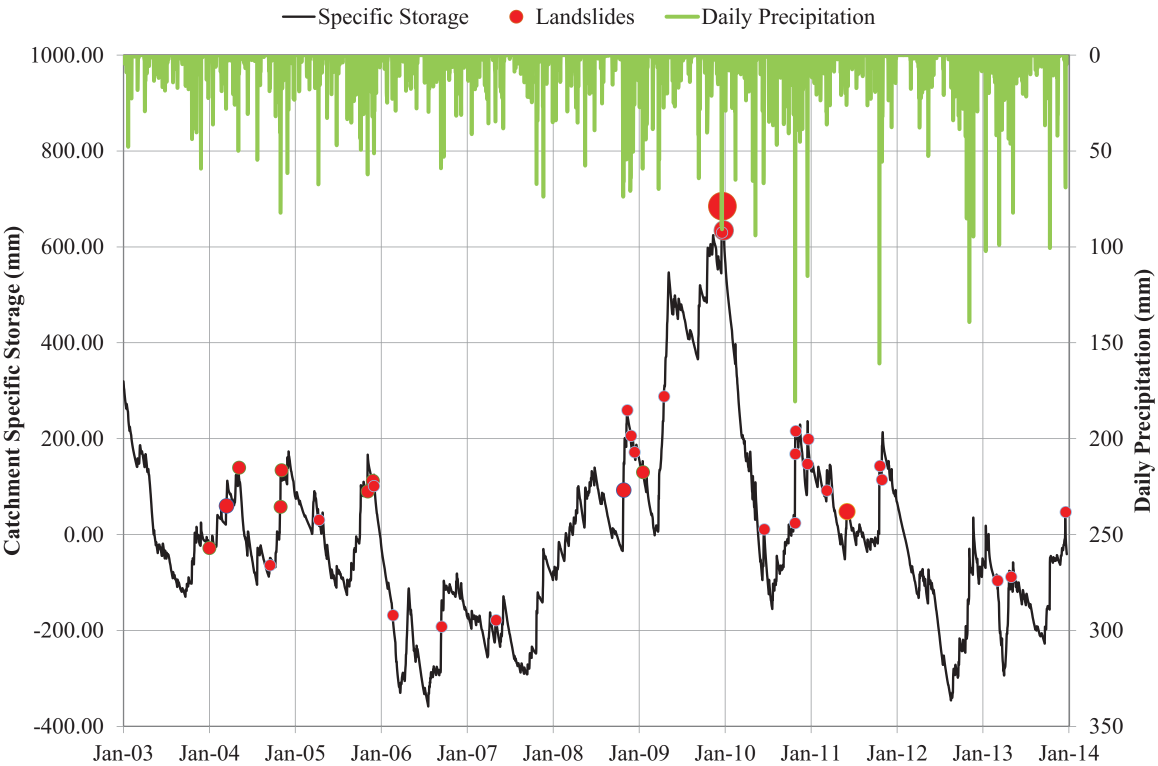

Fig. 3. Daily precipitation, calibrated daily water storage and landslides events in the catchment of Scoltenna at Pievepelago (the dimension of the red dots reflects the number of recorded landslides in that day).

In order to get deeper insight in the information content of meteorological and hydrological variables useful for landslide prediction, the previously described Bayesian approach has been applied. In particular, four variables related to the precipitation events have been analyzed, namely: daily precipitation, P_d (sub-daily precipitation was not analyzed as, at the best, the accuracy of landslide timing in the inventory was daily); event precipitation, *H*; precipitation event duration, *D*; precipitation of the antecedent 15 days, P_{d5} (also accumulated precipitation over 30 days was considered, but it resulted less significant for landslide triggering). Figure 4 shows the obtained conditional probability of landslide occurrence in the four cases. In order to conventionally define a rainfall event, when

P_d>1.0mm occurred the day has been considered rainy. A precipitation event is every uninterrupted sequence of rainy days. According to such a definition, 490 events with duration ranging from 1 day to 15 days, and event precipitation between 1.1mm and 321mm, have been identified.

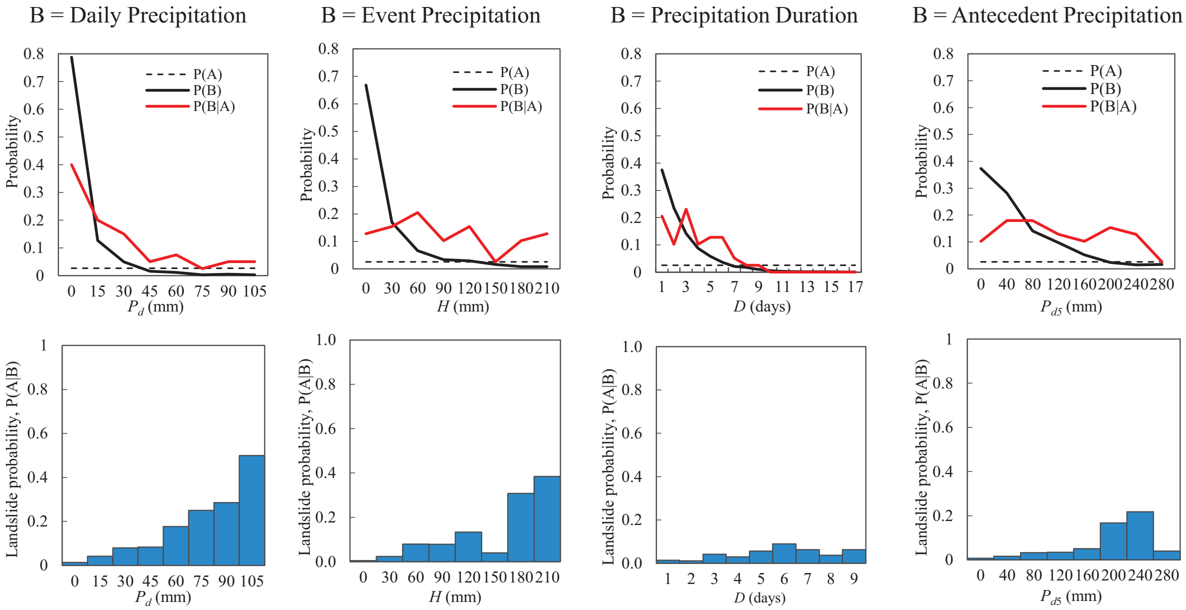

Fig. 4. Conditional landslide probability distributionsevaluated with a univariate Bayesian analysis for four meteorological variables.

From the plotted landslide conditional probability distributions, it looks clear that the most significant meteorological variable is the daily precipitation, P_d, rather than event precipitation, H. This result indicates that most of the landslides occurring within the Scoltenna catchment are suddenly triggered by short and intense precipitations. However, the values of conditional landslide probability as high as 0.2, obtained considering antecedent precipitation (P_{d5}) as the conditioning variable, indicate that, at least in some cases, also predisposing conditions related to slower hydrological processes may play a role.

Additionally, two variables related to the catchment water balance have been tested, the daily specific runoff(Q) and the specific water storage, (S). Figure 5 shows the obtained conditional landslide probability distributions. Very high conditional landslide probability values correspond to high specific runoff, even as high as 1.0 for Q>39mm. Given the limited extension of the catchment and its flashy behaviour indicated by the high runoff coefficient, the highest daily runoff values occur immediately after the most intense rain storms, and especially when the soil within the catchment is wet. This result confirms that the most significant triggering variable is the daily precipitation, with a limited contribution of the predisposing soil wetness conditions. As water in the Scoltenna catchment seems to be stored not only in the soil but also in the deeper groundwater system, the specific storage is not an appropriate proxy for landslide predisposing conditions in this area.In fact, when S attains high values, the probability of landslides remains smaller than 0.2.

Nonetheless, even for a limited fraction of the observed landslides, it is still possible that introducing the hydrological information provided by catchment specific storage can improve the predictive performance of empirical purely meteorological landslide thresholds. To test such a hypothesis, the meteorological precipitation event Intensity-Duration threshold (I-D) has been compared with a hydro-meteorological threshold based on event precipitation, H, and catchment specific storage, S (H-S). For both the thresholds, which have been identified by maximizing the True Skill Statistic, TSS, as described in section 2.3, a power-law equation $Y=A\times X^n$ has been adopted. As the specific storage can assume negative values, for which the power-law equation with negative exponent is not defined, S has been normalized in the interval [S_{min}=-500mm, S_{max}=1000mm], which largely contains the minimum and maximum values attained by S during the considered period.

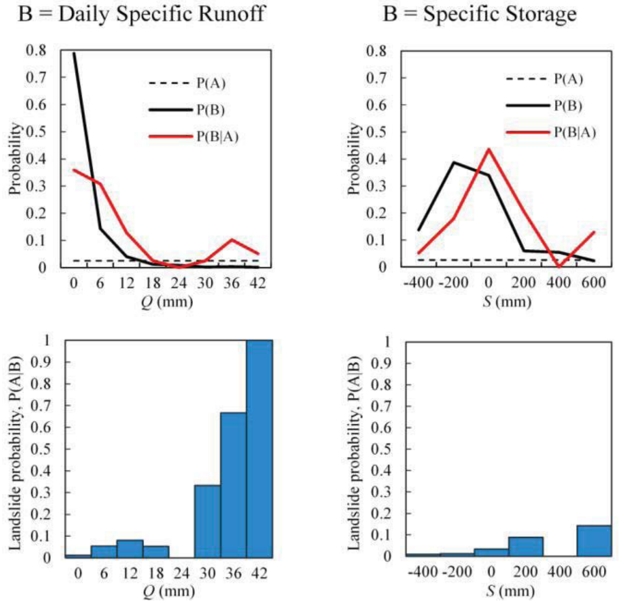

Fig. 5. Conditional landslide probability distribution evaluated with a univariate Bayesian analysis for two hydrological variables.

The obtained thresholds, which are plotted in Fig. 6 together with the dots, representing all the observed events, have the following equations:

$$I = 5.10 D^{-1.56}$$
$$H = 25.7 \left(\frac{S - S_{min}}{S_{max} - S_{min}} \right)^{-0.408} \tag{6}$$

Both the thresholds perform very well, as reported in Table 1, which gives the performance indicators of the two tested thresholds. However, the proposed hydro-meteorological threshold only once fails predicting actually occurred landslides, while in six cases (around the 10% of the total number of observed landslides) the *I-D* threshold does not correctly identify the triggering conditions. Conversely, the application of the *H-S* threshold gives rise to about seven false alarms per year (approximately 16% of the total observed rainfall events), which is twice as much as the *I-D* threshold. The choice of the threshold most suitable for landslide early warning purposes should be taken accounting for the costs of missing and false alarms. However, even in a case in which the meteorological forcing is the main factor causing landslide triggering, the inclusion of the hydrological information at catchment scale seems valuable for the definition of effective empirical landslide thresholds.

Table 1. Performance indicators of the two tested thresholds for landslide triggering assessment.

Indicator	*I-D* threshold	*H-S* threshold
True Skill Statistic, *TSS*	0.825	0.836
True Alarms, T_A	55	61
Missed Alarms, M_A	6	1
False Alarms, F_A	37	79

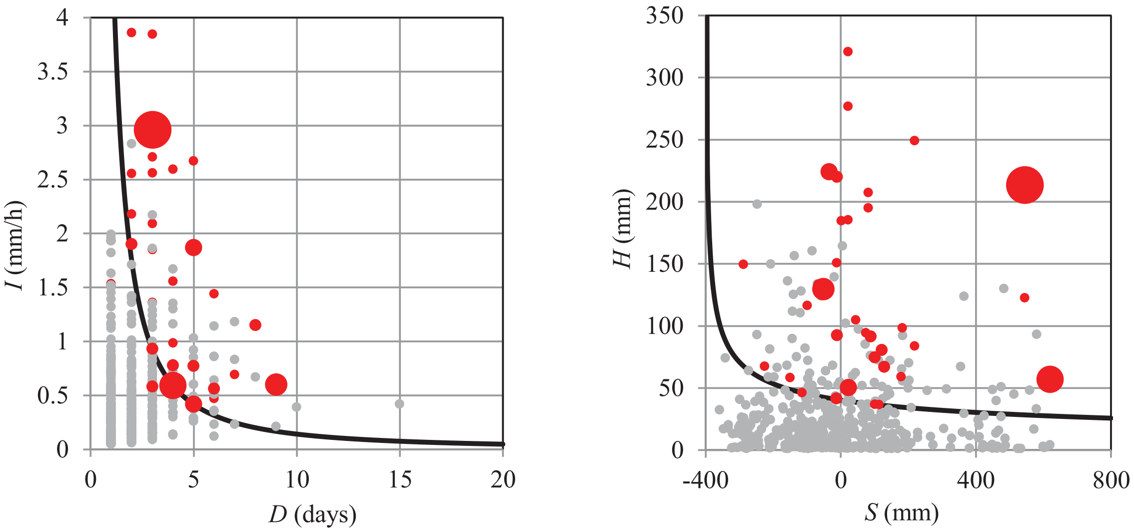

Fig. 6. Empirical meteorological (Precipitation Intensity-Duration, *I-D*, left)and hydro-meteorological (Event Precipitation-Specific Storage, *H-S*, right) landslide thresholds (the dimension of the red dots reflects the number of landslides triggered by the same event).

4. Conclusions

The application of empirical hydro-meteorological thresholds for landslide triggering assessment was proposed and compared with the usually adopted thresholds, based on meteorological information alone. In particular, thenewly proposed hydro-meteorological threshold is based on event precipitation and catchment specific storage (*H-S* threshold), evaluated with a simplified lumped water balance equation. The newly proposed threshold and the usually adopted meteorological landslide threshold based on precipitation intensity and duration (*I-D* threshold) have been applied to the catchment of river Scoltenna at Pievepelago, in the northern Apennines (Italy), for which meteorological and discharge data were available for the period 2002-2013. The univariate Bayesian analysis carried out for several meteorological and hydrological variables indicates that, in the studied catchment, the main factor leading to landslide triggering is the daily precipitation, with little influence of antecedent conditions. Nonetheless, even in such an unfavorable case, the *H-S* threshold predicts landslide triggering at least as good as the *I-D* threshold, indicating that the inclusion of hydrological information can improve the performance of the commonly adopted empirical thresholds based on meteorological information alone.

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