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Discussions

Analysing the relationship between rainfalls and landslides to define a mosaic of triggering thresholds for regional scale warning systems

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Abstract

We propose an original approach to develop rainfall thresholds to be used in civil protection warning systems for the occurrence of landslides at regional scale (i.e. tens of thousands kilometres).

A purposely developed software is used to define statistical intensity-duration rainfall thresholds by means of an automated and standardized analysis of rainfall data. The automation and standardization of the analysis brings several advantages that in turn have a positive impact on the applicability of the thresholds to operational warning systems. Moreover, the possibility of defining a threshold in very short times compared to traditional analyses allowed us subdividing the study area in several alert zones to be analyzed independently with the aim of setting up a specific threshold for each of them. As a consequence, a mosaic of several local rainfall thresholds is set up in place of a single regional threshold.

We subsequently analyzed how the physical features of the test area influence the parameters and the equations of the local thresholds, founding a significant correlation with the prevailing lithology.

A validation procedure and a quantitative comparison with some literature thresholds showed that the performance of a threshold can be increased if the areal extent of its test area is reduced, as long as a statistically significant landslide sample is present. In particular, we demonstrated that the effectiveness of a warning system can be significantly enhanced if a mosaic of site specific thresholds is used instead of a single regional threshold.

1 Introduction

Rainfall-triggered landslides are one of the main natural hazards, responsible of casualties and economical losses worldwide (Petley, 2012). To reduce this impact, the scientific community is working on forecasting the occurrence of landslides and to set

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up warning systems. When working over large areas (e.g. thousands of squared kilometres), the computational load required and the difficulty in assessing the spatial organization of geotechnical parameters prevent the application of physically based models (Baum et al., 2010; Agostini et al. 2013; Rossi et al., 2013). As a consequence, when the case of study is a large district or region, the approach used is usually based on empirical rainfall thresholds (Brunsden, 1973; Aleotti, 2004; Hong et al., 2005; Tiranti and Rebuffetti, 2010; Cannon et al., 2011; Martelloni et al., 2012; Lagomarsino et al., 2013). Among all rainfall thresholds approaches, the one using intensity-duration thresholds (Caine, 1980) is perhaps the most popular: it has been proved particularly valid for shallow landslides (Caine, 1980; Crosta and Frattini, 2001; Ahmad, 2003; Jakob and Weatherly, 2003; Aleotti, 2004; Guzzetti et al., 2008; Giannecchini et al., 2012) and it has been successfully applied also to landslides in general (Zimmermann et al., 1997; Hong et al., 2005; Brunetti et al., 2010; Rosi et al., 2012).

Although widely used, this approach is currently affected by some drawbacks that hinder a fully operational application to early warning systems. One of the main problems is a certain degree of subjectivity in some state-of-art procedures used to obtain the I/D relationship. The definition of the threshold from the I/D points has been long visually drawn with manual fitting (e.g. Caine, 1980; Giannecchini et al., 2012) and only recently this issue has been solved proposing objective and robust statistical approaches to identify a threshold with a chosen confidence level form a given cloud of I/D points (Guzzetti et al., 2007, 2008; Brunetti et al., 2010; Rosi et al., 2012).

However, even the definition of the I/D points themselves poses problems of subjectivity that can in turn affect the applicability of the thresholds to warning systems. In fact, especially when considering complex pluviometric rainfall paths where subsequent bursts of rain of varying intensity and duration alternate with short periods of absent or moderate rain, the whole rainfall event has to be summarized in a single I/D point: this procedure is not straightforward, as the result may vary depending on the choice of the reference rain gauge and on the interpretation of the pluviometric path. In particular, the starting and end point of the critical rainfall event (Aleotti, 2004) some-

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times could not be clearly and univocally identified (e.g. when the hour of occurrence of the landslide is not known with sufficient precision). Most part of the studies resort to subjective interpretations but on one hand this can influence the results (Guzzetti et al., 2008), on the other hand a subjective decision in the analytical process cannot be consistently replicated by an automated warning system.

The maximum degree of objectivity, standardization and replicability is obtained when the analysis to define the threshold and the warning system are based on rainfall parameters calculated and measured in a given time spawn: this approach ensures that the rainfall analysis can be easily and consistently replicated by automated warning systems. Indeed, at present most part of operational warning systems are based on rainfall parameters as measured over a given duration (Wilson, 2000; Chleborad, 2003; Cardinali et al., 2006; Cannon et al., 2008, 2011; Lagomarsino et al., 2013).

However, I/D approaches have been proved very effective in defining the minimum rainfall conditions that can potentially trigger landslides (Guzzetti et al., 2008; Brunetti et al., 2010), but this aim is slightly different from the objective of an operational EWS, where a balance between false alarms and missed alarms is usually required (Staley et al., 2013).

This work proposes an original approach to overcome the aforementioned issues: the threshold is drawn according to rigorous statistical techniques; the I/D points are defined according to an automated analysis (Segoni et al., 2014) that can be easily and consistently replicated by an automated warning system; the proposed procedure is completed by a back analysis aimed at minimizing errors of commission (i.e. false positives); lastly, the empirical relationship between meteoric events and landslide triggering is strengthened by defining a mosaic of local thresholds instead of a single regional threshold.

The applicability of the thresholds to early warning systems for civil protection purposes (and thus the effectiveness of the proposed methodology) has been tested by means of a validation procedure that provided satisfactory results. The validation was

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extended also to some literature thresholds, so as to perform a quantitative comparison for a better evaluation of the effectiveness of our approach.

Finally, we investigated the extent to which the environmental setting of a study area influences the rainfall analysis and the resulting threshold equation, with the aim of finding some physical background in the empirical intensity–duration relationship.

2 Material and methods

2.1 Test site

The proposed methodology was applied in the Tuscany region (23 000 km^2), which is located in Central Italy and is characterized by a mainly hilly (66.5 %) and mountainous (25.1 %) territory, with limited lowland areas (8.4 %) corresponding to intermontane basins and to the southern coastline (Fig. 1a).

Tuscany is characterized by a variety of lithological units with very different mechanical properties. The hilly territories are mainly constituted by granular or cohesive terrains or by soft rocks. The north and the east are occupied by the reliefs of the Apennine folds and trusts belt, made up of mainly flysches, while in the north-western sectors a metamorphic units outcrops. Lastly, in smaller but still relevant portions of the territory, evaporites, carbonatic rocks, effusive rocks and intrusive rocks are present.

Tuscany has a typical Mediterranean climatic regime with mild and moist winters, hot and dry summers and two peaks of precipitation (the main one in autumn and the secondary one in spring or winter), while summer is always the driest period of the year. Areal distribution of rainfalls is markedly influenced by the relief: in the north-western part of the region, in particular, mean annual precipitations (MAP) are about 2000 mm $year^{-1}$ (with annual peaks of 3000 mm $year^{-1}$), while southern Tuscany is characterized by very lower rainfall amounts (about 600 mm $year^{-1}$ MAP) as showed in Fig. 1b and discussed by Rapetti e Vittorini (1994).

To account for the high variability of meteorological and physiographic settings encountered in the study area, and to get more accurate rainfall thresholds, the test site was partitioned into 25 Alert Zones (AZ) following the main regional divides (Fig. 1). Each AZ was independently analysed to devise a site-specific rainfall threshold.

2.2 Input data

To define the rainfall thresholds, data from over 2000 landslides (Fig. 1a), occurred between 2000 and the beginning of 2009, were collected. These data were split into two dataset: calibration dataset (2000–2007) and validation dataset (2008–2009). Data were collected mainly from the archives of Tuscany Civil Protection, but also from local authority archives, from national and local newspapers and from existing datasets of recent research projects (Catani et al., 2013; Mercogliano et al., 2013; Rosi et al., 2013).

Every landslide was filed in a geo-database with a unique ID, its spatial location, the main characteristics (when known), the occurrence date, and every other available information. Almost all the landslides had not the exact occurrence time, but only the day of occurrence was reported. For about the 10 % of landslides a more accurate timing was available (e.g. "during the evening" or "in the night"). Considering that in many large scale rainfall threshold studies the exact timing of occurrence is unknown (Guzzetti et al., 2007), the landslide database could be considered sufficiently accurate.

Rainfall data were collected from 332 rain gauges distributed throughout the region (Fig. 1b). Their hourly rainfall time series were organized in a database and joined with other information including coordinates and alert zone. The dates (day and, if available, hour) of occurrence of landslides were used to query the rainfall database and to extract, for each landslide, the rainfall data of all the rain gauges of the corresponding AZ.

2.3 Methodology

To define the regional mosaic of thresholds, a recently proposed methodology (Segoni et al., 2014) was applied separately to every alert zone. This methodology is largely automated and thus is useful to manage a large amount of data and to carry out the large number of analyses needed to define 25 different thresholds in a single region. The methodology is explained and discussed in detail in Segoni et al. (2014); the basic characteristics are summarized hereafter.

A software named MaCumBA (Massive Cumulate Brisk Analyzer) (Segoni et al., 2014) analyses the recordings of each rain gauge located in the same AZ. The software automatically carries out the following tasks, otherwise traditionally performed manually and in a subjective way over a limited number of rainfall paths:

Identification, in the rainfall data, of the critical rainfall.

Definition of the critical parameters used to describe the rainfall event (namely critical intensity I and critical duration D).

a-posteriori selection of the most appropriate rain gauge for the characterization of each landslide event, within all the rain gauges of the same AZ.

The selected I/D values are plotted in a graph, where each point represents the rainfall conditions that in the past resulted in the triggering of a landslide.

Two thresholds are automatically defined using two different frequentist statistical approaches: the confidence interval technique and the prediction interval technique (Hahn and Meeker, 1991).

Thresholds are defined using the power law firstly proposed by Caine (1980) and thus they are expressed by the general equation

$$I = \alpha D^{\beta}$$

where I is the rainfall intensity, D is the rainfall duration and α (>0) and β (<0) are empirical parameters defined by means of the aforementioned statistical analysis.

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The automated procedure is sensitive to some user-defined parameters. Some of them can be properly defined using GIS analyses (e.g. the maximum distance allowed between a landslide and the rain gauges to be used for the characterization of the triggering rainfall), some correspond to political decisions (e.g. the confidence level of the threshold, which in this work, according to the Tuscany Civil Protection Agency, was set to 95 %), some cannot be decided in advance. This is the case of the parameter called "no rain gap", which accounts for the number of hours without rain needed to consider two rainfall events as separate. The no rain gap is of paramount importance for two reasons: first, it allows a standardized analysis of the rainfall series; second, it allows warning systems to analyze rainfall recordings/forecasts in a consistent and completely automated way. However, setting different *no rain gaps* produces different clouds of I/D points and different rainfall thresholds, thus an objective criterion is needed to identify the configuration that produces the most reliable results. Since the use of the software MaCumBA allows calculating thresholds in short times, we performed for each AZ several runs using different *no rain gap* values; then each obtained threshold underwent a back analysis aimed at estimating its performance over the entire testing period, so as to be able of identifying and selecting the threshold characterized by the lowest number of false alarms, confidence levels being equal. The detail of this part of the methodology can be found in Segoni et al. (2014) and a graphic example is shown in Fig. 2. A similar approach of choosing the threshold that minimizes errors among different possibilities can be found in Staley et al. (2013).

3 Results

Using the procedure summarized in the previous section, a rainfall threshold was defined for each alert zone (AZ) of the region; the equations are presented in Table 1.

In some alert zones the database presented a limited number of landslides, therefore it was not possible to perform a significant statistical analysis. In such cases, we chose to group together some adjacent AZs on the basis of their characteristics (geological setting, topography, rainfall regime), until a significant number of landslides was reached.

This procedure was necessary for the central coast and the archipelago (AZ C1-2-3-4); the almost flat alert zone B2 (which was grouped to the landslide-rich AZ B3); the inland D1 and D3 alert zones; the southern F1-F4 and F2-F3.

Alongside the threshold equation, the automated analysis allowed defining for each AZ an important parameter (namely *no rain gap*), that corresponds to the consecutive number of hours without rain that are needed to consider two rainfall events as separate. The no rain gap is of paramount importance for the implementation of the threshold for civil protection purposes, as it provides automated early warning systems with a consistent criterion to analyse rainfall data.

3.1 Validation

To evaluate the proposed approach and the effectiveness of the thresholds mosaic for civil protection purposes, a validation procedure was carried out using an independent dataset (landslides and rainfall data from January 2008 to January 2009).

The validation procedure was performed simulating an operational employ in a civil protection warning system: if the threshold were in use, when an alarm would have been issued and when not? And comparing these dates with the landslide dataset, how many correct predictions, false alarms and missed alarms would have been reported?

According to this approach, for each alert zone every rainfall event was classified as true positive (TP or correct prediction: some landslides were triggered in correspondence of a threshold overcoming), true negative (TN: the threshold was not overcome and no landslide was triggered), false positive (FP, or false alarm, i.e. threshold overcome without landslides triggering), or false negative (FN, or missed alarm: the threshold was not overcome, but some landslides were triggered).

The validation results are shown in Table 2 and are aggregated at the regional level in a contingency table (Table 3).

4 Discussion

4.1 From a single regional threshold to a regional mosaic of thresholds

The mosaic of thresholds defined for the Tuscany region, was compared with two literature thresholds involving, either in whole or in part, the same area (Fig. 3): the threshold proposed by Brunetti et al. (2010) for the whole Italy and the threshold proposed by Rosi et al. (2012) for the whole Tuscany. Other literature thresholds were not considered since, at local or regional scale, thresholds perform reasonably well only in the area where they were developed and cannot be easily exported to other areas (Crosta, 1989).

The first outcome of this comparison is that the national threshold proposed by Brunetti et al. (2010) is significantly lower than any other threshold, thus it is likely to commit a relevant number of false positive errors if applied to the Tuscany warning system. However, it should be stressed that the threshold proposed by Brunetti et al. (2010) is not expected to provide a balanced between false positives and false negatives, because it was conceived with a different aim, that is defining the minimum rainfall condition that can potentially lead to landsliding. In this light, the threshold performs vey well, as it low-bound the other thresholds used in this comparison.

The work of Rosi et al. (2012) and the one presented here involve the same study area (Tuscany) and have the same goal (a threshold as much balanced as possible to be used in a civil protection warning system); thus, a comparison between them is fully appropriate and allows comparing the two methodologies. In particular, we are interested in discovering if the splitting of the region in a mosaic of local thresholds, defined using the automated routines of the MaCumBA software, could bring to a relevant improvement of the predicting capabilities of the regional warning system.

To this end, the four elements of the contingency table (Table 3) were combined to calculate some indexes that are traditionally used to quantitatively assess the performances of a model (Martelloni et al., 2012). The same statistics were calculated for the validation of the methodology proposed in this work and for the validation of a hypothetical application in the whole Tuscany region of the regional threshold proposed by Rosi et al. (2012) and the national threshold (Brunetti et al., 2010) (Table 4).

The comparison between the validation statistics of Table 4 clearly shows that the effectiveness of thresholds can be increased focusing the analysis on a smaller area. Consequently, a site-specific threshold is more precise than a general threshold applied to a single subdivision (passage from the national to the regional threshold) and a set of local thresholds is more effective than a single threshold. This proves the validity of our approach of devising a mosaic of thresholds instead of a single regional rainfall threshold. This approach is not new (see e.g. Martelloni et al., 2012) but is rarely used, as many works prefer to gather a large number of landslides for larger areas. This is partially conditioned by the necessity of increasing the landslide population to be used for statistical analyses: the larger the landslide population, the more robust the statistical analysis, the more reliable the threshold. The pros and cons of the splitting up of the study area into smaller subdivisions to be analyzed independently should be carefully evaluated and counterbalanced.

On one hand, the splitting up cannot be pushed too further as a statistically significant number of landslides is needed to obtain reliable thresholds. It is not easy to establish the minimum number of landslides needed: in this work we obtained satisfactory results (Table 2) in alert zones with 12 landslides (Table 1) or with a higher number of landslides triggered by just 8 rainfall events, but the international literature reports case studies where significant thresholds were defined even with smaller datasets (Chen and Wang, 2014).

On the other hand, the splitting up of the territory brings the advantage of considering a uniform and homogeneous set of landslides, lithology and meteorological condition, thus strengthening the empirical correlation between I/D values and landslide triggering. Moreover, if a threshold pertains to a limited area, its operational employ in Civil Protection procedures is advantaged, since a warning issued for a restricted area can be managed more easily than an alarm issued for a whole region involving dozens of cities and millions of inhabitants.

4.2 Relationships between thresholds and physical variables

Recently various studies compared rainfall thresholds either with results of physical modelling (Alvioli et al., 2014) or with geospatial analyses of the environmental variables (Rosi et al., 2012; Lagomarsino et al., 2013) with the aim of finding a physical background in the empirical intensity–duration relationship.

The definition of 18 thresholds, obtained with the same methodology in a restricted area, is a unique opportunity to make significant comparisons and to investigate what lies beyond the empirical relationship between cause (rainfall) and effect (landslide) and how different physical settings can influence threshold equations. Since the spatial distribution of the landslides in the study area is not homogeneous and depends on the physical setting (geology, geomorphology, rainfall regime, human influence), and since the main parameters of the thresholds exhibit a relevant degree of variability (Table 1), it is interesting to investigate if the physical features of the various alert zones can be put in relation with the parameters of their thresholds.

For this analysis, each threshold was characterized by means of the following parameters: α, β, the area under the threshold (AUT), and the no rain gap (NRG). The first two parameters are directly derived by the threshold equation and describe the power law relationship between intensity and duration. In a log-log plot, α represent the intercept in the y-axis and defines how "high" a threshold is at low durations, while β represents the steepness of the threshold, therefore with low β values even a threshold with high α values can become "low" for high durations. AUT defines the area under the threshold and thus quantifies how much a threshold is "high" or "low" with respect to both α and β. NRG represents the minimum time gap with absence of rainfall required to consider two rainfall events as separate and it is a very important parameter both for the threshold analysis and for their application to operational warning systems.

First, we checked the degree of correlation between the threshold parameters and found that α and β are quite correlated each other ($R^2 = 0.71$), while NRG do not result correlated with any of the other parameters (α, β and AUT). This last outcome can be interpreted as an indicator of the robustness of the proposed methodology: the optimal no rain gap value cannot be subjectively established in advance, it is very site-specific and a trial and error procedure is needed to define an efficient value for the use in civil protection warning systems. The correlation between α and β means that, in general, the higher the intercept of a threshold, the highest its steepness. We can therefore infer that if an alert zone has "high" α and β parameters, it is not likely to be subjected to landslides triggered by short and intense rainstorm, while prolonged rainfalls may overcome the threshold even with relatively low values of average intensity. Conversely, if α and β are relatively low, short rainstorms can trigger landslides even at relatively low intensities while prolonged rainfall events needs to reach relevant rainfall amounts before triggering landslides. This can be put in relation with the geomechanical and hydrological properties of the terrains and rock characterizing each AZ and thus suggests that the approach of sectioning the study area into independent Alert Zones helps finding a stronger correlation between rainfall and landslides: even if many different lithologies outcrop in Tuscany, only a limited number is present in each alert zone and thus the response to the territory to the rainfall triggers is more homogeneous.

In a second step, we investigated the correlation between the abovementioned threshold parameters (α, β, AUT and NRG) and the main characteristics of the physical setting of each alert zone. We analysed the mean annual precipitation to account for the main triggering factor of landslides and to verify the observations of Govi and Sorzana (1980), according to which the amount of rainfall needed to trigger landslides rises with the mean annual precipitation. Slope gradient and lithology were considered to account for the landslide susceptibility of each area: according to recent studies on the landslide susceptibility of Tuscany (Catani et al., 2013), slope gradient and lithology are the most important predisposing factors.

Table 5 reports the degree of correlation (expressed in R^2 terms) between rainfall parameters and some basic statistics of the numerical variables that were used to characterize the physical setting (mean annual precipitation and slope gradient). Ta-

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ble 5 clearly shows that no R^2 reaches values higher than 0.2, therefore no significant correlation was found.

This outcome is not completely unexpected: a simple empirical correlation between cause-effect can be strengthened by the AZ subdivision as it reduces the variability of the physical setting, but not to the point of making possible to relate the characteristics of the rainfall threshold to just a couple of predisposing or triggering factors. This is confirmed by recent landslide susceptibility studies in the same study area: Catani et al. (2013) demonstrated that optimal susceptibility assessments can take into account up to 21 different parameters.

The influence of lithology on the threshold parameters was investigated comparing the prevailing lithology of each AZ with the parameters of the corresponding threshold. The twelve alert zones characterized by layered rocks (e.g. flysch) exhibit a marked variability of the values of the main threshold parameters: α values range from 15.0 to 405.9, while β values range from -0.651 to -1.29. In the six alert zones where terrains or soft rocks are the prevailing lithology, the same parameters have a smaller variability: α ranges from 29.6 to 50.7, while β ranges from -0.900 to -0.856.

A significant correlation was found between the prevailing lithology of each alert zone and the *no rain gap* of its rainfall threshold: on average, the more permeable the lithology, the highest the *no rain gap* value (Table 6).

A possible interpretation of this outcome is that the most permeable lithologies (granular terrains characterized by conglomerates and sands) are mainly interested by deep seated landslides, which in turn are usually triggered by longer rainfalls, even without particularly extreme intensities. A high no rain gap (up to 36 h) helps the automated algorithm for the identification of the triggering rainfalls to focus on events with medium intensities averaged over long durations. Conversely, relatively impermeable bedrocks (e.g. tuffs, gneisses and intrusive rocks) exhibit a marked contrast of hydraulic properties with the overlying terrain: this condition predisposes to shallow landslides and debris flows, which are typically triggered by short and intense rainfalls. A short no rain gap (10 or 12 h), therefore, helps the algorithm to prevalently recognize rainfall events characterized by short peaks with extreme intensity values. In those alert zones where intermediate situations are present (e.g. terrains of mixed typology and flysches), intermediate values of no rain gap (e.g. 24 h) are more frequently found. This outcome, similarly to other recent studies (Alvioli et al., 2014), proves that the empirical relationship between rainfall and landslides implicitly takes into account the physical background of the problem.

5 Conclusions

In this work, we propose an original approach to set up a mosaic of 18 local rainfall thresholds, in place of a single regional threshold, to be used in civil protection warning systems for the occurrence of landslides at regional scale (i.e. tens of thousands kilometres).

The proposed approach is based on the use of a software named MaCumBA (explained and discussed in detail in Segoni et al., 2014), which allows defining statistical intensity-duration rainfall thresholds by means of an automated and standardized analysis of rainfall data. The automation and standardization of the analysis brings several advantages that in turn have a positive impact on the applicability of the thresholds to operational warning systems.

The possibility of defining a threshold in very short times compared to traditional analyses allowed us subdividing the study area in several alert zones to be analysed independently with the aim of setting up a specific threshold for each of them. The subdivision into small alert zones fosters the definition of robust rainfall thresholds as it circumscribes the statistical analysis to a limited and homogeneous area, thus allowing a strong empirical relationship between cause (rainfall) and effect (landslides). However, from a physical point of view, this linkage still remains very complex as it depends from many interplaying factors, and every attempt to relate the threshold parameters to the main numerical variables characterizing the physical setting failed. The only significant correlation was found between the *no rain gap* (NRG) (lapse of time without rainfall needed to consider two rainfall events as separate) and the prevailing lithology of each alert zone: in general the more permeable the terrains/rocks of the alert zone, the highest the no rain gap of the threshold. This outcome provides a physical background to empirical rainfall thresholds and brings to two conclusions: on one hand, it remarks the necessity of devising warning systems based on a mosaic of thresholds rather than on a single regional threshold, as the optimal criterion to be used by the warning system to analyse rainfall data and identify critical rainstorms may differ from an area to another depending of the encountered physical features; on the other hand it stresses the necessity of using the same criterion for the rainfall analysis both during the research stage of rainfall definition and during the operational phase when the warning system performs automated computations in near real time.

However, we come to the conclusion that the subdivision into alert zones cannot be pushed too further as it is limited by the necessity of having a statistically significant landslide sample in each alert zone. Our methodology provided satisfactory results with datasets of minimum 12 and maximum 719 landslides, with the dimension of the dataset not influencing the quality of the results. We therefore believe to have found a robust methodology and an effective compromise between Alert Zone dimension and robustness of the landslide sample, counterbalancing pros and cons of having small or large AZs.

Another important outcome of this work is the necessity, for thresholds aimed at being employed in civil protection warning systems, to be analytically validated. The proposed mosaic of thresholds was validated with an independent dataset: all the pluviometric events recorded from 2008 to 2009 were analyzed and compared with the corresponding landslide dataset. In this way we were able to count correct predictions and errors of commission (false alarms) and omission (missed alarms); subsequently we calculated some quantitative indexes commonly used to express the effectiveness of models. This procedure allowed to conclude that our methodology had obtained an acceptable balance between missed alarms and false alarms that encouraged the employ of the mosaic of threshold in a regional civil protection warning system. Furthermore, the validation procedure was repeated for some literature threshold and the quantitative comparison of the results demonstrated that the performance of a warning system can be enhanced if a specific threshold is defined for a given region rather than applying a general threshold, moreover this enhancement can be increased if a mosaic of site specific threshold is used instead of a single regional threshold.

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Table 1. Equations and main parameters of the thresholds.

Alert zone	Threshold	No Rain Gap (h)	Number of landslides	Number of rainfall events that triggered landslides
A1	$I = 61.4D^{-0.781}$	18	246	27
A2	$I = 34.0D^{-0.856}$	18	196	32
A3	$I = 52.4D^{-0.734}$	24	719	79
A4	$I = 101.5D^{-0.99}$	18	90	13
B1	$I = 33.8D^{-0.806}$	20	27	12
B2-3	$I = 22.5D^{-0.651}$	24	61	34
B4	$I = 49.9D^{-0.733}$	24	208	34
B5	$I = 405.9D^{-1.29}$	24	44	17
C1-2-3-4	$I = 49.2D^{-0.77}$	24	69	28
D1-3	$I = 40.5D^{-0.9}$	24	39	22
D2	$I = 31.6D^{-0.764}$	12	60	23
D4	$I = 33.5D^{-0.742}$	15	12	11
E1	$I = 20.0D^{-0.66}$	12	26	8
E2	$I = 29.6D^{-0.745}$	12	40	8
E3	$I = 20.9D^{-0.779}$	10	51	13
E4	$I = 15.0D^{-0.69}$	32	166	11
F1-4	$I = 37.2D^{-0.884}$	24	39	25
F2-3	$I = 50.7D^{-0.775}$	36	44	20

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Table 2. Results of the validation procedure for each AZ. FP: False Positives; FN: False Negatives; TP: True Positives; TN: True Negatives.

Alert zone	FP	FN	TP	TN
A1	1	0	5	165
A2	2	0	21	115
A3	1	3	18	184
A4	1	1	4	91
B1	1	0	5	114
B2-3	0	2	7	95
B4	0	1	7	60
B5	0	1	5	171
C1-2-3-4	0	1	8	134
D1-3	6	0	5	108
D2	0	1	3	109
D4	0	3	6	97
E1	7	0	2	106
E2	0	0	2	134
E3	2	0	4	238
E4	3	0	4	76
F1-4	5	1	7	120
F2-3	1	0	5	127

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Table 3. Contingency table summarizing the validation procedure at regional level; the numbers represent, clockwise from the upper left corner, true positives, false alarms, true negatives and missed alarms.

		Observed truth	
		Landslide	No landslide
Prediction	Landslide	118	30
	No landslide	14	2244

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Table 4. Validation statistics of the mosaic of thresholds defined in this work, compared with literature thresholds proposed by Rosi et al. (2012) and Brunetti et al. (2010); as explained in the text, TP stands for true positives, TN for true negatives, FP for false positives, FN for false negatives.

		This work	Regional threshold	National threshold
Sensitivity	TP/(TP + FN)	0.894	0.896	0.958
Specificity	TN(FP + TN)	0.987	0.732	0.692
positive predictive power	TP/(TP + FP)	0.797	0.448	0.430
negative predictive power	TN/(TN + FN)	0.994	0.967	0.986
Efficiency	(TP + TN)/(TP + TN + FP + FN)	0.982	0.764	0.744
Likelihood ratio	Sensitivity/(1-specificity)	67.761	3.347	3.111

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Table 5. R^2 values expressing the correlation between rainfall threshold parameters (α, β, combinations of α and β, Area Under Threshold and No Rain Gap) and main numerical variables that characterize the physical setting.

		A	β	α/β	$\alpha\cdot\beta$	AUT	NRG
Mean annual precipitation	Max (a)	0.097	0.021	0.109	0.091	0.098	0.031
	Mean (b)	0.082	0.019	0.095	0.075	0.083	0.036
	Sd (c)	0.067	0.008	0.062	0.071	0	0
	Min	0.140	0.074	0.162	0.127	0.141	0.084
Slope gradient	Mean (d)	0.154	0.056	0.158	0.151	0.15	0.010
	Max (e)	0.052	0.004	0.073	0.042	0.053	0.039
	Sd (f)	0.020	0.007	0.022	0.019	0	0.024
Rainfall and morphology combinations	a · d	0.167	0.056	0.099	0.071	0.081	0.031
	$a\cdot e$	0.095	0.021	0.112	0.087	0.096	0.030
	$b\cdot d$	0.139	0.043	0.154	0.131	0.140	0.024
	$b\cdot e$	0.080	0.017	0.181	0.160	0.168	0.025

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Table 6. Variation of no rain gap values in Tuscany alert zones in relation to the prevailing lithology.

Prevailing lithology	No Rain Gap (hours)		
	Mean	Minimum	Maximum
Intrusive rocks	10	10	10
Gneiss	12	12	12
Effusive rocks	12	12	12
Terrains of mixed typology (cohesive and granular)	20.3	18	24
Flyschs	21.9	12	24
Marls	24	24	24
Granular terrains	30.4	24	36

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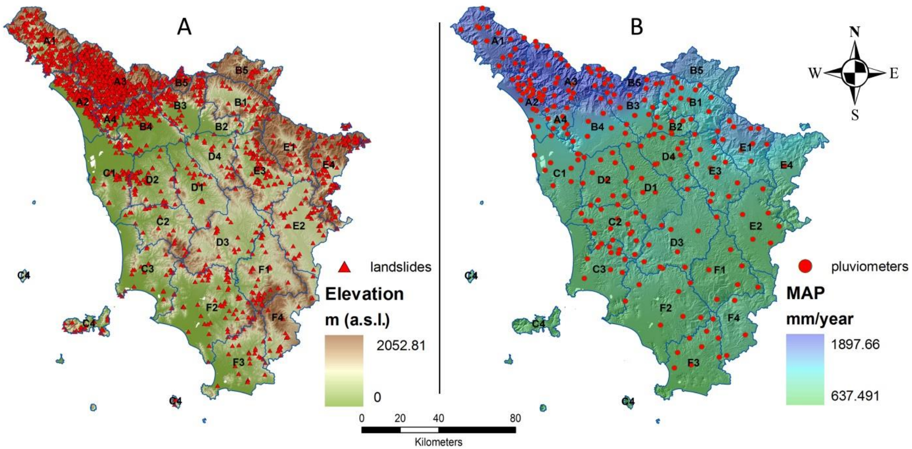

Fig. 1. The Tuscany region, subdivided into 25 alert zones (AZ), with landslide inventory laid over the digital elevation model **(a)** and the pluviometers distribution laid over the mean annual precipitation map **(b)**.

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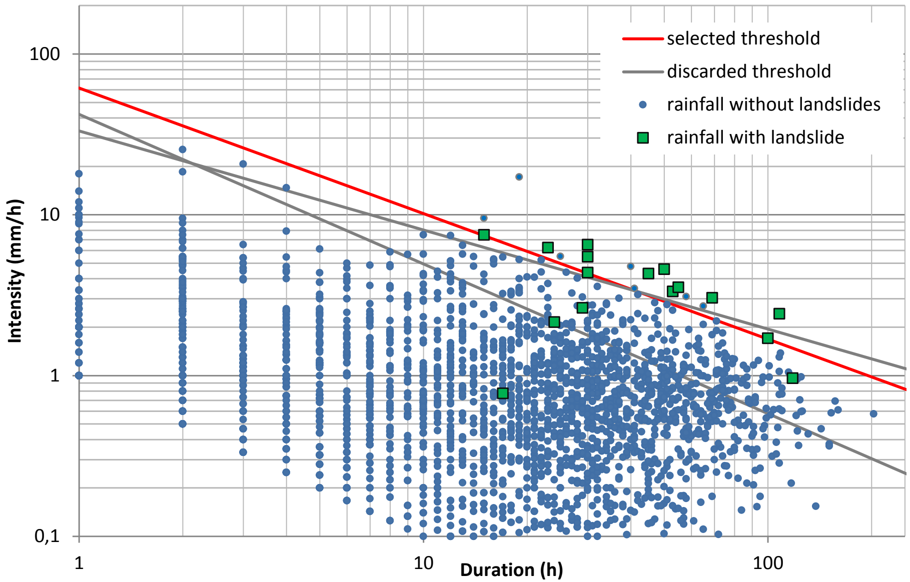

Fig. 2. Rainfall threshold defined for AZ A1, compared with two alternative thresholds discarded because of a larger number of false alarms (blue dots above the threshold).

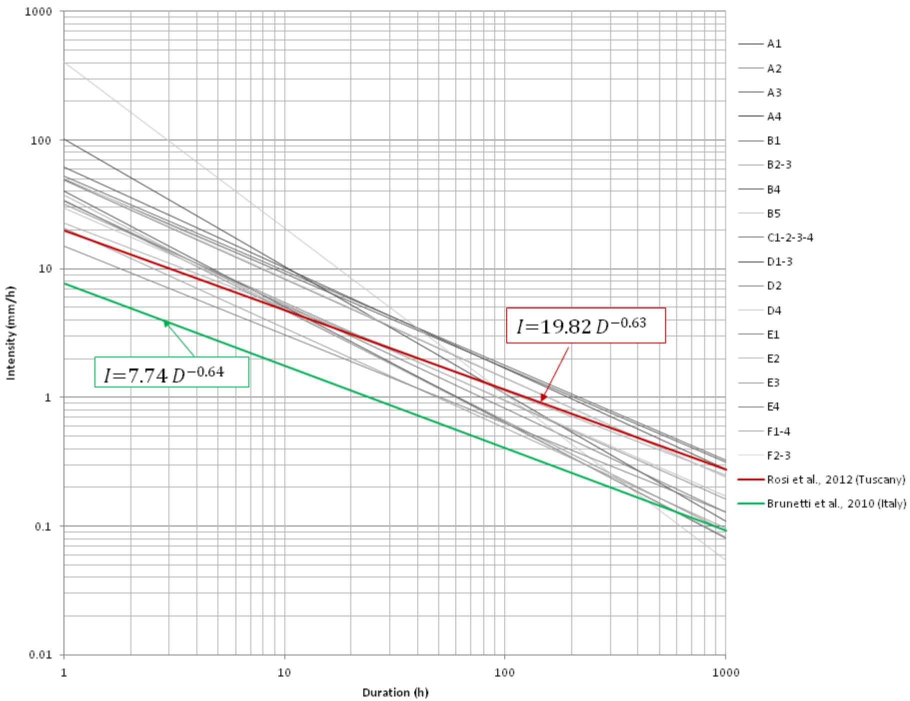

Fig. 3. Comparison between rainfall thresholds defined in Tuscany and literature thrshold involving the same area.

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