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Brief communication: Using punctual soil moisture estimates to improve the performances of a regional scale landslide early warning system

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Abstract. We improved a state-of-art RSLEWS (regional scale landslide early warning system) based on rainfall thresholds by integrating punctual soil moisture estimates. We tested two approaches. The simplest can be easily applied to improve other RSLEWS: it is based on a soil moisture threshold value under which rainfall thresholds are not used because landslides are never expected to occur. Another approach deeply modifies the original RSLEWS: thresholds based on antecedent rainfall accumulated over long periods were substituted by soil moisture thresholds. A back analysis demonstrated that both approaches reduced consistently false alarms, while the second approach reduced missed alarms as well.

1 Introduction

Regional scale landslide early warning systems (RSLEWS henceforth) are usually based on empirical rainfall threshold, which in turn are based on rainfall parameters easy to measure and monitor by means of rain gauges (Guzzetti et al., 2007; Baum et al., 2010; Cannon et al., 2011; Segoni et al., 2015a; Piciullo et al., 2017).
However, it is widely recognized that soil moisture conditions before the triggering rainfall event can play a crucial role in the initiation of landslides, especially for deep-seated landslides and for terrains with complex hydrological settings (Wieczorek, 1996; Martelloni et al., 2012).
Unfortunately, the influence of soil moisture conditions is difficult to be adequately considered in RSLEWS. One of the most widespread approaches is establishing rainfall threshold based on the rainfall amount accumulated during a given period before the landslide occurrence or before the triggering rainfall event (Guzzetti et al., 2007, and references therein). The length of these timespans varies widely in the international literature, e.g. from a few days (Calvello et al., 2015) to a few months (Cardinali et al. 2006). All these methodologies share the approach of considering antecedent rainfall a proxy for soil moisture. A smaller series of studies takes advantage of direct measures of soil moisture with remotely sensed data (Brocca et al., 2015; Laiolo et al., 2015) but their integration in RSLWS is not straightforward and it is limited to few case studies (Ponziani et al., 2012).

This work explores the possibility to exploit punctual soil moisture values estimated at few discrete points and to correlate them with the landslide triggering over wide areas (thousands of squared kilometers).
We test this hypothesis in the regional warning system of the Emilia Romagna Region (Italy), which is based on the combination of short term and long term rainfall measures to forecast the occurrence of landslides, as described in detail in Martelloni et al. (2012) and Lagomarsino et al. (2013). We developed an alternate version of the RSLEWS, substituting long term measures with soil moisture estimates obtained by TOPKAPI, a state-of-the-art physically based model (Ciarapica and Todini, 2002). The different versions of the RSLEWS are compared and, given the satisfactory outcomes, the results are discussed in light of the possible application of the proposed methodology to the regional warning system.

2 Materials and method

Test site is the Emilia Romagna Region (Northern Italy). This region is characterized by a morphology ranging from high mountains in the S-SW to wide plains towards NE. The mountain chain of the region belongs to the Northern Apennines, which is a complex fold-and-thrust arcuate orogenic belt originated in response to the closure of the Ligurian Ocean and the subsequent collision of the European and continental margins which started in the Oligocene (Agostini et al., 2013). The mountainous part of the region is affected by surficial and deep-seated landslides, which can be triggered by short and intense rainfalls or by prolonged rainy periods, respectively (Martelloni et al., 2012).
One of the instruments used to manage landslide hazard is a RSLEWS called SIGMA, which is based on a complex decisional algorithm considering the overcoming of statistical rainfall thresholds (Martelloni et al. 2012). The thresholds are defined in terms of standard deviation (σ) from the mean rainfall amount accumulated during progressively increasing time steps. The algorithm considers two different periods of cumulative rainfall: daily checks of 1, 2 and 3-day cumulative rainfall (short period) are used to forecast shallow landslides; a series of daily checks over a longer and variable time window (ranging from 4 to 243 days depending on the seasonality) is used to forecast deep seated landslides in low-permeability terrains (Lagomarsino et al. 2013). To increase the effectiveness of the model, the mountainous part of the region has been divided into 25 homogeneous territorial units (TU), each monitored by a reference rain gauge, as fully described in Lagomarsino et al. (2013) and depicted in Figure 1.
For most of the hydrographic basins of the region, ARPAE-ER (Regional Agency for Prevention, Environment and Energy of Emilia Romagna) provides the mean soil moisture value at hourly time step. These are values estimated by the TOPKAPI (TOPoghaphic Kinematic APproximation and Integration) model (Ciarapica and Todini, 2002), which is an inflow-outflow model that can provide high resolution hydrological information.
We use these data to calculate the mean daily soil moisture value for each TU. We use daily aggregation because SIGMA is normally run daily, and it uses daily aggregations of hourly rainfall measurements; therefore, a higher temporal resolution would be unnecessary. In case the territory of some TUs is occupied by more than one basin, a weighted mean is used as averaged value.

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Similarly, since the final objective of this work is coupling soil moisture data with rainfall data measured over discrete points (a network of rain gauges, one for each TU), we are not interested into distributed modeling of soil moisture, but a single soil moisture value is needed for each TU. This approach is not completely new, as in the same test site Martelloni et al. (2013) used punctual measurements of temperature to incorporate in SIGMA a module accounting for snow accumulation/depletion processes.

3 Alternate approaches

3.1 Mean soil moisture (MSM) threshold

We compared all landslide occurrences in the years 2009-2014 and MSM (mean soil moisture) at each TU. We verified that for each TU a threshold MSM value can be identified under which landslides are never triggered, independently from the rainfall amount. As a consequence, taking this limit into account could prevent SIGMA from committing false alarms in case of abundant rainfalls outside the rainy season, when the soil is dry. The MSM threshold varies generally from 73% (TU 23) to 88% (TU 21). The only exception to this rule is TU 20, where an event of 3 landslides occurred in 01/06/2013 with a MSM of 54%, although all the other landslides of the TU occurred with MSM equal or higher than 75%.

We decided to modify SIGMA algorithm using a threshold based on MSM = 75%, equal for all TUs. Basically, the modified version of the algorithm checks the MSM value and uses the module of rainfall only if MSM>75%. Under this threshold, no landslide is expected and the original SIGMA algorithm based on rainfall thresholds does not starts. Above the threshold, landslides could be expected if particular rainfall conditions are verified, therefore SIGMA algorithm is launched.

A back analysis performed for the years 2009-2014 over the 7 test TUs shows a marked reduction of false alarms: false alarms in the first warning level decrease from 320 to 231 (-28%), false alarms in the second warning level decreases from 169 to 141 (-17%) and false alarms in the third warning level decreases from 13 to 5 (-62%). To correctly evaluate the effectiveness of a EWS, the improvement concerning false alarms should be weighed against the behavior concerning missed alarms. We verified that the introduction of the MSM threshold causes the increase of false alarm counts only by 1. The already mentioned event occurred in 01/06/2013, consisting in three landslides (lowest alarm level according to Lagomarsino et al., 2013). Since this was a very minor event and since lowering the MSM threshold to 54% would result in an almost total loss of the benefits in terms of false alarm reduction, the 75% threshold was considered successfully tested and the 01/06/2013 event was considered an acceptable tradeoff in the light of a general improvement of the warning system.

3.2 SIGMA-U

After these preliminary but encouraging results, we decided to integrate soil moisture thresholds more deeply into the original SIGMA algorithm, and we substituted rainfall thresholds based on long accumulation periods with statistical soil moisture thresholds. Following the same procedure used in Martelloni et al. (2012) for rainfall data to build σ curves, we calculated for every TU the time series of soil moisture (u), assessing the mean values and the standard deviations. After this procedure, for each TU every soil moisture value (U) could be expressed in terms of multiples of standard deviation from u.

After that, we deeply modified the original decisional algorithm of SIGMA, discarding all the long-period rainfall σ curves in favor of soil moisture σ curves. While the former rainfall σ curves were checked for long periods up to 243 days, the new soil moisture σ curves are checked for cumulative periods that start from 1 day and arrive up to 15 days, at 1 day increasing time steps. Rainfall threshold based on rainfall sigma curves are still present in the new version of the algorithm, but are used only for short periods (1 day, 2 days and 3 days antecedent rainfall).

The new version of the algorithm, which was called SIGMA-U, is shown in Fig. 2.

A back analysis was performed using landslide, soil moisture and rainfall data of the period 2011-2014 to compare the performances of SIGMA and SIGMA-U. The test was performed in all TUs where soil moisture values were available (14 out of 25, as shown in Figure 1) and the results are summarized in table 1.

The results of the back-analysis clearly show an overall improvement of the forecasting algorithm. False alarms are reduced, and most important, the more dangerous the alarm level, the higher the reduction: false alarms issued at warning level 1, which are negligible, decreased by 10%, while the very important warning level 3 was erroneously issued 11 times instead of 19 (-42%). False alarms at the intermediate warning level 2 were reduced from 221 to 152 (-31%).

Missed alarms are reduced as well: while SIGMA missed 69 alarms, SIGMA-U missed 56 alarms (-19%). This corresponds to a total of 118 missed landslides instead of 155 (-24%).

4 CONCLUSION

We improved a state of the art RSLEWS based on rainfall thresholds (SIGMA, Martelloni et al., 2012; Lagomarsino et al., 2013) by integrating punctual soil moisture estimates. We tested two different approaches.

The first is the simplest: it is based on a soil moisture threshold value (75% in this study) under which rainfall thresholds are not used because landslides are expected to never occur. When tested with a back analysis, this approach reduced consistently false alarms, but produced an additional missed alarm. This approach is very simple and can be easily replicated in other cases of study after a simple calibration against the local soil moisture and landslide datasets.

The second approach is more complex and is based on the idea that rainfall thresholds based on antecedent rainfall accumulated over very long periods can be substituted by soil moisture thresholds. A back-analysis demonstrated that a new version of the model based on soil moisture and short term rainfall is by large more effective than the original version based on short term rainfall and long term rainfall, as both false alarms and missed alarms were consistently reduced.

The research is still ongoing and before arriving to a full integration on the regional landslide warning system of Emilia Romagna, further tests are needed. These tests include: (i) the use of punctual soil moisture measurements coming from other sources (e.g. remotely sensed data or direct measurements at selected test sites); (ii) the refinement of the spatial resolution of the alerts by integrating soil moisture measures, rainfall thresholds and susceptibility maps (Segoni et al., 2015b); (iii) the improvement of the model taking into account different threshold values of sigma for each TU, after a thorough site-specific calibration.

References

Agostini, A., Tofani, V., Nolesini, T., Gigli, G., Tanteri, L., Rosi, A., Cardellini, S., and Casagli, N.: A new appraisal of the Ancona landslide based on geotechnical investigations and stability modelling, Q. J. Eng. Geol. Hydroge., 47, 29–43, doi:10.1144/qjegh2013-028, 2013.

Baum, R.L., and Godt, J.W.: Early warning of rainfall-induced shallow landslides and debris flows in the USA, Landslides, 7, 259–272, 2010.

Brocca, L., Ciabatta, L., Moramarco, T., Ponziani, F., Berni, N., Wagner, W., Petropoulos, G.P., Srivastava, P., and Kerr, Y.: Use of satellite soil moisture products for the operational mitigation of landslides risk in central Italy, In: Satellite Soil Moisture Retrievals: Techniques & Applications. Amsterdam, The Netherlands, Elsevier, 231–247, 2016.

Calvello M., d'Orsi, R.N., Piciullo, L., Paes, N., Magalhaes, M.A., and Lacerda, W.A.: The Rio de Janeiro early warning system for rainfall-induced landslides: analysis of performance for the years 2010–2013, Int. J. Disast. Risk Reduc., 12, 3–15, doi:10.1016/j.ijdrr.2014.10.005, 2015.

Cannon, S., Boldt, E., Laber, J., Kean, J., and Staley, D: Rainfall intensity duration thresholds for postfire debris-flow emergency response planning, Natural Hazards, 59, 209–236, 2011.

Ciarapica, L., and Todini, E.: TOPKAPI: A model for the representation of the rainfall-runoff process at different scales, Hydrological Processes, 16(2), 207–229, 2002.

Guzzetti, F., Peruccaci, S., Rossi, M., and Stark, C. P.: Rainfall thresholds for the initiation of landslides in central and southern Europe, Meteorol. Atmos. Phys., 98, 239–267, 2007.

Lagomarsino, D., Segoni, S., Fanti, R., and Catani, F.: Updating and tuning a regional-scale landslide early warning system, Landslides, 10, 91–97, 2013.

Laiolo, P., Gabellani, S., Campo, L., Silvestro, F., Delogu, F., Rudari, R., ... and Crapolicchio, R. (2016). Impact of different satellite soil moisture products on the predictions of a continuous distributed hydrological model, International Journal of Applied Earth Observation and Geoinformation, 48, 131–145, doi:10.1016/j.jag.2015.06.002, 2015.

Martelloni, G., Segoni, S., Fanti, R., and Catani, F.: Rainfall thresholds for the forecasting of landslide occurrence at regional scale, Landslides, 9, 485–495, 2012.

Martelloni, G., Segoni, S., Lagomarsino, D., Fanti, R., and Catani, F: Snow accumulation/melting model (SAMM) for integrated use in regional scale landslide early warning systems, Hydrology and Earth System Sciences, 17, 1229–1240, 2013.

Piciullo, L., Gariano, S.L., Melillom M., Brunetti, M.T., Peruccacci, S., Guzzetti, F., and Calvello, M.: Definition and performance of a threshold-based regional early warning model for rainfall-induced landslides, Landslides, 14, 995–1008. doi: 10.1007/s10346-016-0750-2, 2017.

Ponziani, F., Pandolfo, C., Stelluti, M., Berni, N., Brocca, L., and Moramarco, T.: Assessment of rainfall thresholds and soil moisture modeling for operational hydrogeological risk prevention in the Umbria region (central Italy), Landslides, 9(2), 229–237, 2012.

Segoni, S., Battistini, A., Rossi, G., Rosi, A., Lagomarsino, D., Catani, F., Moretti, S., and Casagli, N.: Technical note: an operational landslide early warning system at regional scale based on space–time variable rainfall thresholds, Nat. Hazards Earth Syst. Sci., 15, 853–861, 2015a

Segoni, S., Lagomarsino, D., Fanti, R., Moretti, S., and Casagli, N.: Integration of rainfall thresholds and susceptibility maps in the Emilia Romagna (Italy) regional-scale landslide warning system, Landslides, 12, 773–785, 2015b.

Wieczorek, G.F.: Landslide triggering mechanism. In: Turner AK, Schuster RL (eds) Landslides investigation and mitigation, special report. Transportation Research Board. National Academy Press, Washington, 247(4), 76–89, 1996.

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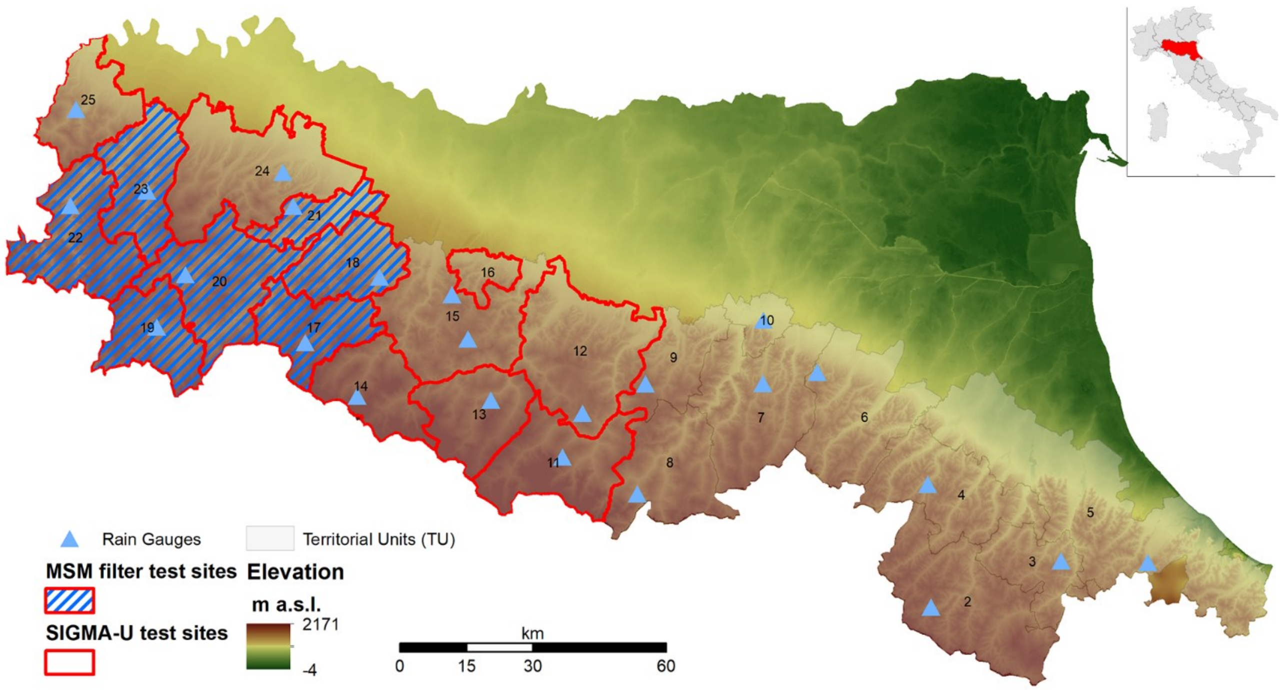

Figure 1: Test site showing the partition in Territorial Units (TU) and highlighting the TUs used as test sites.

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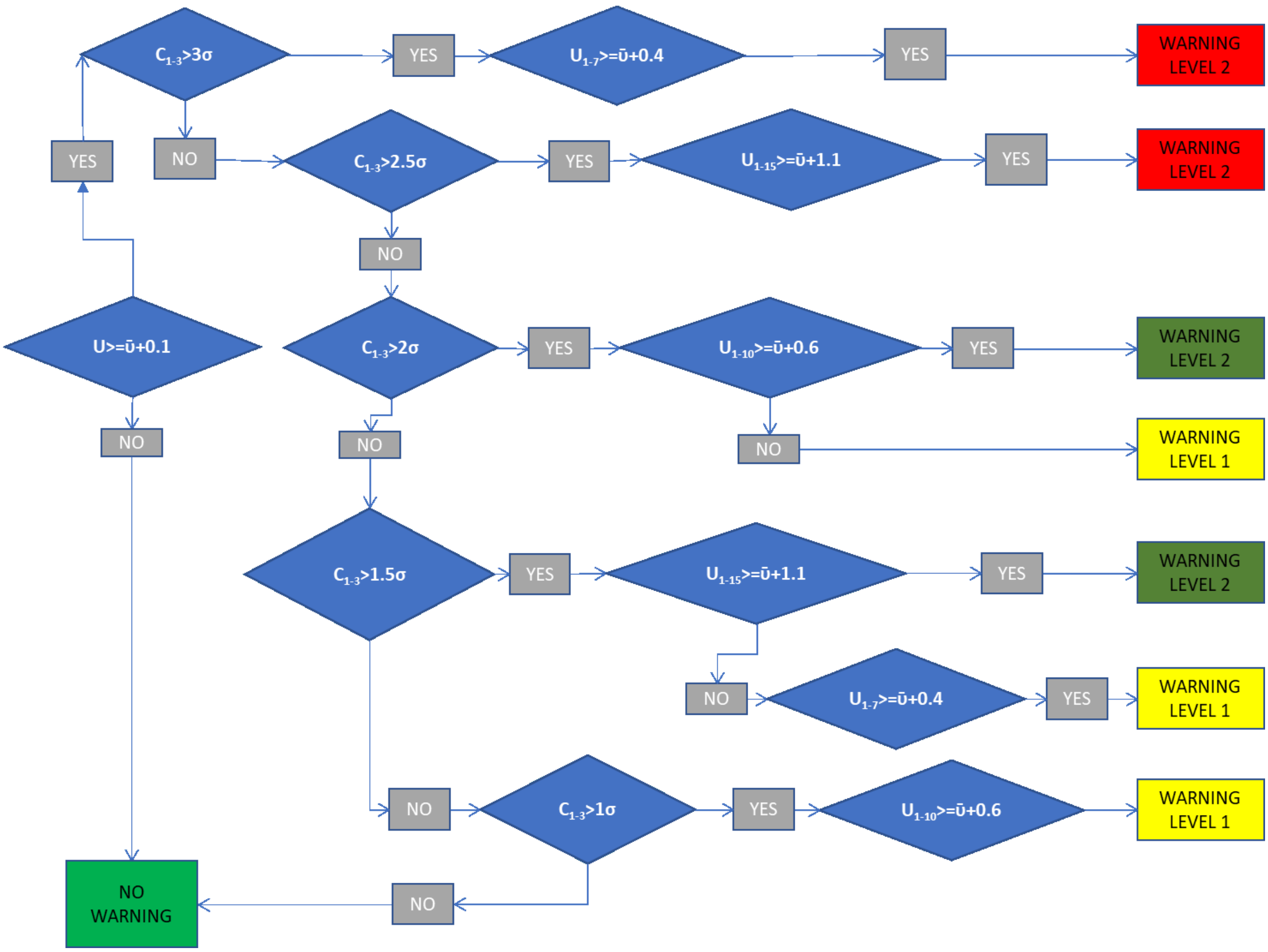

Figure 2: Scheme of the SIGMA-U algorithm. C: cumulative rainfall. U: soil moisture; ῡ: average soil moisture.

Table 1: Quantitative evaluation of the performances of the models SIGMA (Lagomarsino et al., 2013) and SIGMA-U (this paper).

		SIGMA	SIGMA-U	Variation	Variation (%)
False alarms	Warning level 1	549	492	-57	-10%
	Warning level 2	221	152	-69	-31%
	Warning level 3	19	11	-8	-42%
Missed alarms	Number of alarms	69	56	-13	-19%
	Number of missed landslides	155	118	-37	-24%