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Article

Improving Landslide Forecasting Using ASCAT-Derived Soil Moisture Data: A Case Study of the Torgiovannetto Landslide in Central Italy

Luca Brocca [1,*], Francesco Ponziani [2], Tommaso Moramarco [1], Florisa Melone [1], Nicola Berni [2] and Wolfgang Wagner [3]

[1] Research Institute for Geo-Hydrological Protection, National Research Council, I-06128 Perugia, Italy; E-Mails: tommaso.moramarco@irpi.cnr.it (T.M.); florisa.melone@irpi.cnr.it (F.M.)

[2] Umbria Region Functional Centre, Foligno, I-006121 Perugia, Italy; E-Mails: nberni@regione.umbria.it (F.P.); fponziani@regione.umbria.it (N.B.)

[3] Institute of Photogrammetry and Remote Sensing, Vienna University of Technology, A-1040 Vienna, Austria; E-Mail: ww@ipf.tuwien.ac.at

* Author to whom correspondence should be addressed; E-Mail: luca.brocca@irpi.cnr.it; Tel.: +39-075-5014-418; Fax: +39-075-5014-420.

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Abstract: Predicting the spatial and temporal occurrence of rainfall triggered landslides represents an important scientific and operational issue due to the high threat that they pose to human life and property. This study investigates the relationship between rainfall, soil moisture conditions and landslide movement by using recorded movements of a rock slope located in central Italy, the Torgiovannetto landslide. This landslide is a very large rock slide, threatening county and state roads. Data acquired by a network of extensometers and a meteorological station clearly indicate that the movements of the unstable wedge, first detected in 2003, are still proceeding and the alternate phases of quiescence and reactivation are associated with rainfall patterns. By using a multiple linear regression approach, the opening of the tension cracks (as recorded by the extensometers) as a function of rainfall and soil moisture conditions prior the occurrence of rainfall, are predicted for the period 2007–2009. Specifically, soil moisture indicators are obtained through the Soil Water Index, SWI, a product derived by the Advanced SCATterometer (ASCAT) on board the MetOp (Meteorological Operational) satellite and by an Antecedent Precipitation Index, API. Results indicate that the regression performance (in terms of correlation coefficient, r) significantly enhances if an indicator of the soil moisture conditions is included. Specifically, r is equal to 0.40 when only rainfall is used as a predictor variable and increases to r = 0.68 and r = 0.85 if the API and the SWI are used respectively. Therefore, the coarse spatial resolution (25 km) of satellite data notwithstanding, the ASCAT SWI is found to be very useful for the prediction of landslide movements on a local scale. These findings, although valid for a specific area, present new opportunities for the effective use of satellite-derived soil moisture estimates to improve landslide forecasting.

Keywords: soil moisture; shallow landslides; remote sensing; ASCAT

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1. Introduction

Landslides are a frequent and widespread geomorphological phenomenon that can cause the loss of human life and damage to property worldwide, and Italy is one of the countries most prone to landslide risk [1,2]. Therefore, predicting the spatial-temporal occurrence of landslides represents an important scientific and operational issue [3–5]. Many studies have provided a static representation of landslide susceptibility by mapping the areas with higher probability of occurrence based on geologic, morphologic, soil and land use characteristics (e.g., [6]). Other works have investigated the temporal initiation of landslides as a function of rainfall, *i.e.*, through the use of rainfall intensity-duration curves (e.g., [7–11]). However, the prediction of both the spatial and temporal occurrence of landslides still remains a complex task. Recently, physically-based models simulating the soil wetting dynamic response to spatial-temporal rainfall variability in complex terrain have been developed in order to enhance the predictability of shallow landslides [5,12–17]. These studies have highlighted that rainfall alone is not adequate to identify slope instability and that the initial soil moisture conditions play a significant role in the triggering of shallow landslides (e.g., [8, 18–20]). Godt *et al.* [21] argued that the landslide-triggering rainfall must be considered in terms of its relationship with antecedent rainfall. For example, a heavy rainfall event within a dry period is not likely to be able to trigger shallow landslides, whereas the opposite is true for low rainfall within a wet period. Moreover, Pelletier *et al.* [22], among others [16,23], recommended replacing the antecedent precipitation indices with actual soil moisture observations because these two quantities are frequently poorly correlated (e.g., [24–26]).

Some recent studies have investigated the linkage between soil moisture and landslide occurrence by using, besides modeling [3,24], soil moisture data derived by *in-situ* [15,27–30] and satellite sensors [23,31,32]. In particular, Hawke and McConchie [30] investigated the relationship between rainfall, soil moisture observations, piezometric head and landslide occurrences in a small area (Lake Tutira catchment) of New Zealand, which has episodically been affected by extensive land sliding. After a period of extremely high antecedent moisture conditions, a slope failure took place in an area close to the monitoring network. It was observed that the slope failure occurred when maximum soil moisture conditions, though not maximum pore-water pressures, were recorded. By using satellite-derived surface soil moisture data (obtained by the Advanced Microwave Scanning Radiometer, AMSR), Ray and Jacobs [31] also detected a strong relationship between landslide events, rainfall and soil moisture conditions. Ponziani *et al.* [3] analyzed the role of the antecedent soil moisture conditions for landslide triggering at regional scale (~8,400 km^2) by using a landslide inventory and applying a soil water balance model in a recent study in the Umbria Region, central Italy. Soil moisture conditions were found to be as important as event rainfall intensity for the initiation of landslides even though the issues of accuracy and completeness of the landslide inventory prevented the authors from achieving more general conclusions (see also [28]). This analysis set the basis for the implementation of an operative early warning system for landslide risk prevention in the area that makes use of rainfall and soil moisture thresholds ([3], http://www.cfumbria.it/).

In this regional early warning system, great attention is paid to landslides located near urban and touristic areas. Among them, the Torgiovannetto landslide, located near the famous town of Assisi, has been equipped with an extensometer monitoring network. The network has been operating since 2005 after a very large slide involving a 140,000 m^3 wedge occurred in 2003. A meteorological station for monitoring rainfall and air temperature with half-hourly temporal resolution is also in operation. Measurements have shown that the upper part of the slope is still subject to movements that are associated with periods of high rainfall [33]. This could be explained by the increase of pore pressures (due to rainfall) in the rock mass causing a reduction of the shear strength along the stratification planes [34]. However, Graziani *et al.* [33] observed that during dry periods, the rapid increase of the water level in the fractures alone is not sufficient to re-activate sliding.

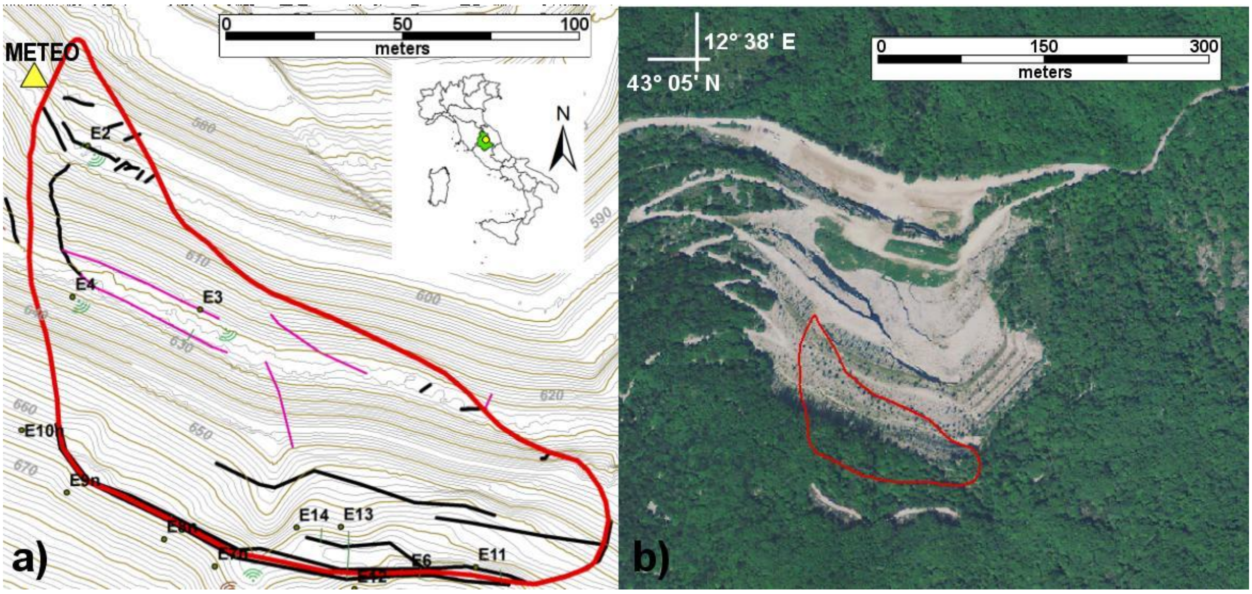
On this basis, the purpose of the present work is to evaluate the capability of satellite-derived soil moisture estimates to predict Torgiovannetto landslide movements by using a simple multiple linear regression analysis. In particular, satellite soil moisture data obtained through the Advanced SCATterometer (ASCAT) on board the MetOp (Meteorological Operational) satellite are used for the assessment of wetness conditions. For a comparison, an Antecedent Precipitation Index, usually employed as indicator of wetness conditions, is also considered. The half-hourly rainfall observations, together with the crack opening data derived by the extensometer network, have been employed. The study period ranges from October 2007 to June 2009.

2. Study Area and Data Set

The Torgiovannetto rock slope is located in an abandoned stone quarry close to the town of Assisi in central Italy. Figure 1(a) shows the morphology of the quarry area with the location of the extensometers network and of the meteorological station, while Figures 1(b) shows the aerial view of the quarry. The main front of the quarry, oriented approximately along the SE-NW direction, has an average dip of about 38°. In this area, the rock mass is composed of regular stratifications of limestone, with intercalations of thin, weak clay layers [34]. Due to the orientation of the bedding planes (almost parallel to the quarry front) and to the presence of the weak clay layers between the hard calcareous strata, the upper part of the slope is in marginal stability conditions [33]. A limited number of slope failures have been reported on several occasions, and several tension cracks running parallel to the quarry face have been observed on the upper part of the slope. Based on inclinometer measurements, the sliding surface is sharply localized at the top of a highly fractured zone at a depth of ~12 m.

The monitoring network is composed of 13 extensometers, 5 inclinometers and a meteorological station (see Figure 1(a)). In fact, due to the potential for catastrophic failure that could affect a suburban road passing close to the quarry, the Umbria regional Civil Protection Centre is responsible for the alert procedure based on the rate of opening of cracks. Depending on the extensometer, the thresholds of crack opening rates are either 0.5 or 1 mm/day.

Figure 1. (**a**) Map of the Torgiovannetto landslide area (contour lines = 2 m) with tracers of the major discontinuities, the boundary of the landslide, the location of the extensometer network (E) and the meteorological station (METEO). (**b**) Aerial view of the quarry.



ASCAT Soil Water Index Product

The Advanced SCATterometer (ASCAT) is a real-aperture radar instrument successfully launched on board the MetOp satellite in 2006 that measures radar backscatter at C-band (5.255 GHz) in VV polarization. The spatial resolution of ASCAT is 25 km (resampled at 12.5 km) and, for Western Europe, measurements are generally obtained at least once a day. The surface soil moisture product is retrieved from the ASCAT backscatter measurements using a time series-based change detection approach previously developed for the ERS-1/2 scatterometer by Wagner *et al.* [35]. In this approach soil moisture is considered to have a linear relationship to backscatter in the decibel space, while the surface roughness is assumed to have a constant contribution in time. By knowing the typical yearly vegetation cycle and how it influences the backscatter-incidence angle relationship for each location on the Earth, the vegetation effects are removed [36], revealing the soil moisture variations. The derived surface soil moisture product (corresponding to a depth of 2–3 cm) ranges between 0% (dry) and 100% (wet) and is available for the period 2007–2010. Validation studies of the ASCAT soil moisture products assessed their reliability for estimating both *in-situ* and modeled soil moisture observations across different regions in Europe [37–40], Africa [41] and Asia [42], thus addressing their use for practical applications. In particular, it was found that the ASCAT soil moisture product has fewer problems in mountainous regions in Europe than other products [40], a significant aspect of its application in terms of landslides prediction.

However, for many applications (including shallow landslide prediction), the knowledge of soil moisture for a very thin surface layer is not sufficient. In this study, the semi-empirical approach (also known as exponential filter) proposed by Wagner *et al.* [35] is adopted to obtain a root-zone soil moisture product (SWI, Soil Water Index) that depends on a single parameter, T (characteristic time length) representing the time scale of soil moisture variation. In this study, the Soil Water Index, SWI_T, indicates that it is a function of the T parameter. The recursive formulation of the method relies on [35,37]:

$$SWI_T(t_n) = SWI_T(t_{n-1}) + K_n\left[m_s(t_n) - SWI_T(t_{n-1})\right] \tag{1}$$

where $m_s(t_n)$ is the surface soil moisture product observed by the satellite sensor and t_n is the acquisition time of $m_s(t_n)$. The gain K_n at time t_n is given by (in a recursive form):

$$K_n = \frac{K_{n-1}}{K_{n-1} + e^{-\left(\frac{t_n - t_{n-1}}{T}\right)}} \tag{2}$$

and it ranges between 0 and 1. For the initialization of this filter, K_1 and $SWI_T(t_1)$ were set to 1 and $m_s(t_1)$, respectively [37]. The reader is referred to Wagner *et al.* [35] for a detailed description of the ASCAT retrieval algorithm and the exponential filter approach.

3. Methods

In this study, the movement of the Torgiovannetto landslide related to different rainfall events is investigated by using a multiple linear regression analysis following a similar approach applied by Brocca *et al.* [26,43] for flood estimation. This approach estimates the role of rainfall and soil moisture conditions on the landslide movement for a sequence of rainfall events and is applied to evaluate the possible improvement that can be obtained by using satellite-derived soil moisture data. The multiple regression model is thus mainly used as a diagnostic tool and not as a predictive tool (even though it could be also be applied for this purpose).

At the beginning, the sequence of rainfall events is extracted from the time series of hourly rainfall observations. In particular, an event starts at the time when rainfall becomes greater than zero and its ending is determined as the time when a period of 6 hours with negligible cumulated rainfall occurs (<1 mm). Next, the significant rainfall events, *i.e.*, the ones exceeding a rainfall threshold of 10 mm are selected. Secondly, several variables are inferred for each rainfall events, and used as predictors in the multiple linear regression equation. In particular, the maximum rainfall for durations from 1 to 48 hours along with the mean and the total rainfall values are considered. The initial soil moisture values derived by the ASCAT SWI_T and an Antecedent Precipitation Index, API_N, computed as the rainfall cumulated for N days before the start of a specific event, are then employed as estimators of the Antecedent Wetness Conditions, AWCs. Finally, the extensometer crack aperture, dH, computed as the difference between the recorded displacement between the end and the start of each rainfall event, is considered as the predictand. Generally, the multiple linear regression equation can be written as:

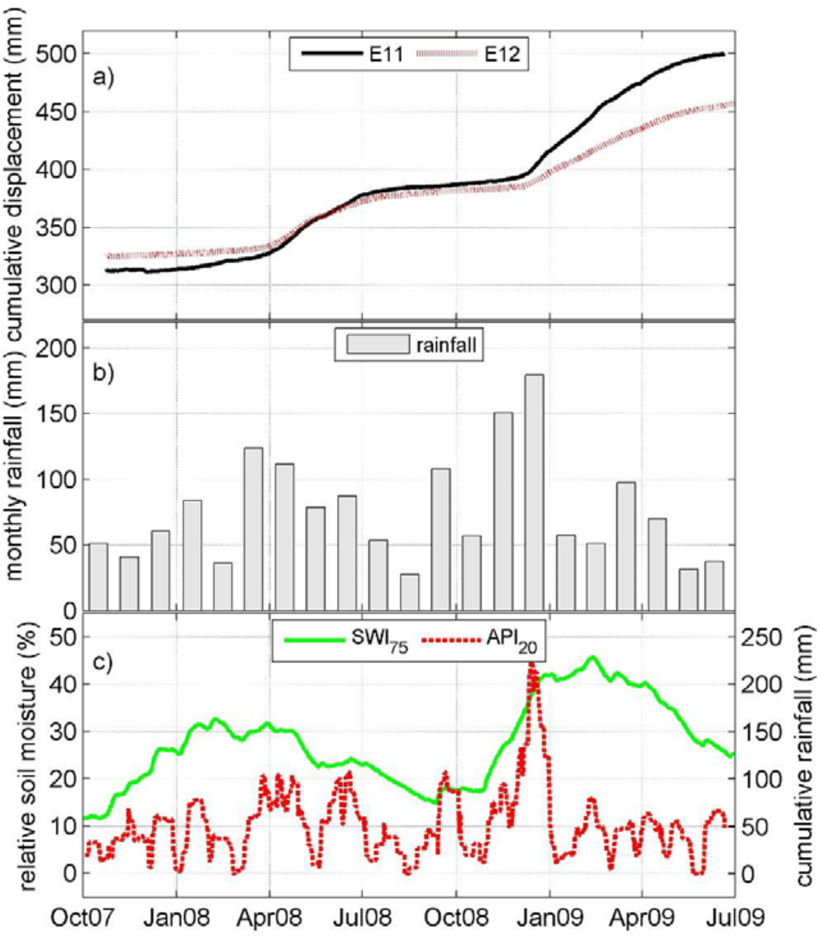
$$d\hat{H} = \beta_0 + \sum_{i=1}^{n} \beta_i X_i \tag{3}$$

where $d\hat{H}$ is the estimated extensometer crack aperture, X_i are the predictors variables (rainfall characteristics and AWCs) and β are the regression coefficients that can be estimated by applying the least-square method, *i.e.*, minimizing the Root Mean Square Error, RMSE, between the observed, dH, and the estimated, $d\hat{H}$, crack aperture values. The stepwise regression analysis employed several attempts to select the best predictors, *i.e.*, the ones providing the highest performance in terms of RMSE.

4. Results

A preliminary analysis to evaluate the reliability and quality of the displacements recorded by the extensometers was carried out. Specifically, the time series of the 13 extensometers were visually compared and the E11 and E12 extensometers, located at the top of the slope (see Figure 1(a)) close to the main fracture of the quarry area, were found to be the two most reliable sensors. We note that these two sensors show very little noise in the data and no gap in the study period. Other extensometers are installed on minor fractures and, as expected, they were found to be less representative of the movement of the main wedge. Figure 2(a) displays the time series of the displacements for the E11 and E12 extensometers, showing a very similar pattern with the higher rates in the winter-spring seasons and the lowest values in summer, thus clearly related to the rainfall [33] and soil moisture pattern (see Figure 2(b,c)).

Figure 2. Time series of: (**a**) cumulative displacements recorded by the E11 and E12 extensometers located at the top of the slope (see Figure 1), (**b**) monthly rainfall, and (**c**) relative soil moisture obtained by the ASCAT Soil Water Index, SWI_T, with $T = 75$ days and the Antecedent Precipitation Index, API_N, with $N = 20$ days.



The total displacements are equal to ~190 and ~130 mm for the E11 and E12 sensor, respectively, corresponding to an opening rate of ~0.30 and ~0.20 mm/day. As we are mainly interested in showing the relative relation between crack aperture, rainfall and soil moisture conditions, the values recorded by a single extensometer, E11, are chosen and used in the following analysis because it historically shows the higher displacement rate with the longest recording history. We note that the results obtained with the extensometer E12 (not shown here) are found to be quite similar.

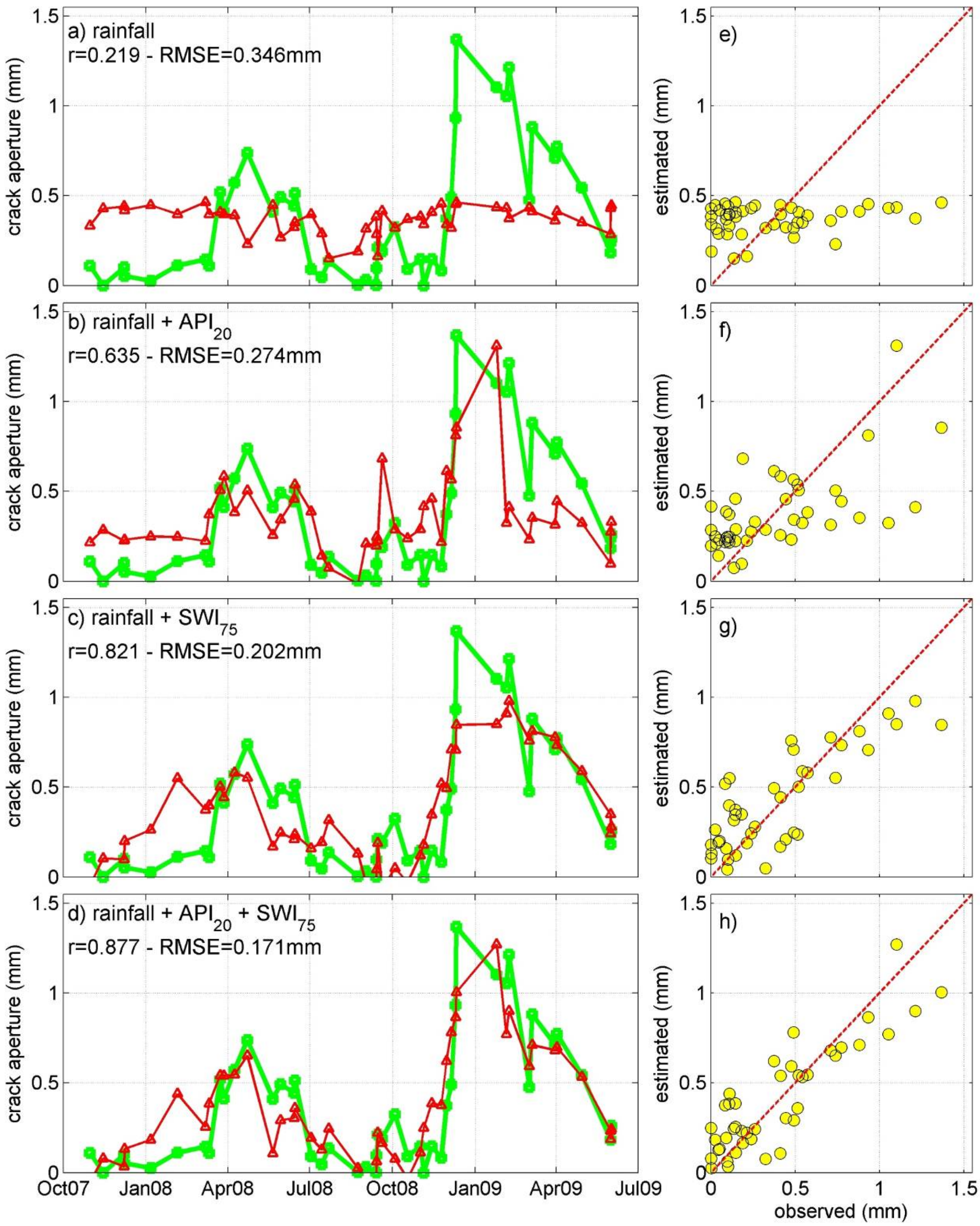
By applying the above described procedure, 46 rainfall events were extracted in the period 2007–2009 whose main features are reported in Table 1 in terms of rainfall and AWCs along with the observed values of the crack aperture for the E11 extensometer. As a first step, the optimal values for the T and N parameters are computed by maximizing the correlation coefficient, r, of the SWI_T (for the pixel containing the study area) and API_N time series with the observed crack aperture data. The estimated values (T = 75 and N = 20 days) have a physical meaning because they represent a high storage capacity of the soil layer that influences the slope movements, as can be expected for this particular type of rock slope for which the movement is expected to be related to deep soil layers [33,34]. It should be noted that the soil moisture values should not be interpreted as the actual values observed in the slope but only as indicators of the wetness state of the slope that can be used to predict its movements. As a second step, the best rainfall and AWC predictors, X_i, are obtained through a stepwise regression analysis and taking account of the cross-correlation between the predictors to assure the well-posedness of the inverse problem. The optimal predictors are found to be: (1) the maximum rainfall value over a duration of 1 hour, $P_{max\text{-}1h}$, (2) the total rainfall of the event, P_{tot}; (3) the API_{20} and (4) the SWI_{75}.

Subsequently, different configurations of the best model (*i.e.*, the one with all 4 best predictors) are analyzed with the aim of understanding the different impact of rainfall and soil moisture conditions on the landslide movement. The first configuration uses only the rainfall variables ($P_{max\text{-}1h}$ and P_{tot}) as predictors, the second and the third configurations use the rainfall variables together with the API_{20} and the SWI_{75}, respectively; and the last configuration uses all the predictors. Figure 3 shows the results for all the configurations in terms of time series of the observed and estimated crack aperture, the scatter plots are also displayed to better visualize the regression performance. For the first configuration (Figure 3(a,e)), the estimated crack aperture poorly follows the rainfall pattern with significant underestimation of large values; the obtained r and RMSE are equal to 0.219 and 0.346 mm, respectively. By considering also the API_{20} (Figure 3(b,f)), results significantly improve (r = 0.635) with a better reproduction of the seasonal magnitude of crack aperture. A further significant improvement is obtained when the SWI_{75} (Figure 3(c,g), r = 0.821) is adopted as estimators of the AWCs. For this case a slight overestimation in the period January–March 2008 and underestimation in the period December 2008–February 2009 can be observed whereas for the same periods the API_{20} provides a better agreement with observations. Consequently, if the API_{20} and the SWI_{75} are considered together with rainfall variables (Figure 3(d,h)), the accordance between the observed and estimated crack aperture is reasonably good for the whole period resulting in r = 0.877 and RMSE = 0.171 mm. Additionally, the disagreement between the observed and estimated crack aperture might be due to the non linearity of the infiltration and evaporation process that would affect the relation between rainfall, soil moisture and the landslide movement while in this first study a linear model has been tested.

Table 1. Main characteristics of the selected rainfall events with the best predictors used in the multiple regression analysis ($P_{max\text{-}1h}$: maximum rainfall over a duration of 1 hour, P_{tot}: total rainfall, SWI_{75}: ASCAT Soil Water Index with T = 75 days, API_{20}: Antecedent Precipitation Index with N = 20 days, dH: crack aperture).

Date	Duration (h)	$P_{max\text{-}1h}$ (mm)	P_{tot} (mm)	SWI_{75} (%)	API_{20} (mm)	dH (mm)
07-10-30 17:30	6.5	6.6	14.7	15.3	37.8	0.109
07-11-14 08:00	10.5	4.0	28.8	18.7	68.9	0.000
07-12-07 17:30	7.5	1.8	13.8	22.0	21.4	0.101
07-12-08 04:30	10.0	3.6	21.2	22.8	42.6	0.052
08-01-06 08:00	12.0	1.4	12.4	27.1	22.0	0.025
08-02-04 23:30	6.5	4.2	18.2	32.9	41.9	0.111
08-03-07 05:00	12.0	1.6	20.8	28.8	33.4	0.145
08-03-11 02:00	10.0	3.6	13.0	29.8	54.6	0.109
08-03-23 10:00	13.0	4.0	21.2	31.2	97.6	0.520
08-03-27 17:00	4.5	3.4	10.6	31.5	90.6	0.413
08-04-08 15:00	11.0	6.2	34.0	30.3	105.3	0.573
08-04-22 14:30	3.5	10.8	12.6	30.6	104.6	0.739
08-05-21 01:00	12.5	2.4	21.8	22.4	44.6	0.411
08-05-29 18:30	1.5	9.5	15.1	22.2	73.3	0.492
08-06-13 16:30	3.0	6.6	12.0	23.1	79.8	0.444
08-06-14 10:30	7.0	6.0	17.2	23.3	103.2	0.513
08-07-02 14:30	4.5	3.8	14.4	22.6	60.8	0.090
08-07-14 12:30	2.5	8.4	14.2	21.4	29.0	0.045
08-07-22 00:00	5.5	15.2	21.8	20.3	53.6	0.136
08-08-23 14:30	3.0	13.4	20.6	16.1	27.6	0.003
08-09-01 15:30	6.0	7.6	17.4	14.8	45.0	0.032
08-09-12 19:30	5.5	5.2	21.8	14.1	42.5	0.001
08-09-13 09:30	3.0	9.2	19.6	15.8	62.1	0.097
08-09-14 17:00	1.0	15.1	25.6	16.2	89.9	0.212
08-09-19 08:00	9.0	2.6	10.8	17.4	107.3	0.190
08-10-03 21:30	6.0	7.6	18.8	16.9	62.7	0.324
08-10-17 18:00	2.5	4.8	12.6	17.1	32.1	0.090
08-11-01 00:30	15.0	5.0	20.8	19.9	58.2	0.147
08-11-04 17:30	6.5	6.2	14.8	21.9	75.8	0.000
08-11-13 12:30	5.5	4.2	23.0	26.4	92.5	0.146
08-11-24 12:30	21.0	4.0	39.2	28.8	75.2	0.084
08-11-30 02:00	5.5	5.8	11.0	31.7	105.6	0.374
08-12-05 12:30	6.0	8.2	24.4	34.5	129.6	0.491
08-12-10 02:30	11.5	2.8	27.6	36.6	164.6	0.933
08-12-10 22:30	13.0	4.2	43.8	39.2	208.4	1.369
09-01-24 20:30	13.5	1.2	15.4	43.8	228.2	1.102
09-02-04 16:00	13.0	1.8	11.6	46.8	40.8	1.054
09-02-07 13:30	6.5	2.2	13.2	46.2	61.8	1.213
09-03-02 05:00	9.0	1.8	10.8	41.3	17.2	0.477
09-03-05 06:30	8.0	2.6	10.2	42.5	42.4	0.881
09-03-30 20:30	1.5	5.0	11.8	40.1	46.0	0.710
09-04-01 21:30	5.0	2.6	10.2	40.3	60.0	0.773
09-04-29 14:00	5.5	5.4	11.6	34.5	49.2	0.543
09-05-31 10:00	2.5	8.4	13.0	26.0	18.0	0.183
09-05-31 15:30	10.5	2.2	13.2	26.0	31.2	0.239
09-06-01 04:30	13.5	2.0	17.0	26.5	48.6	0.260

Figure 3. Comparison between observed (circles) and estimated (triangles) crack aperture from the beginning to the end of the selected rainfall events: (**a–d**) time series, and (**e–h**) scatter plots (r: correlation coefficient, RMSE: root mean square error). The predictors are: (a,e) rainfall variables (*i.e.*, total rainfall and maximum rainfall for duration of 1 h; (b,f) rainfall and Antecedent Precipitation Index, API_N, with N=20 days; (c,g) rainfall and ASCAT Soil Water Index, SWI_T, with T = 75 days; (d,h) rainfall, API_{20} and SWI_{75}.



Finally, by analyzing the standardized coefficients of the linear regression, *i.e.*, the coefficients obtained after all regression variables (independent and dependent) are set to have a mean of zero and a standard deviation of one, the relative weight of each predictor can be quantitatively determined. For the configurations 2–3, for which rainfall variables and a single AWC indicator are used, the most important factor is always represented by the AWC predictors (API_{20} and SWI_{75}); in the configuration 4 (with all the predictors) the standardized coefficients are found to be equal to 0.13, 0.04, 0.36 and 0.74 for $P_{max\text{-}1h}$, P_{tot}; API_{20} and SWI_{75}, respectively. Specifically, the SWI_{75} is the most significant predictor with a weight ~50% and ~80% higher than the API_{20} and $P_{max\text{-}1h}$, respectively. On the other hand, in configuration 4, the standard deviations of the coefficients are found to be similar with values ranging between 0.085 and 0.092.

5. Conclusions

The influence of rainfall and soil moisture conditions in the estimation of the movements of a well monitored slope located in central Italy, the Torgiovannetto landslide, has been investigated here. The results of the multiple regression analysis clearly indicate that ASCAT-derived soil moisture estimates can be effectively used to predict the crack aperture of the slope with reasonable accuracy (r = 0.821). A lower accuracy is obtained with the Antecedent Precipitation Index, thus confirming the need to employ actual soil moisture observations to reach a high reliability (e.g., [22]). We note that, even considering the encouraging results shown here, the coarse spatial resolution of ASCAT data (25 km) could represent a significant limitation in the attempt to predict small scale landslide movements and this aspect needs further analysis. The regression model implemented in this study, coupled with a quantitative precipitation forecast obtained by numerical weather prediction models, can be used to predict the crack aperture of the Torgiovannetto slope in an operational context even though it is only based on a simple empirical relationship.

On the basis of these encouraging results, the use of more complex physically-based models linking the rainfall and soil moisture conditions with the landslide movement will be the object of future investigations. Moreover, the availability of ASCAT satellite soil moisture data on a global scale presents new opportunities for the integration of this data set in landslide forecasting systems. However, the results of this study are only valid for this specific investigated case study and further studies analyzing the relationship between rainfall, soil moisture and landslide movement in different regions are needed in order to generalize these findings.

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