

# Temporal trends in extreme rainfall intensity and erosivity in the Mediterranean region: a case study in southern Tuscany, Italy

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**Abstract** Worldwide climate is likely to become more variable or extreme with increases in intense precipitation. In Mediterranean areas, climate change will increase the risks of droughts, flash floods and soil erosion. Despite rainfall intensity being a key factor in erosive processes, in these areas information on extreme rainfall intensity and the associated erosivity, based on high-temporal resolution data, is either non homogeneous or scarce. These parameters thus need to be assessed in order to highlight suitable adaptation strategies. In this paper, an hourly rainfall intensity (RI) data series is analyzed together with the corresponding 1-min rainfall intensity maximum (RI<sub>m</sub>) of 23 rainfall gauges located in Tuscany, Italy, in an area highly vulnerable to erosion. The aim is to look for temporal trends (1989–2010) in extreme rainfall intensity and erosivity. Fixed effect logistic regression shows statistically significant temporal increases in the number of RI and RI<sub>m</sub> exceedances over the 95th percentile threshold. Winter is shown to be the season with the strongest increasing trend in coastal and inland rainfall gauge groups, followed by spring for the coastal group and autumn for the inland group. Linear regressions show that in the inland group there is a temporal increase in rainfall erosivity and on a seasonal basis, the highest increase is observed in autumn. By contrast, for the coastal group this increasing trend is only detectable for spring and winter. Such an increase in rainfall erosivity and its potential continuation could have a strong adverse effect on Mediterranean land conservation.

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## 1 Introduction

In recent years, global climate change has received increasing attention (Berrang-Ford et al. 2011). This attention has been fostered by concerns that the climate is forecast to worsen conditions, according to simulations from climate change models under various scenarios, and that these tendencies will have strong negative implications on the natural environment and society (Easterling et al. 2000; Maracchi et al. 2005). As stated by the Intergovernmental Panel on Climate Change (IPCC 2013) the climate is likely to become more variable or extreme with a very likely increase in the frequency of intense precipitation. With specific regard to the regions that are more vulnerable to climate variability, such as the Mediterranean areas (Burlando and Rosso 2002; Giorgi and Lionello 2008), climate change will increase the risks of drought, flash floods, flooding and consequently soil erosion. In order to facilitate the development of effective adaptation strategies in these areas, climate change trends need to be identified also in terms of frequency and intensity of extreme events.

Climate models have been largely used for assessing the past and making projections into the future, but given their unproven reliability on a small scale (Tebaldi et al. 2006; Koutsoyiannis et al. 2008), we need more knowledge of the local effects of climate change so that we can search for potential signals of modifications in rainfall using long-term observational records.

Over the last few years, daily to hourly observations have been largely investigated and statistically significant temporal trends in extreme storm events have been highlighted for several areas at regional and local scales (e.g. Easterling et al. 2000; Frei and Schär 2001; Ramos and Martínez-Casasnovas 2006; Zolina et al. 2008; Mueller and Pfister 2011). By contrast, to date, observed temporal trends of extreme rainfall events over Mediterranean areas have not been spatially homogeneous and an overall trend has not been identified (e.g. Crisci et al. 1999, 2002; Moonen et al. 2002; Brunetti et al. 2002, 2004; Fatichi and Caporali 2009; Beguería et al. 2010). This may be due to the uneven morphology of the Mediterranean region, or to the fact that observations of extreme events are scarce, making trend detection very difficult (Brunetti et al. 2002).

Two precipitation modes, or a mixture of the two, occur in Mediterranean areas: low intensity continuous rainfall with a stratiform nature and very large spatial scales, and short-period convective processes, with spatial scales of a few kilometres (Diodato 2004; Berg et al. 2013). The latter is largely associated with highly intensive rainfall. Since rainfall intensity is a key factor in affecting erosive processes, storm events characterized by a very high intensity have a huge impact on soil erosion risk (Renard et al. 1997; Nunes et al. 2009; Mueller and Pfister 2011). Many studies have suggested that a large amount of soil erosion is often associated with a limited number of intensive-to-extreme rainfall events (e.g. González-Hidalgo et al. 2010; Svoray and Ben-Said 2010). A local increase in the frequency or intensity of extreme rainfall events may therefore result in further soil degradation (Märker et al. 2008). To take into account the contribution of these events to erosion risk in the framework of climate change, high-temporal rainfall resolution data are needed in addition to an appropriate rainfall gauge network density (Capecchi et al. 2012). However their availability is often limited to short-term series and only few studies have used these data to directly derive rainfall erosivity (e.g. Ángulo-Martínez and Beguería 2009; Meusburger et al. 2012) although high soil losses and catchment sediment yield are found (Bazzoffi 2007; Bagarello et al. 2011, 2013; Vanmaercke et al. 2012).

Starting from the inconsistencies in the Mediterranean extreme rainfall temporal trends and from the scarcity of information on rainfall erosivity based on high-temporal resolution data, our aim was to evaluate the temporal trends in extreme rainfall intensity and erosivity in a

Mediterranean area which has been suffering from severe hydrogeological events and land degradation (Bonari and Debolini 2010). Using high-temporal resolution rainfall intensity data, a 22-year trend in extreme rainfall intensity frequencies and erosivity was investigated in southern Tuscany, Italy on a monthly, seasonal and annual basis.

## 2 Materials and methods

### 2.1 Study area and rainfall gauges

The study area was located in southern Tuscany, Italy (Online Resource 1; Online Resource 2). The area covers 5000 km<sup>2</sup> with an altitude from 1 to 810 m above sea level. Climatic conditions are typically Mediterranean. Mean annual precipitation is 730 mm year<sup>-1</sup>, ranging from 508 to 1002 mm year<sup>-1</sup> (Online Resource 2). Precipitation shows a maximum in November (148 mm month<sup>-1</sup>) and a minimum in July (5 mm month<sup>-1</sup>) (data not shown). Mean minimum and maximum temperatures are 0 and 32 °C in February and July, respectively (<http://www.lamma.rete.toscana.it/node/3533>). The soil texture according to the USDA classification system (Soil Survey Staff 1975) is clay loam, sandy loam and loamy sand. The study area was chosen because of the high agricultural vocation and the soil erosion risk due to severe storm events (Bonari and Debolini 2010; Diodato et al. 2011; [http://eussoils.jrc.ec.europa.eu/ESDB\\_Archive/pesera/pesera\\_data.html](http://eussoils.jrc.ec.europa.eu/ESDB_Archive/pesera/pesera_data.html)).

Online Resource 1 shows the location of the 23 rain gauges belonging to the network of the Tuscany Region (<http://www.cfr.toscana.it/>), as well as the land use characterisation on the basis of the aggregated classes (EEA 2006). For each rainfall gauge, Online Resource 2 reports the code number, name, elevation, geographical position, coastal distance, aspect and mean annual rainfall depth.

### 2.2 Rainfall intensity dataset collection and preparation

Rainfall intensity (RI) data were recorded from 1989 to 2002 and from 2003 to 2010 at 1-h and 15-min temporal resolution, respectively (Online Resource 3). Rainfall intensity maximum (RIm) data were also recorded. RIm is the maximum 1-min amount of rainfall observed at a temporal resolution of 1 h or 15 min. There were no changes in location, instrument type, measuring procedure or recording technique thus the data recorded can be considered temporally stable. In order to obtain a longer-term dataset, the 15-min RI and RIm were aggregated to hourly data, using the RI sum and the RIm maximum, respectively. Hourly rainfall intensity (mm/h) and hourly rainfall intensity maximum (mm/min) are hereinafter referred to as RI and RIm.

Given the short period of observation and the high temporal resolution of the dataset, we did not estimate and replace missing data, but retained only those records with less than 10 % of missing data (Online Resource 3). The RI and RIm availability period, total missing data and number of years with less than 10 % missing data were determined and are shown in Online Resource 3 for each rain gauge. All data analyses were performed using the R statistical language and packages (<http://www.R-project.org>).

### 2.3 Definition of rainfall gauge homogeneous groups on the basis of rainfall intensity

Given the spatial variability in the rainfall regimes, in order to more easily detect temporal trends, homogeneous spatial groups of rainfall gauges were selected before analysing the

temporal trend (Katz et al. 2002). We assigned the rainfall regime of the gauges into homogenous groups by Redundancy analysis (RDA) on the basis of the influence of environmental variables, such as altitude, aspect, coastal distance and geographical coordinates (Online Resource 4), on the 22-year 50th, 80th, 90th, 95th and 99th RI and RIm percentiles. RDA analysis was performed by Canoco for Windows v. 4.5 (ter Braak and Smilauer 2002). The rainfall gauges were a priori divided into two groups (coastal and inland) on the basis of the RDA triplot sample cloud. Canonical analysis of the principal coordinates (CAP) was used to test the validity of the assigned rainfall gauge groups as well as the success level of the classification. The CAP was based on a Bray-Curtis similarity matrix, adding a dummy variable of one on the square root transformed data, using Primer 6 & PERMANOVA plus (Anderson et al. 2008).

#### 2.4 Assessment of extreme rainfall frequency temporal trends

To investigate the temporal trends in the extreme rainfall frequency, measured as the RI and RIm numbers of exceedances over the 95th percentile thresholds, we computed their annual, seasonal (astronomical definition) and monthly (agronomical high-risk months: September, October, November and December) values and studied the values as a function of time and of the rainfall gauge homogenous group. The RI and RIm thresholds for each group were calculated as the median of the 95th percentiles. Several authors have suggested using the 90th or 95th percentile as extreme rainfall indexes (Haylock and Nicholls 2000; Salinger and Griffiths 2001).

For each group (coastal and inland) the annual, seasonal and monthly RI and RIm number of exceedances over the 95th percentile threshold were fitted against time by a fixed effect logistic regression. Temporal trends were estimated and the statistical significances were tested. Following Frei and Schär (2001), a quasibinomial model was used to take into account the possible extra variability with respect to the binomial distribution. In the model, the number of trials was set as the total number of observation hours. The logistic regression parameters, such as the time coefficient ( $\beta$ ), representing the change in the logit of the probability of success for a unit change in time, and the  $P$  values were computed. The magnitude of the temporal trend over the 22-year period of observation was expressed as the odds ratio [ $OR_{22} = \exp(\beta * 22)$ ] which approximates the relative change in the ratio of the event probability against non-event probability during the period of observation (Frei and Schär 2001). The logistic regressions were performed by R (<http://www.R-project.org>). The differences between RI and RIm temporal trends of the groups and of the seasons were performed as described in Online Resource 4.

#### 2.5 Computation of single-storm erosion indexes and assessment of their temporal trends

As described by the Revised Universal Soil Loss Equation (RUSLE) (Wischmeier and Smith 1978; Renard et al. 1991), which is the most widely used equation to predict soil losses from cultivated fields due to erosive storms, the  $R$ -factor gives the relationship between rainfall and sediment yield by quantifying the erosive potential of raindrops. By definition, the  $R$ -factor is the cumulative sum of the single-storm erosion index (EI) values for a given period. The EI values were defined as the total single-storm kinetic energy (E) times the peak rainfall intensity during a 30-min period (I30).

To identify an erosive single-storm event, we adopted the criteria given by Wischmeier and Smith (1978). For each erosive storm, in order to compute the E values, the unit energy of the time interval multiplied by the associated rainfall volume were summed. To calculate the unit

energy values, we used Brown and Foster's equation (1987), which has already been used for Mediterranean conditions (Capolongo et al. 2008).  $E$  values were multiplied by the maximum intensity (I30) to derive the single-storm erosion index values (EI30). The EI30 were calculated for each erosive event, according to the RUSLE handbook instructions (Renard et al. 1997), from the 8-year 15-min available dataset. Since a minimum of 22-years of  $R$ -factor data is recommended to smooth out short-term variations (Renard et al. 1997), we could not utilise the 8-year EI30 dataset to investigate the  $R$ -factor temporal trend. Therefore, we utilised the hourly dataset, which has an average availability period slightly lower than 22 years (Online Resource 3). In detail, the maximum rainfall 60-min intensity (I60) and the EI60 values were computed and the goodness of the relationship between EI30 and EI60 was tested using linear regression.

A linear regression was used to estimate and test the annual, seasonal and agronomical high-risk month  $R$ -factor temporal trends for each group. The regression parameters, such as the slope (Time-coeff.), representing the absolute change in  $R$ -factor values for a time unit increase (1 year), and the  $P$  values, were computed. The linear regressions were performed using R (<http://www.R-project.org>). The differences between  $R$ -factor temporal trends of the groups and of the seasons were performed as described in Online Resource 4.

### 3 Results

#### 3.1 Definition of rainfall gauge homogeneous groups

The RDA analysis showed that environmental variables explained about 32 % (I and II axes) of the whole variance. The Monte Carlo permutation test highlighted that coastal distance and altitude were significant explanatory variables ( $P=0.008$  and  $P=0.018$ , respectively) (Online Resource 5). The clustering test, CAP analysis, found a highly significant difference in the rain gauge groups ( $P<0.001$  using 9999 permutations) and revealed a high classification success (83 %) confirming our a priori separation into coastal and inland groups.

#### 3.2 Assessment of extreme rainfall frequency temporal trends

In this study, extreme RI and RIm frequencies are defined as the hourly RI and RIm number of exceedances over the 95th percentile threshold during the period of observation. Logistic regression was used to characterize the extreme RI and RIm frequency temporal trends over the 22-year observation period. For winter, spring and December the regression showed upward statistically significant trends of extreme RI frequency for both groups, while for annual, autumn and November extreme RI frequency positive trends were revealed only for the inland group (Table 1). The highest relative changes in the ratio of the RI exceedance probability against non-exceedance probability during the 22-year period, given by the  $OR_{22}$ , were observed in winter both for the coastal and inland groups. The maximum  $OR_{22}$  value was observed for December in the inland group (5.6). By contrast, statistically significant negative trends of the RI frequency were observed in the inland group in the summer and September. In addition, the PERMANOVA analyses showed that the interactions between time (T) and group (G) were statistically significant ( $P\leq 0.017$ ) for annual, spring, September, October and November extreme RI, revealing that temporal trends were different between groups (Online Resource 6). As far as bigger temporal resolutions are concerned, through extreme RIm frequency, the strength of temporal trends generally increases. In fact extreme RIm frequency statistically significant trends were positive on an annual, winter, spring, autumn, November

and December basis for both groups, and also for October in the inland group (Table 1). The highest RIm OR<sub>22</sub> values were in winter both for the coastal and inland group, with a peak for December in the inland group (24.3). By contrast, statistically significant negative trends of the RIm frequency were observed in September. The PERMANOVA analyses showed that the interactions between T and G were statistically significant ( $P \leq 0.019$ ) for annual, summer, autumn and September extreme RIm frequencies (Online Resource 6).

As regards seasons (S), there were statistically significant differences between all pairs of seasonal extreme RI and RIm frequency comparisons, except for the inland group in RI summer vs spring and for the coastal group in RIm summer vs spring and autumn vs summer (Online Resource 7). Significant interactions between time and season ( $T \times S$ ) revealed that extreme RI and RIm frequency temporal trends were different between seasons, except for RI summer vs spring and RIm winter vs spring contrasts in the inland group, and for RIm winter vs spring, summer vs spring, autumn vs spring and autumn vs summer contrasts in the coastal group.

### 3.3 Computation of single-storm erosion indexes and assessment of their temporal trends

A very strong significant relationship ( $R=0.97$ ;  $P < 0.001$ ) was detected between the single-storm erosion index values calculated using 15-min rainfall intensities (EI30) and the single-storm erosion index values, calculated using 60-min rainfall intensities (EI60) (Online Resource 8). We therefore identified EI60 as a very good descriptor of EI30 and we were able to use the 22-year EI60 dataset.

Linear regression was utilized to characterize the *R*-factor temporal trend over the 22-year observation period. This regression showed annual, winter, spring, autumn and monthly (October, November and December) statistically significant upward trends for the inland group ( $P \leq 0.016$ ; Table 2), whereas in the coastal group there were only positive trends in winter, spring and December ( $P \leq 0.040$ ). In the coastal group, although the summer increasing trend was not significant ( $P=0.055$ ), there were statistically significant trends for June and July (data not shown). The changes in *R*-factor values were 14.2 and 49.7 per year in the coastal and inland groups, respectively. On a seasonal basis, the highest value was observed in the inland group for autumn (22.5). By contrast a negative trend was detected for September in the coastal group.

The PERMANOVA analysis showed that annual, spring, summer, autumn and September *R*-factors were influenced by group (G) ( $P \leq 0.035$ ; Table 3). There were also statistically significant interactions ( $T \times G$ ) in the autumn and all the agronomical high-risk month *R*-factors ( $P \leq 0.014$ ). As regards seasonal *R*-factors, PERMANOVA analyses revealed statistically significant differences between all pair seasonal comparisons, except for autumn vs summer (Online Resource 9). Concerning the interaction between time and season ( $T \times S$ ), statistically significant *P*-values were found for all the comparisons, except for winter vs spring.

## 4 Discussion

### 4.1 Assessment of extreme rainfall frequency temporal trends

In this study, high-temporal resolution data were used to detect the temporal trends and spatial patterns of the extreme rainfall frequency in a Mediterranean area, which is highly vulnerable to erosion. Temporal positive trends, together with spatial differences between coastal and

**Table 1** Time coefficients ( $\beta$ ), odds ratio ( $OR_{22}$ ) and  $P$  values of fixed effect logistic regressions between: hourly rainfall intensity (RI; mm/h) number of exceedances over the 95th percentile threshold and time; hourly rainfall intensity maximum (RIm; mm/min) number of exceedances over the 95th percentile threshold and time. The logistic analyses were performed on annual, seasonal and monthly basis by a quasi-binomial distribution

Time interval	Hourly RI number of exceedances over the 95th percentile threshold <sup>a,c</sup>						Hourly RIm number of exceedances over the 95th percentile threshold <sup>b,c</sup>					
	Coastal group			Inland group			Coastal group			Inland group		
	$\beta^c$	$OR_{22}$	$P$	$\beta$	$OR_{22}$	$P$	$\beta$	$OR_{22}$	$P$	$\beta$	$OR_{22}$	$P$
Annual	0.008	1.192	0.091 <sup>d</sup>	0.024	1.701	<0.001	0.047	2.823	<b>0.004</b>	0.031	1.962	<0.001
Seasonal												
Winter	0.034	2.113	<b>0.010</b>	0.053	3.209	<0.001	0.121	14.325	<b>0.006</b>	0.109	11.001	<0.001
Spring	0.017	1.454	<b>0.061</b>	0.031	1.978	<b>0.001</b>	0.079	5.686	<b>0.004</b>	0.053	3.209	<0.001
Summer	-0.010	0.803	0.171	-0.024	0.590	<b>0.012</b>	0.028	1.852	0.139	-0.013	0.751	0.122
Autumn	0.009	1.219	0.147	0.043	2.575	<0.001	0.047	2.812	<b>0.029</b>	0.072	4.874	<0.001
Monthly												
September	-0.011	0.785	0.174	-0.039	0.424	<0.001	0.014	1.361	0.307	-0.032	0.495	<b>0.005</b>
October	-0.017	0.688	0.076	0.011	1.274	0.195	0.009	1.219	0.401	0.058	3.582	<0.001
November	0.003	1.068	0.397	0.043	2.575	<b>0.002</b>	0.007	1.166	<b>0.017</b>	0.068	4.464	<0.001
December	0.044	2.633	<b>0.010</b>	0.078	5.562	<0.001	0.102	9.431	<b>0.042</b>	0.145	24.288	<0.001

<sup>a</sup> 6.00 and 5.90 mm h<sup>-1</sup> coastal and inland RI 95th percentile, respectively

<sup>b</sup> 1.03 and 0.96 mm min<sup>-1</sup> coastal and inland RIm 95th percentile, respectively

<sup>c</sup> A quasi-binomial distribution was assumed to take into account the overdispersion because the data variance was higher than the nominal binomial variance

<sup>d</sup> in bold statistically significant values ( $P < 0.05$ )

<sup>e</sup> thresholds calculated as median of the 95th percentiles



**Table 2** Time-coefficients and *P* values of linear regression analyses between the Revised Universal Soil Loss Equation *R*-factor (RUSLE *R*-factor) and time. The linear regressions were performed on annual, seasonal and monthly basis

Time interval	RUSLE <i>R</i> -factor (MJ mm ha <sup>-1</sup> h <sup>-1</sup> )			
	Coastal group		Inland group	
	Time-coeff.	<i>P</i>	Time-coeff.	<i>P</i>
Annual	14.180	0.144 <sup>a</sup>	49.710	< <b>0.001</b>
Seasonal				
Winter	6.046	< <b>0.001</b>	9.336	< <b>0.001</b>
Spring	7.920	<b>0.003</b>	8.434	<b>0.016</b>
Summer	9.177	0.055	4.903	0.276
Autumn	-10.914	0.132	22.943	< <b>0.001</b>
Monthly				
September	-8.125	<b>0.036</b>	0.280	0.471
October	-4.642	0.166	6.232	<b>0.004</b>
November	-1.765	0.389	10.724	<b>0.002</b>
December	<b>2.961</b>	<b>0.040</b>	8.289	< <b>0.001</b>

<sup>a</sup> in bold statistically significant values (*P*<0.05)

inland areas were detected, with a high level of significance, using both the hourly RI and the RI<sub>m</sub> number of exceedances over the 95th percentile threshold. These trends are in agreement with already observed long-term increasing trends in the extreme event frequency/magnitude in many regions of the world, although the indices and methodologies often do not coincide (Easterling et al. 2000; Alexander et al. 2006).

Our results seem to concur with those revealed in north and central Europe (Frei and Schär 2001; Zolina et al. 2008; Mueller and Pfister 2011). Focusing on the more variable patterns reported for the Mediterranean basin, our observed increase in intense events is in agreement with the short-duration rainfall changes reported in Tuscany, Sicily and Spain (Ramos and Martínez-Casasnovas 2006; Arnone et al. 2013; Bartolini et al. 2013, 2014). By contrast Reiser and Kutiel (2011), in their study on the precipitation regime over the entire Mediterranean region, did not observe significant temporal positive changes in extreme events and Moonen

**Table 3** Revised Universal Soil Loss Equation *R*-factor (RUSLE *R*-factor) calculated on the basis of the Wisheimer and Smith equation (1978) modified on an hourly basis and the PERMANOVA analyses of the effects of time (T; years as fixed factor), group (G; coastal-inland as a fixed factor) and their interaction (T × G)

Time interval	RUSLE <i>R</i> -factor (MJ mm ha <sup>-1</sup> h <sup>-1</sup> )		PERMANOVA		
	Coastal	Inland	T	G	T×G
Annual	1055.9±72.9 <sup>a</sup>	1093±68.9	<b>0.001</b> <sup>b</sup>	<b>0.035</b>	0.478
Seasonal					
Winter	84.6±7.8	137.4±13.4	<b>0.001</b>	<b>0.005</b>	0.235
Spring	130.4±16.1	189.3±19.0	<b>0.001</b>	<b>0.002</b>	0.142
Summer	257.0±31.8	383.7±40.6	<b>0.001</b>	<b>0.003</b>	0.279
Autumn	551.0±55.4	344.4±25.4	<b>0.001</b>	0.119	0.463
Monthly					
September	228.4±27.3	188.1±18.7	<b>0.001</b>	0.252	0.075
October	192.8±29.8	122.8±11.2	<b>0.001</b>	0.142	<b>0.014</b>
November	217.3±35.2	148.1±19.0	<b>0.001</b>	0.226	<b>0.002</b>
December	75.7±9.6	76.1±10.5	<b>0.001</b>	0.165	<b>0.003</b>

<sup>a</sup> Values are means ± SE of each group  
<sup>b</sup> in bold statistically significant values (*P*<0.05)



et al. (2002), in a site close to our study area, only found few cases. Such inconsistencies might be due to the temporal resolution of the data records or to the fact that different indices were used to study the phenomena.

Regarding the short-duration rainfall maximum data, used in studies such as those carried out for the whole of Tuscany by Fatichi and Caporali (2009) and by Crisci et al. (2002), increasing trends were reported for some rainfall gauges. As regards our area, Crisci et al. (1999) found an increasing trend using a 3-h annual extreme rainfall time series recorded by the Grosseto rainfall gauge. In our study, the extreme 1-min peak intensity (R<sub>1m</sub>) frequency increased the most, which may be due to the enhanced convective activity, which has been identified as a possible result of climate change (Berg et al. 2013). Although a decreasing trend in total precipitation has been detected (Brunetti et al. 2006; Bartolini et al. 2014), short-duration intense rainfall could increase, thus leading to stronger soil erosion and decreased infiltration.

We also found a marked contrast between wintertime and summertime trends, both for extreme RI and R<sub>1m</sub> frequencies. For winter we found the strongest sign, which is likely not directly linked to a rise in air temperature since Bartolini et al. (2012) did not observe any significant increase winter temperature in Tuscany. This contrast may arise from different synoptic circulation modes which are known to influence rainfall regimes and the associated parameters (Lionello et al. 2008; Vallebona et al. 2008; Bartolini et al. 2013). In fact, the observed RI and R<sub>1m</sub> trend inversion, occurring in October/November, corresponds to the beginning of the westerly flows associated with the Atlantic depressions.

#### 4.2 Computation of single-storm erosion indexes and assessment of their temporal trends

The increased erosivity (*R*-factor) that we found for the inland areas is in agreement with the temporal trends observed in southern Italy by Diodato and Bellocchi (2009) who reported increased annual rain erosivity, and also with those observed from May to July and in October by Meusburger et al. (2012) for Switzerland. However, unlike previous works, we observed no statistically significant increased signal in August and September, though we did find a clear increasing winter *R*-factor trend. In contrast with our findings, Ángulo-Martínez and Beguería (2012) found a general decrease in annual and seasonal erosivity for Spain.

The aim of our regressions was to investigate whether there was a positive or negative relationship between *R*-factors and time over the observed period. This is achieved by assuming a locally linear model, without any speculations on future trends or on the determination of the cyclic or anthropogenic nature of the causes. The likely climate-change driven increase in rainfall erosivity that we have described and its potential future continuation could have strong adverse effects for the study area and potentially for a larger area of the Mediterranean, such as an exacerbated soil degradation and transfer of sediments, nutrients and contaminants into the water table (IPCC 2007; Ercoli et al. 2013).

With regard to soil erosion, it is not only rainfall intensity and duration that are important, but also land cover, together with slope and soil physical parameters, such as texture, moisture and aggregation (Masoni et al. 1999; Bedini et al. 2009). In our study areas, industrial crops (i.e. tomatoes), winter cereal and maize-based cropping systems mainly characterize the coastal sites, whereas forage-livestock with extensive grazing systems and winter cereal systems are found in the inland area (Marraccini et al. 2012). As the steepest temporal *R*-factor trend was found in the inland areas in autumn, it occurred exactly in the main period of soil exposure to rainfall, since the majority of fields are ploughed and sown with cold season cereals or left fallow. As a result of the slope of the terrain, hilly inland areas are even more vulnerable to soil erosion than coastal areas. Moreover, summer and autumn were the periods

accounting for most of the erosivity, similarly with what reported for the central Spain by López-Vicente et al. (2008).

Soil protection measures could be based on the establishment of permanent soil cover through an increase in perennial forage cultivation and the application of cover cropping techniques such as living mulch and/or intercropping. Tree planting would also reduce crop evapotranspiration, since water availability is a limiting factor in the study area. Sowing winter cereals earlier, i.e. in October, would achieve effective cover and root system development already in November. Crop residue retention at the soil surface and reduced or no-tillage systems would also be valuable techniques in these areas.

## 5 Conclusions

This study highlighted an upward trend in the extreme rainfall intensity and intensity maximum frequency, measured through the number of exceedances over the 95th percentile, and in the rainfall erosivity for the last couple of decades in a Mediterranean region (Southern Tuscany, Italy). Winter is the season with the strongest signal, followed by spring for the coastal areas and autumn for the inland area. As regards erosivity, an increase in the  $R$ -factor values was observed in the inland areas on annual basis, with the highest trend in autumn, and in the coastal areas only for spring and winter. We should therefore be aware of these signals and implement proper adaptation strategies so that the soil can be protected when the highest risk of erosivity is expected. Future work should focus on understanding which large-scale circulation patterns are likely associated with extreme erosive events in the Mediterranean in order to use them as easily available erosion risk predictors.

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