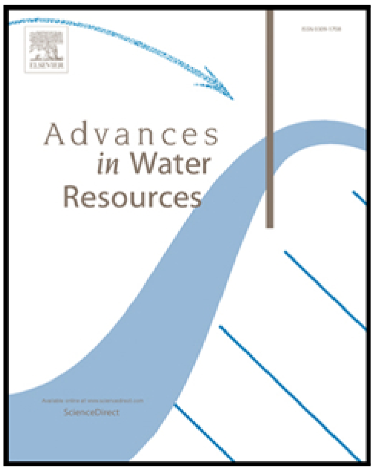

Influence of temporal data aggregation on trend estimation for intense rainfall

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Highlights

- Rainfall data to be used in the hydrological practice is available in aggregated form
- Aggregated form produce the underestimate of annual maximum rainfall depth (H_d)
- Errors in the H_d evaluation from data with coarse time aggregations can be corrected
- Correction of the H_d values can change the sign of the trend from positive to negative

Influence of temporal data aggregation on trend estimation for intense rainfall

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Abstract

Due to their influence on design guidelines, there is great interest in quantifying the possible impacts of climate change on extreme rainfall return levels. These studies can be affected by existing distortions in available rainfall historical series. The effect of the temporal aggregation (or time resolution), t_a, of rainfall observations on the estimation of trends in annual maxima over the last 100 years is examined here. We have used long-term historical rainfall observations with various temporal aggregations, due to the progress of recording systems through time, at 10 representative meteorological stations located in an inland region of Central Italy. Series of annual maximum rainfall depths, H_d, for given durations, d, have been then derived. It is well known that H_d values derived from rainfall data characterized by every t_a may involve underestimation errors, that for t_a>≈10 minutes can become important. Considering that all selected stations were installed in the first half of the twentieth century, each H_d series can be assumed as inhomogeneous since it contains values obtained by rainfall data with t_a values ranging from fine (e.g. 1 minute) to coarse (e.g. 24 h),thus with different

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levels of underestimation. By using a recently developed mathematical relation between average underestimation error and the ratio t_a/d, we then correct each H_d value has been corrected through two different approaches, obtaining quasi-homogeneous series. Successively, commonly used climatic trend tests, including least-squares linear trend analysis, Mann-Kendall, Spearman's rank correlation, and Sen's method, have been applied to the inhomogeneous and quasi-homogeneous H_d series. The results show that the underestimation of H_d values with coarse t_a plays a significant role in the analysis of the effects of climatic change on extreme rainfalls. Specifically, the correction of the H_d values can change the sign of the trend from positive to negative, mainly for series characterized by high probability to include H_d values with $t_a/d=1$.

KEY WORDS extreme rainfall; climate change; trend analysis; rainfall data; temporal aggregation

1. Introduction

Overwhelming evidence suggests that climate change, mainly due to greenhouse gas emissions from human activities, has been modifying the hydrologic cycle and exerting impacts on the environment with significant implications for water resources (Barnett et al., 2008). Mean global surface temperatures show an increase of about 0.7° C in the last century (IPCC, 2007 and 2014) and, based on the Clausius-Clapeyron relation, for each 1° C increase in global temperature the precipitable water increases by ~7% (Lenderink and Van Meijgarrd, 2008; Hardwick-Jones et al., 2010). Furthermore, in the context of global warming, it is expected that temperatures will increase near to the surface and decrease in the upper troposphere, favoring thermodynamic instability and the chances of deep convection (Kunkel, 2003). Therefore the associated increase in average rainfall is typically variable over the planet, not only because the atmospheric warming and water vapor trends have local non-uniformity, but also because of other factors such as the frequency and intensity of meteorological systems and their respective changes (Re and Barros, 2009).

Variations in extreme rainfall can be distinct from those in average rainfall. Because extreme precipitation, by its nature, is more erratic, observed trends are less spatially coherent than trends in average rainfall. However, increasing temperatures directly imply an increase in the maximum water vapor in the atmosphere and hence the maximum amount of rainfall, so an increase in extreme rainfall is a robust expectation from rising temperatures. Globally, there are more places where heavy rainfall is increasing than decreasing. Across much of the United States, for example, 1- and 2-day extreme rainfall events are becoming much more frequent (DeGaetano, 2009; Janssen et al., 2014). Overall, models have wide spread but are reasonably centered around the average observed rate of increase in extreme 1-day rainfall in the Northern Hemisphere mid-latitudes, but they tend to underestimate the rate of increase in extreme rainfall in the tropics (Asadieh and Krakauer, 2015).

Fatichi and Caporali (2009) found an absence of trends for mean precipitation and the intensity of extreme events of duration 3 h, 6 h and 12 h in Tuscany, a region of Central Italy, over the period 1916-2003. Similarly, Quirmbach et al. (2012) found that over 1950-2008 there were no significant trends in the number of annual extreme precipitation events for the North Rhine-Westphalia region. Analyses for other regions of Italy, both in the North and in the South, indicate an increase of extreme rainfall events (Bonaccorso et al., 2005; Brunetti et al., 2000). A similar study was conducted by Hydalgo-Munoz et al. (2011) in Andalusia (Spain) where an increase of extreme events in wintertime was observed in the period 1955-2006.

Many scientific papers (e.g. Gershunov and Cayan, 2003; Schreck and Semazzi, 2004; Grimm and Tedeschi, 2009; Haylock et al., 2006; Cayan et al., 1999; Gershunov, 1998; Aryal et al., 2009; Kamruzzaman et al., 2011; Kendon et al., 2018) contain experimental evidence that temporal oscillations in the occurrence of high rainfall intensities are somehow linked to large-scale atmospheric and oceanographic oscillations, such as the NAO or ENSO. Willems (2013) used 107 years of rainfall data recorded at Uccle (Brussel, Belgium) to show cyclic variations with period 30-40 years, indicating that trends over short time periods (<40 years) may be simply a result of large-scale atmospheric changes.

From the above scientific literature clear evidence emerges. Firstly, the analysis of trends in annual maximum rainfall depths, H_d, associated with a given duration, d, should be carried out only for long-term rainfall data recorded, for example, from the earliest decades of the last century (see also Teegavarapu and Nayak, 2017) to allow for biases introduced by large-scale oscillations of the climate system. When the time series length is less than one oscillation cycle it may coincide with an oscillation high period or an oscillation low period. Hence, rainfall statistics derived from such periods may be distorted from the longer-term statistics (Willems, 2013). Secondly, analyses on the H_d series for durations less than 1 h are not available since, for prolonged periods, historical rainfall data have been recorded with different temporal aggregations (or time resolutions), t_a, linked to the technologic progress of recording systems through time. Currently, through tipping bucket sensors, rainfall amounts are recorded in a data-logger for each tip-time associated with a fixed rainfall depth, but until the last decades of the 21st century rainfall data were recorded only over paper rolls (pluviograph), typically with hourly t_a (Bonaccorso et al., 2005; Fatichi and Caporali, 2009). In addition, especially before the Second World War, there are many years for which only daily rainfall data are available, recorded each day at 9 a.m. local time (in Italy and some other countries; other countries have different recording times) and measuring the accumulated rainfall during the previous 24 h.

Many studies have been performed to determine the potential underestimation errors in the H_d evaluation, starting from rainfall data with a coarse t_a (Hershfield and Wilson, 1958; Hershfield, 1961; Weiss, 1964; Harihara and Tripathi, 1973; Natural Environment Research Council, 1975; Van Montfort, 1990; Huff and Angel, 1992; Faiers and al., 1994; Dwyer and Reed, 1995; Van Montfort, 1997; Young and McEnroe, 2003; Yoo et al., 2015; Papalexiou et al., 2016; Morbidelli et al., 2017). All of them agree that for d comparable with t_a the actual maximum accumulations may be significantly underestimated, with errors of up to 50% (see also Fig. 1). Long H_d series always include a percentage of values derived from coarse rainfall data (typically old data), involving the aforementioned problem of underestimation, and another percentage derived from continuous data (recorded in the last 20-30 years). Consequently, these H_d series can be considered as inhomogeneous.

Morbidelli et al. (2017) defined a procedure to obtain quasi-homogeneous series of annual maximum rainfall depths that involves data derived through different temporal aggregations due to the progress of recording systems with time. For each different d value interval, a mathematical relation between average underestimation error and the ratio t_a/d can be used to correct the H_d values.

With the awareness that many H_d series contain a relevant number of underestimated values due to the availability of only coarse resolution rainfall data (e.g. daily), the main objective of this paper is to evaluate whether this unavoidable problem significantly affects trend analyses which determine if climate change is having an impact on extreme event intensities and frequencies. Commonly used climatic trend tests, including least-squares linear trend analysis, Mann-Kendall, Spearman’s rank correlation, and Sen’s method, have been applied to the inhomogeneous and quasi-homogeneous H_d series. The comparison of the results obtained by the same trend test should not be significantly influenced by a few critical elements concerning the hypothesis of stationarity/non-stationarity (Lins and Cohn, 2011; Kutsoyiannis and Montanari, 2015; Serinaldi et al., 2018) of the investigated H_d series. A second objective of the paper is to verify if the more common homogeneity tests are able to detect in the H_d series the existence of anomalies due to the use of rainfall data characterized by temporal aggregations that change over time. To limit the influence of possible climate oscillations, only time series with durations of up to 95 years are used.

insert here Fig. 1

2. Study area and rainfall data

Umbria region (8456 km^2), located in an inland zone of central Italy (Fig. 2) is our study area; it is characterized by a complex orography along the eastern seaboard, where the Apennine Mountains exceed 2000 m a.s.l., and is mainly hilly in the central and western areas, with elevations ranging from 100 to 800 m a.s.l. A wide percentage of the study area is included within the Tiber River basin. In fact the Tiber River crosses the region from North to South-West receiving water from many tributaries, mainly located on the hydrographic left side.

Annual rainfall totals vary across the region, with mean value of about 900 mm but ranging from 650 mm to 1450 mm (based on 1921-2015 and a network of more than 90 rain gauges). Higher monthly rainfall values generally occur during the autumn-winter period, together with floods caused by widespread rainfall. Mean annual air temperature ranges between 3.3 °C and 14.2 °C with maximum values during the month of July and minimum in January.

The region is currently monitored through a dense rain gauge network (about 1 rain gauge for each 90 km^2) with most stations continuously connected to a central unit through a radio link, while before the year 1992 only few rain gauges, with measurements made every sixty minutes, were installed.

Over the past 15 years the region has been affected by five significant droughts (2001 to 2003, then in 2007, 2012, 2015 and 2017) as well as by six dangerous flood events (one occurred in 2005, one in 2008, one in 2010, two in 2012 and one in 2013) with very large impacts in economic terms.

In this study, we use rainfall data from 10 stations characterized by long available time series (from January 1, 1921 to December 31, 2015) with their best temporal aggregation variable over time from 24 h (for very old data) to 1 minute (typically in the last 20-30 years). Only one station was included in the network earlier used by Morbidelli et al. (2017). Their geographic position is shown in Fig. 2, while for each selected station the main characteristics of the time series are reported in Table 1, with details on the percentage of available rainfall data characterized by specific temporal aggregation, t_a.

insert here Fig. 2

insert here Table 1

The spatial and temporal variability of rainfall in the Umbria region can be studied by analyzing the historical records from the following four rain gauge stations, representative of the complexity of the regional climate (see also Fig. 2 and Table 1): Città di Castello (located in the North of the region, along the Tiber River Valley); Gualdo Tadino (North-East, Apennine Mountains); Spoleto (South-East, Clitunno River Valley) and Todi (South, Tiber River Valley). The rainfall regime of the study area is synthesized in Fig. 3, through the monthly rainfall distribution of four selected representative stations; the monthly coefficient of variation, CV_m, defined as the ratio between the standard deviation and the mean monthly rainfall, is in the interval 0.25-0.31, with values inversely proportional to the specific site's annual total rainfall. The rainfall depth during each month of the year in the Gualdo Tadino station is always higher than in the other stations. Fig. 3 clearly shows the rainfall regime of the region, with the highest and lowest rainfall depths that typically occur in November and July, respectively.

insert here Fig. 3

3. Methods

The accumulated rainfall recorded over a time interval d, x_d, can be obtained through the following procedure (Burlando and Rosso, 1996; Boni et al., 2006):

$$x_d(t) = \int_t^{t+d} x(\tau) d\tau \tag{1}$$

where x(t) is the rainfall rate at time t.

Then, the annual maximum rainfall depth over a duration d, H_d, may be easily determined:

$$H_d = max[x_d(t): t_0 < t < t_0 - d + 1year] \tag{2}$$

where t_0 is the starting time of each year.

Here, we identify a large number of very long series of annual maximum rainfall depths associated with durations 1 h, 3 h, 6 h, 12 h, 24 h and 48 h. Each of these series, hereinafter called "uncorrected" because they contain some underestimated H_d values (see also Morbidelli et al., 2017), is then used to verify the existence of possible trend induced by climate change. Specifically, we consider the following tests: 1) least-squares linear trend analysis; 2) non-parametrical Mann-Kendall test (Mann, 1945; Kendall, 1975); 3) the Spearman rank correlation test (Khaliq et al., 2009); 4) the Sen's method (Sen, 2012).

Successively, the above mentioned tests were repeated on two different corrected versions of the same series (hereinafter called "corrected") in which the underestimation error due to the coarse temporal aggregation of historical rainfall data was minimized/eliminated. The two versions differ for the deterministic or stochastic approach adopted during the correction phase.

In the deterministic approach, an average correction is identically applied to all H_d values characterized by the same ratio t_a/d. To this aim, the average underestimation errors have been determined through the relations earlier proposed by Morbidelli et al. (2017) on the basis of rainfall data recorded by a rain gauge network very different from that used here for another objective.

Thus, with the deterministic approach each underestimated H_d value deriving from rainfall data characterized by a specific t_a has been corrected through the use of eq. (8) by Morbidelli et al. (2017). Note that all corrections deriving from these equations for which the average underestimation error become less than 1% are neglected.

In the second approach, of stochastic type, a more complex procedure has been adopted. Each single deterministic error, $E_{\%}$, may be considered as an exponentially distributed random variable with a probability density function dependent on a mean value, that is linked with the ratio t_a/d. The choice of the exponential distribution, perfectly coherent with Papalexiou et al. (2016), derives from the performance comparison, in terms of Pearson's chi-square test, of the more common statistical distributions. Furthermore, the random variable $E_{\%}$ is demonstrated to have an inverse correlation with the corresponding rainfall depth. For each H_d series that contains a defined number of underestimated values, 1000 realizations of the random variable $E_{\%}$ with the required characteristics (exponential pdf and mean value achievable through eq. (8) by Morbidelli et al., 2017) were first generated and then used to correct the underestimated H_d, respecting the inverse correlation between errors and rainfall depths.

Independently from the adopted test (least-squares linear trend analysis, Mann-Kendall, Spearman, Sen), to provide an overall representation of the random $E_{\%}$ effect, a Monte Carlo technique has been used (Papalexiou et al., 2016). More specifically, when a series of n annual maximum rainfall depths, H_{d_i} (i=1, …, n), of assigned d obtained from data characterized by coarse t_a has to be corrected with a stochastic approach, these steps could be followed:

1- the parameter of the exponential distribution function, equal to the inverse of the $E_{a\%}$ achievable with eq. (8) by Morbidelli et al. (2017) has to be quantified;

2- a set of underestimation errors $E_{\%_i}$(i=1, …, n), respecting the probability density function of point 1 has to be generated;

3- each generated $E_{\%_i}$ value has to be combined with a specific uncorrected H_{d_i} on the basis of the inverse correlation between these quantities;

4- each H_{d_i} has to be corrected in accordance with the following equation:

$$H_{d_i}^{corr} = \frac{H_{d_i}^{uncorr}}{\left(1 - E_{\%_i}\right)} \qquad \text{(i=1, …, n)} \qquad (4)$$

where $H_{d_i}^{corr}$ and $H_{d_i}^{uncorr}$ are the corrected and uncorrected H_{d_i} values, respectively;

5- steps 2, 3 and 4 have to be repeated 1000 times.

As is well known, homogeneity tests may be used to identify modifications to observational practices, station relocations and changes in measuring techniques (e.g. Kendon et al., 2018). In principle, homogeneity tests may also be able to detect the existence of anomalies in H_d series due to the use of rainfall data characterized by temporal aggregations that change over time. To this aim we use two different methods: the standard normal homogeneity test (SNHT) for a single break point (Alexandersson, 1986), and the Pettitt test (Pettitt, 1979). Both tests consider that the H_d values are independent and identically distributed. Under the alternative hypothesis, both tests assume that an evident break with a specific temporal position is present. Most studies recommend to make homogeneity tests in a relative way, by using one or more neighboring stations that are supposedly homogeneous (Peterson et al., 1998), but there are cases where the homogeneity analysis may be only performed through absolute tests, which use the single station series under investigation. In our study area, all rain gauges changed their recording systems (from paper rolls characterized by t_a=1 h to data-logger able to register each tip-time) within the same decade (1985-1995) so relative testing is pointless. Therefore, the mathematical formulations of the SNHT and Pettitt tests, whose detailed descriptions may be found in Alexandersson (1986) and Pettitt (1979), have been here performed in their absolute declination (Wijngaard et al., 2003).

4. Results and discussion

4.1 Annual maximum rainfall depth series

For each station, to quantify the maximum number of H_d series, we considered all existing rainfall data. In recent years, mainly since 1992, it is possible to obtain rainfall data recorded in data-loggers for each tip time associated with a fixed rainfall depth (no more than 0.2 mm). In this case each rainfall event was summarized by aggregating the number of tips over a t_a equal to 1 minute. Nevertheless, for long time series, a considerable amount of rainfall data were available with hourly recording system, as a consequence of the paper rolls adoption. Furthermore, in the absence of other possibilities, daily information derived from observation made each day at 9:00 a.m. was used. An example of the available H_d series carried out is shown in Table 2 for Città di Castello rain gauge station, where for d=1 h there are 27 values (53% of the total), placed in the period 1921-1991, characterized by t_a/d=1 and consequently with single underestimation errors up to 50% and average error equal to ~11% (Morbidelli et al., 2017).

For all analyses carried out in this paper, 60 H_d time series obtained considering 6 different durations (1 h, 3 h, 6 h, 12 h, 24 h and 48 h) and the 10 longest record rain gauge stations reported in Table 1, were selected.

insert here Table 2

4.2 Least-squares linear trend analysis

As a first test, we fitted a least-squares linear trend to the annual maxima for 6 durations at 10 stations (60 datasets). For the uncorrected H_d series, the number of positive least-squares linear trends, equal to 28, barely outnumbers the negative ones, equal to 27 (see values in bold in Table 3). Opposing results were obtained for the corrected H_d series, independent from the deterministic or stochastic approach adopted. In fact, after corrections, cases with negative least-square linear trends become equal to 36 and 34 for the deterministic and stochastic approaches, respectively, whereas the positive ones become, in both cases, 22 (in Table 3, see values with normal and italic characters for the deterministic and stochastic approaches, respectively). The comparison of the two corrected values in Table 3 shows that the approaches used to correct the H_d underestimation produce quite equivalent results (see also Fig. 4). Since this similarity has been always observed, independently by the considered test, hereinafter it will only be considered the distinction between uncorrected and corrected series.

insert here Table 3

insert here Fig. 4

Table 3 clearly shows that corrections of H_d values produce significant effects on the least-square linear trends, especially for series characterized by durations 1 h and 24 h in which the probability of the presence of values with $t_a/d=1$ is particularly high.

Figures 5 and 6 show a comparison between uncorrected and corrected annual maximum rainfall depths observed at Umbertide for durations 1 h and 24 h, respectively. It can be seen that the uncorrected series show a positive trend (Fig. 5a and 6a) while the correct series linear trends are negative (Fig. 5b and 6b). Neither of trends in Fig. 5 and 6 are significant, but they are anyway important in terms of general trend evaluation.

Note that when the objective is a definition of a specific climatic trend, missing data may be crucial. In these cases it is very important to work with a continuous period of data or to infill the missing information. However, in this paper the objective was the comparison between uncorrected and corrected H_d series. In our opinion possible missing data (each time series analyzed here includes all data from the last 25-30 years and, except for the period of the Second World War, the few other years with missing data have occurred randomly) do not influence the aforementioned comparison because they are in series (uncorrected and corrected).

insert here Fig. 5

insert here Fig. 6

Regarding the influence of climatic change on heavy rainfalls, from the results of Table 3 it is very difficult to find a clear indication on the relationship between trends and geographic position, altitude above sea level and mean annual rainfall characteristics of each station. Actually, all selected stations in the North of the region (Città di Castello, Gualdo Tadino, Gubbio and Umbertide) evidenced a prevailing positive trend, despite their non-homogeneous altitude. In fact, two of them are characterized by a significant value of altitude (for Gualdo Tadino equal to 599 m a.s.l. and for Gubbio equal to 471 m a.s.l.) whereas two by a relatively low value (Città di Castello and Umbertide, both around 300 m a.s.l.). Instead, in the South of the region almost all the stations (except Orvieto and Terni) evidenced negative trends.

4.3 Non-parametric Mann-Kendall test and Spearman rank correlation test

To release from the assumption of a linear trend, the analysis of the 60 time series was successively performed by the non-parametric Mann-Kendall (Mann, 1945; Kendall, 1975) and the Spearman rank correlation (Kaliq et al., 2009) tests, which are frequently used to detect trends in heavy rainfall (Fu et al., 2004; Houssos and Bartzokas, 2006; Ramos and Martinez-Casasnovas, 2006; Su et al., 2006; Fatichi and Caporali, 2009, Rashid et al, 2015). For the uncorrected series, by using for both tests a significance level equal to 0.05, the percentage without significant trends is always the same, independent of the adopted test. More specifically, for both tests this percentage is higher than 93%, with 2 series (Spoleto station with rainfall durations 24 h and 48 h) characterized by a negative trend and 2 series (Gubbio station with rainfall durations 1 h and 24 h) by a positive trend.

Instead, after the correction, the Mann-Kendall and the Spearman rank correlation tests evidenced 3 cases with a negative trend and no positive case. In addition to the H_d series for Spoleto station with d=24 and 48 h, also that of Todi with d=1 h becomes characterized by a negative trend. It is interesting to note that in this last case the least-square linear trend was negative also before the correction with eq. (3), with slope of the linear regressions equal to -0.05 mm/year. However, as shown in Fig. 7, after the correction the negative trend became exacerbated (slope of the linear regression equal to -0.12 mm/year).

Finally, it is evident that in the transition from uncorrected to corrected H_d series, the application of the Mann-Kendall and the Spearman rank correlation tests produce different results particularly when d=1 or 24 h where, as specified above, the probability of the presence of values with t_a/d=1 is particularly high.

insert here Fig. 7

4.4. Sen's slope method

The Sen's innovative method (Sen, 2012) has been recently adopted in many analyses (Sonali and Kumar, 2013; Guclu, 2016; Oztopal and Sen, 2016; Guclu et al., 2018; Guclu, 2018), especially for a comparison with classical methods; it is based on the realization of two ordered sub-series (in ascending order) and offers the following advantages: 1) the chance to show visual results on the graph, and 2) the possibility to consider five trend types (monotonic increasing and decreasing, non-monotonic increasing and decreasing, and no trend conditions) instead of the usual three types (monotonic increasing and decreasing, and no trend condition).

Similarly to what already emerged using the most classic methodologies, also the adoption of the Sen's method produces different results when applied to the uncorrected and corrected annual maximum rainfall depths series. As an example, Fig. 8 shows the application of the method for both the uncorrected and corrected H_d series observed at Todi considering d=1 h. As it can be seen in Fig. 8a the uncorrected series shows a no trend condition, because all values are close to 1:1 line, while in Fig. 8b the correct series evidences a clear monotonic decreasing trend (details on the results interpretation can be found in Sen, 2012).

insert here Fig. 8

4.5 Series length

The above results show that temporal aggregation of rainfall data can have a significant role in the analysis of the effects of climatic change on extreme rainfall intensities. In principle, this problem could be solved by using only rainfall data available with temporal aggregation of 1 minute. However, for most geographical areas historical data with t_a=1 minute are available only for the last 20-30 years. Fig. 9 shows that exhaustive results in terms of linear regression can be obtained by using at least 60 years of data. In addition, when only the most recent 20-40 years of data are used, the risk of misleading results is very high. As a consequence, series derived from rainfall data with t_a=1 minute, in every part of the World characterized by lengths of up to 30 years, can never be used. Furthermore, as shown in Fig. 10, in some cases the more recent values (f.i observed in the last 10 years) when compared to those of the entire period can provide different indications of change based on whether the series are corrected or uncorrected.

It may be concluded that there is no climatic index or test that can be usefully conducted on H_d series composed of values resulting from years with rainfall data characterized by t_a=1 minute, because their length is too short. For example, using these short series in the 60 cases selected here (of length up to 25 years), the non-parametric test of Mann-Kendall offers different results from those previously discussed, showing no trend for 58 cases, an increasing trend for Gualdo Tadino station with d=24 h and a decreasing trend for Città di Castello station with d=3 h.

insert here Fig. 9

insert here Fig. 10

4.6 Homogeneity tests

The standard normal homogeneity test (SNHT) for a single break point (Alexandersson, 1986) and the Pettitt test (Pettitt, 1979) were applied to the 60 H_d series, considered in their uncorrected form, where the inhomogeneity due to the use of rainfall data with coarse temporal aggregation should be evident.

However, break conditions detected with both absolute tests were very limited and never simultaneous (8 and 7 cases for SNHT and Pettitt tests, respectively). Furthermore, detected inhomogeneities could not be justified by metadata, and not even by changes in the recording practice with a significant modification of rainfall temporal aggregation.

As an example, Fig. 11 shows the annual maximum rainfall depths for d=24 h at Città di Castello station with a clear indication of the 1991/1992 change in rainfall temporal aggregation from 24 h to 1 minute (see also Table 2). Therefore, H_d values in the period 1921-1991 should be strongly underestimated (up to 50%) while successive years are correctly determined. Despite the existence of a discontinuity localized in the years 1991/1992, the two tests suggest possible breaks in 1927 (SNHT) and 1948 (Pettitt).

This suggests that the detection of breaks in H_d series due to inhomogeneities for coarse rainfall time aggregation is not possible, because this inhomogeneity, even when very evident, cannot produce sufficiently large break points to be detectible.

This confirms that if the standard deviation of the considered variable is significantly high, as in the precipitation case, then the probability that inhomogeneity will escape detection increases (Wijngaard et al., 2003).

insert here Fig. 11

5. Conclusions

Historical rainfall data are available with different temporal aggregations, within the range 1 minute-24 h, linked to the progress of recording systems through time. Therefore, in many geographical areas of the World, long annual maximum rainfall depth series can become inhomogeneous because characterized by a percentage of values obtained from coarse data (generally old data), involving the problem of underestimation, and another percentage derived from continuous data (recorded more recently). In principle, this may affect subsequent analyses, including those which aim to examine the effect of climate change on extreme event intensities and frequencies. However, by using the mathematical relation recently proposed by Morbidelli et al. (2017), between average underestimation error and the ratio t_a/d, each H_d value may be corrected, obtaining quasi-homogeneous H_d series which can then be reassessed for trends over time.

The main objective of this paper was to evaluate whether the underestimation errors of the H_d due to the availability of coarse temporal aggregation data significantly affect the most common methods used to evaluate trend signals in intense rainfall, without considering specific analyses on the possible limits of the adopted trend tests and the stationary/non-stationary characteristics of the selected time series.

The major findings and conclusions of this study, conducted over 10 long-record, high-resolution rain gauges using data for 1921-2015, and based on the comparison of the results obtained with both corrected and uncorrected series, are the following:

- The underestimation errors due to coarse t_a produce significant effects on the least-squares linear trend analysis of the H_d values. In fact, since a prevalence of increasing and decreasing trends for uncorrected and corrected series, respectively, was observed, it is obvious that the correction can change the sign of the trend. The correction of the H_d values, performed with both deterministic and stochastic approaches, produces more evident effects for series where the probability of the presence of values with $t_a/d=1$ is particularly high (d=1 h and d=24 h).

- The non-parametric Mann-Kendall test and the Spearman rank correlation test, both with a significance level 0.05, are less sensitive than the least-squares linear trend to corrections of the H_d values. For both tests, using the 60 uncorrected time series selected in this paper, only 2 cases are characterized by a negative trend and 2 cases by a positive one. After the H_d corrections, cases with negative trends become 3 and there are no cases with positive trend.
- Also the adoption of the innovative Sen's method produces different results when applied to the uncorrected and corrected annual maximum rainfall depths series.
- The hypothetical solution to consider only rainfall data with t_a=1 minute is not possible because in most geographical areas these data exist only for the last 2-3 decades, while trend identification requires at least 60 years of data due to the effect of large-scale climate oscillations at multi-decadal time-scales.
- The existence of anomalies in the H_d series due to the different temporal aggregations of rainfall data cannot be detected by common homogeneity tests because any consequent discontinuity, even when very evident, does not produce sufficiently large break points, at least for the annual maximum series.

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Table 2

Rainfall data observed at Città di Castello: **a**nnual maximum rainfall rates (in mm) for different durations, d, and aggregation times, t_a.

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Table 1

Main characteristics of the selected rainfall stations. The geographic position is in Universal Transvers Mercator (UTM) coordinates computed by using the WGS84 ellipsoid model. ARD_{ta} is the percentage of available rainfall data characterized by specific temporal aggregation, t_a.

Raingauge station	Altitude (m a.s.l.)	UTM33 X (m)	UTM33 Y (m)	Mean annual rainfall (mm)	CV annual rainfall (-)	Available data period	ARD_{ta} (%)		
							t_a=1 min	t_a=60 min	t_a=1440 min
Amelia	321	287958.95	4714829.47	1019.3	0.273	1921-2015	27	31	42
Città di Castello	304	277642.78	4815738.32	882.2	0.209	1921-2015	44	34	22
Foligno	220	310678.44	4758225.28	862.5	0.233	1916-2015	28	43	29
Gualdo Tadino	599	319870.30	4789952.56	1159.4	0.254	1921-2015	19	54	27
Gubbio	471	302788.77	4802328.54	1014.2	0.207	1921-2015	35	41	24
Orvieto	311	263178.10	4733559.19	830.3	0.224	1921-2015	18	55	27
Spoleto	353	314951.81	4736161.87	1018.4	0.193	1921-2015	19	52	29
Terni	123	307122.66	4714603.29	915.7	0.198	1921-2015	20	46	34
Todi	329	288088.74	4740318.87	850.9	0.213	1921-2015	35	42	23
Umbertide	305	284866.84	4798836.42	917.1	0.237	1921-2015	24	43	33

Table 2
Rainfall data observed at Città di Castello: annual maximum rainfall rates (in mm) for different durations, d, and aggregation times, t_a.

	duration (h)							duration (h)					
year	**1**	**3**	**6**	**12**	**24**	**48**	**year**	**1**	**3**	**6**	**12**	**24**	**48**
1921					45.9	78.3	**1965**	28	49	70	108.2	111.2	132.6
1922	10				42.9	72.7	**1966**	33.5	37	46	62.4	67.4	69.2
1923					55.8	84.5	**1967**	29.6	39	39.2	39.4	39.6	42.4
1926					32.4	46.5	**1968**	27.8	39	57	73.6	74.2	84.4
1927					21.3	37.4	**1969**	26	37.4	49.8	58.6	61	65.3
1928					75	106.2	**1970**	18.4	21.8	23.8	33	45.8	58.4
1929	17.1	22.4	22.4	22.4	38.6	63.1	**1971**	14	25.8	30.2	43.2	48.2	58.2
1930	14	35	35	56.5	69	105	**1972**					36.4	57.6
1931					69	119.4	**1973**					59.2	59.6
1932	25.4	29.8	37	46	62.2	65.9	**1982**					68.2	70.6
1933	15	20.6		52.8	74	89	**1989**					56.6	86
1934	21						**1990**					31.2	61
1937					158.6	178.3	**1991**					51.2	61
1938	45.2	66.6	66.8	67	83	83	**1992**	35.5	61.3	67.7	72.6	74.7	83
1939	15.8	23.4	33	54.8	88	92.6	**1993**	36.7	42.5	43.6	44.3	44.8	71.4
1940		26.2			62.4	78.4	**1994**	34.8	35.4	36.5	50.4	65	83
1941					158	165.4	**1995**	24.1	26.7	32.4	44.1	62.8	63.4
1942	33.6	33.6	46.6	58.8	65.2	65.4	**1996**	21.1	30.4	52.7	73.7	78.9	106.4
1943	17.4	27.2	35.4	48.4	56.2	59.8	**1997**	18.4	30.9	35.9	55.9	80	93.2
1946	23.8	43	49.4	59.4	69	78	**1998**	21.4	29.6	31.2	36.1	54.7	58
1947	40.2	40.2	40.2	47.4	59	64.5	**1999**	27.3	28.6	34.4	40.1	43.7	66.3
1948	15.4	24.2	28	36	67.8	76.2	**2000**	22.1	33.2	37.7	51.9	74.8	93.9
1950	23	28.6	41.4	50	50.4	50.5	**2001**	23.2	25.8	45.9	49.9	50.5	59.6
1951	20				42.4	49.2	**2002**	20.7	26.8	29.2	38.8	51.5	60.5
1952					54	63.6	**2003**	23.1	28.6	30.5	32	43.5	70
1953					49.5	66	**2004**	27	27.1	27.2	30.2	48.7	60.5
1954					41	62.2	**2005**	26.8	35.1	39.1	50.2	77.7	89.3
1955	15	20	37	44	47.4	55.4	**2006**	22.1	33.5	46.4	65.4	83.1	86.8
1956					34.5	68.5	**2007**	18.7	24.3	29.8	31.1	39	47.3
1957					36	46.6	**2008**	23.6	24	29.4	42.4	62	76.6
1958	14.5				42.2	58.6	**2009**	25.1	25.5	25.9	26.5	38.1	53.7
1959					51.6	69.4	**2010**	28.1	31.1	51.3	70	73.4	83.5
1960					104	140	**2011**	21.4	29.5	37.3	38.7	40.4	50
1961					45.4	61.2	**2012**	31.2	32.4	35.7	65.3	119.6	163.4
1962	30.8	30.8	30.8	36	49	66.8	**2013**	25.2	31.8	46.1	68.8	93.5	106.4
1963	28.4	32.6	51	56.5	61	79.6	**2014**	22.5	23.7	32.6	45.3	47.1	69.1
1964	39.2	39.2	46.4	54.5	69.8	72.4	**2015**	19.6	24.8	28.6	48.1	67.3	70.6

Legend:

- t_a = 1 minute
- t_a = 1 hour
- t_a = 1 day

Table 3

Slope (in mm/year) of the least-squares linear regressions of annual maximum rainfall depths for the selected stations and for different rainfall durations. Values for the uncorrected, corrected with deterministic approach and corrected with stochastic approach series are reported with bold, normal and italic characters, respectively.

Rain gauge station	**Duration (h)**					
	1	3	6	12	24	48
Amelia	**+0.01** -0.05/*-0.02*	**-0.22** -0.24/*-0.22*	**-0.22** -0.24/*-0.23*	**-0.17** -0.18/*-0.17*	**-0.05** -0.13/*-0.11*	**-0.17** -0.21/*-0.18*
Città di Castello	**+0.04** -0.01/*-0.01*	**-0.04** -0.05/*-0.05*	**-0.06** -0.07/*-0.06*	**-0.04** -0.04/*-0.04*	**-0.01** -0.12/*-0.05*	**-0.06** -0.11/*-0.09*
Foligno	**+0.05** +0.01/*0.00*	**-0.03** -0.04/*-0.04*	**-0.04** -0.05/*-0.05*	**0.00** 0.00/*0.00*	**+0.09** +0.04/*+0.04*	**+0.07** +0.04/*+0.04*
Gualdo Tadino	**+0.06** +0.02/*+0.01*	**-0.02** -0.03/*-0.03*	**-0.06** -0.07/*-0.07*	**+0.14** +0.14/*+0.14*	**+0.04** -0.04/*0.00*	**-0.05** -0.09/*-0.07*
Gubbio	**+0.11** +0.07/*+0.07*	**+0.05** +0.04/*+0.04*	**+0.10** +0.09/*+0.09*	**+0.10** +0.09/*+0.10*	**+0.19** +0.11/*+0.14*	**+0.15** +0.12/*+0.12*
Orvieto	**-0.01** -0.05/*-0.03*	**-0.11** -0.12/*-0.11*	**+0.01** +0.01/*+0.01*	**+0.04** +0.03/*+0.04*	**+0.16** +0.10/*+0.13*	**+0.14** +0.10/*+0.12*
Spoleto	**+0.06** +0.03/*+0.01*	**+0.01** -0.01/*-0.01*	**-0.08** -0.08/*-0.08*	**-0.15** -0.16/*-0.16*	**-0.25** -0.33/*-0.28*	**-0.43** -0.48/*-0.44*
Terni	**+0.10** +0.06/*+0.02*	**+0.19** +0.18/*+0.17*	**+0.17** +0.17/*+0.17*	**+0.10** +0.10/*+0.10*	**0.00** -0.07/*-0.09*	**-0.06** -0.09/*-0.07*
Todi	**-0.05** -0.12/*-0.09*	**-0.19** -0.21/*-0.20*	**-0.21** -0.22/*-0.22*	**-0.24** -0.25/*-0.24*	**-0.02** -0.11/*-0.07*	**0.00** -0.04/*-0.02*
Umbertide	**+0.03** -0.01/*-0.02*	**+0.07** +0.06/*+0.06*	**0.00** -0.02/*-0.01*	**0.00** 0.00/*0.00*	**+0.05** -0.02/*+0.02*	**+0.06** +0.03/*+0.05*

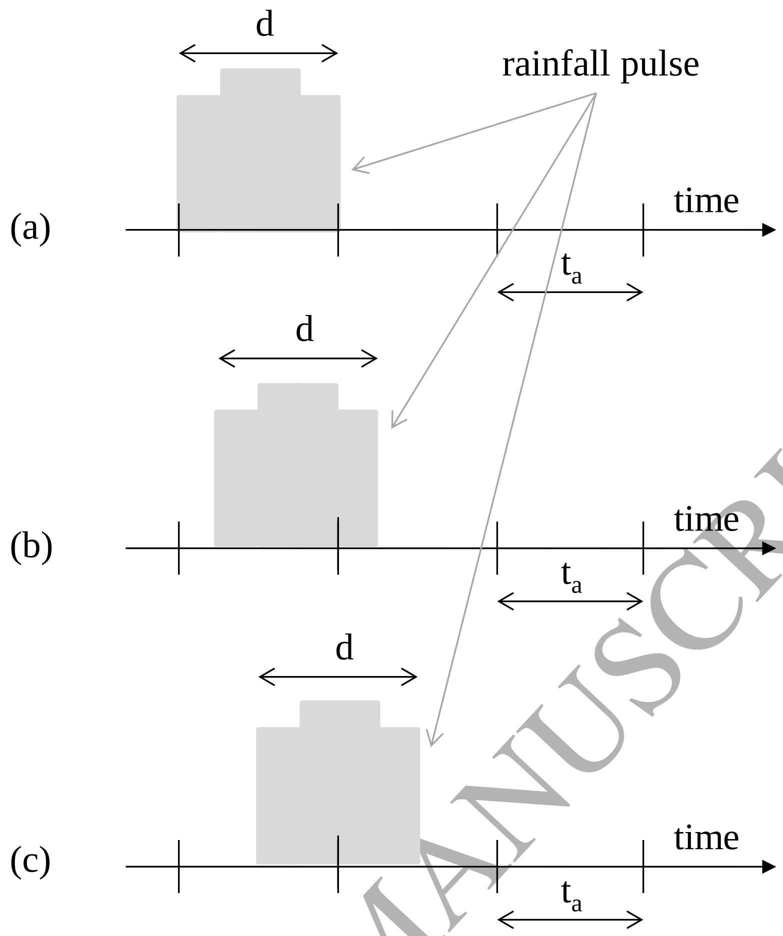


Fig. 1. Schematic representation of a rainfall pulse with duration, d, equal to the measurement aggregation time, t_a, of the rainfall data: (a) condition where a correct evaluation of the annual maximum rainfall rate of duration d, H_d, is possible; (b) condition for a generic underestimation of H_d; (c) condition for the maximum underestimation of H_d (equal to 50%).

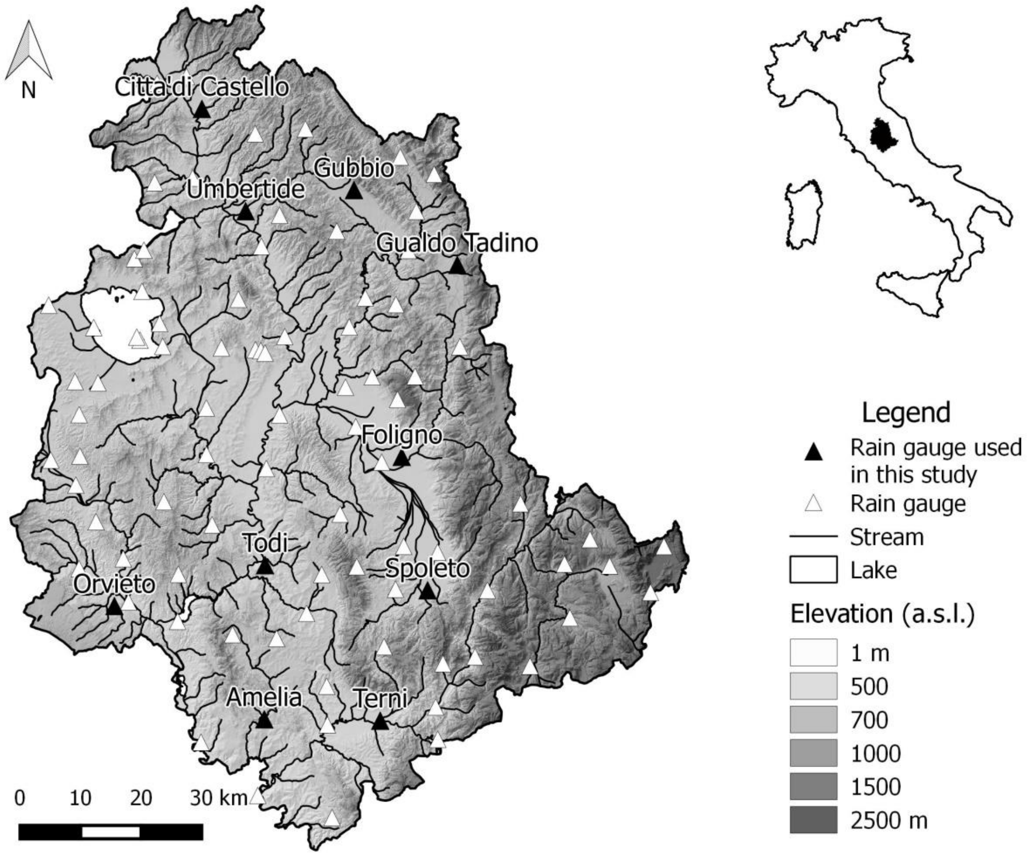


Fig. 2. Morphology and rain gauge network of the study area. The position of the rain gauges used in the analysis is also specified.

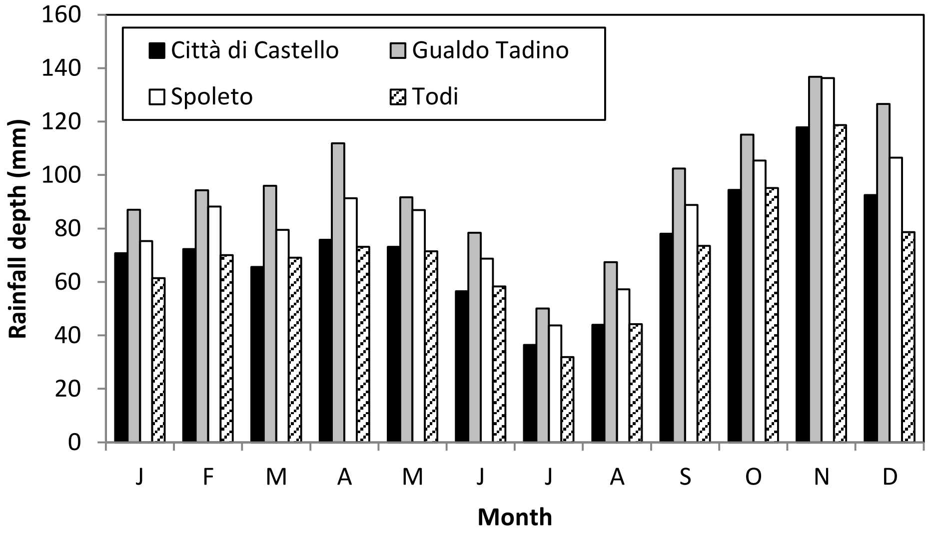


Fig. 3. Mean monthly rainfall observed at four representative rain gauge stations.

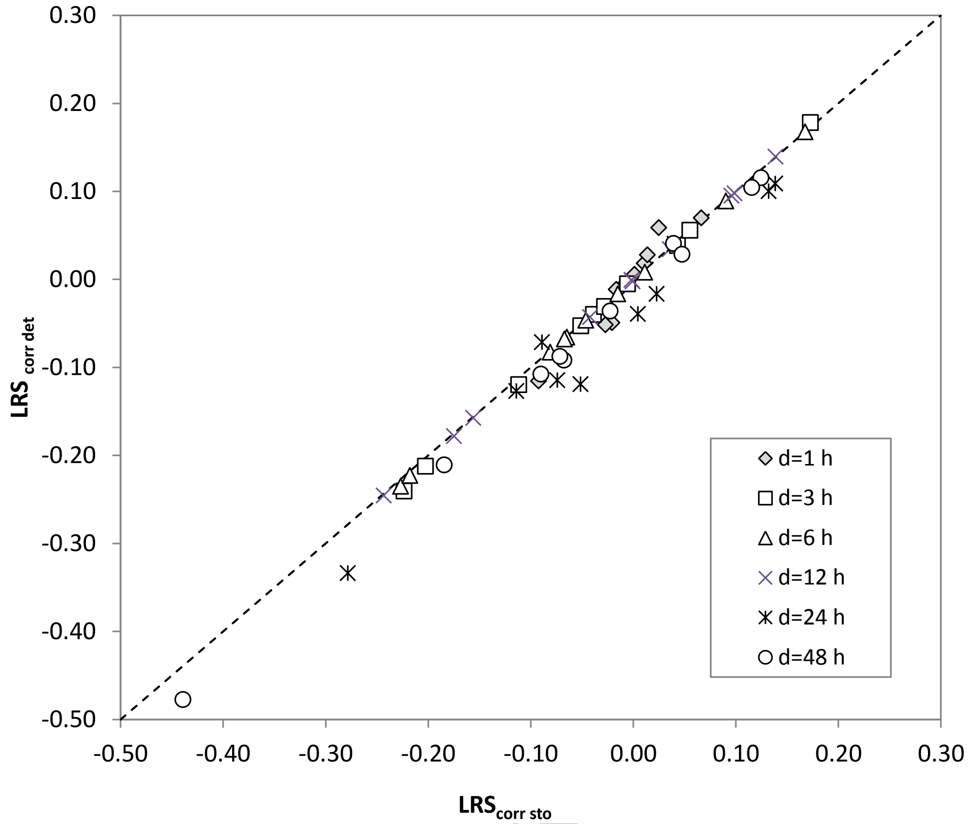


Fig. 4. Slope of the corrected series with stochastic approach, $LRS_{corr\ sto}$, versus the corresponding values derived from correction with deterministic approach, $LRS_{corr\ det}$, for the 60 H_d time series obtained considering 6 different durations (1 h, 3 h, 6 h, 12 h, 24 h and 48 h) and the 10 rain gauge stations reported in Table I.

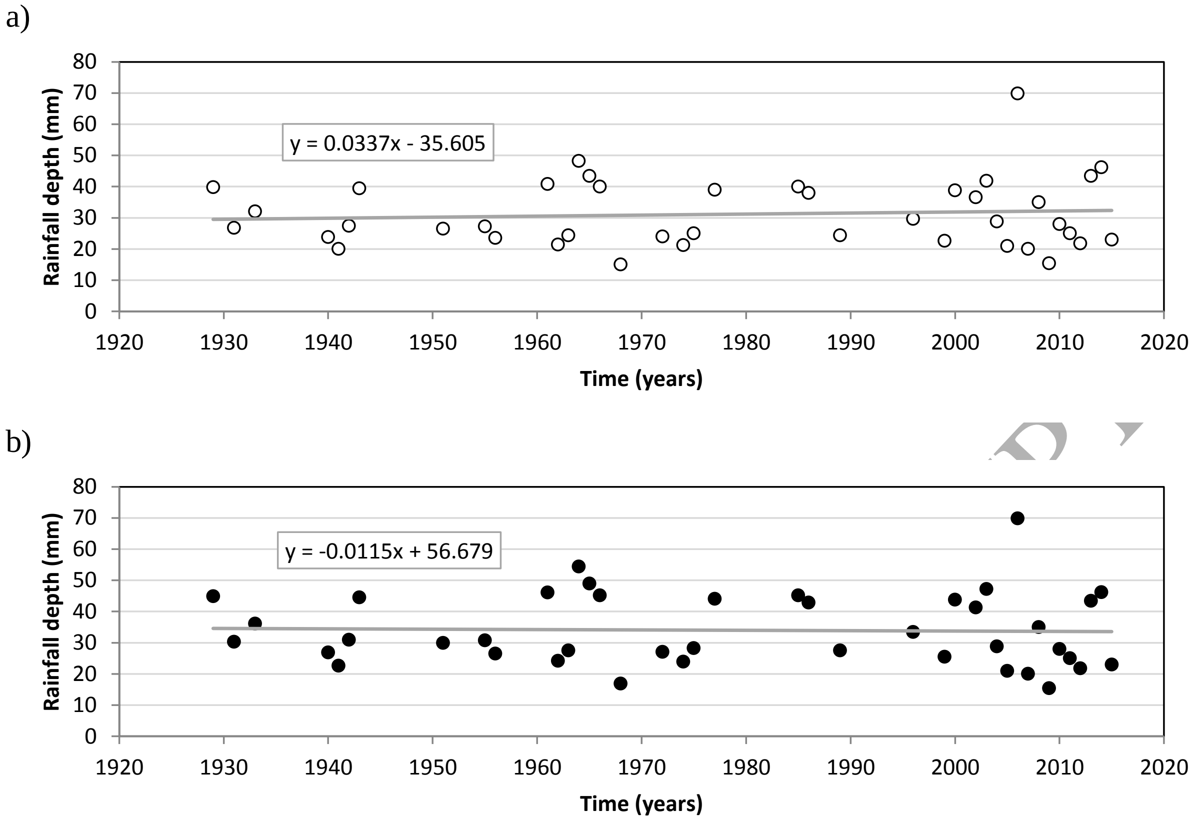
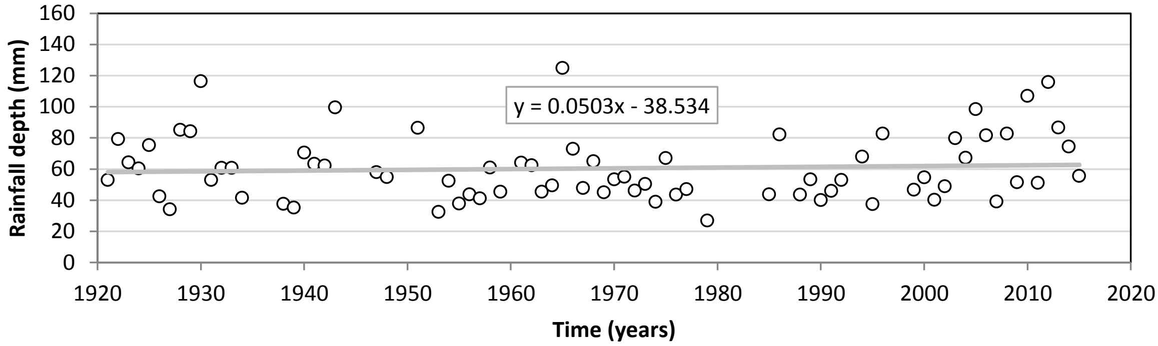


Fig. 5. Time sequence of annual maximum rainfall depths for duration 1 h with the respective linear trends, for Umbertide station: a) Uncorrected series; b) Corrected series with the deterministic approach. Available data within the period 1929-2015.

a)



b)

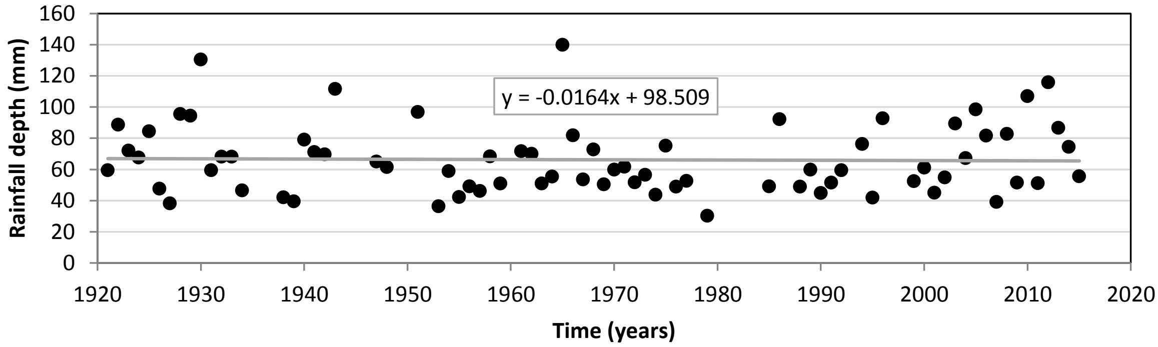
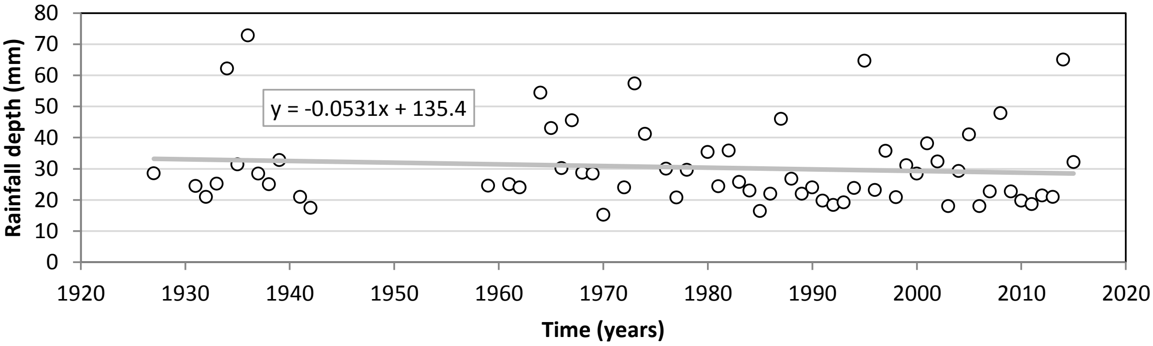


Fig. 6. Time sequence of annual maximum rainfall depths for duration 24 h with the respective linear trends, for Umbertide station: a) Uncorrected series; b) Corrected series with deterministic approach. Available data within the period 1921-2015.

a)



b)

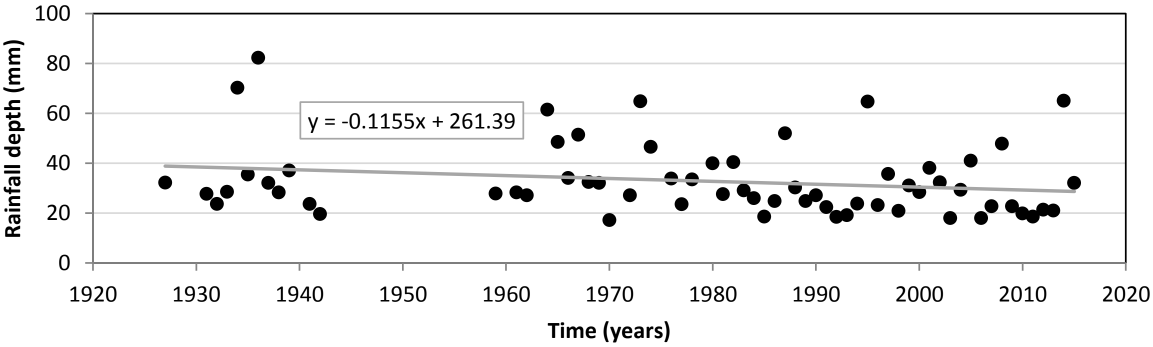
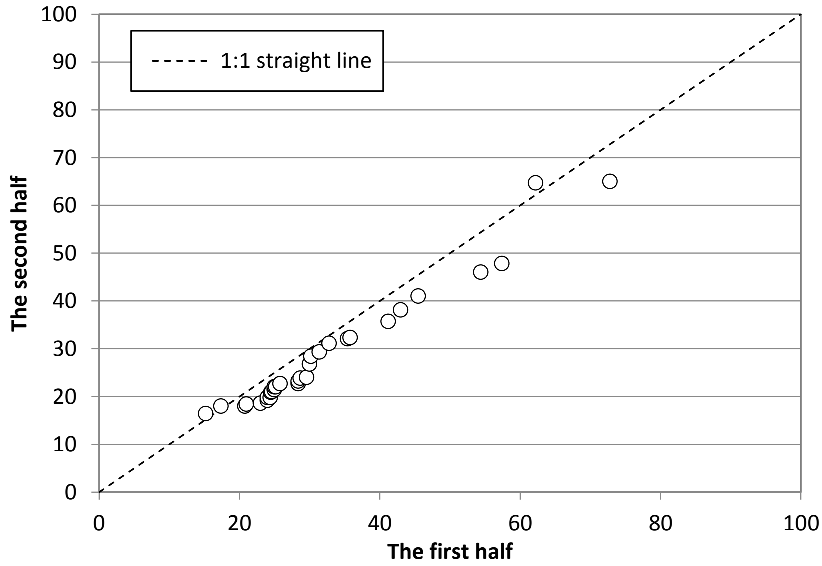


Fig. 7. Time sequence of annual maximum rainfall depths for duration 1 h with the respective linear trends, for Todi station: a) Uncorrected series; b) Corrected series with deterministic approach. Available data within the period 1927-2015.

a)



b)

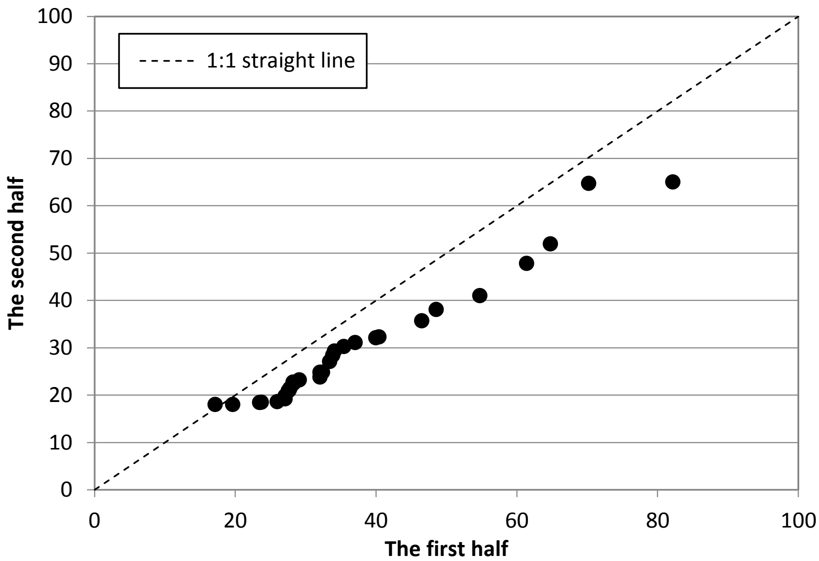


Fig. 8. Trend conditions according to Sen's method for the annual maximum rainfall depths for Todi station and duration equal to 1 h: a) Uncorrected series; b) Corrected series. Available data within the period 1931-2015.

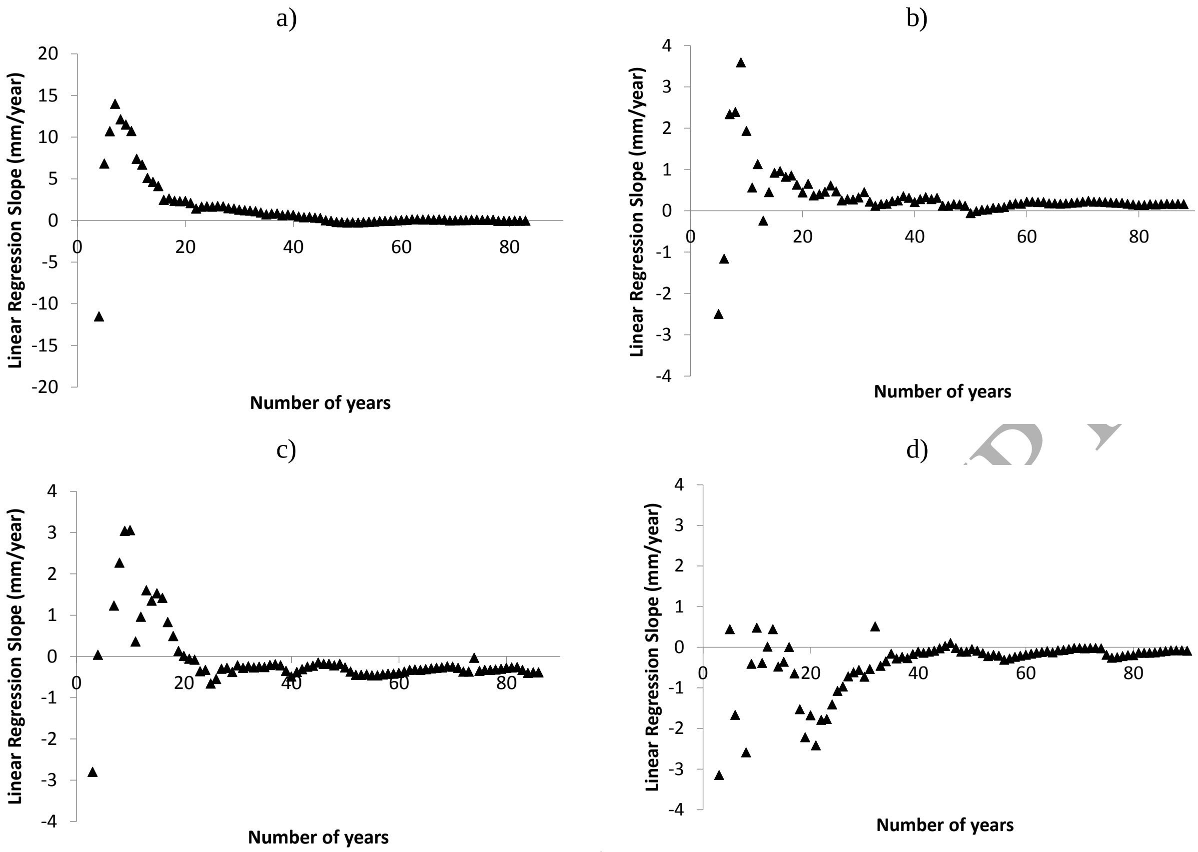
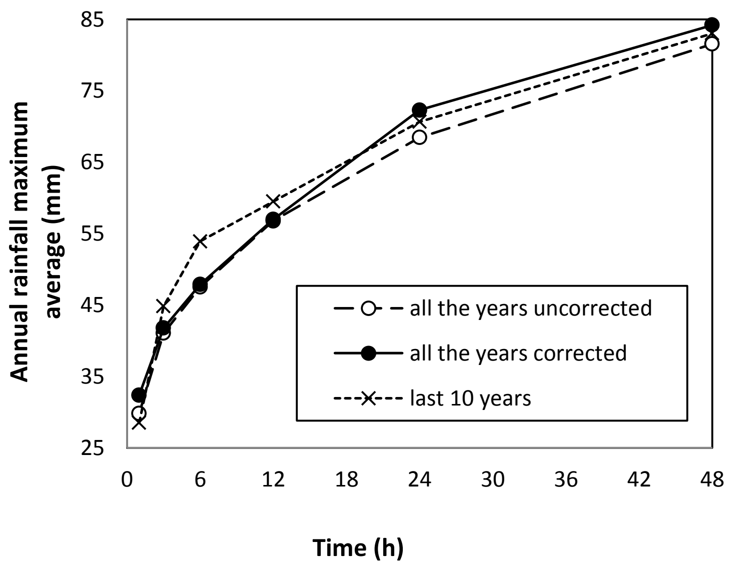


Fig. 9. Linear regression slope (in mm/year) of the H_d (d=24 h) as a function of the considered number of years: (a) Gualdo Tadino station; (b) Gubbio station; (c) Spoleto station; (d) Todi station

a)



b)

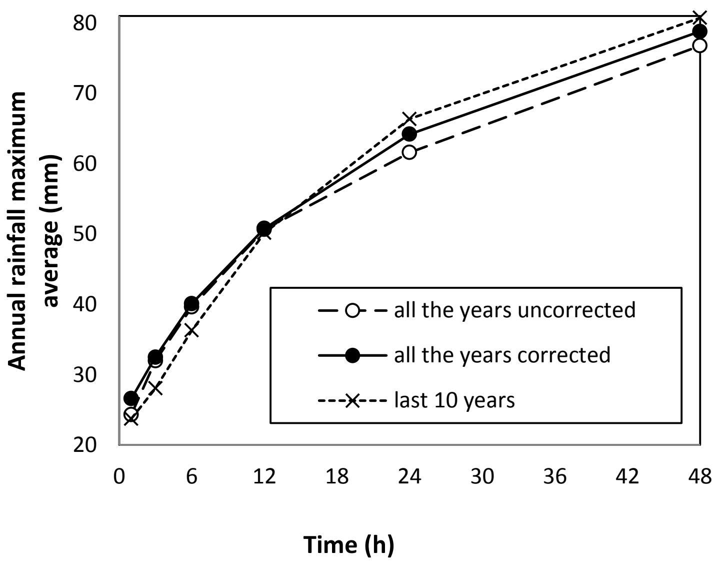


Fig. 10. Comparison between annual rainfall maximum averages, for durations between 1 and 48 h, calculated in the last 10 years and considering the entire observed period for both uncorrected and corrected series: a) Terni rain gauge station; b) Città di Castello rain gauge station.

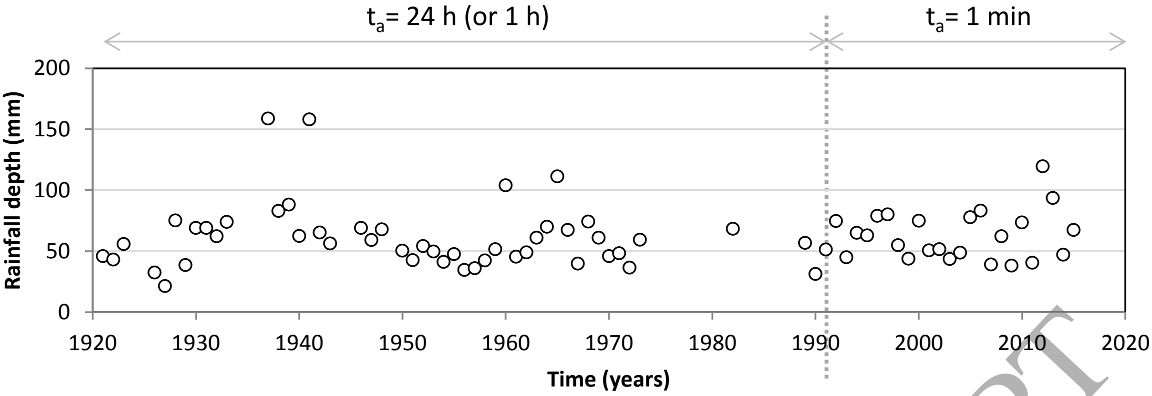


Fig. 11. Time sequence of annual rainfall maximums for duration 24 h for Città di Castello station (period 1921-2015). The discontinuity of the rainfall data temporal aggregation is also indicated (between the years 1991/1992).