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Trend analysis of annual and seasonal rainfall time series in the Mediterranean area

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ABSTRACT: Precipitation trend analysis, on different spatial and temporal scales, has been of great concern during the past century because of the attention given to global climate change by the scientific community. According to some recent studies, the Italian territory has been suffering a precipitation decrease, especially in the last 50 years, and the southern areas seem to be more affected. The aim of the present study is to analyse rainfall time series over a wide time interval and a wide area, detecting potential trends and assessing their significance. For this purpose, 211 gauged stations, mainly located within the Campania region, southern Italy, have been analysed for the period 1918–1999. An accurate database has been set up through a data quality and time series homogeneity process. Statistical analysis of the database highlight that (1) the trend appears predominantly negative, both at the annual and seasonal scale, except for the summer period when it appears to be positive; (2) over the whole reference period, positive and negative trends are significant respectively for 9 and 27% of total stations and (3) over the last 30 years, a negative trend is instead significant for 97% of the total stations. Copyright © 2009 Royal Meteorological Society

1. Introduction

Precipitation trend analyses, on different spatial and temporal scales, has been of great concern during the past century because of the attention given to global climate change from the scientific community: they indicate a small positive global trend, even though large areas are instead characterized by negative trends (IPCC, 1996). With regard to the European context, negative trend areas are more pronounced in the central and southern regions, corresponding to the Mediterranean basins, whose most relevant characteristic is extreme rainfall variability, both in space and time (Piervitali *et al*., 1997; Schonwiese and Rapp, 1997; Romero *et al*., 1998; Millán *et al*., 2005; Mehta and Yang, 2008). The implications of these changes are particularly significant for these areas, stressed by the combination of a dry climate and an excessive water demand.

Studies involving Italian long records confirm a strong decrease in precipitation trends over Italy, with a rainfall reduction of about 135 mm in the southern regions during the last 50 years (Palmieri *et al*., 1991; Brunetti *et al*., 2004; Brunetti *et al*., 2006). Moreover, significant negative annual precipitation trends are reported for limited southern Italy areas in Diodato (2007) for the Campania region, Piccarreta *et al*. (2004) for the Basilicata region

and Cancelliere and Rossi (2003) and Cannarozzo *et al*. (2006) for the Sicily region.

The large variability in time and space requires that, for accurate unbiased results, long-term climate analyses be based on homogeneous data. A homogeneous climate data series is defined as one where variations are caused only by variations in weather and climate (Conrad and Pollak, 1950). Most long-term climatic series are affected by non-climatic factors indeed: changes in instruments, station location, station environment and so on make climate data unrepresentative of temporal climate variability. Inhomogeneities produce either sharp discontinuities or gradual bias in the data. Adjustments are needed to compensate for such a bias. A comprehensive review of direct and indirect homogeneity adjustments of climate data is given by Peterson *et al*. (1998). Direct methodologies, to test for data homogeneity, consist of station history metadata files inspection and studies of the effects of specific changes in instrumentation; indirect methodologies are instead mainly based on a number of statistical and graphical techniques to detect non-homogeneities.

The presented case study is a large area, of about $25\,000$ km², including the Campania region, in southern Italy. Available data consists of annual and monthly precipitation time series for 382 sites, from 1918 to 1999, analysed to detect potential trends and their significance. At first, the study deals with an analysis of data quality and time series homogeneity through direct and indirect methodologies, following some of the most reliable procedures recently proposed in the technical and scientific

* Correspondence to: Antonia Longobardi, Dipartimento di Ingegneria Civile, Università degli Studi di Salerno, 84084 Fisciano (SA), Italy. E-mail: alongobardi@unisa.it

literature (e.g. Szentimrey, 1999). The combination of changing points identification criteria by metadata inspection and statistical tests leads to the grouping of climate data in classes of different accuracy levels. Trend detection analysis is then performed through parametric and non-parametric tests only for high-level accuracy homogeneous data. The parametric t-test assesses whether the slope coefficient of the fitted linear regression is significantly different from zero, indicating the presence of a linear trend in this case. The slope coefficient sign would then indicate whether it is a positive or a negative trend. The Mann–Kendall non-parametric test would moreover confirm the existence of a positive or negative trend for a given confidence level. Trends are analysed both at the annual and at the seasonal scale. On the one hand, trends at the annual scale measure the inter-annual variability, which would have a negative or positive tendency. On the other hand, the implications of changes at the seasonal scale are particularly significant for water resource management processes related to seasonal cycles: as shown, for example, in Longobardi (2008), an intra-annual variability from season to season can be the determinant in soil moisture dynamics and consequently on soil water balances, especially in areas such as the Mediterranean basins, stressed by the combination of a dry climate and an excessive water demand.

In summary, the main objectives of this paper are

1. to combine direct and indirect methods for data homogeneity detection;
2. to analyse precipitation data accuracy and to group precipitation data into classes of different accuracy levels;
3. to test for parametric and non-parametric trends, both at the seasonal and annual scale, in high accuracy precipitation data classes.

Preliminary comments on the spatial pattern of rainfall trends are also given in a final discussion, where the authors attempt to illustrate potential correlations with the complex morphological features of the investigated region.

2. The database and time series homogeneity tests

Available data consist of annual and monthly precipitation time series for 382 sites, from 1918 to 1999, located across the Campania region and the Lazio region, southern Italy, covering a region of about 25 000 km^2. The source of data is the Servizio Idrografico e Mareografico Nazionale SIMN (1919–1999). A climate normal is defined by convention as the mean of the climatological variable over a 30-year period (WMO, 1989) and, to comply with this definition, the number of suitable sites included in this study was reduced to 211. Therefore, the record length ranges from 30 to 81 years. The location of the gauging stations and a digital elevation model of the studied area are shown in Figure 1.
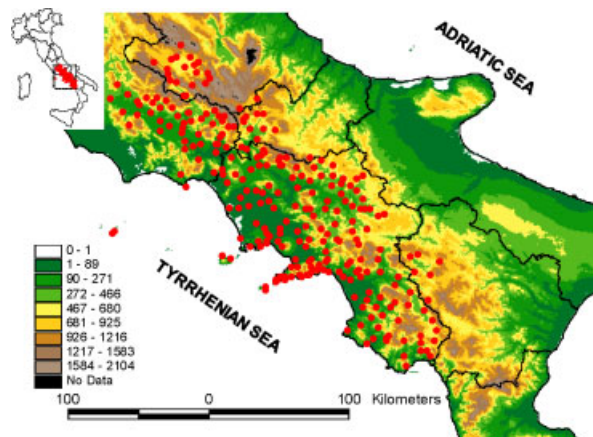

Figure 1. Case study area digital elevation model and database stations location. This figure is available in colour online at www.interscience.wiley.com/ijoc

Direct and indirect methods are combined in this study to test for annual rainfall data homogeneity: potential changing points, with a major change within the time series, are identified through metadata inspection, t-test and a modified Ward's method test. The grouping of time series in classes of different levels of accuracy is the result of homogeneity tests comparison. Time series classification is better explained in the following paragraphs.

2.1. Metadata inspection

As a preliminary step in any analysis of homogeneity, it is highly instructive to plot the time series on a linear scale. Plot visual inspection could reveal the existence of marked changes in the time series, which can be further investigated by statistical procedures. For the case study database, plot inspection immediately reveals the existence of missed data for some of the stations, however, with a limited extension in time. Failure in data collection and thus missed data has mainly occurred during the period 1940–1950, which is during and immediately after the Second World War. Even though missed data is not necessarily related to non-homogeneity, changing points could be contained within this period. Metadata inspection also indicated that a change in the gauge's height and/or location appears for a large number of stations around the year 1970, when an important revision occurred in the administrative organization of the SIMN. Further potential break points could then also occur around the year 1970.

2.2. The Student's t-test

The t-test (Hald, 1952; Panofsky and Brier, 1968) assesses whether the means of two groups are not statistically different from each other (null hypothesis H$_0$: $\mu_1 = \mu_2$). It can be performed both in the case of homogeneous (omoschedastic case) or non-homogeneous (eteroschedastic case) sample variances. In the eteroschedastic case (Welch test), if n_1 and n_2 are the

sample sizes and S_1 and S_2 are the sample variances, then the degree of freedom

$$\upsilon = \frac{\left[S_1^2/n_1 + S_2^2/n_2\right]^2}{\dfrac{\left(S_1^2/n_1\right)^2}{n_1 - 1} + \dfrac{\left(S_2^2/n_2\right)^2}{n_2 - 1}} \quad (1)$$

is always smaller than that in the omoschedastic case. This would entail that, for a given significance level, the critical region of the Welch test is wider than that corresponding to the Student's test and, consequently, that the null hypothesis (H$_0$: $\mu_1 = \mu_2$) is rejected for a smaller number of gauged stations. The omoschedastic test then represents the more conservative case, and therefore has been selected to assess data homogeneity.

If the variances in the two samples are assumed to be equal, the t-test statistic, which has a Student's distribution, is defined as

$$t_{n1,n2} = \frac{\overline{X}_1 - \overline{X}_2}{S} \sqrt{\frac{n_1 n_2}{n_1 + n_2}} \quad (2)$$

where n_1 and n_2 are the sample sizes, $\overline{X}_1$ and $\overline{X}_2$ are the respective sample means and S is the sample variance, calculated as

$$S = \sqrt{\frac{n_1 S_1^2 + n_2 S_2^2}{n_1 + n_2 - 2}} \quad (3)$$

If the calculated t value is above the threshold chosen for statistical significance (usually the 0.05 level), then the null hypothesis, H$_0$ ($\mu_1 = \mu_2$), that the two groups do not differ is rejected in favour of an alternative hypothesis, which states that the groups do differ (H$_a$: $\mu_1 \neq \mu_2$). The critical region for a given significance level α is $|t_{n1,n2}| \geq t_{(\alpha/2,\upsilon)}$ (two-tailed test), where υ is the degree of freedom, which is $\upsilon = n_1 + n_2 - 2$ for equal variances.

The t-test is applied supposing that each year of the monitored period could represent a potential changing point, thereby breaking the sample series into two sub-set series, whose size is n_1 and n_2 (with $n_1 + n_2$ equal to the total sample size) and calculating whether, for a given confidence level, differences between the sub-set series are significant or not.

2.3. A modified and simplified Ward's test

Ward's minimum variance method is the most used clustering technique in climate research (Kalkstein *et al.*, 1987). It calculates the means of all variables within each cluster, then calculates the Euclidean distance to the cluster mean of each case and finally sums across all cases, minimizing the within-cluster sum of squared distances. For a particular one-dimensional X random variable, assuming that it can be divided only into two sub-sets, whose sizes are n_1 and n_2, the deviance of the

process X, according to the Huygens decomposition, can be written as

$$\mathrm{dev}(X) = \sum_{i=1}^{n_1 + n_2} (X_i - \mu_X)^2$$

$$= \sum_{i=1}^{2} \sum_{j=1}^{n_i} (X_{i,j} - \mu_{X_j})^2 + \sum_{i=1}^{2} n_i (\mu_{X_i} - \mu_X)^2 \quad (4)$$

Therefore, a modified version of the Ward's technique is applied in this study: a maximum number of two clusters is allowed and the maximization of the second term of the second member of Equation (4), the Euclidean distance to the cluster mean of each case, is considered as the target. Maximization of the deviance between clustering groups corresponds to the maximization of differences between groups and thus to the minimization of within-cluster variability.

2.4. Homogeneity analysis results and groups classification

The rainfall time series homogeneity is tested through comparison of the three aforementioned approaches. Time series homogeneity can be clearly stated for some stations, but results are unclear in other cases: in some circumstances, metadata do indicate a break point but statistical methods do not (or vice versa), in some other cases statistical results are not in agreement, i.e. changing points indicated by the t-test and by the Ward's test do not occur at the same time. Because of such circumstances, we found it advisable to group database stations into classes of different levels of data accuracy, as indicated in Table I.

Class A and class B group the stations corresponding to homogeneous time series, for which the t-test does not reject the null hypothesis. If metadata do not indicate a changing point in the time series, then the corresponding station belongs to class A, otherwise to class B. Class A and class B are the highest-level data accuracy classes and correspond to the 76% of the whole database.

Class C and class D group the stations corresponding to the time series that cannot be clearly stated as being non-homogeneous. As a matter of fact, in these cases break points detected by the application of the t-test do not match (in time) break points detected by the application

Table I. Stations grouping and data accuracy classes.

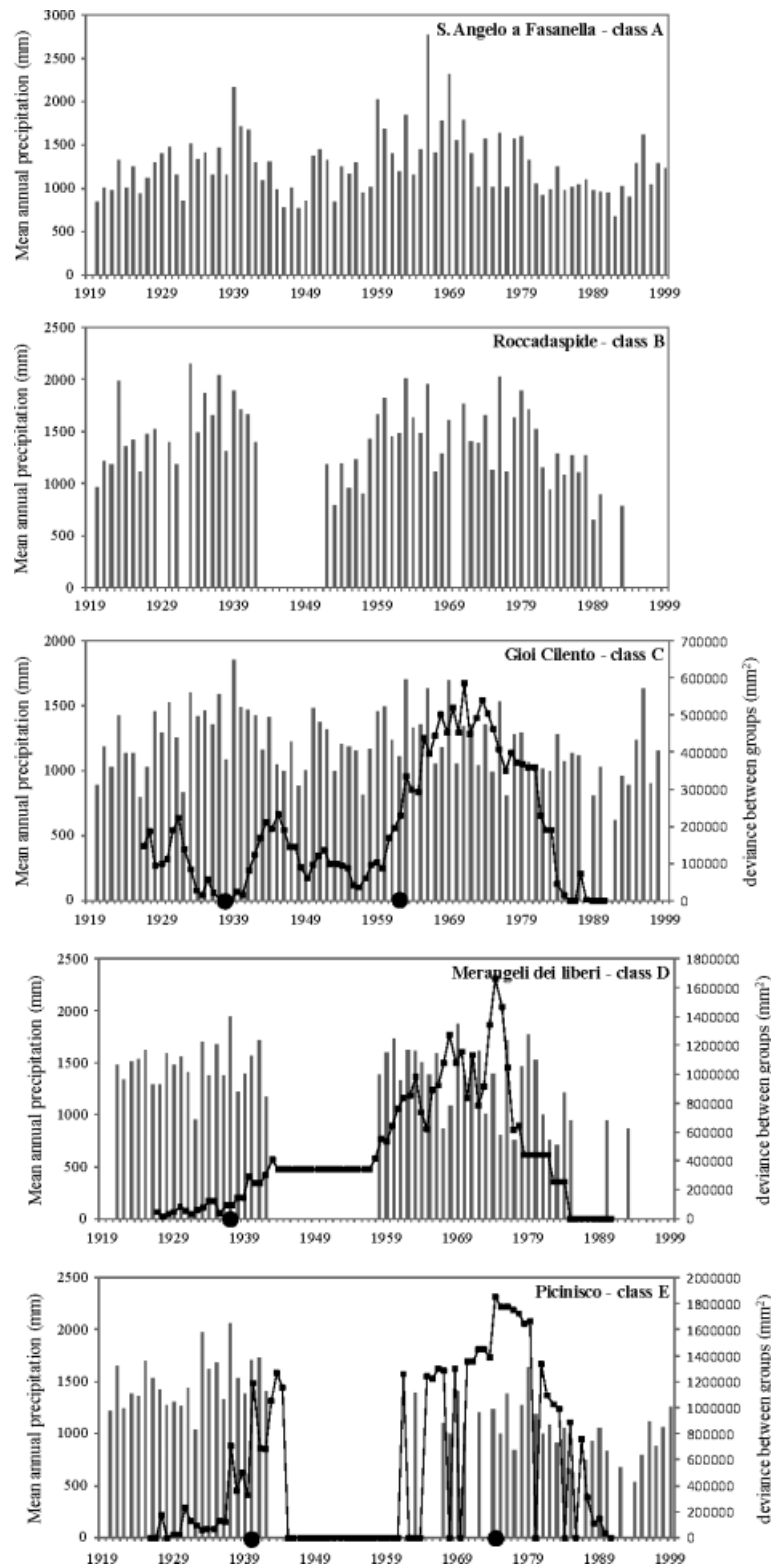| Classes	Changing points existence			Homogeneity	Number of Stations (in each group)
	Metadata	t-test	Ward's method		
A	No	No	No	Yes	54
B	Yes	No	No	Yes	106
C	No	Yes	No	?	11
D	Yes	Yes	No	?	31
E	Yes	Yes	Yes	No	9

Figure 2. Changing points detection methods comparison: *t*-test break points are marked with black circles; Ward's test break points are indicated by the occurrence of the deviance between groups maximum (relative or absolute).

of Ward's test. If metadata do not indicate a changing point in the time series, then the corresponding station belongs to class C, otherwise to class D.

Class E groups stations corresponding to the non-homogeneous time series. In these cases, a clear match between the *t*-test and Ward's test changing points is

detected. Class E is the least accuracy level data class and corresponds to the 4% of the whole database.

Examples of time series histograms of annual precipitation (grey bars) for stations belonging to different groups are given in Figure 2. In the same figure, the *t*-test changing points are indicated with a black circle, whereas

Ward's test changing points correspond to the occurrence of the maximization (absolute or relative) of the deviance between groups function, indicated with a black dotted line. No break points are indicated for class A and B stations as they correspond to the homogeneous series, as previously stated. The t-test break points are instead indicated for class C and D stations, but they do not match the timing of the deviance between groups' maximization. The t-test change points are also indicated for class E station and they match the timing of the deviance between groups' maximization.

3. Trend analysis

A trend is a significant change over time exhibited by a random variable, detectable by statistical parametric and non-parametric procedures. Onoz and Bayazit (2003) showed that the parametric t-test has less power than the non-parametric Mann–Kendall test when the probability distribution is skewed, but that, in practical applications, they can be used interchangeably, with identical results in most cases. With the aim of trend detection and cross verification, both parametric and non-parametric statistical procedures are applied to the precipitation time series grouped in the highest-level accuracy classes, A and B. The precipitation time series are aggregated in the annual time series and also in trimesters (spring, summer, autumn and winter) to further observe potential changes at the seasonal scale. Moreover, to quantify whether trends appear particularly severe during a particular time interval of the reference period, time series are also divided into the following three partially overlapping 30-year periods: 1918–1947, 1944–1973 and 1969–1999.

3.1. Student's t-test

The parametric test considers the linear regression of the random variable Y on time X. The regression coefficient β (or the Pearson correlation coefficient) is the interpolated regression line slope coefficient computed from the data. It is known that the statistic

$$t = \frac{\beta}{\sqrt{\dfrac{\sum \left(Y_i - \hat{Y}_i\right)^2}{(n-2)\sum \left(X_i - \overline{X}\right)^2}}} \tag{5}$$

follows the Student's t distribution with $n - 2$ degrees of freedom, where n is the sample size. The null hypothesis H_0: $\beta = 0$ (no trend) is tested against the hypothesis H_0: $\beta \neq 0$ at a chosen level of significance α. The hypothesis that there is no trend is rejected when the t value computed by Equation (5) is greater in absolute value than the critical value $t_{\alpha/2}$.

3.2. Mann–Kendall test

Mann (1945) presented a non-parametric test for randomness against time, which constitutes a particular application of Kendall's test for correlation commonly known as the 'Mann–Kendall' or the 'Kendall t test' (Kendall, 1962). Letting $X_1, X_2, \ldots, X_n$ be a sequence of measurements over time, Mann proposed to test the null hypothesis, H_0, that the data come from a population where the random variables are independent and identically distributed. The alternative hypothesis, H_1, is that the data follow a monotonic trend over time. Under H_0, the Mann–Kendall test statistic is

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(X_j - X_i) \tag{6}$$

where

$$\text{sgn}(\theta) = \begin{cases} +1 \ldots..\theta > 0 \\ 0 \ldots..\theta = 0 \\ -1 \ldots..\theta < 0 \end{cases} \tag{7}$$

Under the hypothesis of independent and randomly distributed random variables, when $n \geq 8$, the S statistic is approximately normally distributed, with zero mean and variance as follows:

$$\sigma^2 = \frac{n(n-1)(2n+5)}{18} \tag{8}$$

As a consequence, the standardized Z statistics follow a normal standardized distribution:

$$Z = \begin{cases} \dfrac{S-1}{\sigma} & if \quad S > 0 \\ 0 & if \quad S = 0 \\ \dfrac{S+1}{\sigma} & if \quad S < 0 \end{cases} \tag{9}$$

The hypothesis that there is no trend is rejected when the Z value computed by Equation (9) is greater in absolute value than the critical value Z_α, at a chosen level of significance α.

3.3. Trend analysis results

As for the identification of time series changing points, a preliminary graphical inspection is highly instructive and meaningful. The annual rainfall time series, averaged over the whole dataset, is illustrated in Figure 3. The corresponding interpolated regression line is also plotted. The variability around the mean value, that is about 1200 mm, is rather pronounced, despite the smoothing effect induced by the average computation over a large area, and a decrease in the annual average rainfall is evident, given the slope of the regression line. The slope of the yearly time series is about -35 mm/10 years, giving an estimated decrease of about 280 mm in the period 1918–1999, which corresponds to about 23% of the annual value, according to previous results found in similar geographical and climatic contexts. Annual time series histograms show similar trend patterns for the most part of meteorological stations, in agreement with the t-test and Mann–Kendall test results (Table II) where the percentage of stations with a significant positive or negative trend is reported for 99, 95 and 90% confidence levels.
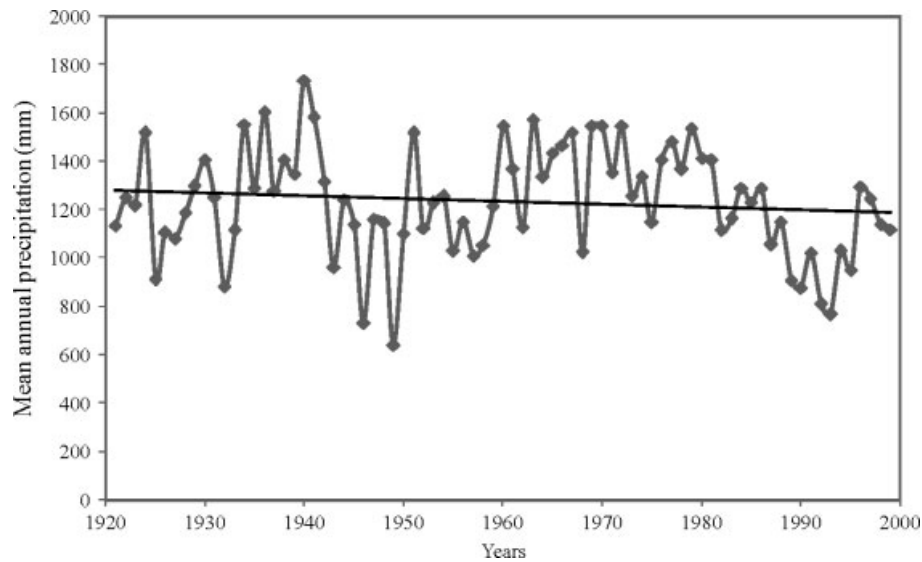
Figure 3. Annual precipitation time series and corresponding interpolated regression line. In this picture, the time series (from 1918 to 1999) of the average over the most reliable datasets (class A and class B) is illustrated.

Table II. Percentage of stations with a significant positive or negative trends (Mann–Kendall test).

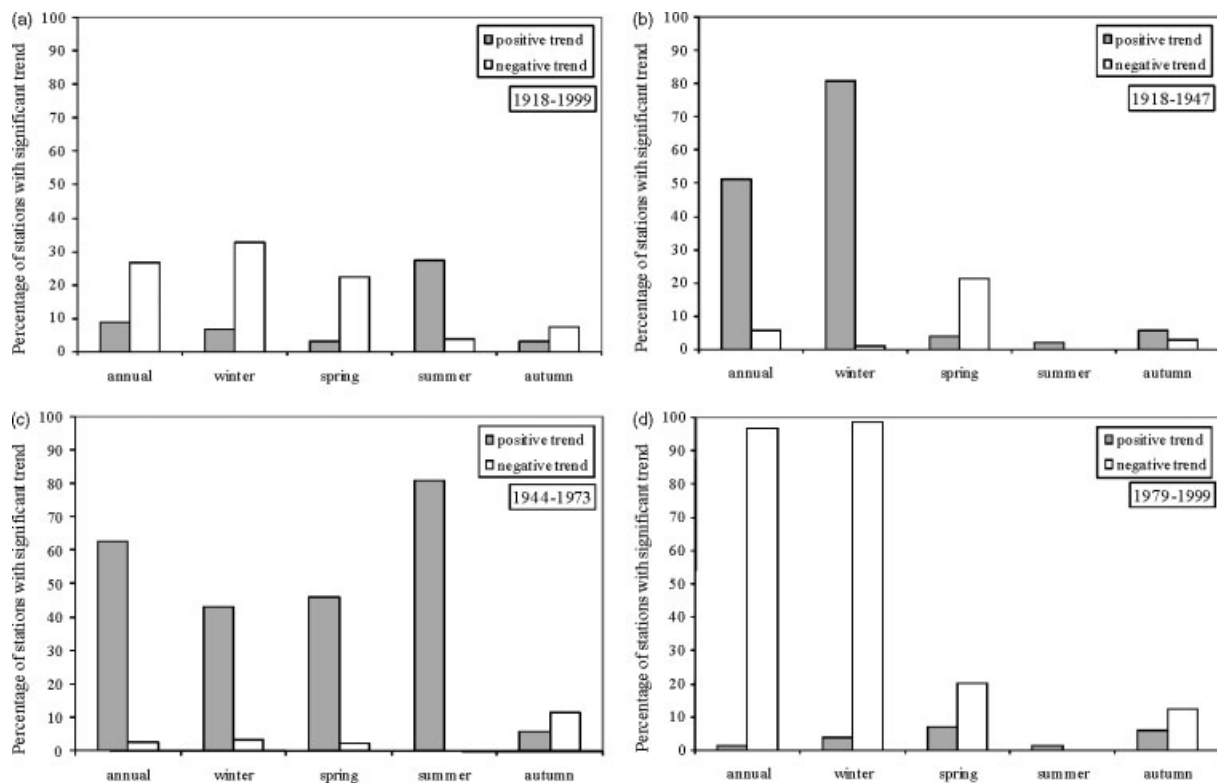|	Positive trend			Negative trend		
α	0.01	0.05	0.1	0.01	0.05	0.1
Annual	1	3	9	8	16	27
Winter	1	2	7	7	22	33
Spring	0	1	3	3	13	23
Summer	3	18	27	1	2	4
Autumn	0	3	3	1	3	8

Figure 4. Mann–Kendall test results for positive and negative trend detection ($\alpha = 0.1$) over the most reliable datasets (class A and class B).

Table III. Percentage of stations with a significant positive or negative trend during periods 1918–1947, 1944–1973 and 1969–1999 (Mann–Kendall test).

α	1918–1947						1944–1973						1969–1999					
	Positive trend			Negative trend			Positive trend			Negative trend			Positive trend			Negative trend		
	0.01	0.05	0.1	0.01	0.05	0.1	0.01	0.05	0.1	0.01	0.05	0.1	0.01	0.05	0.1	0.01	0.05	0.1
Annual	13	38	51	1	5	6	17	51	63	0	1	2	2	2	2	51	83	97
Winter	23	59	81	0	0	1	5	23	43	0	1	3	4	4	4	34	88	99
Spring	0	2	4	1	11	21	16	29	46	0	2	2	1	5	7	1	7	20
Summer	0	0	2	0	0	0	25	65	81	0	0	0	0	1	1	11	0	0
Autumn	0	3	6	0	1	3	1	4	6	0	3	11	0	2	6	0	4	12

During the period 1918–1999, negative trends are evident both at the annual and seasonal scale, excluding the summer trimester when a positive trend can be observed. The percentage of stations showing a significant trend is however moderate, coming to a maximum of 27% at the annual scale, and at 33 and 4% respectively during the winter and summer trimesters ($\alpha = 0.1$, Figure 4).

The magnitude of the trends are instead stressed and highly significant in particular time intervals of the reference period, as indicated in corresponding t-test and Mann–Kendall test results (Table III). The period from 1944–1973 shows a generalized positive trend throughout the year, with a large number of stations with significant trends coming to a maximum of 81% during the summer season ($\alpha = 0.1$). The periods from 1969–1999 shows instead a negative trend, which is particularly evident during the winter season, with a significant trend at the 90% confidence level for almost all of the time series ($\alpha = 0.1$, Figure 4).

The combined existence of positive and negative trends, along with the differences in the results referred to the particular observed time interval, does not allow to draw conclusions of a general tendency for the investigated large-scale area. Illustrated analyses describe the empirical evidences of potential dynamics in cumulate, annual and seasonal precipitation, and they have been applied at the point scale to each gauged site selected according to the introduced homogenization procedure. But a thorough investigation of the involved physical processes is required. A preliminary analysis of the spatial variability of the observed trend parameters is proposed in the following.

3.4. Preliminary findings on spatial variability

To investigate the observed spatial variability of the annual precipitation trend, the regression line slope for point data and the inverse distance weight (IDW) method, one of the simplest interpolation techniques, have been selected to obtain the map illustrated in Figure 5. It indicates the mean annual precipitation reduction (negative trend) or increase (positive trend) throughout the region. As previously commented, a negative trend is remarkable over the whole area, but the description of its spatial pattern appears complex, even in a preliminary analysis. A severe negative trend

can be clearly observed over large areas, apparently corresponding to the main reliefs of the region, running north-west to south-east (Figure 1). This circumstance indicates that, for the presented case study, rainfall spatial variability and consequently corresponding trends investigation cannot neglect the interaction between the complex territory morphology.

In fact, in a previous study at the regional scale (Longobardi *et al.*, 2006), concerning a wider area compared to that investigated in this paper and a mean annual precipitation database, the authors found that rainfall variability is strongly affected by the presence of mountain ranges. Figure 6(a) reports some results of the mentioned study, illustrating the mean annual rainfall map obtained using a geo-statistical interpolation technique. Considering a generic transect area (Figure 6(a), red rectangle), it was observed that the mean annual precipitation pattern follows the orography pattern because of the important barrier effect caused by the presence of mountain ranges located along the transect area. Similar features can be noted if the rainfall trend pattern is commented upon. Figure 6(b) illustrates, moving south-west towards north-east, the transect elevation and, for each of the gauged stations located within this area, the corresponding negative
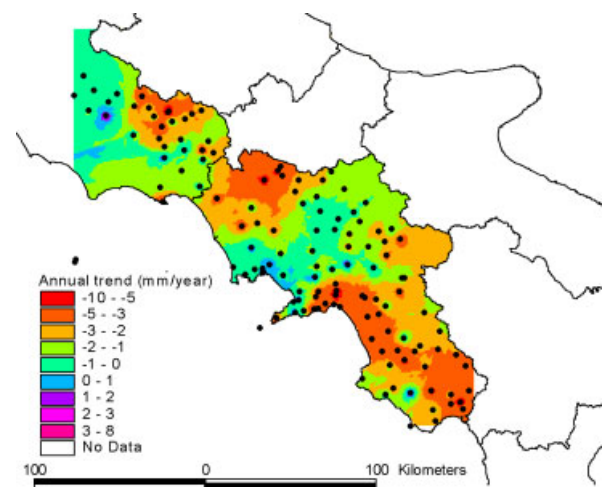

Figure 5. Map of mean annual precipitation reduction (negative trend, red colour scale) or increase (positive trend, blue colour scale) in millimetres per year. This figure is available in colour online at www.interscience.wiley.com/ijoc
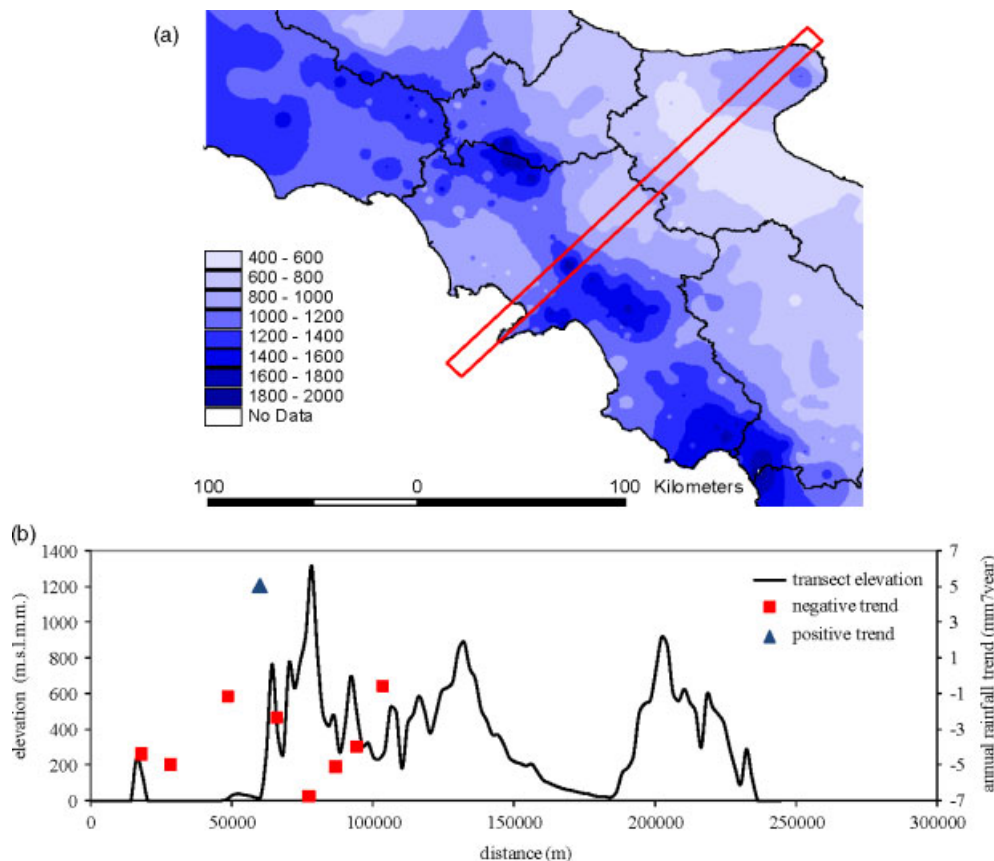
Figure 6. (a) Mean annual precipitation map (mm); (b) digital elevation model along the red rectangle transect, gauged stations location and corresponding observed mean annual rainfall reduction (negative trend, red colour) or increase (positive trend, blue colour) in millimetres per year. This figure is available in colour online at www.interscience.wiley.com/ijoc

(red squares) and positive (blue triangles) trend intensity. Larger negative trends match the highest elevations, but the interaction with territory morphology is not obvious, probably because of different reasons. First of all, the lack in point data, along the transect direction, sets a boundary and prevents the identification of involved physical processes. A spatial extension of the database would be necessary is this sense. In addition, it has to be noted that meteorological events relevant to the studied region have different geographical origins and, in some cases, are not affected by the presence of orographic barriers. From this point of view, precipitation variability over the studied area also has to be read in a context of synoptic type events assessment, as illustrated in some recent studies concerning the Mediterranean basin (Millán *et al.*, 2005), through the identification of the geographical origin and of the relative importance of different meteorological events. To this aim, the database should be extended both in space and time, that is, the temporal variability (time series) of a number of additional meteorological stations have to be collected.

4. Conclusion

The aim of the present study was to analyse rainfall time series, detecting potential trends and assessing their significance over a wide area of about 25 000 km^2 in

southern Italy, and over a wide time interval (1918–1999). To this purpose, climatic data have been preliminarily tested for data homogeneity and consequently grouped into classes of different accuracy levels. Only the most accurate level time series, which represents 76% of the whole database, were tested for trend detection, both at the annual and seasonal scale, performed by parametric *t*-test and the non-parametric Mann–Kendall test. According to some recent studies, concerning both geographical contiguous areas and a global geographical context, it has been found that, at the annual scale, the studied region is experiencing a negative trend, whereas at a seasonal scale a positive trend during the summer trimester is also remarkable. Detected trends appear extremely severe during the last 30 years, when they are significant for almost 97% of the meteorological stations.

At this step of the research, the authors advise the need for more information for a comprehensive analysis. Even though a large number of stations show a significant negative trend in cumulate precipitation, a positive trend has also been reported for a limited number of gauged sites. If the existence of a negative or a positive trend cannot be related to specific site features and to their relationships with different meteorological event types, then it could be assumed that the cumulate precipitation reduction or increase, at a particular site, is the result of a statistical variability. In this case, more sophisticated

geostatistical techniques, rather than simple IDW, should be applied to capture the spatial variability and to interpolate positive and negative trends. This circumstance could also lead to the conclusion that, over the study area, the estimated yearly precipitation rate of reduction would be indeed smoother. Furthermore, fluctuation during the period 1940–1950, which was one of the driest ever experienced, at least for an Italian context, has also to be further investigated to better explain the trend over the whole period.

To this aim, further perspectives of the research, which are currently in progress, would require the following:

1. A spatial extension of the database to cover the whole region between the Tyrrhenian and the Adriatic coastlines, performing the proposed homogenization procedures and data quality analysis. The database spatial extension is an important requirement for the following point '3'. as the importance of the identification and selection of dominant meteorological events having different geographical origins has been observed for the study region.
2. The improvement of a rainfall spatial variability model, accounting for non-linear effects induced by complex morphological features.
3. The total rainfall disaggregation into daily precipitation to make the identification of different meteorological events type possible, to assess their spatial and temporal characteristics and their dynamics on a temporal base.

Acknowledgements

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