Analysis of spatial and temporal rainfall trends in Sicily during the 1921–2012 period

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Abstract Precipitation patterns worldwide are changing under the effects of global warming. The impacts of these changes could dramatically affect the hydrological cycle and, consequently, the availability of water resources. In order to improve the quality and reliability of forecasting models, it is important to analyse historical precipitation data to account for possible future changes. For these reasons, a large number of studies have recently been carried out with the aim of investigating the existence of statistically significant trends in precipitation at different spatial and temporal scales. In this paper, the existence of statistically significant trends in rainfall from observational datasets, which were measured by 245 rain gauges over Sicily (Italy) during the 1921–2012 period, was investigated. Annual, seasonal and monthly time series were examined using the Mann–Kendall non-parametric statistical test to detect statistically significant trends at local and regional scales, and their significance levels were assessed. Prior to the application of the Mann–Kendall test, the historical dataset was completed using a geostatistical spatial interpolation technique, the residual ordinary kriging, and then processed to remove the influence of serial correlation on the test results, applying the procedure of trend-free pre-whitening. Once the trends at each site were identified, the spatial patterns of the detected trends were examined using spatial interpolation techniques. Furthermore, focusing on the 30 years from 1981 to 2012, the trend analysis was repeated with the aim of detecting short-term trends or possible changes in the direction of the trends. Finally, the effect of climate change on the seasonal distribution of rainfall during the year was investigated by analysing the trend in the precipitation concentration index. The application of the Mann–Kendall test to the rainfall data provided evidence of a general decrease in precipitation in Sicily during the 1921–2012 period. Downward trends frequently occurred during the autumn and winter months. However, an increase in total annual precipitation was detected during the period from 1981 to 2012.

1 Introduction

Spatial and temporal variations in temperature and precipitation are likely the most evident effects of the changes occurring in the Earth's climate system. According to the latest report by the Intergovernmental Panel on Climate Change (IPCC 2013), mean global surface temperature increased and one of the most significant consequences of this increase may be the alteration of the hydrological cycle at global and local scales (Held and Soden 2000; Arnell et al. 2001). Indeed, the rising atmospheric moisture content associated with warming might be expected to generate an increase in mean global precipitation (Trenberth 1998; Jones et al. 1999). Based on global averages, precipitation over land increased by approximately 2 % during the 1900–1998 period (Dai et al. 1997; Hulme et al. 1998), but regional variations are highly significant. Precipitation has generally increased over land north of 30°N over the period 1900–2005, while downward trends dominate the tropics since the 1970s (IPCC 2013).

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The international literature includes several studies of rainfall trends that were carried out at different temporal scales, from daily to annual, and in different areas of the world. Also, methodologies used in these studies are different. Cheung et al. (2008) examined change in rainfall using data for the period 1960–2002 from 13 watersheds in Ethiopia. By regressing annual watershed rainfall on time, results from the one-sample t test showed no significant changes in rainfall for any of the watersheds examined. Beside parametric test, such as the t test, non-parametric techniques are widely diffused for trend analysis. Luo et al. (2014) analysed the variability of precipitation in the Haihe River Basin (China) through the rank-based non-parametric Mann–Kendall statistical test, finding a general decreasing trend. In India, Kundu et al. (2014) investigated on the presence of trend in rainfall series recorded from 1871 to 2011, applying the Mann–Kendall test and Sen's slope. Results showed a decrease in rainfall magnitude in most of the series.

Regarding the Mediterranean region, some studies highlighted the presence of a general negative trend in precipitation, although the western area of the Mediterranean Basin is marked by an increase in the number of rainy days and the intensity of precipitation (Esteban-Parra et al. 1998; Luis et al. 2000). Piervitali et al. (1998) found a negative trend in precipitation in the Mediterranean Basin during the 1950s. In northern Europe, mean annual precipitation showed a 2 % increase during the period from 1990 to 2000, while in the South, precipitation decreased by 20 % (Klein Tank et al. 2002). Despite a reduction in mean annual rainfall, heavy precipitation events increased for large parts of the Mediterranean area (Alpert et al. 2002; Brunetti et al. 2004; Maheras et al. 2004). A direct consequence of these trends is the increase in the occurrence of extreme events, such as floods due to extreme storms and droughts due to longer dry periods. More recently, Norrant and Douguédroit (2006) used monthly and daily records from 63 weather stations in the Mediterranean to examine several precipitation indices and found a few negative trends during the winter months.

Rodrigo and Trigo (2007) analysed 22 sites of daily precipitation records over the period 1951–2002 for the Iberian Peninsula, using the Mann–Kendall statistic and a linear regression model. Moreover, the difference between the means of two subperiods was examined applying a t test. More recently, Karpouzos et al. (2010) investigated the temporal variability of precipitation over the period 1974–2007 in an area located in Northern Greece. In this study, different methodologies were applied to detect changes in annual, monthly and seasonal precipitation, including tests for monotonic trend (Mann–Kendall test, sequential version of the Mann–Kendall test, Sen's estimator of slope) and a test for step change (the distribution-free CUSUM test). Results showed a significant decrease of precipitation in spring.

In Italy, a decrease in precipitation occurred over the last 50 years that has mainly affected the southern areas (Brunetti et al. 2006; Diodato 2007; Longobardi and Villani 2010; Ferrari et al. 2013). Polemio and Casarano (2008) found that precipitation in Southern Italy decreased during the 1821–2001 period. Annual moving averages showed that minimum values were reached during the periods from 1989 to 1991 and 1999 to 2001. This negative trend is especially apparent for winter precipitation.

With regard to Sicily, Cannarozzo et al. (2006) applied the Mann–Kendall test in order to verify the existence of trend in annual, seasonal and monthly rainfall in 247 rain gauge stations in Sicily (Italy) during the 1921–2000 period. Results showed the existence of a generalised negative trend for the entire region; nevertheless, in this analysis, the effect of serial correlation of data on test results was not taken into account.

With the aim of investigating the existence of trends in historical data, this study focused on total annual, seasonal and monthly rainfall series recorded by 245 rain gauges during the 1921–2012 period in Sicily. The non-parametric Mann–Kendall test was used to identify statistically significant trends in these series. The trend analysis was carried out at the local and regional scale with significance level α equal to 0.1, 0.05 and 0.01. The dataset was first processed to remove the influence of serial correlation on the test results.

Once trends were detected, a spatial interpolation technique was used to investigate on spatial distribution of trends in Sicily. The trend analysis was then carried out, focusing on the last 30 years of the dataset (1981–2012), to identify the changes in the direction of the trends in the most recent decades. The study also evaluated the precipitation concentration index (PCI) and its variations during the periods under examination. The use of this index is quite frequent in several countries (e.g. Apaydin et al. 2006; Luis et al. 2011) and also in Italy and, in particular, in the southern regions (Cannarozzo et al. 2006). The analysis of the PCI values proved to be useful to investigate changes in the temporal distribution of rainfall during the year.

2 Dataset

Sicily, the area of study, is an island of approximately 25, 700 km^2, located in southern Italy and characterised by a Mediterranean climate with mild winters and hot, generally dry summers; the climate is mainly influenced by hot winds blowing from the North African coast (Sirocco). The total annual precipitation in the area ranges from 400 mm/year at lower elevations to 1300 mm/year at higher elevations. The mean annual temperature varies between 10.8 and 18.9 °C, and the highest values (18.5–19.5 °C) are located along the coast, while the lowest values (10.5–13.5 °C) are characteristic of the highest elevations.

Historical rainfall series for the period from 1921 to 2012, measured by 245 rain gauges across Sicily (Fig. 1), have been provided by the *Osservatorio delle Acque - Agenzia Regionale per i Rifiuti e le Acque* (*OA-ARRA*) of Sicily.

A preliminary examination of the monthly rainfall series showed that approximately 20 % of the total number of monthly values is missing. Because the investigation of rainfall trends requires homogeneous and complete series covering the entire period of analysis, a method of spatial interpolation, hereafter described, was used to create a complete dataset. Once a complete dataset of monthly rainfall was achieved, data were aggregated at annual and seasonal scales. Seasons were defined as follows: autumn included September, October and November; winter included December, January and February; spring included March, April and May; and summer included June, July and August.

3 Methods

3.1 Spatial interpolation of precipitation data

The use of discontinuous time series in the trend analysis of hydrometeorological variables could lead to unreliable results and errors. For this reason, the reconstruction of missing data, before performing any statistical test, is essential to verify the existence of a trend.

In this study, the evaluation of missing data was carried out at the monthly scale using a procedure based on a geostatistical spatial interpolation technique, the residual ordinary kriging (Odeh et al. 1995). Good performances of this method were reported by Goovaerts (2000), Lopez-Granados et al. (2002) and Takata et al. (2007). The residual ordinary kriging allows the separation of the two different types of spatial variability, i.e. deterministic (trend) and stochastic. Stochastic variability may be further categorised into spatially dependent and spatially independent components. The spatially dependent component is generally evaluated through a variogram, which must be determined, while the spatially independent component is linked with measurement imprecision, which is relatively small and almost indistinguishable from the measurement. Therefore, if x is a location in the area of study, the rainfall at x, $P(x)$, can be evaluated with the following expression:

$$P(x) = m(x) + \varepsilon(x), \tag{1}$$

where $m(x)$ is the deterministic component, and $\varepsilon(x)$ is the spatially dependent stochastic component. In this study, the residual ordinary kriging was applied on a monthly basis in accordance with the following steps:

- Evaluation of the deterministic component, $m(x)$, using a geographically weighted regression;
- Determination of the stochastic component, $\varepsilon(x)$ (residuals);
- Application of the ordinary kriging to the residuals;
- Estimation of the rainfall data as the sum of the deterministic component and the stochastic component.

Fig. 1 Location of rain gauges and mean total annual precipitation over the 1921–2012 period
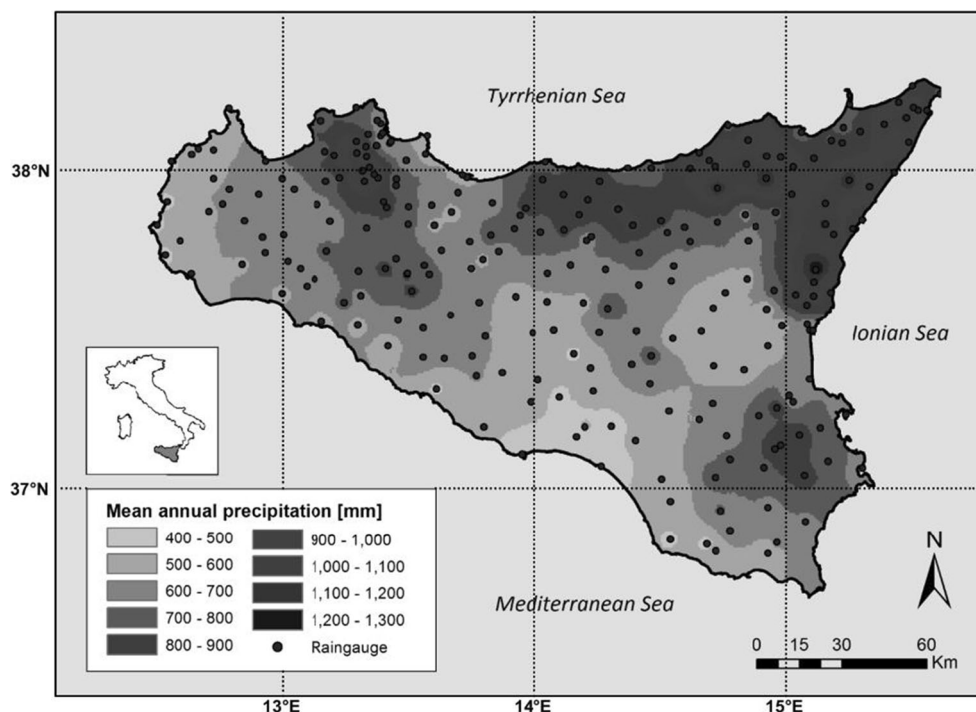
The result of the procedure is a complete dataset that includes all the monthly precipitation data for each station for the 1921–2012 period. Specifically, for each rain gauge, working or not working, the annual and monthly precipitation was estimated through the geographically weighted regression. For the working rain gauges, the estimate was compared with the measured data to determine the residual. Subsequently, the dataset was examined again, and the missing data were estimated as sum of the precipitation values determined by the regression and the residuals. The residuals, where the rain gauges did not worked, were not known; therefore, they were obtained by performing an interpolation through the ordinary kriging of the calculated residuals. The parameters of the geographically weighted regression were estimated for each month. Similarly, a spherical semi-variogram for each month was used to describe the variability of the measure with location.

The root mean square errors and the standard deviations obtained in the estimation of monthly rainfall by residual ordinary kriging resulted to be lower than those produced by other methods, such as inverse distance weighted, ordinary kriging and multiple linear regression. In a previous study (Bono et al. 2005), this methodology was applied and validated for Sicily, providing a complete dataset of monthly rainfall for the 1921–2000 period.

3.2 Precipitation concentration index

The spatial and temporal variability of rainfall is an important component to understand the water balance dynamics at different scales for water resources management and planning. In a watershed, the homogeneity of water supply increases with decreasing spatial variability of rainfall, and water supply is more perennial when the rainfall is less variable in time (Kawachi et al. 2001). The analysis of temporal and spatial variability of rainfall was performed over the years by means of coefficients and indexes formulated for information theory or economic sciences. Among these, the Shannon entropy (Shannon 1948) and the Gini coefficient (Gini 1921) are the most frequently used also in hydrological applications.

The modification of the Gibbs–Martin index of employment diversification (Gibbs and Martin 1962) provided to Oliver (1980) a specific index aimed to precipitation analysis, the precipitation concentration index (PCI). This index was introduced to analyse the monthly heterogeneity in the amount of rainfall over the year and represents a powerful indicator of the temporal distribution of precipitation. The PCI is one of the most used tool to assess the pluvial regime of a given location as shown by the number of applications in literature (e.g. Luis et al. 2000; Cannarozzo et al. 2006).

In this study, the PCI was calculated on an annual scale for each rain gauge according to the following equation:

$$\text{PCI} = \frac{\sum\limits_{i=1}^{12} p_i^2}{\left(\sum\limits_{i=1}^{12} p_i\right)^2} \cdot 100, \tag{2}$$

where p_i is the monthly precipitation in month i. As described by Oliver (1980), PCI values below 10 indicate uniformity in the distribution of monthly rainfall throughout the year, while values ranging from 11 to 20 denote seasonality. Values of PCI above 20 represent a strong irregularity of precipitation distribution (i.e. high precipitation concentration).

3.3 Detection of trends in hydrometeorological variables

Several statistical procedures can be used to detect trends, particularly parametric and non-parametric tests. In this study, the non-parametric Mann–Kendall test for trend detection (Kendall 1962; Mann 1945) was used. This test identifies the presence of a trend without making an assumption about the properties of the distribution. Moreover, non-parametric methods are less influenced by the presence of outliers. In a trend test, the null hypothesis, H_0, is that there is no trend in the population from which the data are drawn, while hypothesis H_1 is that there is a trend in the records. The test statistic, Kendall's S (Kendall 1962), is calculated as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sign}\left(y_j - y_i\right), \tag{3}$$

where y are the data values at times i and j, n is the length of the dataset, and sign() is the sign function (for full test description see Helsel and Hirsch 1992).

Local significance levels (p values) for each trend test can be obtained from the following relationship:

$$p = 2 \cdot [1 - \Phi(|Z_S|)], \tag{4}$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of a standard normal variate and Z_S is the standardised test statistic.

The magnitude of the trends was evaluated using a non-parametric, robust estimate determined by Hirsch et al. (1982):

$$\beta = \text{Median}\left(\frac{x_j - x_l}{j - l}\right) \qquad \forall \ l < j, \tag{5}$$

where x_l is the l-th observation.

The convenience to inquire on the presence of long-term tendency in a series, without having to make an assumption

about its distributional properties, made the test one of the most frequently used methodology for trend analysis. Nevertheless, the test has the disadvantage to being applicable to univariate data. Moreover, the use of the test requires the availability of long and continuous series. For these reasons, in recent years, a great number of alternative approaches based on the Bayesian inference was developed and applied (Korecha et al. 2007; Tebaldi and Sansò 2009; Kim et al. 2009). Indeed, these methodologies can deal with incomplete datasets in trend analysis, taking advantage from the improvement of estimates precision due to the inclusion of informative prior knowledge (Coles and Tawn 1996). In spite of these advantages, the development of Bayesian models used to be limited by numerical difficulties (Renard et al. 2006).

3.4 Regional test for trend

The detection of a regional trend in a hydrometeorological variable can be assessed by the following expression:

$$S_m = \frac{1}{m} \sum_{i=1}^{m} S_k, \qquad (6)$$

where $S_k{}^k$ is the value of Kendall's S statistic in the kth rain gauge in a region with m rain gauges. If the rain gauges are not correlated spatially, the standardised test statistic can be calculated as described by Douglas et al. (2000).

According to Lettenmaier et al. (1994), the spatial cross-correlation of data affects the result of a regional Mann–Kendall test by increasing the expected number of trends. Livezey and Chen (1983) highlighted the need to consider the field significance of the outcomes from a set of statistical tests. To determine the field significance of the regional value of Mann–Kendall statistics, Douglas et al. (2000) adopted a bootstrap resampling approach. This technique, described by Efron (1979), was used in this analysis to determine the critical value for the percentage of stations expected to show a trend by chance. Specifically, the bootstrap method has been used to determine the cumulative distribution function of the statistic S_m in Sicily and the associated field significance. The bootstrap procedure can be briefly summarised by the following steps (Burn and Hag Elnur 2002):

1) Extract 1 year from the time series;
2) For each station, collect rainfall data for that year;
3) Repeat step 1 and 2 until a new dataset, with the same dimensions as the original, is generated;
4) Calculate the statistic S_m for the new dataset;
5) Repeat the above steps for a number of times N to obtain N values of S_m and use the N value of S_m to define the cumulative distribution function.

In this analysis, N was set equal to 1000. The empirical cumulative distribution function (ecdf) of S_m was obtained by ranking the 1000 values of S_m in ascending order and assigning a non-exceedance probability using the Weibull plotting position formula:

$$F\left(S_{m,i}\right) = \frac{i}{1+N} \qquad i = 1, ..., N, \qquad (7)$$

The ecdf allows the definition of the level of significance associated with each value of S_m. The null hypothesis is accepted when this level of significance is lower than a fixed value.

3.5 Influence of serial correlation in the analysis of trends

To assess the extent of serial correlation in the precipitation and temperature data, the lag-1 serial correlation coefficients were evaluated, and the empirical cumulative distribution function, ecdf, was subsequently assessed. The ecdf (Fig. 2) shows that 50 % of the data has a serial correlation coefficient ranging between 0.35 and 0.46. The presence of serial correlation at lags greater than 1 was analysed as well. As shown in Fig. 2, the values of the serial correlation coefficient progressively decrease from lag-1 to lag-3. Specifically, in the case of lag-2, the ecdf shows that the 50 % of the data has a serial correlation coefficient ranging between 0.15 and 0.25; this range is equal to $-0.02 \div 0.04$ for serial correlation at lag-3.

The application of the Mann–Kendall test requires the assumption that data are serially independent. However, hydrological time series frequently exhibit statistically significant serial correlations. A study carried out by von Storch (1995) showed that a positive serial correlation increases the probability that the test will detect a trend when it does not exist; this
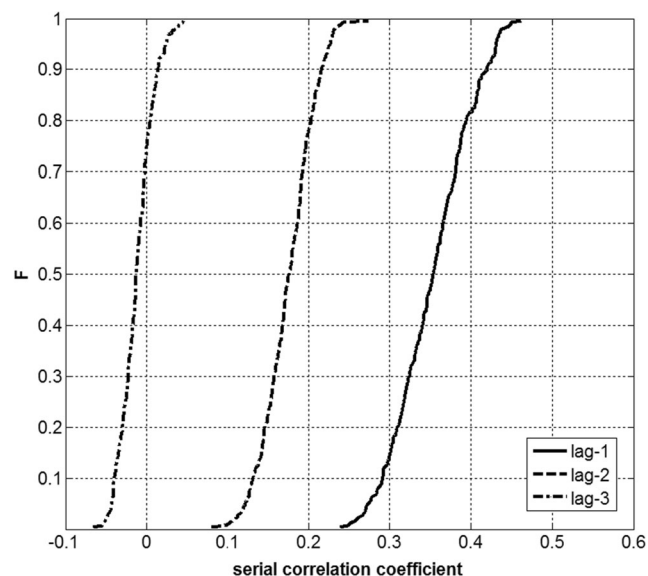

Fig. 2 Empirical cumulative distribution function (ecdf) of lag-1, lag-2 and lag-3 serial correlation coefficients for monthly precipitation

leads to the rejection of the null hypothesis of no trend. For this reason, the authors proposed a procedure called *pre-whitening*, which removes the serial correlation, assuming a lag-1 autoregressive (AR(1)) model, and then applies the Mann–Kendall test to the serially independent residuals. According to Yue and Wang (2002), the *pre-whitening* procedure eliminates the serial correlation effect in the Mann–Kendall test, but at the same time, it disadvantageously removes a portion (equal to the lag-1 autocorrelation coefficient) of the trend from the series and thus reduces the probability of rejecting the null hypothesis when it is false. Because the *pre-whitening* procedure for eliminating the serial correlation effect in the Mann–Kendall test could lead to a potentially inaccurate assessment of the significance of a trend, an alternative method proposed by Yue et al. (2002) was applied in this study. The procedure, called trend-free pre-whitening (TFPW), assumes that a hydrological time series can be represented by a linear trend and an AR(1) component with noise and is summarised by the following steps:

1) The magnitude of the trend is evaluated using Eq (5), as proposed by Hirsch et al. (1982). If β is almost equal to zero, it is not necessary to continue to conduct trend analysis because no trend exists. If it differs from zero, the trend is assumed to be linear, and the sample data are detrended using the expression:

$$X'_t = X_t - T_t = X_t - \beta t, \tag{8}$$

where X_t is the value of the series at time t.

2) The lag-1 serial correlation coefficient, ρ_1, of the detrended series, X'_t, is calculated using the expression proposed by Salas et al. (1980), and the AR(1) is then removed from X'_t as follows:

$$Y'_t = X'_t - \rho_1 X'_{t-1}, \tag{9}$$

After applying the TFPW procedure, the residual series should be an independent series.

3) The identified trend, T_t, and the residuals, Y'_t, are combined by

$$Y_t = Y'_t + T_t, \tag{10}$$

The Y_t series could preserve the true trend and is no longer influenced by the effects of autocorrelation.

4) The Mann–Kendall test is then applied to the Y_t series to assess the significance of the trend.

The TFPW approach provides an improved assessment of the significance of trend using the Mann–Kendall test, as

described by Yue et al. (2002). Nevertheless, the procedure removes only lag-1 autocorrelation; therefore, it could be insufficient to remove the entire influence of serial correlation. Whenever a serial correlation at lags greater than 1 is present in data, other methodologies should be applied. For example, Hamed and Rao (1998) proposed a modified Mann–Kendall test based to eliminate the effects of autocorrelation, using the modified variance of the Mann–Kendall statistic to replace the original one, if the lag-i autocorrelation coefficients were significantly different from zero at the 5 % level.

For the case of study presented here, the effects of lag-2 and lag-3 serial correlation on the Mann–Kendall test results can be neglected due to the lower values of serial correlation coefficients (Fig. 2).

4 Results and discussion

4.1 Annual, seasonal and monthly local rainfall trends

The results of the Mann–Kendall test revealed that total annual precipitation was mostly affected by negative trends during the 1921–2012 period. Figure 3 illustrates these results. As measured in 57.1 % (140), 49.8 % (122) and 35.5 % (87) of the rain gauges, annual rainfall significantly decreased for α equal to 0.1, 0.05 and 0.01, respectively. Positive trends were detected in a small number of series; 3.7 % of the series (9 rain gauges) experienced an increase for $\alpha = 0.1$. At the same significance level, no trends were found in 39.2 % of the rain gauges (96). The magnitudes β of the negative trends ranged from −5.3 to −0.5 mm/year, and the magnitudes of the positive trends varied in the range of 0.7 ÷ 3.4 mm/year. Figure 4 shows the total annual rainfall and the relative trends for the rain gauges in which the positive and negative trends with the highest values of β were detected (Linguaglossa and Buccheri with β equal to 3.4 and −5.3 mm/year, respectively).

The comparison of the above-mentioned results with those of the study previously carried out by Cannarozzo et al. (2006) for the same area of study revealed some differences. As regards to annual data, Cannarozzo et al. (2006) found that the 62 % of analysed rain gauges have shown a significant negative trend for $\alpha = 0.05$, while in the analysis presented here, the 49.8 % of rain gauges was affected by a decreasing trend with the same significance level. This moderate difference (12.2 %) in the percentages is due to the application of the test to trend-free pre-whitened series. Indeed, the TFPW allowed to reduce the type I error, i.e. the incorrect rejection of the null hypothesis when there is actually no trend.

Regarding seasonal rainfall, Fig. 5 shows that positive and negative precipitation trends exist for each season at all significance levels. The histograms show that negative trends are more frequent in autumn and winter, specifically in 91 and 137 of the 245 rain gauges, respectively for α equal to 0.1,

Fig. 3 Percentage of rain gauges with statistically significant trends in total annual precipitation for α equal to 0.1, 0.05 and 0.01
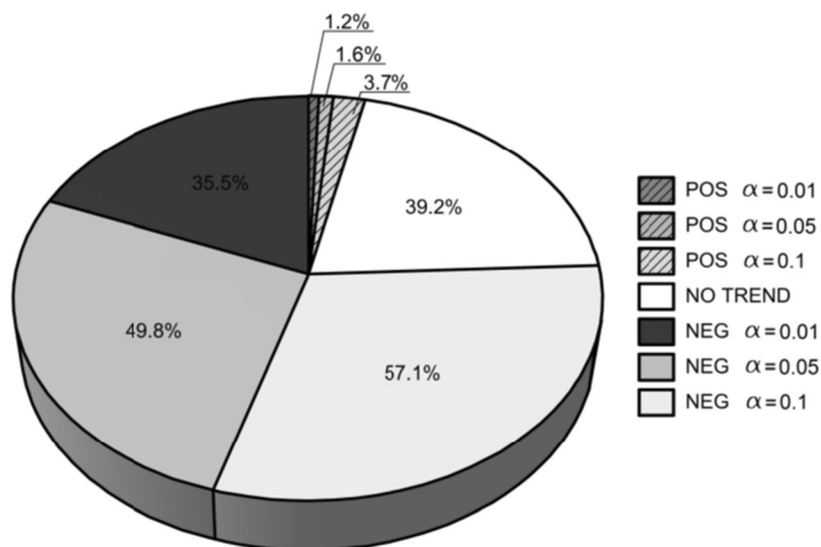

0.05 and 0.01. Therefore, the decrease in annual rainfall should mainly be attributed to the negative trends occurring in winter and autumn. Some positive trends were found in autumn and summer. In winter, only one positive trend was detected in the Erice rain gauge. Spring is the season with the lowest number of both positive and negative trends.

The monthly rainfall analysis allowed for the identification of the months that are most responsible of the detected seasonal trends. The histograms in Fig. 6 illustrate the results obtained from the monthly rainfall analysis. December is the month that shows the highest number of negative trends (97, 65 and 12 series for α equal to 0.1, 0.05 and 0.01, respectively). Because few trends were found in January and February, negative trends in December mainly contribute to the decrease in winter rainfall. August and October are the months that show the greatest number of trends, both positive and

negative. October is the month that is mainly responsible for the positive and negative trends in autumn. The summer negative trends can be attributed to the decrease in rainfall during all the summer months, particularly June and August. The increase in rainfall in April does not produce a seasonal tendency because the number of positive trends in spring is very low (10 trends for α = 0.1). The lowest number of positive trends occurs in January and November, and September does not show any negative trends.

Table 1 summarises the results obtained at each temporal scale and for each significance level. Table 2 shows the range of variation in the magnitude β of the positive and negative trends and the range of variation of p values for each temporal scale.

In summary, results are in agreement with the analysis carried out by Cannarozzo et al. (2006), in which a general
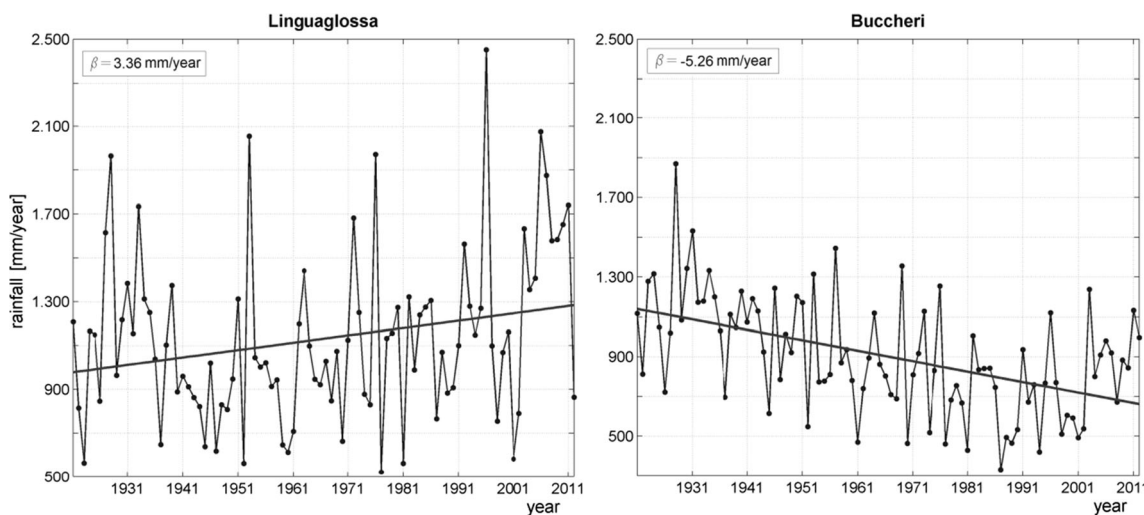
Fig. 4 Total annual rainfall and relative trends for the rain gauges in which the positive and negative trends with the highest magnitudes β (mm/year) were detected (*Linguaglossa* and *Buccheri* respectively)
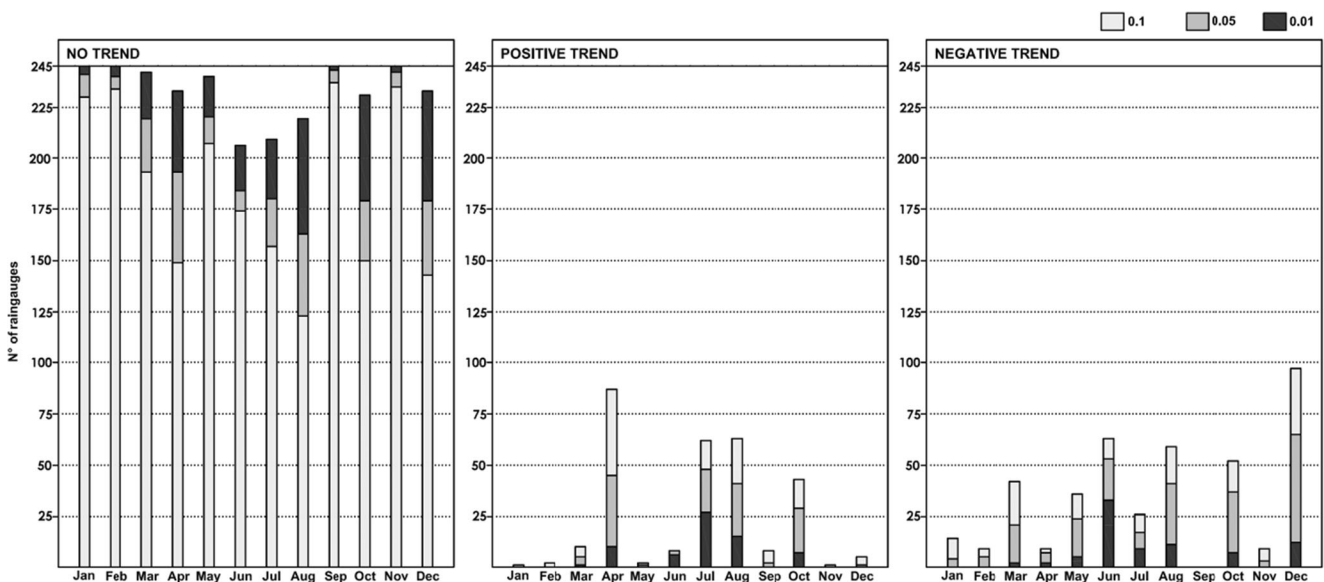
Fig. 5 Number of statistically significant trends in total seasonal rainfall for 0.1, 0.05 and 0.01 significance levels
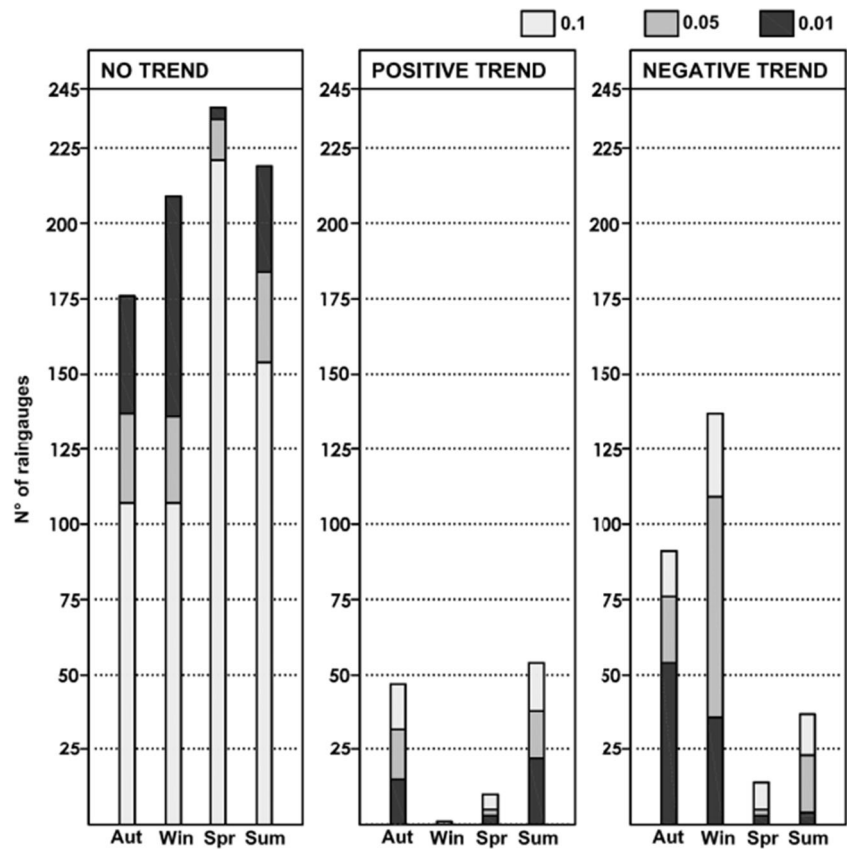
reduction of rainfall was detected in most of the examined series, mainly in annual and winter data. Nevertheless, in this analysis, a greater number of significant negative trends during autumn was detected (91 rain gauges for $\alpha = 0.1$), if compared with the previous study (32 rain gauges for $\alpha = 0.1$). Moreover, significant positive and negative trends have been found in summer data, while Cannarozzo et al.

(2006) have not detected trends for this season. The difference between the results obtained in this study with those of the previous study revealed the importance of taking into account for the removal of serial correlation from dataset.

The analysis highlighted advantages and limits of performing a trend analysis through the applied methodology. The Mann–Kendall test has the usual advantages of non-

Fig. 6 Number of statistically significant trends in total monthly rainfall for 0.1, 0.05 and 0.01 significance levels

Table 1 Mann–Kendall test results for annual, monthly and seasonal rainfall over the 1921–2012 and 1981–2012 periods

Data	1921–2012									1981–2012								
	$\alpha = 0.1$			$\alpha = 0.05$			$\alpha = 0.01$			$\alpha = 0.1$			$\alpha = 0.05$			$\alpha = 0.01$		
	NT	POS	NEG	NT	POS	NEG	NT	POS	NEG	NT	POS	NEG	NT	POS	NEG	NT	POS	NEG
Year	96	9	140	119	4	122	155	3	87	40	205	0	58	187	0	104	141	0
Jan	230	1	14	241	0	4	245	0	0	244	1	0	244	1	0	245	0	0
Feb	234	2	9	240	0	5	245	0	0	222	22	1	235	10	0	245	0	0
Mar	193	10	42	219	5	21	242	1	2	207	33	5	236	9	0	245	0	0
Apr	149	87	9	193	45	7	233	10	2	240	5	0	243	2	0	245	0	0
May	207	2	36	220	1	24	240	0	5	58	97	90	108	73	64	200	25	20
Jun	174	8	63	184	8	53	206	6	33	154	90	1	183	61	1	218	27	0
Jul	157	62	26	180	48	17	209	27	9	180	49	16	200	32	13	224	14	7
Aug	123	63	59	163	41	41	219	15	11	65	38	142	88	30	127	137	16	92
Sep	237	8	0	243	2	0	245	0	0	217	28	0	233	12	0	242	3	0
Oct	150	43	52	179	29	37	231	7	7	219	26	0	234	11	0	244	1	0
Nov	235	1	9	242	0	3	245	0	0	165	23	10	197	13	35	230	5	57
Dec	143	5	97	179	1	65	233	0	12	237	7	1	243	2	0	245	0	0
Aut	107	47	91	137	32	76	176	15	54	167	76	2	189	53	3	221	21	3
Win	107	1	137	136	0	109	209	0	36	196	44	5	217	25	3	244	1	0
Spr	221	10	14	235	5	5	239	3	3	88	142	15	121	111	13	189	51	5
Sum	154	54	37	184	38	23	219	22	4	67	149	29	91	132	22	161	72	12

parametric tests that is robustness against departures from normality (Yue and Pilon 2004) and low sensitivity to abrupt

Table 2 Ranges of magnitudes β (mm/year) of positive and negative trends and range of p values

Data	Range of β [mm/year]		Range of p value
	Positive trends	Negative trends	
Year	0.74 ÷ 3.36	−5.26 ÷ −0.49	$1.89 \cdot 10^{-10}$ ÷ 0.97
Jan	0.02	−1.15 ÷ −0.22	0.02 ÷ 1.00
Feb	0.035 ÷ 0.32	−0.78 ÷ −0.12	0.02 ÷ 0.99
Mar	0.012 ÷ 0.21	−0.31 ÷ −0.01	0.0002 ÷ 0.98
Apr	0.006 ÷ 0.43	−0.24 ÷ −0.004	0.001 ÷ 0.93
May	0.035 ÷ 0.06	−0.22 ÷ −0.004	$5.22 \cdot 10^{-5}$ ÷ 0.99
Jun	0.001 ÷ 0.01	−0.19 ÷ −0.001	$6.41 \cdot 10^{-12}$ ÷ 1.00
Jul	0.001 ÷ 0.12	−0.06 ÷ −0.001	$1.67 \cdot 10^{-8}$ ÷ 1.00
Aug	0.001 ÷ 0.16	−0.22 ÷ −00002	$2.48 \cdot 10^{-5}$ ÷ 0.99
Sep	0.005 ÷ 0.50	–	0.05 ÷ 1.00
Oct	0.003 ÷ 0.29	−0.61 ÷ −0.001	0.001 ÷ 0.99
Nov	0.17	−0.62 ÷ −0.11	0.01 ÷ 0.99
Dec	0.1 ÷ 0.22	−1.01 ÷ −0.05	0.0005 ÷ 1.00
Aut	0.004 ÷ 1.22	−1.45 ÷ −0.003	$8.83 \cdot 10^{-7}$ ÷ 1.00
Win	0.42	−3.43 ÷ −0.23	0.0002 ÷ 1.00
Spr	0.07 ÷ 0.76	−1.12 ÷ −0.21	0.0004 ÷ 1.00
Sum	0.0004 ÷ 0.23	−0.56 ÷ −0.006	$1.74 \cdot 10^{-8}$ ÷ 0.99

breaks due to inhomogeneous time series (Tabari et al. 2011). Nevertheless, the application of the test requires a long and continuous dataset, and whenever the test detects a statistically significant trend, it provides no insight into causes of the detected trend. Moreover, the Mann–Kendall test has the disadvantage of only being applicable to univariate data and is not amenable to simultaneous analysis of multiple sources of variation. For this reason, a multivariate analysis should be carried out, with the purpose of assessing the spatial consistency of trends, as shown by Neppel et al. (2011). Therefore, further developments of this study should be focused on the application of a multivariate analysis in order to overcome the difficulty to explain and interpret at regional scales the changes detected at the local scale (Spagnoli et al. 2002; Svensson et al. 2005).

Parametric tests are more powerful when the variable is normally distributed, but much less powerful when it is not, compared with the non-parametric tests (Hirsch et al. 1991). Further analysis could involve the application of parametric tests and the comparison of their results with those of Mann–Kendall test. A rainfall distribution analysis should be performed, since parametric tests are no distribution free.

4.2 Regional trends analysis

To evaluate trends at the regional scale, the regional Mann–Kendall test and the bootstrap procedure were used and

compared. For the annual data, the Mann–Kendall test at the regional scale indicated the existence of a negative trend at each of the significance levels ($S_m = -547.76$). As reported in Table 3, the test also revealed the existence of trends for all the scales of data aggregation, from annual to monthly, with the only exception being spring rainfall, which was not affected by a regional trend for $\alpha = 0.05$. These results must be attributed to the fact that a spatial interpolation method was used to obtain a complete dataset. This procedure introduced spatial correlation to the data, which affected the test results. The use of the bootstrap technique allowed for this effect to be removed from the results. Figure 7 illustrates the bootstrap *ecdf* obtained for annual precipitation and used to define the level of significance associated with each value of the S_m statistic. The bootstrap procedure yielded results that, in most of the cases, are very different from those provided by the regional test (Table 3). For $\alpha = 0.1$, both of the tests (regional and bootstrap) detected the presence of a regional trend in annual rainfall. At the monthly scale, April, October and December rainfall were affected by a negative regional trend (S_m equal to -421.0, -406.1 and -424.0, respectively) while the seasonal data exhibited a regional negative trend in autumn ($S_m = -497.0$) and winter ($S_m = -496.9$). Of these, only annual, autumn and winter rainfall still present a trend for $\alpha = 0.05$. For $\alpha = 0.01$, the bootstrap procedure revealed the absence of a regional trend at each temporal scale. For the same significance level, the bootstrap analysis in the study by Cannarozzo et al. (2006) revealed a significant regional trend for annual data, probably due to the fact that the dataset was not processed for removal of serial correlation.

4.3 Spatial distribution of rainfall trends

The spatial representation of the observed trends in rainfall enables a better understanding of the variations in rainfall in Sicily over the period from 1921 to 2012. The observed trends were spatially interpolated and raster surfaces were created by applying the inverse distance weighted (IDW) interpolation method. For the case of study, the IDW method can be considered an appropriate interpolation method, since rainfall data are moderately correlated to elevation. Specifically, the linear correlation coefficient is equal to 0.42 for total annual rainfall.

Figure 8 shows the spatial distribution of the trends in annual rainfall in Sicily by significance level and the relative magnitudes of these trends in mm/year (for $\alpha = 0.1$). Most of the study area is dominated by decreasing trends, with a few small zones showing positive trends. A wide area affected by negative trends (at significance levels up to 0.01) is located in the southeastern part of the island, where reduction occurred with the greatest magnitude (from -5.2 to -1.5 mm/year). Another wide, not completely connected area showing negative trends is located to the northwest. However, the detected trends are not spatially distributed according to wide homogeneous areas.

The spatial interpolation of the seasonal results revealed the absence of clear patterns in this case as well (Fig. 9). In autumn, small areas affected by positive trends are located along the Tyrrhenian coast and in the northwestern part of the island. The rest of the region is dominated by negative trends that are concentrated along the Mediterranean coast and in the northwestern part of the region. Winter rainfall decreased across most of the island, although some areas did not show statistically significant trends. The spatial pattern of negative trends in winter is similar to that of the annual negative trends.

The interpolation of spring rainfall trends identified some scattered areas that are distributed without any particular spatial pattern. Otherwise, spring is the season with the lowest number of significant positive and negative trends.

Regarding summer rainfall, two wide areas are characterised by increasing trends, one in the eastern part of the island and one in the south along the Mediterranean coast. Some scattered areas, in which negative trends occurred, can be observed as well.

The comparison of trend analysis results and a regional climate model (RCM) output can be useful to evaluate if trend analysis results are reliable. Coppola and Giorgi (2010) provided results of climate change projections over the Italian

Table 3 Results of regional Mann–Kendall test and bootstrap procedure

Significance level	Test	Year	Month												Season			
			Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Aut	Win	Spr	Sum
0.1	MK regional	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
	bootstrap	•	No	No	No	•	No	No	No	No	No	•	No	•	•	•	No	No
0.05	MK regional	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	No	•
	bootstrap	•	No	No	No	No	No	No	No	No	No	No	No	No	•	•	No	No
0.01	MK regional	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	No	•
	bootstrap	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No

The symbol "•" indicates the existence of a regional trend

Fig. 7 Bootstrap cumulative distribution function of the statistic S_m calculated for total annual rainfall series
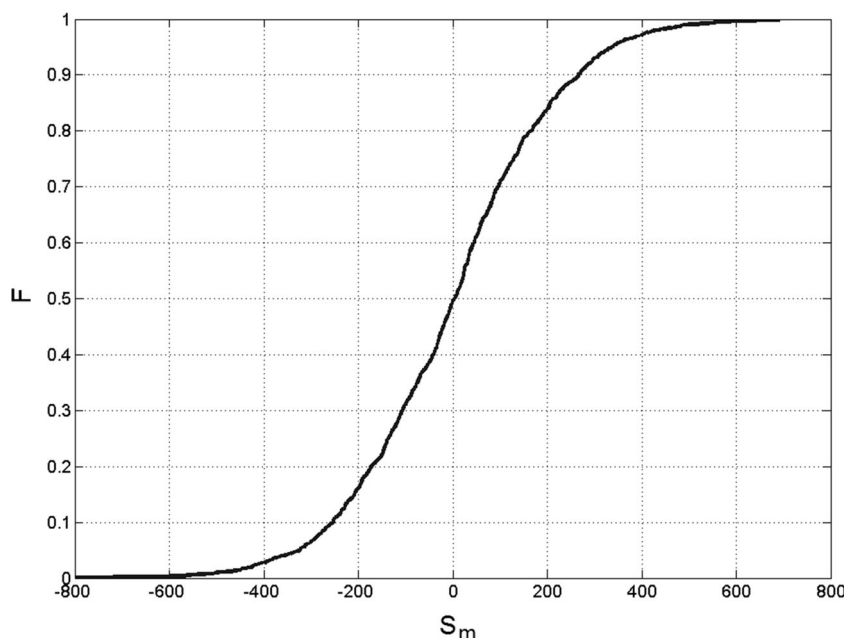

peninsula for the twenty-first century from the CMIP3 global and the PRUDENCE (Christensen et al. 2007) regional model experiments. According to this study, the climate change signal over the area of study shows a seasonal variation, with decreasing precipitation in summer (locally up to −40 %) and increasing and decreasing of winter precipitation at North and South, respectively. This result is in agreement with the trend analysis presented here that detected a decrease of rainfall, in particular during winter months. Although global and intermediate resolution regional models can provide robust broad-scale signals over a region, local forcings due to the complex topography and coastlines of Italy substantially affect the fine-scale climate change signal. For this reason, high-resolution models are required to adequately describe the area of study and produce specific local climate change information.

Trend analysis results, coupled with RCM output or stochastic weather generators available in literature, could provide valuable information in order to define possible future climate scenarios. It is important to note that a climate scenario is not intended to explicitly represent the true future climate because it represents just one of many possible climate outcomes. Nevertheless, a trend analysis can provide useful information about past temporal variations in rainfall to develop new strategies to address future variations.

4.4 Trends over the 1981–2012 period

According to the latest report by the IPCC (2013), the number of heavy precipitation events over land has increased in more regions than decreased since approximately 1950. In Europe, there have likely been increases in either frequency or intensity of heavy precipitation with some seasonal and/or regional
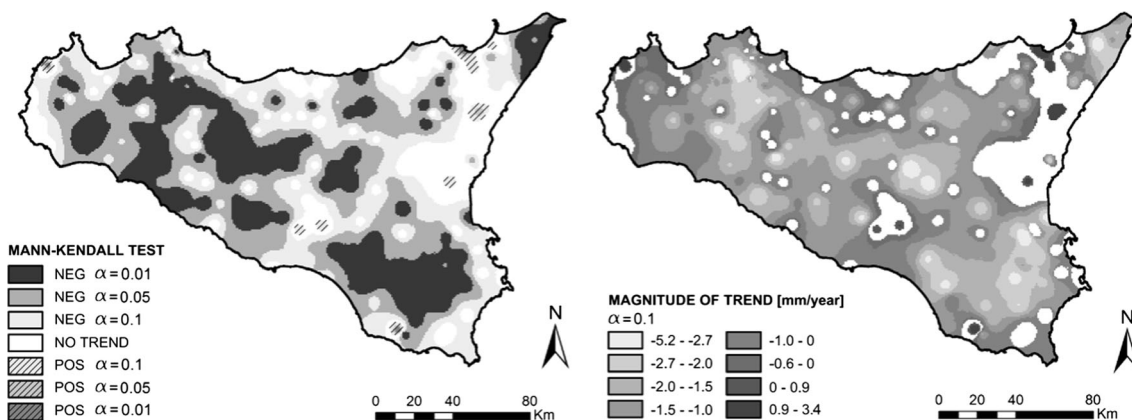
Fig. 8 Spatial distribution of Mann-Kendall test results and trend magnitudes (mm/year) for total annual rainfall (1921–2012)
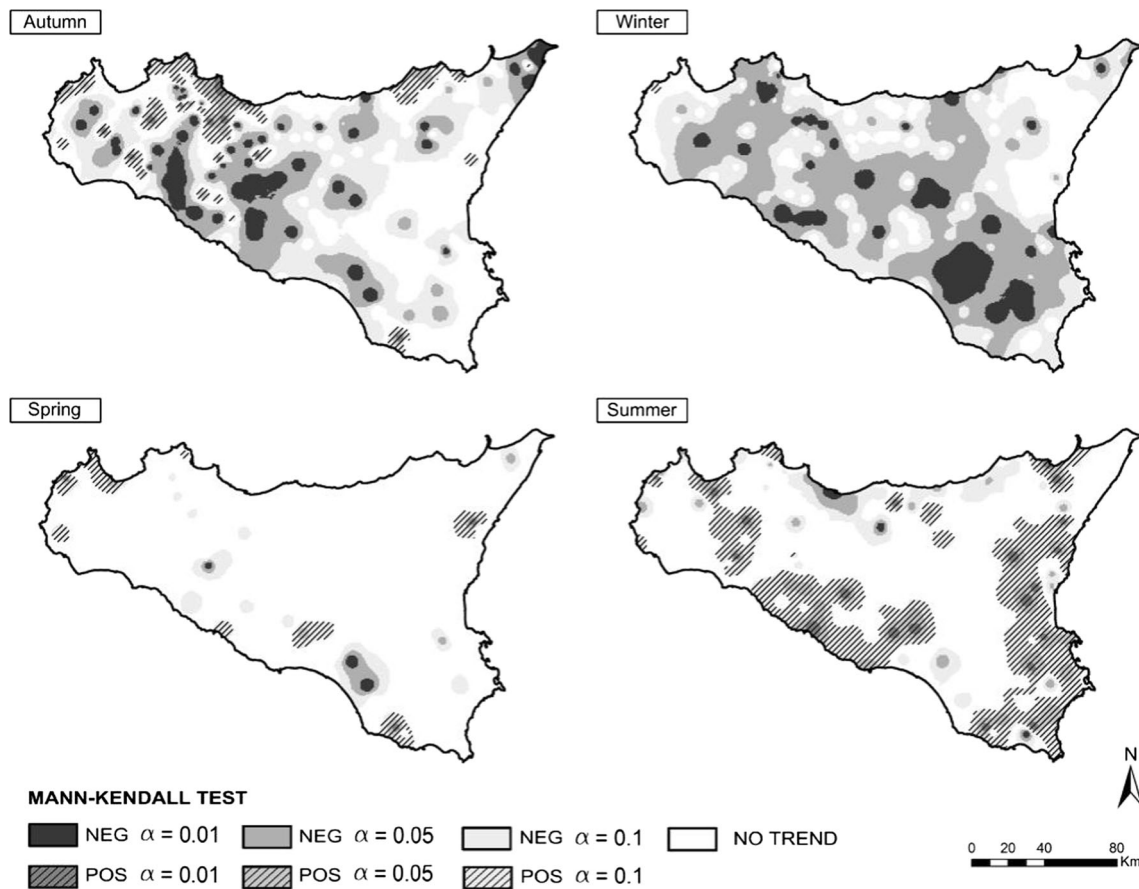
Fig. 9 Spatial distribution of Mann-Kendall test results for total seasonal rainfall (1921–2012)

variation. A number of devastating, extreme rainfall events occurred in Europe over the last decade. Germany, England and Italy have been the most affected, mainly during the summer months.

A study carried out by Alpert et al. (2002) indicated that some specific Mediterranean regions exhibit a paradoxical increase of extreme rainfall in spite of decrease in totals due to global greenhouse gas warming. Gao et al. (2006)

Fig. 10 Variation of mean total annual precipitation between the 1921–1980 period and the 1981–2012 period
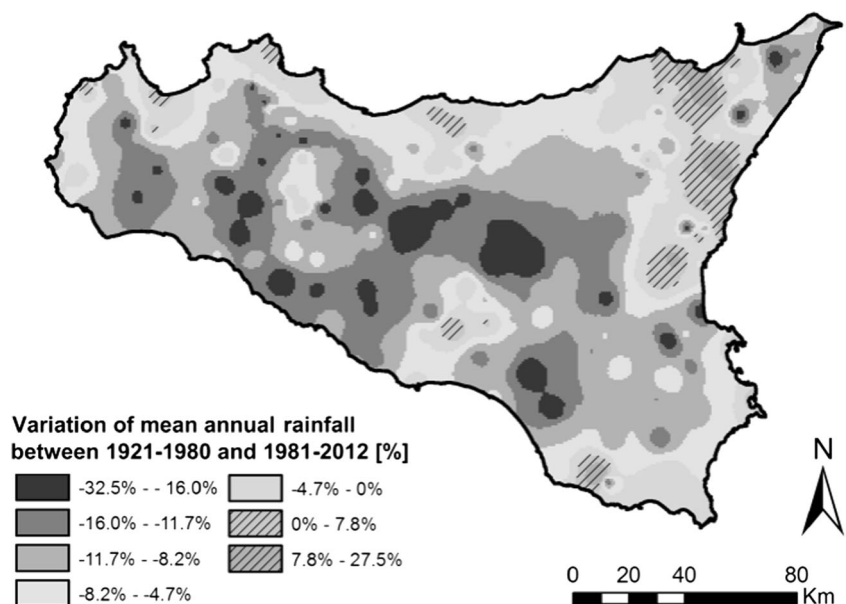
Fig. 11 Total annual rainfall and relative trends for the *Alcantara* raingauge (southeastern Sicily) during the 1921–2012 period (negative trend) and the 1981–2012 period (positive trend)
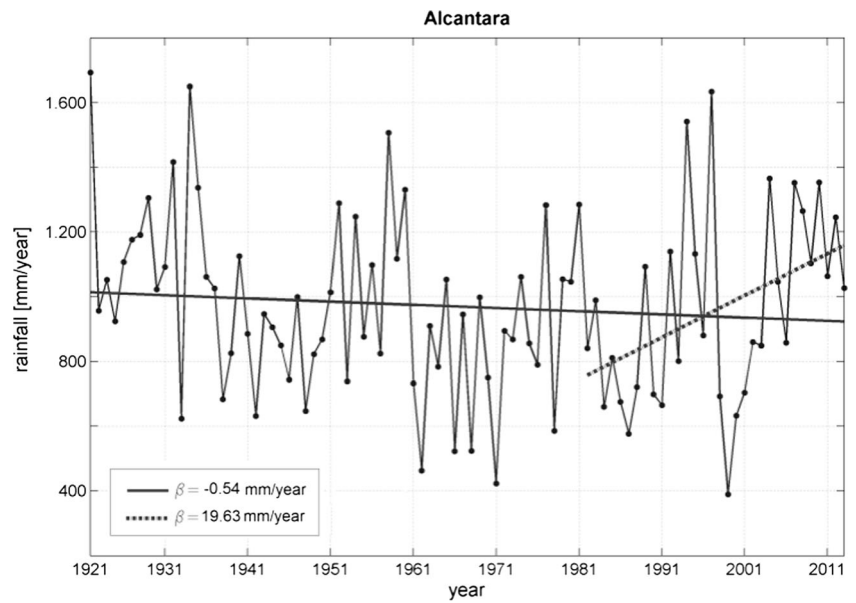
highlighted that in this area, topography can induce fine-scale features to the mean and extreme precipitation change signals, and therefore, those fine resolution models are necessary to provide more detailed future climate change projections.

It has to be marked that the Mediterranean region is located in a transition zone between the arid climate of North Africa and the temperate and rainy climate of central Europe, and it is affected by interactions between mid-latitude and tropical processes. Therefore, even relatively small modifications of the general circulation can produce substantial changes in the Mediterranean climate (Giorgi and Lionello 2008). Mariotti et al. (2002) showed that a significant influence of ENSO on rainfall exists in regions of the Euro-Mediterranean sector with seasonally changing characteristics. A composite analysis of ENSO events indicates that, during an El Niño, western Mediterranean rainfall has a 10 % increase in the autumn preceding the mature phase of an event and a 10 % decrease in spring after the mature phase of an event.

The irregular distribution of rainfalls and its high variability from year to year in the Mediterranean area make it difficult to know if Mediterranean rainfalls are changing. In this context, further analysis are required in order to determine if the recent rainfall changes in the Mediterranean area could be related to the interannual variability of climate or whether they are due to global warming.

As regards to the area of study, it could be useful to investigate short-term rainfall trends to detect possible changes in direction in the latest decades. For this reason, the trend analysis was repeated and focused on the last 30 years of data, i.e. the period from 1981 to 2012. A recent period of at least 30 years was selected, as recommended by the World Meteorological Organization (WMO 1992), for climate analysis.

First, the mean annual rainfall for the periods of 1921–1980 and 1981–2012 was compared. Figure 10 shows the percentage variations between these values. In the last 30 years, mean
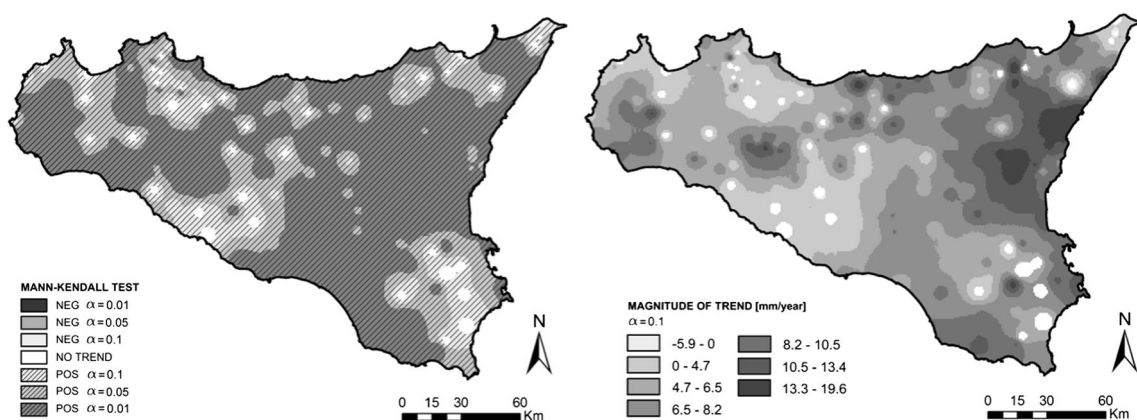
Fig. 12 Spatial distribution of Mann–Kendall test results and trend magnitudes (mm/year) for total annual rainfall (1981–2012)
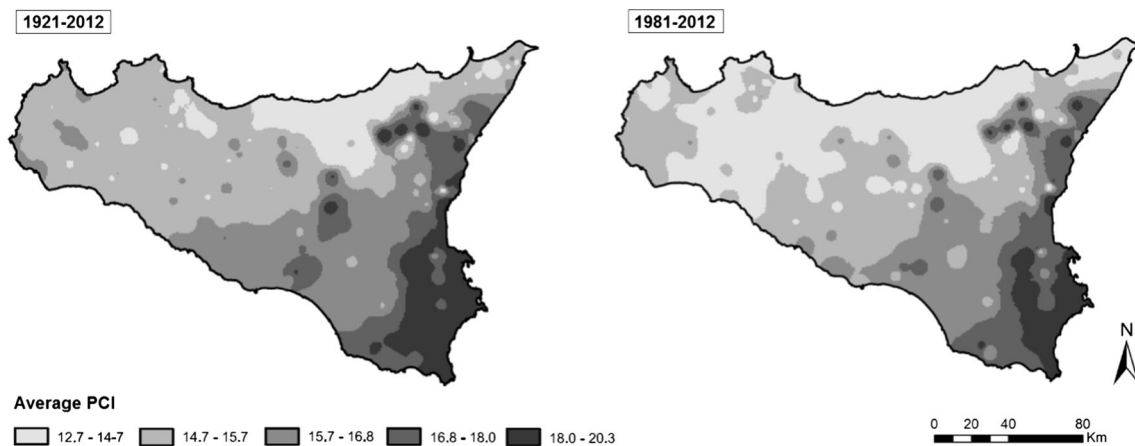
Fig. 13 Average precipitation concentration index (PCI) for the 1921–2012 period and the 1981–2012 period

annual rainfall decreased across most of the island, and this was very pronounced in the central part of Sicily, where mean annual rainfall declined by up to 32.5 %. The mean reduction in rainfall for the period of 1981–2012 shows a spatial pattern similar to that observed for the negative trend over the 1921–2012 period. Some increases occurred in small scattered areas.

The trend analysis for the period of 1981–2012 provided results in contrast with those obtained over the long term. Indeed, positive trends occurred more frequently and at most of the temporal scales (Table 1). At the annual scale in particular, negative trends are absent. At the seasonal scale, positive trends prevail in every case. A considerable number of negative trends was only found in August.

At the annual scale, the greatest increase occurred for the Alcantara rain gauge located at the East. In Fig. 11, the negative trend and the positive trend over the period from 1981 to 2012 are compared. The magnitude of the 30-year positive trend is equal to 19.6 mm/year, a remarkable value with respect to the long-term trend ($\beta = -0.5$ mm/year).

The spatial interpolation of the detected trends highlights the presence of a wide area characterised by an increase in total annual precipitation over the last 30 years in the eastern

part of Sicily (Fig. 12). The magnitudes of the trend range between 2.8 and 19.6 mm/year, while the mean increase is approximately 8 mm/year.

Combining these results with the ones reported in Fig. 10, it can be concluded that total annual rainfall did decrease in the last 30 years if compared with the previous period from 1921 to 1980. However, the total amount of rainfall has exhibited a generally positive trend in the short term. The reason for this change in trend direction needs to be investigated to verify if the recent positive trends can be attributed to increasingly extreme rainfall. In Italy, many authors (e.g. De Michele et al. 1998; Pagliara et al. 1998; Brath et al. 1999) have claimed a tendency toward increasing of high-intensity rainfall in urban areas. Moreover, investigating when the change in trend direction occurred is another critical issue that requires further analysis.

4.5 PCI trend analysis

To investigate the possible temporal and spatial variations in PCI, the index was calculated on an annual scale for each series for the 1921–2012 period and the 1981–2012
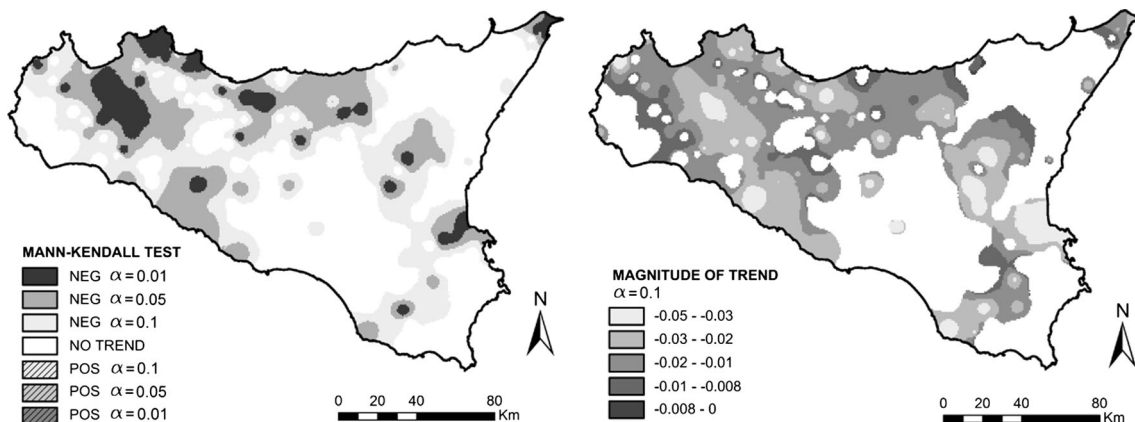
Fig. 14 Spatial distribution of Mann–Kendall test results and trend magnitudes (mm/year) for PCI (1921–2012)
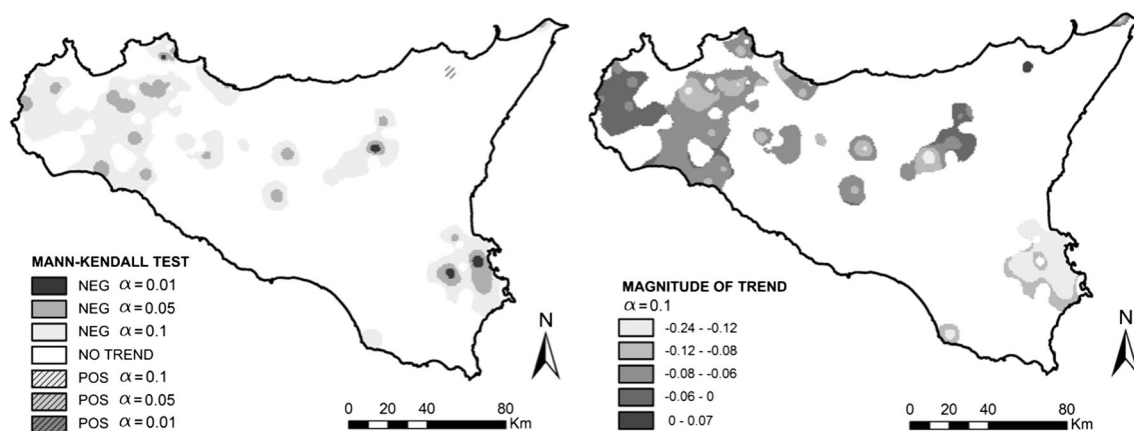
Fig. 15 Spatial distribution of Mann–Kendall test results and trend magnitudes (mm/year) for PCI (1981–2012)

subperiod. Figure 13 shows that the PCI ranges from 12.7 to 20.3 in both periods and spatially increases from northwest to southeast. Spatial patterns are slightly different because, in the map of the 1981–2012 period, a wider area is characterised by lower index values (ranging from 12.7 to 14.7) compared with the same area from 1921 to 2012. In both periods, the highest values (from 18.0 to 20.3) of PCI are concentrated in the southeastern part of the island along the Ionian coast.

A decrease in PCI values was detected in the 1921–2012 period in some small areas (Fig. 14), for which the magnitude of the trend ranged from −0.008 to −0.05. For these areas, the presence of a negative trend implies that the rainfall distribution during the year is becoming more uniform. This result is in agreement with the analysis on PCI trend carried out by Cannarozzo et al. (2006), in which a decrease of the index was found over the period 1921–2000.

For the period from 1981 to 2012, a lower number of trends were detected, but the magnitudes were higher (from −0.24 to −0.06). Figure 15 shows the spatial distribution of the trends and their magnitudes. Two small areas located in the northwest and the southeast were characterised by negative trends. Only one positive trend was detected in the northeast ($\beta = 0.07$).

The presence of few negative trends in the PCI values during the 1981–2012 period strengthens the hypothesis that the increase in total annual rainfall should be attributed to a possible increase in extreme rainfall events. Indeed, the small number of trends in the PCI series over the last 30 years indicates that the annual distribution of rainfall has not varied remarkably. Therefore, an increased occurrence of extreme events could explain the short-term positive rainfall trends.

5 Conclusion

Rainfall trend analysis for 245 rain gauges in Sicily was carried out on an annual, seasonal and monthly basis. The non-

parametric Mann–Kendall test was used at three different significance levels (0.1, 0.05 and 0.01) for the periods of 1921–2012 and 1981–2012. The variations in the precipitation concentration index were also investigated to verify if there was a trend in the temporal distribution of rainfall during the year. During the period from 1921 to 2012, a reduction in rainfall occurred at the annual scale, mainly due to negative trends in winter and autumn. These trends are statistically significant at the regional scale for a significance level up to 0.05. For lower values of α, the bootstrap analysis revealed that these trends are not significant. The analysis of monthly and seasonal trends showed that the annual precipitation reduction is mainly due to the decrease of rainfall amount during winter and summer months. Nevertheless, further analysis should be performed in order to verify if these results were affected by the scale of data. With this aim, the use of data transformations, such as logarithmic or square root, could be a valuable approach, since monthly rainfall is unlikely normally distributed. Indeed, a transformation is a replacement of data that changes the shape of their distribution, reducing or removing skewness.

For the period of 1981–2012, an increase in total annual rainfall was detected. Positive trends were found in most of the monthly series. The opposite tendencies revealed by the trend analysis for the two periods under consideration highlighted the influence of the chosen temporal interval on the significance and direction of the detected trends. Nevertheless, performing the trend analysis for different periods could be useful to identify changes in trend direction or an increase or decrease in its magnitude.

At spatial level, the interpolation of spring rainfall trends identified no particular spatial pattern probably due to the fact that spring is the season with the lowest number of significant positive and negative trends. Regarding summer rainfall, two wide areas are characterised by increasing trends, one in the eastern part of the island and one in the South along the Mediterranean coast. Since the Sicilian rainfall regime is characterised by dry summers, the presence of relatively large

areas with increased rainfall requires further investigation to assess whether or not these trends are related to climate change that, according to several studies (e.g. Alpert et al. 2002; Giorgi and Lionello 2008), is occurring over the Mediterranean area.

Future analyses are necessary to verify whether the recent positive trends could be attributed to possible trends in extreme rainfall. Moreover, the small number of trends in the PCI series over the last 30 years indicates that the distribution of rainfall during the year has not varied remarkably.

As regards to temporal rainfall variability in Sicily, further research could include the calculation of alternative indexes, such as the Shannon entropy or the Gini coefficient, and the comparison of results with those obtained for the PCI.

The comparison of trend analysis results with those obtained in the study by Cannarozzo et al. (2006) revealed some differences that may be attributable to the fact that the latter was conducted on a dataset that has not been previously subjected to a removal procedure of the serial correlation.

Despite the limitations of the methodology, previously discussed, the results provided in this study are still valuable, even if trends in historical rainfall data are not indicative of possible future tendencies. Knowledge of past spatial and temporal rainfall patterns could be key to assessing possible anthropogenic impacts on the future climate.

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