6

Drought Assessment in a Changing Climate

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1. Introduction

Drought is a natural and recurrent feature of climate. It occurs in all climatic zones, even if its characteristics vary significantly from one region to another, and differs from aridity that is a permanent feature of climate restricted to low rainfall areas. Drought originates from a deficiency of precipitation (less than normal) over an extended period of time, usually a season or more (Wilhite & Glantz, 1985; Bordi & Sutera, 2007). However, since precipitation is related to the amount of water vapor in the atmosphere, combined with the upward forcing of the air masses containing that water vapor, a reduction of either of these may favour the onset of drought conditions. Thus, the phenomenon can be triggered by an above average prevalence of high-pressure systems, by winds carrying continental rather than oceanic air masses, or by high temperatures that enhance evaporation. Moreover, drought is a creeping phenomenon that slowly sneaks up and impacts many sectors of the economy, the environment, and operates on many different time scales (Wilhite et al., 2007). For example, soil moisture conditions respond to precipitation deficits occurring on a relatively short time scale, whereas groundwater, streamflow, and reservoir storage respond to precipitation deficits arising over many months. As a result, drought cannot be viewed solely as a physical phenomenon but it should be considered in relation to its impacts on society. The American Meteorological Society (1997) grouped drought definitions and types into four categories: meteorological, agricultural, hydrological and socioeconomic (Heim, 2002).

Based on all these definitions that nowadays are commonly accepted by the scientific community, three main issues emerge to be important for a comprehensive drought assessment: 1) Development of a drought index able to objectively assess drought conditions of regions characterized by different hydrological regimes and to evaluate the different kinds of droughts, 2) Perform a drought risk analysis in order to prevent the negative impacts of droughts, and 3) Understanding the link between climate variability and drought occurrence in relation to a changing climate. The first point has been addressed first by McKee et al. (1993) by developing the Standardized Precipitation Index (SPI), which is a drought index based only on monthly precipitation. The idea was to quantify the precipitation deficit for multiple time scales that reflect the impacts of drought on the availability of the different water resources. Since the index is standardized through an equal-probability transformation (see next section and Bordi & Sutera, 2004 for details), dry and wet conditions can be monitored in the same way as well as a comparison between locations with different climates is possible. For these reasons the SPI is widely applied for drought monitoring purposes, and in 2009 it has been recommended for characterizing meteorological drought around the world (see Lincon declaration on drought indices, Hayes et al., 2011). Recently, two new standardized drought indices have been proposed for drought variability analysis on multiple time scales, the Reconnaissance Drought index (RDI, Tsakiris et al., 2007) and the Standardized Precipitation Evapotranspiration Index (SPEI, Vicente-Serrano et al., 2010). The indices are based on the supply-demand concept and take into account precipitation (P) and potential evapotranspiration (PET, hence temperature through the Thornthwaite equation). Although both indices comply with the requirement of the standardization, some questions concern their effective capability to better capture temperature changes, and, more importantly, the more appropriate basic variable to be used for drought assessment (i.e. P, P/PET or P–PET, see Raziei et al., 2011).

To address the second point, a full understanding of the third point on climate variability is required. The traditional approach to drought management is reactive, relying largely on crisis management. This approach is usually ineffective because the response comes too late, is poorly coordinated, and costly. In addition, the post-impact response to drought tends to reinforce the existing water resource management methods that often contribute to increase the societal vulnerability to drought. For these reasons, in recent years, governments and institutions involved in water resources management showed more interest in learning how to employ proper risk management techniques to reduce vulnerability to drought and, therefore, lessen the impacts associated with future drought events (Wilhite et al., 2000). In coping with drought following a proactive approach, the first step is the monitoring of the phenomenon and the understanding of the temporal variability of drought events, also in relation to a changing climate (Hayes et al., 2004).

All drought indices developed so far (see the reviews by Heim, 2002 and Keyantash & Dracup, 2002), including the standardized ones mentioned before, are based on drought as a relative concept: drought is defined as the negative departure of meteorological/water-related variables from some pre-established mean conditions (often referred to as calibration period that according to WMO recommendation should be at least 30 years long). By definition, drought occurrence should not depend on slow variations of climate conditions, since a normal climate is defined as the averaged conditions over the long-term record. Unfortunately, data have finite time span so that the stability of the average may undermine an objective assessment, especially when a drift on this random behaviour occurs. Of course, if we were certain that such a drift were of a deterministic kind a few differentiations of the original time series would be in order and would be enough to restore the original definition of climate. However, the situation may be disrupted if the assumptions on the nature of the trend are fallacious or even simply overstated. Moreover, other moments of the climate variables may be very well not stationary. In these cases the entire probability distributions would be affected, and in particular their tails that are, after all, what we are more interested. Things may be even more worsen if variables, relevant for drought occurrence, change differently both in space and time. If, for example, precipitation and temperature in a given location respond differently to climate changes we could overweight one variable with respect to the other reaching unwise conclusions on future drought occurrences.

In the present paper we address the question of how drought indices should be used in a changing climate conditions, i.e. the variables of interest are not stationary. In particular, we evaluate the impact of the observed climate drift on drought assessment. We focus our attention on the European sector providing an updated drought analysis based on the SPI on 24-month time scale computed using the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis precipitation data from January 1948 to June 2011. The choice of the SPI is motivated by the simplicity and advantages mentioned above, while the long time scale is selected just to filter out high frequency fluctuations in drought signals, highlighting the long-term behaviours to which we are interested on. Moreover, through sample analyses at selected grid points, it is evaluated the existence of a reference calibration period over which the distribution parameters underlying the SPI computation remain stable when a data update is taken into account. In particular, the effect of using a reference calibration period, shorter than the full data record available, on the SPI computation is studied for different climate tendencies. Some conclusions and discussions on future outlooks are provided in the final section.

2. Data and methods

Data used for the analysis are monthly mean precipitation rates retrieved from the NCEP/NCAR reanalysis archive for the period January 1948–June 2011. They are available on the regular grid 1.9°x1.9° in longitude and latitude. Such precipitation data have been derived from the primary meteorological fields of the NCEP medium range forecasting spectral model with 28 "sigma" vertical levels and a triangular truncation of 62 waves, equivalent to about 210-km horizontal resolution. The model is based on the assimilation of a set of observations, such as land surface, ship, rawinsonde, aircraft and satellite data (Kalnay et al., 1996). These data were quality controlled and assimilated with a data assimilation system kept unchanged over the reanalysis period. Though precipitation is not directly assimilated, but derived completely from the model 6-hour forecast, its midlatitude features have been compared favourably with observations and several climatologies (Janowiak et al., 1998; Trenberth & Guillemot, 1998). Since for the present study we have considered the area centred over Europe (25.72°N–71.43°N, 13.13°W–60.00°E), we may feel enough confidence on the data quality.

Hydrological dry/wet conditions over Europe, updated to June 2011, have been assessed through the SPI on 24-month time scale. The SPI computation for a given location and month of the year is based on the long-term precipitation record accumulated over the selected time scale. The empirical probability distribution of the accumulated precipitation is fitted to a theoretical distribution that is then transformed through an equal-probability transformation into a normal distribution. Usually, the two-parameter Gamma distribution is used for fitting the observed precipitation distribution, even if in particular regions other choices may result more suitable (Guttman, 1999). In the present study, we apply the original definition of the SPI by McKee et al. (1993) that is based on the two-parameter Gamma probability density function defined as:

$$g(x) = \frac{1}{\beta^{\alpha}\, \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \quad \text{for } x > 0 \tag{1}$$

where α and β are the shape and scale parameters, respectively, positive defined, x the precipitation amount and

$$\Gamma(\alpha) = \int_0^{\infty} y^{\alpha-1} e^{-y}\, dy \tag{2}$$

with Γ(α) the Gamma function. Even if we recognize that the first source of uncertainty in the SPI computation is the determination of the probability density function, we point out that for our purposes such a choice is not relevant, i.e. the issues addressed here apply regardless of the underlying distribution.
Given the time scale of interest, and for each month of the year, the shape and scale parameters are optimally estimated using the maximum likelihood solutions. The resulting parameters, $\hat{\alpha}$ and $\hat{\beta}$, are then used to find the cumulative probability of an observed precipitation event as:

$$G(x) = \int_0^x g(x)\,dx = \frac{1}{\hat{\beta}^{\hat{\alpha}}\,\Gamma(\hat{\alpha})}\int_0^x x^{\hat{\alpha}-1} e^{-x/\hat{\beta}}\,dx \tag{3}$$

Letting $t = x/\hat{\beta}$, equation (3) becomes the incomplete Gamma function

$$G(x) = \frac{1}{\Gamma(\hat{\alpha})}\int_0^x t^{\hat{\alpha}-1} e^{-t}\,dt \tag{4}$$

Since the Gamma is undefined for x = 0, while a precipitation distribution may contains zeros, the cumulative probability becomes:

$$H(x) = q + (1-q)G(x) \tag{5}$$

with q the probability of a zero (if n is the number of precipitation observations and m the number of zeros in the precipitation time series, q can be estimated by m/n). The cumulative probability $H(x)$ is then transformed to the standard normal random variable Z with zero mean and unit variance, which is the value of the SPI. By using the approximation provided by Abramowitz and Stegum (1965) that converts cumulative probability to the standard normal random variable Z, we have:

$$\begin{aligned} Z = SPI &= -\left(\tilde{t} - \frac{c_0 + c_1\tilde{t} + c_2\tilde{t}^2}{1 + d_1\tilde{t} + d_2\tilde{t}^2 + d_3\tilde{t}^3}\right) \quad for\ 0 < H(x) \le 0.5 \\ Z = SPI &= +\left(\tilde{t} - \frac{c_0 + c_1\tilde{t} + c_2\tilde{t}^2}{1 + d_1\tilde{t} + d_2\tilde{t}^2 + d_3\tilde{t}^3}\right) \quad for\ 0.5 < H(x) < 1.0 \end{aligned} \tag{6}$$

where $\tilde{t} = \sqrt{\ln\left(1/(H(x))^2\right)}$ for $0 < H(x) \le 0.5$, $\tilde{t} = \sqrt{\ln\left(1/(1-H(x))^2\right)}$ for $0.5 < H(x) < 1.0$, while $c_{0,\,1,\,2}$ and $d_{1,\,2,\,3}$ are constants. Thus, conceptually the SPI represents a z-score, or the number of standard deviations above or below that a precipitation event is from the mean (Bordi & Sutera, 2004). Positive SPI values indicate greater than median precipitation, and negative values indicate less than median precipitation. The SPI classes are defined as: values between –0.99 and +0.99 denote near normal conditions, between –1 and –1.49 moderately dry (hereafter D1), between –1.5 and –1.99 severely dry (hereafter D2) and less than –2 extremely dry (hereafter D3) conditions. The same applies to positive values for wet classes (hereafter W1, W2 and W3 for moderately, severely and extremely wet conditions).

In analyzing the spatial variability of drought across Europe the Principal Component Analysis (PCA) is applied to the SPI field. The PCA consists in computing the covariance matrix of the input data with the corresponding eigenvalues and eigenvectors (Rencher, 1998). The projection of the SPI fields onto the orthonormal eigenfunctions provides the principal components or PC score time series. In guiding a proper interpretation of the results shown in the next section, we remark that the spatial patterns (eigenvectors), properly normalized (divided by their Euclidean norm and multiplied by the square root of the corresponding eigenvalues) are called "loadings" and represent the correlation between the original data (SPI time series at single grid points) and the corresponding PC score time series.

In analyzing the long-term drought variability, as in Bordi et al. (2009) we have evaluated both the linear trends and the leading nonlinear components in the SPI time series. To extract the long-term linear trend we have used the least-squared method to fit a linear model to the time series, while the leading nonlinear components in the SPI time series are extracted using the Singular Spectral Analysis (SSA). SSA technique is a nonparametric spectral estimation method based on embedding a time series in a vector space of dimension M (see Ghil et al., 2002 for details on the technique). In the present study, following Bordi et al. (2009), we have reconstructed the signal considering only the leading component by selecting a window length of M = 70 months (i.e. about 1/10th of the time series) because it provides statistically meaningful estimates of the largest resolvable fluctuation period.

3. Results

Firstly, the impact of the actual climate trend (linear and nonlinear) on drought variability in the European sector is assessed. The study is complemented by sample analyses at three selected grid points considered representative of the different climate drifts observed in the available data record. Secondly, the existence of a reference sample size that provides stable estimates of the Gamma distribution parameters, when additional (more recent) data are taken into account, is evaluated.

3.1 The impact of the climate drift on drought variability

We started our analysis by applying the Mann-Kendall test to the NCEP/NCAR monthly precipitation time series from January 1948 to June 2011. The result is shown in Fig. 1a where grey areas denote p-values less than the significance level of 0.01 (i.e. the test rejects the null hypothesis of trend absence). As can be noted, most of northern regions, central Europe and north Africa are characterized by trends of not specified nature, probably affected by seasonality (here not removed). When the accumulated precipitation on 24-month time scale is considered, the statistical test provides the result shown in Fig. 1b. As expected, the area characterized by trend is larger because of the correlation introduced by the accumulation procedure. The application of the statistical test to the SPI on 1-month and 24-month time scales provides the same results (not shown) illustrated in Fig. 1a and 1b, respectively. This means that whenever the precipitation time series has a statistically significant trend, the same holds for the associated SPI on the same time scale.

To investigate which kind of climate drift characterizes the SPI time series in the area of interest, we have applied the PCA to the SPI field. The leading mode of the spatial variability is shown in Fig. 2a, while the associated PC score time series and the fitting linear and nonlinear trends are shown in Fig. 2b. The first loading pattern explains 20.1% of the total variance and seems remained unchanged compared to the one shown by Bordi et al. (2009) in their Fig. 4 where the update was limited to February 2009.

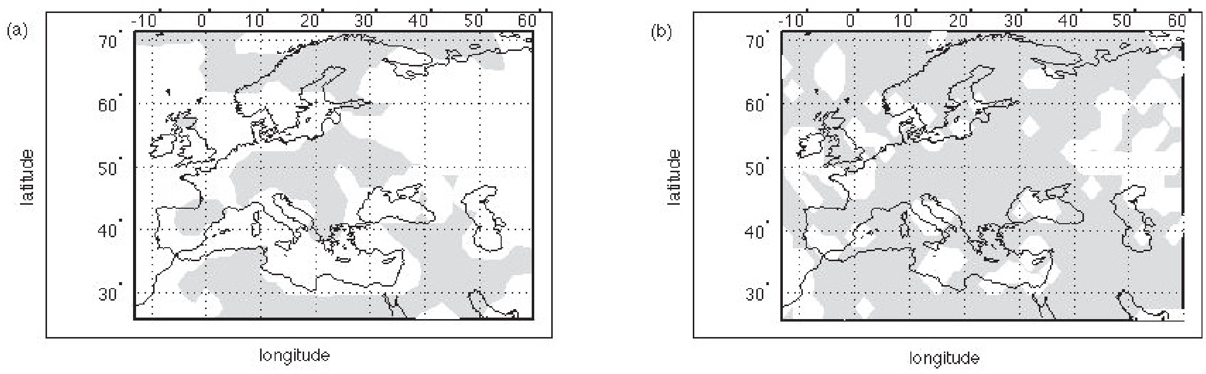

Fig. 1. Results of Mann-Kendall test applied to monthly and accumulated (on 24-month time scale) precipitation time series. Grey areas denote p-values less than the significance level of 0.01.

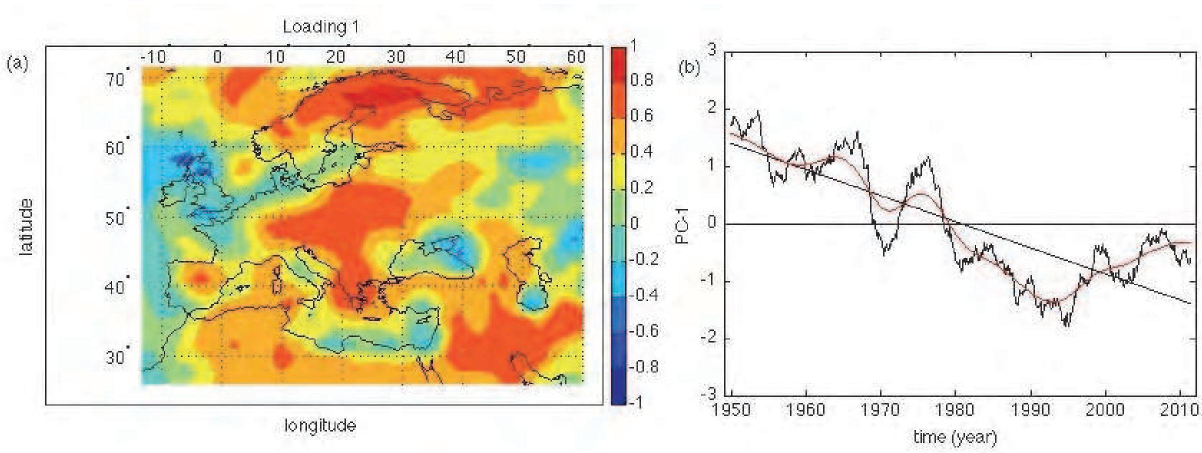

Fig. 2. PCA of the SPI field on 24-month time scale: (a) first loading, (b) First PC score time series and fitting linear and nonlinear trends (black straight line and red line, respectively).

The same holds for the first PC score (PC-1) time series that in the latest two years confirms the fluctuation around –0.5 (i.e. the climate drift occurred from about 1997 onward). The R^2 associated with the linear trend is now 65.4% and the one associated with the reconstructed signal using the leading SSA component is 91.8%. Again, it appears more suitable to represent the long-term SPI variability through a nonlinear fitting instead of the linear one. Thus, the interpretation of the results after this recent update remains basically the same: regions characterized by high positive loading values from the mid seventies onward have experienced prevailing dry events with a change in the last 15 years or so toward near normal conditions (see Bordi et al., 2009 for an in depth discussion). It is worth noting that the PCA technique does not isolate the trend component in the first PC score but just extracts the leading component that maximises the total variance of the SPI field. This means that, for example, the second PC score (not shown) also has a linear trend component, less pronounced, but it is statistically significant at 0.01 level (R^2 = 5.5%).

Now, in analysing the effect of the observed climate drift on drought variability, we have two possibilities: the first one is to remove the observed trend (linear or nonlinear) from the precipitation time series at each grid point, while the second consists in removing the trend on the SPI time series. The first option could provide several problems because of the possible negative values of precipitation derived by subtracting the estimated trend. Thus, it turns out that precipitation (the input variable for the SPI computation) is no more positive defined and the fitting of the empirical precipitation distribution with the two-parameter Gamma is no more possible. Based on the results obtained before (Fig. 1), the second option appears the most suitable. Thus, we continued our analysis by removing the linear and nonlinear trend components from the SPI time series at each grid point, standardizing the SPI residuals time series, and performing again the PCA. Results obtained when the linear trend is removed are shown in Fig. 3a, b, while when the nonlinear trend is excluded are in Fig. 3c, d.

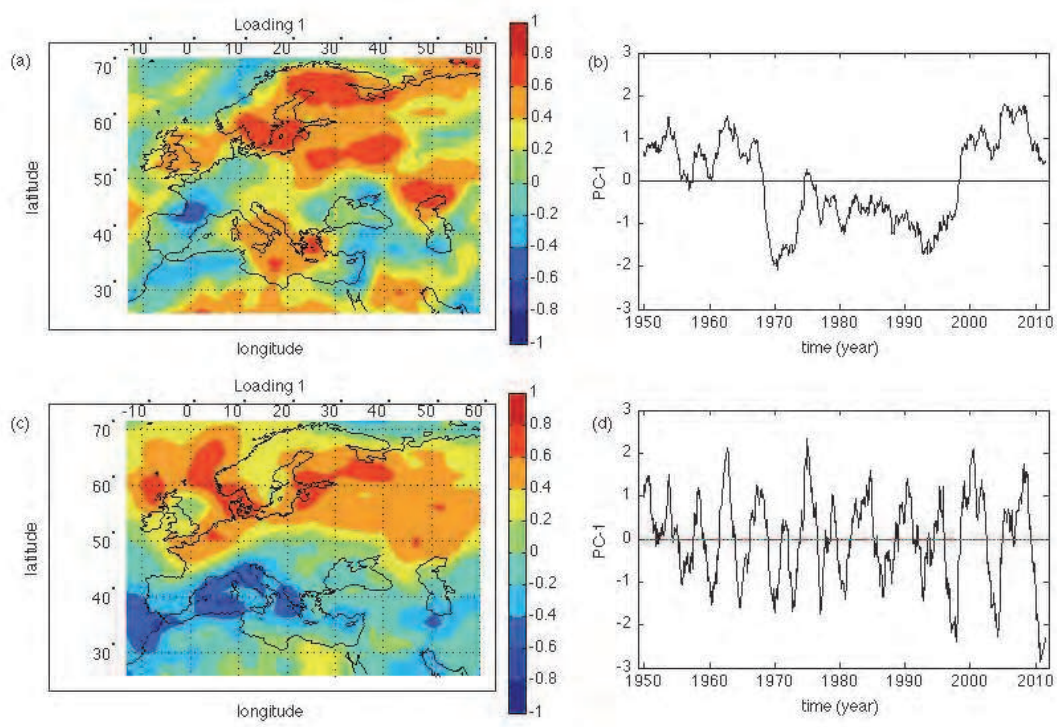

Fig. 3. PCA of the SPI field after removing the linear/nonlinear trend: (a) first loading and (b) first PC score for linear trend removing, (c) first loading and (d) first PC score for nonlinear trend removing.

In case of the removal of linear trend removing the first loading pattern, explaining 14.1% of the total variance, shows high positive values (i.e. high correlations between the standardized residuals of the SPI series and the corresponding PC score) in northern Europe, in the middle of the Mediterranean basin and part of north Africa. The associated PC score has, by construction, no linear trend component, and shows a pronounced minimum around the seventies. Embedded in multi-year fluctuations, three distinct “phases” are noticeable: two periods characterized by positive values, from the beginning of the time record to the seventies and from around 1997 to present, and another one with negative values in between. It is interesting to compare these results with the ones previously obtained by Bordi and Sutera (2001) for the time section 1950–2000 (see their Panels VI and VII): the addition of the last eleven years has changed remarkably the first loading and the corresponding PC score. This is because the estimated linear trend changed when the time record has been extended. Also, since the reference period used for estimating the Gamma parameters is longer and the precipitation time series are not stationary, the SPI values have been affected by the update (class transition of events).

In case of the removal of nonlinear trend, the first loading explains 13% of the total variance and has a north-south structure. The corresponding PC score is characterized by multi-year fluctuations with a prevalent periodicity around 5.5 years; hence, as expected, the time variability of the SPI residuals is strongly affected by the estimates of the nonlinear trend components (i.e. the choice of M in SSA decomposition). These results suggest that the uncertainty on the nature of trends (linear or nonlinear) leaves undetermined the natural climate variability, which is highly dependent from the assumptions made on the observed tendencies for their estimation.

At this stage of the analysis, it appears interesting to quantify the effect of the estimated climate drift on drought classes. At this purpose, we have computed for selected grid points the percentage of events in each drought/wet class by considering the original SPI time series and the de-trended ones. Due to the high spatial variability of the observed climate trends, we have selected the grid points so that they are representative of no linear trend conditions (North Germany), upward (North England) and downward (Scandinavia) linear trend. Note that the grid points are the same discussed in Bordi et al. (2009) in order to allow the reader to follow the effect of the update of the data subjected to the current climate drift.

Results are illustrated in Fig. 4. In Fig. 4a, b, c we have reported the time behaviour of the precipitation accumulated on 24-month time scale at the three grid points. From a quick look of the bar plots, the different long-term linear trends appear evident, which are the same characterizing the corresponding SPI time series illustrated in Fig. 4d, e, f. In case of linear trend absence (Fig. 4g), we have changes in drought classes only when the first nonlinear SSA component is removed from the SPI time series. The most evident effect is on the severe wet class W2 that changes from 4% to about 7.5%. In case of an upward linear trend (Fig. 4e), accounting for 36% of the total variance of the SPI signal, the impact of removing the trend (both linear and nonlinear) is more evident, especially on moderate and extreme dry/wet classes (Fig. 4h). In the third case (Fig. 4f), the SPI series has high positive correlation with the leading PC score illustrated in Fig. 2b, and the linear downward trend accounts for about 35% of the total variance. The major change (Fig. 4i) occurs for the moderate drought class that increases the percentage of events when the trend is removed; the same holds for the moderate wet class, while for the extreme wet class there is a loss of events when the linear trend is removed. These examples show how the climate drift affects the frequency of occurrence of dry/wet events, showing that it depends on the nature of the estimated trend (linear or nonlinear). In general, it seems that the impact is more pronounced on moderate dry/wet classes (D1 and W1), but taking into account the lower probability of occurrence of the severe and extreme classes, small changes of those events are equally remarkable.

3.2 Reference sample size in a changing climate

Since the computation of the SPI requires the preliminary fitting of a probability distribution to monthly precipitation aggregated at the selected time scale, the index value for a given

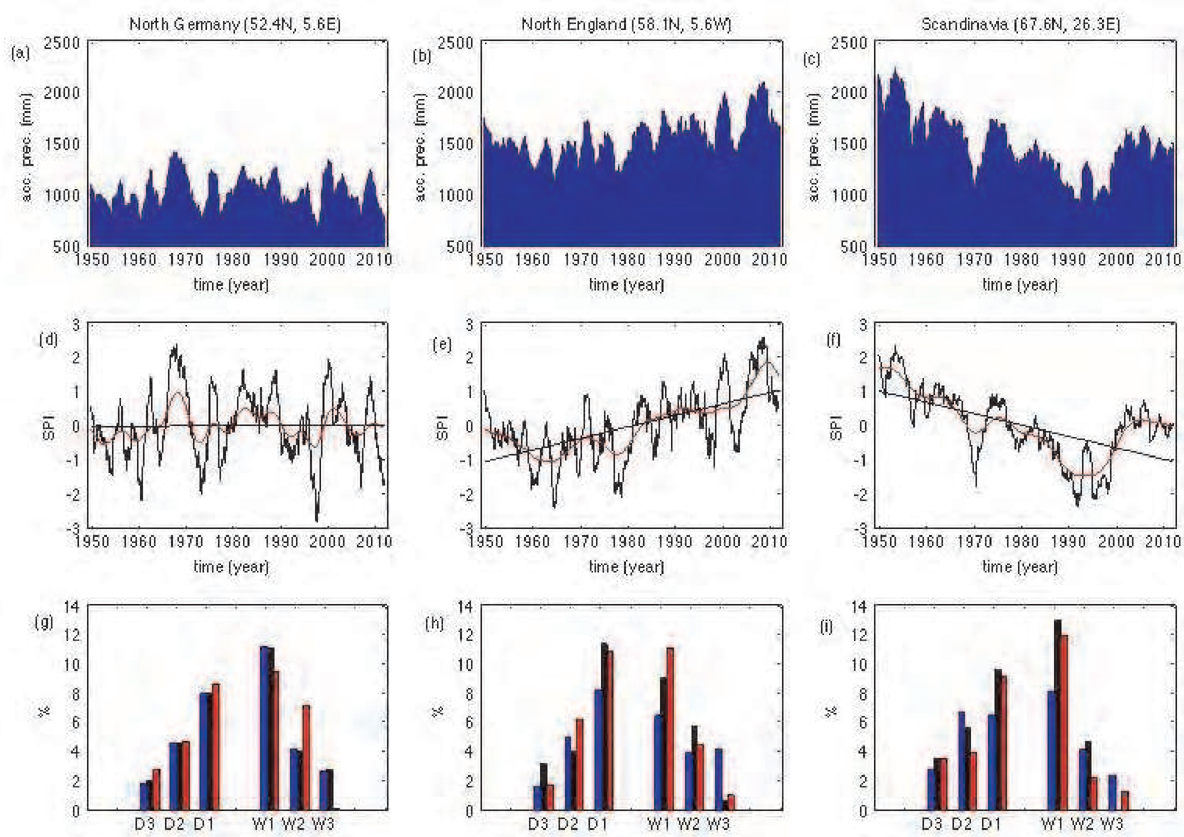

Fig. 4. Accumulated precipitation time series on 24-month time scale at three selected grid points: (a) North Germany, (b) North England, (c) North Europe. SPI time series are in (d), (e) and (f). Straight black lines are the fitting linear trends, red curves the leading SSA components. Bar plots (d)–(f) are the percentages of events in each dry and wet class for the original SPI (blue), the SPI with linear trend removed (black), and the SPI with the leading SSA component removed (red). D1 (W1), D2 (W2) and D3 (W3) stand for moderate, severe and extreme drought (wet) classes, respectively.

year and month will depend on the sample size adopted for its estimation. Usually, the size of precipitation data has to be long enough in order to yield a reliable estimation of the parameters related to the index. McKee et al. (1993) suggested that the length of record for precipitation used in the SPI calculation is "ideally a continuous period of at least 30 years". Guttman (1994) and, later on, Wu et al. (2005) investigated further this problem concluding that longer records are necessary for a stable estimation of the distribution parameters. Unfortunately, the long record requirement of high quality data (observations or reanalysis) cannot be met in most cases, even in the US where precipitation record length varies from one station to another across a region. Moreover, the presence of a trend in the underlying precipitation time series will affect adversely the estimation of the distribution parameters and, therefore, the SPI values. In fact, because the climate is changing, different time periods have different climate mean conditions. In addition, as shown before, the observed trend varies spatially so that the stability of the distribution parameters may be different from one region to another.

In the present subsection we investigate the effect on the SPI computation of the last 15 years, when a change in drought variability is detected. In particular, we address the question whether a reference sample size exists in a changing climate given the actual record length of about 63 years, i.e. the distribution parameters estimated over the reference record remain stable when additional (more recent) data are taken into account in the SPI computation. For the three grid points previously selected as representative of different climate tendencies, we have estimated for each month of the year the parameters (α and β) of the Gamma distributions fitting the accumulated precipitation on 24-month time scale. First, the estimates have been performed using data from 1948–1995 and then 1 year at a time has been added up till 2010 (for a total of 15 years added). Next, the SPI time series for the full record length have been computed using these parameter estimates. This is an application of the "relative" SPI introduced by Dubrovsky et al. (2009). Assuming as the best estimate of α (β) be the one obtained using the full record length, we have computed the percent relative error for each added year as:

$$\varepsilon_{\alpha} = \frac{\alpha_i - \alpha_N}{\alpha_N} \quad (3)$$

with i = 1, 2, … N, and N = 15. The same holds for β. Voluntarily, the absolute value has not been applied to (α_i–α_N) in order to retain the information on the decreasing/increasing behaviour of the Gamma parameters as a function of time. In Fig. 5, for the three selected grid points, the relative error (in %) on α and β, the SPI time mean and the standard deviation as a function of the number of years added to estimate the distribution parameters are shown.

From the figure it can be noted that for North Germany (absence of statistically significant linear trend in the SPI series), the relative errors on the Gamma parameters are bounded at 10%, and the mean and the standard deviation of the relative SPI are close to 0 and 1, respectively. This result shows that the distribution parameters remain almost stable in the latest 15 years, resulting in a preservation of the basic characteristics of the SPI. Thus, in this case the period 1948–1995 can be taken as a reference calibration period for assessing recent climate conditions; this is because the climate mean conditions had not remarkably changed in the latest 15 years. In case of North England, instead, where an upward linear trend has been detected in the SPI time series, the relative errors on the Gamma parameters are higher and cross the threshold of 10% just when almost all the recent 15 years are taken into account. The mean and standard deviation of the relative SPI strongly depart from 0 and 1, respectively. This suggests that in this case the whole precipitation record must be considered in computing the SPI, and a shorter record is not suitable for assessing current drought conditions. Lastly, for the grid point located in Scandinavia, where the SPI showed a downward linear trend embedded in a long-period fluctuation, results suggest that a suitable calibration period for the computation of the relative SPI may be 1948–2005, i.e. by excluding the latest five years no remarkable errors occur in the Gamma parameters estimates.

In applying the relative index, another problem arises: even small changes in the distribution parameter estimates (relative errors below 10%) might change the number of dry/wet events falling in each SPI dry/wet class. To quantify this effect we have reported in Table 1 the percentage of dry/wet events for the calibration period 1948–2010 (full record) and 1948–1996 (short record). It is worth noting that when a very long time record is considered, by construction, each SPI class corresponds to a known probability (for example, extreme dry events occur with probability 2.3%). Here, the deviations from the nominal probability values are due to the limited record size.

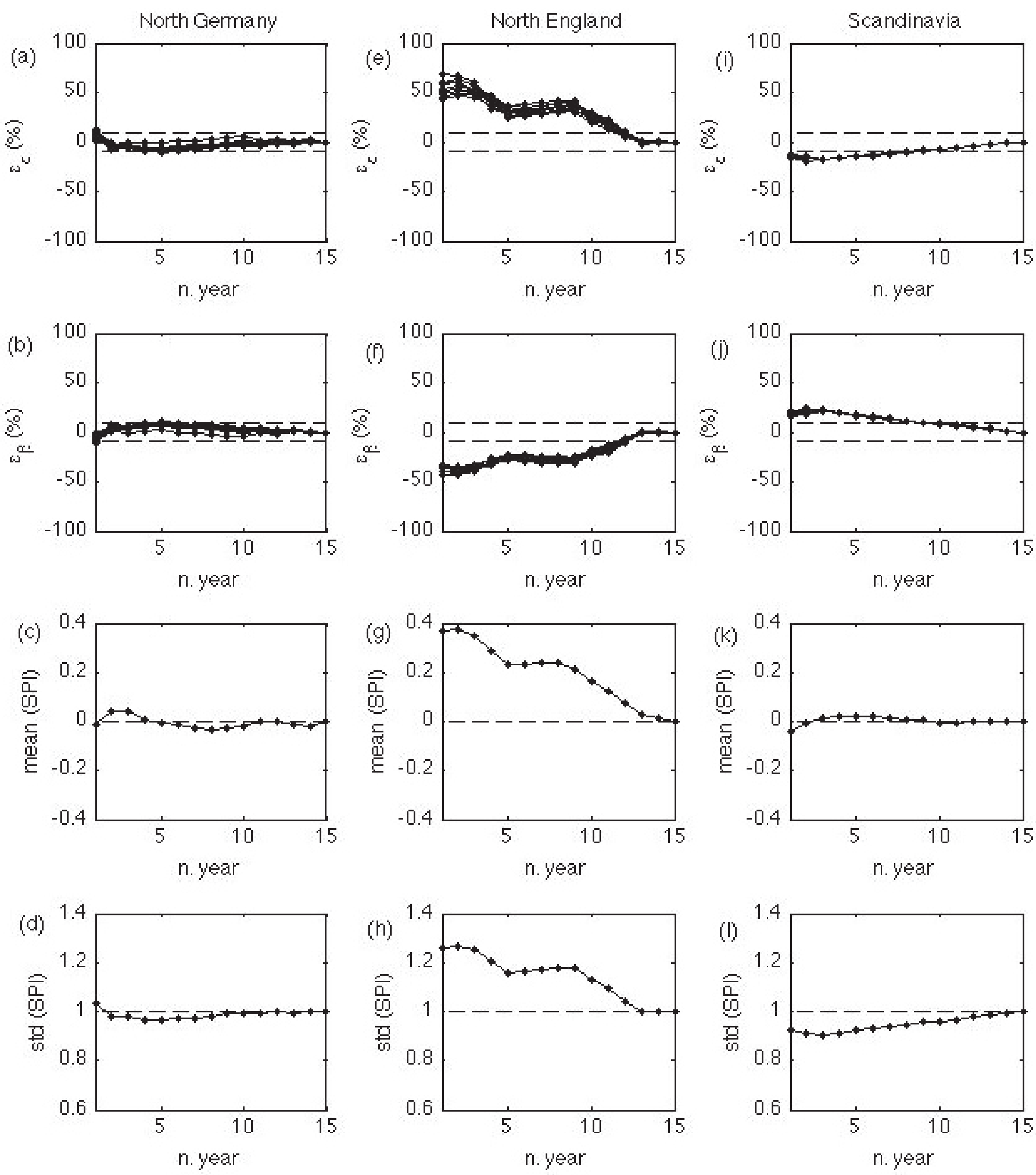

Fig. 5. For the three selected grid points: percent relative error on α and β for each month of the year, SPI time mean and standard deviation as a function of the number of years added for the Gamma parameter estimates. Horizontal dashed lines on ε_α and ε_β time behaviours denote the +10% and –10% levels.

	North Germany		Norh England		Scadinavia	
Dry/wet classes	Full record	Short record	Full record	Short record	Full record	Short record
D3 (extreme dry)	2.2	2.3	1.6	2.3	2.7	1.0
D2 (severe dry)	4.1	4.6	5.0	4.6	7.1	7.0
D1 (moderate dry)	8.5	8.6	8.3	7.1	6.5	8.0
W1 (moderate wet)	11.1	10.5	6.5	11.5	8.2	6.5
W2 (severe wet)	4.2	4.6	4.0	6.7	4.1	5.5
W3 (extreme wet)	2.7	3.0	4.2	10.2	2.5	0.1

Table 1. Percentage of dry/wet events in each class when the SPI at the three reference grid points (North Germany, North England, Scandinavia) is computed using the full record length of data or the shorter period 1948–1996 for estimating the Gamma parameters.

Table 1 shows that for North Germany there is only a slight change of the percentage of events in each class, while for the other two grid points the differences are more evident. To be point out is the great increase of extreme wet events in North England, while the opposite occurs in Scandinavia. The impact on dry classes seems less dramatic.

To better understand these changes we show in Fig. 6 the monthly precipitation aggregated on 24-month time scale as a function of the corresponding SPI values for the two calibration periods: full record (blue) and shorter record (1948–1996, red). The dispersion of the points in the plots is related to the month-to-month variability within the year (SPI values are calibrated separately for each month). It is interesting to note how the precipitation threshold levels associated with dry/wet classes changed noticeably in the three locations. For example, while for the grid point in North Germany there are no appreciable changes, for the grid point in North England there are noticeable differences, especially for the wet classes. The threshold level on the accumulated precipitation for extreme wet conditions (SPI > 2) is about 1950 mm when the calibration period is the full record, while it is reduced to about 1800 mm when the calibration period is shorter (1948–1996). This is the reason why the relative SPI computed on the shorter time period provides a higher percentage of extreme wet events. Similar considerations can be made for the other classes.

Summarizing, since climate conditions vary spatially and temporally, and the climate tendencies (for example, long-term linear trends) highly depend on the record length considered, there is not a general rule for establishing whether a reference sample size, shorter than the full data record available, exists and can be used as a calibration period for the SPI computation. Such a calibration period should be long enough to ensure the stability

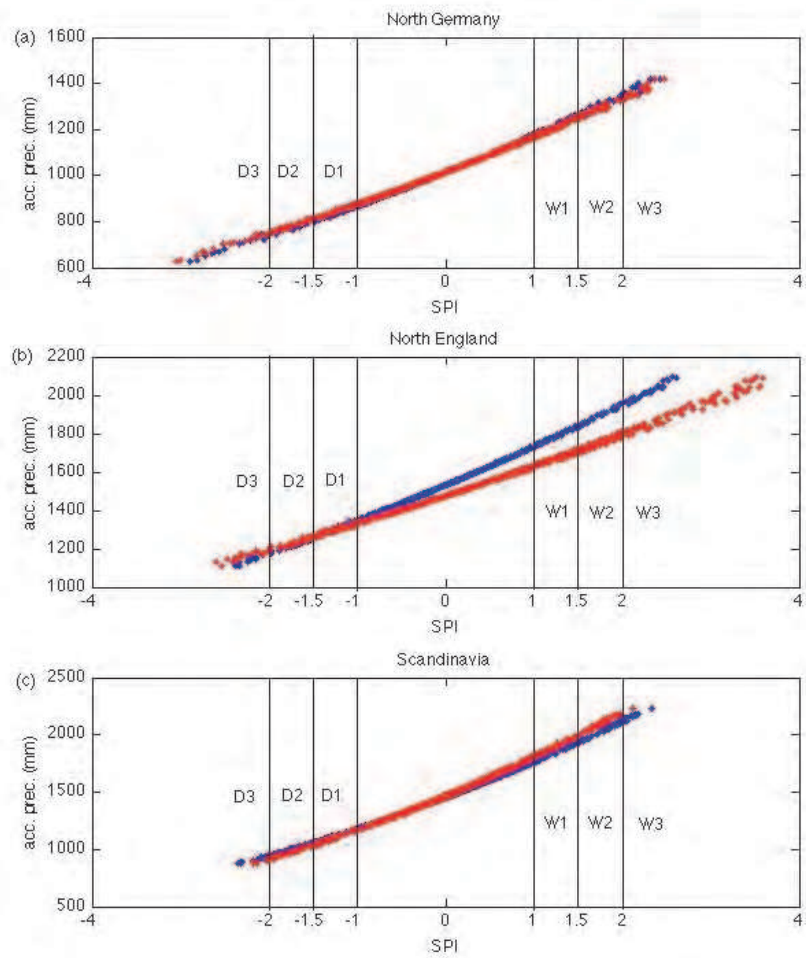

Fig. 6. Accumulated precipitation on 24-month time scale as a function of the corresponding SPI values for the three selected grid points. The SPI Gamma parameters have been estimated using the full precipitation record (blue) and the shorter period 1948–1996 (red). Vertical black lines denote the different dry/wet classes. Units of precipitation are mm.

of the Gamma distribution parameters underlying the index computation even when additional (more recent) data are taken into account. The methodology here proposed, and illustrated through a few examples, may be of reference for addressing the problem in a changing climate conditions. First of all, it is preferable to provide a regionalization of drought conditions in the area of interest, identifying sub-regions characterized by independent drought variability. At this purpose, the application of the PCA with VARIMAX rotation can be a useful tool (see for example Bordi & Sutera, 2001, Raziei et al., 2010 and references therein), or, as suggested by Hannachi et al. (2009), the alternative rotation method based on the Independent Component Analysis (ICA) can be used. Then, for each sub-region a study of the stability of the Gamma parameters can be carried out as a function of the record length. As a general rule, and as illustrated before, it is expected that the SPI time series not characterized by statistically significant long-term linear trends are not much affected by the update of recent data, provided that the reference sample size is long enough to yield a reliable estimation of the parameters. Differently, the SPI at sub-regions characterized by upward or downward long-term linear trends may be quite affected by the update. However, a shorter (with respect to the full record length available) reference period can be found depending on the long-term structure of the SPI tendency. The different results obtained for the grid points at North England and Scandinavia, in fact, suggest that the presence of a linear trend in the SPI series does not exclude the possibility to define a shorter reference calibration period. Moreover, whenever a reference period is defined and the relative SPI applied, a check on the percentage of events falling in each dry/wet class is desirable, to quantify even the effect of small differences between the SPI values computed using the full record and the shorter one. Lastly, the impact of the data update on the precipitation thresholds associated with the SPI dry/wet classes (Fig. 6) appears of interest to quantify the recent changes of climate conditions.

4. Conclusion

In the present paper we have illustrated some approaches for assessing drought conditions in a changing climate. The analysis has been focused on the European sector using the NCEP/NCAR reanalysis precipitation data from 1948 to 2011 (June). This is for continuity with the previous study by Bordi et al. (2009) where the authors analysed the recent changes occurring in drought and wetness conditions over Europe after the update to 2009.
Since for drought analysis a standardized and multi-scale drought index is preferred to facilitate the quantitative comparison of drought events at different locations and time scales, we chose the SPI on 24-month time scale for our study. The long time scale is selected to filter out high frequency fluctuations in drought signals, highlighting long-term behaviours to which we are interested on. Moreover, we applied the original definition of the SPI based on the fitting of the empirical accumulated precipitation distributions with the two-parameter Gamma function. It is worth noting that our arguments are independent on the theoretical probability density function underlying the SPI computation.
After verifying (through the Mann-Kendall test) that if there is a trend in precipitation time series at a given location the same holds for the associated SPI, we have performed the PCA of the SPI field and analysed the leading spatial mode and temporal principal component score. As expected, the first loading remained the same after the recent update (only two more years) and the corresponding PC score confirmed the actual tendency toward near normal conditions in the areas characterized by high positive loading values. Then, the long-term tendency of the SPI time series at each grid point is estimated through a linear and nonlinear fitting, and removed from the original index signals. The resulting SPI residuals were standardized and decomposed into principal components. The first loading and PC score obtained represent the leading mode of space and time drought variability when the estimated climate drift is removed. It turns out that the results are very different, dependent on the nature of the trend (linear or nonlinear). Moreover, in case of the nonlinear trend, here estimated through the SSA with a time window M of 70 months, the oscillatory behaviour of the first PC score depends on the choice of M. For three sample grid points, considered representative of climate conditions with not statistically significant linear trend and statistically significant upward and downward trend, we have quantified the class change of dry/wet events due to the trend removal. The key studies show how the climate drift affects the frequency of occurrence of dry/wet events, showing that it depends on the nature of the estimated trend. It appears that the impact is more pronounced on moderate dry/wet classes but, taking into account the lower probability of severe and extreme events, small changes of those events are equally remarkable.

In the second part of the paper we have addressed the question of the reference sample size useful for the computation of the relative SPI proposed by Dubrovsky et al. (2009). For the three grid points previously considered, we have estimated for each month of the year the parameters α and β of the Gamma distributions fitting the monthly precipitation accumulated on 24-month time scale. The estimates have been performed using data from 1948–1995 and then 1 year at a time has been added up till 2010 (for a total of 15 years added). Using such parameter estimates, the SPI time series for the full record length have been computed. Results suggest that in case of linear trend absence, the period 1948–1995 can be taken as a reference calibration period because the climate mean conditions, and hence α and β, had not remarkably changed in the last 15 years. For the second grid point considered, instead, the whole precipitation record must be taken into account for properly assessing recent climate conditions. Lastly, for the third grid point, a suitable calibration period is estimated to be 1948–2005. Thus, the different results obtained for the latter grid points (North England and Scandinavia) suggest that the presence of a linear trend in the SPI series does not exclude the possibility to define a shorter calibration period.
The impact of the data update on the precipitation thresholds associated with the SPI dry/wet classes (Fig. 6) appears of interest to quantify the recent changes of climate conditions. It is worth noting that this approach, also finds a useful application in case of drought analysis in a different climate, i.e. comparison of dry/wet conditions between the control run of a given general circulation model and the corresponding scenario run. This kind of analysis is nowadays very common due to the increasing interest in future climate projections related to the increasing greenhouse gases emission (see for example Burke & Brown, 2008; Sheffield & Wood, 2008; Bothe et al., 2011). In dealing with this issue by using a standardized drought index, like the SPI, there are three viable strategies: compute the SPI using the full data record (control plus scenario), compute the relative SPI (relative to the control climate mean conditions), or compute the SPI separately for the control and future run. Since, by construction, the future climate is expected to be different from the control, the first choice will change drastically the SPI values computed for the control (present climate), without providing useful information. The second option, based on the relative SPI, has the shortcomings discussed above (i.e. the index does not preserve the zero mean and unit variance) and its interpretation can be misleading since the dry/wet classes refer to the Gamma distributions of the present climate, kept (wrongly) unchanged in the future. In other words, the loss of the standardization of the SPI is due to the erroneous fits of the actual precipitation distributions. The third option, instead, offers the possibility to properly compute the SPI in the two time sections, but now the index classes are relative to two different climate mean conditions. Thus, in this case the mapping of the accumulated precipitation versus the SPI values, both for the control and the projection, can provide an estimation of the new precipitation thresholds associated with dry/wet events. These thresholds may be then used to estimate the return times of extreme events when a point over threshold method is applied (see Bordi et al., 2007 and references therein).
In concluding, based on the high spatial variability of the observed climate trends and its dependence on the time section considered (usually too short for a comprehensive drought assessment), future efforts should be devoted to the analysis of synthetic precipitation time series where the nature of the trend is prescribed, with no limitation on the record length. In this way, the climate drift is known and its impact on drought can be studied applying different drought indices, testing their suitability under various changing climate assumptions (i.e. for example, change of the mean or variance in the precipitation

distributions). In particular, it should be interesting to start from the observed climate conditions in the last 60 years or so and simulate possible future evolutions of the variable of interest (in our case the precipitation). Then, perform a risk analysis associated with the underlying assumption on the climate trend. This will be the topic of a next study.

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6. References

Abramowitz, M. & Stegum, I. A. (1965). *Handbook of Mathematical Functions*, Dover Pub., ISBN 0-486-61272-4, New York, USA.

American Meteorological Society (AMS) (1997). Meteorological Drought-Policy Statement. *Bulletin of American Meteorological Society*, Vol.78, No.5, (May 1997), pp. 847–849, ISSN 0003-0007.

Bordi, I. & Sutera, A. (2001). Fifty Years of Precipitation : Some Spatially Remote Teleconnections. *Water Resources Management*, Vol.15, No.4, (August 2001), pp. 247–280, ISSN 0920-4741.

Bordi I. & Sutera, A. (2004). Drought Variability and its Climatic Implications. *Global and Planetary Change*, Vol.40, No.1, (January 2004), pp. 115–127, ISSN 0921-8181.

Bordi, I. & Sutera, A. (2007). Drought Monitoring and Forecasting at Large-Scale, In: *Methods and Tools for Drought Analysis and Management*, G. Rossi, T. Vega and B. Bonaccorso, (Eds.), pp. 3–27, Springer-Verlag New York Inc., ISBN 13: 9781402059230, New York, US.

Bordi, I., Fraedrich, K., Petitta, M. & Sutera, A. (2007). Extreme Value Analysis of Wet and Dry periods in Sicily. *Theoretical and Applied Climatology*, Vol.87, No.1-4, (January 2007), pp. 61–71, ISSN 0177-798X.

Bordi, I. ; Fraedrich, K. & Sutera, A. (2009). Observed Drought and Wetness Trends in Europe : An Update. *Hydrology and Earth Systems Sciences*, Vol.13, No.8, (August 2009), pp. 1519–1530, ISSN 1027-5606.

Bothe, O.; Fraedrich, K. & Zhu, X. (2011). Large-Scale Circulations and Tibetan Plateau Summer Drought and Wetness in a High-Resolution Climate Model. *International Journal of Climatology*, Vol.31, No.6, (May 2011), pp. 832–846, ISSN 0899-8418.

Burke, E.J. & Brown, S.J. (2008). Evaluating Uncertainties in the Projection of Future Drought. *Journal of Hydrometeorology*, Vol.9, No.2, (April 2008), pp. 292–299, ISSN 1525-755X.

Dubrovsky, M.; Svoboda, M.D.; Trnka, M.; Hayes, M.J.; Wilhite, D.A.; Zalud, Z. & Hlavinka, P. (2009). Application of Relative Drought Indices in Assessing Clmate-Change Impacts on Drought Conditions in Czechia. *Theoretical and Applied Climatology*, Vol.96, No.1-2, (April 2009), pp. 155–171, ISSN 0177-798X.

Ghil, M.; Allen, M.R.; Dettinger, M.D.; Ide, K.; Kondrashow, D.; Mann, M.E.; Robertson, A.W.; Saunders, A.; Tian, Y.; Varadi, F. & Yiou, P. (2002). Advanced Spectral Methods for Climatic Time Series. *Reviews of Geophysics*, Vol.40, No.1, (September 2002), pp. 3.1–3.41, ISSN 8755-1209.

Guttman, N.B. (1994). On the Sensitivity of Sample L Moments to Sample Size. *Journal of Climate*, Vol.7, No.6, (June 1994), pp. 1026–1029, ISSN 0894-8755.

Guttman, N.B. (1999). Accepting the Standardized Precipitation Index : A Calculation Algorithm. *Journal of the American Water Resources Association*, Vol.35, No.2, (April 1999), pp. 311–322, ISSN 1093-474X.

Hannachi, A.; Unkel, S.; Trendafilov, N.T. & Jolliffe, I.T. (2009). Independent Component Analysis of Climate Data: A New Look at EOF Rotation. *Journal of Climate*, Vol.22, No.11, (June 2009), pp. 2797–2812, ISSN 0894-8755.

Hayes, M.J.; Wilhelmi, O.V. & Knutson, C.L. (2004). Reducing Drought Risk: Bridging Theory and Practice. *Natural Hazards Review*, Vol.5, No.2, (May 2004), pp. 106–113, ISSN 1527-6988.

Hayes, M.; Svoboda, M.; Wall, N. & Widhalm, M. (2011). The Lincon Declaration on Drought Indices: Universal M eteorological Drought Index Recommended. *Bulletin of American Meteorological Society*, Vol.92, No.4, (April 2011), pp. 485–488, ISSN 0003-0007.

Heim Jr, R.R. (2002). A Review of Twentieth-Century Drought Indices used in the United States. *Bulletin of the American Meteorological Society*, Vol.83, No.8, (August 2002), pp. 1149–1165, ISSN 0003-0007.

Janowiak, J.E.; Gruber, A.; Kondragunta, C.R., Livezey, R.E. & Huffman, G.J. (1998). A Comparison of the NCEP-NCAR reanalysis Precipitation and the GPCP Rain Gauge-Satellite Combined Dataset with Observational Error Considerations. *Journal of Climate*, Vol.11, No.11, (November 1998), pp. 2960–2979, ISSN 0894-8755.

Kalnay, E.; Kanamitsu M.; Kistler R.; Collins W.; Deaven, D.; Gandin L.; Iredell M.; Saha, S.; White, G.; Woollen, J.; Zhu, Y.; Leetmaa, A.; Reynolds, R.; Chelliah, M.; Ebisuzaki, W.; Higgins W.; Janowiak, J.; Mo, K.C.; Ropelewski, C.; Wang, J.; Jenne, R. & Joseph, D. (1996). The NCEP/NCAR 40-year Reanalysis project. *Bulletin of American Meteorological Society*, Vol.77, No.3, (March 1996), pp. 437–471, ISSN 0003-0007.

Keyantash, J. & Dracup, J.A. (2002). The Quantification of Drought : An Evaluation of Drought Indices. *Bulletin of American Meteorological Society*, Vol.83, No.8, (August 2002), pp. 1167–1180, ISSN 0003-0007.

McKee, T.B. ; Doesken, N.J. & Kleist, J. (1993). The Relationship of Drought Frequency and Duration to Time Scales, *Proceedings of the AMS 8th Conference on Applied Climatology*, pp. 179–184, Anaheim, CA, January 17–22, 1993.

Raziei, T.; Bordi, I.; Pereira, L.S. & Sutera A. (2010). Space-Time Variability of Hydrological Drought and Wetness in Iran Using NCEP/NCAR and GPCC Datasets. *Hydrology and Earth System Sciences*, Vol.14, No.10, (October 2010), pp. 1919–1930, ISSN 1027-5606.

Raziei, T.; Bordi, I.; Pereira, L.S. & Sutera A. (2011). Detecting Impacts of a Changing Climate on Drought Characteristics in Iran, *Proceedings of the VI International Symposium of EWRA on Water Engineering and Management in a Changing Environment*, Catania, Italy, June 29–July 2, 2011, ISSN 2038-5854.

Rencher, A.C. (1998). *Multivariate Statistical Inference and Applications*, John Wiley & Sons Inc., ISBN 0-471-57151-2, New York, USA.

Sheffield, J. & Wood, E.F. (2008). Projected Changes in Drought Occurrence Under Future Global Warming from Multi-Model, Multi-Scenario, IPCC AR4 Simulations. *Climate Dynamics*, Vol.31, No.1, (July 2008), pp.79–105, ISSN 0930-7575.

Trenbert, K.E. & Guillemot, C.J. (1998). Evaluation of the Atmospheric Moisture and Hydrological Cycle in the NCEP/NACR reanalyses. *Climate Dynamics*, Vol.14, No.3, (March 1998), pp. 213–231.

Tsakiris, G.; Pangalou, D. & Vangelis, H. (2007). Regional Drought Assessment Based on the Reconnaissance Drought Index (RDI). *Water Resources Management*, Vol.21, No.5, (May 2007), 821–833, ISSN 0920-4741.

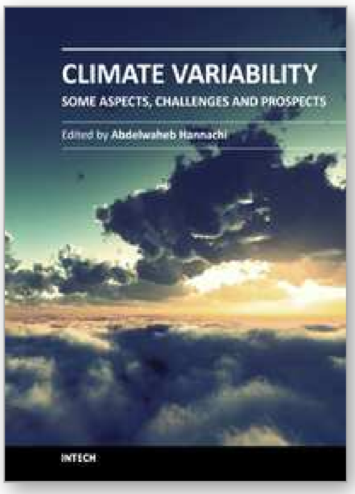
Vicente-Serrano, S.M.; Buguería, S. & Lòpez-Moreno, J.I. (2010). A multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. *Journal of Climate*, Vol.23, No.7, (April 2010), pp. 1696–1718, ISSN 0894-8755.

Wilhite, D.A. & Glantz, M.H. (1985). Understanding the Drought Phenomenon: The Role of Definitions. Water International, Vol.10, No.3, (available online 22 January 2009), pp. 111–120, ISSN 0250-8060.

Wilhite, D.A. ; Hayes, M.J. ; Knutson, C. & Smith, K.H. (2000). Planning for Drought : Moving from Crisis to Risk Management. *Journal of the American Water Resources Association*, Vol.36, No.4, (August 2000), pp. 697–710, ISSN 1093-474X.

Wilhite, D.A. ; Svoboda, M.D. & Hayes, M.J. (2007). Understanding the Complex Impacts of Drought: A Key to Enhancing Drought Mitigation and Preparedness. *Water Resources Management*, Vol.21, No.5, (May 2007), pp. 763–774, ISSN 0920-4741.

Wu, H. ; Hayes, M.J. ; Wilhite, D.A. & Svoboda, M.D. (2005). The Effect of the Length of Record on the Standardized Precipitation Index Calculation. *International Journal of Climatology*, Vol.25, No.4, (March 2005), pp. 505–520, ISSN 0899-8418.



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This book provides a general introduction to the popular topic of climate variability. It explores various aspects of climate variability and change from different perspectives, ranging from the basic nature of low-frequency atmospheric variability to the adaptation to climate variability and change. This easy and accessible book can be used by professionals and non professionals alike.