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Potential predictability of dry and wet periods: Sicily and Elbe-Basin (Germany)

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With 7 Figures

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Summary

The purpose of this paper is to evaluate a viable tool for the potential predictability of dry and wet spells. We select two regions in Europe that have distinct precipitation regimes: Sicily and Elbe basin (Germany). The analysis of dryness and wetness in these regions from 1951 to 2000 is based on the Standardized Precipitation Index (SPI) computed on a long-time scale (two years) and the evaluation of their time-space variability is carried out using Principal Component Analysis. Results suggest that periodicities ranging from 3.4 to 12 years characterise the SPI signals in both regions and essentially drive the main dry and wet occurrences. In Sicily, at variance with the Elbe basin, superimposed to this variability there is also a clearly detectable linear trend that is perhaps related to long-term periodicity. Moreover, the shift in phase found between the common periods implies that often on the longer time scale if the Elbe region has dry conditions, Sicily is wet and viceversa. The reconstruction of the SPI time series by considering the periodicity that greatly contribute to the total power spectrum variance gives good results and provides good opportunities for predictability.

1. Introduction

Europe is situated at the sensitive tale end of the North Atlantic stormtrack. Thus, it is not surprising that there are regions which suffer occasional wet or dry spells causing serious water shortage or extreme floods. Such extreme events have been reported in the last few years with the dryness in Sicily and wetness of the Elbe river attracting attention because of the severity and damages (for example the severe drought in Sicily in 1988–1990 or the wet period in Elbe in 2002). These phenomena, which occurred in the two regions, initiated our study and co-operation to search for their potential predictors by analysing the recent history, identifying possible mechanisms, and evaluating the anticipated skill. Here the emphasis lies on the longer time scales involved. At first glance, these processes are governed by different time scales: the extended dry or wet periods are associated with long-term variability, whereas floods are triggered by the short term and intensive event of a single or a fast sequence of frontal or convective complexes. However, when the long-term behaviour is considered, the two climate extremes may be a realisation of a common underlying mechanism.

To understand this physical connection, the phenomenology of these events at this time scale should be known. Unfortunately, the study of climate variability on long-time scales is still at the beginning stage, mostly because of lacking a comprehensive consistent, homogeneous and validated data base. Nevertheless progress may be made extracting as much information as possible by exploiting existing subsets of data as the one presented in the paper. The study is embedded in a set of drought assessments for Europe (Bordi and Sutera, 2001, 2002), which are based on the Standardized Precipitation Index (SPI, McKee et al., 1993; Guttman, 1999; Keyantash and Dracup, 2002). As the SPI characterises the water deficit and surplus by the precipitation field alone, it can be easily computed, and, as the index is standardised, it is also suitable for comparing different regions (Hayes et al., 1999). Several studies have demonstrated that the SPI is a useful tool to be established operationally as part of a drought watch system

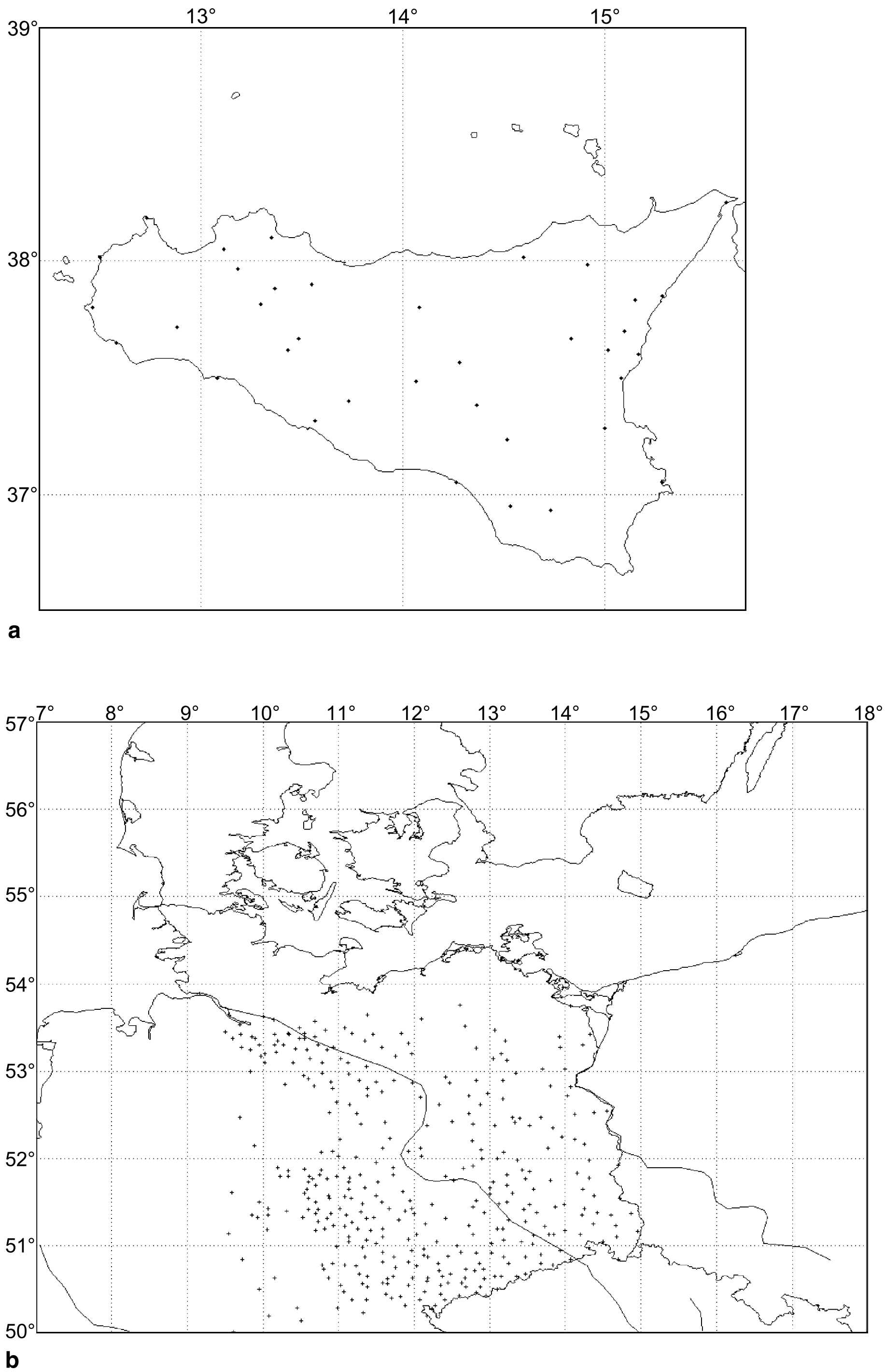


Fig. 1 Location of stations in (**a**) Sicily and (**b**) the Elbe basin in Germany

to monitor climate variability. Here we extend the preceding analyses of the SPI potential to monitor dryness and wetness to its potential predicting dry and wet spells. Section 2 describes the data analysed and the methods applied, Section 3 analyses the space-time variability of the regions, and an outlook for long-term forecast is provided in Section 4.

2. Data and methods of analysis

Periods of wetness and dryness are analysed by an index, which depends only on the monthly mean precipitation recorded at single stations. These are 36 stations chosen among the ones reporting rainfall in Sicily from 1951 to 2000 by following Alecci et al. (2000) criterions (see Fig. 1a for the location of stations). The 369 stations for the German part of the Elbe basin referring to the same period are chosen because the length of their record and the lack of missing values (see Fig. 1b). These data sets are the subject of the following analysis.

The SPI, defined first by McKee et al. (1993) for a single station to describe periods of dryness and wetness, has been applied to the two regions. It is based on long time series of monthly precipitation and it is computed by fitting a probability density function to the frequency distribution of precipitation summed over the time scale of interest (1, 2, 3 months, etc.). This is performed separately for each month of the year and each location in space. Each probability density function is then transformed into the standardised normal distribution, which readily allows comparison between distinct locations and analytical computation of exceedance probabilities. Values of the standardised normal variable are grouped into classes that identify the severity level of a drought or wet events (Bordi and Sutera, 2001, see also the Appendix). The index may be computed for different time scales allowing the various types of drought to be addressed: the shorter time scales for meteorological and agricultural drought, the longer ones for hydrological drought, etc. A time scale of 24 months has been proven as a suitable time scale, which captures the low frequency variability avoiding an explicit annual cycle. Note that short-time windows are not the focus of this analysis as we are primarily interested in the long-term aspect of dryness and wetness (see Keyantash and Dracup, 2002).

To capture the pattern of co-variability of the SPI at different station data, we employ the principal component analysis (PCA). This leads to a data reduction generating a set of linearly independent spatial patterns (loadings). They display spatial variability in terms of statistically deduced spatial modes or patterns, which describe the correlation between the SPI-series at single stations and the corresponding scores (principal component time series). These spatial patterns are ordered with respect to their contribution to the total variance denoted in percent (details are given by Rencher 1998, see also Bordi and Sutera, 2001). Moreover, to analyse the time variability, the scores are subjected to power spectrum analysis to identify their behaviour in the frequency domain (Jenkins and Watts, 1968). The power spectra have been computed by using the Tukey-Hamming spectral window at $M = 288$ lags and the 95% confidence levels based on the null hypothesis that the data are generated by a red noise with 5 degrees of freedom are shown, as well as the related confidence intervals.

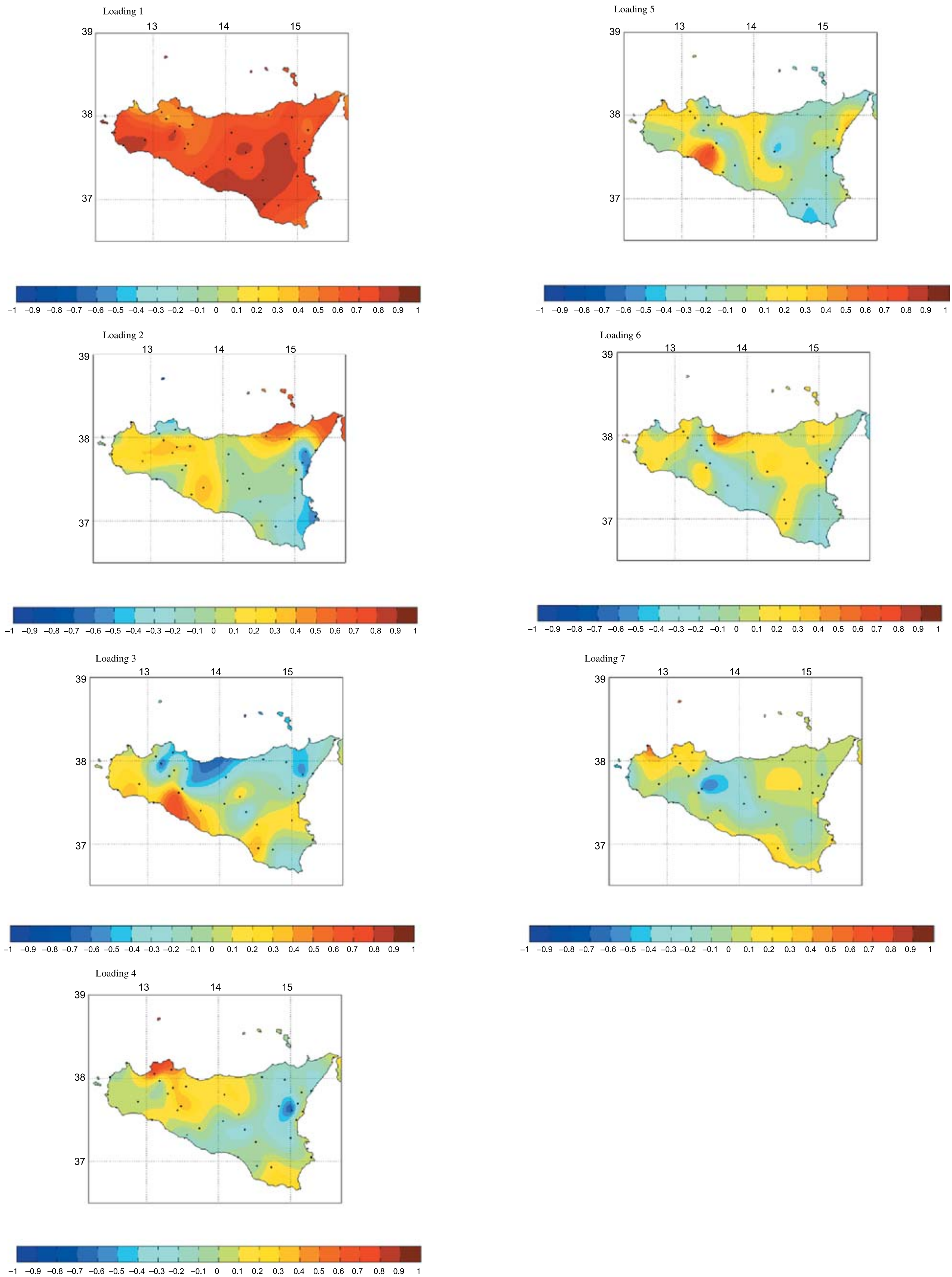
Spectral peaks and gaps characterise distinct periodicities while power-law scaling in a sufficiently wide frequency band may indicate long-term memory effects.

3. Results

We made the choice to present the number of loadings for each region such that they explain

Table 1. Percentage variance explained by the loadings for Sicily and Elbe basin

n. PCs	% variance Sicily	% variance Elbe basin
1	48.1	64.5
2	9.1	7.7
3	7.2	4.4
4	5.7	3.4
5	4.8	
6	3.5	
7	3.4	
Cumulative Variance (%)	81.8	80.0



a

Fig. 2. Loading patterns of the principle components of the SPI on 24-month time scale in Sicily (**a**) and Elbe basin (**b**). The percentage of the explained variance is shown in Table 1

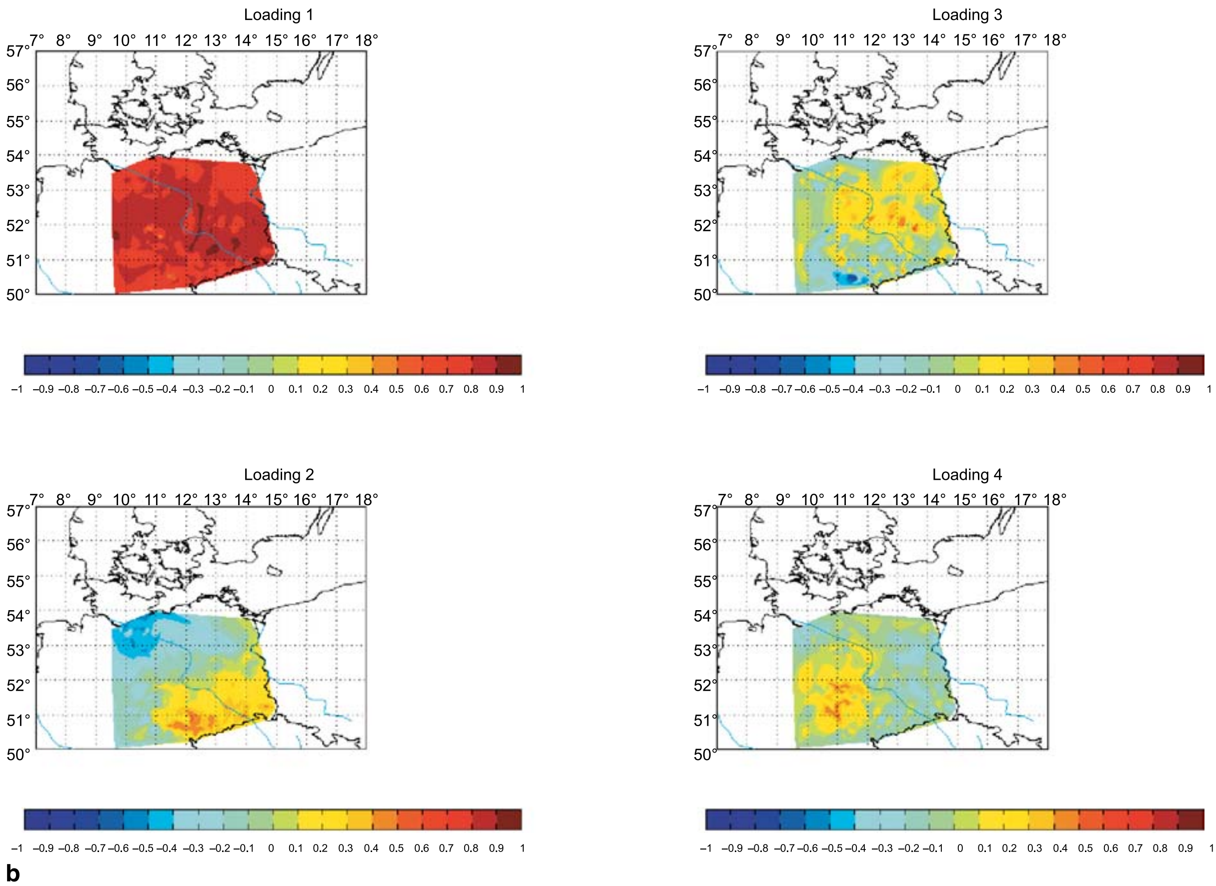


Fig. 2 (*continued*)

the same total amount of cumulative variance (see Table 1). No rotation was performed to let the method select the global nature of the pattern and not highlight regions, which here will be done with a different approach. Figure 2a and b show the loadings for Sicily and Elbe basin respectively. To reach about 80% percent of the variance Sicily requires seven loadings whereas the Elbe basin needs only four (this is probably due to the different numbers of stations in the two regions). Note that the first loading of both regions explains about 50% or more of the total variance. In Fig. 3a and b the corresponding PC-scores are shown.

The first loadings are spatially homogeneous and positive in both domains. The associated PC-scores describe the temporal behaviour of regions as a whole. The PC-1 score for each region shows long-term oscillations with the main difference that, for Sicily a trend is detectable whereas there is no apparent trend for Elbe basin. However, the Elbe basin shows a trend in the PC-3 score, which reflects a dipole pattern (third loading in Fig. 2b) with a negative and a positive centre in the SW and the NE of the basin. Note that only 4.4% describe dryness (wetness) increasing monotonously in the NE (SW) part of the basin. A trend component is also detected in PC-2 for Sicily: this PC explains 9.1% of the total variance and characterises the western and northern–eastern part of the region (see higher positive values on the loading).

In summarising, the occurrence of dry and wet periods appears to be dominated by the oscillation of the first PC for both regions. Thus a power spectrum analysis will be performed on the scores of the PC-1 alone.

Results of the spectral analysis are presented in Fig. 4a and b. Two broad band peaks are found both for Sicily and Elbe basin and the central frequencies for each band is shown in

Table 2. The statistically significant periods for both basins are close and hardly distinguishable given the short length of the time series. It must be noted that, considering the 95% confidence interval on a single spectral line, other peaks might also be statistically significant as 9.6 year for Sicily and 12.0–9.6 year for Elbe basin.

Nevertheless, to show the impact of these periodicities on drought and wet periods, we synthesise the time series by filtering out all the band frequencies listed in Table 3. Each

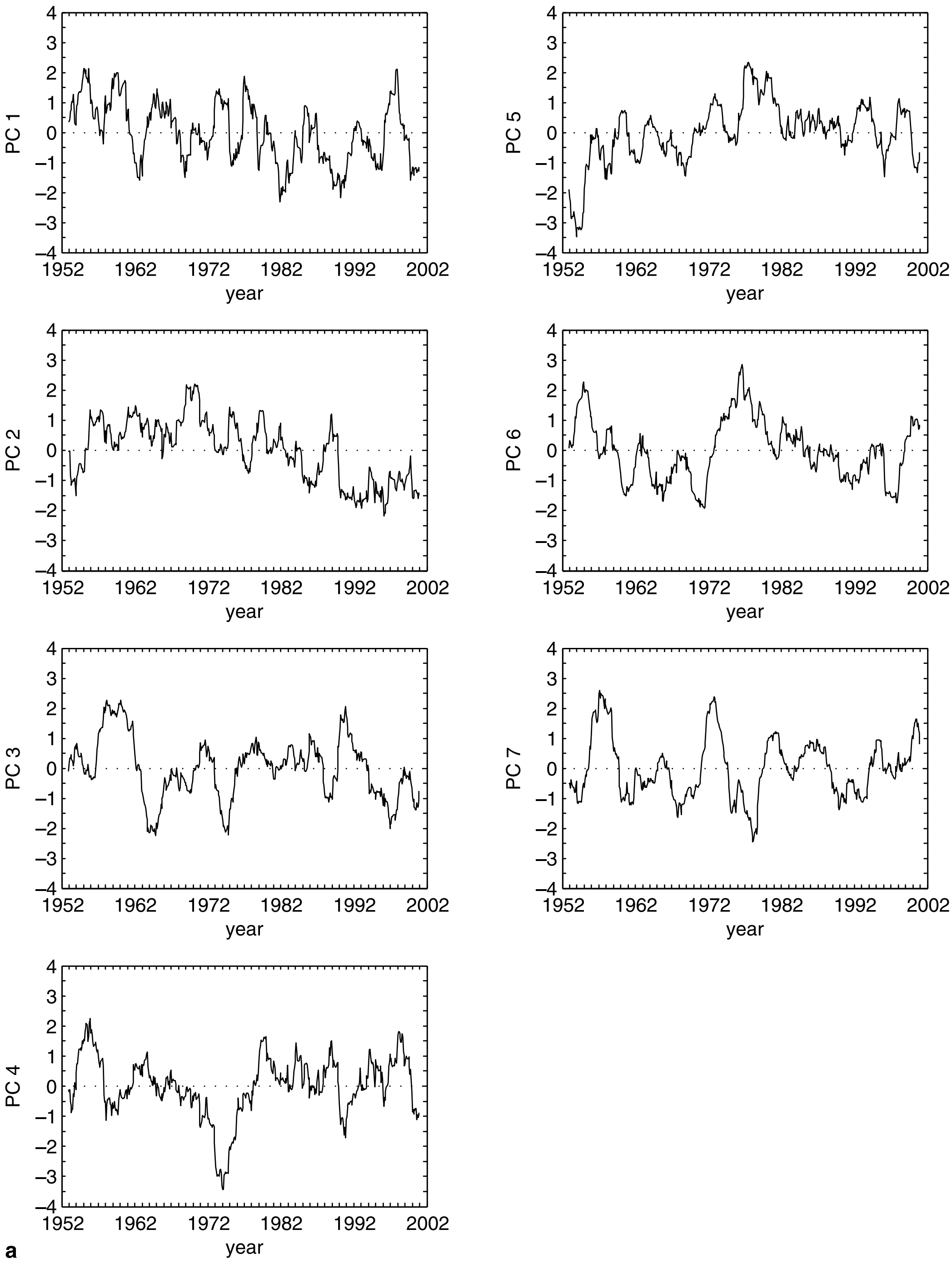


Fig. 3. Time series of the principle components scores of the SPI on 24-month time scale for Sicily (**a**) and the Elbe basin (**b**), corresponding to the loadings presented in Fig. 2

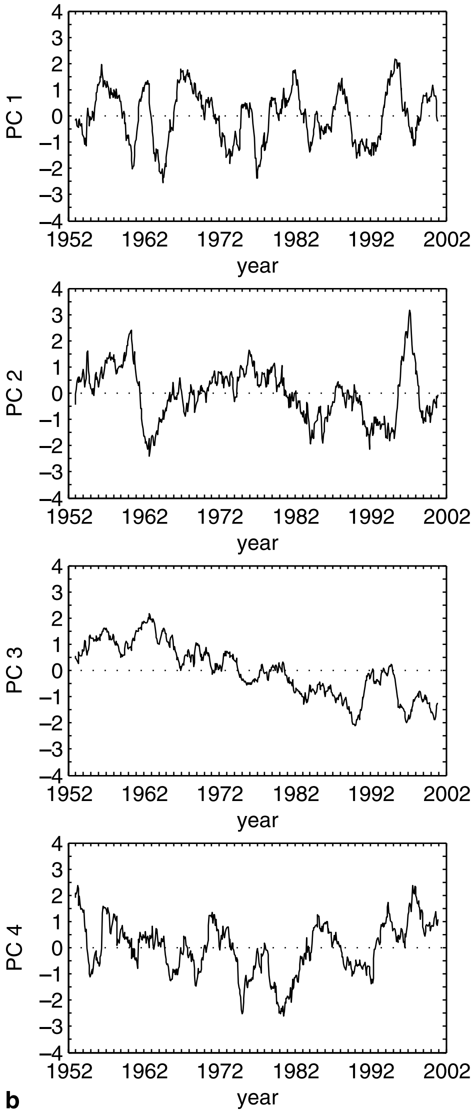


Fig. 3 (*continued*)

spectral band consists of all significant frequencies, which contribute to the statistically significant peaks. The criterion applied for selecting periods to be considered consists in retaining those that explain at least 2% of the power spectrum variance. However, the most relevant frequencies explain more than 10% of variance (see Table 3). Similar frequency bands have been noted in the SPI computation for Italy and Europe based on the NCEP/NCAR re-analysis data set (Bordi and Sutera, 2001, 2002). It must be also pointed out that for Sicily, due to the short time series available, the trend seems to be linear, but perhaps it is related to the long periods detected (say 48 and 24 year) although their statistical significance cannot be ascertained. For a partial corroboration, however, we have inspected longer precipitation time series in Sicily (here not shown), where there is evidence that the negative trend that characterises the last fifty years is merely related to long periodicities. Moreover, among the relevant peaks there is one close to the 11-year solar cycle.

A comparison of the PC-1 time behaviour and the corresponding re-synthesised time series for Sicily and Elbe basin is shown in Fig. 5a and b. The main drought and wet periods in both regions are essentially represented by these dominating periods. These lead to a high potential predictability both by statistical and/or dynamical methods. However, the latter method would require a physical explanation in terms of the underlying processes. We did not find any conclusive mechanism though some frequency involved may suggest some sun-weather relation (Labitzke and Van Loon, 1992; Van Loon and Labitzke, 1998).

To show that the same behaviour can be found at a single station we analysed two time series: one for Sicily (station n. 21, Gela) and one for the Elbe basin (station n. 15, Doberlug-Kirchhain). They are characterised to be highly correlated (0.9 for both) with the first PC score. The power spectrum (not shown) has statistical significant periodicity at roughly the same sequence of frequencies of the PC-1. In Fig. 6a and b we show the SPI and the periodically relevant components for the two stations. It can be noted that for these two stations the periodic component explains just about the full climatic variability of the SPI signals. Moreover, for Sicilian stations, if we do not consider the longer periods, a relevant portion of the index variance should be left unexplained because it is related to the long-term trend.

In looking for the time correlation of the two regions, we performed a cross spectral analysis for the first PCs. Results for the main low frequencies are summarised in Table 4. The statistical confidence of the cross-spectrum amplitude is determined following Jenkins and Watts (1968). In particular, in our case a value of the squared coherence greater than 0.74 threshold

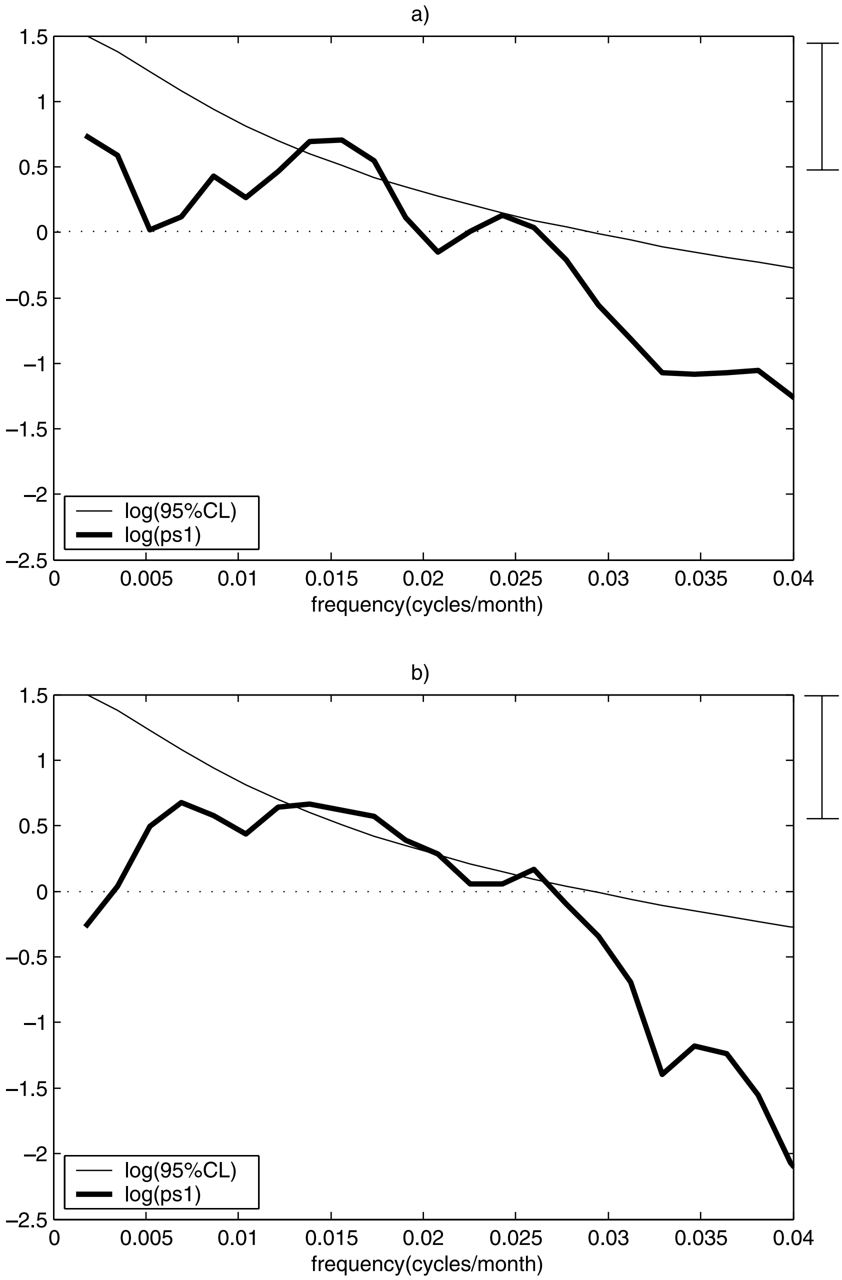


Fig. 4. Logarithm of the power spectrum of the first principal components (PC-1) for Sicily (**a**) and the Elbe basin (**b**). The thin line is the 95% confidence level based on "red noise" null hypothesis with 5 degrees of freedom. The horizontal line is the 95% confidence interval

Table 2. Frequencies (cycles per month) and periods (in years) of the largest power for the statistically significant peaks determined for the first scores of the principle components of Sicily and the Elbe basin

	Frequency (cycles month^{-1})	Period (year)
PC1 Sicily	0.00867	9.6
	0.01386–0.01560	6.0–5.3
	0.02426	3.4
PC1 Elbe basin	0.00693–0.00867	12.0–9.6
	0.01213–0.01386	6.9–6.0
	0.02600	3.2

value (assuming 5 degrees of freedom) denotes periods with a statistical confidence at 90% level. This means that periods from 6.9 to 4.8 year (denoted by asterisk in Table 4) are related and they are phase shifted of about 2 years. Furthermore, the cumulative variance explained by these periods is about 40% (see Table 3). If we use 95% confidence level, the threshold is 0.83; thus, only the statistical confidence of the 6.9 year period becomes just marginal. It must be noted that 48 year period is probably due to a linear trend pre-

Table 3. Periods retained for reconstructing the PC-1 scores time series and the SPI-24 for two sample stations in the two regions, Sicily and Elbe basin. The power spectrum variance explained by each periodicity is also listed

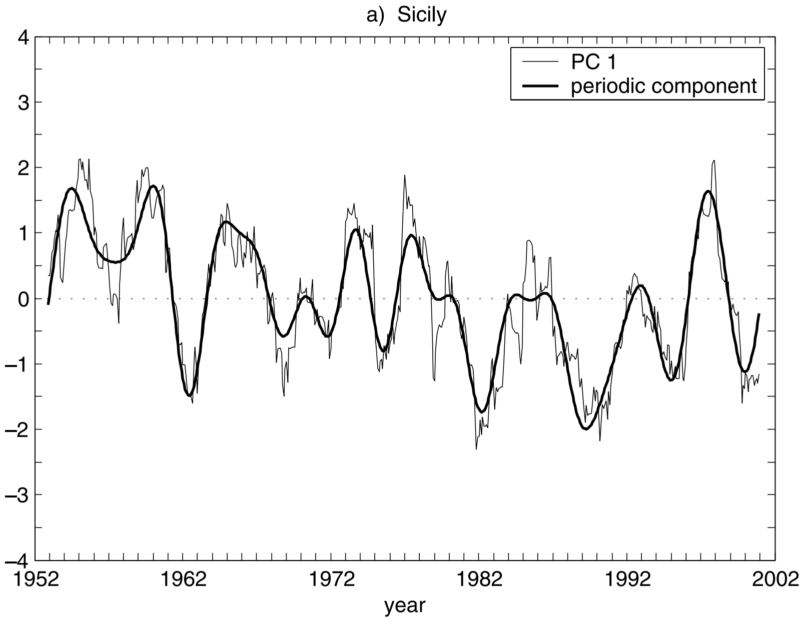
Channel	Station n. 21 Sicily		PC1 Sicily		Station n.15 Elbe basin		PC1 Elbe basin	
	Period (year)	Variance (%)	Period (year)	Variance (%)	Period (year)	Variance (%)	Period (year)	Variance (%)
1	48.1	22.4	48.1	19.4	–	–	–	–
2	24.0	3.5	24.0	6.9	–	–	–	–
3	–	–	–	–	16.0	2.6	16.0	7.4
4	–	–	–	–	12.0	13.1	12.0	11.8
5	9.6	14.0	9.6	10.6	9.6	17.8	9.6	9.6
6	–	–	–	–	8.0	2.1	–	–
7	6.9	20.3	6.9	6.4	6.9	20.0	6.9	13.0
8	6.0	10.2	6.0	12.4	6.0	6.4	6.0	9.7
9	5.3	8.7	5.3	11.5	5.3	2.6	5.3	8.3
10	4.8	3.8	4.8	9.0	4.8	13.0	4.8	10.4
11	4.4	2.3	–	–	4.4	2.8	4.4	2.8
12	–	–	4.0	2.0	–	–	4.0	6.1
14	–	–	3.4	3.8	3.4	4.9	3.4	2.0
15	–	–	3.2	2.2	3.2	3.3	3.2	4.9
Cumulative variance (%)		85.2		84.2		88.6		86.0

sent in Sicily PC-1 (see PC-1 in Fig. 3a); the cross-spectral analysis suggests that might be a weak trend in Elbe as well. These results imply that overall on long time scale, if the Elbe region is in drought, Sicily is in wet conditions.

4. Discussion: Potential predictability of drought and wet periods

Previously we have shown that about 40% of the relative variance for the SPI-24 in the two regions are associated with cyclic phenomena. Thus, we have a potential predictability. The crudest method to assess this potential predictability may be outlined as follows. A "forecast" of the SPI-24 time series is obtained, first, by training with the periodic signal until December 1999, then the signal is forward extrapolated from January 2000 to August 2002 and compared with the available updated SPI values for the Elbe. As an example we show the results in Fig. 7 for stations n. 15 (Doberlug-Kirchhain) and n. 60 (Potsdam). The method seems to be successful in following the index behaviour for the last 32 months. It should be noted that a forecast for periods less than two years may fail because we are considering the SPI on 24-month time scale, that by its definition filters out shorter periodicities. The high frequencies characterising the SPI24 signal, in fact, are essentially due to random noise. For this reason only a predictability of the envelop of the index time series is expected leaving the high frequency fluctuations unresolved.

Thus, we may conclude that there is potential for predictability (to be exploited by using more properly designed statistical methods) of droughts and wet periods, at least for these two regions, which we believe are characteristic for the continental European and Mediterranean areas. In fact, most of the precipitation over the Mediterranean basin is controlled by the uplift and convergence of moist air along the orographic slopes, while the precipitation patterns of central Europe may be described by the classical frontal schemes of the mid-latitudes with a simpler phenomenological relationship between precipitation and surface temperature, soil moisture, etc. Despite the fact that the Mediterranean climate differs from the one of central Europe, the mechanism controlling drought occurrence on this time scale should be the same for the two regions analysed. Unfortunately, the physical origin of the common unveiled periodicities remains at present not easily detectable, as



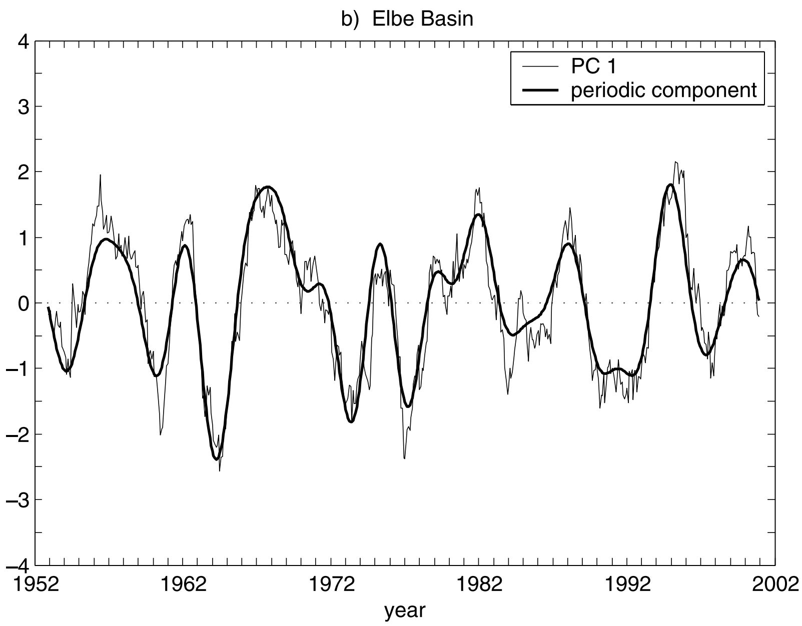


Fig. 5. Time series of the first principal components scores and the reconstructed time series by retaining the main periodic components for (**a**) Sicily and (**b**) Elbe basin. The periods considered are listed in Table 3

well as their relationship with other climatic phenomena.

For solar influence, we can suppose a modulation of the stratospheric circulation as a possible link to explain our findings in the long period variability, but a mechanism that connects the solar and tropospheric-stratospheric oscillations on this scale has not yet been found. Furthermore, preliminary investigations, based on the NCEP/NCAR re-analysis data set, suggest that variations of the sea level pressure field cumulated on 24-month time scale contain a component on the 10–12 year scale, but the physical origin of the possible connection with the precipitation field is not understood. On the other hand, a cross spectral analysis (not shown) of PC-1 time series with both NAO (North Atlantic Oscillation) index and SOI (El Niño-Southern Oscillation Index) does not present any statistically significant evidence of a common variability. Some studies, in fact, describe only the correlation between NAO and winter rainfall in

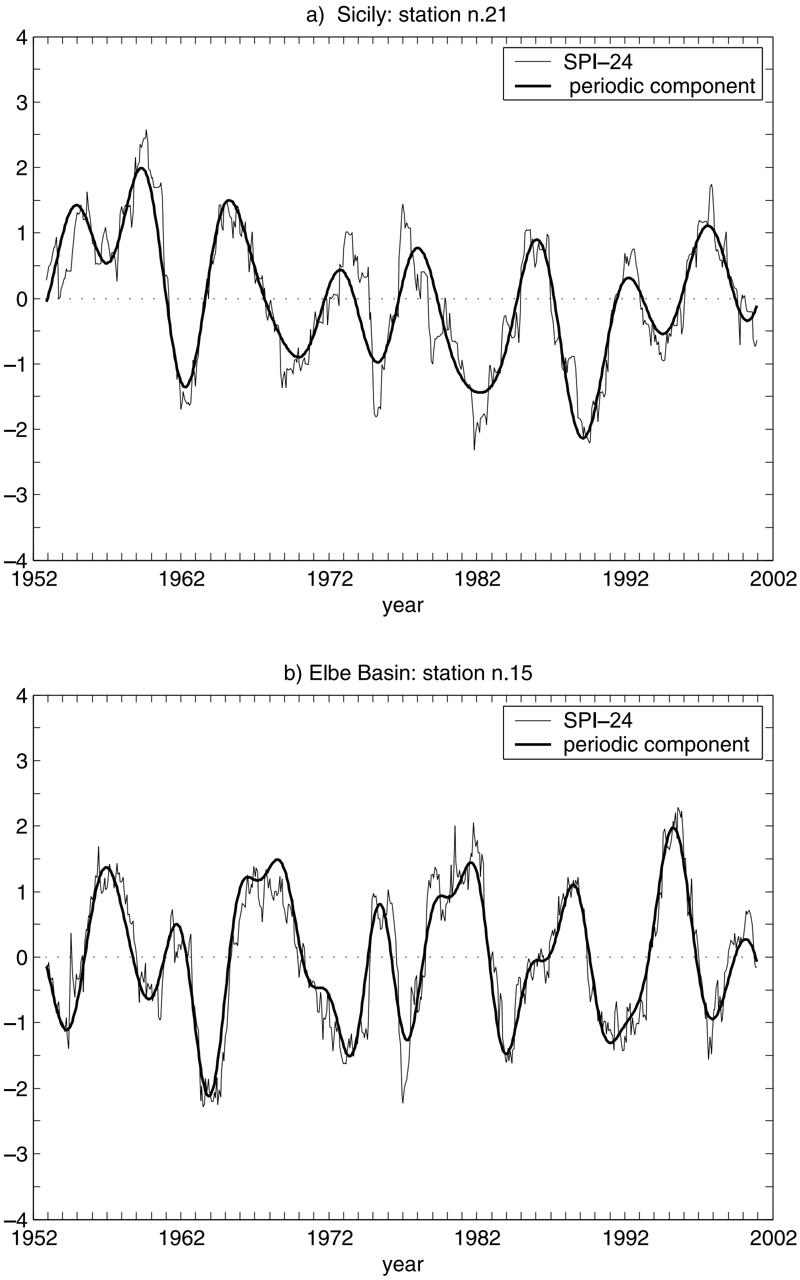


Fig. 6. Time series of the SPI on 24-month time scale and the reconstructed time series by retaining the main periodic components for (**a**) Sicily, station n. 21, and (**b**) Elbe basin, station n.15. The periods considered are listed in Table 3

Table 4. Cross-amplitude spectrum, phase shift (in radiant and month) and squared coherence for periods from 48 to 3.2 year obtained by the cross-spectral analysis of PC-1 scores for Sicily and Elbe. Asterisks denote the periods at the 90% confidence level

Period (year)	Cross-amplitude	Phase (rad)	Phase (year)	Squared coherence
48.1	1.67	−0.80	−6.11	0.88*
24.0	0.86	−0.89	−3.40	0.03
16.0	0.76	−2.62	−6.67	0.03
12.0	0.55	1.65	3.16	0.00
9.6	2.36	0.93	1.43	0.31
8.0	1.60	1.46	1.86	0.26
6.9	3.33	2.34	2.56	0.76*

(*continued*)

Table 4 (*continued*)

Period (year)	Cross-amplitude	Phase (rad)	Phase (year)	Squared coherence
6.0	4.65	2.52	2.41	0.89*
5.3	4.54	2.69	2.29	0.94*
4.8	3.48	2.89	2.21	0.85*
4.4	1.61	3.06	2.13	0.68
4.0	0.79	2.98	1.90	0.21
3.7	0.33	3.06	1.80	0.01
3.4	0.89	2.92	1.60	0.27
3.2	1.05	2.98	1.52	0.46

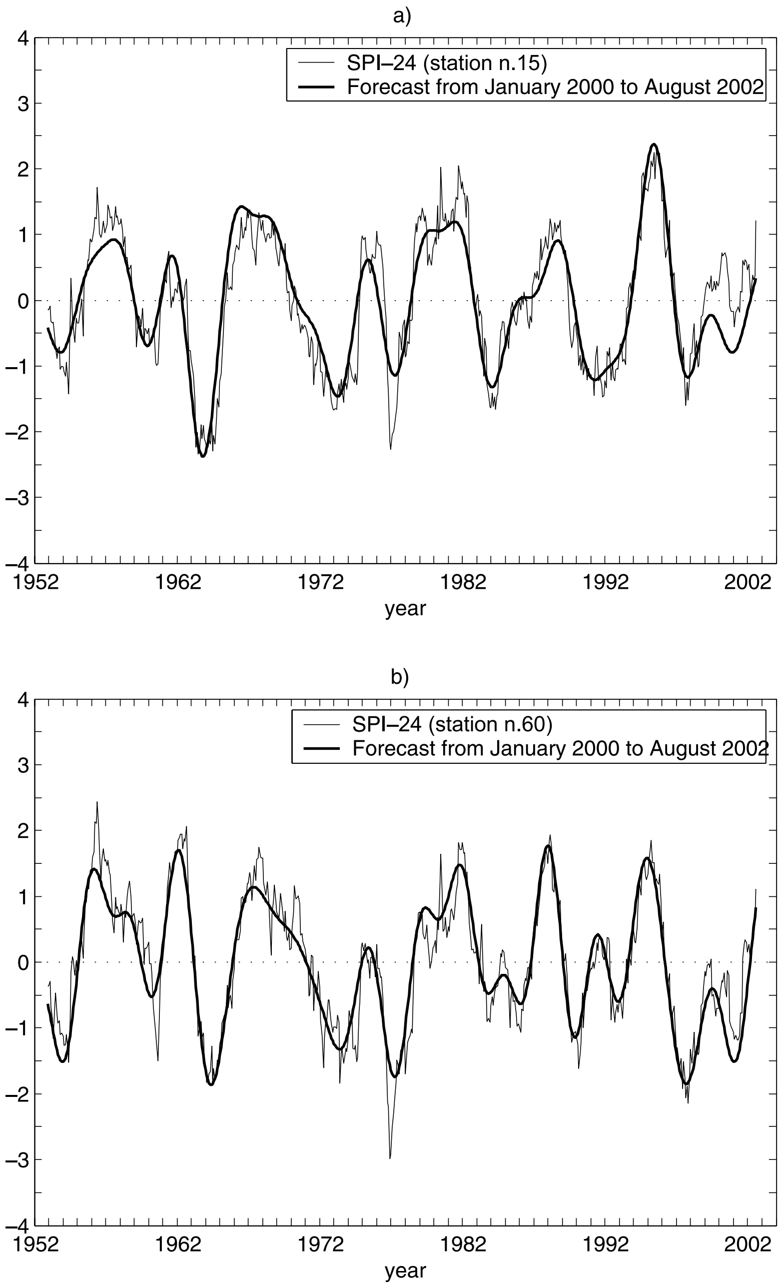


Fig. 7. Time series of the SPI on 24-month time scale from December 1952 to August 2002 (thin line) and the forecast from January 2000 to August 2002 (thick line) by extrapolating the periodic components of the signal for the German stations n. 15 (**a**) and n. 60 (**b**)

Europe (see for example Lamb and Peppler, 1987; Hurrell, 1995), while, despite the global impact of the El Niño-Southern Oscillation, there is little hard evidence of ENSO impacts in Europe (Fraedrich, 1994; Rodó et al., 1997). An alternative interpretation of the origin of these perodicities should be that suggested by Tourre et al. (1999) by analysing the dominant patterns of the joint sea surface temperature and sea level pressure variability in the Atlantic Ocean. The authors found frequency bands close to those identified in the present paper suggesting that a significant part of the observed variability in the Atlantic can be described by an equatorial mode, akin to ENSO, interacting with NAO. Thus, it appears of great importance to devote future efforts into the investigation of the source of these periodicities discussed above and their relationship with the other meteorological variables.

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Appendix

The method of computing the SPI may be found extensively described in Guttman (1999) or in Bordi and Sutera (2001). Nevertheless, for the sake of completeness, we will describe here the main steps for its computation. The SPI application for a specific month of the year, for a given time scale (i.e. the variable for computing the index is the precipitation cumulated on the given time scale starting from the considered month and going backward) and at any location, requires a long-term monthly precipitation database. The probability function of the cumulative precipitation up to that month is determined from the long-term record by fitting a gamma function to the data. By letting $t = \mathrm{X}/\tilde{\beta}$ we have:

$$G(\mathrm{X}) = \int_0^{\mathrm{X}} g(\mathrm{X})\, d\mathrm{X} = \frac{1}{\Gamma(\tilde{\alpha})} \int_0^{\mathrm{X}} t^{\tilde{\alpha}-1} e^{-t}\, dt \tag{1}$$

where $\tilde{\alpha}$ is a shape parameter, $\tilde{\beta}$ is a scale parameter and $\Gamma(\tilde{\alpha})$ is the gamma function. In addition x is, given a particular month, the cumulative precipitation on the time scale selected. Since the gamma function is undefined for $\mathrm{X} = 0$ and the precipitation field may contain zeros, the cumulative probability becomes:

$$H(\mathrm{X}) = Q + (1 - Q)\, G(\mathrm{X}) \tag{2}$$

where Q is the probability of zero precipitation. $H(\mathrm{X})$ is then transformed to a normal variable by means of the following approximation (Abramowitz and Stegun, 1965):

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

where:

$$\begin{aligned} t &= \sqrt{\ln\left(\frac{1}{(H(\mathrm{X}))^2}\right)} \quad \text{for } 0 < H(\mathrm{X}) \le 0.5 \\ t &= \sqrt{\ln\left(\frac{1}{(1.0 - H(\mathrm{X}))^2}\right)} \quad \text{for } 0.5 < H(\mathrm{X}) < 1.0 \end{aligned} \tag{4}$$

and c_0, c_1, c_2, d_1, d_2, d_3 are constants. Hence, the SPI represents a Z-score or the number of standard deviations (above or below) that an event deviates from the mean. The index can be computed on different time scales (typically 1, 3, 6, 12 and 24 months) allowing, among other things, to monitor short-term water supplies, such as soil moisture, important for agricultural production, and long-term water resources, such as ground water supplies, stream flow or reservoir levels. The classification of dry and wet spells resulting from the SPI computation is shown in the following table:

SPI value	Class
Greater than 2	Extremely wet
From 1.5 to 1.99	Very wet
From 1.0 to 1.49	Moderately wet
From −0.99 to 0.99	Near normal
From −1 to −1.49	Moderately dry
From −1.5 to −1.99	Severely dry
Less than −2	Extremely dry

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