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Spatial Patterns and Temporal Variability of Drought in Western Iran

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Abstract An analysis of drought in western Iran from 1966 to 2000 is presented using monthly precipitation data observed at 140 gauges uniformly distributed over the area. Drought conditions have been assessed by means of the Standardized Precipitation Index (SPI). To study the long-term drought variability the principal component analysis was applied to the SPI field computed on 12-month time scale. The analysis shows that applying an orthogonal rotation to the first two principal component patterns, two distinct sub-regions having different climatic variability may be identified. Results have been compared to those obtained for the large-scale using re-analysis data suggesting a satisfactory agreement. Furthermore, the extension of the large-scale analysis to a longer period (1948–2007) shows that the spatial patterns and the associated time variability of drought are subjected to noticeable changes. Finally, the relationship between hydrological droughts in the two sub-regions and El Niño Southern Oscillation events has been investigated finding that there is not clear evidence for a link between the two phenomena.

Keywords Drought variability · Standardized precipitation index · Principal component analysis · ENSO events

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1 Introduction

Drought is a normal, recurrent feature of climate that may occur everywhere even if its characteristics and impacts vary significantly from region to region (Wilhite 1997). It is defined as a natural temporary imbalance of water availability, consisting of a persistent lower-than-average precipitation, of uncertain frequency, duration and severity, of unpredictable or difficult to predict occurrence, resulting in diminished water resources availability and carrying capacity of the ecosystems (Pereira et al. 2002). Thus, an objective evaluation of drought condition in a particular area is the first step for planning water resources in order to prevent and mitigate the negative impacts of future occurrences. For this purpose, along the years, several indices have been developed to evaluate the water supply deficit in relation to the time duration of precipitation shortage (see Keyantash and Dracup 2002; Heim 2002 and references therein). Among them, the most commonly used for drought monitoring are the Palmer Drought Severity Index (PDSI, Palmer 1965) and the Standardized Precipitation Index (SPI, McKee et al. 1993). The PDSI is based on the supply-and-demand concept of the water balance equation for a two-layer soil model. It depends on several local coefficients that are estimated using local hydrological norms related to temperature and precipitation averaged over some calibration period (at least 30-year period, according to the World Meteorological Organization recommendation). The basis of the index is the difference between the amount of precipitation required to retain a normal water balance level and the actual precipitation.

Nevertheless, if we wish to compare drought conditions of different areas, which often have different hydrological balances, the most important characteristic of any index is the standardization. The SPI complies with this requirement. It is, in fact, a standardized index that can be computed on different time scales, so as to allow monitoring most of drought types (i.e. meteorological, agricultural, hydrological). The SPI computation for any location is based on the long-term precipitation record cumulated over the selected time scale. This long-term record is fitted to a probability distribution (usually a Gamma distribution, Guttman 1999), which is then transformed through an equal-probability transformation into a normal distribution. Positive SPI values indicate greater than median precipitation, and negative values indicate less than median precipitation (Bordi and Sutera 2001). Thus, because the SPI is normalized wetter and drier climates can be represented in the same way.

Guttman (1998) compared the Palmer Drought Index (an older version of the PDSI) with the SPI through a spectral analysis in order to evaluate the application accuracy. He recommended the SPI as a more useful drought index because it is standardized and contains a probabilistic interpretation, so it can be used in risk assessment and decision-making. Paulo and Pereira (2006) compared the PDSI and the SPI concluding that the linear correlation coefficient between the two indices is higher for the 12-month time scale.

Morid et al. (2006) examined the performances of seven drought indices requiring only rainfall data for drought detection and monitoring in the Tehran province of Iran. They concluded that, despite different underlying statistical distributions, the SPI performed in a similar manner with regard to drought identification and drought onset, and that the SPI and Effective Drought Index (EDI) could be recommended for operational drought monitoring in the region; however, the EDI requires daily precipitation, which constitutes a serious limitation for its operational use.

Thus, due to its advantages, the SPI appears to be the most powerful drought index. Many authors including, Hayes et al. (1999), Szalai and Szinell (2000), Bordi and Sutera (2001), Lloyd-Hughes and Saunders (2002), Lana et al. (2001), Vicente-Serrano et al. (2004), Tsakiris and Vangelis (2004), used the SPI to monitor drought in many regions, while others have used the SPI to predict drought class transitions adopting Markov-chain and log linear models (Paulo et al. 2005; Paulo and Pereira 2007; Moreira et al. 2008), or to forecast droughts with stochastic and neural networks modelling (Mishra and Desai 2005).

Studies on climate variability are important for the design and management of water resource systems. However, such analysis may be difficult when data from many stations are used. The principal component analysis (PCA) is a convenient and useful method to reduce inter-correlated variables into a few linearly uncorrelated ones. Many authors, using observations or re-analysis data (Bordi and Sutera 2001, 2002; Bonaccorso et al. 2003; Bordi et al. 2004a, b, 2006; Vicente-Serrano et al. 2004), applied the PCA to the SPI for analyzing the temporal and spatial variability of drought. In particular, Bordi et al. (2006) showed that the National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) and ERA-40 re-analysis products capture a linear trend as a primary feature of the climatic signal, both at global and large regional level, though the spatial location of this climatic behavior differs greatly between the two data sets. Thus, a stringent comparison with the rain gauge observations is suggested to check the reliability of the re-analysis data and properly understand the long-term variability in a region.

Moreover, some authors studied the possible link between precipitation regimes around the world and El Niño Southern Oscillation (ENSO), since this climatic signal may contribute to the predictability of precipitation variability and anomalies in many tropical and subtropical regions (Ropelewski and Halpert 1996; Vicente-Serrano 2005; Peel et al. 2002). The influence of ENSO on autumn precipitation in Iran was studied by Nazemosadat and Cordery (2000) who found a negative correlation between the Southern Oscillation Index (SOI) and rainfall for almost all the country, but stronger and more consistent in the southern foothills of the Alborz Mountains, northwestern districts and central areas. Nazemosadat and Ghasemi (2004) further explored these relationships and proposed a mechanism to justify the seesaw fluctuation of winter precipitation over the southwestern and southeastern Caspian Sea coasts showing that it is likely that the interaction between the Siberian high and ENSO controls rainfall variability over these regions. However, the possible relationship between ENSO and drought phenomenon, objectively monitored through a standardized drought index, remains an open question.

On these grounds, using both rain gauge observations and NCEP/NCAR re-analysis data, we carried out an analysis of drought variability in western Iran by decomposing the SPI time series into principal components. The motivations are:

1. Precipitation in Iran has a high spatial and time variability. There are regions in the south of Caspian Sea, which receive up to 2,000 mm of annual precipitation, whereas portions of central and eastern part of the country get less than 50 mm. Furthermore, most of the precipitation in Iran falls during the winter and autumn seasons, due to the prevalence of humid westerly winds of Mediterranean origin (Domroes et al. 1998; Dinpashoh et al. 2004; Raziei and Azizi 2007). However, there are regions in the northwestern part of the country that are characterized

by high precipitation also during spring. These features make difficult the management of water resources in Iran, especially during water shortage periods. The SPI appears to be a useful tool for comparing the climatic conditions of these areas characterized by different hydrological regimes;

2. Iran experienced recurring drought events. For instance ten out of the 28 provinces were affected by one of the worst and prolonged droughts in 1998–2001 period, leaving an estimated 37 million (over half the country's population) vulnerable to food and water shortage. Twenty provinces experienced precipitation shortfalls during winter and spring 2001 (Agrawala et al. 2001). While some efforts have been done to study the precipitation variability in Iran (Domroes et al. 1998; Dinpashoh et al. 2004; Soltani and Modarres 2006; Raziei and Azizi 2007), no comprehensive study on drought (i.e. deviation of actual precipitation from a historically established norm), supported by a standardized drought index, has been performed for the region. Drought studies, in fact, are important to better develop policies and measures that support drought risk management for the region;
3. The analysis of the climatic variability in the last 50 years at global scale using the SPI (see Bordi and Sutera 2001; Bordi et al. 2006) showed a linear trend as the primary feature of the drought variability, but never a comparison with the rain gauge observations has been made for Iran. This would be useful to properly adopt the re-analysis product as a tool for drought monitoring in the country.

Furthermore, following the investigations mentioned above on the possible impact of ENSO on precipitation regimes in different areas of the world, we propose a comparison between extreme phases of SOI and major droughts/wet periods in western Iran as deduced from the SPI analysis. This is to understand if disastrous drought events, which often adversely impact Iran, might be partly attributed to this teleconnection.

The paper is organized as follows. In Section 2 there is a description of the data used for the study, while Section 3 provides information on the methodology adopted. Section 4 shows the main results obtained from the PCA of the SPI on 12-month time scale, using both observations and re-analysis data, and from the comparison between SOI and drought/wet events. The summary and conclusions are given in Section 5.

2 Study Area and Data

Western Iran comprises an area extending from about 26–39° N to 45–51° E. The region is mostly occupied by Zagros Mountain systems (Fig. 1a), which faces the direction of the prevailing moisture bearing systems and receives between 200 to 600 mm of precipitation per year (Domroes et al. 1998; Dinpashoh et al. 2004). Due to the latitudinal extent and its complex relief structure, the precipitation amount varies highly over the region.

Monthly precipitation data from 196 stations in the region were made available by the Iranian Water Resources Institute and the Iranian Meteorological Organization. Homogeneity of the median and variance was evaluated using the Mann–Whitney homogeneity test, and trend and independence were checked using the Mann–Kendall and Kendall autocorrelation tests, respectively (Helsel and Hirsch 1992).

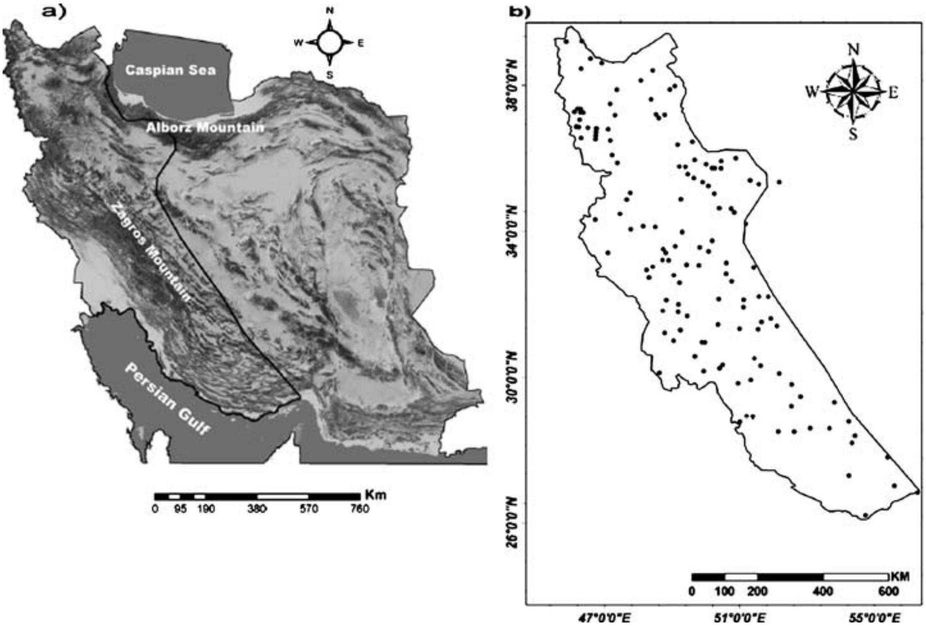

Fig. 1 **a** Topographic map of Iran and **b** stations network across the study area

Results showed that 56 stations had to be discarded due to low data quality and having more than 5% missing values. The remaining 140 stations (Fig. 1b) cover 36 hydrological years from October 1965 to the September 2000. The stations constitute a well-distributed network throughout the study area. Missing values for each station were estimated using Move4 technique (Maintenance of Variance Extension), which develops a linear equation such that a reasonable and unique extended record is generated and the variation of data series is maintained (Vogel and Stedinger 1985; Paulo et al. 2003).

The re-analysis product used in this study is the monthly precipitation rate retrieved from the NCEP/NCAR data set. Precipitation fields are available from January 1948 to present on a regular grid 1.9 × 1.9° in latitude and longitude and have been derived from the primary meteorological fields by means of a re-analysis procedure. Details about the assimilation model and the re-analysis project can be found in Kalnay et al. (1996). Here we have considered the area 23.8–41.0° N, 43.1–63.8° E (120 grid points) and two time sections: October 1965–September 2000 and January 1948–December 2007.

3 Methodology

The SPI is usually computed over multiple time scales ranging from 1 to 48 months, which reflect the impact of drought on the availability of the different water resources. Among users there is a general consensus about the fact that the SPI on shorter time scales (say 3 and 6 months) describes drought events affecting agricultural practices, while on the longer ones (12 and 24 months) it is more suitable for water resources management purposes. In this paper, results concerning the 12-month time scale (SPI-12 hereafter) are discussed. This is because in Iran there are areas where significant portions of the available water reservoirs are managed on a time scale of a single year (i.e. they are filled in during the rainy season and empty out in the dry season). Notice that, using this time scale we avoid the seasonal cycle, while the memory effect associated with the inter-annual variability is still accounted for. The SPI time series were computed following the method described by McKee et al. (1993).

To capture the patterns of co-variability of drought at different stations, the PCA (Rencher 1998) was applied to the SPI-12 time series. The method consists in computing the covariance matrix of the SPI data with the corresponding eigenvalues and eigenvectors. 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"; they represent the correlation between the original data (in our case, the SPI-12 time series at single stations) and the corresponding principal component time series.

In order to find more localized spatial patterns of variability we applied the Varimax rotation to the loadings (Richman 1986; von Storch and Zwiers 1999). This method allows finding areas within the region that have rather independent climatic variability, i.e. the rotated principal components are temporally orthogonal (Rencher 1998). Following the rule by North et al. (1982), we have estimated the sampling errors of the eigenvalues associated to principal components and we have established how many loadings to retain for rotation. For the cases here analyzed, using both rain gauge observations and re-analysis precipitation data, only the first two eigenvalues are well separated within 95% confidence level. Thus, the time variability of drought events across the study area was represented by the two rotated PC score time series. It is worth to notice that the rotated PC scores provide the common time behavior of the SPI time series in those areas where the corresponding loadings have maximum values leaving undetermined the magnitude of drought/wet spells occurred on each station.

Finally, to investigate the relationship between ENSO and dry/wet periods in western Iran, we compared the 12-month running mean SOI from October 1966 to September 2000 with the SPI-12 time series of two stations representative of the identified sub-regions. For the study we used the standardized monthly SOI, which is freely available on the web at the URL http://www.cpc.noaa.gov/data/indices.

4 Results

4.1 Rotated PCA of the SPI-12 Time Series for Western Iran: Observations

We applied first the PCA to the SPI-12 time series computed for western Iran using rain gauge observations. Based on Fig. 2, which shows the first ten eigenvalues of the PCA with the corresponding 95% confidence intervals, we have selected only the first two loadings for Varimax rotation. The percentages of the total variance explained

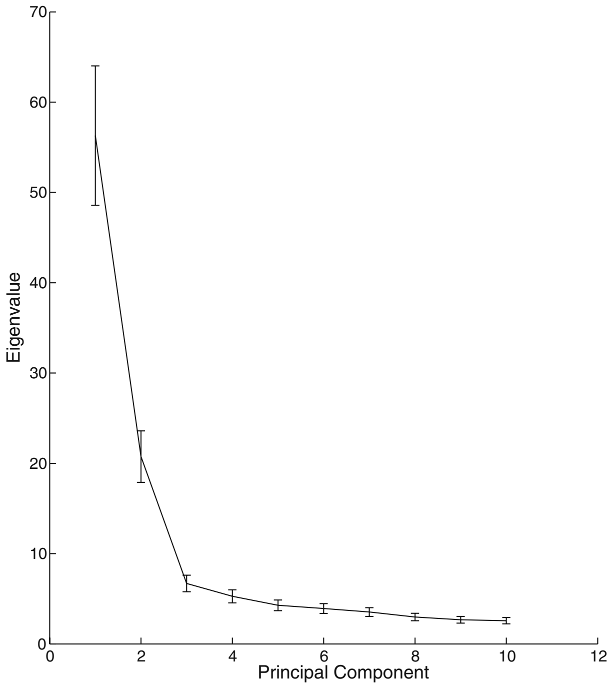

Fig. 2 First ten eigenvalues and the corresponding *error bars* at 95% confidence level for the principal components of the SPI-12 computed using rain gauge data

by the retained loadings are 40.16% and 14.80% respectively, for a cumulative variance of 54.96%. These loadings, here not shown, have high positive values over the whole area with the exception of some stations in the north (Loading-1), and positive values mainly in the northern part of the study area (Loading-2).

As illustrated in Fig. 3a, b, the orthogonal rotation applied to these spatial patterns provides more localized areas of drought variability. The two rotated loadings account for 27.75% and 27.21% of the total variance respectively, while the cumulative variance remains unchanged with respect to the un-rotated case. The first rotated loading (R-Loading 1) has positive values in the south of the study area, reaching maximum values in southwestern regions. The corresponding rotated PC score (RPC-1, Fig. 3c) shows multi-year fluctuations and remarkable dry events of different magnitudes are expected to be occurred at single stations in the south around 1967, 1971, 1974, 1984, 1986 and 1994. Moreover, a weak long-term linear trend towards positive values, e.g. wet periods, from the eighties onward is detectable. Nevertheless, such a trend accounts only 6.5% of the total variance of the signal (see Table 1) and is not statistically significant at 95% confidence level. The second loading has positive high values mainly in the north of the study area and the corresponding score (RPC-2) shows multi-year fluctuations embedded on a long-term linear trend towards negative values, e.g. dry periods (Fig. 3d). This tendency seems to be driven by the worst drought event occurred in 1999, however, as before, the unveiled trend is weak and explains only a small percentage of the RPC-2 variance, i.e. 8.7%.

Thus, the rotated loadings seem to well localize in space two distinct sub-regions, the northern and southern part of western Iran, that are characterized by different

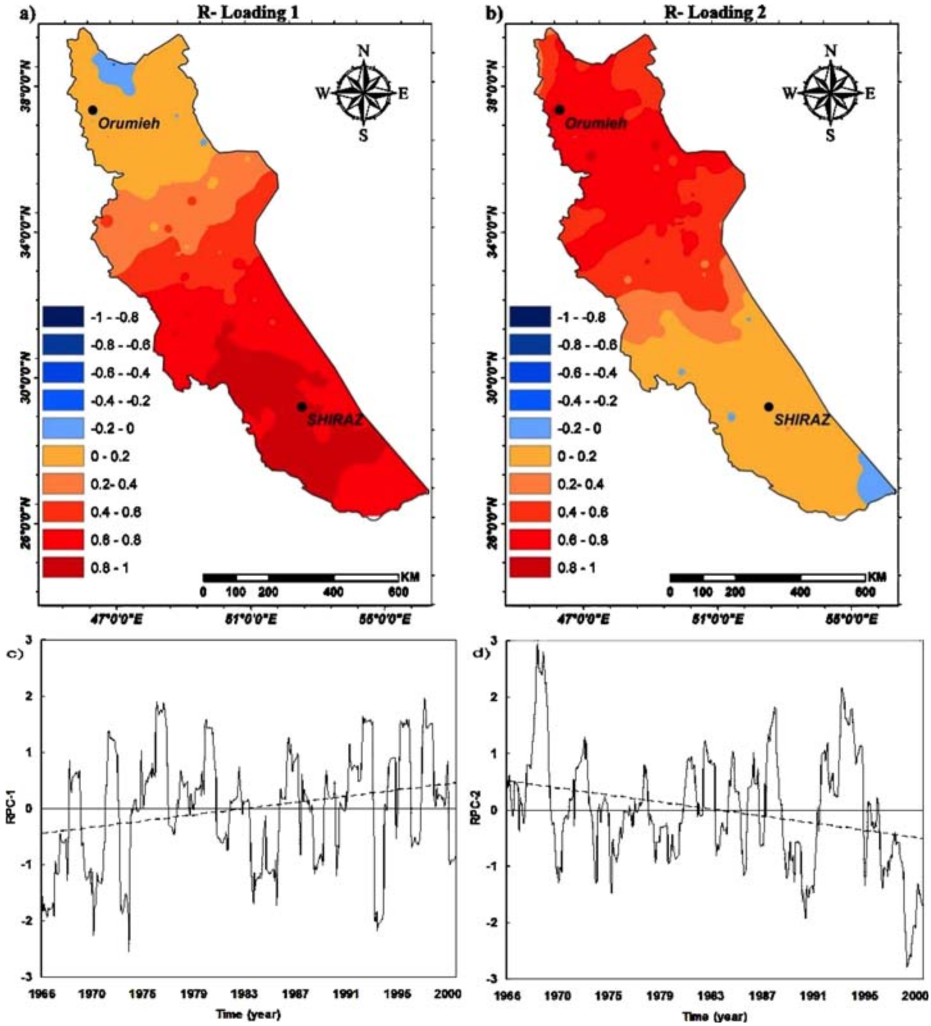

Fig. 3 **a**, **b** First two rotated loading patterns (R-Loading) of the SPI-12 in western Iran computed using rain gauge data, and **c**, **d** the corresponding standardized rotated PC scores (RPC) for the period October 1966–September 2000. *Dashed line* denotes the fitting linear trend. *Black bullets* in **a** and **b** are the locations of the stations Shiraz and Orumieh considered representative of the two identified sub-regions

drought variability. This is probably related to the different precipitation regimes in the two areas: in the south the maximum precipitation amounts occur in autumn and winter seasons, while in the north, during winter and spring (Raziei and Azizi 2007).

To better illustrate the different climatic behaviors characterizing western Iran, let us consider the SPI-12 time series for the stations Shiraz in the south and Orumieh in the north (see black bullets in Fig. 3a, b for their locations within the region) as representative of the two sub-regions. The SPI-12 signal at these stations

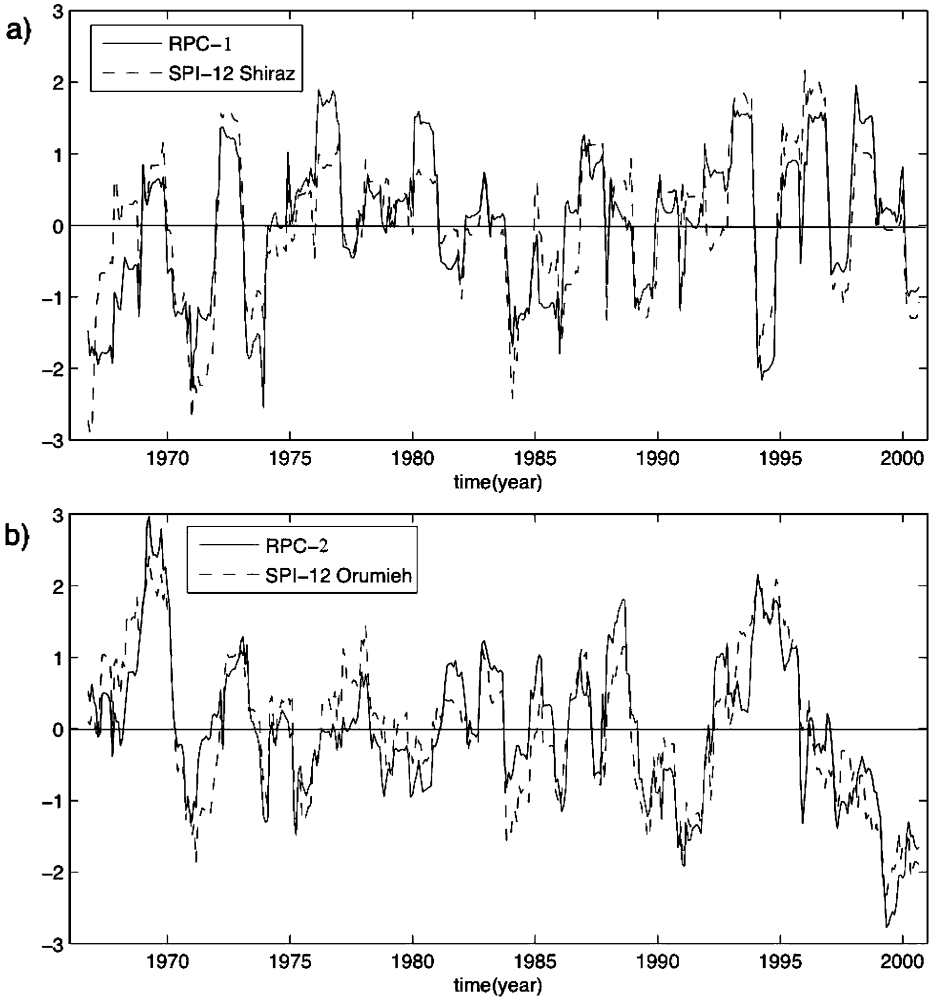

Fig. 4 Time behaviors of: **a** RPC-1 and SPI-12 for the station Shiraz in the south, **b** RPC-2 and SPI-12 for the station Orumieh in the north

(Fig. 4), in fact, have high positive correlation coefficients with RPC-1 and RPC-2 respectively, e.g. 0.84 and 0.88. It can be seen that the two sites are characterized by a different climatic variability. For example, while in 1999 Orumieh experienced a severe/extreme drought, Shiraz was characterized by near normal conditions; on the contrary, in 1994 Orumieh was affected by a wet period, while Shiraz by a severe drought (Fig. 4).

In the next subsection we will analyze the agreement of these results with those from large-scale analysis carried out using the NCEP/NCAR precipitation data set. Furthermore, we will investigate changes in the spatial pattern and temporal variability of drought when a longer time record is considered.

4.2 Rotated PCA of the SPI-12 Time Series for Iran: Analysis at Large-Scale

We have applied the PCA to the SPI-12 time series (October 1966–September 2000) computed using NCEP/NCAR precipitation data for the whole Iran. According to the rule by North et al. (1982), the eigenvalues corresponding to the first two loadings are well separated, while the third and fourth show degeneracy. Moreover, the first loading (here not shown) that explains 37.33% of the total variance, has high positive values over most of Iran, while the second one, explaining 14.14% of the total variance, has positive values in the north of the study area. Thus, as in the previous case we applied a Varimax rotation to these two loadings in order to obtain more spatially localized patterns of variability.

Results obtained by orthogonal rotation are shown in Fig. 5. The first rotated loading accounts for 35.40% of the total variance and has positive values in the central–southern part of the country (below 35° N), reaching maximum values in the southwestern Iran. The corresponding rotated PC score (Fig. 5c) resembles RPC-1 obtained for western Iran using observations (Fig. 3c). However, at variance with Fig. 3c, a very weak linear trend of the opposite sign is here detectable that explains just 2.3% of the variance of the signal (Table 1). The second rotated loading, which

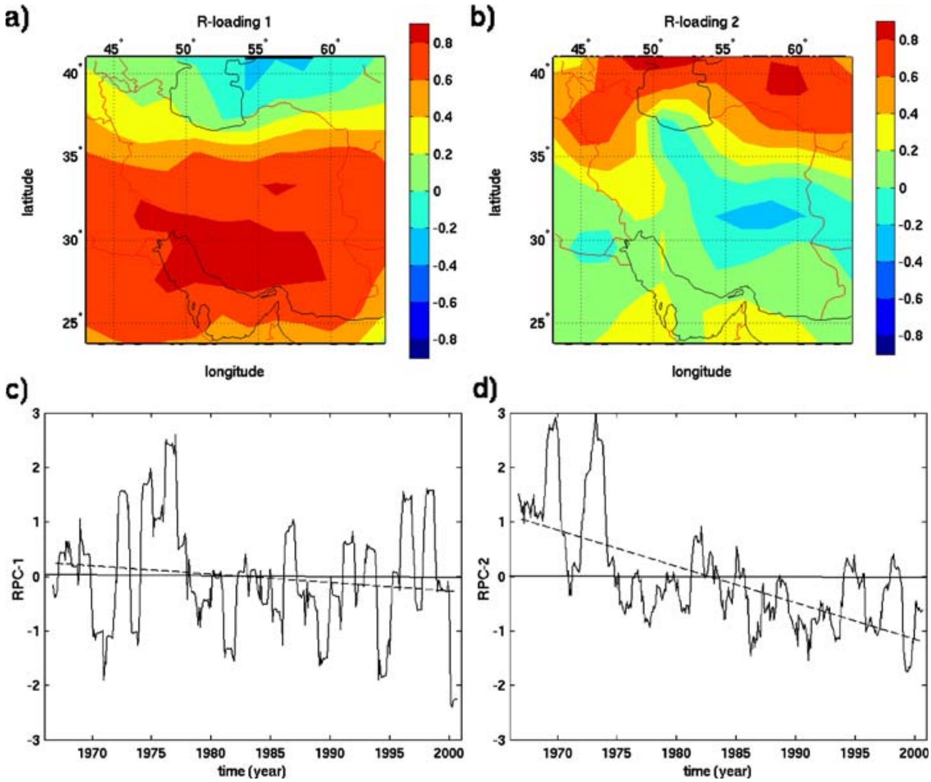

Fig. 5 **a**, **b** First two rotated loading patterns (R-Loading) of the SPI-12 computed using NCEP/NCAR precipitation data, and **c**, **d** the corresponding standardized rotated PC scores (RPC) for the period October 1966–September 2000. *Dashed line* denotes the fitting linear trend

Table 1 Values of the angular coefficients (p_1) and intercepts (p_2), with 95% confidence bounds, of the linear trend in the rotated PC scores of the SPI-12 for different data sets and record length. The last two columns refer to the sum square error and the R-square statistics

Data	Period	$p1$ (year^{-1}) with 95% confidence bounds	$p2$ (dimensionless) with 95% confidence bounds	SSE	R-square
RPC-1 observations	Oct. 1966–Sept. 2000	0.0261 (0.0165, 0.0357)	−51.72 (−70.76, -32.69)	380.3	0.0657
RPC-2 observations	Oct. 1966–Sept. 2000	−0.0304 (−0.0399, −0.0209)	60.34 (41.55, 79.14)	370.6	0.0871
RPC-1 NCEP/NCAR	Oct. 1966–Sept. 2000	−0.0154 (−0.0252, −0.0056)	30.52 (11.06, 49.99)	397.7	0.0229
RPC-2 NCEP/NCAR	Oct. 1966–Sept. 2000	−0.0667 (−0.0742, −0.0592)	132.30 (117.40, 147.20)	232.1	0.4282
RPC-1 NCEP/NCAR	Dec. 1948–Dec. 2007	−0.0383 (−0.0416, −0.0351)	75.86 (69.39, 82.33)	404.8	0.4283
RPC-2 NCEP/NCAR	Dec. 1948–Dec. 2007	−0.0083 (−0.0126, −0.0040)	16.41 (7.94, 24.89)	693.8	0.0201

explains 16.07% of the total variance, has positive values in the north of the study area, including the north of western Iran. The corresponding RPC-2 shows multi-year fluctuations embedded on a long-term linear trend towards negative values from the eighties onwards (Fig. 5d) and accounts for about 43% of the variance of the time series. Thus, the re-analysis data show a downward linear trend in the northwestern Iran like the observations but of doubled amplitude and provides a great portion of the variance of signal, suggesting that the quantification of this climatic tendency and related discussions must be done with caution.

In Fig. 6a comparison among the rotated PC scores obtained using the observations in western Iran and those using the re-analyzed data for the whole country is shown. An inspection of the figure suggests that RPC-1 and RPC-2 time series for the two data sets have a good agreement if we take into account the different origin of the precipitation data used and the different area coverage. This is confirmed by the correlation coefficients: 0.66 for the RPC-1 time series and 0.54 for the RPC-2, with p-values less than 0.01 in both cases.

Given the satisfactory agreement between the regional and large-scale analysis for the period October 1966–September 2000, we have extended the analysis to a longer period using the NCEP/NCAR precipitation data from January 1948 to December 2007. As in the previous cases the Varimax rotation has been applied to the first two loadings of the SPI-12 time series. Results are shown in Fig. 7. The first rotated loading explains 24.81% of the total variance, while the second one 22.36%, providing a cumulative variance of about 47%. It can be noted that these spatial patterns differ from those obtained for the shorter period (Fig. 5a, b) though they identify approximately the same sub-regions, e.g. the southern and the northwestern Iran. On the other hand, the RPC-1 (Fig. 7c) resembles the RPC-2 of Fig. 5d, as well as RPC-2 behaves like RPC-1 of Fig. 5c, in the common time section 1966–2000. Furthermore, the long-term linear trend characterizing RPC-1 (northwestern regions) is reduced if compared to that of RPC-2 in Fig. 5d, though it explains the same percentage of variance (about 43%, see Table 1). Thus, these findings highlight

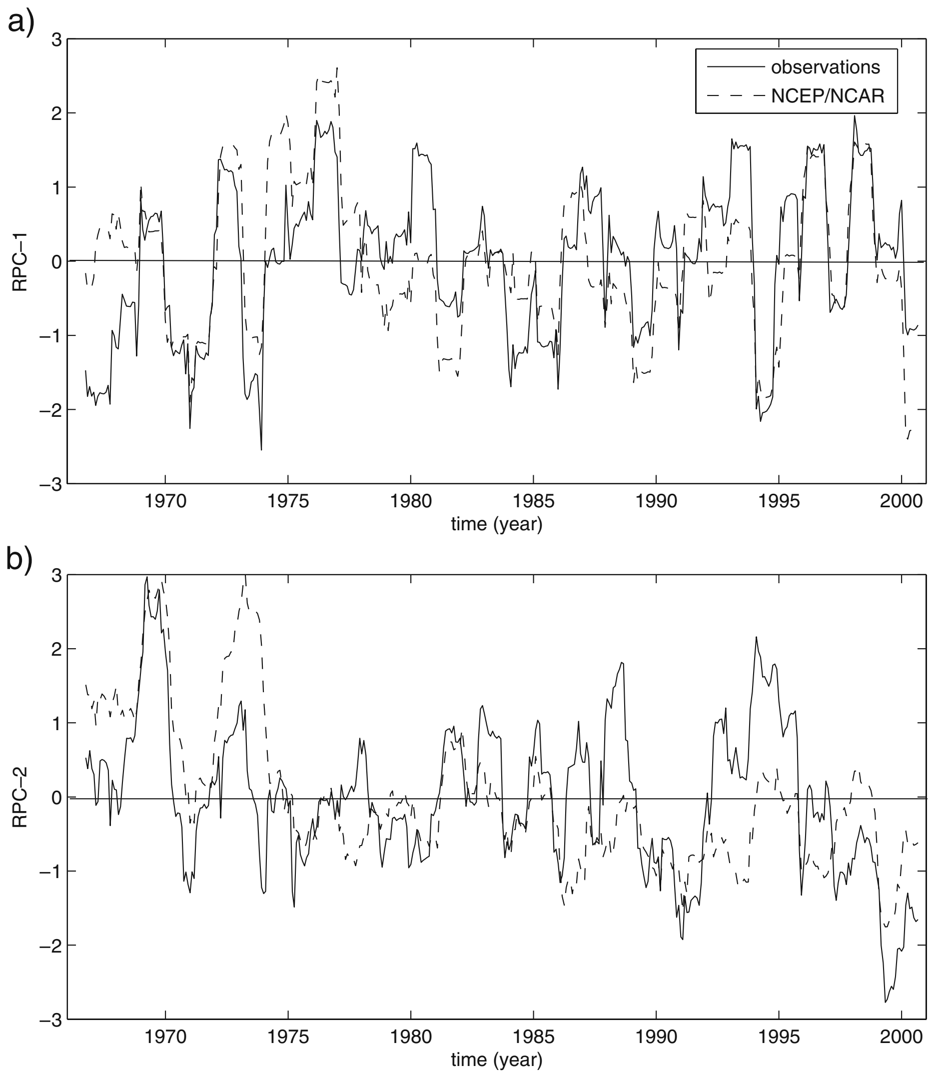

Fig. 6 **a** Time behaviors of the first rotated PC scores (RPC-1) of the SPI-12 computed using rain gauge observations (*solid line*) and NCEP/NCAR precipitation data (*dashed line*); **b** as before for the second rotated PC scores (RPC-2)

the shortcoming of having observations covering a limited time section, since the main spatial patterns of drought variability and the associated climatic trends may change when longer periods are taken into account.

4.3 Drought Events and SOI Phases

Let us consider the stations Shiraz (south) and Orumieh (north) considered representative of the two identified sub-regions. Figure 8 shows the 12-month running mean

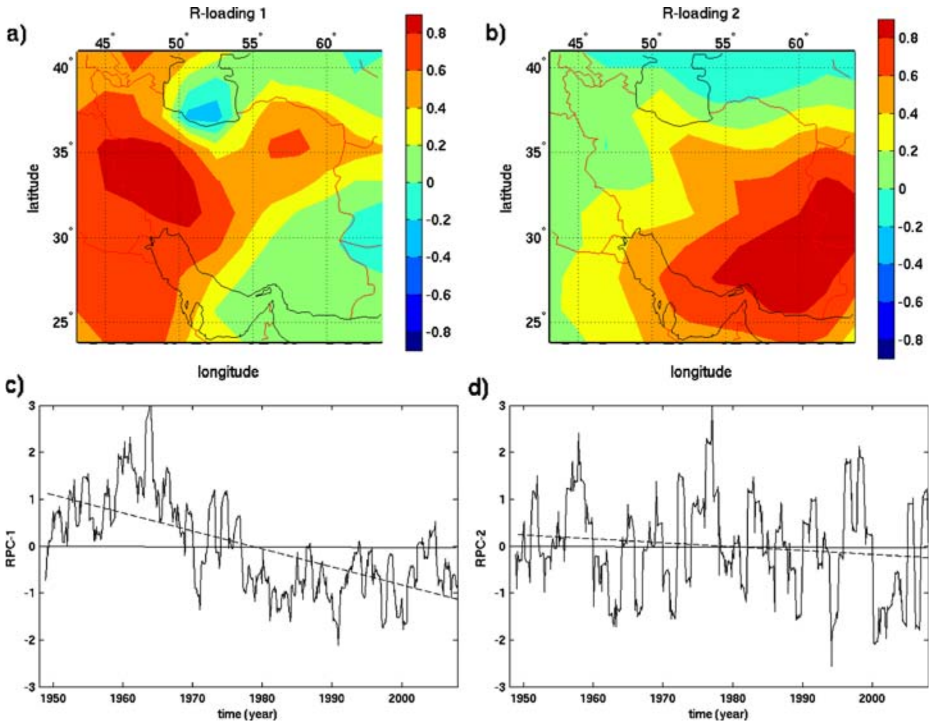

Fig. 7 **a**, **b** First two rotated loading patterns (R-Loading) of the SPI-12 computed using NCEP/NCAR precipitation data from January 1948 to December 2007, and **c**, **d** the corresponding standardized rotated PC scores (RPC) for the period December 1948–December 2007. *Dashed line* denotes the fitting linear trend

of the standardized SOI and the SPI-12 time series at these stations. The correlations between SOI signal and the SPI-12 time series at Shiraz and Orumieh are very low (correlation coefficients –0.26 and –0.39 respectively) though they are statistically significant (p-values close to zero). These results suggest that there is not clear evidence for a connection between ENSO phenomenon and hydrological droughts in western Iran. In fact, although the phases of the SOI and the drought index occasionally suggest an association between La Niña/El Niño events and drought/wet spells, there are periods when such correspondence fails (see for example the years 1978 and 1998 in Fig. 8a or the years 1992 and 1998 in Fig. 8b). In particular, if we focus on the two major El Niño events, 1983 and 1998, we note that both stations provide SPI-12 values within the range $(-1, 1)$ denoting near normal conditions for the two sites.

By considering the SPI on 3-month time scale (SPI-3) computed using the averaged precipitation in the two identified sub-regions, we find better results for the autumn season defined as the period October–December. This implies correlation coefficients between the autumn SOI and the SPI-3 time series in December to be about -0.5 with p-values less than 0.05. The result is in agreement with previous studies on the relationship between rainfall in Iran and ENSO (Nazemosadat and Cordery 2000; Nazemosadat and Ghasemi 2004). However, as in the previous case,

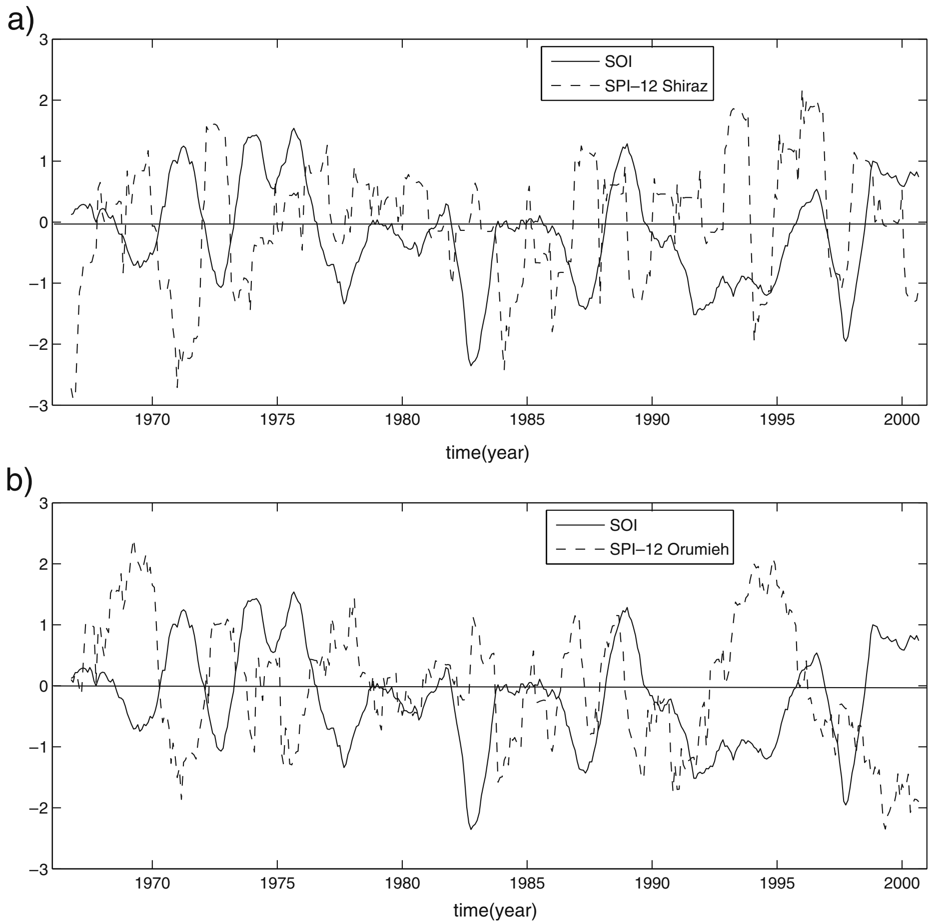

Fig. 8 Time series of the 12-month running mean SOI from October 1966 to September 2000 (*solid line*) and the SPI-12 (*dashed line*) for **a** the station Shiraz, **b** the station Orumieh

we cannot conclude that meteorological droughts in December are strictly related to La Niña events, since there are periods when there is not such correspondence.

It is worth to notice that, since historically an El Niño usually recurs every 3–7 years, as does its La Niña counterpart, if we wish to further investigate any statistical significant correlation between El Niño and meteorological/hydrological droughts longer time series of observations are needed.

5 Conclusions

The time and space variability of drought in western Iran was studied by using rain gauge data from 140 stations distributed uniformly over the area. Drought conditions were assessed through the SPI computed on 12-month time scale, while their variability was analyzed applying the PCA to the index time series. Applying the Varimax rotation to the first two loadings we found two sub-regions having different climatic variability: the southern and northern part of the study area. Thus, for an efficient water resources management under dry conditions and in planning measures for mitigating the adverse impacts of future drought occurrences, these sub-regions should be separately considered.

The analysis at large-scale, carried out with the NCEP/NCAR re-analysis data shows a satisfactory agreement for the period 1966–2000, given the different origin of the data sets. Moreover, it seems that in the northwestern Iran the re-analysis data provides a long-term linear trend towards drier periods from the eighties onward more pronounced with respect to the observations. When a longer time period is considered, such a trend is reduced and the leading spatial patterns of variability change. This means that the regionalization here proposed based on observations from 1966 to 2000 should be checked for longer data sets before using it for water management purposes.

Finally, we have investigated the relationship between hydrological drought/wet events and extreme phases of the Southern Oscillation (La Niña/El Niño episodes). Results indicate that even if occasionally dry/wet events are associated with positive/negative phase of SOI, we cannot conclude that there is a stringent correlation between the phenomena. Further investigations should be done using longer time records of observations to evaluate the usefulness of these results for drought prediction and early warming systems.

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