

AN ANALYSIS OF DROUGHT SPATIAL PATTERN OVER IRAN WITH RESPECT TO DIFFERENT SPI TIME SCALES

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ABSTRACT:

Drought regionalization, namely the identification of sub-regions within a country characterized by independent climatic variability and different drought characteristics, is of particular interest for drought risk assessment and water resources management at regional level. The present study provides an analysis for Iran of the stability of drought spatial patterns as a function of the time scale used for computing the Standardized Precipitation Index (SPI) in assessing the different kind of droughts. The Global Precipitation Climatology Centre (GPCC) gridded precipitation dataset with a spatial resolution of 0.5 degree in longitude and latitude is used for the study. The leading spatial patterns of drought variability for the period 1951–2007 have been analysed by applying the Principal Component Analysis (PCA) and Varimax rotation to the SPI field computed on 1, 3, 6, 12, 24, and 36-month time scales. Results show four sub-regions for some time scales (1, 6, 12 months), while three sub-regions are identified for the remaining time scales. It is found that the southern sub-region is the most stable with respect to the SPI time scale, while the other sub-regions show less spatial homogeneity. For all considered time scales a comparison with APHRODITE dataset for the Middle East is provided showing that there is a similar sensitivity of the spatial modes to the index time scales. Differences between the two datasets are related to the different sources of data. The analysis suggests that, when high-resolution precipitation data are considered, modes of drought variability have a degree of sensitivity to the time scales usually adopted for monitoring the different kinds of droughts.

1 INTRODUCTION

Drought, as a natural phenomenon, is considered as an integrated part of climate variability composed of three defining attributes as duration, severity and magnitude (Dracup et al. 1980). However, areal extent and frequency of drought should also be considered as other important characteristics (Pereira et al., 2009). Thus, in analysing drought phenomenon in a region all these aspects should be taken into account.

The identification of homogenous regions within a country characterized by independent drought variability is of particular interest for drought risk assessment and for a more efficient water resources management at regional level. Many authors have analysed spatial patterns and time variability of drought in different areas (Bordi and Sutera, 2002; Bonaccorso et al., 2003; Bordi et al., 2004; Vicente-Serrano, 2006; Raziei et al., 2009). However, spatial patterns of drought over a region might change as a function of the time scale considered, i.e. the type of drought analysed. Vicente-Serrano (2006) showed that using rain-gauge data over the Iberian Peninsula the spatial patterns of droughts are conditioned to the Standardized Precipitation Index (SPI) time scale, pointing out the increasing spatial complexity of drought modes as the time scale of the index is increased. Recently, Raziei et al. (2011) have assessed the spatial and temporal variability of hydrological drought over Iran using observational, gridded and reanalysis datasets. By applying the SPI on 12-month time scale for assessing drought conditions, four distinctive sub-regions have been identified. In another paper (Raziei et al., 2010), the authors showed that the same holds for the SPI on 3, 6 and 24-month time scales, i.e. similar sub-regions were found using the same data (GPCC gridded data and NCEP/NCAR reanalysis) and methodology (Principal Component Analysis and Varimax rotation). However, further analyses were suggested to properly compare the results obtained for the Iberian Peninsula and Iran, and establish if the sensitivity of drought spatial modes to the SPI time scale can be considered as a general rule applicable to other countries. This is because the origin of the different sensitivity of drought regionalization may be due to the different precipitation regimes characterizing the two countries or to the different spatial resolution (or source) of data used for the analysis. In dealing with the latter open question, the present paper provides an analysis for Iran using two gridded precipitation datasets with high spatial resolutions. Since Raziei et al. (2010) used a coarse spatial resolution (2.5 and about 2 degrees in longitude and latitude for GPCC and NCEP/NCAR, respectively), here the GPCC precipitation dataset of 0.5 degree in longitude and latitude is considered for the analysis.

The Global Precipitation Climatology Centre (GPCC) has produced and released several products, including the recent Full Data Reanalysis Product Version 5, which consists of global land surface monthly precipitation at different spatial resolutions. The GPCC dataset is based on all stations, near real-time and non real-time, and covers the period 1901–2009 (Schneider et al., 2008). Recently, Dinku et al. (2008) have evaluated the performance of GPCC Full Data Reanalysis Product Version 3, covering the period 1951–2004, using a gauge network over complex topography in Africa. They found a good agreement between the gridded product and the reference rain-gauge data. Also, Raziei et al. (2010, 2011) have assessed the spatial and temporal variability of drought over Iran using the GPCC Full Data Product Version 4, finding good and satisfactory agreement with observations and NCEP/NCAR reanalysis, respectively.

Furthermore, daily gridded precipitation dataset from the Asian Precipitation-Highly-Resolved Observational Data Integration Towards the Evaluation of Water Resources (APHRODITE) project for the Middle East (Yatagai et al., 2008; 2009), with a spatial resolution of 0.5 degree in longitude and latitude, is used in this study to evaluate its applicability in drought variability analysis and for comparison with GPCC dataset.

Dry and wet conditions have been assessed applying the Standardized Precipitation

Index (SPI) as defined by McKee et al. (1993). The index is widely used in drought monitoring centres and in several drought studies (Lloyd-Hughes and Saunders 2002; Tsakiris and Vangelis 2004). The SPI, based only on monthly precipitation, is in fact a useful tool for capturing the climate variability associated with water shortage or surplus in different areas, and has several advantages (Keyantash and Dracup 2002). Furthermore, in analyzing the spatial variability of drought across Iran the Principal Component Analysis (PCA) has been applied to the SPI field computed on different time scales. Finally, Varimax rotation method allowed finding homogeneous areas within the country that have rather independent drought variability.

2 DATA AND METHODS

Data used for the analysis are monthly precipitation from GPCC Full Data Product Version 5 and from APHRODITE gridded precipitation dataset for the Middle East.

The GPCC Full Data Product Version 5, updated in December 2010, is a gauge-based gridded monthly precipitation dataset for the global land surface, available in spatial resolutions of 0.5, 1 and 2.5 degrees in longitude and latitude. The dataset covers the period from 1901 to 2009 and is based on both non real-time and real-time stations (Schneider et al., 2008). Several quality controls have been applied before gridding (Beck et al., 2005).

The APHRODITE daily precipitation dataset for the Middle East [20°E–65°E, 20°N–50°N], consists of a total of 1394 stations (including stations of GTS with only 5 or more years of records) from all countries in the domain, have been used (Yatagai et al., 2008). The latest version of APHRODITE (APHRO_V1003R1), which involves 337 Iranian meteorological stations, is also used in the present study. The Iranian stations are composed of 154 World Meteorological Organization (WMO) stations and of 183 non-WMO stations, spread throughout the country and covering different temporal periods, with the longest ones starting in the 1960s (Yatagai et al., 2008). The APHRODITE dataset covers the time period from 1951 to 2007.

For both GPCC and APHRODITE datasets only grid points over Iran have been taken into account and the common time section 1951–2007 has been considered for the analysis.

In order to assess spatial patterns of meteorological, agricultural, and hydrological droughts over Iran, the SPI on 1, 3, 6, 12, 24 and 36-month time scales have been computed for both datasets. The SPI is based on precipitation field alone and its computation for any location is based on the long-term precipitation record accumulated over the selected time scale. The long-term record is fitted to a probability distribution, usually a Gamma distribution, which is then transformed through an equal-probability transformation into a normal distribution. The index is a useful tool for monitoring the different kinds of drought and comparing climatic conditions of areas governed by different hydrological regimes.

To capture the spatial patterns of drought co-variability, for a given SPI time scale, the PCA (Rencher 1998) was applied to the SPI field computed using both GPCC and APHRODITE datasets. The PCA 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” and represent the correlation between the original data (SPI time series at single grid points) and the corresponding principal component time series.

In order to find more localized spatial patterns of variability the Varimax rotation has been applied to the loadings. This method allows finding areas within the region that have rather independent climatic variability, i.e. the rotated principal components are temporarily orthogonal (Rencher 1998). Following the rule by North et al. (1982), the sampling errors of the eigenvalues associated to the principal components have been estimated, allowing to establish how many loadings to retain for rotation.

3 RESULTS

To capture the leading modes of spatial variability of the different types of droughts (meteorological, agricultural and hydrological) across Iran, and to check whether they change in relation to time scale of the SPI, the PCA is applied to the SPI time series computed for different time scales (1, 3, 6, 12, 24 and 36 months) using GPCC and APHRODITE datasets.

Based on the scree plot and the North’s rule of thumb (Fig. 1), for each dataset and time scale the first four loadings (or the first three) have been retained for Varimax rotation. The percentages of the total variance explained by the un-rotated and Varimax rotated PCs for GPCC and APHRODITE datasets are presented in Table 1 and 2, respectively.

Table 1 Explained variances (%) of un-rotated (UR) and Varimax rotated (VR) PCs for the GPCC dataset.

PC	SPI-1		SPI-3		SPI-6		SPI-12		SPI-24		SPI-36	
	UR	VR	UR	VR	UR	VR	UR	VR	UR	VR	UR	VR
1	32.8	16.8	34.9	19.7	36.9	22.0	36.6	21.8	37.9	22.6	37.0	23.2
2	10.0	13.1	10.7	15.8	11.0	15.6	10.5	18.4	10.9	21.3	11.9	20.8
3	5.0	11.5	5.6	15.7	6.1	11.0	7.0	10.5	6.5	11.4	7.8	12.7
4	4.0	10.3			4.3	9.7	5.3	8.6				
Total	51.7	51.7	51.2	51.2	58.3	58.3	59.3	59.3	55.3	55.3	56.7	56.7

Table 2 Explained variances (%) of un-rotated (UR) and Varimax rotated (VR) PCs for the APHRODITE dataset.

Mode	SPI-1		SPI-3		SPI-6		SPI-12		SPI-24		SPI-36	
	UR	VR	UR	VR	UR	VR	UR	VR	UR	VR	UR	VR
1	38.9	19.5	35.9	16.1	35.9	22.8	35.1	22.1	35.3	21.9	34.5	22.2
2	10.8	14.3	10.7	14.1	11.0	15.5	10.4	17.7	10.8	19.7	11.7	20.2
3	6.0	13.3	6.2	13.8	6.7	15.3	7.6	13.3	7.7	12.2	9.1	13.0
4	4.6	13.2	4.7	13.5								
Total	60.3	60.3	57.5	57.5	53.6	53.6	53.0	53.0	53.7	53.7	55.4	55.4

The rotated loadings (REOFs) obtained for the different time scales using GPCC dataset are shown in Fig. 2. For the time scales of 1, 6 and 12 months four sub-regions have been identified, while for the time scales of 3, 24 and 36 months the sub-regions reduce to three.

In case of four sub-regions, the areas characterized by independent drought variability are central-western, south-eastern, northern (including the Caspian Sea), and north-western. It is worth noticing that these sub-regions are similar to those obtained for the time scales of 3, 6, 12 and 24 months using GPCC Full Data Product Version 4 with a spatial resolution of 2.5 degree in longitude and latitude (Raziei et al., 2010, 2011). In case of the SPI on 3-month time scale, the northern and north-western sub-regions appear merged into a single area of variability (see REOF3 in Fig. 2b). Differently, for longer time scales (24 and 36 months) the northern sub-region is represented by the REOF3, while the north-western region seems to be merged with the central sub-region represented by REOF2. Thus, results for GPCC dataset suggest that the most stable mode of drought variability with respect to the SPI time scale is the one identifying the south-eastern sub-region, while the other modes show differences in the spatial structure as a function of the time scale considered. Such sensitivity to the index time scale may be due to the high resolution of the gridded data that results in a higher spatial variability limiting the efficiency of the Varimax rotation method in identifying homogeneous areas within the country. Moreover, as the time scale is increased the high frequency fluctuations of the SPI are filtered out and the (spatial) differences in the low-frequency behaviours emerge more clearly, leading to more ‘complex’ drought modes (less spatially homogeneous).

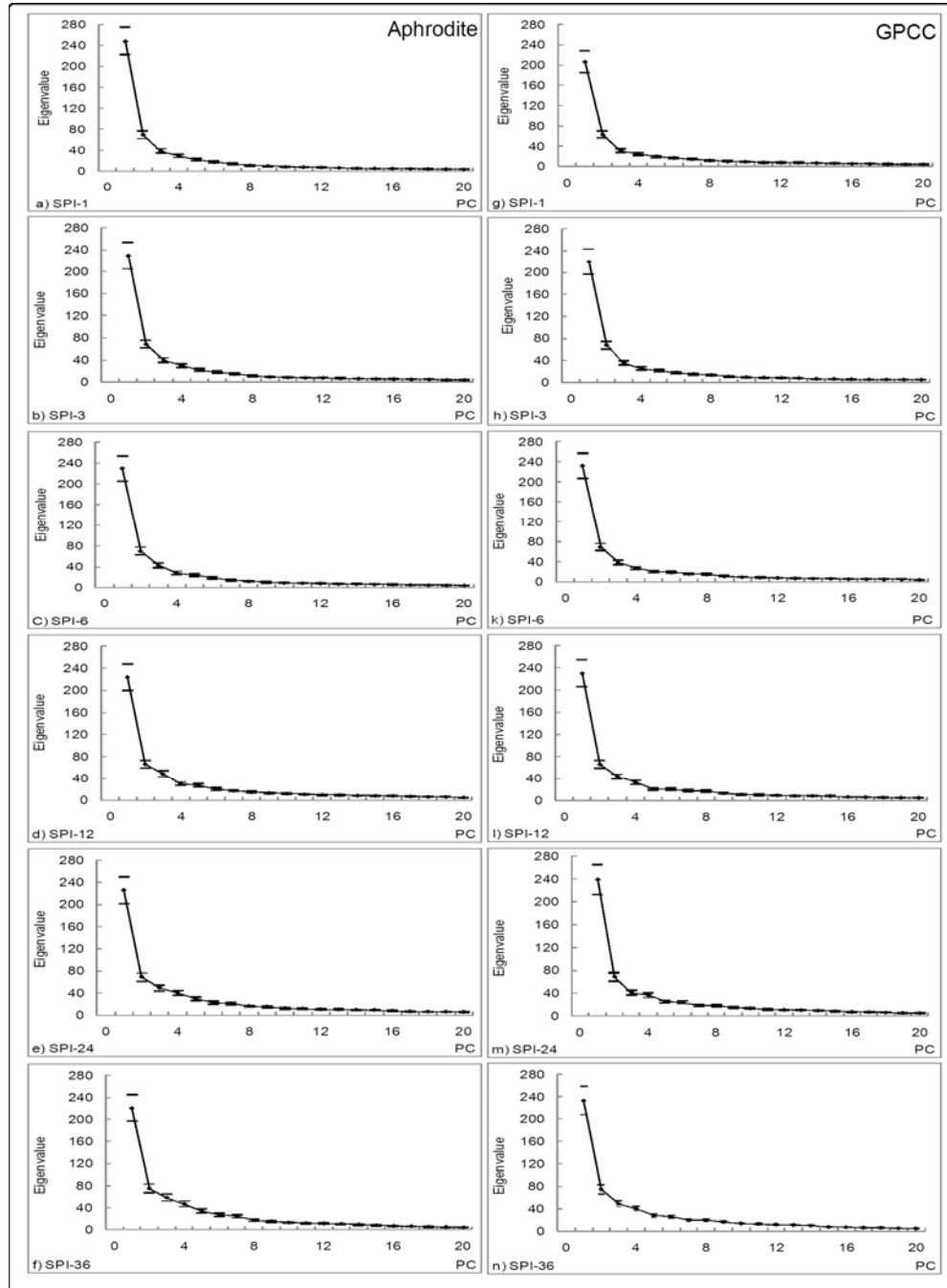


Figure 1. The scree plots and the associated estimated sampling errors of the eigenvalues corresponding to the principal components of SPI at different time scales: (a–f) APHRODITE, (g–n) GPCC.

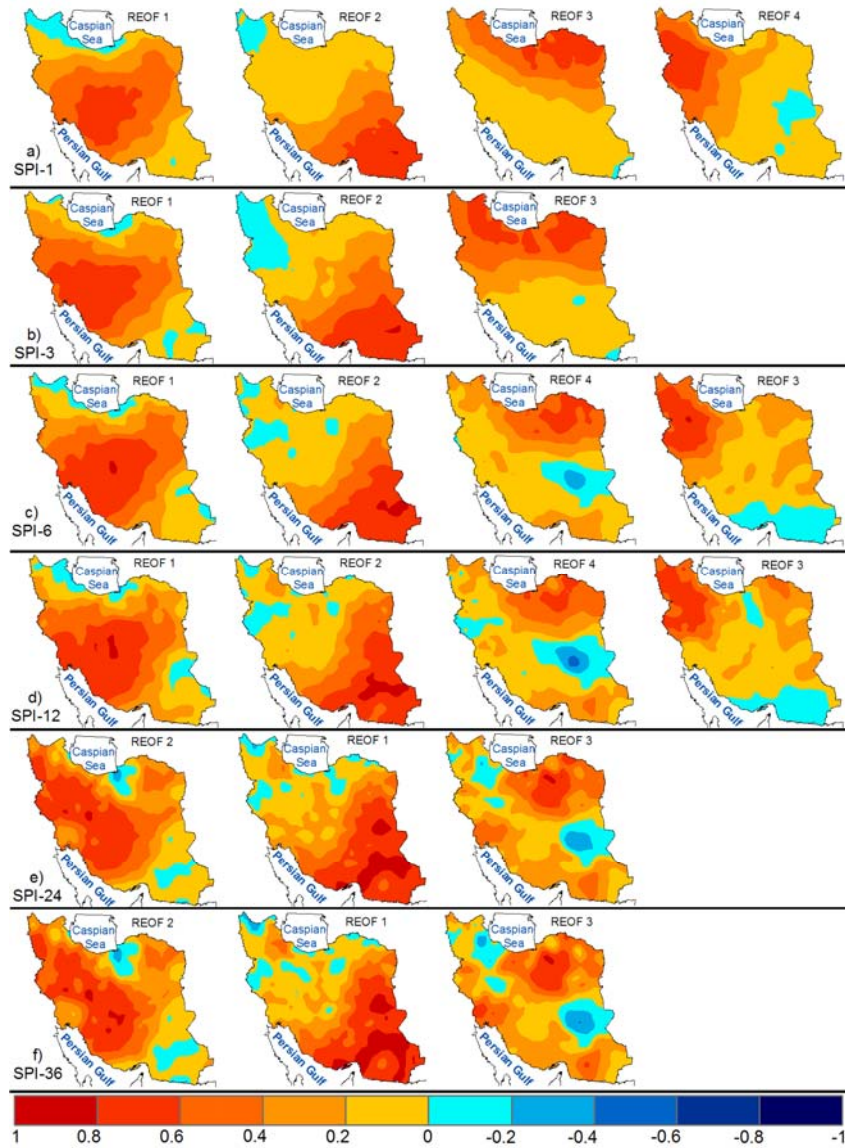


Figure 2. The Varimax rotated loadings of the SPI at different time scales for GPCC dataset.

The rotated loadings obtained for APHRODITE dataset are shown in Fig. 3. In this case, four sub-regions have been identified for the time scales of 1 and 3 months, while three sub-regions are found for the remaining time scales. The four sub-regions are those located in central-eastern, south-eastern, northern including the Caspian Sea region, and central-western areas. They appear to be stable moving from 1 to 3-month time scale, while they change for longer time scales (greater spatial inhomogeneity). In particular, for 6–36 months time scales the central-eastern and -western sub-regions

seem to be represented by a single region having high positive loading values in central-western area (see REOF1 in Fig. 3c–f). Thus, as for GPCC also for APHRODITE dataset a sensitivity of the rotated loadings to the SPI time scale is found. The differences in the spatial patterns obtained by the two datasets for a given time scale is due to the different sources of data, whose impacts can be noticeable when a high spatial resolution is considered.

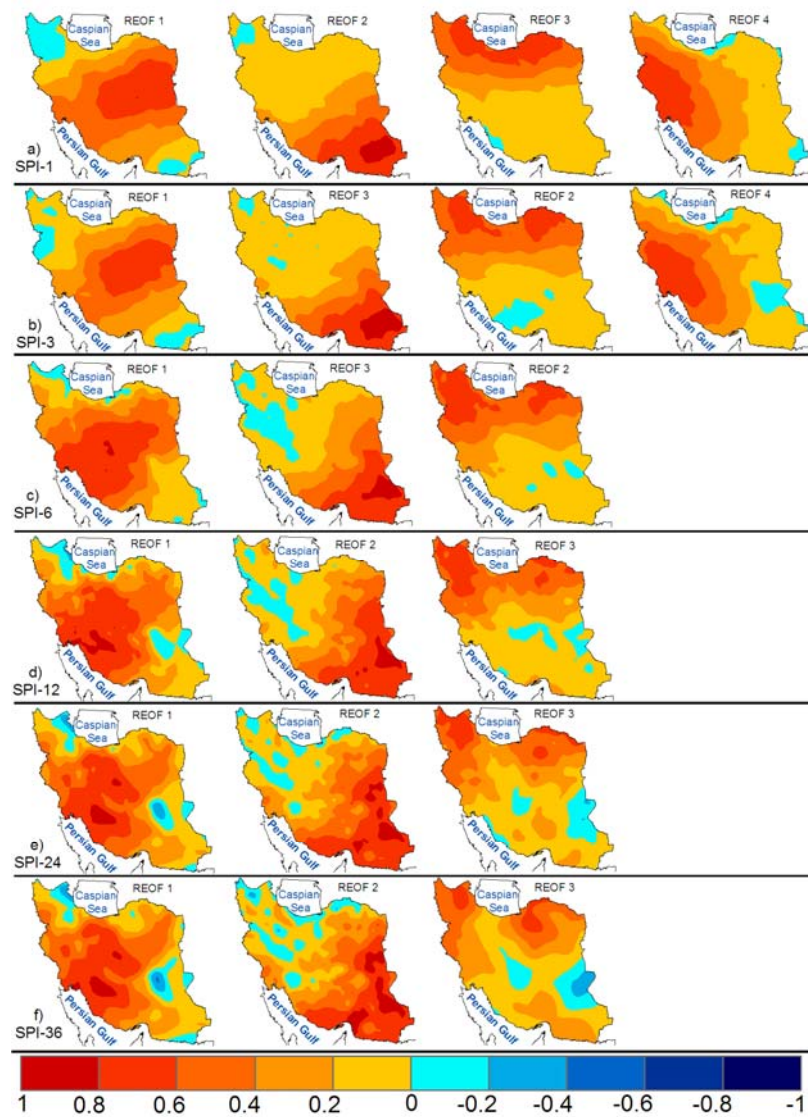


Figure 3. The Varimax rotated loadings of the SPI at different time scales for APHRODITE dataset.

4 CONCLUSIONS

Results obtained for GPCC dataset suggest that there is a degree of sensitivity of the identified sub-regions to the SPI time scale. The south-eastern sub-region is found to be the most stable with respect to the time scale considered, while the other identified sub-regions showed spatial heterogeneity. On the contrary, recently, Raziei et al. (2010, 2011) found four stable spatial patterns for the SPI computed on different time scales using GPCC data with a coarse spatial resolution (2.5 degree in longitude and latitude). All these findings lead to the conclusion that drought regionalization (at least in Iran) is sensitive to the time scale considered for the SPI computation when high-resolution data are taken into account for the analysis.

Results obtained with a different gridded precipitation dataset, APHRODITE, having the same spatial resolution, showed a similar sensitivity of the sub-regions with respect to the SPI time scale. Differences in the identified sub-regions are found between the two datasets that may be related to the different sources of data.

Further investigations are required in order to demonstrate the key role of the spatial resolution of precipitation data on drought regionalization when other countries characterized by different climate variability are considered.

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