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Spatial and temporal variability of precipitation and drought in Portugal

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Abstract. The spatial variability of precipitation and drought are investigated for Portugal using monthly precipitation from 74 stations and minimum and maximum temperature from 27 stations, covering the common period of 1941–2006. Seasonal precipitation and the corresponding percentages in the year, as well as the precipitation concentration index (PCI), was computed for all 74 stations and then used as an input matrix for an R-mode principal component analysis to identify the precipitation patterns. The standardized precipitation index at 3 and 12 month time scales were computed for all stations, whereas the Palmer Drought Severity Index (PDSI) and the modified PDSI for Mediterranean conditions (MedPDSI) were computed for the stations with temperature data. The spatial patterns of drought over Portugal were identified by applying the S-mode principal component analysis coupled with varimax rotation to the drought indices matrices. The result revealed two distinct sub-regions in the country relative to both precipitation regimes and drought variability. The analysis of time variability of the PC scores of all drought indices allowed verifying that there is no linear trend indicating drought aggravation or decrease. In addition, the analysis shows that results for SPI-3, SPI-12, PDSI and MedPDSI are coherent among them.

1 Introduction

In Portugal, precipitation mainly occurs in the autumn and winter months and is characterized by a large time variability. Droughts are relatively frequent. Drought can be defined as a natural but temporary imbalance of water availability, consisting of persistent lower-than-average precipitation of uncertain frequency, duration and severity, of unpredictable or extremely hard to predict occurrences, resulting in diminished water resources availability and reduced carrying capacity of the ecosystems (Pereira et al., 2009).

Various drought indices have been developed with the objective of showing that a drought is in progress or has occurred, as well as to identify the intensity, duration, severity, magnitude and spatial variability of droughts (Mishra and Singh, 2010). Most relevant indices include the Palmer Drought Severity Index, PDSI (Palmer, 1965) and the Standardized Precipitation Index, SPI (McKee et al., 1993, 1995), which are considered herein together with a modification of the PDSI for Mediterranean conditions, the MedPDSI (Pereira et al., 2007; Pereira and Rosa, 2010). The SPI is a normalized index for calculating the deviation from the precipitation normal, allowing identification and characterization of droughts at different time scales. Shorter time scales like 3 months seem to be adequate for the identification of agricultural droughts, while longer time scales, e.g. 12 months, better describe hydrological and water resources droughts (Mishra and Singh, 2010; Paulo and Pereira, 2006). The PDSI, unlike the SPI, uses precipitation associated with evapotranspiration and a soil water balance is performed. It was created to characterize and evaluate meteorological droughts by measuring the deviations between the observed and the expected precipitation, which are first transformed into an anomaly moisture index and then into a drought index, which is classified in terms of severity (Palmer, 1965). The MedPDSI is a modification of the original PDSI to adapt it to the Mediterranean conditions. It mainly consists of (a) assuming a rainfed olive orchard as a drought reference crop, (b) replacing the potential climatic evapotranspiration (ET) computed with the Thornthwaite method by the reference ET computed with the FAO-PM method (Allen

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et al., 1998) to estimate the actual evapotranspiration (ETa) of the reference olive orchard, (c) computing ETa with the dual crop coefficient approach, thus, partitioning it into plant transpiration and soil evaporation to make ETa more sensitive to the available soil water, (d) performing a sequential soil water balance that overcomes the limitations of the original Palmer formulation, (e) replacing the climate characteristic used for the standardization of the Palmer moisture anomaly index z by the inverse of the standard deviation of the monthly moisture departures, which are precursors of the z index. The resulting soil water balance components show a better adherence to the vegetation reality than for the original PDSI, e.g., actual ET for the MedPDSI is higher during winter and spring and is generally lower in summer, and the MedPDSI is more sensitive to dry and wet anomalies than the PDSI (Pereira et al., 2007; Paulo et al., 2012; Rosa et al., 2010a).

Geostatistical and multivariate techniques are commonly used to analyze the spatial and temporal variability of precipitation, droughts and other variables of interest. Precipitation and drought spatial variability analyses through the principal component analysis (PCA) have been undertaken by many authors (e.g., Bonaccorso et al., 2003; Cannarozzo et al., 2006; Raziei et al., 2008, 2009). A few of these studies refer to the Iberian Peninsula, not detailing Portuguese conditions (e.g., Rodriguez-Puebla et al., 1998; Serrano et al., 1998; Vicente-Serrano et al., 2006). Various studies were conducted for Portugal on temporal variability of precipitation using spectral analysis (Antunes et al., 2006; Corte-Real et al., 1998), non-parametric trend tests (de Lima et al., 2010), or geostatistical techniques applied to precipitation extremes (Durão et al., 2009). Santos et al. (2010) used PCA and cluster analysis to study the spatial patterns of droughts with the SPI at different time scales in mainland Portugal. Costa (2011) also focused on the same region in a spatial and temporal analysis of droughts.

The present research aims to study the spatial variability of precipitation and drought over entire mainland Portugal. The selected drought indices are SPI-computed at 3- and 12-month time scales, the PDSI and MedPDSI. To identify sub-regions characterized by different precipitation regimes and drought variability, the PCA with varimax rotation was applied to various sets of precipitation-based variables and drought indices time series, respectively.

2 Data and methods

2.1 Data

For the present study monthly precipitation and temperature data from 27 meteorological stations and monthly precipitation records from 47 rainfall stations were used (Fig. 1a). The common time period for the analysis was 1941 to 2006 (66 yr). Therefore, for the analysis of variability of precipitation and computation of SPI, monthly precipitation data from 74 stations were used, while only 27 meteorological stations having also monthly maximum and minimum temperature were used for computation of PDSI and MedPDSI.

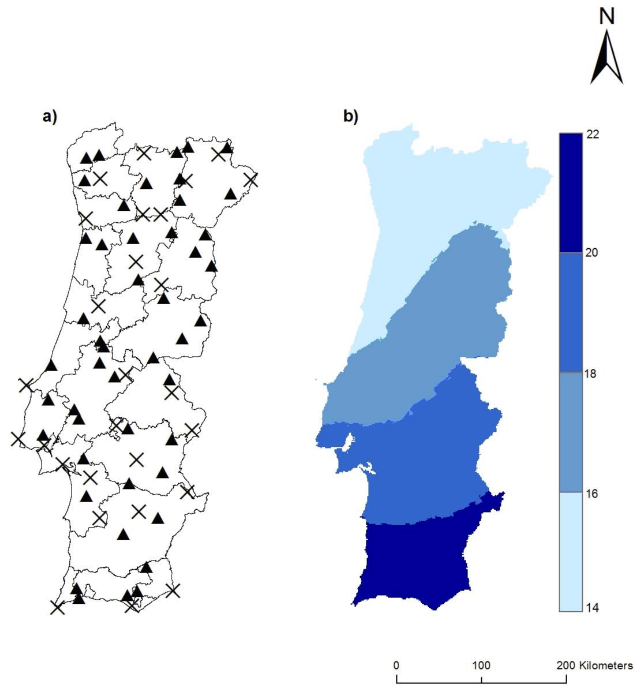

Fig. 1. **(a)** Distribution of meteorological stations (x) and pluviometric stations (▲); **(b)** Spatial pattern of the precipitation concentration index.

Annual precipitation datasets were investigated for randomness, homogeneity and absence of trends. The Kendall autocorrelation test, the Mann–Kendall trend test and the homogeneity tests of Mann–Whitney for the mean and the variance (Helsel and Hirsch, 1992), as described by Paulo et al. (2003) and Rosa et al. (2010b), were used for this purpose. In cases when the hypothesis of homogeneity fails (significance level of 5 %), the monthly precipitation series was corrected by the method of cumulative residuals using the homogeneous dataset of the nearby stations as a reference series and considering a confidence level of 80 % (cf. Allen et al., 1998). Linear models using maintenance of variance extension techniques, which preserve the variance and extreme order statistics of the reference site in the filled series (Hirsch, 1982; Vogel and Stedinger, 1985), were applied to estimate missing monthly precipitation or maximum and minimum temperature data. The reference sites were selected as those having the highest linear correlation coefficient relative to the station of interest.

2.2 Methods

Two sets of variables were used to delineate precipitation patterns. The first includes 5 variables: the 4 mean seasonal

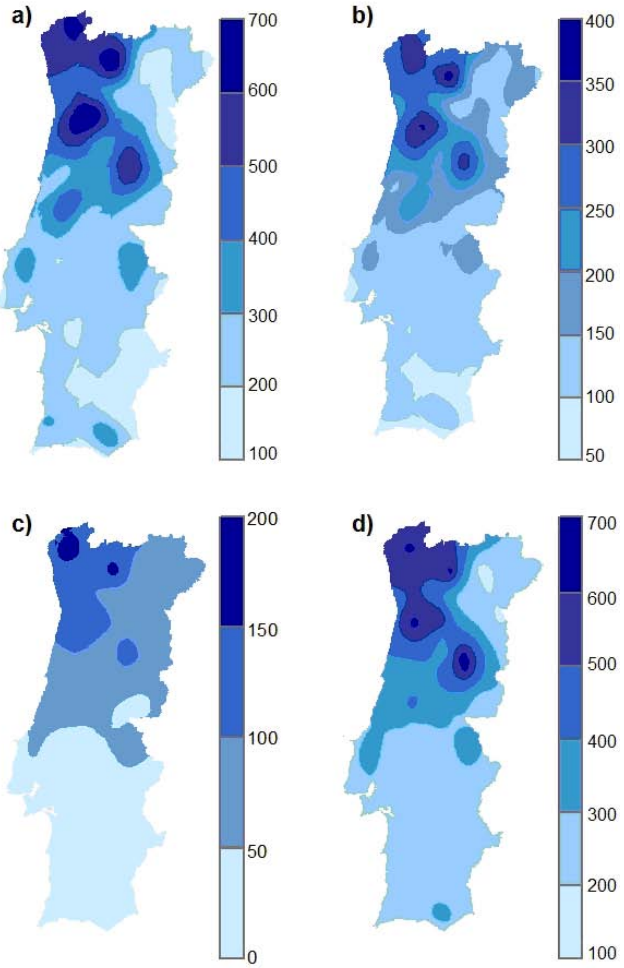

Fig. 2. Spatial distribution of seasonal precipitation amounts: **(a)** winter, **(b)** spring, **(c)** summer; **(d)** autumn.

precipitation amounts and the precipitation concentration index (PCI) relative to each weather station. The PCI is an intra-annual precipitation variability index defined as the ratio of the monthly squared precipitation to the squared annual precipitation (De Luís et al., 2000). The index ranges from less than 10, when monthly rainfall distribution over the year is quite uniform, to values above 20, corresponding to climates with substantial monthly variability in rainfall and large concentrations of the precipitation in a few months. The second set includes 9 variables, with the percentage of seasonal precipitation in the annual total in addition to the 5 variables of the first set. The approach follows that adopted by Raziei et al. (2008). Using two sets of variables aims at checking if appropriate results may be achieved with fewer variables. All variables were normalized prior to PCA application.

The procedures used to compute the SPI follow those proposed by Edwards (2000) and are described by Paulo et al. (2003). The calculation of PDSI and MedPDSI was performed with local calibration of the indices and is described by Pereira et al. (2007) and Pereira and Rosa (2010).

The PCA is a technique for forming new uncorrelated variables that are linear combinations of the original ones (Sharma, 1996). The principal components are computed in a decreasing order of importance; the first component explains the maximum possible variance of total data, and the second component explains the maximum variance not yet explained, meaning that the last component is the one that least contributes to explain the variance of the original data. The PCA is obtained by calculating the eigenvalues and eigenvectors from the correlation matrix, where the eigenvectors give information about the weight that the original data have in the new-formed components and the eigenvalues provide the amount of explained variance by each new variable. When normalized, the eigenvectors are called "loadings" and they represent the correlation between the original data and the corresponding principal component time series. The PCA can be computed in several modes, including the R-mode and S-mode PCA (Richman, 1986), which differ on the type of data used and the way that data is organized as an input matrix for PCA. The R-mode PCA is used here for precipitation regionalisation in order to obtain the interrelationship between the considered variables, while the S-mode PCA is used for capturing drought variability and allows the identification of co-variability between the stations, considering the time variability of a given drought index.

The R-mode PCA was applied to the two above-mentioned precipitation sets separately, in order to recognize the most influencing parameters responsible for climate patterns delineation, to be used subsequently in cluster analysis. To capture spatial patterns of drought variability over Portugal, the S-mode PCA was applied to 74 series of SPI-3 and SPI-12, and 27 series of PDSI and MedPDSI, separately; i.e., we performed S-mode PCA four times, one for each index. The quality of the PCAs was tested using the Kaiser-Meyer-Olkin (KMO) statistic (Sheskin, 2007), whereas the decision on how many components to retain was made using North's rule of thumb (North et al., 1982). The varimax rotation, which is an orthogonal method used to maximize the variance between the weights of each principal component, was used to identify areas with independent drought variability (Raziei et al., 2009). The loadings corresponding to each dataset were mapped to show the spatial patterns of drought variability across the country; their associated PC scores were used for drought indices inter-comparison and trend analysis.

The resultant retained PC scores corresponding to R-mode PCAs were then subjected to cluster analysis (CA) to better identify different precipitation sub-regions (Marzban and Sandgathe, 2006). The Ward method, which is an agglomerative hierarchical cluster analysis method, was used here (Sharma, 1996). Additionally, the distribution of the cumulative seasonal precipitation at selected stations within the identified sub-regions was checked using the

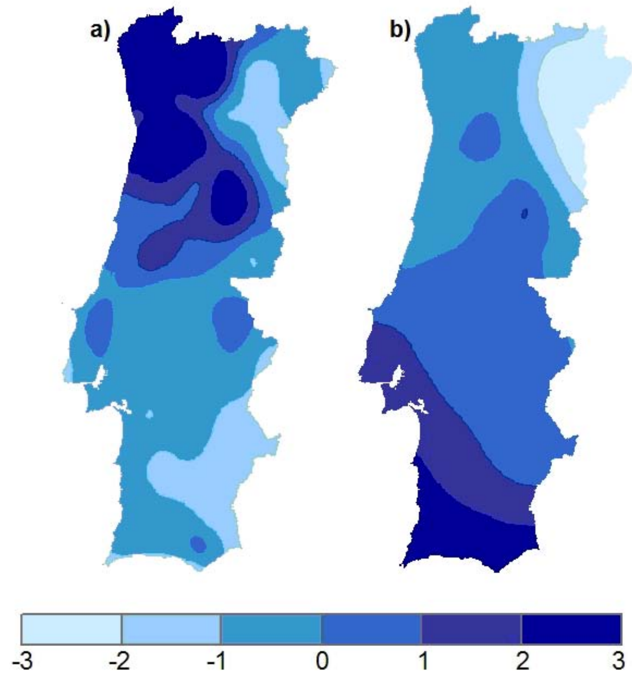

Fig. 3. Spatial distribution of the first **(a)** and second **(b)** rotated PC scores of precipitation over Portugal using 9 variables.

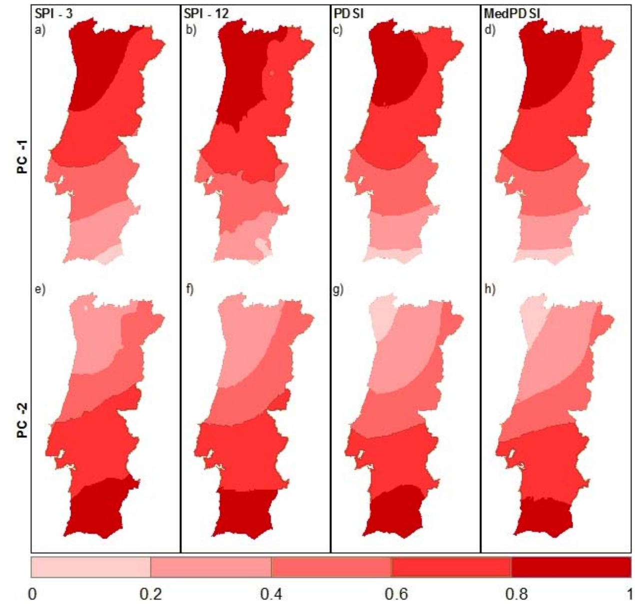

Fig. 4. Varimax rotated loadings of the used drought indices: SPI-3 (**a** and **e**); SPI-12 (**b** and **f**); PDSI (**c** and **g**), MedPDSI (**d** and **h**).

Kolmogorov-Smirnov test to examine the null hypothesis that the distributions are the same (results not shown).

3 Results

3.1 Precipitation patterns

The spatial patterns of PCI are presented in Fig. 1b, which shows a gradual variation from north to south, indicating that the precipitation in Northern Portugal has slight seasonality, while it shows substantial seasonality in the southern regions where the precipitation is very concentrated in a few months of the year. This is well-confirmed by the spatial pattern of seasonal precipitation represented in Fig. 2, illustrating that northern areas receive more even seasonal precipitation, whereas spring and summer are dry seasons for the southern areas.

The KMO statistics applied to the precipitation sets with 9 and 5 variables are respectively 0.72 and 0.79, thus, suggesting that both are adequate for PCA (KMO test > 0.5). Following North's rule of thumb and inspection of the scree plots of the eigenvalues associated with both considered sets, two principal components (PCs) were retained and then rotated using varimax rotation. Table 1 shows the explained variances of un-rotated and varimax rotated components. Considering the set of 9 precipitation variables, the first two PCs explain 91.5 % of the total variance; the first two rotated components associated with these 9 variables account for 46.2 % and 45.3 % of the total variance. In the case of the set of 5 variables, the first two components account for 98.4 % of total variance. However, the first two rotated components explained respectively 67.4 % and 31 % of the total variance, hence indicating that the second component is less important and might not be considered. The spatial pattern of the first un-rotated loading relative to the 5 variables sets showed a dipole pattern (not shown), pointing relatively to the same sub-regions represented by the first two leading rotated loading patterns of the 9 variables set. Thus, in Fig. 3 only the results for the 9 variables set are shown as they better represents the precipitation sub-regions of Portugal. This is likely to be due to the fact that variables not included in the 5 variables set are those illustrating the seasonal percentage of precipitation, which are of great importance to explain the spatial variability together with PCI (Table 2). The percentages of spring, summer and autumn precipitation in conjunction with the PCI values are responsible for differentiating Northern from Southern Portugal. Therefore, it could be concluded that the 9 variables set is the best for representation of the spatial variability of precipitation and delineation of precipitation based sub-regions.

The Kolgomorov-Smirnov test was applied to verify if the northern and southern sub-regions identified in Fig. 3 could be considered statistically different; results show p-values <0.01 when comparing Braga in north with Faro in south. For the set of 9 variables, CA was applied to the first two rotated PC scores using the Ward method. However, results did not improve the classification of precipitation represented by varimax PC score patterns and therefore CA results are

Table 1. Explained variances of the un-rotated and rotated components corresponding to sets with 9 and 5 variables.

PC	9 variables		5 variables	
	Un-Rotated (%)	Varimax Rotated (%)	Un-Rotated (%)	Varimax Rotated (%)
PC-1	58.7	46.2	83.6	67.4
PC-2	32.8	45.3	14.7	31.0
Cumulative	91.5	91.5	98.3	98.4

Table 2. Rotated loadings associated with the PC scores illustrated in Fig. 2.

Variables	Rotated loadings			
	9 variables set		5 variables set	
	PC1	PC2	PC1	PC2
Winter precipitation amount	0.996	0.037	0.972	0.214
Spring precipitation amount	0.958	−0.259	0.883	0.455
Summer precipitation amount	0.906	−0.383	0.799	0.568
Autumn precipitation amount	0.989	0.065	0.997	0.184
PCI	−0.484	0.780	−0.226	−0.969
Winter precip. %	0.218	0.863		
Spring precip. %	−0.038	−0.949		
Summer precip. %	0.264	−0.912		
Autumn precip. %	−0.315	−0.878		

not shown herein. Note that results in Fig. 3 are in agreement with those in Fig. 2, which means that the spatial distribution of PC1 and PC2 represent well the spatial distribution of precipitation throughout the country.

3.2 Drought: spatial variability and trend

Based on North's rule of thumb and the scree plot, the first two components were retained for all used drought indices. The two retained components for each drought index were varimax rotated. Table 3 illustrates the explained variances of un-rotated and varimax rotated components for the four drought indices. In all cases, the cumulative total explained variances of the two retained PCs are higher than 75 %; the highest value is for the SPI-12 (83.2 %) and the lowest for the PDSI (75.1 %). The first un-rotated PC explains much of the total variance for all the PCAs, ranging from 65 % for the PDSI to 75 % in case of SPI-12. The explained variance of the first varimax rotated PC accounts for 39.6 % and 46 % for PDSI and SPI-12, respectively.

Figure 4 depicts the spatial distribution of the rotated loadings over Portugal for the four drought indices, suggesting that the country is composed of two distinct sub-regions characterized by different drought variability. The loading patterns for all drought indices are identical, delineating North-Western and Southern Portugal as two distinctive sub-regions with different drought variability and characteristics. The first component has the highest positive loading over the northern part of the country, including the regions with higher annual rainfall and lower evapotranspiration. As for the first PC loading, the loading patterns corresponding to the second component are very similar for all the drought indices, indicating Southern Portugal as a distinct sub-region, considering drought variability. Apparently, the first component coincides relatively well with the humid areas in the north and the second component refers to the dry sub-humid and semi-arid areas in Southern Portugal.

Achieving the same sub-regions, Northern and Southern Portugal, both precipitation and drought variability reflect the role played by latitude in controlling precipitation and consequently drought variability over the country. These features agree with the country's climate classification according to Köppen (IM, 2011), which refers to a temperate climate with A dry and mild summer (Csb) in the littoral and the northern areas, a temperate climate with a dry and hot summer (Csa) in the south and the interior, and a steppe climate (Bsk) in a very small area of southeastern. The time behaviour of the drought indices MedPDSI and SPI-12 for a northern location, Braga, and a southern one, Faro, makes evident that the dry and wet occurrences and respective intensity are different between the identified sub-regions, while in each representative station both indices are in close agreement (Fig. 5). The sub-regions identified here are in close agreement with those obtained by Santos et al. (2010), applying PCA to SPI

Table 3. Explained variance (%) by the loadings with and without rotation for the 4 drought indices.

PC	SPI-3		SPI-12	
	Un-Rotated	Varimax Rotated	Un-Rotated	Varimax Rotated
PC-1	72.3	43.1	75.0	46.0
PC-2	8.4	37.6	8.2	37.3
Cumulative	80.7	80.7	83.2	83.2
	PDSI		MedPDSI	
	Un-Rotated	Varimax Rotated	Un-Rotated	Varimax Rotated
PC-1	65.4	39.6	65.9	40.7
PC-2	9.7	35.5	9.8	35.0
Cumulative	75.1	75.1	75.7	75.7

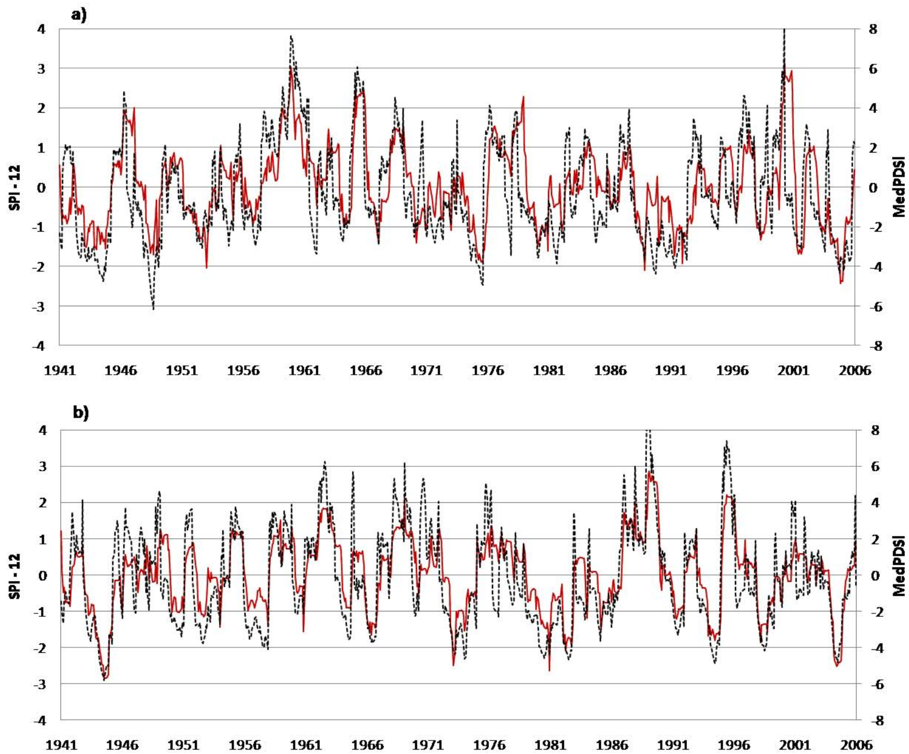

Fig. 5. Time behaviour of MedPDSI (- - -) and SPI-12 (—) for two stations **(a)** Braga in the northern region and **(b)** Faro in the southern region.

at different time scales. It is worth noticing that present results indicate a good agreement between the four indices.

Table 4 shows the correlation coefficients between the PC scores of all drought indices used. The lowest correlation is between SPI-3 and SPI-12, which is due to different time scales; the highest correlation is observed between the PDSI and MedPDSI for both PC scores, which relates to the fact that both indices are computed with the same variables, and apparently because of inherent long-term memory and seasonal time variability (Rosa et al., 2010a). The agreements between the PC scores of SPI-3 and SPI-12 with those for PDSI and MedPDSI are also reasonably high for both PC scores, though their time scales are different. Thus, the correlations between the second PC score of SPI-12 with those for PDSI and MedPDSI are much higher than that of SPI-3 with those of PDSI and MedPDSI.

The time variabilities of the PC scores of all four indices were examined for trend using a linear least square model (Fig. 6). Results show that the PC score time variabilities are consistent among the sub-regions, suggesting that there

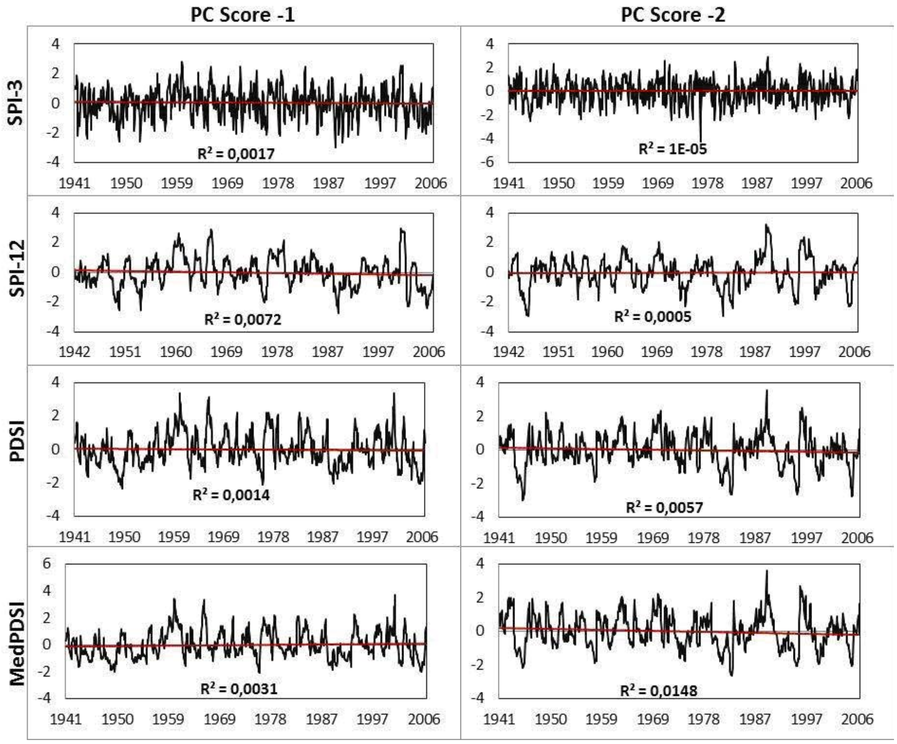

Fig. 6. Time variability of the PC scores of the drought indices and the respective linear trend (–).

Table 4. Correlations between the PC scores of all the drought indices.

PC1	SPI-3	SPI-12	PDSI	MedPDSI
SPI 3	1	0.24	0.59	0.56
SPI 12		1	0.50	0.50
PDSI			1	0.94
MedPDSI				1
PC 2	SPI-3	SPI-12	PDSI	MedPDSI
SPI 3	1	0.25	0.44	0.41
SPI 12		1	0.66	0.68
PDSI			1	0.87
MedPDSI				1

is no evidence for a long-term trend for drought increase or decrease in both identified sub-regions and for the 4 indices. This absence of trend is justified by the quite small linear trends in precipitation and temperature identified by Paulo et al. (2012). These results are also in agreement with those found by Moreira et al. (2006) and Sousa et al. (2011) for Portugal. The first authors used log-linear models applied to contingency tables relative to SPI drought class transitions and found no trend in drought occurrence and severity for the last 60 yr. The second used a modified version of the Mann-Kendal test applied to the self-calibrated PDSI for a period of 100 yr and found no trend for increasing drought occurrence and severity in Portugal. It is important to note that results from all considered indices are compatible.

4 Conclusions

The spatial variability of the precipitation was studied using R-mode PCA. Two sub-regions with different precipitation patterns were identified, one representing the North-Western and the other the Southern Portugal. The cluster analysis did not induce any improvement in this study, since the maps computed with the PC scores allowed a more accurate understanding of the precipitation than with the CA.

The drought spatial variability was assessed by applying S-mode PCA to different drought indices (SPI-3, SPI-12, PDSI and MedPDSI); for all four cases two distinctive sub-regions were identified. The first one covers the north and the second one the southern part of Portugal. These results are in agreement with the identified precipitation variability, and are also consistent with recent studies on drought variability. PC1 explains the drought variability in the northern sub-region, while PC2 mainly refers to the southern sub-region. This applies to all drought indices considered. Results of all drought indices are similar in the identification of the sub-regions and regarding the scores, which are highly correlated, except for the SPI-3 month because of its smaller time scale. Checking the stability of the identified sub-regions using fine resolution, gridded datasets should be a topic for future research.

A trend analysis using a linear least squares model was performed using the PC scores of the four drought indices and, again, results are similar among them, not showing evidence of a trend for either an increase or decrease of drought occurrence or severity in both sub-regions. These results agree with those of previous studies on the temporal analysis of droughts in Portugal. Further analysis will be developed for various climate change scenarios and models to better examine impacts of climate change on drought tendencies over the target area.

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