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Spatial and temporal variability of droughts in Portugal

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[1] An analysis of droughts in mainland Portugal based on monthly precipitation data, from September 1910 to October 2004, in 144 rain gages distributed uniformly over the country is presented. The drought events were characterized by means of the Standardized Precipitation Index (SPI) applied to different time scales (1, 6, and 12 consecutive months and 6 months from April to September and 12 months from October to September). To assess spatial and temporal patterns of droughts, a principal component analysis (PCA) and K-means clustering (KMC) were applied to the SPI series. In this way, three different and spatially well-defined regions with different temporal evolution of droughts were identified (north, central, and south regions of Portugal). A spectral analysis of the SPI patterns obtained with principal component analysis and clusters analysis, using the fast Fourier transform algorithm (FFT), showed that there is a manifest 3.6-year cycle in the SPI pattern in the south of Portugal and evident 2.4-year and 13.4-year cycles in the north of Portugal. The observation of the drought periods supports the occurrence of more frequent cycles of dry events in the south (droughts from moderate to extreme approximately every 3.6 years) than in the north (droughts from severe to extreme approximately every 13.4 years). These results suggest a much stronger immediate influence of the NAO in the south than in the north of Portugal, although these relations remain a challenging task.

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1. Introduction

[2] Droughts are still among the least understood extreme weather events affecting large worldwide areas and having serious impacts on society, environment, and economy. Droughts are complex natural hazards that distress significant areas of the world every year, though with different severities. In Europe the drought of 2003 affected 19 countries with a total estimated cost that exceeded 11.6 billion Euros (http://www.euraqua.org). The costs estimated for Portugal during the 2005 drought were 285 million Euros, with half of this amount related to losses from the hydroelectric power production sector; many other sectors such as agriculture, forestry, and water supply also suffered severe losses. According to the Portuguese Water Institute, in 2005, 80% of the country experienced the worst drought in 60 years (http://www.eumetsat.int/Home/Main/Media/News/005280?l=en). In the southern part, which is also the driest part, agriculture represents the main activity sector, so high correlation must be expected between drought occurrence and agricultural outputs.

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[3] Shortage of water poses a great threat to nature, quality of life, and economy. Increasing water demands lead to confiicts among competing water users that are most pronounced during drought periods [*Hisdal and Tallaksen*, 2003]. The study of the climate variability may contribute to a more correct management of such extreme climatic occurrences. Recently, there has been debate on the apparent increase, regarding the event frequency and the affected area, of droughts and on the possible physical causes of such circumstance. In the Mediterranean basin, if precipitation decrease pointed out by the climate change models [*Bates et al.*, 2008] is confirmed, the consequences would be severe in terms of the progressive scarcity of surface water due to the high demand for agricultural, industrial, and tourist activities and of the intensification of erosion and desertification processes [*López-Bermúdez and Sánchez*, 1997; *New et al.*, 2002; *Vicente-Serrano et al.*, 2004].

[4] To assess the drought occurrence in mainland Portugal and to understand the historical and recent climatic variability, it is worthwhile to study the long-term time series of precipitation regarding their nonhomogeneous climatic and hydrological conditions. For very restricted areas, some authors have analyzed the drought phenomenon by comparing results from well-known scientific indices, such as the Standardized Precipitation Index (SPI) and the Palmer Drought Severity Index (PDSI) [*Paulo and Pereira*, 2006; *Domingos*, 2006], by studying the intensity and frequency of drought events [*Pires*, 2003], and by predicting drought categories [*Moreira et al.*, 2006, *Paulo and Pereira*, 2007, 2008].

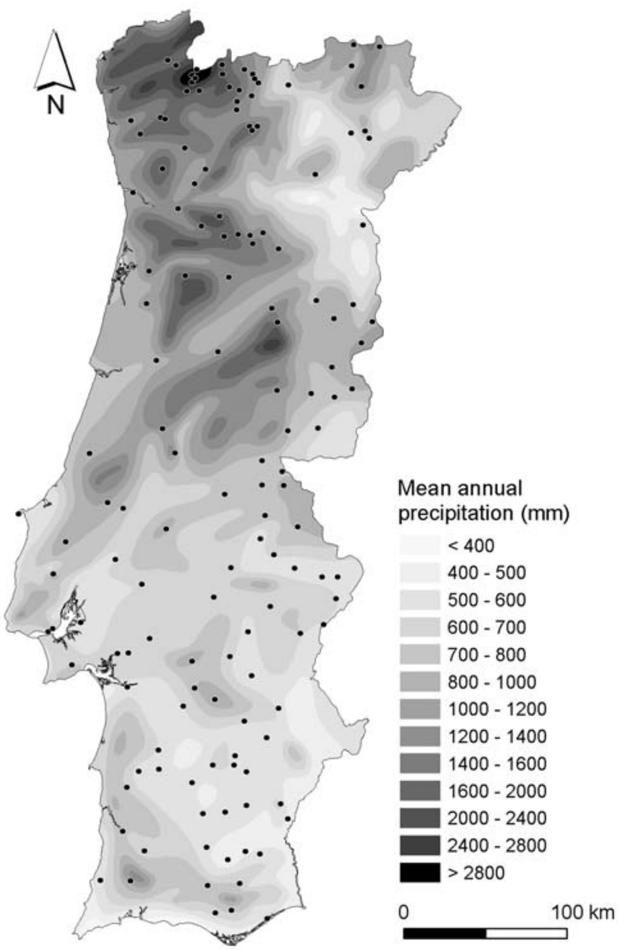

Figure 1. Mean annual precipitation in Portugal mainland. The dots represent the location of the 144 rain gages utilized in the drought analysis.

[5] One of the main goals of the present study was to identify spatial patterns of droughts in Portugal, a small western European country (area of 89015 km^2) characterized by strong precipitation variability (both in time and in space), using principal components analysis (PCA) and nonhierarchical clusters, which are two different methods often utilized to identify homogenous climatic regions. By applying the two methods the authors intended to see if both produced equivalent results or if one of them was preferable, thus providing guidelines for future studies for Portugal.

[6] The analysis was based on 94 years of precipitation data, from 1910–1911 to 2003–2004 (hydrologic years starting 1 October), in 144 rain gages uniformly distributed over the country. With such an extent in terms of the number and distribution of the rain gages and of the length of the recording period, this study is the first to be conducted in Portugal and it is the first time that the spatial distribution of drought temporal patterns is made throughout the country based on comprehensive data. The precipitation records were directly collected from the database of the Portuguese Water Institute which is the national authority responsible for the hydrologic data collection and validation, namely regarding the removal of the nonhomogeneities due to measuring errors. To assess the multiscale drought occurrences, the Standardized Precipitation Index (SPI) (T. B. McKee et al., The relationship of drought frequency and duration to time scales, paper presented at 8th Conference on Applied Climatology, American Meteorology Society, Boston, 1993) was applied to the precipitation series.

[7] In the Iberian Peninsula some studies have been made mainly to identify spatial and temporal patterns in climatic and meteorological data. Authors such as *Corte-Real et al.* [1998] and *Romero et al.* [1999] used PCA for classification of precipitation variability or atmospheric circulation patterns, respectively; others like *Rasilla* [2002] and *Esteban et al.* [2005] used an algorithm that combined clusters analysis and PCA for the same purpose. *Vicente-Serrano et al.* [2004] used PCA for the study of droughts in the Valencia region (eastern Spain). In Portugal, some authors tried to ascertain the spatial historical distribution of the meteorological drought patterns [*Santos*, 1983; *Henriques and Santos*, 1999; *Santos et al.*, 2001; *Paulo et al.*, 2003] but based on a very coarse spatial resolution and without achieving results for the whole country.

[8] The characterization of the temporal variability of the droughts can be very useful for an adequate water resources management. For this reason, this study also aims to find the temporal patterns of the droughts within each region identified by the spatial classification. For that purpose, the temporal evolution of the significant PCA components and of the SPI values in each cluster was accomplished. Also the identification of cycles of dry and wet events in those temporal patterns was carried out based on the fast Fourier transform and spectral analysis [*Fleming et al.*, 2002].

2. Study Area and Data

[9] Portugal is located on the western part of the Iberian Peninsula and is influenced by the Atlantic and Mediterranean climatic zones. The mean annual precipitation varies from more than 2800 mm, in the northwestern region, to less than 400 mm, in the southern region, following a complex spatial pattern (N–S/E–W) (Figure 1), in close connection with the relief, far beyond the most determinant factor of the precipitation pattern.

[10] Though a decrease in the precipitation is generally pointed out for mainland Portugal, the results from the general circulation models (GCM) applied to different climate scenarios denote substantial differences meaning that there is a considerable uncertainty regarding the future projections of the precipitation [*Santos and Miranda*, 2008]. One of the most extensive analysis of the spatial and temporal patterns of precipitation in Portugal was developed by J. F. Santos and M. M. Portela (Quantificação de tendências em séries de precipitação mensal e anual em Portugal Continental, paper presented at Seminário Ibero-Americano sobre Sistemas de Abastecimento Urbano SEREA, Lisbon, Portugal, 2008) based on 94 years (from October 1910 to September 2004) of monthly precipitation records in 144 rain gages regularly distributed throughout the country. The monthly precipitation samples had a few gaps that were filled by applying linear regression, which is a common reconstruction technique of hydrologic time series [*Vicente-Serrano*, 2006a]. The analysis of Santos and Portela (presented paper, 2008) showed that most of the trends denoted by the monthly and annual series were

Table 1. Drought Categories According to the SPI Values[a]

Nonexceedance Probability	SPI	Drought Category
0.05	>1.65	extremely wet
0.10	>1.28	severely wet
0.20	>0.84	moderately wet
0.60	>−0.84 and <0.84	normal
0.20	<−0.84	moderate drought
0.10	<−1.28	severe drought
0.05	<−1.65	extreme drought

[a]Values are from *Agnew* [2000].

statistically meaningless, explained by the natural temporal variability of the precipitation. A pronounced and generalized decrease in the precipitation was only detected in March. However, the high spatial heterogeneity of the precipitation makes it difficult to establish an overall pattern. The same precipitation data was used in this paper to analyze droughts based on the Standardized Precipitation Index (SPI) [*Guttman*, 1999; McKee et al., presented paper, 1993].

2.1. Drought Index Calculation

[11] As previous mentioned, in the present paper the Standardized Precipitation Index (SPI), originally developed by McKee et al. (presented paper, 1993) was adopted to assess the drought in mainland Portugal. The SPI, which has become the most popular drought index during the last 2 decades [*Vicente-Serrano*, 2006a], has several advantages, such as (1) great flexibility, as it can be applied at different time scales [*Edwards and McKee*, 1997]; (2) less complexity, comparatively to other indexes, as it requires relatively simple and well set calculations [*Guttman*, 1998, 1999]; (3) adaptability to hydroclimatologic variables besides precipitation [*Seiler et al.*, 2002; *Vicente-Serrano and López-Moreno*, 2005; *López-Moreno et al.*, 2009]; and (4) suitability to spatial representation, allowing comparison between areas within the same region, as it is a normalized index [*Hayes et al.*, 1999; *Lloyd-Hughes and Saunders*, 2002; *Vicente-Serrano*, 2006a, 2006b; *Bordi et al.*, 2004; *Loukas and Vasiliades*, 2004].

[12] The SPI calculated at 1 month is mainly a meteorological drought index [*Hayes et al.*, 1999], at time scales between 3 and 6 months it can be considered an agricultural drought index [*Hayes et al.*, 1999; *Yamoah et al.*, 2000], and at time scales between 6 and 12 months it is considered a hydrological drought index [*Hayes et al.*, 1999; *Komuscu*, 1999; *Vicente-Serrano*, 2006a], becoming useful for monitoring the surface water resources [*Vicente-Serrano and López-Moreno*, 2005].

[13] To ascertain the variability of both spatial and temporal patterns for different types of droughts, in the analysis carried out for mainland Portugal the SPI was used at different time scales, namely at 1 (SPI1), 6 (SPI6), and 12 (SPI12) consecutive months; at 6 months of the dry season (April to September, $SPI6_{Apr\text{-}Sep}$); and at 12 months of the hydrologic year (October to September, $SPI12_{Oct\text{-}Sep}$). SPI1, SPI6, and SPI12 account for the subannual variability of droughts and $SPI6_{Apr\text{-}Sep}$ and $SPI12_{Oct\text{-}Sep}$ account for the interannual variability.

[14] Originally, McKee et al. (presented paper, 1993) adjusted a Gamma distribution function to the precipitation series to compute the SPI index. Afterward, other authors tested several distributions based on different time scales and concluded that the Pearson type III distribution ensured the best fit. This circumstance can be explained by the higher flexibility of the Pearson type III distribution given by its three parameters in comparison with the Gamma distribution with only two parameters [*Guttman*, 1999; *Ntale and Gan*, 2003; *Vicente-Serrano*, 2006a]. A Pearson III distributed random variable x is written as

$$f(x) = \frac{1}{\alpha\,\Gamma(\beta)}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1} e^{-\left(\frac{x-\gamma}{\alpha}\right)} \quad (1)$$

where α, β, and γ are shape, scale, and origin parameters, respectively, for values of x such that $x > 0$. The term $\Gamma(\beta)$ is the Gamma function of β. In the applications carried out x denotes precipitation and the parameters of the Pearson type III distribution were estimated using the L-moments method. According to *Sankarasubramanian and Srinivasan* [1999], the L-moments method has advantages regarding the conventional moments, especially when the size of the sample increases, and with highly biased distributions.

[15] To compute the SPI series, the detailed formulation provided by *Vicente-Serrano* [2005, 2006b] was followed. The drought categories adopted the SPI limits proposed by *Agnew* [2000], shown in Table 1.

[16] The spatial and temporal characterization of the droughts was accomplished by means of principal component analysis (PCA) and nonhierarchical cluster analysis. To ascertain the drought patterns, both procedures were applied to the SPI series, as many other authors have done successfully for the same purpose [*Klugman*, 1978; *Karl and Koscielny*, 1982; *Stahl and Demuth*, 1999; *Bonaccorso et al.*, 2003; *Vicente-Serrano et al.*, 2004].

2.2. Principal Components Analysis

[17] The principal component analysis (PCA) is a common way of identifying patterns in climatic data and expressing the data in such a way as to highlight their similarities and differences [*Smith*, 2002]. Others [*Lins*, 1985; *Tipping and Bishop*, 1999; *Jolliffe*, 2002; *Singh et al.*, 2009; *Kahya et al.*, 2008a, 2008b] define the PCA method as a technique applied to multivariate analysis for dimensionality reduction, emphasizing patterns on data and relations between variables and between variables and observations. The original intercorrelated variables could be reduced to a small number of new linearly uncorrelated ones that explain most of the total variance [*Rencher*, 1998; *Bonaccorso et al.*, 2003]. Some aspects in the use of PCA could be found, such as (1) PCAs are not affected by the lack of independency in the original variables; (2) normality is desirable but not essential; and (3) only an excessive number of zeros could cause problems, which in the applications envisaged is not a concern [*Hair et al.*, 2005]. As stated by *Kalayci and Kahya* [2006], the PCA method does not require normalized data sets as long as the data are not excessively skewed; since SPI is a normalized variable, following the calculation procedure, there were no needs to previously transform data, nevertheless some normality assessment has been made previously to the PCA application.

[18] Considering k variables in a given time period i, $X_{i,1}$, $X_{i,2}$, ..., $X_{i,k}$, k principle components (PCs) are produced for the same time period, $Y_{i,1}$, $Y_{i,2}$, ..., $Y_{i,k}$, using linear combinations of the first ones, according to:

$$\begin{cases} Y_{i,1} = a_{11}X_{i,1} + a_{12}X_{i,2} + \ldots + a_{1k}X_{i,k} \\ Y_{i,2} = a_{21}X_{i,1} + a_{22}X_{i,2} + \ldots + a_{2k}X_{i,k} \\ \qquad \ldots \\ Y_{i,k} = a_{k1}X_{i,1} + a_{k2}X_{i,2} + \ldots + a_{kk}X_{i,k} \end{cases}. \tag{2}$$

[19] In the applications developed the variables $X_{i,k}$ refer to SPI series, k is equal to the number of rain gages (144) and i represents the length of SPI series in each rain gage. For SPI1, SPI6, and SPI12, i varies from 1 to 94 $\times$ 12 = 1128, 1 to 94 $\times$ 12−5 = 1123, and 1 to 94 $\times$ 12−11 = 1117, respectively, and both for $\mathrm{SPI6_{Apr\text{-}Sep}}$ and $\mathrm{SPI12_{Oct\text{-}Sep}}$ from 1 to 94.

[20] In the previous combinations the Y values are orthogonal and uncorrelated variables, such that $Y_{i,1}$ explains most of the variance, $Y_{i,2}$ explains the reminiscent amount of variance, and so on. The coefficients of the linear combinations are called ‘‘loadings’’ and represent the weights of the original variables in the PCs.

[21] PCs extraction could be based on variance/covariance or correlation matrix of data with $\{a_{11}, a_{12}, \ldots, a_{1k}\}$ being the first eigenvector and $\{a_{k1}, a_{k2}, \ldots, a_{kk}\}$ being the eigenvector of k order. Each eigenvector includes the coefficients of the k principal component.

[22] Finally, the amount of variance explained by the first PC is called the first eigenvalue, λ_1, the second is λ_2, so that $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \lambda_4 \ldots \lambda_k$, since each eigenvalue represents the fraction of the total variance in the original data and explained by each component [*Bordi and Sutera*, 2001] so that this proportion can be calculated as $\lambda_j/\sum\lambda_j$. The analysis of the results of PCs can be focused on the eigenvalues, on the correlations between PCs and the original variables (factor loadings), or on the observation coordinates in the PC (factor scores). In this paper, only the correlations between the original data (SPI series) and the PCs were used for classification purposes (that is, for choosing the main PCs). Those correlations are stored in the factorial matrix.

[23] To achieve more stable spatial patterns, a rotation of the principal components with the Varimax procedure was applied. This procedure provides a clearer division between components, preserves their orthogonality, and produces more physically explainable patterns [*Richman*, 1986; *Vicente-Serrano et al.*, 2004]. *Kahya et al.* [2008a, 2008b] referred that the rotation simplifies the spatial structure by isolating regions with similar temporal variations, being the Varimax procedure the most common orthogonal method to improve the creation of regions of maximum correlation between the variables and the components. The patterns defined in this way are referred as rotated principal components (RPCs).

2.3. Nonhierarchical Cluster Analysis

[24] The Cluster analysis technique, similarly to the PCA method, was chosen for its ability to divide the data set into homogeneous and distinct groups having members with similar characteristics [*Shukla et al.*, 2000; *Pulido-Calvo et al.*, 2006]. Cluster analysis is a generic term for a variety of statistical methods that can be used to evaluate the similarity of individual objects in a set. A simple example would be gathering a set of pebbles of different size, shape, and color from a stream shore and sorting similar pebbles into the same pile. This is an example of physical cluster analysis. Statistical methods of cluster analysis achieve this mathematically. The objects in such statistical methods are data rather than real objects (e.g., pebbles).

[25] Using the calculated SPI data, the rain gages should be grouped homogeneously so that similar SPI variations at different time scales will be assigned to the same group, while different variations will be grouped separately. A mathematical criterion to calculate the classification and to judge the quality of the classification must be used. This question can be addressed by the K-means clustering (KMC) method which can reassign each observation to a different cluster with the nearest centroid [*Rhee et al.*, 2008]. *Gong and Richman* [1995] noted that nonhierarchical methods, such as the K-means algorithm, outperformed hierarchical methods (the Ward's method and the average linkage method) when tested with precipitation data.

[26] In general, the K-means method will produce exactly K different clusters of greatest possible distinction, with the goal to (1) minimize variability within clusters and (2) maximize variability between clusters. K-means clustering tries to move cases in and out of groups (clusters) to get the most significant ANOVA results. As result of a K-means clustering analysis, the means for each cluster on each time scale (for example, at $\mathrm{SPI6_{Apr\text{-}Sep}}$ there were 94 values) are examined to assess how distinct the K clusters are. In this paper, the means for each cluster of all dimensions characterize a mean SPI pattern. Ideally, very different means for most, if not all, dimensions used in the analysis are obtained.

[27] The analysis requires that the number of groups or clusters be established beforehand. This aspect is considered as one of the major unresolved issues in the cluster analysis since the number of groups is not known a priori [*Kahya et al.*, 2008a, 2008b]. For this reason in this study, the test was repeated, forming different groups, according to the spatial classification obtained with the PCA method, in order to determine which classification best suited the problem objective or would provide the clearest interpretation of the results. Other authors such as *Stooksbury and Michaels* [1991], *DeGaetano* [1996], and *Rhee et al.* [2008] have also determined the appropriate number of clusters according to the results of other data classification techniques. To evaluate the appropriateness of the classification, the Euclidean distances between clusters was examined [*Daniel*, 1990; *Webster and Oliver*, 1990; *Hair et al.*, 2005].

2.4. Spectral Analysis: Fast Fourier Transform

[28] Spectrum analysis is concerned with the recognition of cyclical patterns in the data. The purpose of the analysis is to decompose a complex time series with cyclical components into a few underlying sinusoidal (sine and cosine) functions of particular wavelengths. In essence, performing spectrum analysis on a time series is like putting the series through a prism in order to identify the wavelengths and importance of underlying cyclical components.

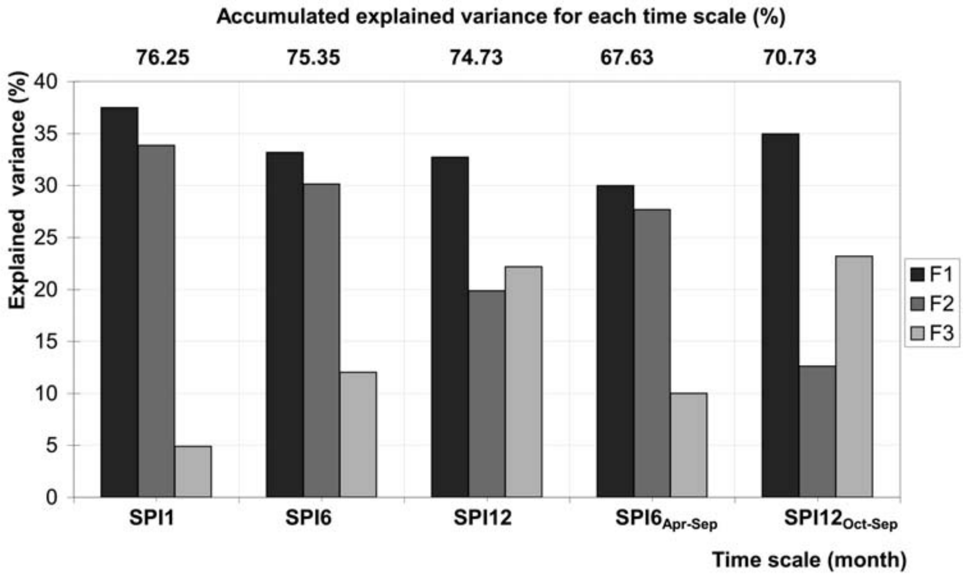

Figure 2. Percentage of variance explained by first three components of PCA, F1, F2, and F3.

As a result of a successful analysis, one might uncover just a few recurring cycles of different lengths in the time series of interest [*Fleming et al.*, 2002].

[29] In this paper, the fast Fourier transform algorithm, or FFT, was used to identify periodicities in the time series of the SPI patterns obtained with the cluster analysis and the PCA method. For the time series analysis, spectral methods, such as the Fourier transform, have been widely implemented. Reviews on the theoretical aspects of Fourier transform are abundant in the literature [*Lo et al.*, 1975; *Park*, 1998; *Pasquini et al.*, 2006; *Gutiérrez-Estrada and Pulido-Calvo*, 2007]. Since these are discrete time series the sampling frequency has been established between 0.0 and 0.5 in order to avoid the rebound effects of the frequencies (aliasing) [*Bloomfield*, 1976]. The FFT provides a pair of values for every wave frequency (Fourier coefficients), which are considered as a complex number with a cosinusoidal component (real part) and a sinusoidal one (imaginary part). Both values can be combined for the periodogram calculation which is a plot of energy versus frequency [*Park*, 1998; *Küçük et al.*, 2009].

3. Results

3.1. Principal Components Analysis: Spatial Variability of Droughts

[30] On the basis of 94 years of monthly precipitation in the 144 rain gages schematically located in Figure 1, 144 series of Standard Precipitation Indexes were obtained for each time scale. As previously mentioned, the length of each SPI series is equal to $94 \times 12 = 1128$, $94 \times 12 - 5 = 1123$, $94 \times 12 - 11 = 1117$, for the time scales of 1, 6, and 12 continuous months (SPI1, SPI6, and SPI12, respectively) and equal to 94 when referred to the 6 months of the dry semester ($SPI6_{Apr\text{-}Sep}$ from April to September) or to the 12 months of the hydrologic year ($SPI12_{Oct\text{-}Sep}$ from October to September). For each time scale, the 144 series of the SPI are comparable as they represent normalized values, according to the SPI underlying concept.

[31] Regarding the PCA and taking into account the variance explained by each rotated component, three main patterns or RPCs, F1, F2, and F3, were identified. These three patterns explain about 75% of the total variance in the original SPI series, for the SPI at 1, 6, and 12 months, and about 70% for the SPI at 6 months from April to September and for the SPI at 12 months from October to September (Figure 2).

[32] The spatial extent of the first three component series (components F1, F2, and F3) was characterized by mapping the values of the factorial matrix. As previous mentioned, for a given time scale this matrix contains the correlations between each component (F1, F2, or F3) and the SPI series at the 144 rain gages. For that purpose the Kriging spatial interpolation method [*Oliver and Webster*, 1990] available on Surfer version 8.01 (http://www.goldensoftware.com/products/surfer/surfer.shtml) was utilized (Figure 3). The results achieved are represented in Figure 3 along with the limits of the main Portuguese watersheds.

[33] Figure 3 shows that between the first two components, F1 and F2, the regions with significant correlation (higher than 0.7) do not overlap, being clearly spatially disjunctive. For all the SPI time scales, the first component highlights an area located in the south of Portugal and it explains between 30% and 37% of total variance (Figure 2). This is the component that explains the largest area within mainland Portugal when comparing with the others RPCs. In some rain gages, the correlations among the values of this component and of the SPI series were higher than 0.8 which means a clear individualized pattern.

[34] The second component, F2, explains around 30% of the total variance for SPI1, SPI6, and $SPI6_{Apr\text{-}Oct}$, being less important for SPI12 and $SPI12_{Oct\text{-}Sep}$, with less variance explained than the component three (F3 of Figure 2). Nevertheless, it is overwhelming that F2 is mainly representative of the northwestern part of Portugal (Figure 3). For SPI6 and SPI12 this second component relates negatively with the SPI series. In general terms, the third component F3 highlights a central region which confines with the regions identified by F1 and F2, and it relates negatively

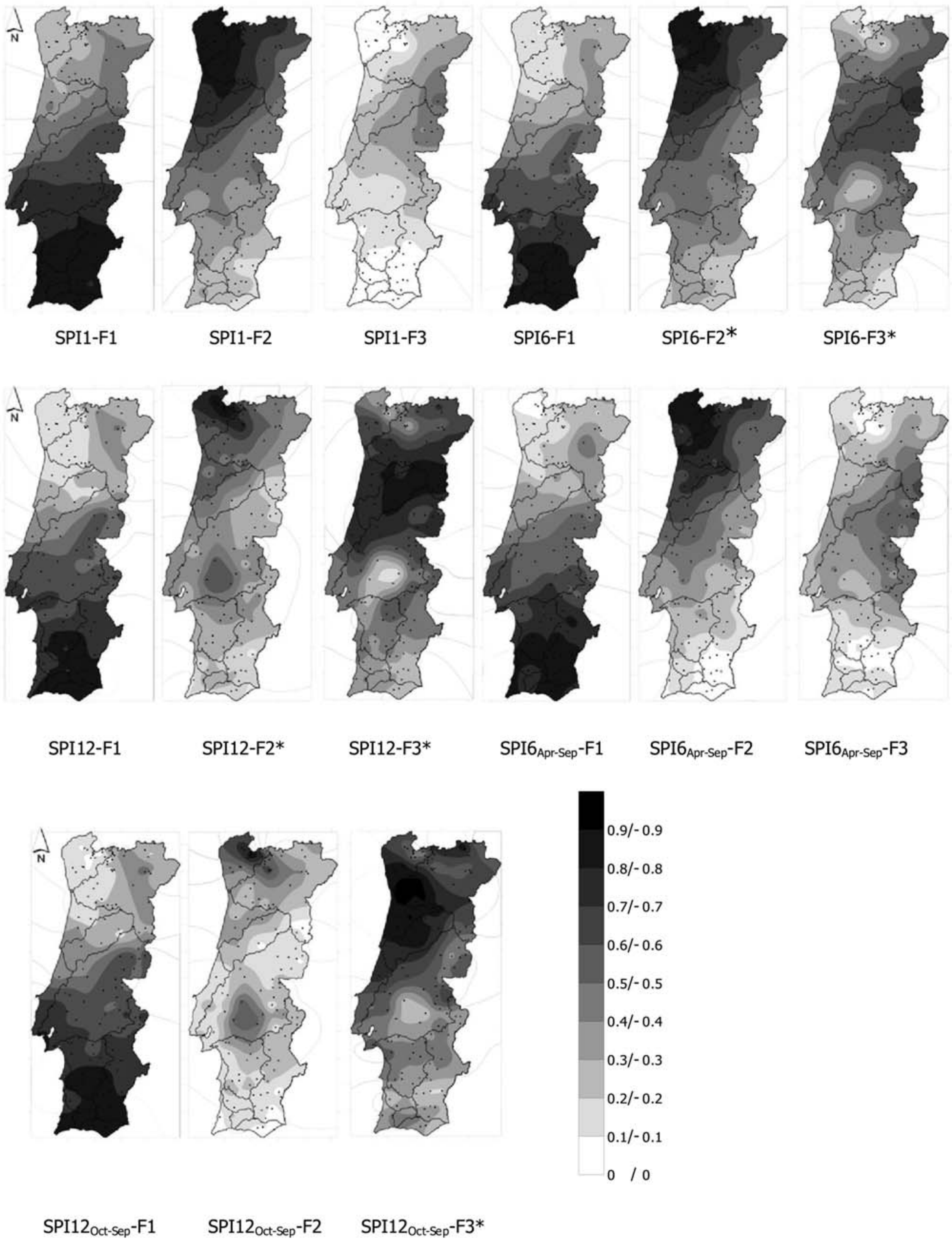

Figure 3. Spatial distribution of the values of the matrix correlation. Components F1 and F2 of SPI at 1, 6, and 12 consecutive months (SPI1, SPI6, and SPI12, respectively); at 6 months from April to September ($SPI6_{Apr\text{-}Sep}$); and at 12 months from October to September ($SPI12_{Oct\text{-}Sep}$) (asterisks indicate negative correlations).

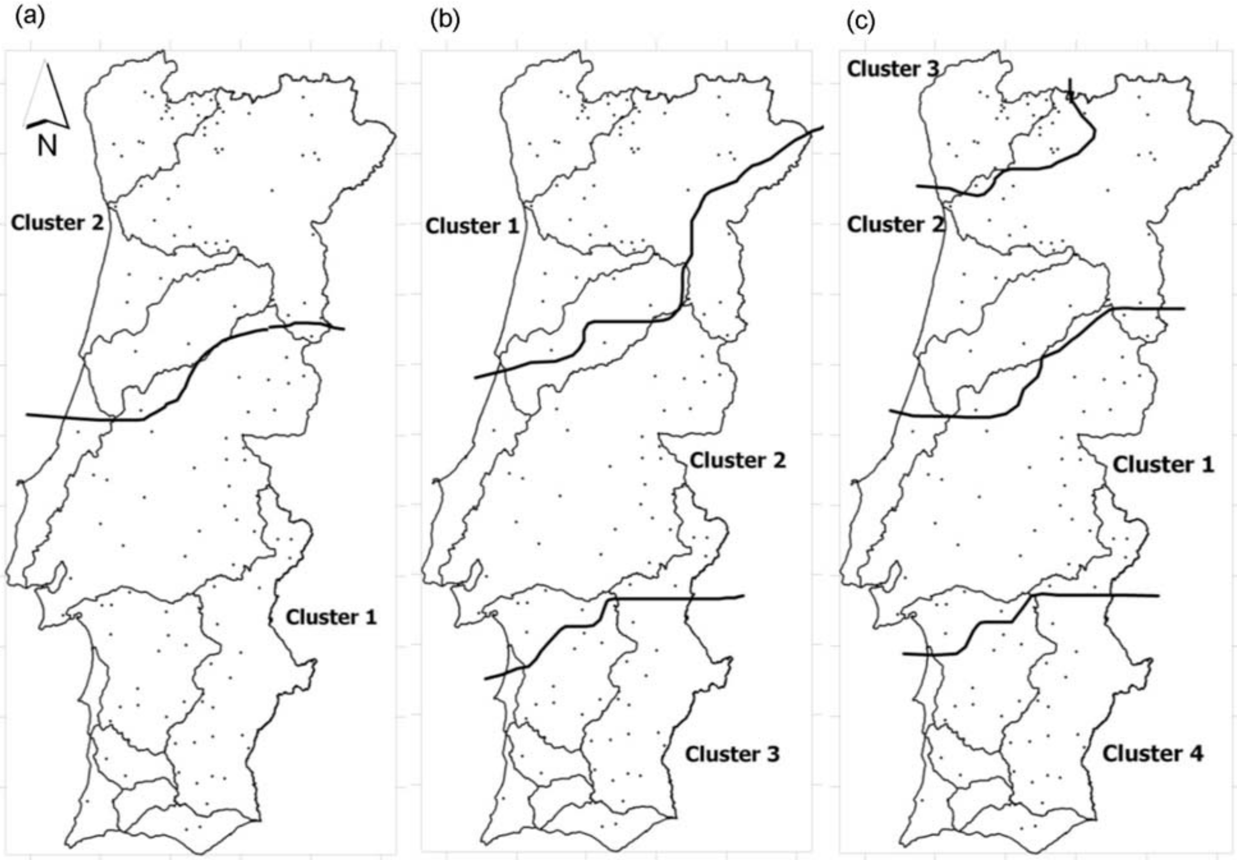

Figure 4. $SPI6_{Apr\text{-}Sep}$ series. Comparison of clusters analysis with (a) two, (b) three, and (c) four classification groups.

with the original series in the case of SPI6, SPI12, and $SPI12_{Oct\text{-}Sep}$.

[35] The previous results indicated that with the three main components F1, F2, and F3 a spatial classification is achieved, with two well-defined regions, one located in the north and the other in the south of Portugal and with an intermediate region that promotes the transition from the wet north to the arid and semiarid south. The spatial classification was similar for all the time scales used.

[36] It should be stressed that from a hydrological point of view the two previous regions are quite different: the north and especially the northwestern region has much more water along with a very regular regime; toward south, the water availability decreases progressively (as denoted by Figure 1) and the regime becomes more and more irregular with more than 75% of the precipitation occurring during a few months of the wet semester.

3.2. Nonhierarchical Cluster Analysis: Spatial Variability of Droughts

[37] For all the SPI series (SPI1, SPI6, SPI12, $SPI6_{Apr\text{-}Sep}$, and $SPI12_{Oct\text{-}Sep}$), the spatial grouping obtained with the cluster analysis was similar to the one given by the PCA. For example, Figure 4 shows the spatial distribution of the clusters formed with the $SPI6_{Apr\text{-}Sep}$ series considering two, three, and four classification groups.

[38] To evaluate the appropriateness of the classifications, the Euclidean distances between clusters were examined. These distances for the clusters analysis with two, three, and four groups are shown in Table 2 for the $SPI6_{Apr\text{-}Sep}$ series. These results show that the best grouping is with three clusters.

[39] Note that clusters 1 (southern rain gages) and 2 (northern rain gages) were relatively more close (Euclidean distance = 0.67) in the classification with two groups in comparison with clusters 1 (northern rain gages) and 3 (southern rain gages) (Euclidean distance = 0.88) in the classification with three groups. So, three different regions that are well-defined spatially (north, central, and south regions) can be considered (Figure 4b). Despite the fact that, compared to the PCA, there is a central region clearly delimited (Cluster 2), the spatial classification that resulted from the cluster analysis is similar to the one obtained with the PCA method (Figure 3), which suggests that both methods can be used to identify spatial areas with different temporal patterns.

[40] The classification with four groups was rejected because the clusters 2 and 3 (northern rain gages) (Figure 4c), which conform approximately the cluster 1 on the analysis with three groups (Figure 4b), presented Euclidean distances more close to the cluster 4 (southern rain gages) of the analysis with four groups in comparison with the classification with three groups (Table 2). So, in Figure 4c the Euclidean distances between cluster 2 (northern rain gages) and 4 (southern rain gages) was 0.72 and between 3 (northern rain gages) and 4 (southern rain gages)

Table 2. SPI6$_{Apr\text{-}Sep}$ Series[a]

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Two Classification Groups				
Cluster 1	0	0.449914		
Cluster 2	0.670756	0		
Three Classification Groups				
Cluster 1	0	0.221728	0.778282	
Cluster 2	0.470880	0	0.351966	
Cluster 3	0.882203	0.593267	0	
Four Classification Groups				
Cluster 1	0	0.207486	0.655584	0.934866
Cluster 2	0.455507	0	0.289587	0.524088
Cluster 3	0.809681	0.538133	0	0.019968
Cluster 4	0.966885	0.723939	0.141311	0

[a]Euclidean distances between clusters for analysis with two, three and four classification groups (distances below diagonal and squared distances above diagonal).

was 0.14, while in Figure 4b the Euclidean distance between cluster 1 (northern rain gages) and 3 (southern rain gages) was 0.88.

3.3. Temporal Pattern and Areal Evolution of Droughts

[41] The seasonal SPI6$_{Apr\text{-}Sep}$ series were chosen for this analysis as they reflect the driest period in Portugal, from the middle of spring to the end of summer, when droughts are most critical as they affect the agriculture sector which is in Portugal the foremost water consuming sector. Also, the spatial classification that resulted from the PCA, Figure 3, showed that both subannual (SPI1, SPI6, and SPI12) or interannual (SPI6$_{Apr\text{-}Sep}$, SPI12$_{Oct\text{-}Sep}$) time scales of SPI led to similar patterns which makes valid to continue the analysis based on one of those scales.

[42] The temporal evolution of the components F1 and F2 of the PCA and of cluster 3 and 1 for three classification groups is shown in Figure 5. Figure 5 shows that the southern part of Portugal (component F1 and cluster 3) suffered several extreme droughts, starting in the beginning of the 1920s, mid 1930s, 1940s, 1950s, and mid 1970s. Some of those droughts were particularly severe as they were prolonged in time such as the one in the mid 1950s. In the northwestern part of Portugal (component F2 and cluster 1), although fewer drought events were detected, two extreme droughts are quite clear: one in the mid 1930s and the other in the beginning of the 1990s. The first episode was short and the second one more prolonged in time.

[43] The results for each area, when comparing both methods (PCA and cluster analysis), are quite similar. In fact the Pearson correlation coefficient between PCA-F1 and cluster 3 was 0.964 and between PCA-F2 and cluster 1 was 0.938, with these high values clearly expressing the proximity of the results.

[44] The differences between the northwestern and southern areas can be related with the water availability and temporal variability, the former region having more water and a regular hydrologic regime, as previously mentioned.

[45] According to PCA and once more for SPI6$_{Apr\text{-}Sep}$, Figure 6 shows the areas of Figure 3 with correlations higher than 0.7. For each one of those areas the percentages of area affected by moderate, severe, and extreme drought (according to the SPI categories of Table 1) were computed. For that purpose an influence area was assign to each rain gage by applying the Thiessen polygon method [*Vicente-Serrano et al.*, 2004] using Arcgis 9.3. The area attributed to a specified drought category was given by the cumulative areas of the rain gages with values of SPI6$_{Apr\text{-}Sep}$ within the limits that define such drought category. The results achieved are presented in Figure 7.

[46] Figure 7 shows that in general terms, the southern part of Portugal (F1) is more affected by drought events than the northwestern part (F2). From 1910 to 2004 the

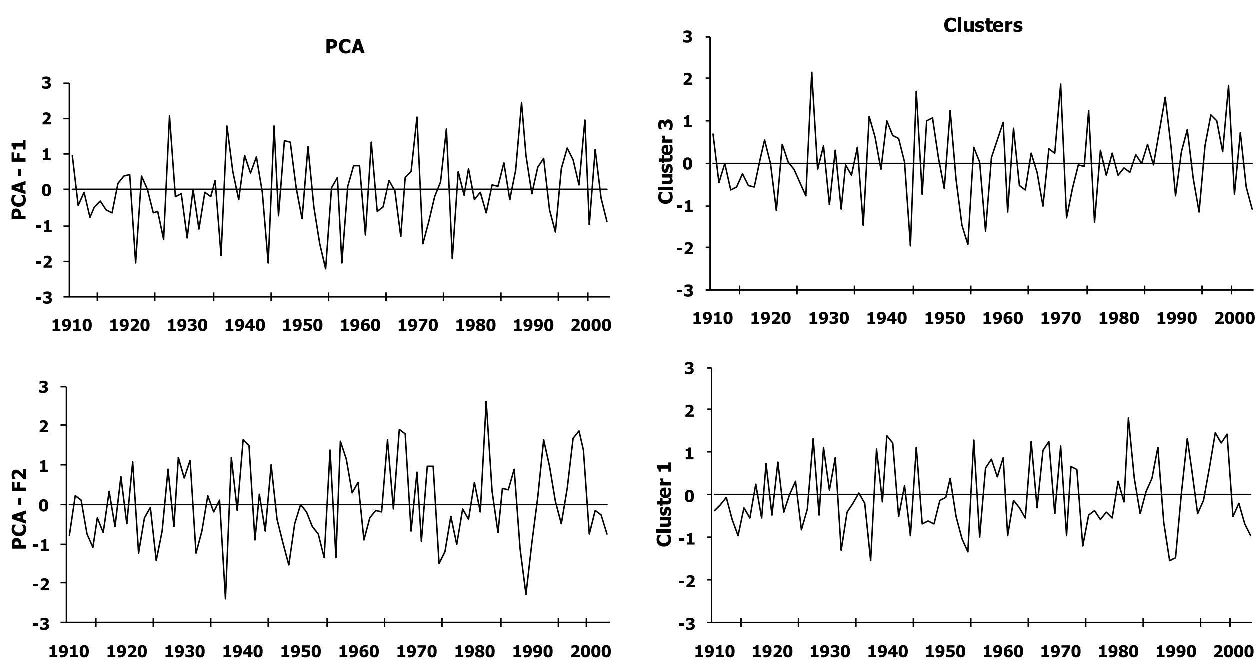

Figure 5. Temporal evolution of components F1 and F2 of the PCA analysis for data series SPI6$_{Apr\text{-}Sep}$ and means of each cluster for analysis with three classification groups.

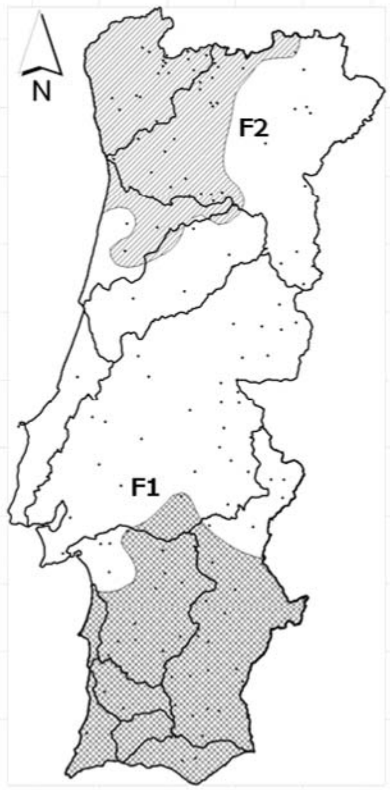

Figure 6. SPI6$_{\text{Apr-Sep}}$. Areas of Figure 3 with correlations higher than 0.7.

number of events affecting more than 50% of the area was 17 in south and 12 in the north. From 1910 to 1930, 20% of the southern region was frequently affected by droughts of moderate category, whereas the rest of the period experienced less drought events but with episodes with very high intensity, especially in mid 1950s where the drought affected the entire southern region (100%) and even had reflexes in the northern region. In this last region a 3-year isolated episode took place from 1988 to 1990, being that the 1989 drought affected the whole area (100%). The most widespread extreme droughts occurred in the southern region with 69% and 73% of area affected in 1944 and 1954, respectively, and in the northern region with 43% in 1954 and 1989.

3.4. Frequency Estimation With Spectral Analysis

[47] The fast Fourier transform technique, or FFT, has been used to analyze the cyclical behavior of the SPI patterns obtained with the PCA for the southern and northern areas of Portugal (F1 and F2, respectively, Figure 3) and with the equivalent clusters obtained with the cluster classification selected (three classification groups, Figure 4b). Figure 8 shows the periodogram plots of the SPI6$_{\text{Apr-Sep}}$ patterns. In the cluster 3 and PCA-F1 (southern area, Figure 4b) there is one clear peak in the periodogram plot. In the cluster 1 and PCA-F2 (northern area, Figure 4b) there are two clear peaks in the periodogram plot.

[48] The frequency is the number of cycles per unit time (where each observation is treated as one unit of time). Thus in the cluster 3 and PCA-F1 the peak frequency of 0.28 corresponds to a period (the number of units of time necessary to complete one full cycle) of 3.6 years. Since each value of the SPI6$_{\text{Apr-Sep}}$ is computed in an annual basis, the results suggest that there is a strong 3.6-year cycle in such SPI index in the southern area. This cyclical behavior can be observed in Figure 5 (PCA-F1 and cluster 3) where between 1953 and 1976 peaks representing drought occurrences occur approximately every 3.6 years.

[49] In the cluster 1 and PCA-F2, the peak frequency of 0.07 corresponds to a period of 13.4 years (a clear peak in both spectral analyses) and the frequency of 0.41 to a period of 2.4 years (a clearer peak in spectral analysis of cluster 1). These results suggest that there are a frequent 2.4-year and

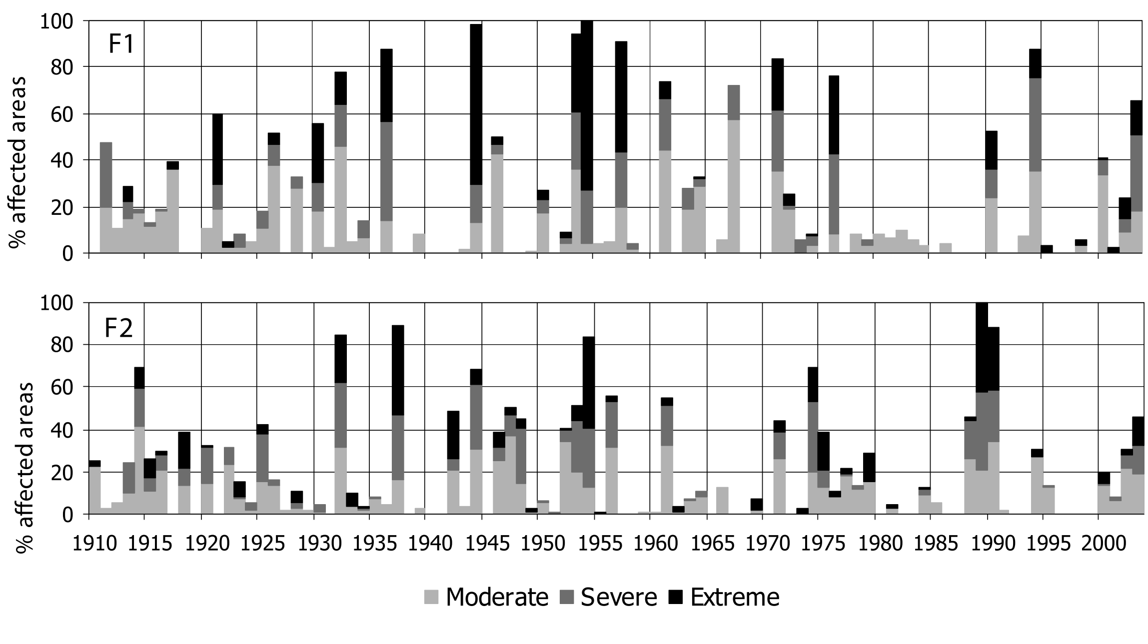

Figure 7. SPI6$_{\text{Apr-Sep}}$ series. Temporal evolution of the percentage of area affected by different drought categories. Two main components of PCA (F1 and F2).

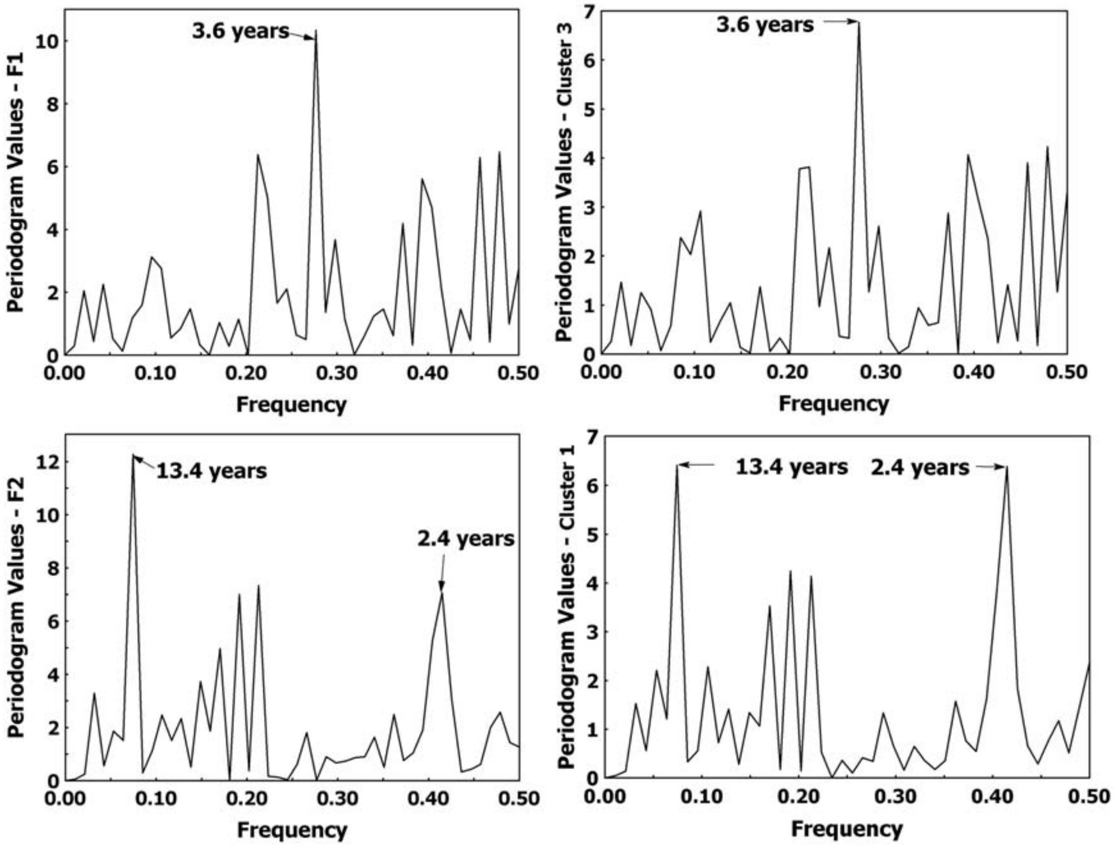

Figure 8. Spectral analysis of $SPI6_{Apr\text{-}Sep}$ patterns (left) obtained with the PCA considering groups F1 (south) and F2 (northwestern); (right) two main classification groups (cluster 1 and 3) for KMC.

13.4-year cycles in the SPI index in the overall northern area. In Figure 5 (PCA-F2 and cluster 1), drought events from severe to extreme are observed approximately each 13.4 years. In 1925 one severe drought was observed that was repeated with higher intensity in 1937 (extreme drought), this is to say, approximately 12–13 years later. The following drought peak (severe drought) occurred in 1949, which suggests again the long-time cycle obtained. Also the short-time cycle of 2.4 years can be observed at some time periods (Figure 5), as for example, the severe droughts of 1949 and 1951 or the moderate droughts of 1969 and 1972. Figure 8 shows once more that the results provided by the PCA and by the cluster analysis are similar, denoting that only one of those methods needs to be applied to characterize the droughts in Portugal.

4. Discussion and Conclusions

[50] As stated by *Wilhite and Svoboda* [2000], the first step for managing drought risk assessment in a given region should be dividing the region into subregions according to spatial drought variability. In this paper the spatial pattern for the droughts in mainland Portugal is presented. Also some features related with the temporal periodicity of droughts were obtained. The characterization thus achieved can provide guidance for drought risk assessment for example, by highlighting the regions more prone to droughts, where additional storage capacity is required for drought protection.

[51] The drought events were characterized by means of the Standardized Precipitation Index (SPI) applied to different time scales (1, 6, and 12 consecutive months and 6 months from April to September and 12 months from September to October). For that purpose 94 years (from October 1910 to September 2003) of monthly precipitation in 144 Portuguese rain gages were used. To identify the spatial patterns of the SPI series, principal component analysis (PCA) and nonhierarchical cluster analysis (KMC) were applied.

[52] The study showed that for the different times scales, both methods resulted in an equivalent areal zoning, with three regions with different behaviors: the north, the center, and the south of Portugal. This three regions are consistent with the precipitation spatial distribution in Portugal mainland, which in general terms decrease from north to south [*Santos*, 1983; *Corte-Real et al.*, 1998; Santos and Portela, presented paper, 2008], with the central mountainous region representing the transition between the wet north and the progressively dry south. As the precipitation decreases the hydrological regime becomes more irregular [*Portela and Quintela*, 2006] and consequently more prone to droughts.

[53] The similarity of the results achieved by PCA and the KMC analysis were an indicative that both methods can be used for drought classification purposes, regarding spatial and temporal pattern analysis. However, the not so clear procedure of evaluating the optimum number of clusters based on the Euclidean distances reinforces the idea that the loadings produced by PCAs provide a more

clear and simple method to recognize distinct temporal patterns.

[54] Previous studies have shown that during positive phases of the North Atlantic Oscillation (NAO), negative SPI averages (indicative of drought conditions) are recorded in southern Europe, whereas the opposite trends occur during negative phases [*Trigo et al.*, 2002; *López-Moreno and Vicente-Serrano*, 2008]. In general, this trend is observed in the SPI patterns obtained in this study. According to *López-Moreno and Vicente-Serrano* [2008], for example, the years 1920, 1957, 1961, and 1990 were identified as having positive phases of the NAO and in our work these years have showed strong negative SPI values when short, medium, and long time scales (1, 6, and 12 months) were considered.

[55] Spectral analysis (energy versus frequency) was particularly useful to detect periodical signals in the SPI time series patterns. The spectral analysis derived from the PCA and the KMC results by applying fast Fourier Transform algorithm were equivalent denoting more frequent cycles of dry events in the southern region (droughts from moderate to extreme approximately every 3.6 years) than in the northern region (droughts from severe to extreme approximately every 13.4 years). The drought short-time periodicity observed in the southern region might be associated with the immediate and significant influence of the North Atlantic Oscillation (NAO) on the precipitation regimes in the Atlantic and Mediterranean sectors [*López-Moreno et al.*, 2007; *López-Moreno and Vicente-Serrano*, 2008; *Küçük et al.*, 2009]. Thus *Polonskii et al.* [2004] and *Küçük et al.* [2009] found that the spectra of the NAO index contain significant peaks corresponding to periods of 2–4 and 6–10 years. However, explaining relations between the NAO and the periodicity of more than 10 years, detected in the northern region, remains a challenging task that should include the study of the interaction of other regional phenomenons such as the soil moisture oscillation [*Sims et al.*, 2002; *Abbot and Emanuel*, 2007].

[56] It may be noted that the conclusions of the spectral analysis need to be reinforced through the research of the process of energy variations in terms of when the drought events occur (energy versus time frequency) which could be developed in future works using the wavelet transform analysis [*Küçük et al.*, 2009]. Thus inferences related with the connection among frequency peaks and effective cycle drought patterns in the data and with the translation of such drought cycles into occurrence probabilities could be obtained. Likewise, additional research needs to be carried regarding the physical mechanisms that explain the results achieved in connection to other local factors, such as the parameters that control temporal changes in the influence of the NAO phases on Portugal droughts or the analysis of other global teleconnection patterns (ENSO and east Atlantic-west Russia, EAWR).

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