Improving the Knowledge of Climatic Variability Patterns Using Spatio-Temporal Principal Component Analysis

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1. Introduction

We may define climate as a statistical synthesis of the weather conditions at a given place or region during a period of time. Climate is different from place to place and also changes with time. For instance, the climate is different in the British Islands, in Central Europe, in the Iberian Peninsula, in the Sahara or in the Amazons. The climate changes from Winter to Summer and from daytime to nigh time.

The climate also shows variations over long periods of time. There are strong evidences of the existence in the past times of glacial and interglacial periods. A brief synthesis on this subject can be seen, for instance, in Duplessy and Morel (1990). There are also evidences of changes in climate over shorter time scales. Some of them are not detectable from direct instrument measures, which just began in a systematic way after the Second World War (Peixoto & Oort, 1992). Considerable effort has been made during the last decade to reconstruct global or northern hemispheric temperatures for the past in a long term perspective (Ljungqvist, 2010), referring for example: von Storch et al. (2004), Wanner et al. (2008), Osborn & Briffa (2006), Mann & Jones (2003), Lee et al. (2008) and Jones et al. (2009).

Besides these changes in time, the climate shows year to year variability.

For quantitative studies of the climate in the near past or present times series of measurements of the climatic elements such as air temperature, atmospheric pressure, precipitation amount, etc., are analysed.

Climatic series are composed in such a way that they filter the seasonal and daily variability. For instance, it can be used climatic chronological series of values of mean air temperature in every January year after year, series of total annual precipitation amount year after year, series of mean atmospheric pressure during every spring year after year, etc.

The climatic series formed in this way do not show seasonality or daily variability and have a statistical behaviour that is, in a first approximation, similar to realizations of white noise or red noise stochastic processes. The principal aim of the statistical climatology analysis is to detect in the series properties that significantly differ that what should be expected from simple realizations of stationary white or red noise. These properties are called "signals" and the remainder part of the series is called the "noise". Typically climatic series have low signal to noise ratios or, in other words, the fraction of variance explained by the signal (or signals) is generally low when compared to the variance of the remainder noise.

For regional studies of climatic variability with interest in spatial and/or spatio-temporal patterns the climatic series to be used are time series of bi-dimensional almost horizontal fields (surface or constant pressure levels). These fields can be specified by a number of irregularly spaced time series in meteorological stations or, preferably, in regular grids. The gridded values are the result of the averaging of synoptic meteorological analysis based in the observations in the region and performed by methods that use interpolation with physical consistency (e.g., Kalnay et al., 1996; Kistler et al., 2001). The term reanalysis refers to *ad posteriori* analyses using constant procedures over a large period of time, to avoid inhomogeneities that could otherwise be introduced in the series by the modification of the analysis methods over time.

Principal Component Analysis (PCA) is commonly used in understanding the principal modes of climatic variability of an atmospheric variable. PCA is based on a compression method that reduces the variability to some number of modes explaining a considerable part of the field variance. A detailed analysis of the mathematics of the Empirical Orthogonal Functions (EOFs) approach to both scalar and vector fields can be found in Peixoto and Oort (1992). In von Storch and Zwiers (1999) is presented also a detailed description of the technique with applications in climatology. The method is applied on this study, both to a small country or region (e.g. Portugal, in case of winter seasonal precipitation) and to an extended area like the atmospheric surface pressure over the North Atlantic, allowing the knowledge of the most important variability modes, namely the well known leading mode of climate variability over the North Hemisphere, the North Atlantic Oscillation (NAO).

The Singular Spectral Analysis (SSA) is a recent tool used in time series analysis. Contrary to classical spectral analysis or maximum entropy methods (MEM), where the basis functions are prescribed sines and cosines, SSA produces data-adaptive filters that are able to isolate oscillations spells, which makes the method more flexible and better suited for the analysis of non-linear, anharmonic oscillations (Vautard et al., 1992). Furthermore, SSA allows the decomposition of the temporal series associated to each mode in trends and periodicity component series. These series are easier to analyse due to the obvious noise reduction and permits the grouping of selected temporal reconstructed components of the detected modes.

However, PCA just allows the evaluation of the principal spatial modes and how the respective spatial patterns evolve in time. The quasi-meridional NAO behaviour has been reported in several studies (Hurrell, 1996; Hurrell & van Loon, 1997) where analyses are performed by methods just based on PCA. However some authors used or are using, depending on the season, different locations mainly for the southern pole of the NAO index: Azores (Rogers, 1984), Lisbon (Antunes et al., 2006) and Gibraltar (Jones et al., 1997). These different locations are justified by the non-stationary seasonal behaviour of the poles of the oscillation that is evident when seasonal PCA is performed seasonally (e.g. Hurrell et al., 2003).

The analysis of space-temporal variability, that is, the spatio-temporal analysis of modes evolving in space and time may provide more information about the underlying physical system (Vautard, 1995). In fact, a spatio-temporal analysis of the North Atlantic mean sea level pressure field reveals that the first mode of variability only behaves like what was supposed to be the NAO pattern, in extreme high and low NAO index phases. This space-time analysis shows that the principal mode of oscillation is not always quasi-meridional, as it is frequently assumed, but has an oscillation pattern that changes assuming different orientations with time (Antunes et al., 2010).

The application of PCA to the annual or seasonal precipitation amount in Portugal reveals very simple variability patterns (Serrano et al., 2003). In winter the consideration of just three Empirical Orthogonal Functions (EOFs) explains 94% of the total variability and the first mode, associated with precipitation anomalies of the same sign over the whole region, explains 85% of the total variance.

The analysis performed by SSA is able to detect periodic characteristics in the time variability of the precipitation amount (Antunes et al., 2000) but these signals are not found to be statistically significant. However, when a space-temporal method is applied, the space time periodic signals became statistically significant, revealing again that the Multichannel Singular Spectral Analysis (MSSA) is an efficient tool in the detection of non-purely random characteristics in series with a weak signal/noise relation.

All the signal components, detected by SSA or MSSA, must be tested for their significance to determine if they correspond to real oscillations. Monte Carlo analysis is a recognized method to estimate the confidence intervals of determined significance levels. The tests formulated by Allen and Robertson (1996) assume that data have been generated, according to the null hypothesis, by first-order autoregressive (AR(1)) independent processes (red noise).

Since a large fraction of the surface atmospheric pressure field variance in the North Atlantic can be explained by the NAO (Hurrel, 1996), and considering that the western Portugal is located near the Atlantic Ocean, it is not surprising that very significant correlations can be found between pressure and precipitation amount climatic series.

Recently, several studies tried to detect the Atlantic variability modes (spatio or temporal) at several time scales, and their relations with precipitation variability for the whole Iberian Peninsula, mostly in winter, when the great part of precipitation occurs (e.g. Zorita et al., 1992; Esteban-Parra et al., 1998; Rodriguez-Puebla et al., 1998; Ulbrich et al., 1999; Goodess & Jones, 2002; Trigo et al., 2004).

The analyses using selected components extracted from the spatio-temporal variability reinforce the importance of detection of these noise reduced signals with similar periodic characteristics. The cross correlation functions reveal that there is a potential predictability of winter precipitation in Portugal.

The spatial evolution of the principal variability modes detected by MSSA also allows the knowledge improvement of the behaviour of both variables for the same time steps.

2. Data

The analysis of mean sea level pressure fields was performed using data from the National Centers for Environmental Prediction/National Center for Atmospheric Research

(NCEP/NCAR) reanalysis project from 1949 to 2000 (Kalnay et al., 1996). Data are available in a latitude–longitude grid (2.5° × 2.5°) and refer to monthly means that are subsequently processed resulting in annual and seasonal means. The analysed area of the North Atlantic is bounded by latitudes 20 and 80°N and longitudes 90 and 0°W. Data obtained from reanalysis tend to be spatial-scale dependent causing the violation of the assumption of independence required for the statistical analysis. Thus, to avoid this dependence in adjacent series and the consequent temporal autocorrelation, the first ten principal components obtained by PCA are used instead of all channels of the field grid points. The former are orthogonal, that is, non-correlated for zero time lags.

The analysis of multivariate precipitation time series was performed using 11 stations located in mainland Portugal from 1949 to 2000. The data represent the highest quality-controlled series recorded in Portugal. These data have no missing values and have been subjected to a previous homogeneity analysis. More details about localization, station metadata and a climatologic summary can be found in Antunes (2006). Before processing, the data were normalized, that is, centred around the mean and standardized by the standard deviation.

For both variables, winter refers to the months from December to February. The other seasons are defined similarly and the annual means are calculated from January to December.

3. Methods

3.1 Multichannel singular spectral analysis

PCA is frequently used to compress variability into a reduced number of modes that explain a considerable part of the field variance. However, this method just allows the evaluation of the spatial mode and shows how the respective spatial pattern evolves in time, that is, the EOFs and the associated T-PCs.

The space-temporal variability can be accomplished through the use of multichannel singular spectral analysis (MSSA) which is an extension of SSA, used in time series analysis and described in Vautard et al. (1992).

Considering a spatio-temporal field X_{li}, l being the spatial index ($1 \leq l \leq L$), i the discrete temporal index ($1 \leq i \leq N$) and j the temporal lag, MSSA can be formulated as

$$X_{l,i+j} = \sum_{k=1}^{L \times M} a_i^k E_{lj}^k \qquad 1 \leq l \leq L, \quad 1 \leq j \leq M$$

where the coefficients a_i^k are the spatio-temporal principal components (ST-PCs) and E^k are the eigenvectors of the cross-covariance matrix called spatio-temporal empirical orthogonal functions (ST-EOFs).

The MSSA method computes the lagged cross covariances between the channels, and a multichannel trajectory matrix is created. This is done by first generating each channel (i.e. either the time series of each grid point or the time series of each T-PC) with M lagged copies of itself, M being the number of temporal lags, and then forming the full augmented trajectory matrix (Allen & Robertson, 1996).

This lagged cross covariance matrix T_X of dimension (LxM)x(LxM) is formed by blocks that contain the lagged cross covariances of pairs of channels at lags 0 to M-1:

$$T_X = \begin{pmatrix} T_{11} & T_{12} & \cdots & \cdots & T_{1L} \\ T_{21} & T_{22} & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & T_{ll'} & \cdots \\ \cdots & \cdots & \cdots & \cdots & T_{L-1L} \\ T_{L1} & \cdots & \cdots & T_{LL-1} & T_{LL} \end{pmatrix}$$

where $T_{ll'}$ of dimension (MxM) is the lag covariance of X between channels l and l'.

Singular value decomposition (SVD) was the method applied to this matrix to yield two orthogonal bases, the right and the left singular vectors (Robertson, 1996). The first of these, the eigenvectors of the matrix, are a sequence of spatial modes (ST-EOFs) and the others, the associated principal components (ST-PCs), represent the way how these patterns evolve in time. The orthogonality of the covariance matrix both in time (zero cross covariance of two different ST-PCs at lag 0) and in space (orthogonality of the ST-EOFs) implies that the diagonal of the matrix corresponds to the associated explained variances. These variances are of decreasing importance as the order k increases.

More details of MSSA can be found in Plaut and Vautard (1994).

Both SSA and PCA are particular cases of the MSSA. SSA can be derived considering just one series in analysis:

$$x_{i+j} = \sum_{k=1}^{M} a_i^k E_j^k = X_{ji} \qquad 1 \le j \le M$$

and PCA can be derived from MSSA considering the null time lag:

$$X_{li} = \sum_{k=1}^{L} a_i^k E_l^k \qquad 1 \le l \le L$$

MSSA, being a spatio-temporal variability analysis and allowing the evolution of the spatial patterns in time, improves the knowledge of modes evolving simultaneously in space and time. This analysis solves an eigenvalue matrix problem to be solved of an added embedding dimension of (number of series * window length) (Plaut & Vautard, 1994).

As in other methods of spectral analysis, the window length M is an essential issue in MSSA. Its selection involves a compromise: N being the number of terms of the time series, $N - M + 1$ needs to be large enough to allow adequate signal/noise enhancement, but small enough to guarantee the statistical robustness. In this and previous studies (Antunes et al., 2006, Antunes et al., 2010), the results of the experiments performed by Plaut and Vautard (1994) have been considered: the method does not distinguish between different oscillations of period longer than M, and a window length M typically allows the distinction of oscillations of periods in the range (M/5, M).

3.2 Statistical significance testing

Contrary to classical or maximum entropy spectral analysis, where the basis functions are prescribed sines and cosines, SSA produces data-adaptive filters that are able to isolate oscillations spells, which makes the method more flexible and better suited for the analysis of non-linear, anharmonic oscillations (Vautard et al., 1992). Similar to SSA, if the variance of the series is dominated by an oscillation, MSSA generates a pair of EOFs nearly periodic, with a similar period, and in quadrature (Plaut & Vautard, 1994).

However, these pairs can also be randomly generated realizations of processes which do not have an oscillatory nature and consequently, once detected, must be tested to determine if they correspond to real oscillations.

The null-hypothesis, as formulated by Allen and Robertson (1996), is that data have been generated by L first-order autoregressive (AR(1)) independent processes (red noise), with L being the number of channels.

The null-hypothesis can be rejected if the spectrum of the eigenvalues associated with the modes detected by MSSA is higher than that expected in data generated by red noise processes. The confidence intervals for a given significance level are estimated using Monte Carlo simulations. A large ensemble of normally distributed (gaussian) surrogate noise time series is generated with the null hypothesis characteristics, in the case autoregressive first order processes, with the same length, variance and temporal lag-one autocorrelation as the series that form the centred input channels.

Allen and Robertson (1996) suggest two different significance tests based on the same null-hypothesis: the first using the ST-PCs and ST-EOFs of the data, and the second using the ST-PCs and ST-EOFs of the null hypothesis. In the first test the lag covariance matrix is computed from the data whereas, in the second, the lag covariance matrix is computed from data generated by Monte Carlo methods. The subsequent procedure of projecting data and noise surrogates onto the vector basis is similar in both the tests. The second test is more robust as the former implicitly assumes the existence of a signal before any signal has been identified (Allen and Smith, 1996). Besides that, the second test does not present the artificial variance compression problem that boosts the significance of the first ST-PCs in the detriment of higher order modes.

Tests are based on the WMO Technical Note N° 79 (Mitchell, 1966): a spectral peak is considered significant at the 0.05 level if it goes above the upper limit of the 90% confidence interval with limits 5 and 95% (unilateral or one-tailed test).

4. Pressure variability in the North Atlantic

A Principal Component Analysis (PCA) applied to the mean sea level pressure field of the North Atlantic reveals the North Atlantic Oscillation (NAO) pattern as the principal mode of annual and seasonal variabilities. Before the application of PCA the time series were normalized, that is, centred and standardised to avoid overweighting the locations with larger variance; linear trends for each point of the field were also removed.

This oscillation mode, presented in Figure 1 for all seasons, means that pressure above the mean at mid-latitudes tends to occur simultaneously with pressure below the mean at higher latitudes (positive NAO phase) and vice-versa, pressure below the mean at mid-latitudes tends to occur with pressure above the mean at higher latitudes (negative NAO phase).

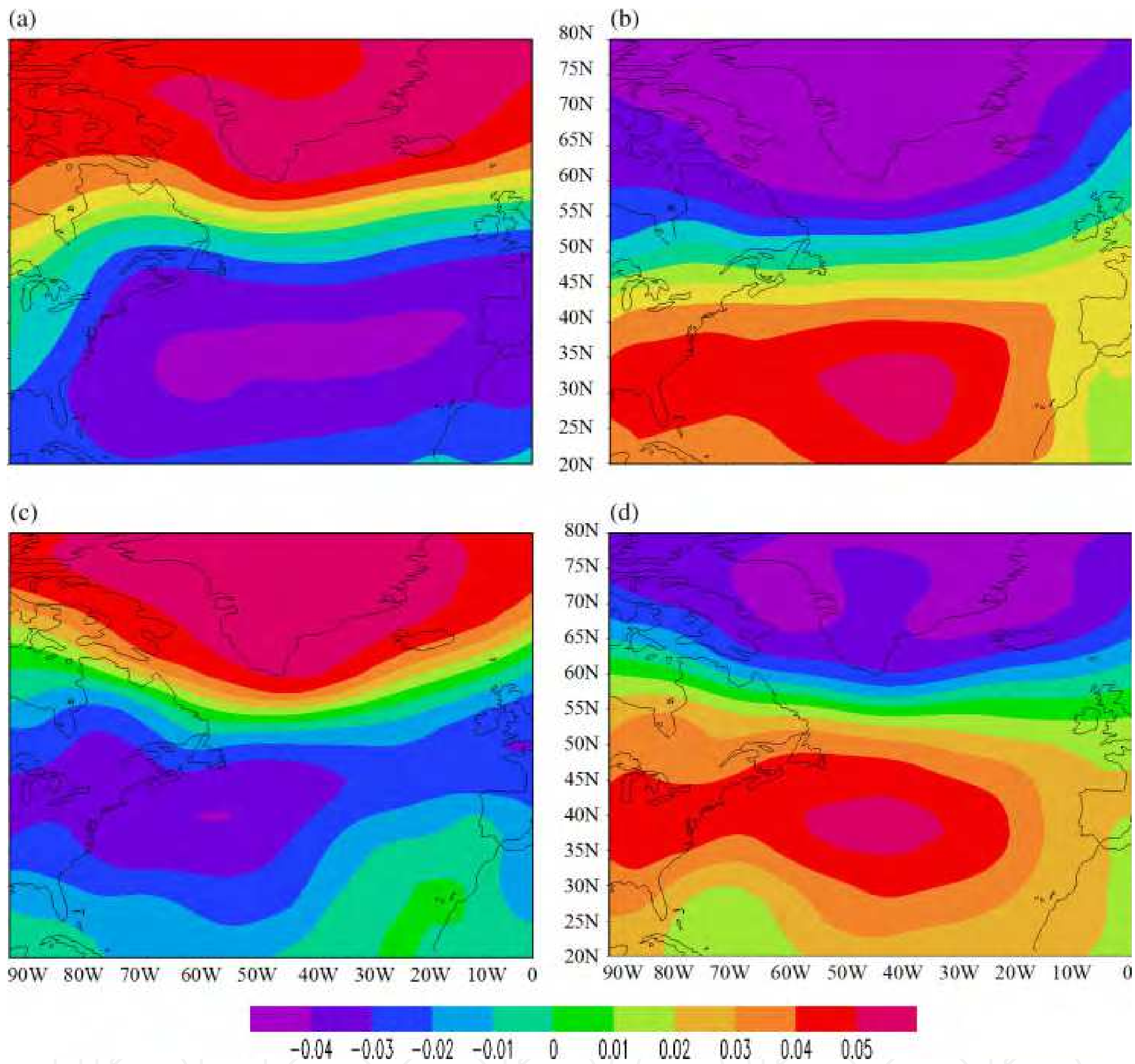

Fig. 1. Representation of the first EOFs of North Atlantic pressure variability in (a) winter, (b) spring, (c) summer and (d) autumn. The units are arbitrary.

The NAO is the principal mode of variability in all seasons but the patterns, namely the locations of the centres of action, differ from season to season. The variance explained by each first seasonal mode also changes depending on the season: it is in winter and in spring that these principal modes explain the most variance of the field variability (43 and 41%, respectively); in summer and autumn these modes just explain 32 and 30%, respectively, of the total pressure variance.

The analysis of the time variability of the temporal principal components (T-PCs) associated with each principal seasonal empirical orthogonal functions (EOFs) was performed using Singular Spectral Analysis (SSA). The same analysis was applied to the T-PC associated with the first annual pressure pattern. The method provides the decomposition of each of these series in reconstructed components, allowing to isolate the part of the signal involved with an oscillation. Table 1 presents the periodicities, estimated by maximum entropy methods, of the first two paired components of each T-PC. Results reveal different periodicities in the first annual and seasonal modes, which are not statistically significant when tested against the red noise null hypothesis at the 0.05 significance level.

Comparison between the periodicities shows that winter is the season with most influence on the annual first mode of the pressure field variability. This season reveals a periodic behaviour of about 9 years.

	Year	Winter	Spring	Summer	Autumn
Periodicity (years)	13.5/15.0	8.8/9.1	4.3/4.4	5.6/6.9	2.1/2.2

Table 1. Periodicities of the first two paired components extracted by SSA from the first annual and seasonal North Atlantic pressure variability modes.

The winter spatio-temporal analysis of the North Atlantic pressure variability performed by the use of multichannel singular spectral analysis (MSSA) reveals that the first two spatio-temporal principal components (ST-PCs) are nearly periodic and in quadrature (Figure 2), satisfying the conditions to represent an oscillation, according to the Plaut and Vautard (1994) criteria.

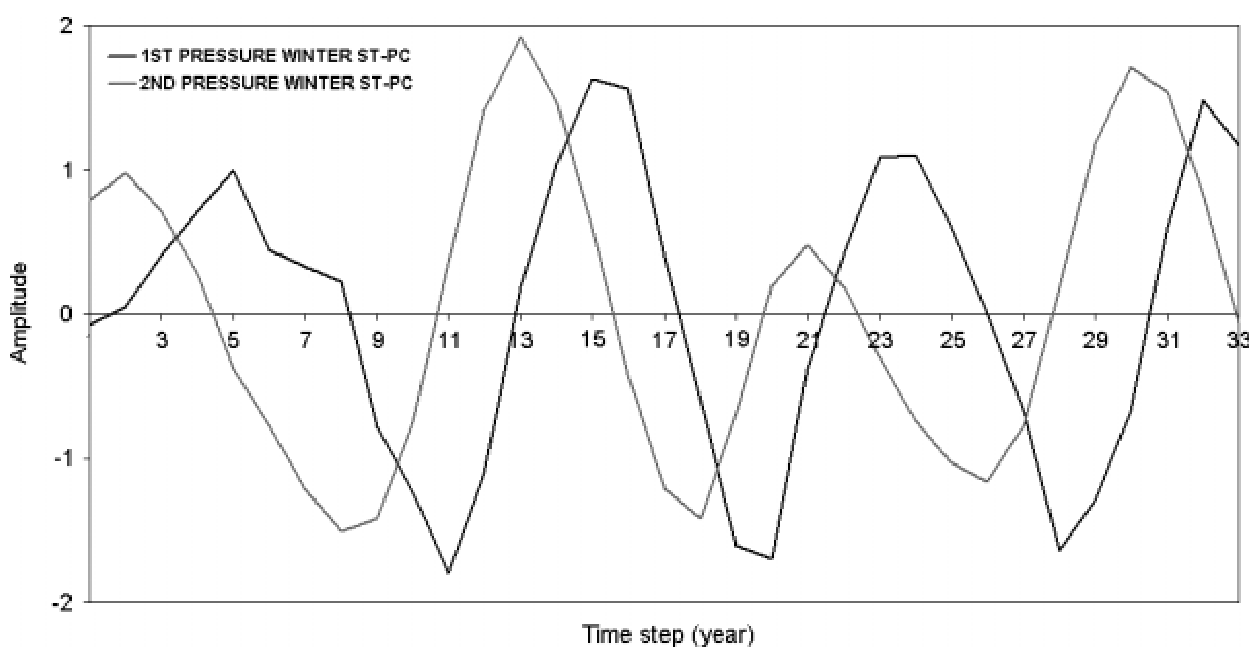

Fig. 2. Temporal evolution of the first two ST-PCs of winter North Atlantic pressure.

They also satisfy a third more restricted condition proposed by the same authors which establishes the existence of the oscillatory pair: in order to guarantee that, at least, one cycle of the oscillation is coherent, it is required to have a periodic behaviour in the ST-PCs cross correlation function with correlation absolute values higher than 0.5 for the two successive extremes on each side of the lag zero (Figure 3). According to Bartlett, the cross correlation confidence intervals corresponding to the 0.05 significance level, estimated from the normal distribution with a standard deviation of ±1*sqrt($N - |\tau|$), where τ represents the temporal lag, is also presented in this figure (von Storch & Zwiers, 1999).

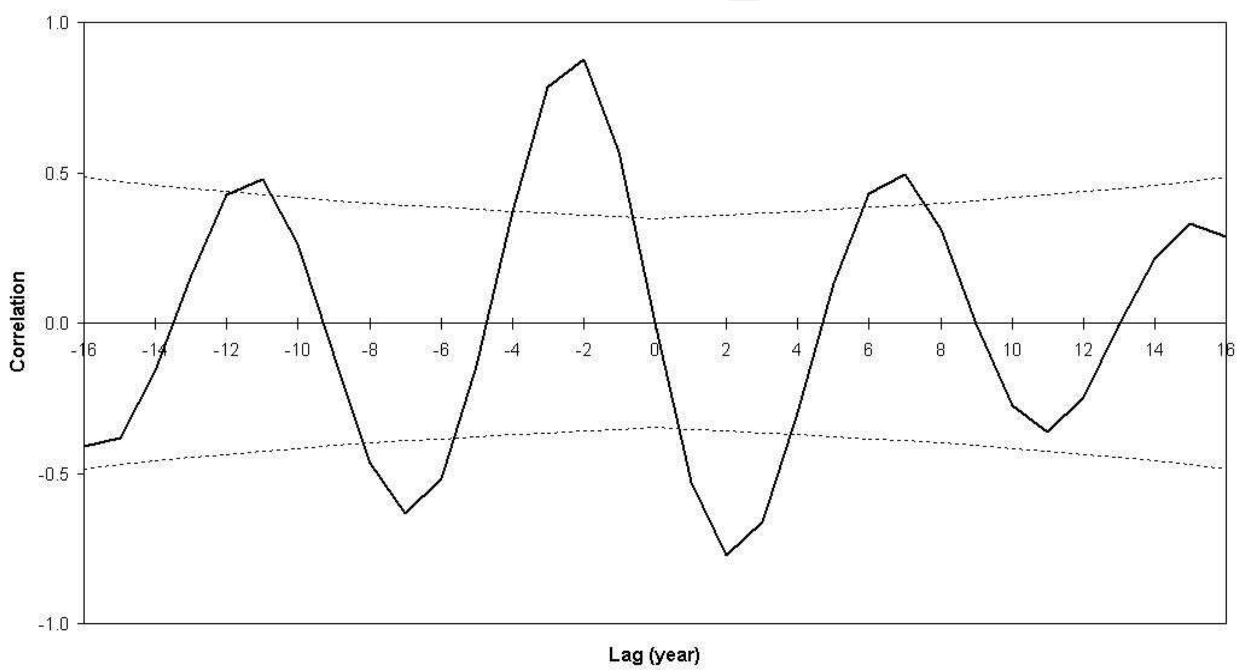

Fig. 3. Lagged cross correlation function between the first and second ST-PCs of winter North Atlantic pressure and confidence intervals of the 0.05 significance level.

Following the methodology presented in Section 3.2, the statistical significance of the oscillations is tested against the null-hypothesis of red noise, at the 0.05 significance level, using Monte Carlo methods. The results, using a base derived from data and also a base derived from the null-hypothesis, are presented in Figure 4(a) and (b), respectively. In the first case, three pairs of significant eigenvalues are detected: the longest significant components show a periodicity of about 9 years, followed by 4.5 and 2.7 years periodicity modes. However, in a more conservative significance test that uses a base derived from AR(1) processes, the analysis just shows the 2.7 years periodicity as significant. Other authors analysing the Northern Hemisphere sea level pressure have already detected this 2/3 years shorter periodicity, but the mechanism behind this peak remains uncertain (Stephenson et al., 2000). Besides that, in the second significance test, which is more stringent than the first because the null-hypothesis is more difficult to reject, the eigenvalue associated with a 9 years periodicity has a spectral density almost reaching the 0.05 significance upper level.

The 9 years spatio-temporal mode is the mode which explains the largest fraction of the pressure winter field variance (15%). Power with this periodicity has already been detected (although not statistically significant) in the T-PCs derived from a simple PCA of the same field.

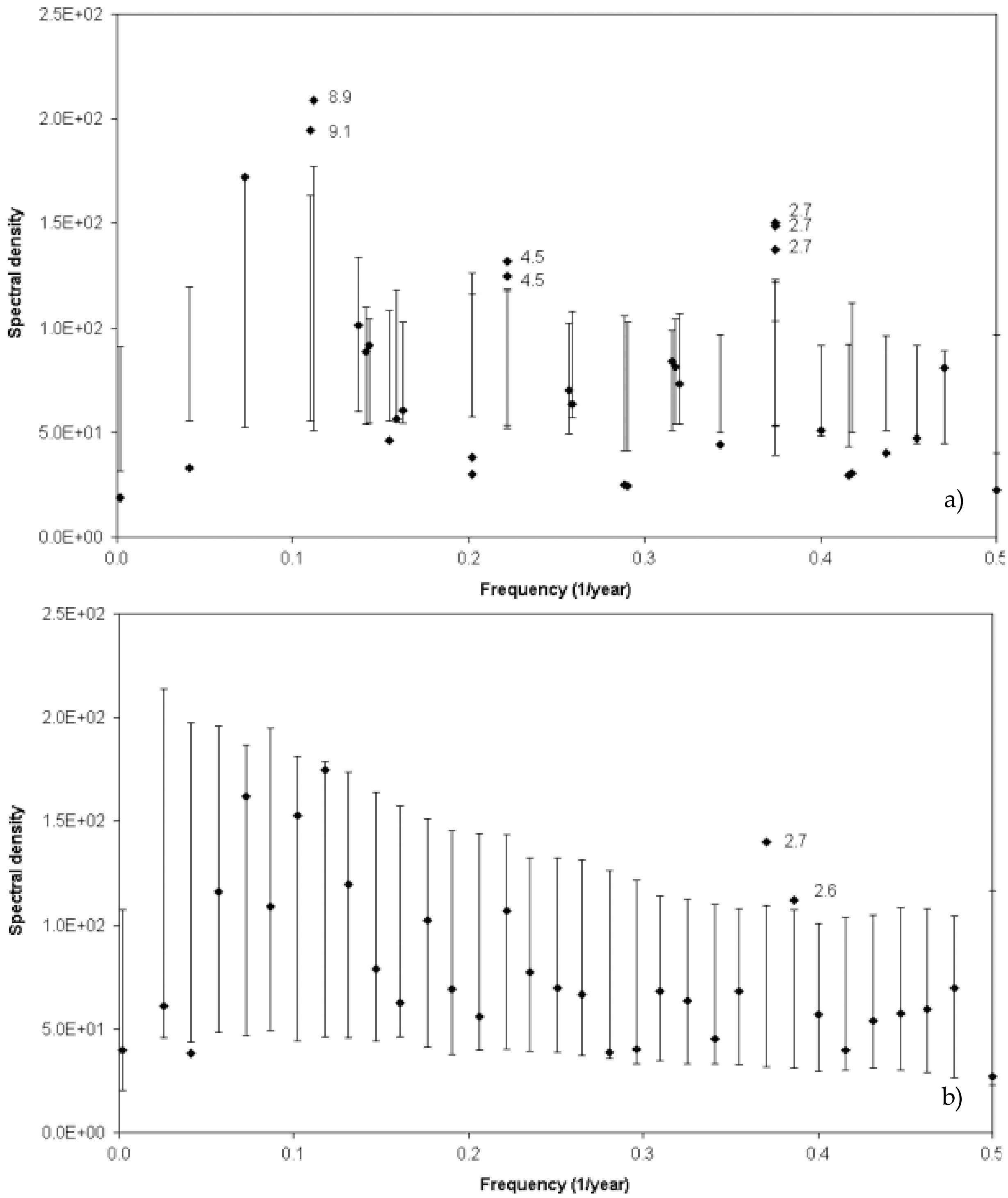

Fig. 4. Monte Carlo significance tests for winter pressure oscillations using a window length M = 25. The vertical bars indicate the 0.05 significance level (one-tailed test) for the red noise null-hypothesis. Periodicities of significant eigenvalues for this hypothesis are also shown. (a) Diamonds show the data eigenvalues projected onto the data-adaptive basis. (b) Diamonds show the data eigenvalues projected onto the null-hypothesis basis.

This winter mode of spatio-temporal variability of about 9 years periodicity in North Atlantic is presented in Figure 5, where the time origin is arbitrary.

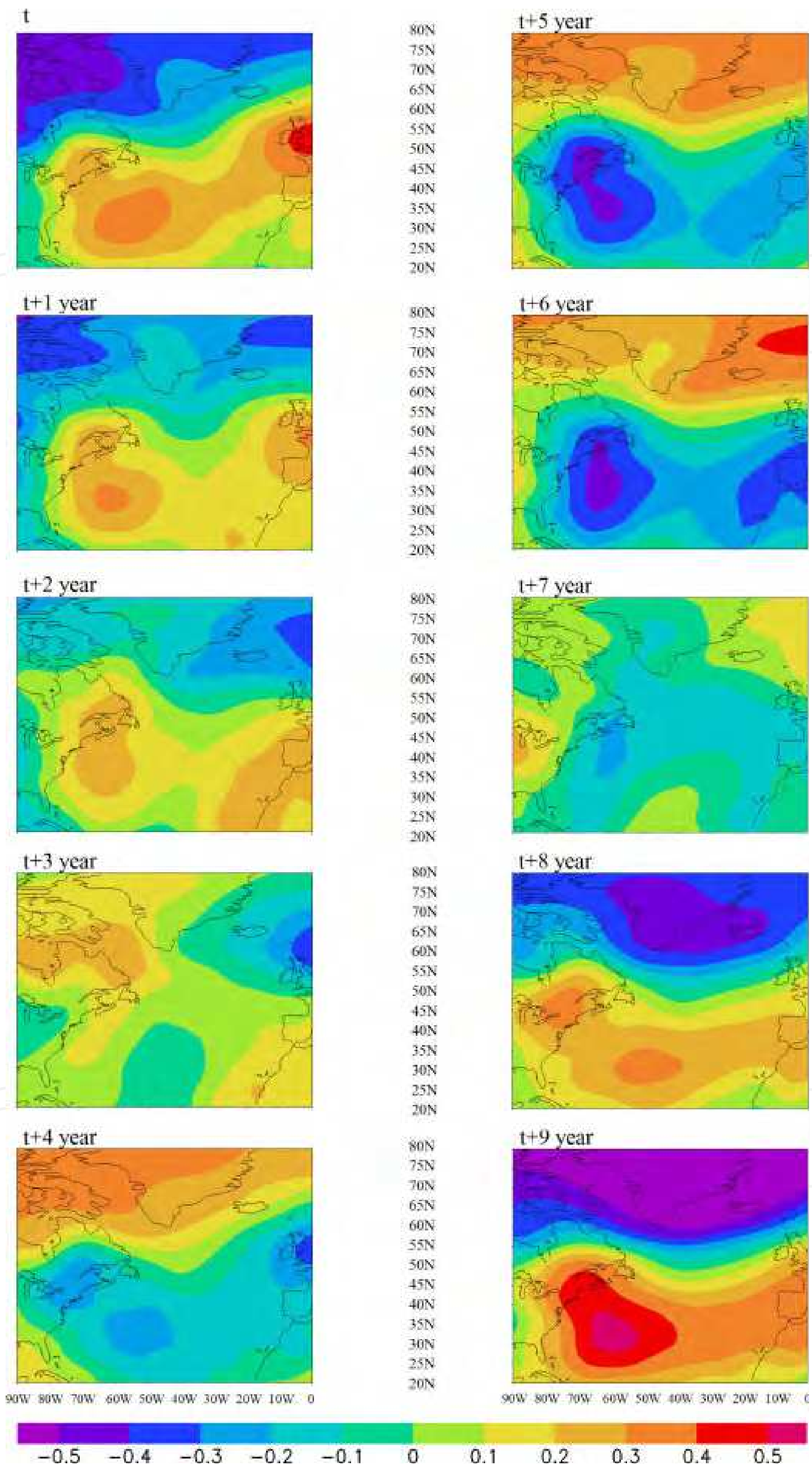

Fig. 5. Spatio-temporal evolution of the first mode of North Atlantic winter pressure variability for 1 year lags. The units are arbitrary.

The mode of oscillation has a quasi-meridional pattern during the high and low NAO index phases, with positive anomalies in the central North Atlantic and negative anomalies at high latitudes. The transition from the positive to the negative phase shows the weakening of pressure at lower latitudes and the strengthening at higher latitudes till half of the period. After that, the opposite evolution occurs, with pressure strengthening at lower latitudes and weakening at higher latitudes. During the cycle, for some lags (e.g. temporal lags of 3 and 7 years) corresponding to transition phases, the patterns are quite different from what is known to be the NAO pattern. In the first case, the principal dipole reveals a W/E orientation at higher latitudes; in the second transition year, there is a diffuse pattern with no clear defined centres of action.

5. Precipitation variability in Portugal

The longest records of annual and seasonal precipitation time series of Portuguese stations, analysed by maximum entropy methods (MEM) do not reveal any characteristics significantly different from white-noise processes (Antunes & Oliveira Pires, 1998). Figure 6 presents, as an example, the variance spectrum for the Lisbon annual precipitation time series (1871/1993) estimated by MEM. In same figure are also presented the 0.1 confidence intervals for the white noise null hypothesis.

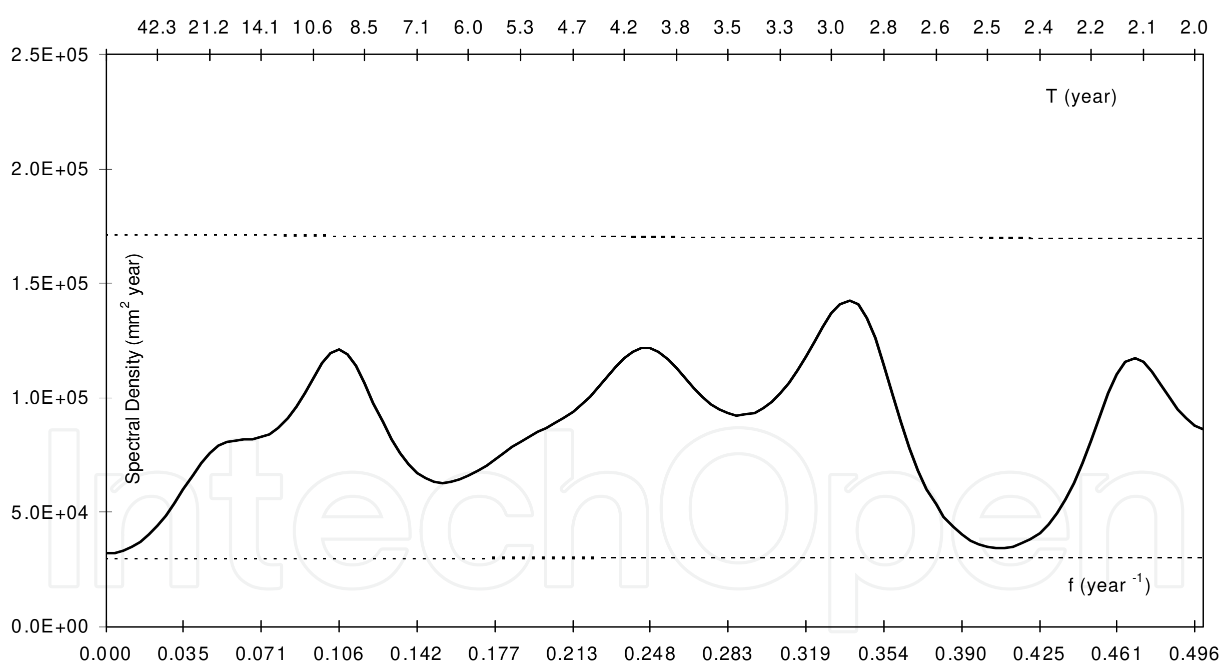

Fig. 6. Lisbon annual precipitation variance spectrum and the 90% confidence intervals for the null hypothesis of white noise.

The singular spectral analysis (SSA) applied to the same series is also unable to detect significant characteristics in precipitation variability (Antunes et al., 2000). Figure 7 presents the singular values estimated by this method, the associated error bars and the 90% confidence intervals estimated using the Monte Carlo methods for the white noise null hypothesis.

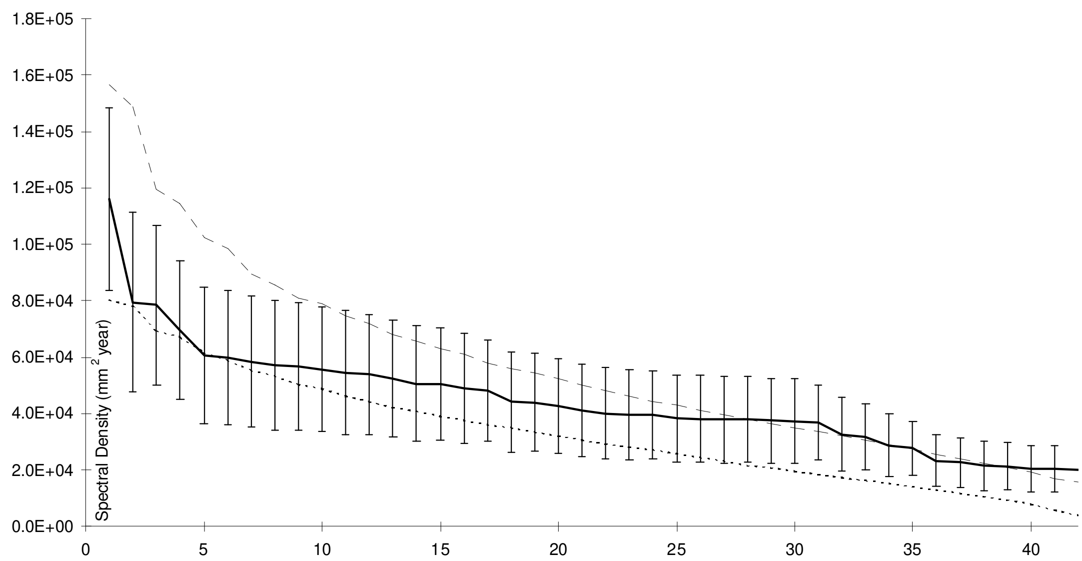

Fig. 7. Eigenvalue spectrum of annual precipitation amount in Lisbon, error bars and the 0.1 significance level for the white noise null hypothesis.

The spatial variability analysis of annual and seasonal precipitation in Portugal using 11 meteorological stations of more than 50 years, performed by PCA, reveal that the first variability mode, that shows precipitation varying in same way in all country, explains a large fraction of the variance (75% in annual precipitation and 85% in winter which is the rainier season). Figure 8 presents the first three Empirical Orthogonal Functions (EOFs) for winter. The second EOF, explaining 6% of variance shows an opposite behaviour between north and southern regions and the third EOF accounting for 3% of total variability shows the opposite relation between littoral and inland, more obvious in northern areas. The second EOF shows that precipitation above the mean in northern areas of the country tends to occur with precipitation below the mean in southern areas and vice-versa; the third EOF reveals the opposite, coastland precipitation above the mean tending to occur with inland precipitation below the mean and vice-versa.

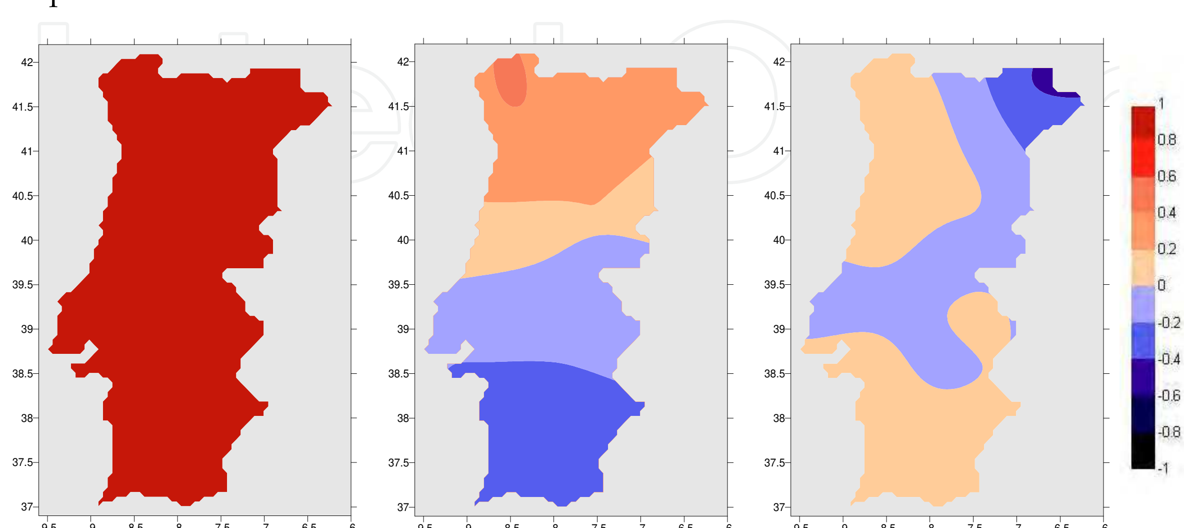

Fig. 8. Principal empirical orthogonal functions of winter precipitation in Portugal.

The analysis of the temporal principal components (T-PCs) associated to each winter spatial mode of precipitation variability does not reveal significant signals in relation to the red noise null hypothesis or even considering the white noise null hypothesis.

Despite not being statistically significant is interesting the results of the singular spectral analysis (SSA) applied to the first T-PC associated to the first winter EOF mode. The method detects in this T-PC two oscillatory pairs that explain 39% of the total variance of the component. The spectral analysis of the reconstructed components (RCs) that form these pairs reveal obvious spectral characteristics around the same frequencies. The principal peaks occur in the 8 years band and the second pair presents shorter periodicity characteristics of about 2.8 years (Figure 9).

Similar oscillatory components of about 9 and 2.7 years periods were detected in the annual precipitation variability (Antunes, 2007). The application of Monte Carlo methods reveals that these signals are not significant, just like in the winter variability. In the other seasons the precipitation variability is characterized by shorter periodic fluctuations, being the signals with longer period comprised between 3.4 and 4.6 years. These results show that the principal mode of annual variability is dominated by the principal precipitation variability mode in winter.

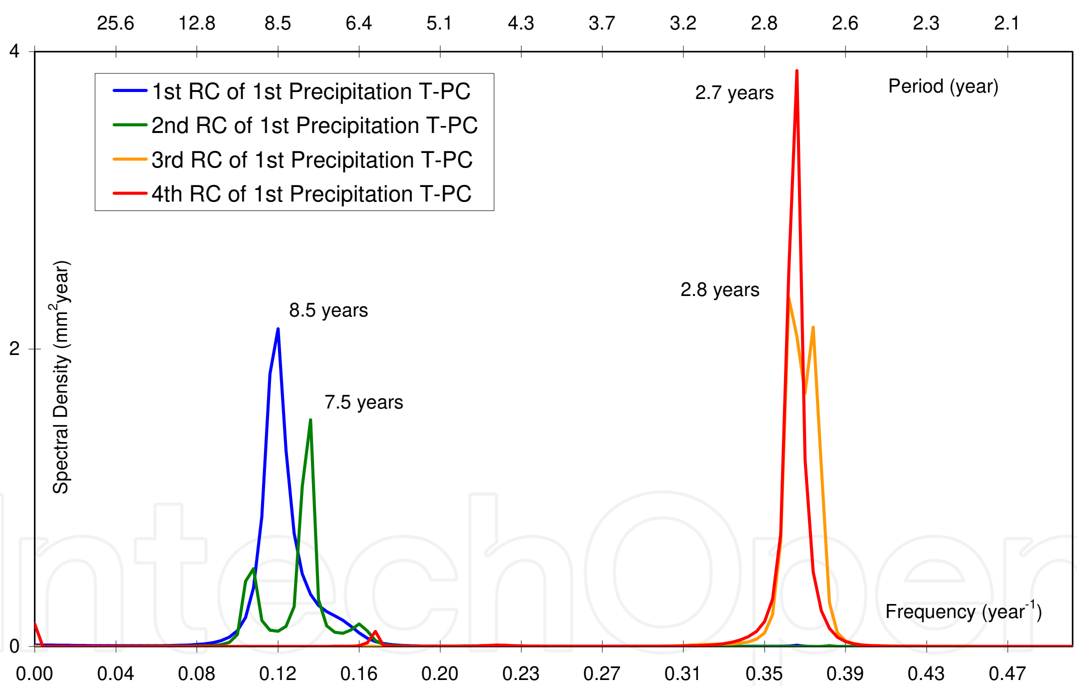

Fig. 9. Variance spectra of the reconstructed components (RCs) extracted by SSA from the first temporal principal component (T-PC) of winter precipitation in Portugal. Main periodicities of each RC are included.

The analysis of winter precipitation temporal variability performed by the use of patterns that evolve spatially allows the detection of periodic signals similar to those already obtained by the methods previously presented. Moreover the consistency of the results, the method identifies these signals as significant, suggesting a more realistic analysis process by allowing the change of the EOFs configuration with time.

The application of the Multichannel singular spectral analysis (MSSA) to the winter precipitation variability reveals the existence of spatio-temporal principal components (ST--PCs) that, due to their similar periodicity, can form oscillatory pairs. Figure 10 shows a pair of these ST-PCs that is nearly periodic and in quadrature, satisfying the conditions to represent an oscillation according to the Plaut and Vautard (1994) criteria.

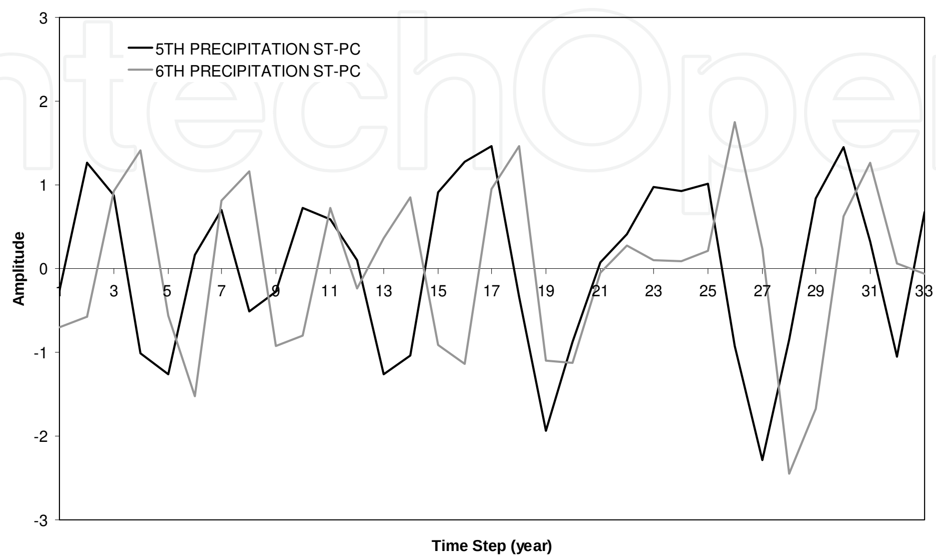

Fig. 10. Temporal evolution of the 5 and 6th winter precipitation ST-PCs in Portugal.

These components also satisfy a third more stringent condition proposed by the same authors which establishes the existence of the oscillatory pair: in order to guarantee that at least one cycle of the oscillation is coherent, a periodic behaviour in the ST-PCs cross correlation function is required, with the absolute values of correlation higher than 0.5 for the two successive extremes on each side of lag zero (Figure 11).

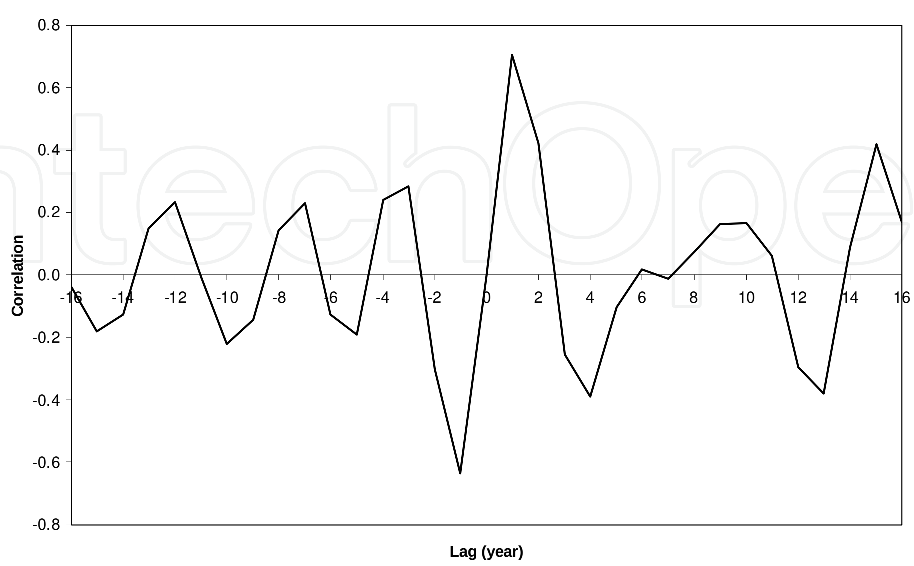

Fig. 11. Lagged cross correlation function between the 5 and 6th winter precipitation ST--PCs in Portugal.

In Figures 12 and 13 are presented the corresponding results of another pair of components with shorter periodicity that satisfies the same criteria.

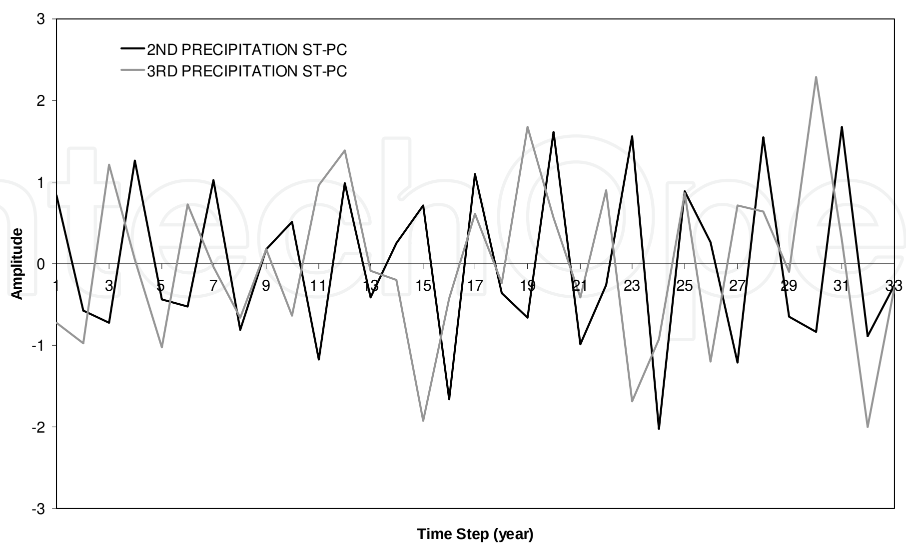

Fig. 12. Temporal evolution of the 2nd and 3rd winter precipitation ST-PCs in Portugal.

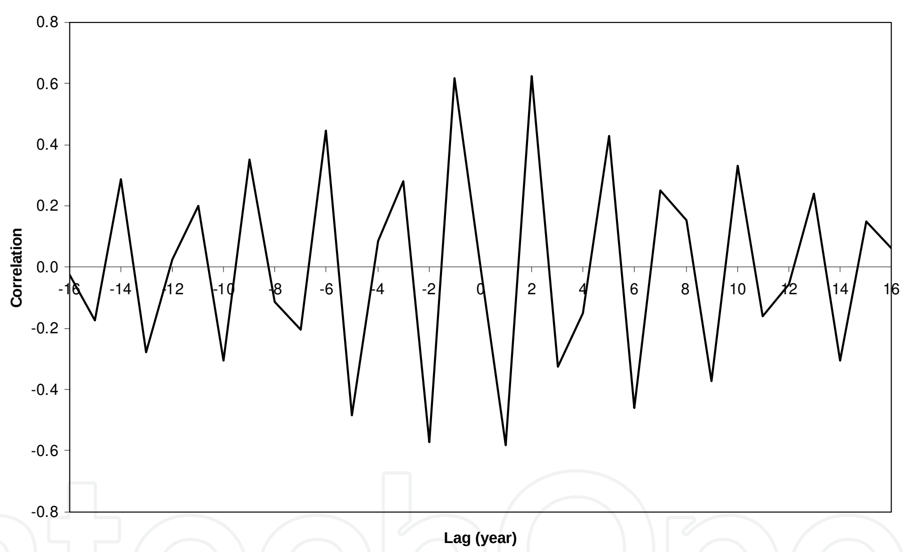

Fig. 13. Lagged cross correlation function between the 2nd and 3rd winter precipitation ST--PCs in Portugal.

Following the methodology presented in Section 3.2, the statistical significance of these oscillations was tested by Monte Carlo methods in relation to the null-hypothesis of red noise at the 0.05 significance level (one tailed test). Results using a base derived from data and a base derived from the null-hypothesis are presented in Figure 14(a) and 14(b), respectively. In the first case, two pairs of significant eigenvalues are detected. The oscillation that presents the higher spectral density reveals a period of about 2.7 years. The second oscillatory mode, consisting of ST-PCs 5 and 6, reveal a period of about 7 years. The eigenvalue associated to a period of about 9 years (ST-PC 4) could not be paired with the previous ones of about 7 years periodicity. The second test confirms the occurrence of a significant signal with a period of about 2.7 years; a signal of 8.4 years periodicity is however near the superior limit of the significance level.

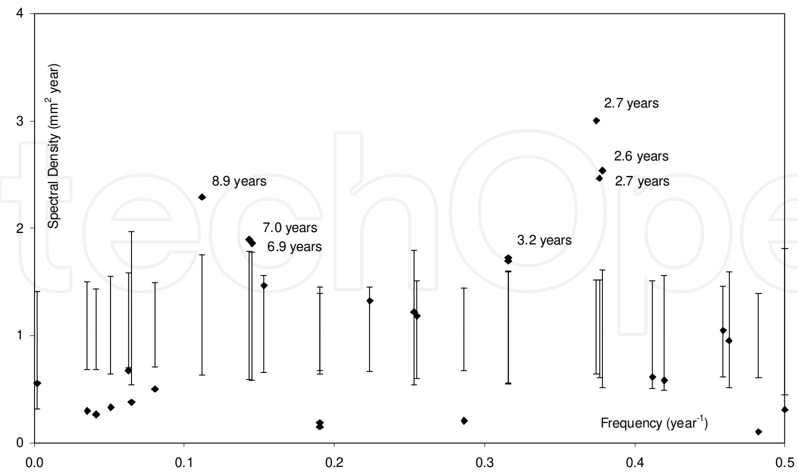

Fig. 14. (a)- Monte Carlo significance tests for winter precipitation oscillations. Diamonds show the data eigenvalues projected onto the data-adaptive basis. The vertical bars indicate the 0.05 significance level (one-tailed test) for the red-noise null-hypothesis. Periodicities of significant eigenvalues for this hypothesis are also shown.

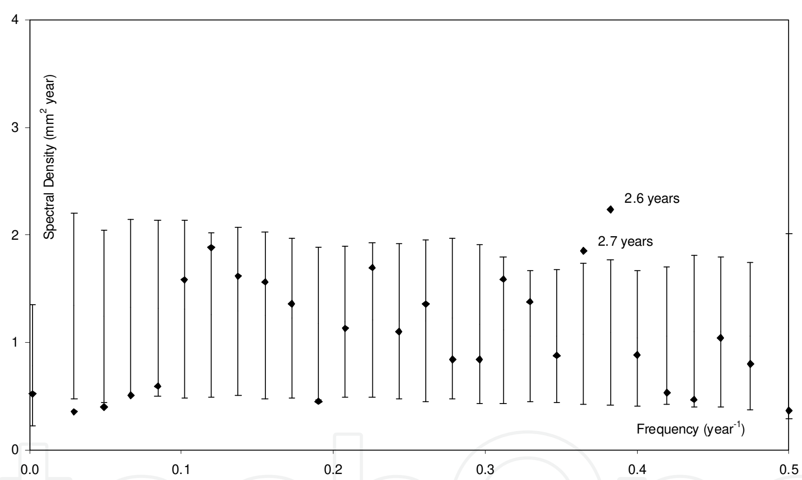

Fig. 14. (b)- Monte Carlo significance tests for winter precipitation oscillations. Diamonds show the data eigenvalues projected onto the null-hypothesis basis. The vertical bars indicate the 0.05 significance level (one-tailed test) for the red-noise null-hypothesis. Periodicities of significant eigenvalues for this hypothesis are also shown.

Although the second, more conservative significance test, just reveals the oscillation with shorter period as significant, the detected periodicity of about 7/9 years must be taken into account. In fact, the same analysis applied to the annual precipitation in Portugal also detects a periodic signal about the 9 years in its variability (Antunes et al, 2006.). In this case it corresponds to the first variability mode, which presents the higher spectral density, explaining 21% of the total annual spatio-temporal variance.

Figure 15 shows the space-time evolution of the winter ST-EOF associated to the ST-PC presenting the 9 years periodicity, for one-year steps during 16 years.

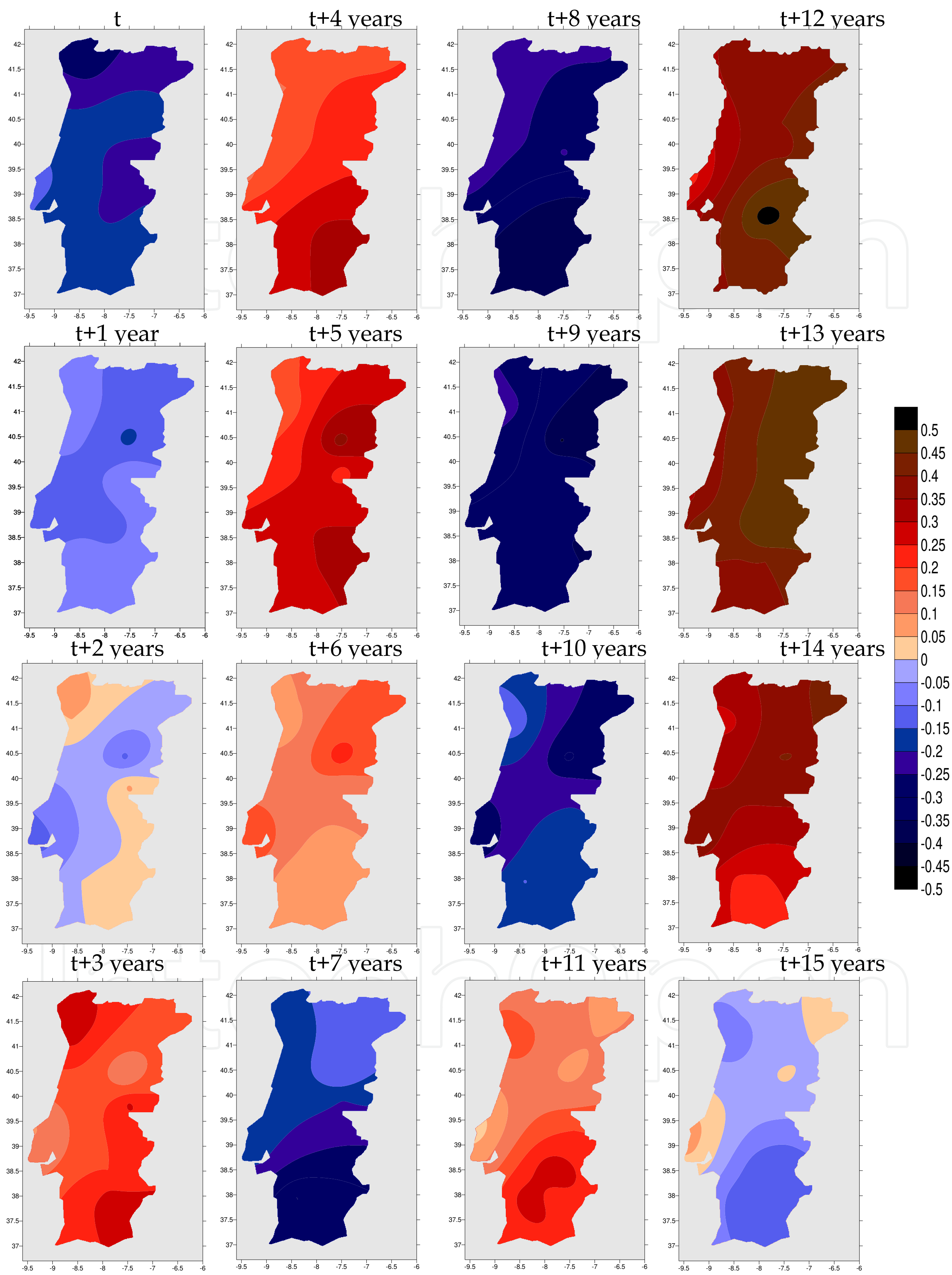

Fig. 15. Space-time evolution of the precipitation winter ST-PC with 9 years periodicity for one year-lags during 16 years. The units are arbitrary.

The most frequent pattern is, as in the PCA, the occurrence of precipitation anomalies of the same sign in the whole region. The spatial evolution of this mode is towards the occurrence of precipitation above the mean during a period of about 4 years following a period of the same duration with precipitation below the mean plus, when existing, a transition period of 1 year to complete the 9 years cycle. A complete period in the figure is identified, for example, by years (t + 7) to (t + 10) with precipitation below the mean, following precipitation above the mean from year (t + 11) to (t + 14) and a transition year represented by the (t + 15) time step. In transition years, the patterns present a same sign zone oriented NW/SE or SW/NE and the opposite sign in the rest of the region.

6. Relations between pressure and precipitation winter variability in Portugal

The possibility of reconstructing the original field for a period equal to the series under consideration based on their spatio-temporal characteristics has advantages over the use of the ST-PCs that are shorter series, with length equal to the time series subtracted by the width of the window. In order to analyse the relations between the pressure in the Atlantic and the precipitation in Portugal, the reconstruction of these fields was performed using a successively larger number of space-time components that successively explain more variance of the fields. These components are reconstructed in the case of pressure to a grid point (40° N, 7.5° W) in Portugal near Lisbon and in the case of precipitation to the point located in Lisbon. The reconstruction performed using 20 components explains 85.5% of the total variance of the winter pressure field in the North Atlantic and the reconstruction of precipitation with the same number of components explains 93.8% of the winter variability.

The use of a great number of reconstructed components (RCs) allows the higher zero lag correlations. However, whatever the number of components in the analysis, these correlations are always significant, ranging between -0.6 and -0.8. As can be seen in Fig 16 there are also significant cross-correlations, with the same sign, for lags of 8 years, which means that there is a periodic correlation of almost sinusoidal type about 8 years between the principal variability modes of pressure and precipitation. Related to the same modes other significant correlations of opposite sign are detected to lags of ±4 and ±12 years. Other significant correlations that occur for other lags result from the sum of components with different frequencies.

The analysis of the same figure reveals that for lags different than the null, it verifies higher correlations (in module) when is used a smaller number of components. However, the smaller the number of components considered, the lower the variance explained of the field.

As a result from the lagged cross correlation functions analysis it can be concluded that the winter pressure field can be used as a good predictor of the precipitation field in the same season in Portugal, since the field itself is capable to be forecasted.

It is also interesting the joint analysis of the pressure and precipitation oscillatory spatio-temporal modes that present the higher spectral density and associated to the 9 years periodicity (fig. 4.a) and 2.7 years (fig. 14.a), respectively. The cross correlation function between these modes reveals significant and positive values for the null lag (Fig.17). The positive signal is important in interpreting the relations between the evolution modes presented in Figure 18, for simultaneous years.

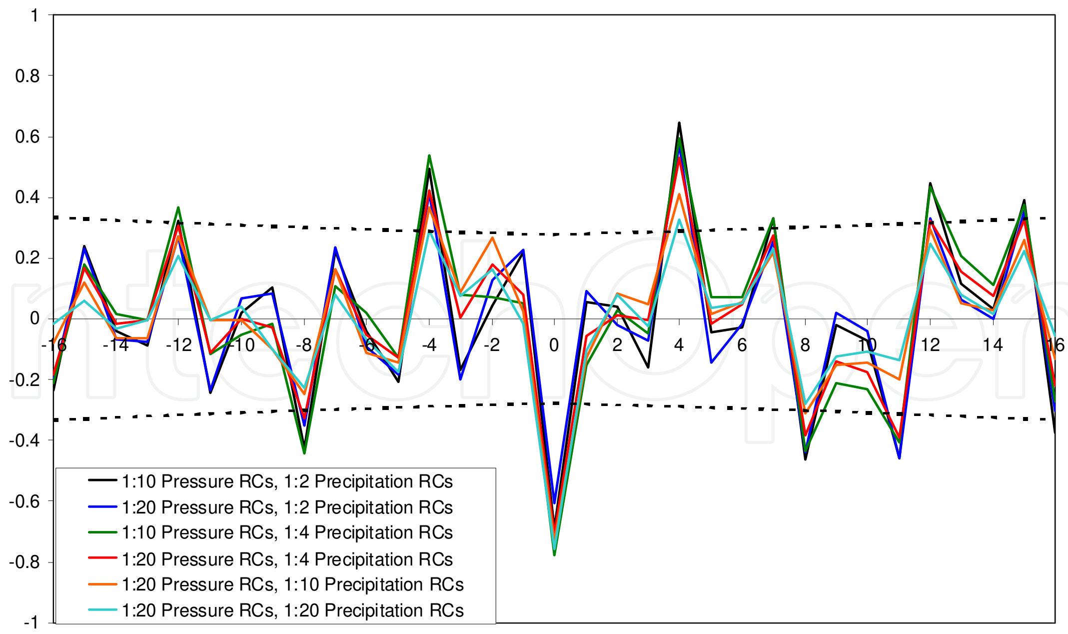

Fig. 16. Lagged cross correlation functions between reconstructed component groups of North Atlantic winter pressure and of Portugal winter precipitation. Confidence intervals of the 0.05 significance level are also presented. Positive lag values correspond to delays of the precipitation reconstructed component groups.

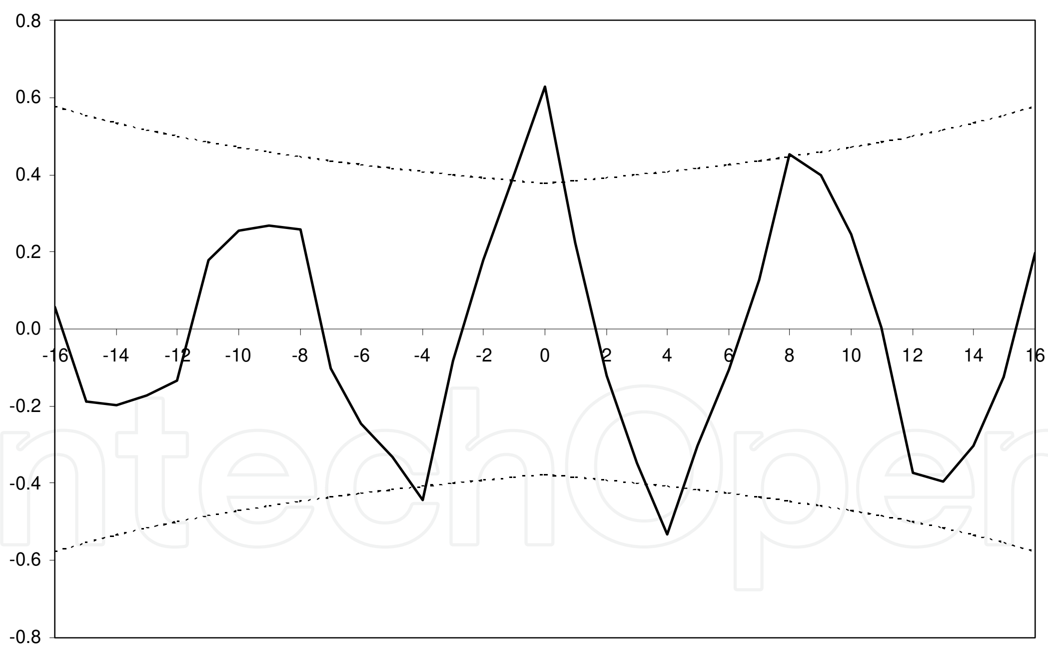

Fig. 17. Lagged cross correlation function between the first winter pressure and precipitation ST-PCs and confidence intervals of the 0.05 significance level.

In the major part of the considered time steps it appears, for the same year, the occurrence of the NAO in positive phase and precipitation below the mean value in Portugal and vice-versa, that is, the occurrence of the NAO negative phase and precipitation above the mean. These relations can be observed in the same figure taking into account the significant correlation obtained for 4 years lags and considering the negative value of this correlation.

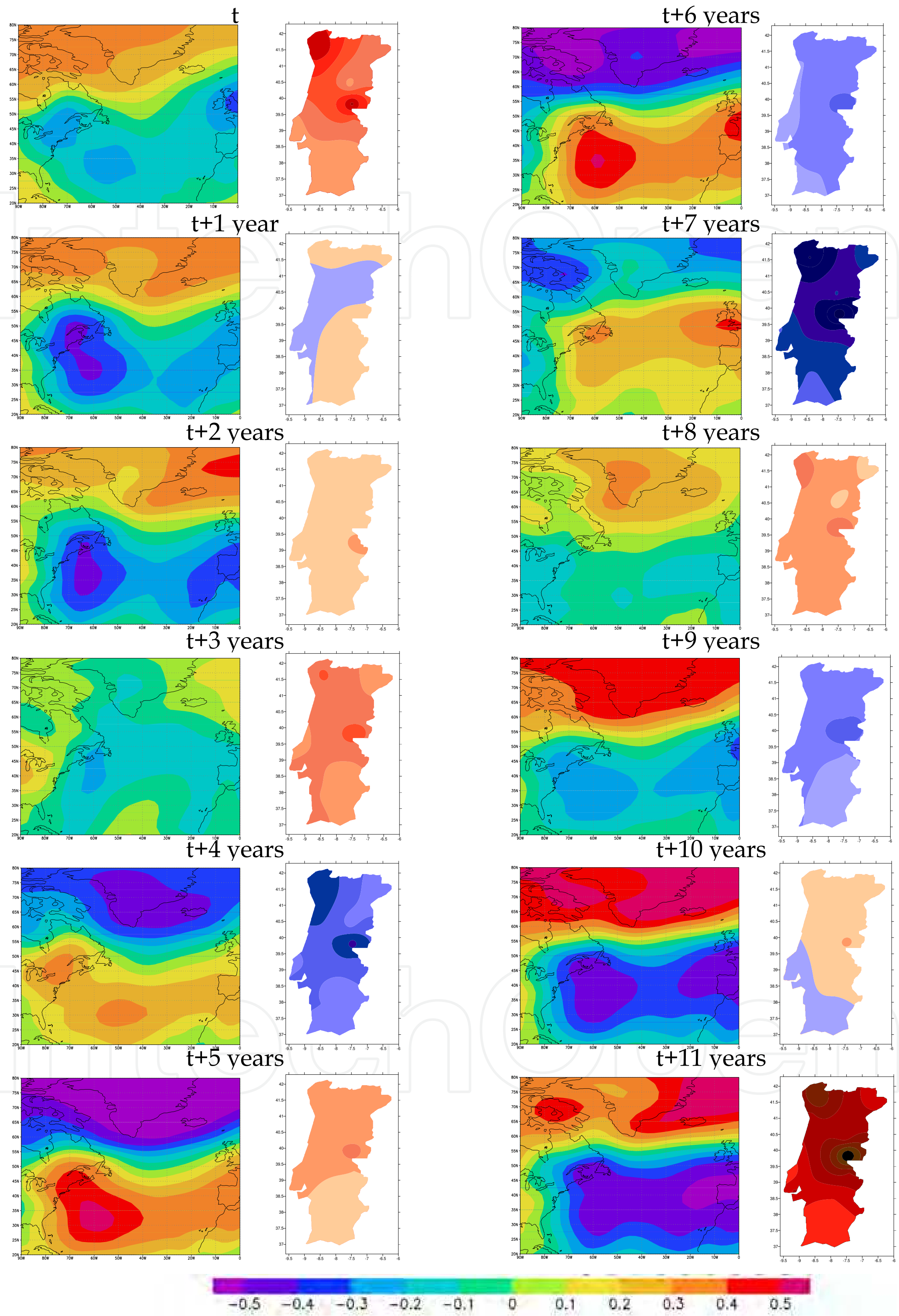

Fig. 18. Space-time evolution of the first pressure variability mode in North Atlantic and of the first precipitation variability mode in Portugal, in winter during 12 years.

7. Conclusions

The North Atlantic mean sea level pressure and the Portuguese precipitation winter variability fields were analysed using several methods including the spatio analysis (PCA), the temporal analysis (SSA) and the spatio-temporal analysis (MSSA).

The application of the multichannel singular spectral analysis in the space–time study allowed the detection of significant modes of variability with periodicity behaviour, both in pressure and in precipitation. These periodic behaviours were previously detected in the temporal principal components extracted from the principal component analysis but, in the time domain, were found as not statistically significant.

In the North Atlantic pressure field variability the detected signals revealed a periodicity of about 9 years. The representation of this mode shows that the oscillation is not quasi-meridional but has different orientations, rotating in a cycle, from the positive North Atlantic oscillation (NAO) phase through the negative NAO phase and again to the positive phase. This principal variability mode only behaves like the traditional NAO pattern in extreme high and low NAO index phases.

The precipitation variability in Portugal reveals periodicity signals of the same order of those detected in the pressure analysis. The representation of the space–time evolution of one of modes reveal that the most frequent pattern is the occurrence of precipitation anomalies of the same sign in the whole region, that is, precipitation above or below the mean. The spatial evolution is towards the occurrence of precipitation above the mean during a period of about 4 years following a period of the same duration with precipitation below the mean plus, when existing, a transition period of 1 year to complete the 9 years cycle. In transition years, the patterns present a same sign zone oriented NW/SE or SW/NE and the opposite sign in the rest of the region.

It were also detected similar signals of shorter periodicity, about 2.7 years periodicity, on variability of both fields. However, these are precisely the signals that remain as statistically significant when a more conservative significance test is applied.

The relations between the North Atlantic mean sea level pressure and the Portuguese precipitation winter variability fields were analysed using groups of reconstructed components estimated by the multichannel singular spectral analysis. The results reveal significant correlations for null lags, even when just a few components are used, meaning that the pressure field can be a good predictor of the precipitation field, since the field itself is predictable and may be forecasted.

The space-time simultaneous evolution of the pressure and precipitation modes with higher spectral density reinforce the importance of this relationship revealing for the same time step the occurrence of the NAO positive phase and precipitation below average in Portugal and vice-versa, the occurrence of the NAO negative phase and precipitation above the mean.

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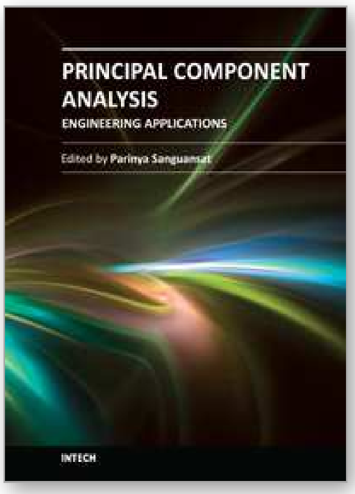

Principal Component Analysis - Engineering Applications
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This book is aimed at raising awareness of researchers, scientists and engineers on the benefits of Principal Component Analysis (PCA) in data analysis. In this book, the reader will find the applications of PCA in fields such as energy, multi-sensor data fusion, materials science, gas chromatographic analysis, ecology, video and image processing, agriculture, color coating, climate and automatic target recognition.