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Evaluation of long-term trends in spring onset in the Northern Europe using Singular Spectral Analysis

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1. INTRODUCTION

During recent decades several papers have shown that the length of growing season is a sensitive indicator of climate change. Many studies have reported an extended growing season (Linderholm et al., 2008; Christidis et al., 2007), mainly related with a earlier onset of spring (Christidis et al., 2007). So Menzel (2003) and McCarty (2001) have argued that the global warming had led to the earlier onset of spring. However, other studies found strong connections between variability of spring onset (SO) and large-scale atmospheric circulation, especially the North Atlantic Oscillation (NAO), suggesting an alternative explanation for the change of SO; (Linderholm et al., 2008). Most of these studies used a limited number of years, with time series started around the 1950s. These time series have shown that the most pronounced changes in SO occurred in the last 30 years of the 20th century, when the NAO reached a strong positive phase (Gámiz-Fortis et al. 2002). The limitation of the data length had left shadow on the causes of the earlier onset of recent spring.

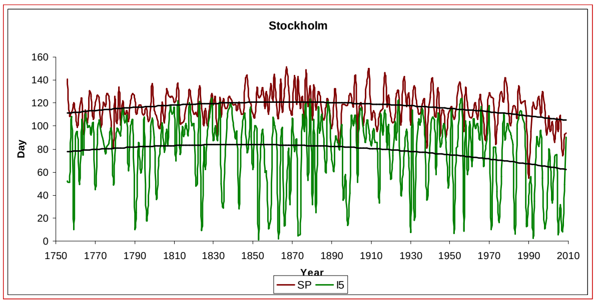
In this work, we follow the suggestion of Qian et al. (2009) about the inappropriate use of linear methods over the whole records of data to study long variations. Alternatively to the method proposed by Qian to study the long term changes of the Stockholm spring onset data, we use Singular Spectral Analysis in order to detect oscillatory behaviour in spring onset indices of three locations in the Northern Europe with long records of daily minimum temperature series.

2. DATA

Data have been obtained from ECA database (http://eca.knmi.nl/), and consist of daily minimum temperature series of three stations placed to the North of Europe: Stockholm, with data spanding from 1756 to 2009; Potsdam, from 1876 to 2009; and Schwerim, from 1890 to 2009. These stations have been selected because they have very long homgeneus daily records.

There is not a unique way for the definition of spring onset. Some definitions come from phenological studies. From the climatological point of view, most definitions are based in passing the 5ºC treshold during some consecutive days. In this paper, the spring onset, SP index, has been defined as the last day of at least 5 consecutive days with Tmin>5ºC.

In this work, it has been also examined an index, I5 based on the first day with Tmin> 5ºC. Figure 1 shows both indices for the stations of Stockolm and Potsdam, along with a polynomial fitting. It can be observed that both indices show similar long trends, particularly for the Stockholm station.



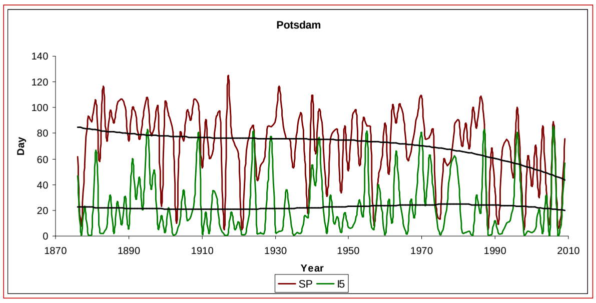


Figure 1. SP and I5 indices for Stockholm and Postdam stations, along with its polynomial fitting, representing the long trend behaviour.

The Potsdam and Schwerim series are very similar, showing the general decreasing trend of the SP since the beginning of the records, and more pronounced decrease since 1970s.

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3. METHODOLOGY

Singular Spectral Analysis (SSA) is a powerful form of the Principal Component Analysis (PCA) of the lag correlation structure of a time series (*Vautard* et al., 1992), which is particularly successful in isolating multiple period components with fluctuating amplitudes and trends in short and noisy series. A comprehensive review, explaining in detail the mathematical foundations of SSA, can be found in Vautard et al. (1992) and Plaut et al. (1995).

SSA consists of the diagonalization of the lagged-autocovariance matrix of a time series. As in the PCA, the eigenvectors or Empirical Orthogonal Functions (EOFs) represent patterns of temporal behaviour, and the Principal Component series (PCs) are characteristic time series. The order election of the lagged-covariance matrix M (window length or embedding dimension) represents a trade-off between significant information and statistical confidence. A common recommendation is to choose $M \approx N/4$, N being the length of the data (Vautard and Ghil*,* 1989). Given M as the dimension of the lagged-covariance matrix, the PCs have length N-M+1. An individual PC contains a very limited number of harmonic components. The detailed reconstruction of a set of significant components, called SSA-filtered components (RCs), of the time series is carried out by an optimal linear square fitting between the corresponding PCs and the original data. A RC represents the contribution of its associated EOF to the variance of the time series; the RCs are additive and their sum provides the original time series. When two eigenvalues of the lagged-covariance matrix are nearly equal and their corresponding eigenvectors are orthogonal, they represent an oscillation. So, SSA extracts and reconstructs periodic components from noisy time series. To determine the corresponding frequencies requires, however, estimations of power spectra. The Maximum Entropy Method (MEM) is used to evaluate the spectral contents of the PC time series corresponding to the EOFs. The MEM consists of fitting an autoregressive model to the time series and then obtaining its associated spectrum. This method has the advantage of having a high spectral resolution, allowing to study and detect possible oscillatory modes in the data.

Special care must be taken in the study of the significance of the results. We study the statistical significance of the SSA results using a Monte-Carlo method, following the indications of Allen and Smith (1996). Monte Carlo SSA (MC-SSA) can be used to establish whether a given time series is linearly distinguishable from any well-defined process, including the output of a deterministic chaotic system, but usually it focuses on testing against the linear stochastic processes which are normally considered as "noise". "Red noise" is often used to refer to any linear stochastic process in which power declines monotonically with increasing frequency, and it is the more common model of noise in climatic studies, being characterized by a first-order autoregressive process, or AR(1). Allen and Smith (1996) provide a comprehensive review of this technique. The MC-SSA algorithm is adapted to eliminate *known* periodic components and test the residual against noise. This adaptation provides sharper insight into the dynamics captured by the data, since known periodicities (like orbital forcing on the quaternary time scale or seasonal forcing on the intraseasonal-to-interannual one) often generate much of the variance at the lower frequencies manifest in a time series and alter the rest of the spectrum.

4. RESULTS

The algorithm used to compute the lagged-autocovariance matrices has been the developed one by Broomhead-King (1986), with M ~ 40 years in all the cases.

For Stockholm station, SP and I5 indices show the same significant oscillatory modes at 97.5 % confidence level. These modes are associated with periods around 8.4, 5.95 and 4.4 years, along with a long trend term (Figure 2). The explained variance of these components is similar for both series, around 42%.

The RC series seem to reproduce better the series since 1864, when a decreasing trend in SO with a value around 8.3 days/century, is found. The last 40 years are characterized by a strong tendency to advance the beginning of spring, with a value close to 3 days/decade.

For Potsdam and Schwerim stations, both indices show similar behaviour. The significant oscillatory modes are associated with periods around 16, 8.4, 5.9, 4.4 and 2.4 years. The variance explained for these modes is around 45%. For SP series, the most relevant oscillation is of 4.4 years, meanwhile for I5 series is 8.4 years. No significant long trends are found for these series, although there is a decrease of the amplitude and mean value of the 4.4 year oscillation since 1970s, coinciding with the period of strong decrease of SO in Stockholm.

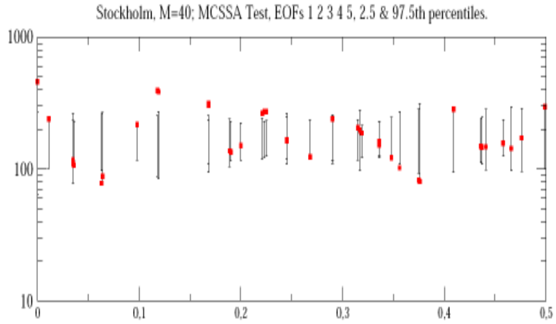

Figure 2. Eigenvalues of the MC-SSA for the SP index series of Stockholm against the null hypothesis of SP series index consists of oscillations of 8.4, 5.9, 4.4 years and long-term trend plus AR(1) noise.

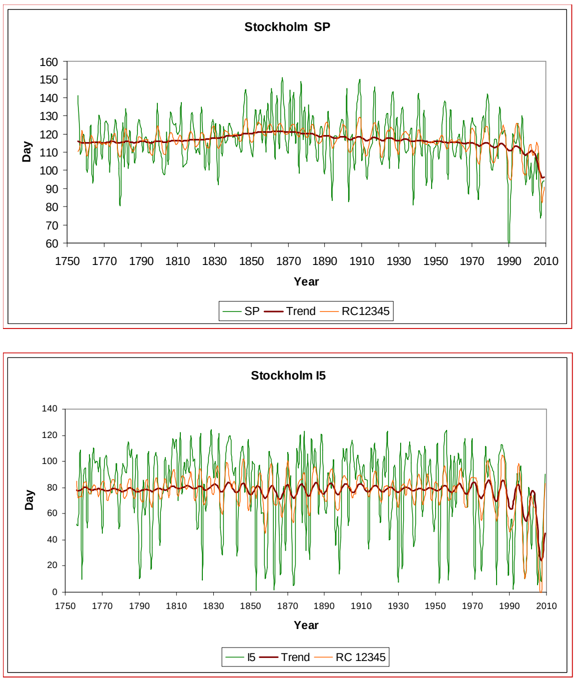

Figure 3. SP (up) and I5 series (bottom) along with the RC components obtained from the significant oscillations.

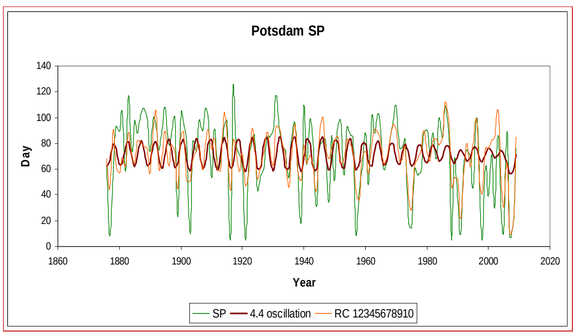

Figure 4. SP series for Potsdam along with the RC components obtained from the significant oscillations and the particular oscillatory mode around 4.4 years.

5. CONCLUSIONS

Our conclusions are similar to those obtained by Qian et al. (2009) for Stockholm, although differ on the date of changing point in the sign of secular trends and in the magnitude of these. Qian et al. (2009) found a clear turning point of secular trend in spring onset at Stockholm around 1884/1885, from delaying to advancing. The delaying trend of spring onset (6.9 days/century) during 1757–1884 and the advancing one (-7 days/century) during 1885–1999 were both significant. We found that the date of this change is around 20 years before, 1864. Previous this year, SO showed an increasing trend of 6.0 days/century, while from 1864 to 2009, there is a decreasing trend of 8.3 days/century, maybe related with the strong decreasing of the last 15 years. In addition to this long trend variability, the SO and I5 index for Stockholm show significant oscillations at frequencies around 8.4, 5.9 and 4.4 years. For Potsdam and Schwerin stations, the variability of the SP is dominated by oscillatory modes, around 16, 8.4, 5.9 4.4 and 2.4 years, but not significant long term trends are found..

The similar behaviour found for SP and I5 indices suggests that changes in the onset spring could be produced by the same mechanism that drives the winter temperature. It is well known that NAO index is significantly correlated with temperature of Northern Europe (Pozo-Vázquez et al., 2001), and some studies have found that phenological and climatic SO are connected to the NAO, especially during the second half of 20th century. However, Qian et al. (2009) found that such connection is robust at inter-annual timescale only for some decades.

Gámiz-Fortis et al. (2002) found that the variability of the NAO index can be represented by a non-linear trend which contains variability at periods of 63 and 100 years, amplitude-modulated oscillations with associated periods around 7.7, 4.8, between 2.3 and 2.4 years and a red noise process. These oscillatory modes could be related with the 8.4, 4.4 and 2.4 years oscillations found in these work. It is interesting to note that, as for the 7.7 year oscillation of the NAO index, the 8.4 year oscillation in the SP and I5 indices studied is more intense during the last 40 years of the record. On the other hand, the opposite is true for the oscillations with period close to 4.4 years. For the NAO index, the 4.8 year oscillation shows a increasing amplitude since 1970, but the opposite is true for the oscillations with periods close to 4.4 years in the SP and I5 indices. So, this relationship between the oscillatory modes of NAO and spring onset indices can explain partially the results of Qian et al. (2009), who argued that it is needed further studies to separate the effects of NAO change and of global warming due to that the significant warming of the spring temperature might be a signal of anthropogenic climate forcing in the last century (Moberg and Bergström, 1997).

6. ACKNOWLEDGMENTS

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