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Analysis

Coupled Climate-Economic Modes in the Sahel's Interannual Variability

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ABSTRACT

We study the influence of interannual climate variability on the economy of several countries in the Sahel region. In the agricultural sector, we are able to identify coupled climate-economic modes that are statistically significant on interannual time scales. In particular, precipitation is a key climatic factor for agriculture in this semi-arid region. Locality and diversity characterize the Sahel's climatic and economic system, with the coupled climate-economic patterns exhibiting substantial differences from country to country. Large-scale atmospheric patterns — like the El Niño–Southern Oscillation and its quasi-biennial and quasi-quadrennial oscillatory modes — have quite limited influence on the economies, while more location-specific rainfall patterns play an important role.

1. Introduction

The study of climate impacts on the economy is a crucial part of assessing the stakes of ongoing global climate change. Thus, Stern (2016) called climate scientists for a closer collaboration with economists to design better models and impact assessment methods. This endeavor, though, requires one to better understand the interactions between two complex chaotic systems: the climatic and the economic one. To cope with this problem, common approaches circumvent the very difficult task of describing the internal dynamics of either system, as well as the nonlinear interactions between the two. Typically, they do so either by formulating damage functions that have little empirical basis or by applying crude regressions to historical time series.

The present work explores an alternative way based on advanced spectral decomposition methods. We focus here on the identification of endogenous dynamics in both the climatic and economic system, and the detection of coupled climate-economic behavior on interannual time scales.

To identify patterns of spatio-temporal behavior in complex datasets, we rely on multichannel singular spectrum analysis (M-SSA), which provides an efficient tool to detect and reconstruct oscillatory modes from short and noisy time series; see Ghil et al. (2002) and Alessio (2016, chapter 12) for a comprehensive overview of the methodology and of related spectral methods.

M-SSA is based on classical Karhunen (1946)-Loève (1945) theory and was introduced into the analysis of nonlinear dynamical systems by Broomhead and King (1986a,b). The methodology has found since countless applications in the geosciences (e.g., Vautard and Ghil, 1989; Ghil and Vautard, 1991) and beyond. More recently, M-SSA has been applied to study the dynamics of macroeconomic activity in the US (Groth et al., 2015) and the synchronization of business cycles, first in a set of three European countries (Sella et al., 2016) and then in more than 100 countries around the world (Groth and Ghil, 2017).

We combine here the climatic and economic system in a cross-panel M-SSA analysis to study coupled climate-economic behavior in the Sahel region. It turns out that, in this setting, M-SSA greatly helps identifying signals of interannual climate variability in the economic time series.

The Sahel's climate is very erratic and repeatedly suffered from severe droughts (Nicholson, 2013); it remains unclear whether the series of droughts has stopped now or not (Masih et al., 2014). Precipitation variability is a key climatic factor for agriculture in semi-arid regions, and thus climate change entails increased risk in such regions (Dilley, 1997). This issue, combined with the high demographic and economic stress on the region, makes it highly vulnerable and hence even more critical to investigate.

Thus, in addition to confirming the cyclic nature of climate and the economy, the paper's aim is to *determine whether climatic oscillations manifest themselves in macro-economic time series from the Sahel region*. To achieve this aim, we apply M-SSA to a dataset aggregating economic and climatic time series from the region. To the best of our knowledge, such an approach has not been tried yet in the ecological economics

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literature, and the present paper should be read as a proof of concept.

The paper is organized as follows. In Section 2, we give a brief introduction to the M-SSA methodology and present a novel statistical significance test that is tailored to this paper's specific problems. Details about the dataset and the framework of the study are given in Section 3, while general characteristics of the time series are briefly presented in Section 4. In Section 5, we discuss the spectral properties of the combined, climatic-and-and economic dataset, while coupled climate-economic behavior is analyzed in Section 6. The results are discussed in Section 7, and the paper concludes with a summary in Section 8.

2. Methodology

In Section 2.1, we briefly describe the main steps of the M-SSA methodology, while in Section 2.2, the methodology for statistical-significance testing is introduced.

2.1. M-SSA

The main aspects of M-SSA are summarized here, and the reader can refer to Ghil et al. (2002) and Alessio (2016, chapter 12) for further details. A helpful illustration of the main mathematical aspects can be found in Groth and Ghil (2017).

The algorithm involves four main steps: (1) embedding, (2) decomposition, (3) rotation, and (4) reconstruction; these steps are outlined in the following.

2.1.1. Embedding

Consider a multivariate time series $\{x_d(n){:}n = 1\ldots N; d = 1\ldots D\}$, with D channels of length N; the first step of M-SSA is to embed each channel into an M-dimensional space, where M, the window length, is a parameter. The *trajectory matrix* is thus generated by taking successive M-lagged copies from the original series

$$\mathbf{X}_d = \begin{pmatrix} x_d(1) & x_d(2) & \cdots & x_d(M) \\ x_d(2) & x_d(3) & \cdots & x_d(M+1) \\ \vdots & & & \vdots \\ x_d(N-M+1) & \cdots & & x_d(N) \end{pmatrix} \tag{1}$$

Hence each trajectory matrix $\mathbf{X}_d$ is composed of M columns of reduced length $N' = N - M + 1$. The *augmented trajectory matrix* is then formed by concatenating all D channels,

$$\mathbf{X} = [\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_D]. \tag{2}$$

2.1.2. Decomposition

M-SSA then proceeds by performing a Singular Value Decomposition (SVD) of the augmented trajectory matrix,

$$\mathbf{X} = \eta^{1/2}\mathbf{P}\boldsymbol{\Sigma}\mathbf{E}', \tag{3}$$

where $(\cdot)'$ denotes the transpose of the argument and the normalization factor η equals $\max\{N', DM\}$. The decomposition yields a set of κ nonvanishing singular values $\{s_1, \ldots, s_\kappa\}$, arranged in descending order along the main diagonal of matrix $\boldsymbol{\Sigma}$, with $\kappa = \min\{N', DM\}$ being the rank of $\mathbf{X}$. The matrix $\mathbf{P}$ of left-singular vectors has size $N' \times \kappa$ and provides a set of κ temporal EOFs (T-EOFs). These T-EOFs of reduced length N' reflect the corresponding behavior of an oscillation.

The matrix $\mathbf{E}$ of right-singular vectors has size $DM \times \kappa$ and provides a set of space-time empirical orthogonal functions (ST-EOFs), arranged as κ columns of length DM; it is composed of D consecutive segments $\mathbf{E}_d$ of size $M \times \kappa$,

$$\mathbf{E}' = [\mathbf{E}_1', \mathbf{E}_2' \ldots \mathbf{E}_D'], \tag{4}$$

each of which is associated with a channel $\mathbf{X}_d$ in $\mathbf{X}$.

Combining Eqs. (2)–(4), we can easily reformulate Eq. (3) into a channel-wise notation,

$$\mathbf{X}_d = \eta^{1/2}\mathbf{P}\boldsymbol{\Sigma}\mathbf{E}_d'. \tag{5}$$

A helpful discussion and illustration of these mathematical properties can be found in Groth and Ghil (2017, Sec. III and Fig. 1).

2.1.3. Rotation

To better separate distinct oscillations, we rely here on a modified varimax rotation of the ST-EOFs, cf. Groth and Ghil (2011) and Portes and Aguirre (2016).

2.1.4. Reconstruction

The dynamical behavior of $\mathbf{X}$ associated with a subset $\mathscr{K} \subseteq \{1, \ldots, \kappa\}$ of ST-EOFs can be obtained from Eq. (3) by

$$\mathbf{R}_{\mathscr{K}} = \eta^{1/2}\mathbf{P}\boldsymbol{\Sigma}\mathbf{K}\mathbf{E}'; \tag{6}$$

here $\mathbf{K}$ is a diagonal matrix of size $\kappa \times \kappa$, with the k-th diagonal element equal to one if $k \in \mathscr{K}$ and zero otherwise. Averaging along the skew diagonals of $\mathbf{R}_{\mathscr{K}}$, i.e., over elements that correspond in Eq. (1) to the same instant in time, finally yields the reconstructed components (RCs).

2.1.5. Participation Index

The squares s_k^2 of the singular values equal the eigenvalue λ_k and quantify the variance in $\mathbf{X}$ that is captured by the corresponding EOF, i.e. the k-th column in $\mathbf{E}$. The contribution of channel d to this variance can be measured by the *participation index*,

$$\pi_{dk} = s_k^2 \sum_{m=1}^{M} e_{dk}^2(m), \tag{7}$$

where the sum ranges over all the elements of the k-th column in $\mathbf{E}_d$. Since the singular vectors have norm one, we get

$$\sum_{d=1}^{D} \pi_{dk} = s_k^2, \tag{8}$$

i.e. the sum of all D participation indices for a given EOF k yields the corresponding variance λ_k (Groth and Ghil, 2011).

2.1.6. Remark

We have followed here the original trajectory-matrix approach of Broomhead and King (1986a,b), which relies on an SVD of $\mathbf{X}$ in Eq. (3). Alternatively, one could obtain $\mathbf{E}$ from the eigendecomposition of the covariance matrix $\eta^{-1}\mathbf{X}'\mathbf{X} = \mathbf{E}\,\boldsymbol{\Lambda}\,\mathbf{E}'$ (Vautard and Ghil, 1989), with the eigenvalues $\boldsymbol{\Lambda} = \boldsymbol{\Sigma}^2$. However, in the case of a rank-deficient covariance matrix, i.e. $DM > N'$, it is more efficient to calculate the eigendecomposition from a reduced covariance matrix, $\eta^{-1}\mathbf{X}\,\mathbf{X}' = \mathbf{P}\,\boldsymbol{\Lambda}\,\mathbf{P}'$ (Allen and Robertson, 1996). Irrespective of the chosen algorithm, all approaches yield the same nonvanishing eigenelements (Groth and Ghil, 2015), and we use the two terms, singular values and eigenvalues, interchangeably here.

2.1.7. Oscillatory Modes

M-SSA provides a decomposition of the dataset into distinct spectral components. The EOFs, though not purely sinusoidal, tend to have a dominant frequency that can be determined via their Fourier transform (Vautard and Ghil, 1989). It is, therefore, common practice to plot the eigenvalues against their corresponding dominant frequencies to obtain an estimate of a time series' spectral decomposition; as initially suggested by Allen and Smith (1996), doing so is more informative than the still widespread practice of providing the “scree diagram” of eigenvalues against their rank.

Like the sine-cosine pairs in a Fourier analysis, the EOFs tend to pair up into oscillatory pairs (Vautard and Ghil, 1989). The two EOFs in such a pair are in phase quadrature and they capture the symmetric and antisymmetric parts of the oscillation: hence, they also have nearly equal dominant frequencies and variance levels.

The varimax rotation introduced by Groth and Ghil (2011) greatly